Strategic Age of Information Under Different Correlation of Sources

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***Abstract*—We analyze a sensing system where multiple sources transmit status updates to a common receiver. We assume that the correlation of transmitted information allows updates from one source to enhance the information freshness of others. We study the objective of minimizing individual information staleness, quantified by the Age of Information (AoI), at the receiver's end. We evaluate both centralized and distributed optimization strategies. In the former case, we select the globally optimal transmission rates for each source to minimize the total average AoI of the system. For distributed optimization, sources are seen as players in a non-cooperative game of complete information, for which we compute the Nash equilibria. As an example, we consider a fixed correlation budget shared among two sources and evaluate the transmission rates depending on the specific level of correlation. Our results show that, under a centralized approach, it is convenient that only the source with more influential content transmits, while the other source reduces its data injection rate. In contrast, independent transmission in a distributed setup leads to greater congestion and higher average AoI. However, as correlation increases, the performance of the distributed system approaches that of the centralized model, indicating that decentralized management becomes effective in highly correlated scenarios.**

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

I. Introduction

Real-time remote sensing involves delivering up-to-date status information about a system. Age of information (AoI) is a metric that quantifies the freshness of status updates transmitted by sensors over time. Its broad adoption as a performance metric is attributed to its versatility across applications and its computational simplicity [1].

Consider a sensor that sends status updates to a receiver at specific time instances denoted by the set $\mathcal{T} = \ldots, \tau_1, \tau_2, \ldots, \tau_N, \ldots$. The AoI at a given time t is

$$\delta(t) = t - \tau_{\ell(t)}\,, \tag{1}$$

where $\ell(t) = \arg\max_j \tau_j \leq t$. A relevant literature on AoI focuses on various kinds of queueing systems [2]–[5], and in this contribution we leverage some of these results.

In particular, we consider the case of multiple sources, as explored in [6]–[10]. The main challenge in AoI studies for such scenarios is treating the information sources as independent agents, each aiming to prioritize its own updates in the queue. This issue can be addressed using *game theory*, which is a popular approach for modeling situations with multiple (competing) AoI values [11]–[13].

However, game-theoretic studies usually just address the competition over the scarcity of communication resources (e.g., a shared server, or a shared medium). Hence, status updates sent by one source congest the network and worsen the AoI value of others. In reality, many scenarios involve sensing sources that are *correlated* with each other [14]. Different agents might monitor the same environment, but at different locations, or measure different but correlated quantities [6], [15]–[18]. In such cases, correlation can be leveraged to improve the transmission [19], [20]. Even though the competition in this case is less impacting, game theory is still a useful instrument to evaluate the system performance, particularly to determine whether the decentralized management of the system achieves efficient performance [21], [22].

Building on this existing literature, this paper offers the following original contributions. First, we extend the system model by considering *different correlation* factors among sources. In this setup, updates from one source i may be valid for another source j as well, with a probability that is different for every (i, j) pair. Next, we use *game theory* to evaluate the inefficiencies in a distributed management [23], where each source independently chooses when to send updates, as opposed to following an optimal pattern. Despite correlation, nodes may still prioritize their own updates, which are guaranteed to improve their individual AoI, but may consider decreasing their activity if the transmission cost increases.

Our findings indicate that, under the global (centralized) optimum, the source with content most correlated to others continues to transmit, while the optimal transmission rate for the remaining sources decreases to zero as correlation increases. In contrast, when the sources choose their transmission rates independently, they continue to transmit regardless of the growing correlation, leading to greater congestion compared to the centralized approach, as each source acts in its own interest. Consequently, the average AoI obtained with a distributed approach is increased. However, at high correlation, the performance of the distributed system tends to that of the centralized model, suggesting that decentralized management becomes more viable in highly correlated environments.

The remainder of this paper is as follows: Section II reviews related work. Section III outlines the system model, while Section IV addresses the centralized optimization of the transmission rate. In Section V, we formalize the problem as a game and analyze its equilibria. Section VI presents numerical results. Finally, Section VII concludes the paper.

II. RELATED WORK

Our investigation is framed in the context of AoI for correlated sources, possibly using game theory for the analysis. In the literature, these aspects were already investigated by the seminal results in [9], where a case of multiple independent sources was studied. That work also suggests a game theoretic investigation, but seen from a perspective akin to a duopoly [24]. In other words, two sources (or any number greater than one) achieve better individual AoI by coordinating their sharing rather than competing, which is the same game theory principle according to which a cartel performs better for companies (but worse for the customers) than market competition.

