# Status Update Scheduling in Remote Sensing Under Variable Activation Delay

Leonardo Badia
Dept. of Information Engineering (DEI)
University of Padova, Italy
email: leonardo.badia@unipd.it

Andrea Munari
Institute of Communications and Navigation
German Aerospace Center (DLR), Weßling, Germany
email: andrea.munari@dlr.de

***Abstract*—Sensor data exchanges in IoT applications can experience a variable delay due to changes in the communication environment and sharing of processing capabilities. This variability can impact the performance and effectiveness of the systems being controlled, and is especially reflected on age of information (AoI), a performance metric that quantifies the freshness of updates in remote sensing. In this paper, we discuss the quantitative impact of a variable activation delay on AoI. We consider an offline scheduling over a finite horizon, and we show the main role of the first and second order moments of the activation delay. Our analysis gives a quantitative boundary on when such term can be neglected and also prompts possible further investigations that can be used to mitigate the increase of AoI and improve the overall performance.**

***Index Terms*—Age of information; Delay effects; Optimal scheduling; Single machine scheduling.**

## I. Introduction

Age of information (AoI) is a performance metric that is recently enjoying great popularity especially in remote sensing scenarios [1]–[4]. It refers to the difference between the present time and the generation instant of the most recently received packet and represents the freshness of the data available at the final endpoint. As such, it is an important metric for evaluating the real-time performance of sensor networks, especially for ambient monitoring, surveillance, and automation in Industry 4.0 or smart living environments, where the timely and accurate detection of events is crucial [5], [6].

Generally, most AoI evaluations [1] assume a negligible delay between the request of a status update and its activation. This approach also addresses situations in which such delay is non-negligible but constant, as the resulting AoI at the receiver's side is simply biased by a constant offset. Conversely, if this delay is *variable*, it may make sense to include it and evaluate its overall impact [7], [8].

The reasons why the delay may be variable to the point of significantly impacting the AoI may be different, being related to the acquisition technology or the transmission chain process. For example, smart living environments use a variety of transducers such as motion, light, or sound, to detect the presence of occupants and trigger various actions, e.g., turning on lighting or raising alarms [9]. Depending on the sensitivity of the sensor and the distance of the object, the delay for this detection can be variable and therefore impact the performance of the systems controlled by the sensor. At the same time, other sensors may be used for closed loop control, such as regulating temperature or humidity in a room, by activating HVAC systems. In this case, the delay between the ambient parameters changing and the sensor detecting their variation also depends on the effectiveness of the control systems adopted [10].

Moreover, in sensor networks, it is common for nodes to be responsible of multiple tasks or functions in addition to responding to requests. This resource sharing can lead to delays in response times, as the sensor may be busy processing other tasks when a request is received. It is worth noting that properly prioritizing tasks and adopt a fair resource sharing is often made complex by the required overhead in practical scenarios, and very often selfish (i.e., not fully efficient) approaches are adopted [11]. Thus, the global delay may be variable because of queueing or congestion delay at the sensor's buffer, depending on the queueing discipline and whether there are multiple users accessing the same link [12]–[14].

Moreover, there may be additional delay components such as processing delays, for example if the received data must be interpreted or extrapolated from multiple sources, or retransmission delays, depending on specific mechanism for error recovery after data packet losses due to noise or interference, such as automatic repeat request (ARQ) [15], [16]. Finally, additional compound delays for multi-hop networks, where the request must be forwarded through multiple nodes before reaching its destination [17], [18].

For the purpose of quantitatively evaluating the impact of delay variability on AoI, we consider in this paper the problem of a finite-horizon offline scheduling of a fixed number of transmissions [19], where the time of departure for a fresh status update may be subject to an extra non-negative activation delay. We show how, due to AoI computations, the relevant terms impacting on the AoI evaluation are the first and second order moment of the random quantity [2], [18].

The work of L. Badia was supported by the RESTART Program, financed by the Italian government with the resources of the PNRR – Mission 4, Component 2, Investment 1.3, theme 14 "Telecommunications of the future."
A. Munari acknowledges the support of the Federal Ministry of Education and Research of Germany in the programme of "Souverän. Digital. Vernetzt." Joint project 6G-RIC, project identification number: 16KISK022.

