Impact of Transmission Delays Over Age of Information Under Finite Horizon Scheduling

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***Abstract*—Sensor communications in real-time systems may be required to report status updates to minimize the so-called age of information metric, which quantifies the freshness of exchanged data. This situation can be heavily impacted by the delays in data transmission, as some updates may reach the destination when their information content is already stale. In this paper, we consider the problem of scheduling sensing updates over a finite time horizon, and discuss the impact of their transmission delay on the resulting data freshness. We tackle the adjustments required for an offline schedule aimed at minimizing the average age of information which, as long as they do not cause the updates to go off the boundaries of the finite horizon, are only dependent on the average transmission delay. We derive a closed form expression for the average age of information, also verified through simulations, and the resulting performance is evaluated under different system conditions. This can be used to further explore the task of delivering timely system updates under general scenarios, e.g., when the statistics of the delay is not known a priori, or under other non idealities.**

***Index Terms*—Age of Information; Sensor networks; Internet of Things; Data acquisition; Transmission delay; Machine to machine communication.**

I. Introduction

Age of Information (AoI) is a measure of data freshness in a communication system representing the time difference between the latest generated content at the source and the instant it is received or observed [1]–[3]. The metric is particularly relevant for applications involving sporadic sensing of the environment, real-time decision-making processes and machine to machine (M2M) communication, to quantify how timely are the system reactions to variations in the system conditions. Relevant examples cover a wide array of applications of next generation communication scenarios, including smart Industry [4], eHealth [5], vehicular networks [6], and more applications of the Internet of Things (IoT) [7].

While AoI offers a neat quantitative perspective on the system performance, its analytical characterization is often discussed under simplifying assumptions. For example, non-idealities such as the system delay between the generation of the data and its delivery at the receiver's side are very often neglected [8], [9]. Such an assumption is certainly correct whenever such delay is approximately constant, leading to a fixed bias on the AoI evaluation. However, the impact of a *variable* delay on the AoI may be more relevant, not only because it skews the computation but also it affects the control decision for example related to the scheduling of the monitoring instants.

In practice, the exchange of status updates from a monitoring sensors can be delayed for various reasons, and every realistic communication system suffers from *transmission* delay caused by physical limitations, especially in terms of *propagation* and *processing*. Propagation delays are considerable whenever the system, or part of it, involves long-delay channels, such as underwater [10], satellite [11], or space communications [12]. It is worth noting that a long delay does not necessarily imply high variability, but for these specific cases this further inconvenience may arise, e.g., due to meteorological conditions [13], [14]. The mere signal propagation delay can be itself variable due to weather and atmospheric conditions even in terrestrial radio links, especially at high frequencies [15].

Similarly, offloading to more computationally powerful servers in the cloud [16], [17] may lead to variable delays that can be assimilated to the aforementioned propagation term. Then, if data sent to the receiver require preliminary processing, and the computation resources needed for the task are found in the cloud, this will similarly result in an additional delay affecting AoI at the receiver's side. Such latency components also include further processing that may happen at the destination, e.g. queueing at the buffer or delays due to congestion, which in turn depend on the presence of multiple users converging on the same node and their access discipline [18]–[20]. Finally, if status updates consist of packets that may be retransmitted over multiple attempts, following an automatic repeat request (ARQ) approach, further delay terms can be introduced, impacting AoI as argued in [21].

In this paper, we include all of these phenomena under a general transmission delay T, modeled as a random variable

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which is known only in its statistical characterization, i.e., through its pdf $f_T(x)$. We further consider the problem of a finite-horizon offline scheduling of a fixed number of transmission instants, driven by AoI minimization [22], which is consistent with the standard challenge of a monitoring system in the IoT. We tackle the quantitative evaluation of the average AoI when each of the scheduled transmission instants t_j are subject to a transmission delay T_j, with independent and identically distributed (i.i.d.) statistics, each following $f_T(x)$. Such delays impact the AoI in that both the reception of each update is postponed by a term T_j, and also the AoI value starts, after the update, from T_j instead of zero, to account for the increased staleness of the message.