Further game theoretic approaches have been proposed to encompass multiple sources that are not just sharing the server but also the medium, which is therefore subject to interference [25], collisions [26], or even an intentional malicious activity [27]. In [21], a similar scenario is considered but focusing on multiple sources independently sending the *same* information. Thus, the problem in this case is not competition, but rather resource waste due to lack of synchronization.

This latter case can be further extended considering the case where multiple sources are (partially) *correlated*, i.e., they have some form of overlap in their information content, which allows an update sent by a certain source to be considered beneficial for the AoI of another quantity [17], [20].

It is often sensible to assume that information content from multiple real-time sources is correlated in the context of environmental monitoring (e.g., sensors monitoring the same area) [15], or when the ultimate objective is to extract features from a data-rich series, e.g., through machine learning [28].

The literature is actually ambiguous on this issue, and no uniform taxonomy exists, with the "age of *correlated* information" (AoCI) as introduced in [18] actually describing a scenario where multiple sources must all deliver information for freshness of information to be reset. In other words, AoCI corresponds to an "and" condition (as opposed to our "or" one) over multiple content, and is computed as the age of the oldest content, a view that is also adopted in [16]. In [23], this is partially amended to age of "federated" information, i.e., the case where a subset of contents is to be updated, but not necessarily all of them, which prompts a game theoretic analysis for their selection. This is also different from the correlation-aware AoI used in [29], which instead refers to the degree of novelty brought by a new update, a concept that is more similar to Version AoI as studied in [10], [30].

We combined these two directions of considering sources with overlapping information content and a game theoretic approach for the first time in [6], where we showed that correlation is useful to not only improve the efficiency for centrally coordinated transmissions as proved by [20], but also decrease the price of anarchy for a game theoretic scheduler. However, in that paper we only considered a generic uniform correlation, whereas it is actually interesting to consider, as is done here for the first time, a possible case of unbalance, and what this entails for the resulting distributed management.

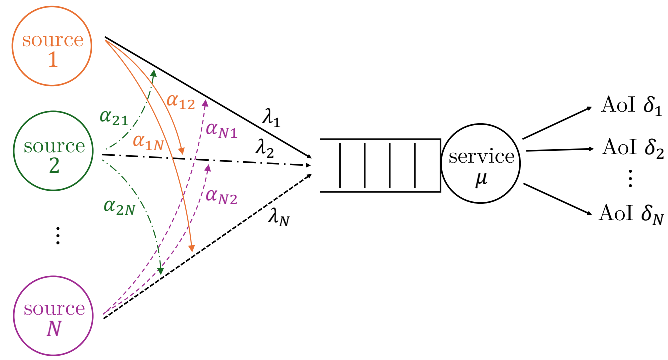

Fig. 1. Queueing system with N sources and correlated content.

III. SYSTEM MODEL

We analyze the scenario depicted in Fig. 1, where multiple sources, represented by the set $\mathcal{N} = \{1, 2, \ldots, N\}$, send status updates to a shared receiver. The receiver organizes all the incoming packets in a First-Come First-Served (FCFS) M/M/1 queue. The status update packets share the same queue, but each packet influences a distinct AoI value associated with its corresponding sending source.

The sources in $\mathcal{N}$ generate traffic according to Poisson processes with arrival rates $\lambda_1, \lambda_2, \ldots, \lambda_N$, respectively. The queue has an overall service rate of μ, and packets from all sources are served under identical conditions, with service times following an exponential distribution and an average duration of $1/\mu$.

A similar scenario was explored in [9], where we assume that the monitored statuses exhibit some degree of correlation, with potentially different correlation factors between pairs of sources. Specifically, the update packet transmitted by the i-th source affects its own AoI value but can also serve as a valid update for source $j \neq i$ with a certain probability; the latter is set as a parameter $\alpha_{ij} \in [0, 1]$ as discussed in the following.

Current advancements in AoI analysis consider memoryless transmission systems modeled as queues with various service disciplines [2], [5], [7], [8]. For simplicity, we focus on an M/M/1 FCFS queue, though more complex queueing systems could be incorporated into the game-theoretic framework without significantly altering the conclusions. The M/M/1 FCFS queue effectively represents independent nodes operating as data sources with configurable transmission rates. Employing more complex systems, while possible, would introduce additional complexity to the analytical derivations, leading to a more cumbersome mathematical analysis. For a comparison between memoryless and deterministic data generation, we refer the interested reader to [31]. While deterministic generation may better represent sensing scenarios with periodic reporting, it does not provide a straightforward closed-form solution. Nonetheless, it has been shown that the same qualitative conclusions apply, with deterministic systems exhibiting AoI values that are effectively scaled-down versions of those observed under memoryless generation.