Our study reveals that a variable activation delay can impact the AoI performance and, as a consequence, the effectiveness of the systems being controlled [20]. As a matter of fact, the increase of AoI is generally limited. Still, this variability may be undesirable and can be mitigated through techniques such as adaptive control or machine learning [21]–[23], in the effort of achieving an overall improved performance of the remote sensing system.

The rest of this paper is organized as follows. Section II discusses related work. Section III presents the analysis and gives a formula for the expected AoI under a variable delay in the case of stateless optimization. Section IV presents some quantitative results and, finally, we conclude the paper in Section V.

## II. Related Work

When evaluating the impact of delay, it is common to treat some terms as constant for the sake of simplicity, especially if they relate to non controllable aspects of the transmission pattern [1], [24]. Thus, it makes sense that delay terms are neglected in AoI evaluation if they just correspond to a constant bias in the evaluations. Moreover, many AoI evaluations related to the approach presented here exploit geometric reasonings on the saw-tooth pattern of the AoI increase over time [5], [19], [25], where the introduction of a constant delay would just rescale the involved areas. This is still the case even if more refined approaches are considered, such as dynamic programming or constrained optimization [26], [27].

However, some existing papers explore the connection between non-trivial cases for the delay and the resulting AoI. For example, [14] studies the relationship between delay, albeit meant as a performance indicator and not an input value, and AoI. This reference is similar to our approach as it considers a single agent scheduling with an optimal pattern for transmission of updates, although the main considerations are based on a general queueing model for AoI, which is a classic parallel line of research [5], [13]. On the same line, [27] considers an analogous problem, tracking more AoI related statistics (e.g., peak, outage) and a joint optimization of AoI and delay.

Conversely, [12] explores the role of a delay externality on the resulting peak AoI, i.e., of the delay elapsed between sending the request and receiving the update. In our case, transmissions are planned beforehand, and we see the delay as involved in the *generation* of the update itself, which is always generated as fresh but postponed from the desired schedule. However, the computations are analogous. Another difference between [12] and the present work is that the authors of the former consider a queueing processor for computing the AoI, and discuss the role of packet preemption and the related online scheduling, whereas the updates we consider are instantaneous, and we quantify the increase in AoI for an offline scheduling where a simpler optimization is performed beforehand.

Another related study was performed in [18], where a multi-hop network is considered, each hop adding independent and identically distributed (i.i.d.) delays, and evaluating the AoI. In that case, the analysis corresponds more to that of a propagation delay, rather than an activation, and also the issue of scheduling of updates in advance is not considered, rather, there is a dynamic forwarding of data with proper policies to keep the AoI contained.

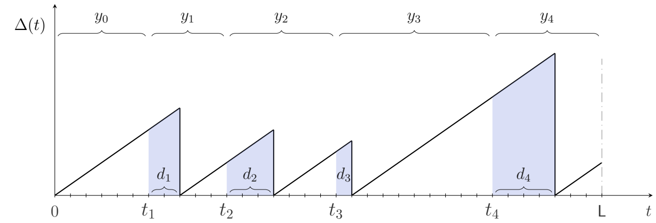


Fig. 1. Example of growth pattern of AoI, considering 4 transmissions over a finite time horizon of duration L. In the diagram, the terms $d_i$ represent the realizations of the random activation delays $D_i$ affecting the corresponding updates.

In this same spirit, [25] considers a non-negligible propagation delay in a queueing analysis for AoI. In that analysis, a geometric approach akin to what used here is employed, as originally proposed by [2] and further exploited in many papers [19]. In [7], an aerial link with non negligible propagation delay is considered, so as to discuss the impact of ARQ on AoI, showing a threshold criterion for the delay term beyond which retransmission is no longer convenient, similar to what also explored in [16]. In [21], an optimal controller is developed for an *online* scheduler in the presence of random two-way delay. Such an approach stands out as a possible solution for the problems identified in the present paper. Finally, [28] considers the impact of AoI of a variable delay with very general statistics. Even though that paper is similar in motivation to the present one, the development is different as they consider a queueing system and the delay is again meant there to increase the propagation time, not the activation time as we do here. Clearly, these two perspectives can be unified in a future investigation.

