Analytical Evaluation of Age of Information in Networks of Correlated Sources

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***Abstract*—Performance metrics such as Age of Information are used to represent data freshness, which is a key element to track in sensing scenarios with sporadic reporting, as typical for example of cyberphysical platforms in industry, health monitoring, agriculture. However, when multiple sensors are employed, all tracking the same scenario, the presence of correlation in the sensed metrics results in the collection of redundant data, which implies interesting quantitative trends. This paper leverages on analytical derivations of age of information for queueing systems, to investigate how this metric behaves in a system of correlated sources, in particular for what concerns the number of sources, their correlation, and their offered traffic. The quantitative results that we obtain can offer interesting insights for planning and managing large scale systems where information is expected to be correlated, such as sensor networks for smart industrial and agricultural applications.**

***Index Terms*—Age of Information; Smart agriculture; Data acquisition; Networks; Modeling.**

I. Introduction

Sensing technologies are facing extreme technological advancements for what concerns the capabilities of individual devices of recording metrics and analyzing the surrounding environment, as well as their coordination for network operation. This leads to smart cyber-physical ecosystems, where sensors and actuators can gather real-time data, monitor relevant metrics, and identify abnormal situations. The applications for this paradigm are countless, including smart cities, intelligent transportation, assisted living, and data processing for agriculture and industry in the digital era [1]–[6].

Many of these scenarios are entangled with living dynamics and might involve life critical applications. Therefore, strict requirements of timeliness and reliability of the data transfer arise, which are expected to be solved by low-latency technologies in the upcoming 5G mobile communications [7], [8]. From the perspective of network analysis, the metric of choice to quantify freshness of data coming from real-time monitoring of status control is often considered to be Age of Information (AoI) [9], [10], which has seen a soaring interest in evaluation paradigms over the last few years, especially due to their analytical tractability in closed-form.

For a sensor sending period status updates, the AoI metric is defined at time t as [11]

$$\Delta(t) = t - \sigma(t) \tag{1}$$

where $\sigma(t)$ is the most recent epoch at time t where a successful update was generated by the sensor and received at the destination. This definition can be extended to different contexts involving optimization of scheduling, performance evaluation, and harmonization of network features, always with a look at AoI as the key performance index [12]–[15].

Notably, AoI is also relevant as tightly connected to energy optimization [16], [17]. In other words, making an efficient data exchange so as to maximize the freshness of data, while at the same time keeping the data rate limited, is a way to contain the energy consumption of the individual sensors, which is another important aspect for all sensing scenarios where the lifetime of batteries at the devices is an issue, such as monitoring remote areas (such as a forest or a plantation) or under extreme conditions [18].

However, there are many scenarios where special aspects connected to the exchanged data may have an impact on its AoI. In a sense, AoI might allow for exploiting *temporal* data redundancy, avoiding unnecessary updates whenever the last exchanged data are still fresh. Another important factor that ought to be taken into account besides this is correlation among data from different sources [19], [20].

In particular, in many sensing scenarios, such as medical devices tracking related metrics [21], but especially ambient sensing with multiple sensors deployed over the same area, as is the case for agriculture and forestry, the data sent by multiple uncoordinated sources can monitor the same metric, or different but nevertheless highly correlated ones [22].

It is reasonable to assume that this form of *spatial* data redundancy can also be exploited to make the exchange more efficient. In particular, the contribution of the present paper is as follows. Exploiting previous analytical frameworks grounded on queuing theory [11], [23]–[27], we treat the sensing environment as a multi-source system, for which we quantify the AoI. Further, we assume a correlation coefficient between the exchanged data [28], and we investigate the dependence of the AoI on three critical parameters, namely, the number of sensors, their offered traffic, and their correlation.

Our investigation can shed light on the involved trends for the AoI so as to help shaping a better design for sensor network integration in smart cyber-physical ecosystems, such as assisted living, precision agriculture, forestry, and livestock farming. It can also lead to less invasive sensing for low-impact technologies in ambient monitoring. Finally, we can also consider it from the standpoint of energy efficiency as an approach to more sustainable sensing methodologies.

