Cost and Correlation in Strategic Wireless Sensing Driven by Age of Information

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***Abstract*—We extend available analytical studies that leverage queueing theory to compute closed-form expressions for the average AoI in queueing systems with multiple sources. Specifically, we consider the following original aspects. First, we assume that multiple sensors are producing interconnected measurements and therefore their status updates correlate with one another. We also consider a cost associated with the measurements and we finally apply non-cooperative game theory to derive the Nash equilibria of the resulting system. Differently from the standard multiple source system, which is analyzed in the literature from the only game theoretic standpoint of competing sources, we show that our system showcases collaborative-like behaviors thanks to correlation among the source transmissions. Moreover, the impact of a sensing cost is to decrease even further the aggressiveness of strategic users, which may lead to the opposite problem, a lower than optimal offered traffic to avoid costs.**

***Index Terms*—Age of Information; Queueing theory; Game theory; Remote sensing; Wireless sensor networks.**

I. Introduction

Depending on the access technology, network management, and application, age of information (AoI) may be a valuable metric for wireless networks. It can be even more relevant than throughput, delay, or loss probability, in remote sensing applications such as environmental monitoring and status reporting about position and movement of self or assisted driving vehicles, which may need to exchange and keep data updates as timely as possible [1]–[5].

AoI is an application-independent metric that refers to the freshness of status updates over time. At time t, if the last update from a monitor was exchanged at $\sigma(t)$, the AoI is defined as $\Delta(t) = t - \sigma(t)$. In the literature, stochastic evaluations have been applied to derive AoI evaluation in classic queueing systems, such as M/M/1, M/M/1/1, or G/G/1 queues with different disciplines [6]–[13]. This is a sort of extension of classic queueing theory, often analogous to finding the steady-state distribution for a Markov chain.

Moreover, there are extensions to cases with multiple sources, most notably in [14], on which our analysis is based, but also in [15]–[18]. These papers also explicitly address the competition among multiple sources, each treated as a different network agent reporting on its own monitored quantity and therefore competing with the others in the queueing process. The main theoretical instrument used to obtain analytical results within a competing scenario is *game theory*, which we also use but with a different twist on the problem [19]–[22].

Indeed, in most of the related research, different sources of information are considered as entirely separate and independent in their contents and also objectives. This means that, whenever game theory is applied, it is for a purely competitive scenario, up to the point of being adversarial, where multiple sources try to gain as much as they can of the service capacity of the queue for their own transmission.

We argue that this scenario may not represent many wireless sensor network deployments, where it is well possible that multiple sources generate independent data, but they often track correlated underlying processes, when not the same one [23]–[26]. In that case, we may think of using game theory, which still is applicable as a framework to understand multi-agent multi-objective problems [27]–[29], not to represent aggressive competition among the sources but rather to investigate whether the anarchical behavior of a distributed system can still obtain an efficient performance in terms of AoI.

In more detail, while we ground our derivations on previously available analytical findings, we bring the following advancements with respect to the existing literature. First of all, we introduce a cost for offered traffic from a source, which is meant to constrain the data generation. This modification would not be strictly needed in the standard queueing scenario, where there is an implicit drawback in being too aggressive, i.e., too high an offered traffic might clog the buffer at the receiver and therefore result in exploding AoI values [14]. On the other hand, this modification is needed in our scenario as we consider a game theoretic perspective for evaluating the efficiency of a distributed source management. The idea is that if data generation processes result in equivalent AoI performance, a lower offered traffic should be preferred as it leads to a more parsimonious system utilization.

After this change, we explicitly consider a scenario with multiple sources that, instead of transmitting entirely unrelated and independent data, and therefore being purely competing distributed agents, we allow for the content of the multiple flows to be *correlated* [26], [30]. This means that any agent can consider the traffic of others as somehow useful to bring relevant information and therefore lowering the AoI of its own source. This can actually be strategically advantageous as it will allow for a decrease of the AoI without paying any cost.