## III. Analytical Framework

We consider a sensor node sending $M$ status updates to a receiver during a finite horizon of duration L. Transmissions are scheduled at instants $t_1, t_2, \ldots, t_M$. The instantaneous AoI $\delta(t)$ is defined as the difference between the current time $t$ and the last instant of reception of an update $u(t)$, i.e.,

$$\delta(t) = t - u(t) \tag{1}$$

since we consider fresh updates to be generated at will [10], [12], [29], and every transmission by the sensor resets the AoI to 0 upon its reception.[1]

[1] We remark that we assume that the updates reset the AoI value to 0, since we consider a continuous time axis [19], [30]. In some similar investigations, especially when the time domain is discrete, a lowest AoI value of 1 is considered instead [2].

Reception of the update is subject to a random activation delay $D \geq 0$. Accordingly, if an update is scheduled at time $t$, it actually takes place at time $t + D$. This results in the AoI trend displayed in Fig. 1. Updates scheduled at times $t_1, t_2, \ldots$ are subject to respective activation delays $D_1, D_2, \ldots$ that are i.i.d.. We denote their pdf as $f_D(d)$.

In our study, we will focus in particular on the average AoI

$$\Delta = \mathbb{E}\left[\frac{1}{\mathsf{L}}\int_0^{\mathsf{L}} \delta(t)\, dt\right] \tag{2}$$

where the expectation is taken over the r.v.s $D_i$, $i \in \{1, \ldots, M\}$. Note that $\Delta$ is function of the chosen transmission times, i.e., of the schedule.

Note that we consider an offline schedule over a continuous time axis for the transmission of updates over a finite time horizon [19]. The motivation for this choice lies in that most sensing applications perform their monitoring tasks over a finite time span, over which they are allowed to send a limited number of status updates for their measurements, mostly due to hardware limitations, finite battery capacity, or even normative reasons [4].

In view of this, we consider a stateless optimization of the transmission pattern, i.e., the schedule is computed in advance, prior to the start of the monitoring task, and cannot be modified online, e.g., accounting for the experienced delays. While this choice might seem restrictive, it may be practical in many settings, where handling the online schedule adaptation is not feasible for low-complexity and battery-powered IoT devices. Moreover, the intent of this paper is to give a quantification of the impact of the activation delay, which would apply in both stateful and stateless optimization [30]. Thus, our findings can be translated to the aforementioned related approaches considering an online scheduler [12], [21], [25], [26].

Without loss of generality, the length of the horizon $\mathsf{L}$ is taken as a unit of time. In other words, we set $\mathsf{L} = 1$ since this will allow us to reason in normalized terms; this means that both delay and AoI are to be meant as a fraction of $\mathsf{L}$.

### A. Periodic update neglecting the delay

If the activation delay is not present, i.e., for the case of $D = 0$, it is immediate to see how the updates ought to follow a regular pattern, where each of them is performed every integer multiple of $Q = 1/(M+1)$.

If we assume that such a periodic pattern is used even in the presence of the activation delay, we can obtain the resulting AoI through geometric considerations over the sawtooth diagram shown in Fig. 1. In particular, the expected AoI can be computed as the normalized sum of the areas of the $M+1$ right isosceles triangles in the AoI pattern [2], [10], [18], whose indices are taken as $0, 1, \ldots, M$ (i.e., the first triangle is denoted as the 0th), and the side of the $j$th triangle is

$$\begin{cases} Q + D_1 & \text{for } j{=}0 \\ Q + D_j - D_{j-1} & \text{for } 1 \leq j < M \\ Q - D_M & \text{for } j = M \end{cases} . \tag{3}$$

Thus, the average AoI is promptly computed as

$$\Delta = \frac{1}{2}\mathbb{E}\Big[(Q{+}D_1)^2 + \sum_{j=2}^{M}(Q{+}D_j{-}D_{j-1})^2 + (Q{-}D_M)^2\Big] \tag{4}$$

$$= \frac{Q}{2} - (M{-}1)\big(\mathbb{E}[D]\big)^2 + M\mathbb{E}[D^2]$$

due to different delay terms being i.i.d., which leads to $\mathbb{E}[D_j D_k] = \big(\mathbb{E}[D]\big)^2$ whenever $j \neq k$.