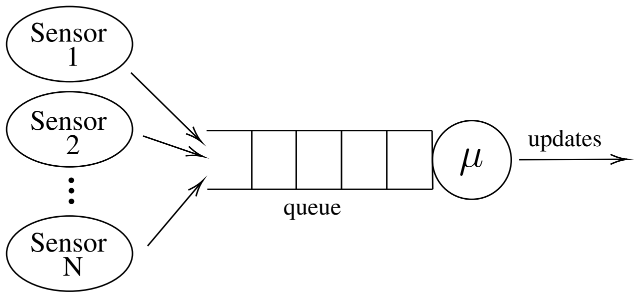

Fig. 1. Queueing system with N sources

The rest of this paper is organized as follows. In Section II, we briefly review reviews models proposed in the literature for AoI optimization in queueing systems, on which we base our analysis. Section II describes the proposed extensions and the closed-form analytical framework. Section III shows numerical results to give a quantitative insight, through either closed-form evaluations or software simulations. Finally, Section IV concludes the paper.

II. Analytical model

Consider a network of N sensors denoted as set $\mathcal{N} = \{1, 2, \ldots, N\}$. Each sensor measures some underlying metric and sends it to a central sink. We set the sensors as generating data with rate λ (the same for all the sensors), enqueued at the sink with first-in-first-out policy. The sink is treated as a single server and service times are exponentially distributed with rate μ. A schematic representation of the considered system is depicted in Fig. 1.

In this section, we will first analyze the system where arrivals at the queue are determined by a Poisson process, then we will show evaluations for a deterministic pattern of measurements according to a periodic measurement scheme.

A. Markov arrivals

We can compute the average AoI $\mathbb{E}[\Delta]$ for each sensor, which can be based on the results for an M/M/1 queue given in [11]. There, a single sensor feeding the queue with rate λ was considered and its average AoI was found to be

$$\mathbb{E}[\Delta] = \frac{1}{\mu}\left(1 + \frac{1}{\rho} + \frac{\rho^2}{1-\rho}\right), \tag{2}$$

where $\rho = \lambda/\mu$.

This result is further extended in [27] to the case of multiple sources. If we consider N memoryless sources, the resulting queuing system is still M/M/1, and, thanks to symmetry, we can consider any of them, say source 1, as being a specific source of interest. Therefore, we can compute the average AoI $\mathbb{E}[\Delta_1]$ for source 1, which is actually identical for all of them, by considering an overall offered traffic of $N\lambda$, but exploiting that only a fraction λ is useful for the AoI of source 1. Thus,

$$\mathbb{E}[\Delta_1] = \frac{1}{\mu}\left[\frac{\rho^2(1-N(N-1)\rho^2)}{(1-N\rho)(1-(N-1)\rho)^3} + \frac{1}{1-(N-1)\rho} + \frac{1}{\rho}\right]. \tag{3}$$

We can now expand this result with the original contribution of considering a correlation factor $\alpha \in [0, 1]$ among multiple sources [28]. In other words, we assume that an update from any source $i \in \{2, 3, \ldots, N\}$ is also able to successfully reset the AoI for source 1. We can treat this case as an adjustment of (3) where the offered load is still $N\rho$, but it now consists of a useful traffic with arrival rate $\big(1+\alpha(N-1)\big)\lambda$ and a competing traffic with arrival rate $(1-\alpha)(N-1)\lambda$.

Thus, the average AoI of the source of interest is [29]

$$\mathbb{E}[\Delta_1] = \frac{1}{\mu}\left[\frac{(\rho+\alpha(N-1)\rho)^2(1-N(N-1)(1-\alpha)\rho^2)}{(1-N\rho)(1-(1-\alpha)(N-1)\rho)^3} + \right. \\ \left. + \frac{1}{1-(1-\alpha)(N-1)\rho} + \frac{1}{\rho+\alpha(N-1)\rho}\right] \tag{4}$$

where we remark that α can tune the degree of interdependency among the sources. In particular, $\alpha = 0$ implies the original multi-source scenario with N independent sources and $\alpha = 1$ leads to all the sources being perfectly correlated, and the system behaving like an M/M/1 queue with arrival rate $N\lambda$ whose AoI is as per (2).

