Status Update Scheduling in Remote Sensing Under Variable Activation and Propagation Delays

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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 work, we discuss the quantitative impact of activation and propagation delays, both taken as random variables, on AoI. In our analysis we consider an offline scheduling over a finite horizon, we derive a closed form solution to evaluate the average AoI, and we validate our results through numerical simulation. We also provide further analysis on which type of delay has more influence on the system, as well as the probability that the system fails to deliver all the scheduled updates due to excessive delays of either kind.

Keywords: Age of Information; Sensor networks; Internet of Things; Data acquisition; Transmission delay; Machine to machine communication.

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1. Introduction

AoI is a performance metric that enjoys recent popularity in remote sensing scenarios [1, 2, 3]. Defined as the difference between the present time and the generation instant of the most recently received packet, it quantifies the freshness of the data available at the final endpoint. As such, AoI is an important metric for evaluating the real-time performance of sensor networks, for ambient monitoring, surveillance, and automation in Industry 4.0 or smart living environments, where timely and accurate awareness of events is crucial [4, 5].

Most AoI evaluations [2] assume a negligible delay between the request of a status update and its activation. This approach also addresses situations in which this delay is non-negligible but constant, as the resulting AoI at the receiver's side is just biased by a constant offset. Conversely, if the delay is *variable*, it makes sense to include it and evaluate its overall impact [6, 7].

The delay may be variable, to the point of significantly impacting AoI. This can happen due to multiple reasons, related to the acquisition technology or the transmission chain process, in which case we will speak of *activation delay*, or *propagation delay*, respectively.

The former kind of delay is typical of smart environments with sensing technology [8]. This variable delay could impact the performance of the real-time system control. At the same time, other sensors may be used for closed loop control, such as regulating temperature or humidity in a room, or water and fertilizer in a smart greenhouse, by activating HVAC systems. In this situation, the delay between the ambient parameters changing and the sensor detecting their variation also depends on the effectiveness of the control systems adopted [9].

Moreover, in sensor networks, it is frequent to utilize the same nodes for multiple functions, so that they partake in many acquisition and transmission chains [10]. This multitasking can lead to delays in response times, as the sensor may be busy processing previously received requests when a new one is received. Properly prioritizing tasks and adopting a fair resource sharing is often made complex by overhead in practical scenarios, and uncoordinated approaches frequently obtain inefficient allocations [11]. Thus, the global delay may be variable because of congestion or queueing delay at the sensor's buffer, depending on the queue discipline and whether multiple users are accessing the same link [12, 13].

Depending on the type of sensors, the technology used, the environmental conditions, and possible multitasking congestions, the activation delay can span several orders of magnitude, from milliseconds to seconds [14].

Propagation delay is usually due to external factors, not directly related to the data acquisition system. A common cause can be weather and atmospheric conditions in aerial links, which can lead to significant fluctuations in AoI as perceived at the receiver's side [15]. Another cause of propagation delay are systems with long delay channels, as, for example, underwater [16] or satellite communications [17], or even terrestrial radio links at high frequencies [18]. Another possible source of propagation delay is the offload of computation to servers in the cloud [19, 20]. This may cause random delays with analogous characterization as the previously mentioned propagation phenomena. Also, even when the transmission time is negligible but the receiving server is congested, the server access discipline can lead to further delays [12, 14, 21]. Lastly, propagation delay can arise in the case of data updates that consist of packets retransmitted over multiple attempts, following an automatic repeat request (ARQ) procedure, as shown in [22].

The extent of propagation delays highly depends on the scenario considered. Single-link propagation with electromagnetic waves (either wireless or wireline) is below the millisecond, but when multi-hop connections are considered and data are sent to remote servers, this can increase up to seconds, with atmospheric conditions and/or retransmissions further affecting it [23]. Finally, extreme scenarios like deep space or underwater acoustic communications can have even slower propagation with delays of minutes or even hours [24].

Activation and propagation delays coexist, and in certain scenarios they can be both significant. For example, satellite imaging clearly suffers from propagation delay introduced by the physical distance but also activation delay depending on the computational weight of the task [15]. Remote sensing processed by cloud servers may instead suffer from an activation delay caused by sensing acquisition in the presence of congestion, whereas uploading data to the cloud may imply a significant propagation delay as well [19]. Depending on the scenario, either type of delay may be more relevant than the other. We also notice that the aforementioned scenarios for extreme communications, where propagation delays are extremely high, are also likely to have low data rates and significant activation delays as well, as they are clearly not constrained by the stringent requirements of ultra-low latency communications.

For the purpose of quantitatively evaluating the impact of both delays variability on AoI, we consider the problem of a finite-horizon offline scheduling of a fixed number of transmissions [25], where the time of departure for a fresh status update may be subject to non-negative activation and propagation delays, denoted as D and T, respectively. We show how, due to AoI computations, the relevant terms impacting the AoI evaluation are the first and second order moment of these random quantities [3, 26]. Our study reveals that both variable activation and variable propagation delays can influence the AoI performance, with the latter being more critical. This variability is undesirable and can be mitigated through techniques such as adaptive control or machine learning [17, 27, 28], in the effort of achieving overall improved performance.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 presents the analysis and computes the expected AoI if the two types of delay are present in the case of stateless optimization. Section 4 presents quantitative results and we conclude the paper in Section 5.

2. Related Work

When assessing 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 [2, 29]. Thus, it makes sense that delay terms are neglected in AoI evaluations if they just correspond to a constant bias.