The average AoI Δ obtained considering an M/M/1 queue with transmission rate λ and service rate μ is [1]

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

where $\rho = \lambda/\mu$ is the load factor of the queue. We assume a normalized service rate of $\mu = 1$, which simplifies the formulas by eliminating the coefficient $1/\mu$ at the beginning and substituting ρ with λ. This leads to

$$\Delta = 1+\frac{1}{\lambda}+\frac{\lambda^2}{1-\lambda}, \tag{3}$$

which can be adapted for a non-unit service rate by re-scaling. The same adjustment applies to all equations introduced thereafter. Also, for the system to be stable, we require $\lambda < 1$.

The AoI-optimal value of λ in (3) is determined to be $\lambda \approx 0.531$ [1]. This implies a strategy that is neither idle too often, nor too aggressive, as λ is somehow intermediate between 0, which would result in stale information, and 1, at which point the queue becomes unstable, leading to extremely high AoI.

In follow-up contributions [7], [9], [32], the results of (3) were extended to the average AoI for N independent sources. From [32, Eqs.(25)–(26)], the expected AoI Δ_j of source j as a function of vector $\boldsymbol{\lambda} = \{\lambda_i\}_{i\in\mathcal{N}}$ can be written as

$$\Delta_j(\boldsymbol{\lambda}) = \frac{1-\Lambda}{(\Lambda-\Lambda_{-j}\mathcal{E}_j)(1-\Lambda\mathcal{E}_j)}+\frac{1}{1-\Lambda}+\frac{\Lambda_{-j}}{\lambda_j} \tag{4}$$

$$\text{where:}\quad \mathcal{E}_j = \frac{1+\Lambda-\sqrt{(1+\Lambda)^2-4\Lambda_{-j}}}{2\Lambda_{-j}} \tag{5}$$

$$\Lambda = \sum_i \lambda_i, \quad \Lambda_{-j} = \Lambda-\lambda_j = \sum_{\substack{i=1\\ i\neq j}}^{N}\lambda_i\,.$$

Note that, thanks to the superposition property of Markov processes, all data injected from sources other than j, with rate Λ_{-j}, can be treated as a single memoryless source.

Building on this literature, we extend the analysis by considering that the packets transmitted by a source may contain data that is correlated with the process monitored by another source, with correlation factors varying for different source pairs. Specifically, a data packet sent by source i can also affect the instantaneous AoI of another source j with probability α_{ij}, similar to how packets from source j influence the AoI of source i [19]. Therefore, the AoI value of source i benefits from packets sent by source i with probability 1 and from packets sent by any other source $j \neq i$ with probability α_{ij}. Due to the memoryless nature of data, α_{ij} can alternatively be interpreted as the fraction of data from source i that is beneficial to source j, rather than as a probability.

IV. Centralized Optimization

We can reformulate (4) by considering this correlation among the data contents. This implies that, while Λ is the same, the rate of transmitted data that are useful for the AoI Δ_j of source j increases to

$$\ell_j = \lambda_j + \sum_{\substack{i=1\\ i\neq j}}^{N}\alpha_{ij}\lambda_i, \tag{6}$$

whereas the injection rate of data that do not enhance Δ_j is

$$L_{-j} = \sum_{\substack{i=1\\ i\neq j}}^{N}(1-\alpha_{ij})\lambda_i. \tag{7}$$

Modifying (4) as per [6] gives the mean AoI of source j as

$$\Delta_j(\boldsymbol{\lambda}) = \frac{1-\Lambda}{(\Lambda-L_{-j}\varepsilon_j)(1-\Lambda\varepsilon_j)}+\frac{1}{1-\Lambda}+\frac{L_{-j}}{\ell_j} \tag{8}$$

where ε_j also follows from replacing Λ_{-j} with L_{-j} in (5):

$$\varepsilon_j = \frac{1+\Lambda-\sqrt{(1+\Lambda)^2-4L_{-j}}}{2L_{-j}} \tag{9}$$

Introducing α_{ij} enables us to distinguish a range of scenarios. When $\alpha_{ij} = 0, \forall i,j$, we encounter the case of multiple independent sources, which is the reference scenario in [9], where the average AoI is given by (4). If $\alpha_{ij} = 1, \forall i,j$, all sources behave as a single flow with transmission rate Λ, reverting to the basic scenario of [1] with a single source injecting $\lambda = \Lambda$, whose average AoI is provided by (3). In the intermediate case where $0 < \alpha_{ij} < 1$, the status updates of the sources are correlated, indicating that some packets transmitted by one source can serve as updates for another [6], [20]. The average AoI in this scenario is described by (8).