The expression in (4) can also be used to optimize the traffic generation at the single sensor. This can be done with a minimization of the expected AoI with respect to the variable λ as

$$\lambda^\star = \arg\min_\lambda \mathbb{E}[\Delta_1], \tag{5}$$

where symmetry considerations lead to a solution where all the sources choose $\lambda_1 = \lambda_2 = \ldots = \lambda_N = \lambda^\star$. Notably, such an optimization can be easily performed in a distributed fashion, thereby allowing for a local implementation on the specific smart sensor that just requires global parameters N and α, or their equivalent quantification in heterogeneous scenarios without symmetric sensors. Computing the first-order derivative of $\mathbb{E}[\Delta_1]$ in (4) with respect to λ we obtain

$$\frac{d}{d\lambda}\mathbb{E}[\Delta_1] = \frac{1}{\lambda^2 C} + \frac{B}{\lambda(B+\mu)^2} - \frac{2\lambda C^2(A-\lambda NB)}{\mu(B+\mu)^3(\mu-\lambda N)} \\ - \frac{\lambda^2 NC^2 A}{\mu(B+\mu)^3(\mu-\lambda N)^2} + \frac{3\lambda BC^2 A}{\mu(B+\mu)^4(\mu-\lambda N)}, \tag{6}$$

where

$$A = \lambda^2 N - \lambda^2 N^2 + \mu^2 + \lambda^2 N^2\alpha - \lambda^2 N\alpha, \tag{7}$$

$$B = \lambda(N-1)(\alpha-1), \tag{8}$$

$$C = N\alpha - \alpha + 1. \tag{9}$$

Then, the optimal generation rate $\lambda^\star$ can be found setting the first-order derivative in (6) equal to 0

$$\frac{d}{d\lambda}\mathbb{E}[\Delta_1] = 0, \tag{10}$$

whose solutions are evaluated numerically. In the following, we denote with λ^* the optimal (AoI-minimizing) choice of the arrival rate λ, and with Δ_1^* the resulting minimal AoI.

B. Deterministic arrivals

We now extend the analysis considering a deterministic generation of data from sensors that suits, for example, the precision agriculture sensor network scenario [30]. The status packets are generated by each of the N sensors at a fixed period, say D. We assume that packets arrive at the queue at regular intervals, therefore the interarrival time between two packets is D/N. For this system we have that the generation rate of one source is $\lambda = 1/D$, so that the total arrival rate at the queue when N sensors are present is $N\lambda$.

If no correlation is present among the multiple sources, we can still treat the system as D/M/1 and, following the same computations as in [11], combined with the approach of [10], the average AoI of one source is given by

$$\mathbb{E}[\Delta_1] = \lambda\left(\frac{1}{\lambda}\mathbb{E}[T] + \frac{1}{2\lambda^2}\right) = \frac{1}{D}\left(D\mathbb{E}[T] + \frac{D^2}{2}\right), \quad (11)$$

where T is a random variable equal to the system time of an update packet. Thanks to symmetry, $\mathbb{E}[\Delta_1] = \mathbb{E}[\Delta_2] = \ldots = \mathbb{E}[\Delta_N]$, and the average system time $\mathbb{E}[T]$ can be written as

$$\mathbb{E}[T] = \mathbb{E}[S] + \mathbb{E}[W] = \frac{1}{\mu} + \mathbb{E}[W]\,, \quad (12)$$

where the random variables W and S correspond to the waiting and service time of a packet, respectively.

In other words, we split the service time, taken from the queue analysis with just one source and Markov service, from the waiting time, in which we consider that the service is deterministic but the actual queue load is multiplied times N due to the presence of the other sources. However, such a separation is possible only if there is no correlation between transmitted packets ($\alpha = 0$). Thus, we can write [11]

$$\mathbb{E}[W] = \frac{\beta}{\mu(1-\beta)}, \quad (13)$$

with

$$\beta = e^{-\mu(1-\beta)\frac{D}{N}} = -\frac{N}{\mu D}\mathcal{W}\left(-\frac{\mu D}{N}e^{-\frac{\mu D}{N}}\right), \quad (14)$$

where $\mathcal{W}(\cdot)$ is the Lambert W function. Finally, the expected AoI of source 1 can be obtained as

$$\mathbb{E}[\Delta_1] = \frac{1}{D}\left(\frac{D}{\mu} + \frac{D\beta}{\mu(1-\beta)} + \frac{D^2}{2}\right), \quad (15)$$

which requires a numerical evaluation to determine β as the solution of (14).

If we introduce correlation between packets transmitted by different sources, i.e., we take $\alpha > 0$, the system is no longer characterized by deterministic arrivals and we must resort to treating it as a G/M/1 queue. In this case, the CDF of interarrival times τ is quasi-geometric as it can be written as

$$F_\tau(t) = \begin{cases} 0 & \text{for } 0 \leq t < \frac{D}{N} \\ \alpha(1-\alpha)^{i-1} & \text{for } \frac{iD}{N} \leq t < \frac{(i+1)D}{N} \\ 1 & \text{for } t \geq D \end{cases} \quad (16)$$

with $i = 1, \ldots, N-1$.