Moreover, many studies related to the approach presented here exploit geometric arguments on the saw-tooth pattern of the AoI increase over time [4, 25, 30], 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 [20, 31].

Yet, some existing papers explore the connection between non-trivial delay scenarios and the resulting AoI. For example, [14] studies the connection between delay, albeit meant as a performance indicator and not an input value, and AoI. This reference is analogous to our approach as it considers a single agent scheduling with an optimal schedule for transmission of updates, although the main considerations are based on a general queueing model for AoI, which is a classic parallel direction for research [4, 21]. On the same line, [31] focuses on a similar problem, tracking multiple AoI related statistics (e.g., peak, outage) and a joint optimization of AoI and delay.

Conversely, [12] explores the role of an external delay, i.e., elapsed between sending the request and receiving the update, on peak AoI. This might be considered analogous to propagation delay in our study. Unlike our work however, the main focus is on the role of preemption in the queueing policy.

Another related study was performed in [26], where transmission over multiple hops is considered, each adding independent and identically distributed (i.i.d.) delays, and evaluating AoI. In that case, the analysis corresponds more to that of a propagation delay, and the issue of scheduling the updates in advance is not considered; rather, dynamic forwarding of data with proper policies is studied with the objective to keep the AoI contained.

In a similar spirit, [30] studies a non-negligible propagation delay in a queueing-based analysis for AoI. In that analysis, a geometric approach akin to the one considered in the following is employed, as originally proposed by [3] and exploited in other recent studies [25].

In [6], an aerial link with non negligible propagation delay is considered, leading 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 [32]. In [27], an optimal controller is derived for an *online* scheduler in the presence of random two-way delay. This analysis can be related to [33], which instead of AoI considers the minimization of the estimation error of a monitored process. These studies can be regarded as similar, due to the fact that these two quantities are both seen as increasing penalties as the scheduled updates become sparser. Differently from our paper, they consider an infinite time horizon, whereas we work with a finite set of updates over a limited observation window.

Reference [34] considers the impact on AoI of a variable propagation delay, but does not include the activation delay as we do. Another difference with respect to our work is that they consider an online sampling policy, as opposed to our offline scheduling. In other words, they plan, based on the currently experienced delay, when to perform the next update. Instead, we assign multiple transmission instants at once, exploiting a prior statistics of the delays.

Finally, [1] considers AoI under a variable activation delay, but the analysis is only limited to that. This paper can be considered as an extension of the investigation to both types of delay, also including propagation, which requires a re-design of the entire analysis and prompts novel results and comparisons between the respective impacts of the delay terms.

3. Theoretical Framework

We consider the scheduling over time of M status updates supplied by a sensor across a finite horizon of length L, with the instants of transmission denoted as $t_1, t_2, \ldots, t_M$. The instantaneous AoI $\delta(t)$ at time t is defined, in this scenario, as the difference between t and the moment of receiving the most recent update $u(t)$, i.e.,

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

The ith update can be subject to two random delays: an activation delay D_i and a propagation delay T_i. The former represents the time between data acquisition and transmission from the sensor, i.e., if the sensor acquires the data at time t_i, it will be ready to transmit at time $t_i + D_i$. Instead, T_i is the term considered most often [34] and represents the time elapsed since the release of the data packet from the sensor, before it eventually reaches the destination. Due to this further delay, the update originally scheduled at time $t_i + D_i$ is eventually received at $t_i + D_i + T_i$, and the information carried represents the system state T_i seconds ago. As a consequence, the update resets the AoI value to T_i, instead of 0 as commonly assumed in all the papers where the propagation delay is neglected [35]. The trend of AoI can be observed in Fig. 1.

We assume that all D_i terms are i.i.d. and therefore characterized by the same probability density function (pdf) denoted as $f_D(x)$. The same consideration is valid for the T_i terms, with pdf denoted as $f_T(x)$.

The average AoI Δ is computed as

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

with the expectation taken over the random variables D_i, T_i with $i \in 1, 2, \ldots M$. Note that Δ is a function of the chosen transmission instants $t_1, \ldots, t_M$.

We consider an offline transmission schedule of a constrained number of updates within a finite time span, with continuous granularity [25]. The decision of a finite time horizon is well suited to describe a wide variety of real-world scenarios since most sensing applications present this constraint due to a variety of reasons. The transmission time could be limited by hardware capabilities, e.g. battery lifespan, or by decision policy, e.g. other device need the channel for transmission, or even normative reasons [36].

Accordingly, we study a stateless optimization of the transmission pattern, i.e., the schedule is computed in advance, prior to beginning the monitoring task, and cannot be modified at run-time, e.g., accounting for the experienced delays. While this choice may seem restrictive at first glance, it can actually be practical in many settings, where handling an online schedule adaptation is not feasible for low-complexity and battery-powered IoT nodes. Moreover, our intent is to give a quantification of the impact of variable delays, which would apply in both stateful and stateless optimization. Thus, our findings can be translated to the aforementioned related approaches considering an online