We show the impact of the transmission delay on the choice of the scheduling instants, considering the increase in AoI for a standard periodic update pattern, and discussing how the instants can be optimized to achieve minimal AoI. We derive closed-form analytical expressions that are further evaluated under different system parameters and also verified via simulation. Our analysis enables a better understanding of the impact of transmission delays on AoI in general setups, especially when it affects the system in association with other non-idealities such as erasures [23] or collisions [24], energy unavailability [9], or whenever the statistics of the transmission delay is also unknown and must be preliminarly estimated through learning techniques [25], [26].

The rest of the paper is arranged as follows. Section II discusses related works. Section III presents the theoretical analysis and gives closed-form expressions for average AoI in the presence of variable transmission delays. Section IV exemplifies the analysis with quantitative evaluations and simulations. Lastly, Section V concludes the paper.

II. Related Work

The average value of AoI for a scheduling pattern of system updates is often addressed through geometric considerations, i.e., from the integral of the saw-tooth profile of AoI over time [22], [23], which is also the approach adopted in the present paper. In these analyses, it is often argued that a constant delay in transmitting the updates would lead to a fixed bias of the areas and does not change considerations such as the optimality of a given scheduling pattern. In reality, this is also applicable to more complex optimization approaches for stateful scheduling involving dynamic programming or multi-armed bandits [17], [27].

In [18], the authors consider the impact of request latency on AoI, focusing on a queueing policy with preemption, and latency is related to the service in a buffer. Instead, [28] adopts a similar approach for systems without preemption but with multipath. Differently from those, we treat service as instantaneous, but we superimpose delay as an externality.

The impact of non negligible propagation delay on AoI is considered in [26], specifically focusing on the tradeoff between retransmitting old content with higher accuracy in an ARQ fashion, or dropping it to transmit fresher packets that have never been transmitted before [29].

An optimal *online* scheduling in the presence of random delays is developed in [30], whereas we study a predefined (hence offline) scheduling pattern. The reference also considers a simultaneous control of sensing and controlling operations, whereas we assume persistent sensing and just focus on the transmission of updates as the degree of freedom of the scheduler.

The latter analysis can also be related to [31], which does not consider AoI but rather the minimization of the estimation error of a monitored process. Nevertheless, the issue is similar as long as the two quantities can be seen as penalties that grow larger when the scheduled updates become sparser. The paper furthermore considers an infinite time horizon and not a finite set of updates over a limited observation window, as we do here.

Finally, our approach can be related to the extensive analysis performed in the very recent reference [32], which is the most comprehensive treatment of AoI under variable delay. The work considers an online sampling policy, as opposed to the offline scheduling tackled in this paper. In other words, [32] proposes a strategy to decide, based on the currently experienced delay, when to perform the next update. Conversely, we assign multiple transmission instants at once, based on the a priori statistics of delay, so as to minimize AoI.

It is however possible to combine all of these approaches, together with other non-idealities, for a more comprehensive treatment of real systems in the IoT. Similar to ARQ taxonomies [8], we can think of focusing on multiple statistics for different delay terms (e.g., including propagation, processing, retransmission), and also involve other aspects related to the accuracy of the update [33], error correlation and packet resequencing [21], as well as the costs implied for tracking them through stateful policies [22].

III. Theoretical Framework

We consider the problem of scheduling M status updates sent by a sensor over a finite horizon of length L, where the transmission instants are denoted as $t_1, t_2, \dots, t_M$. In this context, the instantaneous AoI $\delta(t)$ at time t is defined as the difference between t and the instant of reception of the last update $u(t)$, i.e.,

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

Each update can be subject to a random transmission delay, which represents the time elapsed since the release of the data packet from the sensor, before it eventually reaches the destination. Due to this delay, an update originally scheduled at time t_i is received at $t_i + T_i$, and the information it carries is also stale, since it represents the system state T_i seconds ago. As a result, the update resets the AoI value, but not to 0 as commonly assumed in the literature where the transmission delay is neglected [23], yet to T_i. The trend of AoI can be observed in Fig. 1.