As a result, we present a closed-form derivation that explores cost and correlation of multiple sources and derives the resulting Nash equilibria (NEs) of the distributed allocation, comparing it with an optimal resource sharing. The main implication of our analysis is that while entirely disjoint sources can compete for the queue's service capacity but this ultimately results in an efficient distributed sharing, where the NE is sufficiently close to the optimal assignment, such a property does not hold for correlated sources. Even though the resulting AoI is made lower by exploiting the correlation among the sources, this advantage is not fully exploited in a distributed setup, especially for increasing costs, since the agents tend to become lazy and leave the burden of the update to others [29]. Our results can therefore open a new line of investigation for AoI optimization in case of multiple correlated sources, in particular exploring possible ways to make their cooperation more efficient.

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. In Section III, we describe our proposed extensions, which is further analyzed in Section IV by means of game theory. In Section V, we present some numerical results, and we conclude in Section VI.

II. Background

Many studies evaluate the AoI in queueing systems, for various settings but especially based on classic memoryless systems with different disciplines [8], [16], [31]. Even a basic M/M/1 queue with FCFS discipline, which is the entry-level system for any queueing theory student, poses two interesting aspects that make it palatable for an exact analysis. First of all, it is fully characterizable in closed-form, and computing the statistics of the AoI can be simply seen as an extension of classic evaluations pertaining to the queueing delay and/or the number of users in the system.

In addition, the M/M/1 queue presents an interesting behavior for what concerns its AoI. It is well known that its throughput is simply related to its stability, i.e., the arrival rate λ and the service rate μ must satisfy the condition $\lambda < \mu$, and a high throughput is achieved on the border of this condition, i.e., whenever λ approaches μ. On the other hand, the delay is minimized whenever λ is close to 0. The AoI can be optimized instead by offering a traffic that is in a somewhat intermediate condition, i.e., λ close to $\mu/2$, even though the server is slightly biased towards being busy over being idle and so the optimal load factor $\rho = \lambda/\mu$ actually happens to be $\rho^* \approx 0.53$ [7]. In other words, optimizing the AoI in an M/M/1 queue implies seeking for non-aggressive management, where λ is significantly lower than μ, so there is already a self-limitation imposed to the choice of λ.

The quite elegant analytical results presented by Kaul and Yates in [7] and subsequent contributions [14] are important sources of inspiration for the present work. In particular, the full expression of the average AoI Δ for an M/M/1 queue with FCFS policy, which leads to the considerations mentioned above, is given as [7]

$$\Delta = \frac{1}{\mu}\left(1 + \frac{1}{\rho} + \frac{\rho^2}{1-\rho}\right) \tag{1}$$

and the computation is further extended in [14] to the case of multiple sources to a scenario that, for the sake of simplicity, can be thought of consisting of just 2 flows, with parameters λ_1, μ_1, ρ_1, and λ_2, μ_2, ρ_2, respectively.

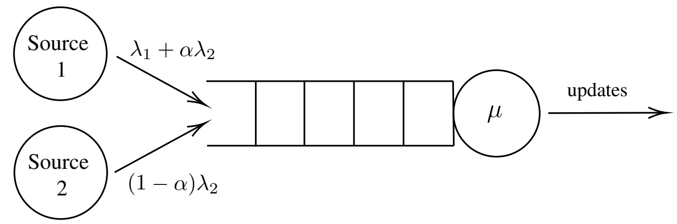

Fig. 1: Queueing system with 2 sources

Some side remarks involve that there are substantially equivalent expressions, at least for what concerns the extensions meant in the present paper, to the cases of M/D/1, D/M/1, G/M/1, and so on, as well as with switching the discipline of the queue to LCFS, adding preemption, and more [6], [15], [16], [18]. For the purposes of our study, all of these evaluations can be considered equivalent, so we just go with the simpler M/M/1 queue. Moreover, as already remarked by [14], the scenario with just 2 sources is representative of an arbitrary number of Poisson sources, since source 1 can be thought as the one of interest, and the others just aggregate every other flow in the network, if needed.