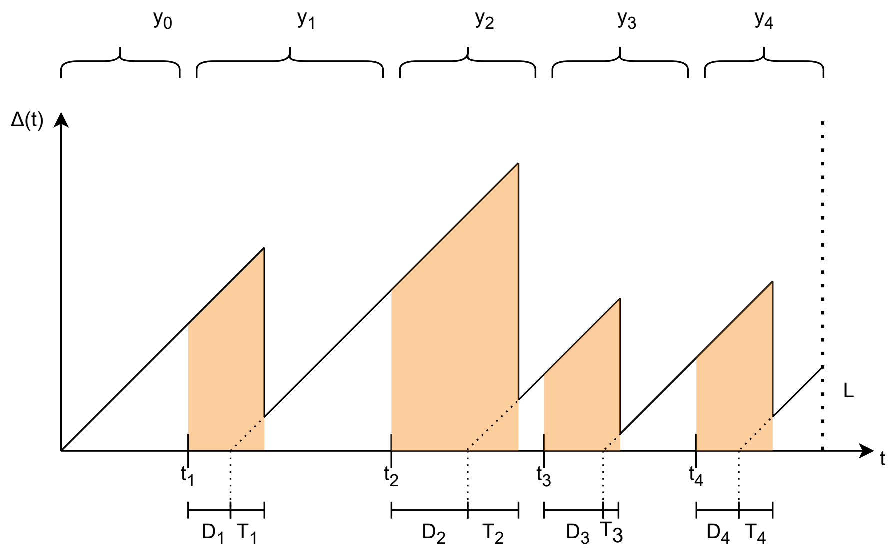

Figure 1: Example of grow pattern of AoI with $M = 4$ transmission and a finite horizon of duration L.

scheduler [35].

Without loss of generality, and for a better representation of our results, we chose $L = 1$. This implies that the delays terms and the AoI will be expressed as values in $[0, 1]$, since they are fractions of L.

3.1. Periodic updates

If neither activation nor propagation delays are present, i.e., for the case of $D = 0$ and $T = 0$, it is immediate to see how the updates ought to follow a regular pattern, where each of them is performed at an integer multiple of a quantity Q defined as

$$Q = \frac{1}{M+1} \tag{3}$$

If such a periodic pattern is used even in the presence of additional variable delays, we can obtain the resulting AoI through geometric considerations over the saw-tooth diagram shown in Fig. 1. The expected AoI can be computed as the normalized sum of the areas of the $M + 1$ isosceles triangles and the M rectangles in the AoI pattern. If $\Delta D_j = D_j - D_{j-1}$ and $\Delta T_j = T_j - T_{j+1}$, then the side of the j-th triangle is

$$\begin{cases} Q + D_1 + T_1, & \text{for } j = 0 \\ Q + \Delta D_j + \Delta T_j, & \text{for } 1 < j \leq M-1 \\ Q - D_M - T_M, & \text{for } j = M. \end{cases} \tag{4}$$

For the side of each rectangle we have

$$\begin{cases} Q + \Delta D_j + \Delta T_j, & \text{for } 1 \leq j \leq M \\ Q - D_M - T_M, & \text{for } j = M \end{cases} \tag{5}$$

and the height of each triangle is T_{j-1}, for $j \geq 2$.

Eventually, the average AoI can be written as

$$\Delta = \mathbb{E}[\Delta_A + \Delta_B + \Delta_C] \tag{6}$$

with Δ_A the area of the first triangle, Δ_C the area of the last trapezoid and Δ_B the area of all the other trapezoids. The three terms can be written as

$$\Delta_A = \frac{(Q + D_1 + T_1)^2}{2} \tag{7}$$

$$\begin{aligned} \Delta_B = &\sum_{j=2}^{M-1} \left(\frac{(Q + \Delta D_j + \Delta T_j)^2}{2} \right) \\ &+ \sum_{j=2}^{M-1} \left(T_{j-1}(Q + \Delta D_j + \Delta T_j) \right) \end{aligned} \tag{8}$$

$$\Delta_C = \frac{(Q - D_M - T_M)^2}{2} + T_{M-1}(Q - D_M - T_M), \tag{9}$$

respectively. Note that due to linearity the expected value can be bring inside the summation. Also, since all D_i and all T_i terms have the same respective distribution, $\mathbb{E}[D_i] = \mathbb{E}[D]$ and $\mathbb{E}[T_i] = \mathbb{E}[T]$, $\forall i$. These considerations allow us to simplify (6) and rewrite it as

$$\begin{aligned} \Delta = &\frac{Q}{2} + M\,\mathbb{E}[D^2] + (M-1)(\mathbb{E}[D])^2 \\ &+ \mathbb{E}[D]\,\mathbb{E}[T] + MQ\,\mathbb{E}[T] \end{aligned} \tag{10}$$

3.2. Optimized update schedule

A better allocation over time of the M updates follows from solving a preliminary constrained optimization, which, according to the discussion above, is then implemented within an offline scheduling. This optimal stateless scheduling can be obtained through analogous geometric considerations over the saw-tooth pattern increase of AoI.

In the general case, the problem can be stated by first computing the expected AoI, and minimizing it. If we define $z_j = \min(t_j + T_j, L)$, i.e., the transmission instants that minimize the AoI, then it is possible to write the AoI as the sum of two terms, i.e.:

$$\Delta = \Delta_1 + \Delta_2 \tag{11}$$

with

$$\begin{aligned} \Delta_1 = & \left(\frac{1}{2} \mathbb{E} \left[\sum_{j=0}^{M} z_{j+1} - z_j \right] \right) \\ \text{s.t.} \quad & z_j = \min(t_j + D_j + T_j, L) \end{aligned} \tag{12}$$

being the area of the j-th triangle and

$$\begin{aligned} \Delta_2 = & \left(\mathbb{E} \left[\sum_{j=0}^{M} T_j \cdot z_j \right] \right) \\ \text{s.t.} \quad & z_j = \min(t_j + D_j + T_j, L) \end{aligned} \tag{13}$$

being the area of the corresponding rectangle.