To derive an AoI expression, we can proceed exploiting some results for a G/M/1 queue such as [10], [24], [26], in relationship with classic findings such as [31] where the average system time $\mathbb{E}[T]$ is derived as follows.

If we denote with $f_\tau(s)$ the Laplace transform of $F_\tau(t)$, and with η the unique root in the unit disk of equation $\eta = f_\tau(s + \mu - \mu\eta)$, the average system time is given by

$$\mathbb{E}[T] = \frac{1}{(1-\eta)\mu}\,. \quad (17)$$

Now, we can proceed analogously to the case without correlation among the sources by inserting (17) into (11).

However, it is worthwhile noting that a full closed form derivation would require a formidably cumbersome expression. Thus, in practical scenarios it would make more sense to leverage simulation results, as will be done in Section III-B.

III. Numerical Results

We present quantitative evaluations to showcase the consequences of the derivations above. We consider an information sink with service capacity $\mu = 1$, and apply the formulas derived for an M/M/1 queue to some specific examples with different parameters. Furthermore, we show the results of numerical simulations, where we consider both Markov and deterministic arrivals.

A. Direct evaluations

Our first set of results presents the application of the formulas of II-A for an M/M/1 queue. We assume that the N sensors generate traffic according to a memoryless process of intensity λ. This value can be tuned to minimize the AoI, and is denoted as λ^* in this case, with the corresponding minimal AoI being Δ_1^*. Finally, a variable correlation factor α is also taken between 0 and 1, to describe *spatial* redundancy between data transmitted by different sensors. In a smart agriculture scenario, where sensors are distributed in a field, placing them far apart may cause a low value of α, while placing them closely together may correspond to a high value of α [28].

The AoI-minimizing value λ^* of the data generation rate for each sensor is shown in Figs. 2 and 3, as a function of N and α, respectively. The figures show that, as N grows, the value of the optimal generation rate for each source, $\lambda^\star$, decreases significantly, from a range of 0.27 to 0.31 at $N = 2$ to a range of 0.04 to 0.06 at $N = 15$. However, the decreasing trend is less pronounced when the $\lambda^\star$ value is compared to the correlation coefficient α. In fact, as the correlation increases, $\lambda^\star$ remains almost constant. This behavior is a result of the fact that we did not include a cost term in our analysis for the offered traffic from a source, which would constrain the data generation [14]. Therefore, in order to keep the AoI value low, each sensor always sends as much data as possible while maintaining the queue stable ($\rho < 1$), ensuring that the server is active for the majority of the time. However, if competition for the server and costs are introduced, the problem would expand in a game theoretic direction where selfish behaviors of the updating agents ought to be considered [32].

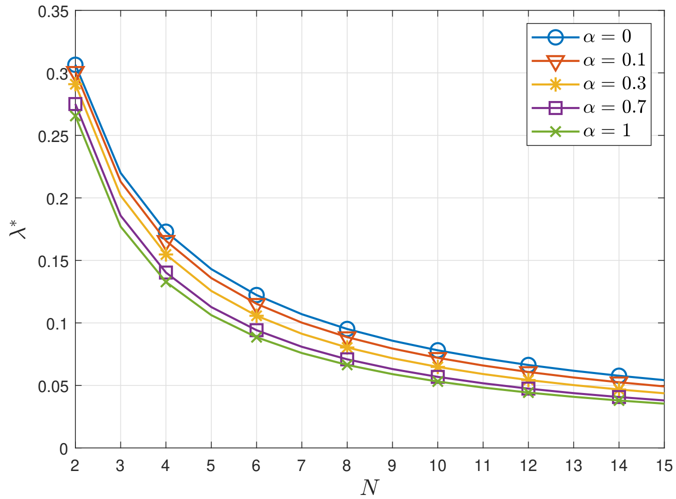

Fig. 2. AoI-minimizing arrival rate λ^* of sources in an M/M/1 queue, as a function of N, for different values of α.