For the case of two independent sources, the average AoI for source 1 is [14]

$$\Delta_1 = \frac{1}{\mu}\left[\frac{\rho_1^2(1-\rho\rho_2)}{(1-\rho)(1-\rho_2)^3} + \frac{1}{1-\rho_2} + \frac{1}{\rho_1}\right] \tag{2}$$

where $\rho = \rho_1 + \rho_2$.

III. System Model

Our extension is based on a system like the one depicted in Fig. 1, where two sources transmit their update packets through an FCFS M/M/1 packet queue. The global service rate of the queue is μ, and packets from either source are identically served. Source $i \in \{1,2\}$ has Poisson arrival rate λ_i, generating offered load $\rho_i = \lambda_i/\mu$.

The first extension with respect to the existing literature is to consider that a fraction $\alpha \in [0,1]$ of the packets transmitted by source 2 contain data that correlate to the process tracked by source 1 so that they are actually able to benefit the AoI of source 1 in the same way that packets transmitted by source 1 do. Consequently, we can reformulate (2) by considering two equivalent sources, whose arrival rates are $\lambda_1 + \alpha\lambda_2$ and $(1-\alpha)\lambda_2$, respectively. Note that in this way the aggregate rate is still unchanged, being equal to $\lambda_1 + \lambda_2$. Also, the load factors of the two sources are $\rho_1 + \alpha\rho_2$ and $(1-\alpha)\rho_2$, respectively.

In this case, the average AoI is given by

$$\Delta_1 = \frac{1}{\mu}\left[\frac{(\rho_1+\alpha\rho_2)^2(1-\rho(1-\alpha)\rho_2)}{(1-\rho)(1-(1-\alpha)\rho_2)^3} + \right. \\ \left. + \frac{1}{1-(1-\alpha)\rho_2} + \frac{1}{\rho_1+\alpha\rho_2}\right] \tag{3}$$

The introduction of α allows to distinguish a continuous range of scenarios, with 3 particular cases:

$\alpha = 0 \longrightarrow$ Two independent sources, which is the scenario of reference in [14] and the average AoI is given by (2)

$\alpha = 1 \longrightarrow$ The two sources behave as a unique flow with arrival rate $\lambda_1 + \lambda_2$, which is the basic scenario of [7] and the average AoI is given by (1)

$0 < \alpha < 1 \longrightarrow$ This is an intermediate situation where the status updates of the two sources are correlated, meaning that some packets transmitted by source 2 can act as updates also for source 1 and vice versa; the average AoI is as per (3).

An interdependence among the sources would be relevant if, for example, they track connected processes, for example, quantities with a cause-effect connection, or simply a positive correlation. Or, they can be even tracking the same process of interest [23], [32].

Notice that the AoI is a concept that makes sense of temporal redundancy, implying that, to have fresh status reports, it is pointless to concentrate updates at close instants, but rather it more convenient to have them spread over the time axis. In the exact same way, our analysis keeps into account spatial redundancy among multiple sources, i.e., the fact that fresh information can be gained from the update related to some interrelated process. If this is the case, exploiting this kind of redundancy would as well avoid needless updates that can cause congestion, not to mention unnecessary energy consumption from remote sensors [17].

IV. Game Theoretic Analysis

Game theory is generally applied to multi-agent systems to frame them into a multi-objective optimization where each agent is driven by its own selfish objectives. For the context of AoI, the immediate application, which is also discussed in some related papers [14], [19], [21], would be to consider that each source is an agent that is totally uninterested in the other sources' performance, and conversely considers the minimization of its own AoI as the sole objective. This leads to an NE solution that can be computed in closed form, thanks to the analytical expressions of the AoI in different systems.

We remark that this very approach can still be translated into our problem, which would imply to differentiate between the globally optimal management, in which the average (or total) AoI of all the sources is minimized, as opposed to the NE, where each source is acting as a selfish player. However, the rationale behind this implementation of game theory does not fully represent our context where correlation among the sources may be present. In this case, the objective of a low AoI can also be achieved by letting the other source transmit, and therefore the competition for the server is blurred.