We assume that all T_i terms are i.i.d. and therefore characterized by the same pdf denoted as $f_T(x)$. The average AoI can be defined 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 T_i with $i \in 1, 2, \dots M$. Also, since $\delta(t)$ is a function of the chosen

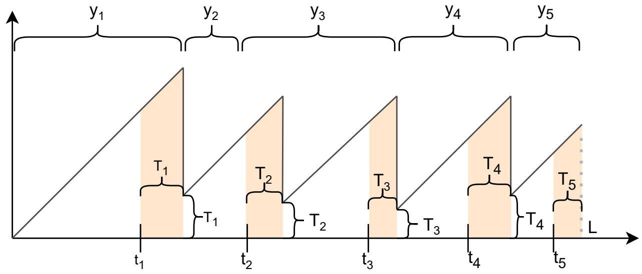

Fig. 1. AoI evolution with $M = 5$ updates. The transmission instants are $t_1 \dots t_5$. The transmission delays for each transmission are $T_1 \dots T_5$. The inter-arrival times are $y_1 \dots y_5$. After each update the AoI is reset to T_j.

transmission instants $t_1, \dots, t_M$, the average AoI Δ can in turn be seen as a function of those same instants.

The problem we want to solve in this scenario is an offline stateless optimization of the transmission instants [22], i.e., the transmission schedule that the sensor will follow is computed in advance without the possibility of online modifications. Although at first glance the choice may seem limiting, it can be of high practical relevance as the offline scheduler requires limited computing power which is often a fundamental constraint for battery-powered IoT devices with little computing capabilities. Also, an online scheduler should require constant feedback and this may not be possible in some scenarios [2], [5], [25].

For a better representation of our results, and without loss of generality, we set $L = 1$. This means that both delay terms and AoI, which are fractions of L, will be expressed as values in $[0, 1]$.

A. *Periodic updates*

Assuming no delay is present, i.e., $T_i = 0 \; \forall i$, it is easy to verify that the minimal AoI can obtained through a regular transmission pattern. Given M updates, the various t_i will be separated by a time

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

If we consider the same pattern in case of non-zero random delay, the average AoI Δ can be evaluated through geometric considerations from Fig. 1. More precisely, the expected AoI is the sum of the area of the M trapezoids plus the initial triangle. For simplicity, each trapezoid can be divided into an isosceles triangle and a rectangle. If we set $\Delta T_j = T_j - T_{j-1}$, then the side of each triangle is

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

whereas, the base of each rectangle is

$$\begin{cases} Q + \Delta T_j, & \text{for } 2 \leq j \leq M \\ Q - T_M, & \text{for } j = M+1 \end{cases} \tag{5}$$

and the height of each triangle is T_{j-1}, for $j \geq 2$. The final 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 areas of all the other trapezoids. The three terms can be written respectively as

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

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

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

Due to linearity, it is possible to bring the expected value inside the summation. Also note that $\mathbb{E}[T_i] = \mathbb{E}[T] \; \forall i$ due to the fact that all T_i have the same distribution. These two considerations allow us to simplify (6) and rewrite it in compact form as

$$\Delta = \frac{Q(1 + 2M\,\mathbb{E}[T])}{2}. \tag{10}$$

B. *Optimized update schedule*

The previous analysis shows that scheduling updates at regular intervals is optimal only in the case of delay equal to zero, i.e., $T_i = 0 \; \forall i$. Otherwise, we face an increase of AoI due to the choice of equally spaced update instants without accounting for the extra delay terms. In this latter case, the AoI can be optimized computing the transmission instants that minimize the area under the curve considering also the alteration introduced by the delay. If we define the transmission instants that minimize the AoI as $z_j = \min(t_j + T_j, L)$ then it is possible to write the AoI as $\Delta = \Delta_1 + \Delta_2$ with

$$\Delta_1 = \left(\frac{1}{2}\,\mathbb{E}\left[\sum_{j=0}^{M} z_{j+1} - z_j \right] \right) \tag{11}$$

being the area of the j-th triangle and

$$\Delta_2 = \left(\mathbb{E}\left[\sum_{j=0}^{M} T_j \cdot z_j \right] \right) \tag{12}$$

being the area of the corresponding rectangle.