### B. Optimal stateless allocation

A better allocation over time of the $M$ updates can be obtained through an optimization, which, according to the discussion above, is implemented within an offline scheduling. Note that the previously derived periodic allocation of one update every $Q$ is optimal if $D = 0$. Otherwise, the optimal stateless scheduling can again be obtained through geometric considerations over the sawtooth pattern increase of AoI.

In the general case, the problem can be stated by first computing the expected AoI as in (4), and by then minimizing it, to obtain

$$\begin{aligned} \min \Delta &= \frac{1}{2}\,\mathbb{E}\Big[\sum_{j=0}^{M}(z_{j+1} - z_j)^2\Big] \\ \text{s.t.} \quad & z_j = \min(t_j + D_j, \mathsf{L})\,. \end{aligned} \tag{5}$$

The analytical computation is in general difficult due to the presence of the minimum that gives a non-linear term. However, if the probability of $D_j$ being larger than $Q$ is negligible, which is sensible since activation delays larger than the gap between the regularly planned updates would severely impact AoI, the analysis becomes tractable, as $\min(t_j + D_j, \mathsf{L}) = t_j + D_j$.

Focusing on this case, as displayed in Fig. 1, it is more convenient to quantify, instead of the transmission instants $t_1, \ldots, t_M$, the $M+1$ inter-transmission intervals $y_0, y_1, \ldots, y_M$, with $y_j = t_{j+1} - t_j$, with $t_0 = 0$ and $t_{M+1} = 1$. The two notations can be easily translated into one another, accounting for the following constraints

$$y_j > 0\,, \text{ for all } j = 0, \ldots, M\,; \qquad \sum_{j=0}^{M} y_j = 1\,. \tag{6}$$

At this point, since the time instants $t_1, \ldots, t_M$ of the updates are delayed by $M$ i.i.d. terms $D_1, \ldots, D_M$, the side of these triangles is $y_0 + D_1$ for the first of them, $y_M - D_M$ for the last one, and $y_j + D_{j+1} - D_j$ for the intermediate ones. The offline scheduling minimizing the expected AoI can be found through solving the following problem, with $D_0 = D_{M+1} = 0$ to simplify the notation

$$\begin{aligned} \min \Delta &= \frac{1}{2}\,\mathbb{E}\Big[\sum_{j=0}^{M}(y_j + D_{j+1} - D_j)^2\Big] \\ \text{s.t.} \quad & (6)\,. \end{aligned} \tag{7}$$

By merging (6) into the objective of (7), we can reformulate the minimizing condition setting the gradient to 0. This actually implies that the first $M$ terms, $y_0, y_1, \ldots, y_{M-1}$ are the solutions of a system of equations, whereas $y_M$ is obtained from (6).

When computing the gradient, it is to be noted that the $y_j$s are deterministic and not subject to any random effect, so they can be taken out of the expectations. Thus, the only random variables are the $D_j$s that appear only in $\mathbb{E}[D]$ terms, and they cancel out in many cases. This leads to the following system of equations

$$y_0 + \sum_{k=0}^{M-1} y_k = 1 - 2\mathbb{E}[D] \tag{8}$$

$$y_j + \sum_{k=0}^{M-1} y_k = 1 - \mathbb{E}[D] \qquad \text{for } j = 1, \ldots, M{-}1$$

with solution

$$y_j = Q \quad \text{for } j = 1, \ldots, M{-}1 \tag{9}$$

$$y_0 = Q - \mathbb{E}[D] \tag{10}$$

$$y_M = Q + \mathbb{E}[D] \,. \tag{11}$$

As a result, the objective function in (5) is obtained as

$$\Delta = \frac{\sum_{j=0}^{M} \mathbb{E}\Big[Q - r_j + r_{j+1}\Big]^2}{2} \tag{12}$$

where $r_0 = r_{M+1} = \mathbb{E}[D]$ and $r_j = D_j$ for $j = 1, \ldots, M$. Plugging in these quantities, a compact expression for the minimum AoI follows:

$$\Delta = \frac{Q}{2} + M\Big(\mathbb{E}[D^2] - \big(\mathbb{E}[D]\big)^2\Big) \tag{13}$$

$$= \frac{Q}{2} + M\sigma_D^2 \,, \tag{14}$$

where $\sigma_D^2$ is, by definition, the variance of $D$.