It is worth noting that the entire concept of AoI arises from the redundancy of information over time. This redundancy suggests that multiple consecutive updates can congest processing at the end server without significantly improving information freshness; therefore, it may be more effective to distribute these updates evenly over time. Our analysis extends this idea to spatial redundancy, indicating that unnecessary updates can be avoided if another source has already transmitted an update about a related or identical process [33].

In this context, the *global optimum* vector $\boldsymbol{\lambda}^\star = [\lambda_1^\star, \dots, \lambda_N^\star]$ of injection rates is given by

$$\boldsymbol{\lambda}^\star = \arg\min_{\boldsymbol{\lambda}} \sum_{j=1}^{N}\Delta_j(\boldsymbol{\lambda}), \tag{10}$$

whose solution can be obtained numerically, or by calculating the first-order partial derivatives of the objective in λ_j, $j = 1,\dots,N$, through (8), and setting them to 0 [22]. We remark that in a global optimization framework, each source selects a distinct transmission rate, optimized to minimize the system's overall average AoI.

V. Distributed Optimization via Game Theory

Game theory analyzes strategic interactions among multiple agents, each pursuing its own objectives. In a similar vein to related works such as [13], [21], we apply this methodology to scenarios involving multiple sources, where each agent aims to minimize its own AoI. This leads to the formalization of a static game of complete information, where the Nash Equilibrium (NE) is computed, often in closed form, using the theoretical framework described above. Although this equilibrium reflects the outcome of distributed optimization by each source, it is typically suboptimal from the standpoint of the global system. Therefore, it can be compared to the globally optimal transmission strategy, which yields a lower AoI for all nodes—i.e., a Pareto-efficient solution.

Studies concerning this approach focus on uncorrelated systems tracked by different nodes, leading to AoI values that are independent of each other. This independence fosters competition and greater inefficiency. Naturally, a globally optimal allocation that reduces the overall AoI is not seen as a NE by the players. While not directly adversarial, the players view the service of data generated by other sources as irrelevant and may prioritize their content instead.

We expect correlation among sources to reduce competitive behavior, as a source can potentially lower its own AoI by allowing others to transmit. To formalize this quantitatively, we define a static game of complete information, $\mathcal{G} = (\mathcal{N}, \mathcal{A}, \mathcal{U})$, where the players set $\mathcal{N}$ corresponds to the N sources. The action set $\mathcal{A} = [0,1]^N$ includes each $\lambda_j \in [0,1]$ as the action of the j-th player, and the utility set $\mathcal{U}$ consists of $-\Delta_{j\, j\in\mathcal{N}}$. The negative sign follows from the game-theoretic convention where utilities represent quantities to maximize, whereas in our case, the average AoI Δ_j represents the objective of the j-th player, a quantity to minimize.

Although decisions are made individually and without coordination—hence the game is *static*—the common knowledge shared among players ensures that, even with selfish goals, they are aware of the broader consequences of their actions. Thus, no player will attempt to monopolize the queue's service capacity with excessive traffic, as this would result in congestion and high AoI.

In our scenario, players are also expected to recognize that they can be less aggressive and leverage correlation to assist each other [14]. Depending on the values of α_{ij}, each player may see that updates from another source can partially benefit their own AoI, encouraging more cooperative behavior. Therefore, applying game theory to this system is not primarily about modeling competition among players, but rather about approaching it as a distributed system management issue, where understanding the overall efficiency is key [13], [23].

The NE can be determined by considering the self-interested perspective of each source, leading source j to calculate its best response (BR) to the transmission rates selected by the other players as

$$\lambda_j^{(\mathrm{BR})}(\lambda_{-j}) = \arg\max_{\lambda_j} \Delta_j(\boldsymbol{\lambda}) \,, \tag{11}$$

where $\lambda_{-j} = \lambda_1, \ldots, \lambda_{j-1}, \lambda_{j+1}, \ldots, \lambda_N$ represents the set of strategies chosen by all sources except the j-th.