Finding the optimal transmission instants z_js minimizing Δ is difficult, given the non-linearity introduced by the minimum. Nevertheless, the computation simplifies if we consider the probability of T_j being larger than Q, i.e,. $P(T_j > Q) < \epsilon$ with ϵ sufficiently small, in which case we obtain $z_j = t_j + T_j$. Note that this consideration makes sense, as a delay larger than Q would have a detrimental impact on the system. The aspect is discussed more formally in Section III-C.

Thus, it is possible to further simplify the analytic solution of the problem considering the *intervals* between transmissions, rather than the transmission instants themselves. Let us denote the intervals $y_j = t_{j+1} - t_j$, with $t_0 = 0$ and $t_M = 1$, satisfying the constraints

$$y_j > 0 \quad \forall j; \quad \sum_{j=0}^{M} y_j = 1\,. \tag{13}$$

Taking into account the interarrival times, the side of the i-th triangle (and the base of the corresponding rectangle) has length $y_j + \Delta T_j$, with $\Delta T_j = T_{j+1} - T_j$, and $T_0 = T_M = 0$. Then Δ_1 and Δ_2 can be written as

$$\Delta_1 = \frac{1}{2}\,\mathbb{E}\left[\sum_{j=0}^{M}(y_j + \Delta T_j)^2\right] \quad (14)$$

$$\Delta_2 = \mathbb{E}\left[\sum_{j=0}^{M}(y_j + \Delta T_j)T_j\right] . \quad (15)$$

Note that due to linearity one can bring the expectation inside the summation. This allows us to expand the sums, delete the common terms and obtain

$$\Delta = \frac{1}{2}\sum_{j=0}^{M} y_j^2 + \mathbb{E}[T]\sum_{j=0}^{M-1} y_j . \quad (16)$$

From (13), the optimal schedule can be found by taking the gradient of (16) and setting it to zero. After some algebraic steps we arrive at the following system of $M+1$ equations:

$$\begin{cases} y_0 = 1 - \sum_{j=1}^{M} y_j, & j = 0 \\ y_j = y_0, & j = 1 \dots M-1 \\ y_M + \sum_{j=0}^{M-1} y_j = 1 - \mathbb{E}[T], & j = M \end{cases} \quad (17)$$

whose solutions are

$$y_j = Q(1 - \mathbb{E}[T]) \quad \text{for } j = 0, \dots, M-1 \quad (18)$$

$$y_M = Q(1 + M\,\mathbb{E}[T]) \quad (19)$$

Using these solutions, it is possible to rewrite (16) as:

$$\Delta = \frac{Q(1 + 2M\,\mathbb{E}[T] - M(\mathbb{E}[T])^2)}{2} . \quad (20)$$

Note that, since the (20) depends only on the first moment of $\mathbb{E}[T]$ (and its square if we expand the second term) the value of AoI remains the same for all the distributions with the same mean, regardless of $f_T(x)$.