## IV. Numerical Results

We show some numerical evaluations of the optimal AoI from (14), for different choices of the statistics of $D$ as well as the number $M$ of transmissions updates available. We notice that increasing the number of transmissions is expected to lower AoI in general, but if these updates are delayed, this noisy effect can cumulate and actually lead to an increase of AoI if the variability of the noise terms is high.

We consider two cases, i.e., with $M{=}4$ and $M{=}5$ updates in the time horizon, which are reasonable choices over a short time span for a sensor with limited capabilities [6]. Moreover, we analyze two different distributions for $f_D(d)$, namely:

- a uniform distribution between 0 and $D_{\max}$,where $D_{\max} = 2\mathbb{E}[D]$, i.e.

$$f_D(d) = \begin{cases} \dfrac{1}{2\mathbb{E}[D]} & \text{for } 0 \leq d \leq 2\mathbb{E}[D] \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

  for which, as is well known, $\mathbb{E}[D^2] = \frac{4}{3}\mathbb{E}[D]^2$.

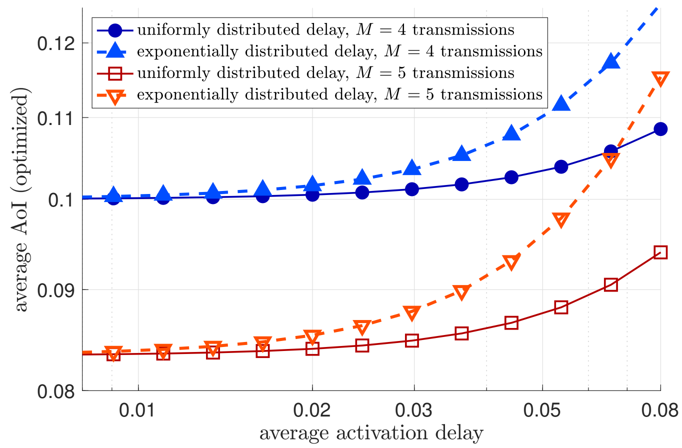


Fig. 2. Normalized expected average AoI.

- an exponential distribution with mean $\mathbb{E}[D]$, i.e.

$$f_D(d) = \begin{cases} \dfrac{\exp(-d/\mathbb{E}[D])}{\mathbb{E}[D]} & \text{for } d \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

  where $\mathbb{E}[D^2] = 2\mathbb{E}[D]^2$.

We take $\mathbb{E}[D]$ going from 0 to 8% of the whole horizon, the latter corresponding to an extremely high variability of the scheduled time instants. We remark that, with choice of parameters, the uniformly distributed random delay never exceeds the finite horizon boundaries, since the lowest average distance between transmission instants is $Q = 0.167$ for the case of $M{=}5$ scheduled transmissions, and the highest possible activation delay is $2\mathbb{E}[D] = 0.16$, which barely fits the pattern between updates and still avoids pushing the last update beyond the end of the horizon, which is a requirement of our analysis.

Conversely, the exponentially distributed random delay can cause the scheduled update to fall after the end of the horizon, but has a negligible probability of doing so. The highest probability of $D$ exceeding L, for the highest considered value of $\mathbb{E}[D]$, is below 5%. This confirms the validity of the previously presented analysis up to a reasonable numerical confidence.

Fig. 2 shows the expected average AoI as a function of the average activation delay. We see that the exponential distribution, which corresponds to a higher variability with respect to the uniform distribution with the same average, causes a slightly higher AoI. Moreover, performing fewer updates naturally causes a higher AoI value, so the curves for $M{=}4$ updates are lower than those for $M{=}5$. When there is no delay, the AoI is, as expected, $[2(M+1)]^{-1}$. As the average activation delay increases, this gap progressively reduces, which is especially true for the exponentially distributed activation delay. This happens because more variable delays cumulate over the time horizon, and ultimately the curve for exponentially distributed activation delay and $M{=}5$, compared to those for $M{=}4$, overtakes those for uniform distribution