An exact analytical computation is made difficult by the presence of the minimum that results in a non-linear term. However, if the probability of $D_j + T_j$ being larger than Q is negligible the analysis becomes tractable, as $\min(t_j + D_j + T_j, L) = t_j + D_j + T_j$. Note that the assumption $P(D_j + T_j > Q) \simeq 0$ is sensible since having a delay larger than the regular gap between planned updates would make the system highly unreliable. A practical transmission schedule could not be implemented for such a system.

Focusing on this case, it is convenient to quantify, instead of the instants $t_1, t_2, \ldots t_M$, the $M + 1$ inter-transmission intervals $y_1, y_2, \ldots y_M$, with $y_j =$

$t_{j+1} - t_j$, with $t_0 = 0$ and $t_{M+1} = 1$. The two notations can be promptly translated into one another, accounting for the following constraints.

$$y_j > 0 \quad \forall j; \quad \sum_{j=0}^{M} y_j = 1 \tag{14}$$

Thus, since the time instants $t_1, \dots, t_M$ of the updates are delayed by M i.i.d. terms $D_1, \dots, D_M$ and M i.i.d. terms $T_1, \dots, T_M$ (also mutually independent with one another) it is possible to rewrite (12) and (13). To simplify the notation, we also consider $\Delta D_j = D_{j+1} - D_j$ and $\Delta T_j = T_{j+1} - T_j$, where for notational consistencies we set the auxiliary terms D_0, D_{M+1},T_0, and T_{M+1} to 0.

Equation (12) becomes

$$\Delta_1 = \frac{1}{2}\,\mathbb{E}\left[\sum_{j=0}^{M}(y_j + \Delta D_j + \Delta T_j)^2\right] \tag{15}$$

while (13) becomes

$$\Delta_2 = \mathbb{E}\left[\sum_{j=0}^{M}(y_j + \Delta D_j + \Delta T_j)T_j\right]\ . \tag{16}$$

Note that linearity allows us to carry the expectation term inside the summation. Following the previous considerations that $\mathbb{E}[D_j] = \mathbb{E}[D]\ \forall j$ and $\mathbb{E}[T_j] = \mathbb{E}[T]\ \forall j$, and after some algebraic steps, it is possible to rewrite (11) as

$$\Delta = \frac{1}{2}\sum_{j=0}^{M} y_j^2 + (y_0 - y_M)\,\mathbb{E}[D] + \mathbb{E}[T]\sum_{j=1}^{M-1} y_j + C \tag{17}$$

with C being a constant term that does not depend on the y_j equal to

$$C = M\,\mathbb{E}[D^2] - (M-1)(\mathbb{E}[D])^2 + \mathbb{E}[D]\,\mathbb{E}[T]\,. \tag{18}$$

Considering the condition given by (14) we can take the gradient of (17) with respect to the y_j and set it to 0. After some algebra, we arrive at the following system of $M+1$ equations:

$$\begin{cases} y_0 + \sum_{j=0}^{M-1} y_j = 1 - 2\,\mathbb{E}[D] - \mathbb{E}[T], & j = 0 \\ y_j + \sum_{j=0}^{M-1} y_j = 1 - \mathbb{E}[D] - \mathbb{E}[T], & j = 1 \dots M-1 \\ y_M = 1 - \sum_{j=0}^{M-1} y_j, & j = M \end{cases} \tag{19}$$

whose solutions are

$$y_0 = Q - \mathbb{E}[D] - \mathbb{E}[T] \quad \text{for } j = 0 \tag{20}$$

$$y_j = Q(1 - \mathbb{E}[T]) \quad \text{for } j = 1, \dots, M-1 \tag{21}$$

$$y_M = Q + \mathbb{E}[D] + MQ\,\mathbb{E}[T] \quad \text{for } j = M \tag{22}$$

As a result, (11) can be rewritten as

$$\Delta = \frac{Q + 2M\sigma_D^2 - MQ(\mathbb{E}[T])^2 + 2QM\,\mathbb{E}[T]}{2}. \tag{23}$$

where σ_D^2 is, by definition, the variance of D.

To check the correctness of the formula, we calculated the expected AoI through both the formula in (23) and the summation in (17). The calculation was carried out for 100 values of D and 100 values of T, between 0.001 and 1, for a total of 10000 combinations of the two possible delays. The average difference between the two results was $\simeq 2.12 \cdot 10^{-18}$.

3.3. Probability of Overflow

Equation (23) is valid only if the condition on the minimum holds, i.e., $\min(t_j + D_j + T_j, L) = t_j + D_j + T_j$. This implies $P(D_j + T_j > Q) < \epsilon$, with ϵ small. A possible method to check this condition is to evaluate the probability of overflow, i.e., that not all scheduled updates are carried out by the system. Due to the random nature of the delays, it always exists the possibility that an update arrives after the finite transmission horizon, especially the last one. This can be written as inequality in the following form $t_M + D_M + T_M > L$ and can be further rewritten using inter-arrival times and obtain the following condition: $S_M = T_M + D_M > y_M$. It is possible to rewrite the probability of overflow as:

$$P(S_M > y_M) = 1 - F_{S_M}(y_M), \tag{24}$$

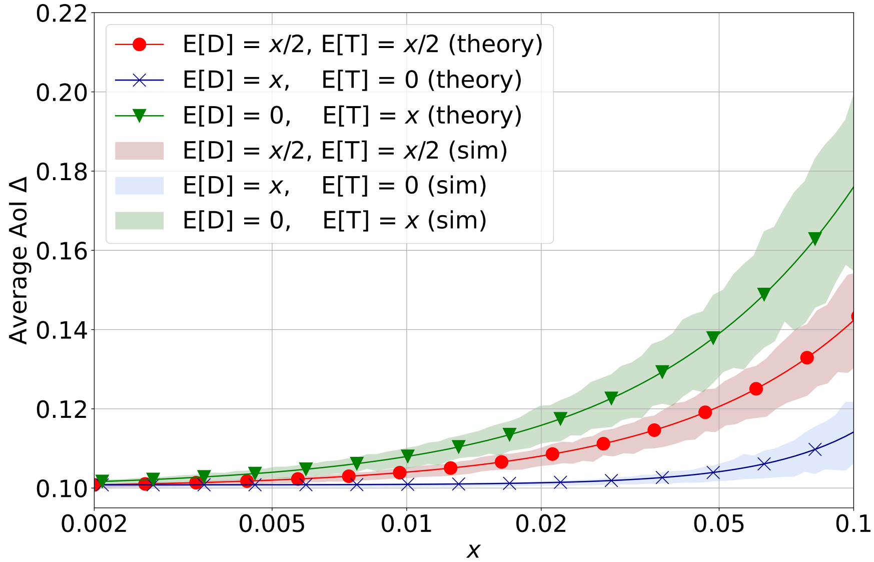

Figure 2: Average AoI in the optimal scheduling. Comparison between simulation and (23) for uniformly distributed delays and $M = 4$.

where $F_{S_M}(x)$ is the cumulative distribution (cdf) of S_M.

Note that S_M is the sum of two independent random variables, and consequently, its pdf is the convolution of those of D_M and T_M. For example, if both T_M and D_M are uniformly distributed, then S_M follows a triangular distribution. If they both follow an exponential distribution, then S_M is a hypoexponential (generalized Erlang) random variable. In general, an exact solution depends on how the delays are distributed. For this reason, we will perform this evaluation by means of simulation in the following section. It is worth noting that the main point of our analysis is that the probability of overflow must be small, not only for the analysis to hold but also as a practical criterion to obtain a meaningful usage of all the opportunities.

4. Results

We now present some numerical results obtained from the previous equations. All evaluations consider an offline scheduling of M transmission opportunities over the interval $[0, L]$ with L=1. To validate the theoretical analysis, we consider the following 3 scenarios: (i) Only activation delay; (ii) Only propagation delay; (iii) Both delay terms. Unless otherwise specified, the comparison is made with the same *total expected delay*, i.e., scenario 3 considers half the expected activation delay of scenario 1 and half the expected propagation delay of scenario 2.

In Fig. 2, we compared (23) with the results of a simulator written in Python.[1] The results obtained through simulation are showed as a shaded area that highlights the average AoI plus/minus the standard deviation. As can be seen from the plot, simulation results match those obtained from (23), with just some numerical noise. The reliability of the analysis decreases as the average delay increases, which emphasizes the role of the overflow probability as discussed later.

Furthermore, the lowest expected AoI is obtained for the delay being only due to activation, whereas propagation delay is shown to have a more detrimental effect. This is also consistent with the theoretical analysis, where D is shown to introduce one fewer additional term in the AoI formulas than T. From an intuitive standpoint, it is also clear how, for the same expected value, the propagation delay impacts more than the activation delay as it causes delay in the reception but also AoI to reset at a higher value.

In Fig. 3, we show how the delay distribution influences the average AoI. We consider the case of $M = 4$ transmission opportunities with uniform and exponential distributions. It is evident that the case with only propagation delay is not impacted by the specific statistics of T, but only its average value, consistently with (23) not containing any higher order moment, but just the term $(\mathbb{E}[T])^2$. For the case with only activation delay, the results are consistent with [1]. For low delay values, which can be quantified as $x < 0.005$, the difference between the uniform and exponential distribution are negligible.

[1]The code is available at: `https://github.com/jesus-333/AoI-Simulation/blob/main/AoI_Delay_BOTH.py`

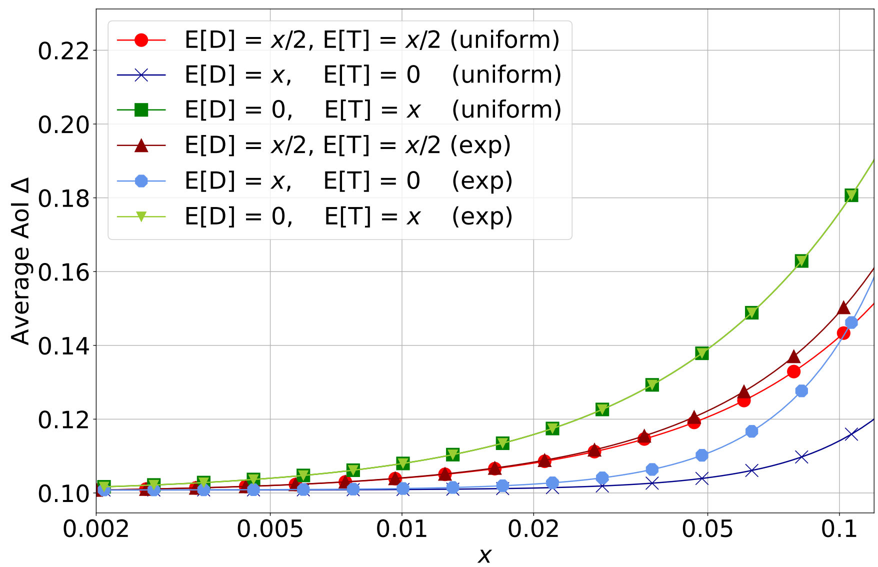

Figure 3: Average AoI under optimal scheduling for different distributions of the delays, $M = 4$. When both delay terms are present, they follow the same distribution.