In this paper, we are interested in extending the utility function for each agent by introducing a cost, so that a source objective is not just represented by a minimal AoI but rather by the minimization of the linear combination of AoI and a cost associated with the offered traffic, and weighted through a cost coefficient $c > 0$. In other words, we define a utility for source 1, which is a function of λ_1 and λ_2 chosen by each players, respectively, as

$$u_1(\lambda_1, \lambda_2) = -\Delta_1 - c\lambda_1 \tag{4}$$

and similarly for source 2, with just an index substitution,

$$u_2(\lambda_1, \lambda_2) = -\Delta_2 - c\lambda_2 \tag{5}$$

Note that the costs are assumed to be symmetric for both sources, but this assumption would be actually easy to relax, and also the negative signs are due to that both the expected AoI and the cost are metrics to be minimized, while the utility is often conventionally taken as a quantity that is desirable to maximize [28], [33].

The introduction of a cost term can be justified by many reasons, including a more realistic characterization of the sources, since it would correspond to the energy expenditure or the updating costs that each source incurs for generating status updates. But especially, the motivation behind adding a cost term is that we need to more explicitly address the strategic interaction among the sources in the case of $\alpha > 0$, i.e., correlation of their updates, to some extent [29].

When individual competing sources are considered, the introduction of a cost term would just be redundant since the individual agents see in the mutual access of the server a limiting factor. In other words, no player will try monopolizing the service capacity μ of the queue with its offered traffic λ as this would lead to congestion and high AoI, even in the single source case. However, we are now focusing on a scenario where the sources are not necessarily competing and can assist each other thanks to correlation [30], [34]. This is pushed to the point that each individual agent may prefer that some other source updates the information, if α is sufficiently high, since it would still lead to a decreasing AoI without paying any cost.

This interaction can still be framed in the context of game theory, but more than being a conflict between competing sources, it is just cast as a distributed management, whose efficiency may be worth assessing [21], [22]. For this to happen, the scenario of multiple sources in the presence of cost and correlation can be framed as a static game of complete information [35], [36]. Formally speaking, we introduce the players as the two sources, their strategies as the choices of λ_1 and λ_2 respectively, and the resulting payoffs as the utilities given through (4).

We remark that in this context, it is possible to find a global optimum as

$$\lambda^* = \arg\max_{\lambda} \big(u_1(\lambda,\lambda) + u_2(\lambda,\lambda)\big) = \arg\min_{\lambda}(\Delta_1 + \Delta_2 + 2c\lambda) \tag{6}$$

where symmetry considerations lead to a solution where both sources choose $\lambda_1 = \lambda_2 = \lambda^*$. The solution is easy to derive in closed-form by finding the first-order derivative of the objective, which can be computed through (3) and setting it as equal to 0.

The NE is also found in a symmetric point, but a different one. Indeed, the NE can be computed by considering the

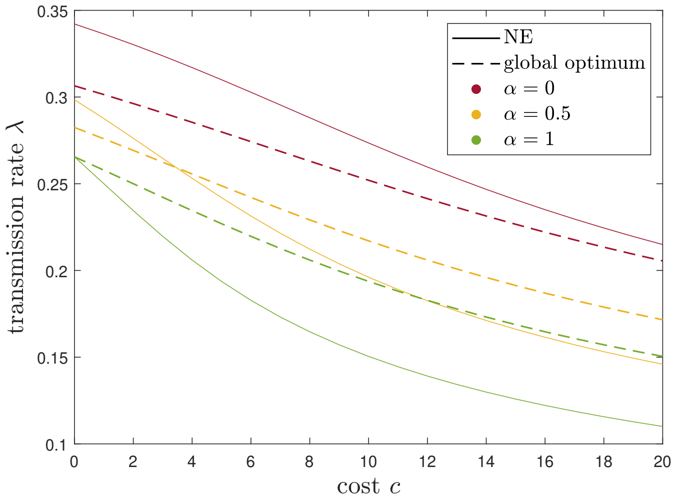

Fig. 2: Arrival rate λ at the NE (solid) and the global optimum (dashed), versus the cost c, for different values of the correlation parameter α.