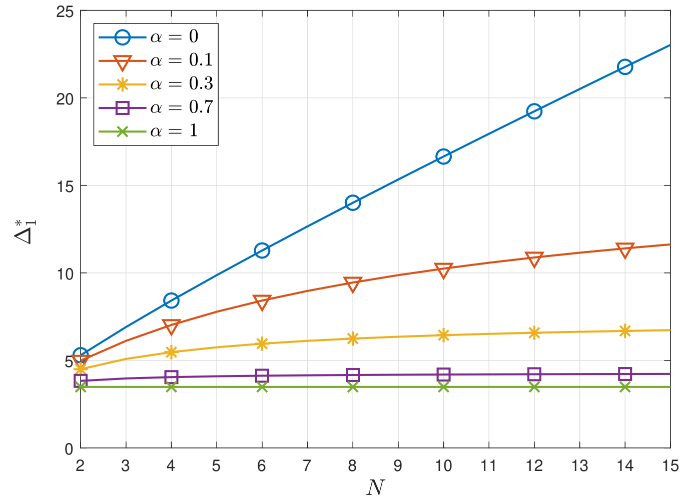

Fig. 4. Minimum expected AoI of a source in an M/M/1 queue, as a function of N, for different values of α.

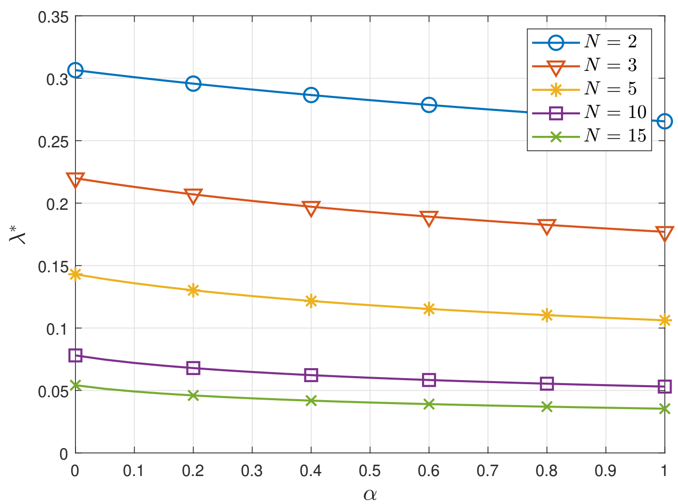

Fig. 3. AoI-minimizing arrival rate λ^* of sources in an M/M/1 queue, as a function of α, for different values of N.

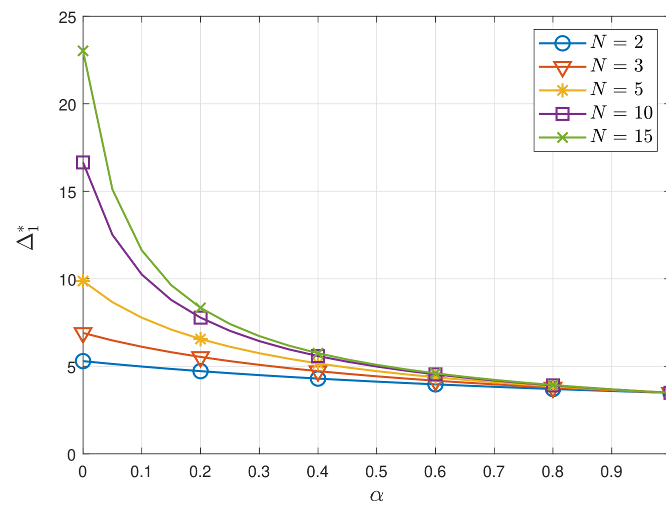

Fig. 5. Minimal expected AoI of a source in an M/M/1 queue, as a function of α, for different values of N.

Finally, the resulting minimal AoI is shown in Figs. 4 (versus N) and 5 (versus α). Fig. 4 shows that, when $\alpha = 0$, the value of $\Delta_1^\star$ increases linearly with N, i.e., the number of sensors. However, as the correlation coefficient α approaches 1, the slopes of the curves tend to decrease. In the limiting case in which $\alpha = 1$, the minimum AoI stays constant as N increases, as the entire set of sensors behaves like a single source. This is even more evident in Fig. 5, where it can be seen that as α tends to 1, the curves describing the trend of $\Delta_1^\star$ for each value of N converge to a value equal to 3.5, which is the minimum AoI of a single source. Moreover, Figs. 4 and 5 clearly show that considering the correlation coefficient α when determining the optimal packet generation rate $\lambda^\star$, allows to significantly reduce the average AoI value. For example, when $N = 15$ and $\alpha = 0.1$, it is halved compared to when $\alpha = 0$.