The NE, denoted as $\boldsymbol{\lambda}^{\mathrm{NE}} = [\lambda_1^{\mathrm{NE}}, \ldots, \lambda_N^{\mathrm{NE}}]$, is achieved when all sources play a BR strategy. In practice, this is found by solving a system of equations, each corresponding to the derivative of player j's BR function with respect to its transmission rate λ_j, set equal to zero.

The difference between the two approaches is subtle but significant. The global optimum involves setting $\boldsymbol{\lambda}^\star$ simultaneously for all sources, whereas at the NE, $\boldsymbol{\lambda}^{\mathrm{NE}}$, each source focuses only on minimizing its own AoI, Δ_j, through its transmission rate, λ_j. In the distributed approach, source j (and all other sources) does not consider minimizing the AoI of the others and has no control over their actions.

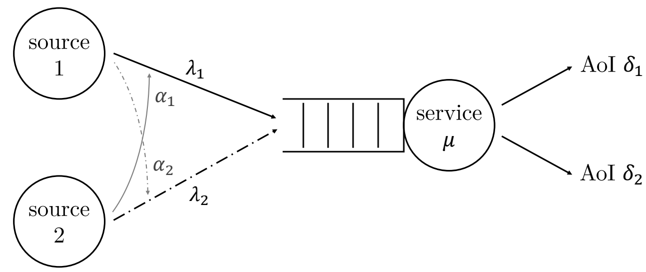

Fig. 2. Two-sources scenario.

Because the service capacity is a shared resource, the NE deviates from the optimal allocation due to inherent differences in objectives and decision-making criteria. The optimal allocation reflects a system working point that is efficient for the entire network, meaning the server is shared in such a way that the average AoI for all users is minimized collectively. In contrast, the NE arises when individual sources make strategic decisions to minimize only their own AoI, disregarding the collective welfare of the network. This selfish approach can result in suboptimal resource allocation, as sources prioritize their own interests over the network's efficiency [9].

VI. Numerical Results

We present the numerical results obtained for a two-source case as depicted in Fig. 2. For ease of notation we set $\alpha_1 = \alpha_{2,1}$ and $\alpha_2 = \alpha_{1,2}$. We consider a *correlation budget* $x \in [0,1]$ that is split between α_1 and α_2, that is $\alpha_1 + \alpha_2 = x$. We will examine three distinct scenarios. In the first one, the correlation budget is evenly distributed between the two sources. In the second scenario, the entire correlation budget is assigned to α_2. In the third and last one, an intermediate case is considered, where $\alpha_1 = 0.2\,x$ and $\alpha_2 = 0.8\,x$. Thus, for all scenarios, $\alpha_1 \leq \alpha_2$, implying that the packets transmitted by source 1 exhibit a higher correlation and are therefore more useful to convey information.

Figs. 3 and 4 show the transmission rates λ_1 and λ_2 of source 1 and 2, respectively, at the global optimum (solid lines) and the NE (dashed lines), versus the correlation budget x, for different allocations of the correlation budget between α_1 and α_2. In the first scenario, the correlation budget is equally divided between the two sources, such that $\alpha_1 = \alpha_2 = x/2$. Here, the transmission rates of sources 1 and 2 decrease slightly with increasing x, both at the global optimum and NE. This decrease remains minimal due to the balanced correlation coefficients between the two sources. Notably, at NE the value of λ_1^{NE} and λ_2^{NE} start from a higher value than the global optimum, as predicted by game theoretic reasonings, but, for increasing x, the two values become close. Moreover, because the correlation budget is evenly distributed between

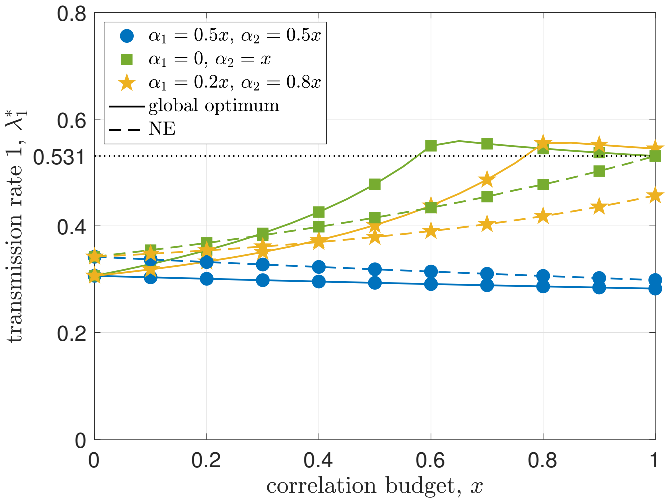

Fig. 3. Source 1 transmission rate λ_1 at the global optimum (solid) and NE (dashed) versus correlation budget x, for different allocations of x between α_1 and α_2.