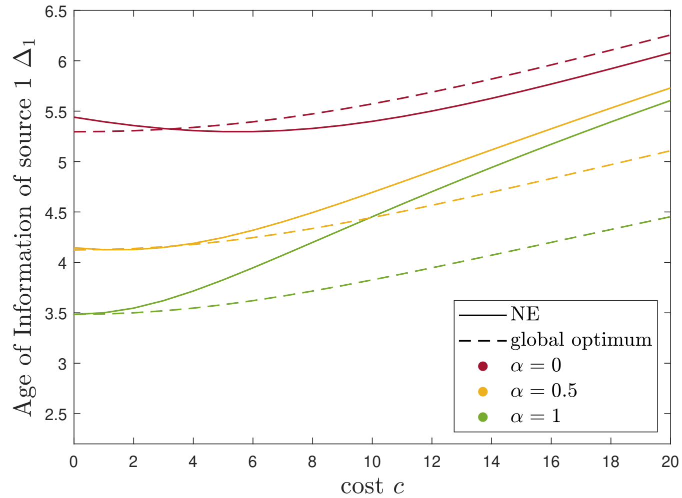

Fig. 3: Average AoI of one source at the NE (solid) and the global optimum (dashed), versus the cost c, for different values of the correlation parameter α.

selfish perspective of an individual source, which leads to source 1 computing

$$\lambda_1^*(\lambda_2) = \arg\max_{\lambda_1} u_1(\lambda_1, \lambda_2) = \arg\min_{\lambda_1}(\Delta_1 + c\lambda_1) \quad (7)$$

that is, the best response of source 1 to any possible choice of λ_2 by source 2. However, this also leads to source 2 choosing instead $\lambda_2^*(\lambda_1)$ and because of the symmetry in the formulas we get that the NE is ultimately achieved at the fixed point of the best response, i.e., the solution in λ of equation $\lambda = \lambda_1^*(\lambda)$ – or equivalently, $\lambda = \lambda_2^*(\lambda)$.

Moreover, given that we assumed a cost directly proportional to λ, it is immediate to see that the globally optimal λ is set in the value satisfying the following condition

$$\frac{\partial\big(u_1(\lambda,\lambda) + u_2(\lambda,\lambda)\big)}{\partial\lambda} = 0 \quad \Rightarrow \frac{\partial\Delta_1}{\partial\lambda} + \frac{\partial\Delta_2}{\partial\lambda} = -2c \quad (8)$$

whereas the NE must satisfy a similar condition but without the partial derivative of Δ_2 and the coefficient 2 multiplying c, since source 1 does not care about minimizing the AoI of the others and only counts its own costs (so, one source only).

In other words, this leads to a classic *tragedy of the commons* [37], where the inefficiency of an NE are caused by the selfish maximization of one player's utility. This is not really in contrast with the greater good of a global optimization, but it just gives a partial view of the problem.

V. Numerical Results

We present some numerical evaluations of the target value of λ computed through different approaches, either from a global perspective or a selfish one of an NE. Given the symmetry of the scenario, all of them result in the same arrival rate $\lambda = \lambda_1 = \lambda_2$ for both sources. For the sake of visual representation, μ is always chosen to be equal to 1.

Fig. 2 compares the optimal choice of the transmission rate from a global standpoint with the selfish perspective of the NE.