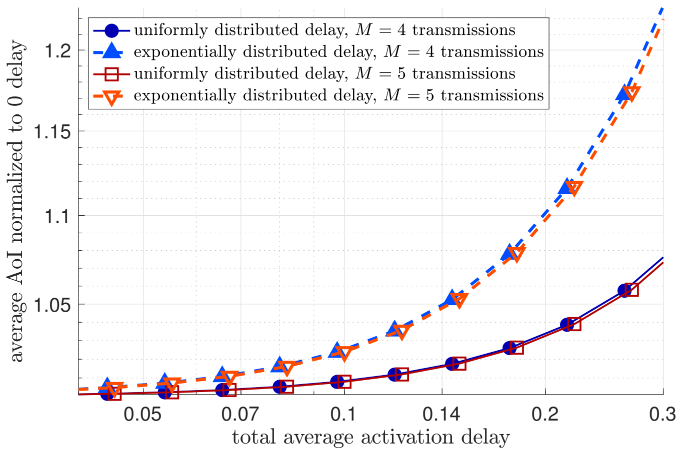


Fig. 3. Ratio between the actual average AoI and the value with zero activation delay vs. total activation delay over the time horizon.

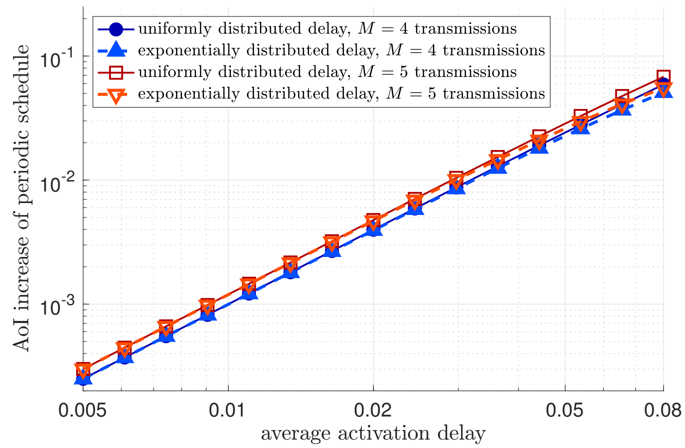


Fig. 4. Average AoI difference between a regular scheduling and the optimal one (with offset), vs. the average delay.

of the activation delay and approaches its counterpart of the exponential distribution.

Fig. 3 displays the multiplicative increase of the expected average AoI with respect to the case of no activation delay. Here, the x-axis displays instead the *total* delay that is experienced in the whole horizon, i.e., $M\mathbb{E}[D]$. From this figure, two conclusions can be drawn. First, if we consider an identical cumulative activation delay induced by the individual terms, the increase in the age of information is basically the same. All that matters is the distribution of the random variable $D$, which is easy to explain by looking at (14), as the only changing terms between the exponential and uniform distribution of the activation delay with the same total is indeed $\mathbb{E}[D^2]$.

Also, the increase of AoI is superlinear in the total average activation delay experienced over all of the transmission opportunities, and, as a result, it stays relatively limited as long as the local delays are small. Numerically speaking, and for these choice of parameters, one can say that if the activation delays are exponentially distributed and their total is $20\%$ of the horizon, an AoI increase by around $10\%$ is experienced; if the total activation delay is lower, or the statistics are more favorable (e.g., the activation delay is uniformly distributed), the increase of AoI is even smaller, so that it may make sense to neglect it.

Conversely, at the opposite end, for total activation delay amounting to $25\%$–$30\%$ of the horizon or more, the AoI soars more rapidly, but we notice that in this case the assumptions for the analysis are weakened and the schedule may actually perform even worse.

Finally, Fig. 4 shows a comparison in terms of AoI increase between the simpler periodic scheduling and the optimal stateless scheduling, discussed in Subsections III-A and III-B, respectively. More precisely, we plot the increase in AoI due to using the suboptimal periodic scheduling of (4) as opposed to (14). Since the optimal stateless scheduling actually boils down to a pseudo-periodic update with a bias of $\mathbb{E}[D]$, the difference is just proportional to this term.

On the one hand, it can be argued that the difference is limited and therefore even a periodic scheduling would suffice to obtain limited AoI, whereas the main problem is actually the value of $\mathbb{E}[D]$ that is an externality. On the other hand, the implementation of the optimal scheduling is also very easy as it just corresponds to a simple offset in the updates, which is therefore reasonable to apply not to cause the increase shown in the figure.