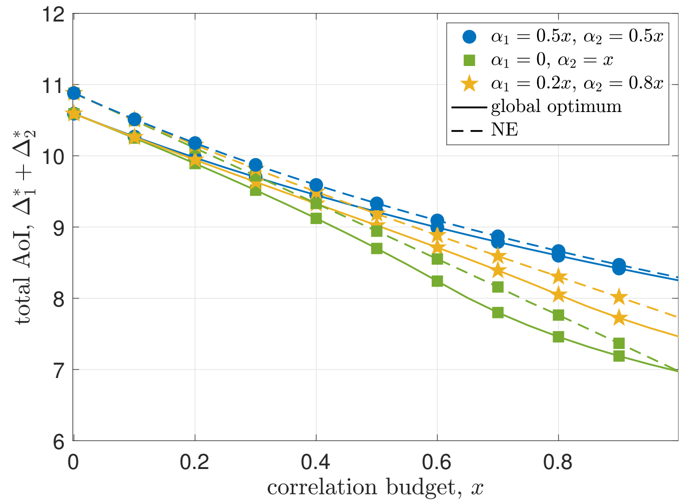

Fig. 5. Average total AoI at the global optimum (solid) and NE (dashed), vs correlation budget x, for different allocations of x between α_1 and α_2.

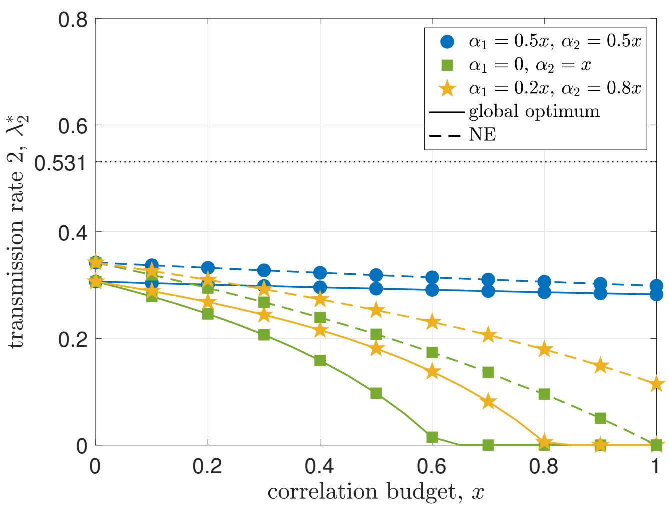

Fig. 4. Source 2 transmission rate λ_2 at the global optimum (solid) and NE (dashed), vs correlation budget x, for different allocations of x between α_1 and α_2.

the two sources, symmetry ensures that the globally optimal transmission rates for both sources, $\lambda_1^\star$ and $\lambda_2^\star$ are equal.

In the opposite scenario, in which $\alpha_1 = 0$ and $\alpha_2 = x$, meaning the entire correlation budget is allocated to α_2, from Fig. 4 we see that source 2 stops transmitting when the correlation budget is $x > 0.6$ at the global optimum. As a result, source 1 increases its transmission rate beyond 0.531, as shown in Figure 3, which is the AoI-minimizing value in a single-source scenario. This occurs since, in a centralized optimization setting, when source 1 is the only one transmitting, it does not merely aim to minimize its own AoI (which is minimized at $\lambda_1 = 0.531$), but must transmit more frequently to compensate for the absence of transmissions from source 2. In contrast, when source 1 acts selfishly, behaving as a strategic player in a non-cooperative game, its transmission rate at the NE never exceeds the optimal value of 0.531, reaching it only for $x = 1$. This is because a selfish source has no incentive to reduce the AoI of the other source, focusing solely on minimizing its own. When x approaches 1, $\lambda_1^\star$ goes to 0.531 as $\alpha_2 = 1$, thus source 2's role becomes entirely redundant, and the two sources act as a single source. A similar pattern is observed in the third scenario, where $\alpha_1 = 0.2\,x$ and $\alpha_2 = 0.8\,x$, with the difference that source 2 stops transmitting when $x > 0.8$, moving the point at which source 1 is the sole transmitter further to the right compared to the previous scenario.