C. Probability of Overflow

As mentioned, (20) holds only if $\min(t_j + T_j, L) = t_j + T_j$, i.e., $P(T_j > Q) < \epsilon$ with ϵ small. One way to check this condition is to compute the probability of overflow, i.e., that the system fails to carry out all scheduled transmissions. In principle, given that the delays are random, all scheduled instants can end up being delivered after the end of the horizon L, but we concentrate on the last one since it is the most likely. Thus, we check whether $t_M + T_M > L$, which, switching to considering the inter-arrival times, can be rewritten as $T_M > y_M$, i.e., the delay of the last transmission T_M being larger than the time y_M before the end of the horizon. This allows us to quantify the probability of overflow as:

$$P(T_M > y_M) = P\left(T > \frac{1 + M\,\mathbb{E}[T]}{M+1}\right) . \quad (21)$$

Thus, the probability distribution of T affects the performance. As an example, if T is uniformly distributed over a period of $2\,\mathbb{E}[T]$, i.e., $T \sim U(0, 2\,\mathbb{E}[T])$ then we can rewrite (21) as:

$$P(T_M > y_M) = \frac{\mathbb{E}[T](M+2) - 1}{2\,\mathbb{E}[T](M+1)} \quad (22)$$

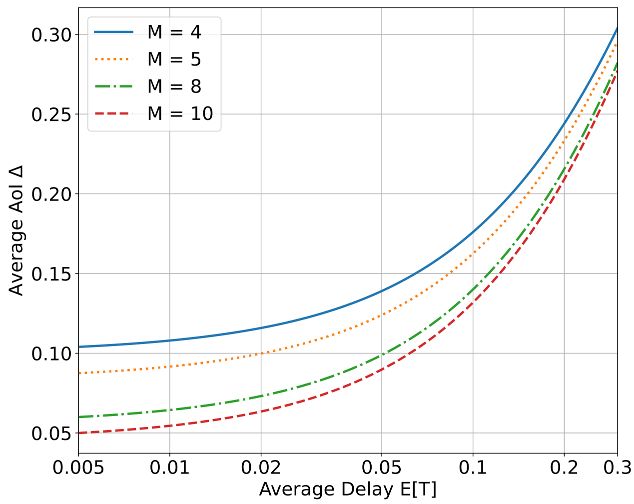

Fig. 2. Average AoI against average delay. Different values of M, i.e., of transmission opportunities, are considered.

On the other hand, if T is exponentially distributed with average $\mathbb{E}[T]$, i.e., $T \sim \exp(\frac{1}{\mathbb{E}[T]})$, then we can rewrite (21) as:

$$P(T_M > y_M) = \exp\left(-\frac{1 + M\,\mathbb{E}[T]}{(M+1)\,\mathbb{E}[T]}\right) . \quad (23)$$

In the next section, we will also present some numerical evaluations of the overflow probability, to better quantify when it can be negligible. We also notice that, beyond causing overflows, very large values of T may also cause the scheduled time instants to swap, which happens when a similar condition of $T_j > y_j + T_{j+1}$ holds for $j < M$. In this case, the impact is just a slight change in the analysis, since it just reverses the order of some indices in the saw-tooth pattern of Fig. 1. This event is less likely than the overflow (due to the condition being stricter). Yet, our numerical evaluations in the following section will also serve to have an estimate of its likelihood, both because we consider simulation to validate the analysis, and because we quantify the overflow probability.

IV. Results

We now present some numerical evaluations of the aforementioned computations.

In Fig. 2, we observe the average AoI versus the average delay for some fixed values of the number of transmissions M. As expected, whenever the average delay increases, the value of AoI also increases. Furthermore, this growth is less significant when M becomes larger. Similarly, as the number of transmissions M increases, the time between updates decreases and consequently the average AoI decreases. The AoI growth is less pronounced for a larger number of transmissions. This is sensible, as a higher number of transmissions reduces the time between the various updates and consequently lowers the metric.