However, as the average delay increases, the average AoI soars much faster for the exponential distribution.

In Fig. 4, we observe how the average AoI varies with the average delay for two different values of M. As expected, a larger number of transmissions decreases the expected AoI. Yet, for example, the curve for only propagation delay but more transmissions (M=5) overtakes that with only activation delay yet fewer transmissions (M=4) when the expected delay value is higher than 0.04, thereby confirming the stronger impact of the propagation delay.

In Fig. 5, the average delay of one kind is kept constant to 0.04, whereas the other follows a uniform distribution whose average value changes as reported on the x-axis. It is again shown that the propagation delay dominates the AoI behavior. Not only does the propagation delay leads to an overall higher AoI, but it also gives a more rapid increase, whereas the AoI for a constant $\mathbb{E}[T]$ and a variable activation delay is approximately constant if $\mathbb{E}[D] < 0.04$.

To further investigate the case with both delays, we consider an average total

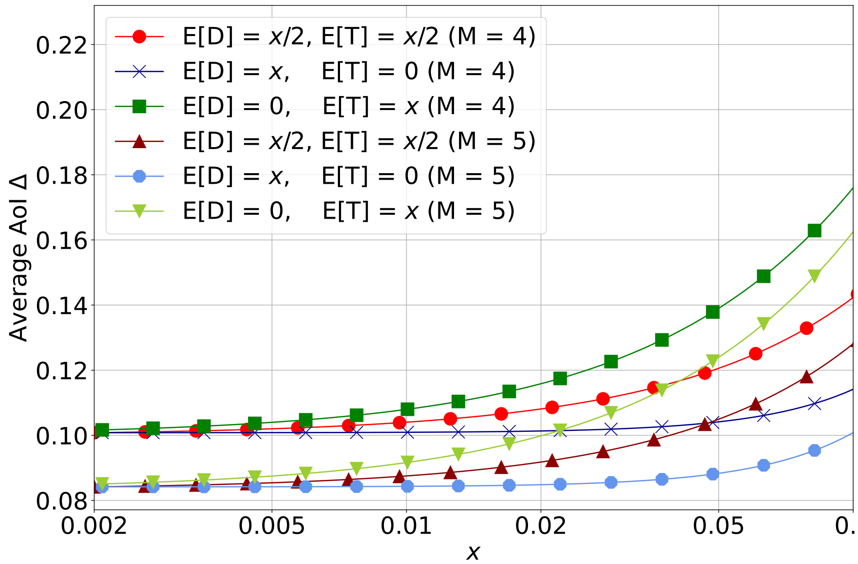

Figure 4: Average AoI under optimal scheduling for different values of M and with uniform distribution of the delays.

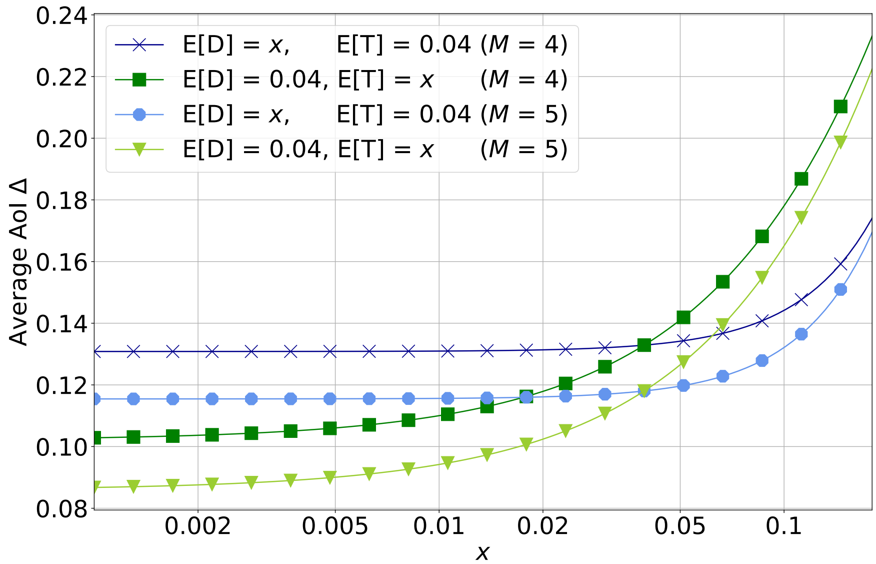

Figure 5: Average AoI in presence of both delays, for different values of M. One delay is set to 0.04 and the other to a variable x. Both delays follow uniform distribution.