## V. Conclusions and Future Work

We considered an offline scheduling of status updates coming from a remote sensor over a finite time horizon, evaluating the impact of the activation delay in the update request and its actuation. We showed how this noisy effect may lead to an increase in the resulting expected average AoI, which is in line with similar results where erasures and retransmissions are considered [19], [30]. In general, the cost of waiting for new information must be balanced against the cost of taking a suboptimal or uncertain action.

This research can be extended in several interesting ways. We could explore the impact of different types of delay on AoI, both qualitatively and quantitatively, for example considering different statistics and/or multiple delay terms such as sensing, transmission, and queueing delay [24], [28]. All of this would lead to different evaluations of the graphs in Fig. 1 and more complex computations. Also, investigating the relative importance of different types of delay could provide a more comprehensive understanding of the factors that affect the age of information in sensor networks.

Extensions of the implications found in this scenario to more general semantic communications, e.g., involving retransmissions, feedback, or the structural texture of the content such as video and multimedia [20], [31] can be further explored. Alternatively, future research could focus on developing new techniques for minimizing sensing delay and improving AoI in sensor networks, for example, by means of machine learning techniques to predict the delay terms caused by competing tasks [22], and this feature can be integrated in the scheduling algorithms to further optimize them. Another way to improve the AoI, which is particularly suggested in the context of ultra-reliabile low-latency communications, is through data duplication over different connectivities [32].

Overall, the study of the impact of sensing delay on the age of information has the potential to lead to significant advancements in the field of sensor networks and enable the development of more efficient and effective sensing systems.

## REFERENCES


[1] S. Kaul, M. Gruteser, V. Rai, and J. Kenney, "Minimizing age of information in vehicular networks," in *Proc. IEEE SECON*, 2011, pp. 350–358.

[2] S. K. Kaul, R. D. Yates, and M. Gruteser, "Real-time status: How often should one update?" in *Proc. IEEE Infocom*, 2012, pp. 2731–2735.

[3] L. Badia, A. Zanella, and M. Zorzi, "Game theoretic analysis of age of information for slotted ALOHA access with capture," in *Proc. IEEE INFOCOM Wkshps*, 2022.

[4] A. Munari, "Modern random access: an age of information perspective on irregular repetition slotted ALOHA," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 3572–3585, Jun. 2021.

[5] R. D. Yates, Y. Sun, D. R. Brown, S. K. Kaul, E. Modiano, and S. Ulukus, "Age of information: An introduction and survey," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1183–1210, May 2021.

[6] A. Zancanaro, G. Cisotto, and L. Badia, "Modeling value of information in remote sensing from correlated sources," in *Proc. IEEE MedComNet*, 2022, pp. 47–53.

[7] D. Li, S. Wu, J. Jiao, N. Zhang, and Q. Zhang, "Age-oriented transmission protocol design in space-air-ground integrated networks," vol. 21, no. 7, pp. 5573–5585, 2022.

[8] L. Badia, "A Markov analysis of selective repeat ARQ with variable round trip time," *IEEE Commun. Lett.*, vol. 17, no. 11, pp. 2184–2187, 2013.

[9] A. J. Corso, E. Tessarolo, M. Guidolin, E. Della Gaspera, A. Martucci, M. Angiola, A. Donazzan, and M. G. Pelizzo, "Room-temperature optical detection of hydrogen gas using palladium nano-islands," *Int. J. Hydrogen En.*, vol. 43, no. 11, pp. 5783–5792, 2018.

[10] P. Rafiee and O. Ozel, "Active status update packet drop control in an energy harvesting node," in *Proc. IEEE SPAWC*, 2020.

[11] L. Prospero, R. Costa, and L. Badia, "Resource sharing in the Internet of Things and selfish behaviors of the agents," *IEEE Trans. Circuits Syst. II*, vol. 68, no. 12, pp. 3488–3492, Dec. 2021.

[12] J. P. Champati, R. R. Avula, T. J. Oechtering, and J. Gross, "Minimum achievable peak age of information under service preemptions and request delay," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1365–1379, May 2021.

[13] L. Crosara, A. Zancanaro, G. Cisotto, N. Laurenti, and L. Badia, "Analytical evaluation of age of information in networks of correlated sources," in *Proc. IEEE MetroAgriFor*, 2022, pp. 323–328.