In Fig. 3, we display the average AoI vs. M for several values of the average delay. As expected, and in agreement with previous results, the average AoI decreases as the number of transmissions increases. The decrease is steeper

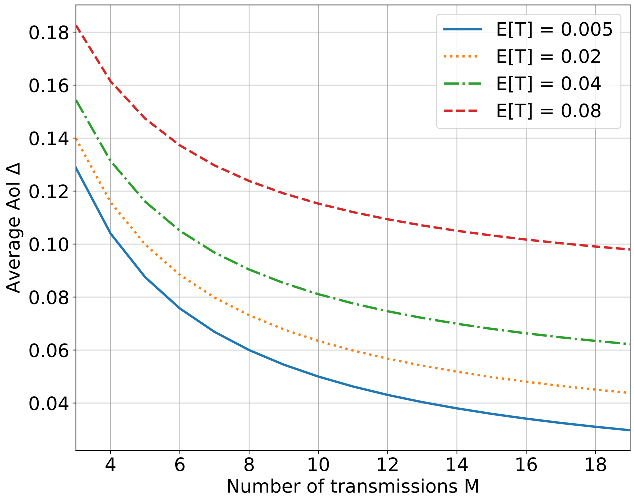

Fig. 3. Average AoI vs the number of transmissions M. Different curves are obtained for different values of the average transmission delay.

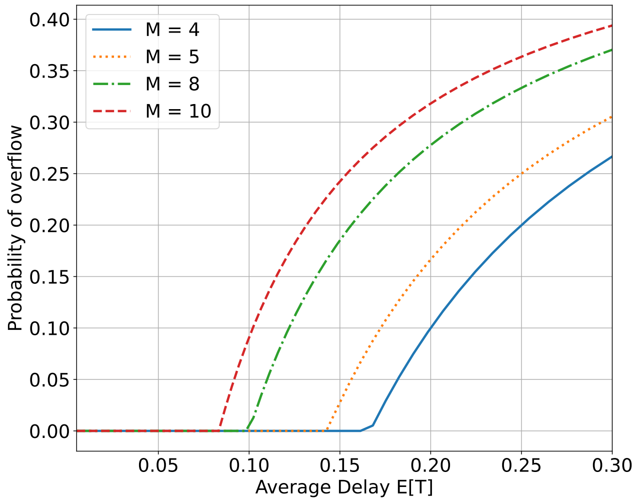

Fig. 5. Overflow probability vs average delay for a uniform delay distribution, for various numbers of transmission opportunities.

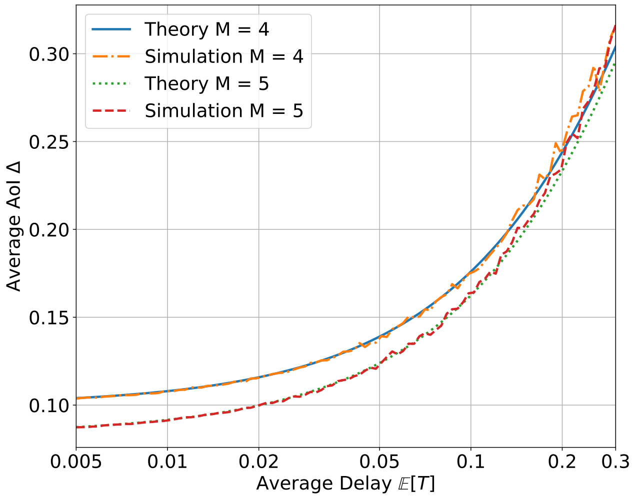

Fig. 4. Comparison between average AoI obtained from theoretical closed form expressions and numerical simulation.

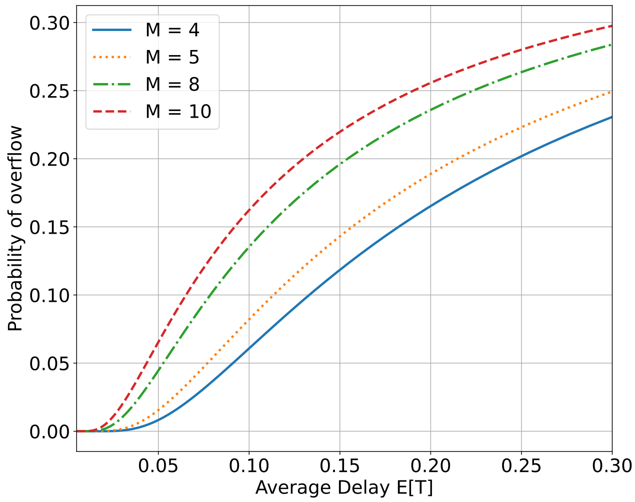

Fig. 6. Overflow probability vs average delay for an exponential delay distribution, for various numbers of transmission opportunities.