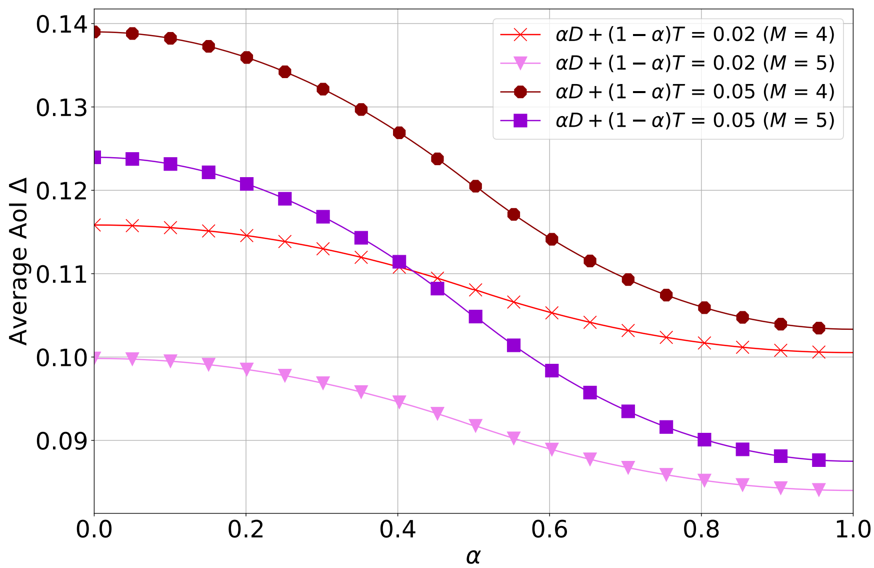

Figure 6: AoI for the linear combination $\alpha D + (1 - \alpha)T$. Both delays follow a uniform distribution.

delay obtained by a linear combination as $\alpha D + (1 - \alpha)T$ with $\alpha \in [0, 1]$. In particular, this would allow to discern cases with the same overall total latency, highlighting how the AoI performance can be different depending on the specific weight that one kind of delay has with respect to the other (see Fig. 6).

The decreasing trend of the curves is consistent with the previous findings, and confirms that the higher the contribution of T to the total delay, the higher the expected AoI.

Fig. 7 shows instead the influence of M on the average AoI for several combination of D and T values. As expected, as M increases the average AoI becomes smaller. Also, the worst performance and the most rapid decrease are always obtained for the scenario where the delay is entirely due to propagation.

Finally, we investigate the probability of overflow discussed in Section 3.3. The results are shown in Figs. 8, 9, and 10 for $M = 4, 5, 6$, respectively, for different types of delay distribution. The results are obtained through numerical simulations in Python. For each point of the plot, we run 4000 simulations

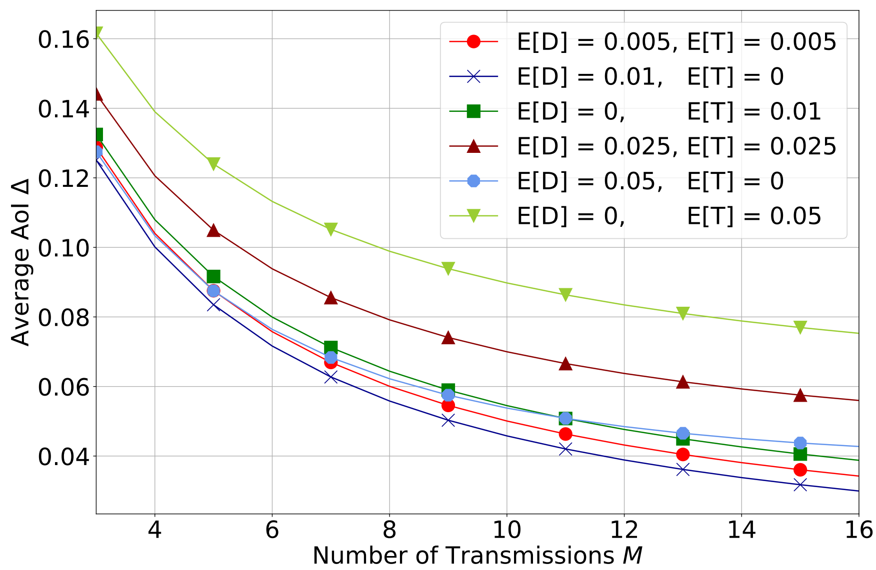

Figure 7: AoI with fixed delay and variable number of transmission M. Both delays follow a uniform distribution.

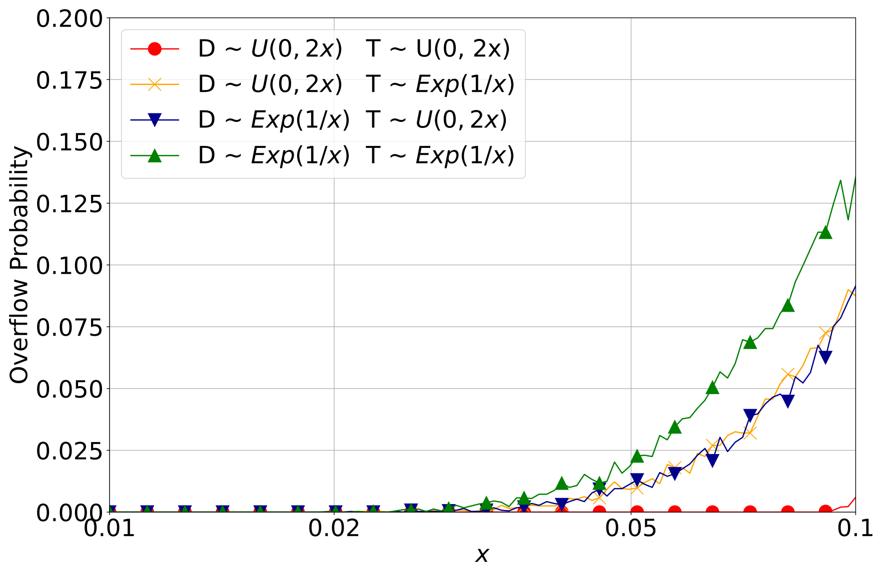

Figure 8: Overflow probability for $M = 4$, computed through simulation. We considered $\mathbb{E}[D] = \mathbb{E}[T] = x$.