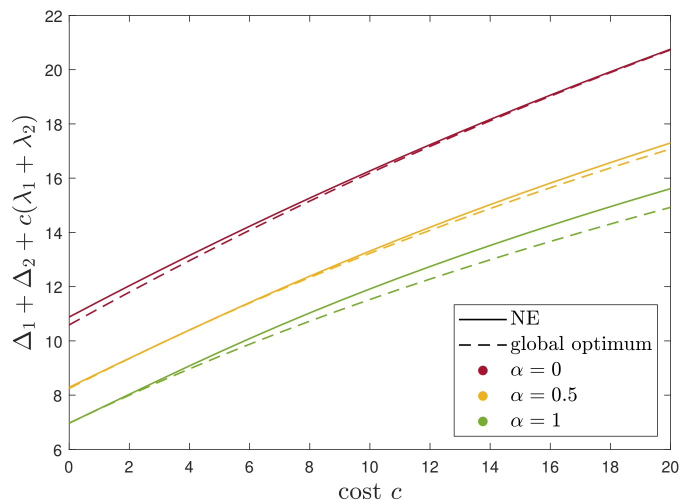

Fig. 4: Total cost $\Delta_1 + \Delta_2 + 2c\lambda$ at the NE (solid) and the global optimum (dashed), versus the cost c, for different values of the correlation parameter α.

Remarkably, the value of λ at NE starts from a much higher value than the optimal λ when $c = 0$ but, for increasing cost, the two values become closer. This behavior reverses when $\alpha = 1$ where initially, for $c = 0$, the optimal value for λ is approximately equal to λ at NE. When the cost increases, the optimal value for λ becomes significantly larger than λ at NE. When $\alpha = 0.5$ the figure shows that the two curves (dashed for optimal λ, solid for λ at NE) intersect for $c \simeq 3.5$.

According to the optimal and NE values of λ depicted in Fig. 2, the average AoI achieved by source 1 is represented in Fig. 3. Note that, given the symmetry of the scenario, also $\Delta_1^* = \Delta_2^*$, either for the global optimum or the NE. Fig. 3 shows that the value of Δ_1 at NE is always higher than the optimal value when $\alpha = 0.5$ or $\alpha = 1$, and the gap between the

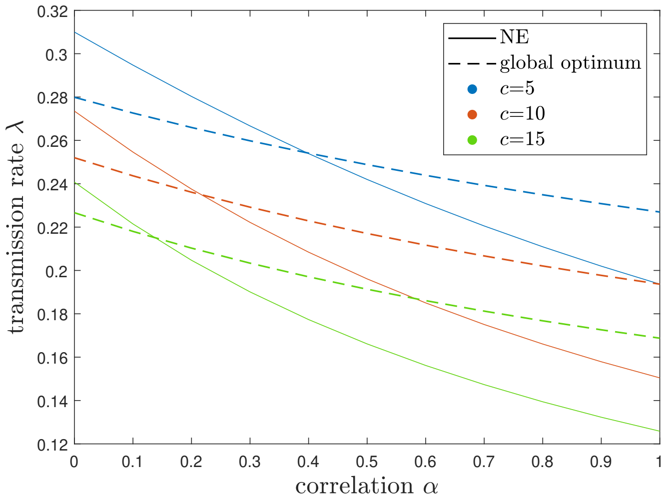

Fig. 5: Arrival rate λ at the NE (solid) and the global optimum (dashed), versus the correlation parameter α, for different values of the cost parameter c.

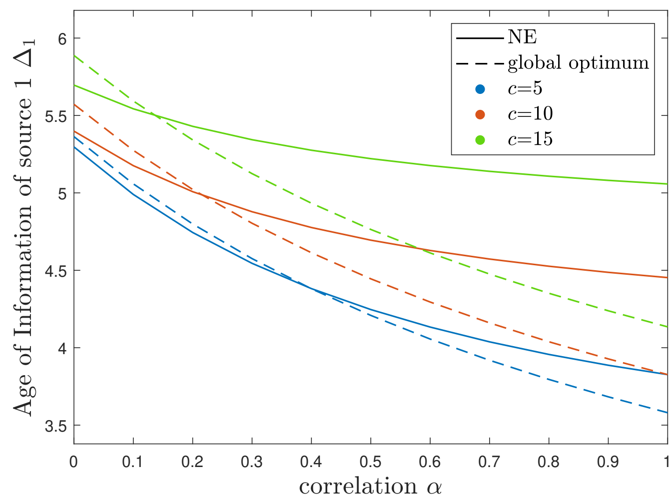

Fig. 6: Average AoI of one source at the NE (solid) and the global optimum (dashed), versus the correlation parameter α, for different values of the cost parameter c.

two curves representing the optimal (dashed) and NE (solid) AoI becomes larger as the cost c increases. We also remark that the AoI at the NE can even be lower than the optimal case (for small α and large costs), which is due to the optimal management not just considering the AoI but also the cost.