In Figs. 6 and 7, we plot the difference between the value of $\mathbb{E}[\Delta_1]$ when a non-optimized $\lambda = 0.02$ is considered, and $\Delta_1^\star$, as a function of the number of sources N and the correlation factor α, respectively.

In general, these plots show the need for an optimized generation rate in the case of multiple sources, to avoid large drifts in the AoI, even though correlation may assist and mitigate the problem of a sub-optimal choice of λ. Even though it may seem that also an increasing N reduces the suboptimality of a poorly chosen generation rate, this just happens because, as N grows, the AoI itself worsens even in the optimal case, due to competition. However, since the figures display the AoI value for a *single* terminal, the overall gap actually worsens as N increases, since the less than linear descent of the AoI implies a growing net loss of total AoI for the entire network.

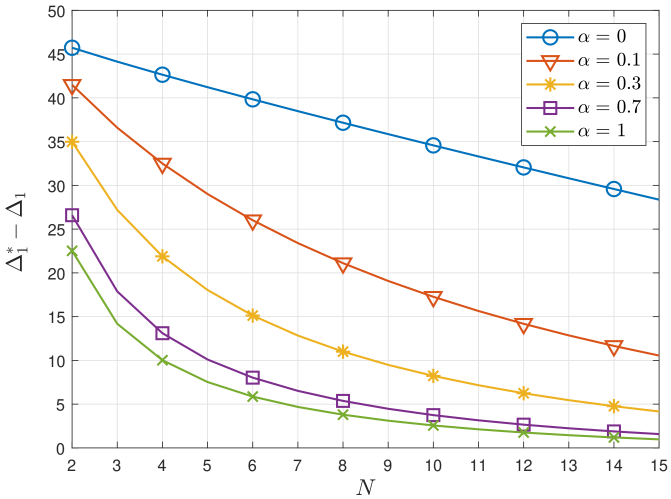

Fig. 6. Expected AoI in an M/M/1 queue, difference between $\lambda = 0.02$ and $\lambda = \lambda^\star$ (minimizing), as a function of N, for different values of α.

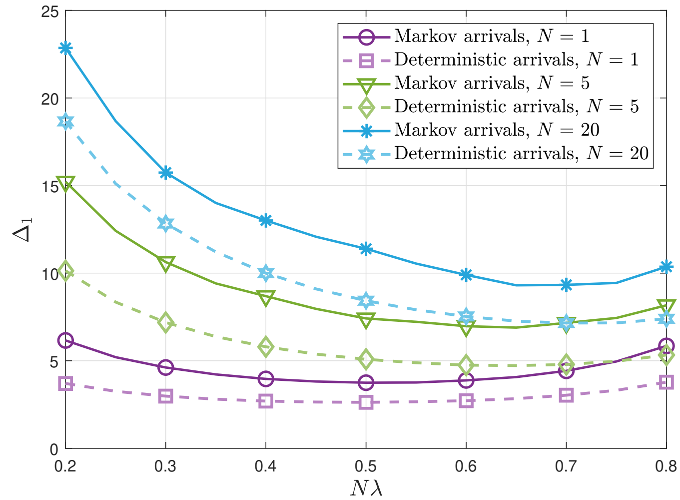

Fig. 8. Results for N sensors generate traffic each with intensity λ, $\mu = 1$ and $\alpha = 0.2$, for Markov (solid lines) and deterministic arrivals (dashed lines).

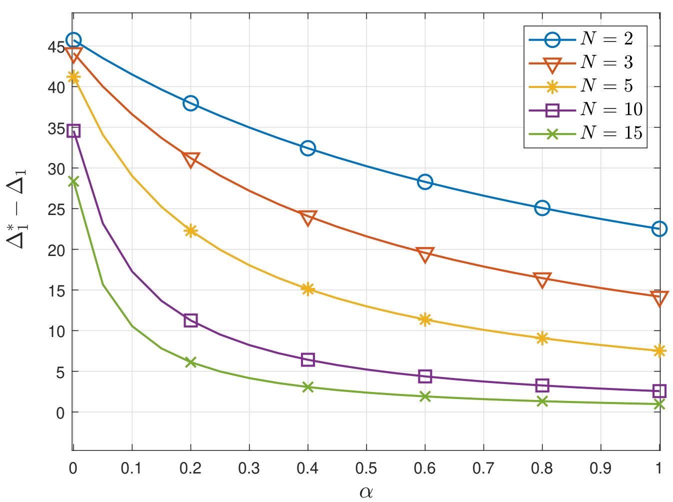

Fig. 7. Expected AoI in an M/M/1 queue, difference between $\lambda = 0.02$ and $\lambda = \lambda^\star$ (minimizing), as a function of α, for different values of N.