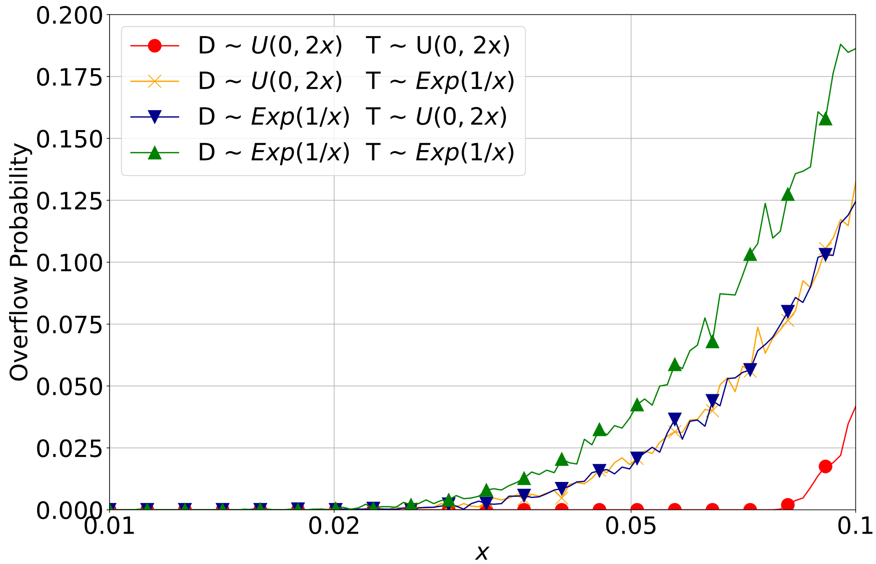

Figure 9: Overflow probability for $M = 5$, computed through simulation. We considered $\mathbb{E}[D] = \mathbb{E}[T] = x$.

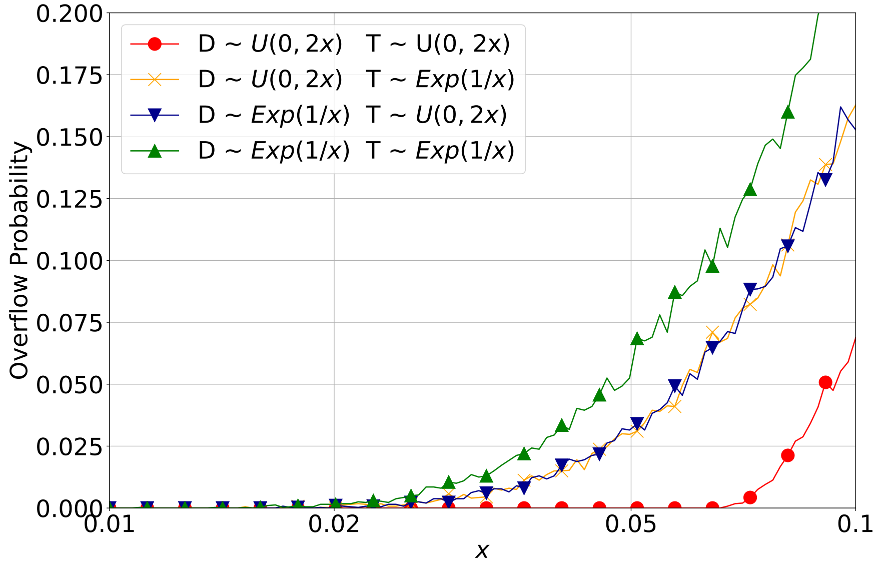

Figure 10: Overflow probability for $M = 6$, computed through simulation. We considered $\mathbb{E}[D] = \mathbb{E}[T] = x$.

and compute the fraction of simulation runs where not all transmissions are eventually carried out within the end of the horizon. Overall, these results confirm that the suggested range of operation, i.e., where the increase in AoI is minimal, also has very low overflow probability, and mostly for the cases where at least one delay component is highly variable (exponentially-distributed), thereby confirming the validity of our analysis. As M increases, for the same average delay, the probability of overflow become larger, since it decreases the slack between updates, i.e., the value Q in (3).

This highlight the trade-off between a low AoI, obtained for high values of M, and the system's tolerance to delay, which is stronger when fewer updates are performed. From the figures, we see that, for the specific cases considered, the the worst results are obtained if both delays are exponentially distributed. This clearly depends on the unbounded character of the exponential distribution. It is also worth remarking that the considered numerical values, especially in the right-most side of the figures, should be put in relationship with the practical implementation, as it may be unrealistic to have delay values that are comparable with Q [1].

5. Conclusions

We studied the offline scheduling of status updates coming from a remote sensor over a finite time horizon, evaluating the impact of variable delays in the update request, its actuation, and its eventual reception at the receiver's side. In more detail, we considered the introduction of activation and propagation delays, both taken as random variables with known statistics. We showed how these delays may lead to an increase in the resulting expected average AoI, which is in line with similar results, where erasures and retransmissions are considered [25, 35]. We further validated our analysis through numerical simulation and showed how the distribution of the delays influences the performance of the system and its probability of failures.

For what concerns both the determination of an optimal scheduling and its implementation within a finite horizon exploiting all the transmission opportunities, the actual AoI performance accurately mirrors most of the studies found in the literature, where a constant delay is assumed, as long as the delays are within certain reasonable values, but significantly deviate for large delays. This suggests that further studies can be devoted to address AoI evaluations, and specific strategies to minimize it, for long delay channels [7, 34]

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