Indeed, the real objective of the optimization, i.e., the total cost function $\Delta_1 + \Delta_2 + 2c\lambda$, is shown in Fig. 4. For an optimal choice of λ (dashed lines), this value is minimized, whereas the NE obtains values that are always slightly higher. It is interesting to remark that, while the case with uncorrelated sources ($\alpha = 0$) achieves an NE that, while being sub-optimal, is very close to the best possible allocation of offered traffic, the gap widens when α increases. This happens in spite of the AoI and the overall objective function being always lower as the correlation increases.

This trend is shown to be even more acute in Fig. 3 for the AoI than for the cost function of Fig. 4, where a worse AoI can be somehow compensated by a better cost. This implies that, while correlation among multiple sources is generally beneficial to the AoI, the selfishness of the individual sources may fail to properly exploit it to the best possible extent.

To further investigate this point, we consider the correlation parameter α as the independent variable in Figs. 5 and 6. Fig. 5 shows the transmission rate λ at the global optimum solution and the NE, for different values of the cost. It can be seen that, for all the cost values, λ is higher at the NE than the globally optimal case. The values of λ are in both cases decreasing in α, which means that in a correlated scenarios the sources can save transmissions. However, the trend is much steeper for the NE, meaning that in a selfish allocation, the sources adopt a lazy behavior where they rely on the other to perform the update and save cost [29]. As a result, the higher the cost, the lower λ and also the lower the α required for the curves to intersect, meaning that for values of α higher than the intersection point, the NE implies a lower λ than the optimal allocation.

Fig. 6 shows the average AoI for one source as a function of the correlation parameter α under different costs. We recall that the optimization is performed over the linear combination of cost and AoI, which explains why the AoI at the NE is actually lower than the cost-optimal allocation at $\alpha = 0$. In this case, the cost of the NE is still higher than the optimal allocation, but this is achieved with a lower AoI, since in the case of no correlation among the sources, the NE describes a slightly more aggressive offered traffic than the optimum. However, as α increases, we observe a decreasing trend in all the curves, for both NE and global optimal allocations. Thus, analogous considerations than for the previous figure hold, with the difference that now the AoI is higher for increasing costs, since a larger c causes the source to be less active and therefore updating less often.

VI. Conclusions

We discussed the role of correlation among multiple sources in remote sensing, and how this can lead to spatial redundancy that can be exploited in an AoI-optimization. Based on existing analytical results for the AoI in multiple source queueing systems, we inserted two parametric terms related to cost of offered traffic and correlation among the source contents, so as to enable a game theoretic evaluation that, in line with the existing discussions on the subject, quantifies the efficiency of a distributed management by the individual sources.

It is important to remark that our game theoretic analysis does not revolve around a competition among the different sources, which is already investigated in the present literature. Indeed, competing behaviors among the sources are partially emended by the correlation of their content that allows for collaboration, rather than conflict. Still, given that generating updates can be seen as a costly operation (in terms of transmission and energy consumption), a distributed management must account for that it would be convenient, from the strategic standpoint of a distributed agent, to avoid sending updates and letting the others do it.

As a result, we show that, while correlation among sources is generally beneficial in lowering the AoI, a distributed management is not always successful, especially if the cost for generating updates is high. This means that the advantage coming from exploiting the correlation may be partially lost due to distributed selfish decisions made by strategic players. This opens the door to better and possibly low-cost strategic interactions.

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