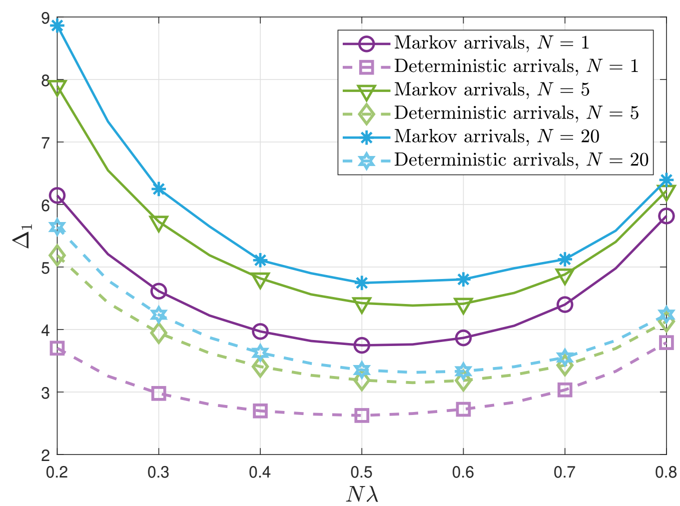

Fig. 9. Results for N sensors generate traffic each with intensity λ, $\mu = 1$ and $\alpha = 0.7$, for Markov (solid lines) and deterministic arrivals (dashed lines).

B. Simulation Results

We present further evaluations of the AoI in different queueing systems considering Markov or deterministic arrivals. Because of the complexity of the resulting formulas, these have been derived through simulation, even though they are in full agreement with the analytical framework shown previously. We simulated two scenarios for each type of arrival process. The scenarios consider a variable number of nodes with different correlation factor α, all other parameters being the same. Specifically, we consider α=0.2 in the first scenario to describe a moderate correlation, and α=0.7 in the second scenario, which implies a high correlation.

Figs. 8 and 9 show the AoI of source 1, Δ_1, versus the total generation rate $N\lambda$, for different values of N, when $\alpha = 0.2$ and $\alpha = 0.7$, respectively. The curves obtained for $N = 1$ are identical to those obtained in [11]. Also, while the performance of the two systems is different, with deterministic arrivals (dashed) the AoI is lower than that of the Markovian system (solid), for any λ. This is because packets with regularly spaced generations behave better in AoI terms and are less likely to congest the system than memoryless arrivals.

Concerning the optimal λ for AoI minimization, which we refer to as $\lambda^\star$, from both Figs. 8 and 9 we can see that the values minimizing the AoI are very similar for deterministic and Markov arrivals.

Moreover, for all cases $\lambda^\star$ decreases as N increases. This is justified as $N\lambda$ stays almost constant or slowly increases (less than linearly) and also correlation among sources can be exploited. In fact, as Fig. 8 shows, when $N = 1$ then $\lambda^\star \approx 0.5$, whereas when $N = 20$ and $\alpha = 0.2$ (so even for a weak correlation) we have that $\lambda^\star \approx 0.7/N = 0.035$.

IV. Conclusions

In this paper, we explored the implications on age of information for remote sensing when correlation among multiple sources is present. Leveraging existing closed-form results for the AoI in queuing systems with multiple sources, we inserted a parametric representation of correlation among sources and quantified its impact via numerical computations.

We show that correlation among sources is generally beneficial in lowering the AoI. However, to properly exploit this spatial redundancy, a proper fine tuning of the parameters (especially the data generation rate) is needed. This possibly requires an agreement of cooperative behavior among the multiple sources.

In this spirit, future extension of the present work may include the definition of proper cost and cooperation models to achieve such a result in a distributed fashion, to be possibly studied through a game theoretic approach [14], also including other relevant aspects such as models for battery consumption and economic analysis of the drives of different actors (e.g., owners of different sources of information) [33], [34].

Finally, this can be further extended to consider security and trust issues [15], [35]–[37], especially related to the correctness or falsification of information injected in the network and its impact on the evaluations presented here.

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