[14] R. Talak and E. H. Modiano, "Age-delay tradeoffs in queueing systems," *IEEE Trans. Inf. Theory*, vol. 67, no. 3, pp. 1743–1758, Mar. 2020.

[15] L. Badia, "On the effect of feedback errors in Markov models for SR ARQ packet delays," in *Proc. IEEE Globecom*, 2009.

[16] E. T. Ceran, D. Gündüz, and A. György, "Average age of information with hybrid ARQ under a resource constraint," *IEEE Trans. Wireless Commun.*, vol. 18, no. 3, pp. 1900–1913, Mar. 2019.

[17] L. Badia, M. Miozzo, M. Rossi, and M. Zorzi, "Routing schemes in heterogeneous wireless networks based on access advertisement and backward utilities for QoS support," *IEEE Commun. Mag.*, vol. 45, no. 2, pp. 67–73, 2007.

[18] B. Buyukates, A. Soysal, and S. Ulukus, "Age of information in multihop multicast networks," *J. Commun. Netw.*, vol. 21, no. 3, pp. 256–267, 2019.

[19] A. Munari and L. Badia, "The role of feedback in AoI optimization under limited transmission opportunities," in *Proc. IEEE Globecom*, 2022, pp. 1972–1977.

[20] E. Uysal, O. Kaya, A. Ephremides, J. Gross, M. Codreanu, P. Popovski, M. Assaad, G. Liva, A. Munari, B. Soret *et al.*, "Semantic communications in networked systems: A data significance perspective," *IEEE Netw.*, vol. 36, no. 4, pp. 233–240, 2022.

[21] C.-H. Tsai and C.-C. Wang, "Unifying AoI minimization and remote estimation–optimal sensor/controller coordination with random two-way delay," *IEEE/ACM Trans. Netw.*, vol. 30, no. 1, pp. 229–242, 2022.

[22] A. Zancanaro, G. Cisotto, and L. Badia, "Challenges of the age of information paradigm for metrology in cyberphysical ecosystems," in *Proc. IEEE MetroLivEn*, 2022, pp. 127–131.

[23] E. Recayte, A. Munari, and F. Clazzer, "Grant-free access: Machine learning for detection of short packets," in *Proc. ASMS*, 2020.

[24] L. Badia, "On the impact of correlated arrivals and errors on ARQ delay terms," *IEEE Trans. Commun.*, vol. 57, no. 2, pp. 334–338, Feb. 2009.

[25] Y. Wang, S. Wu, L. Yang, J. Jiao, and Q. Zhang, "To preempt or not: Timely status update in the presence of non-trivial propagation delay," in *Proc. IEEE VTC Fall*, 2020.

[26] H. Lv, Z. Zheng, F. Wu, and G. Chen, "Strategy-proof online mechanisms for weighted AoI minimization in edge computing," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1277–1292, 2021.

[27] J. Cao, X. Zhu, Y. Jiang, Z. Wei, and S. Sun, "Information age-delay correlation and optimization with finite block length," *IEEE Trans. Commun.*, vol. 69, no. 11, pp. 7236–7250, 2021.

[28] H. Tang, Y. Chen, J. Wang, P. Yang, and L. Tassiulas, "Age optimal sampling under unknown delay statistics," *IEEE Trans. Inf. Theory*, vol. 69, no. 2, Feb. 2023.

[29] J. Sun, Z. Jiang, B. Krishnamachari, S. Zhou, and Z. Niu, "Closed-form Whittle's index-enabled random access for timely status update," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1538–1551, Mar. 2019.

[30] A. Javani, M. Zorgui, and Z. Wang, "On the age of information in erasure channels with feedback," in *Proc. IEEE ICC*, 2020.

[31] V. Vadori, A. V. Guglielmi, and L. Badia, "Markov analysis of video transmission based on differential encoded HARQ," in *Proc. IEEE WoWMoM*, 2016.

[32] M. Centenaro, D. Laselva, J. Steiner, K. Pedersen, and P. Mogensen, "System-level study of data duplication enhancements for 5G downlink URLLC," *IEEE Access*, vol. 8, pp. 565–578, 2019.