for a lower average delay, while it is smoother when the average delay assumes higher values. This is consistent with the fact that, for a fixed number of transmissions, a higher delay implies that each update arrives later, on average, and consequently the AoI is often reset to higher values. This leads to an increase in the average AoI.

To further validate our results, we wrote a simulator in Python and compared the results with the theoretical ones obtained from (20). The results are reported in Fig. 4. For each combination of delay $\mathbb{E}[T]$ and number of transmissions M, we display the average of 100 simulations. As observed from Fig. 4, both results obtained through the theoretical formula and simulation match up to numerical noise.

Figs. 5 and 6 show the overflow probability for the two different distributions. As can be observed, in both cases the probability grows for increased values of M, which lead to a shorter time between updates (i.e., a smaller y_j). Thus, increasing the number of transmissions leads to lower AoI, but also leaves the system more exposed to overflows, i.e., failure to complete all the assigned transmissions.

Lastly, Fig. 7 shows the comparison between the scheduling with the fixed update as per (10) and the optimal scheduling of (20). It is possible to observe the increase in AoI due to the use of suboptimal periodic scheduling. The plot shows indeed that the difference is limited, for small delays, and therefore one may argue that even a periodic scheduling would be sufficient to obtain a limited AoI. However, implementing optimal planning is simple, and does not require many computational resources as it corresponds to a simple shift for each update. It should also be noted that this study assumes the ideality of every other component of the system, no transmission errors, and consequently no need for retransmissions [29]. In real conditions, any cost-effective improvement in system performance is worthwhile.

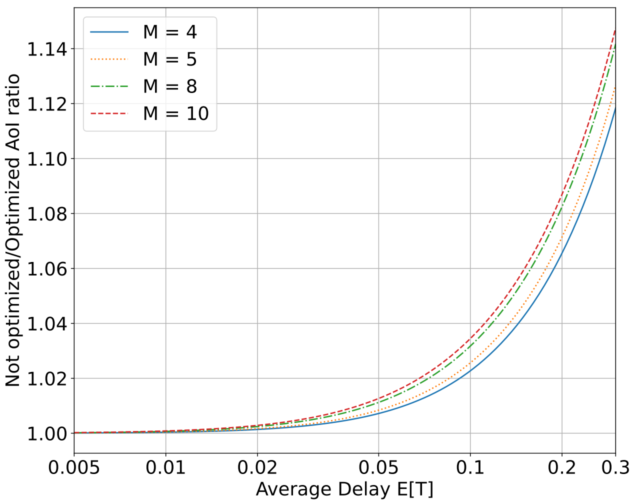

Fig. 7. AoI ratio of periodic vs. optimized schedules, i.e., (10) vs. (20).

V. Conclusions

We discussed the performance in terms of AoI of a finite-horizon scheduling for status updates whose exchange is subject to a random transmission delay. Through geometric considerations, we evaluated the increase in AoI of a periodic schedule in closed-form and also investigated the optimal choice of transmission instants.

The analytic formulation presented in this paper can also be extended and used as a building block for more complex communication scenarios, e.g., with multiple delay components as well as other non-idealities, possibly including parameters estimation and multiple sources.

In particular, the most interesting future extension can be the investigation of scenarios where the transmission delay is not a pure externality, but may be, for example, connected to congestion [24], retransmissions [21] or multiple access from different sensors [4], thus leading to a joint optimization of the transmission schedule also accounting for a closed-loop interaction with the activity of the nodes.

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