So, at the NE, each source aims to minimize its own AoI without accounting for the overall system performance. As a result, source 1 never transmits beyond the AoI-minimizing value of 0.531, and source 2 never stops transmission except when $\alpha_2 = 1$. In contrast, under centralized optimization, source 2's role diminishes as x increases in the second and third scenarios. Specifically, in these cases, source 2 ceases transmission once x is above a certain threshold.

Fig. 5 shows the average total AoI resulting from the transmission rates chosen through either global (solid lines) or distributed optimization (i.e., the NE, dashed lines), versus correlation budget x, for different allocations of x between α_1 and α_2. We first observe that the average total AoI at the NE is consistently higher than that at the global optimum. This demonstrates that when the sources behave selfishly, they increase the overall AoI of the system. Moreover, Fig. 5 demonstrates that as x increases, the total AoI decreases due to the increasing correlation between the sources, which improves the efficiency of the information update process. Additionally, the gap between the global optimum and the NE narrows with increasing correlation among the two sources, indicating that even in a distributed setting, moderate to high correlation can significantly reduce the inefficiency and improve overall system performance [6].

VII. Conclusions

We analyzed the impact of correlated content among multiple sources in a sensor network system, where status updates are transmitted to a common receiver. We developed both centralized and distributed optimization of the transmission rate of each source to minimize the system AoI. Moreover, we considered different correlation factors among the sources.

Our results focused in particular on a two-source scenario, showing that, at the global optimum, the source whose content is more influential on the other continues to transmit and may even increase its rate beyond the single-source optimum, while the optimal transmission rate of the other drops to zero, as the correlation increases. In contrast, at the NE, both sources continue to transmit despite the growing correlation, leading to more congestion compared to the centralized case. As a result, the average AoI at the NE is higher than that in the centralized system. However, when the correlation becomes sufficiently high, the performance of distributed optimization approaches that of the centralized system, making decentralized management feasible in highly correlated environments.

These findings have implications for the design of sensor networks and other distributed systems [26], suggesting that exploiting correlations between sources can significantly enhance performance, particularly in environments where full central control may not be feasible.

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References

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

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

[3] A. Soysal and S. Ulukus, "Age of information in G/G/1/1 systems: Age expressions, bounds, special cases, and optimization," *IEEE Trans. Inf. Theory*, vol. 67, no. 11, pp. 7477–7489, 2021.

[4] A. Kosta, N. Pappas, A. Ephremides, and V. Angelakis, "The age of information in a discrete time queue: Stationary distribution and non-linear age mean analysis," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1352–1364, 2021.

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

[6] L. Badia and L. Crosara, "Correlation of multiple strategic sources decreases their age of information anarchy," *IEEE Trans. Circuits Syst. II*, vol. 7, no. 71, pp. 3403–3407, 2024.

[7] M. Moltafet, M. Leinonen, and M. Codreanu, "Average AoI in multi-source systems with source-aware packet management," *IEEE Trans. Commun.*, vol. 69, no. 2, pp. 1121–1133, Feb. 2020.

[8] M. Costa, M. Codreanu, and A. Ephremides, "On the age of information in status update systems with packet management," *IEEE Trans. Inf. Theory*, vol. 62, no. 4, pp. 1897–1910, 2016.

[9] R. D. Yates and S. K. Kaul, "The age of information: Real-time status updating by multiple sources," *IEEE Trans. Inf. Theory*, vol. 65, no. 3, pp. 1807–1827, Mar. 2018.

[10] R. D. Yates, "The age of gossip in networks," in *Proc. IEEE ISIT*, 2021, pp. 2984–2989.

[11] K. Zhang, X. Fang, D. Wang, Y. Lv, and X. Yu, "Distributed Nash equilibrium seeking under event-triggered mechanism," *IEEE Trans. Circuits Syst. II*, vol. 68, no. 11, pp. 3441–3445, 2021.

[12] L. Badia, A. Zanella, and M. Zorzi, "A game of ages for slotted ALOHA with capture," *IEEE Trans. Mobile Comput.*, vol. 23, no. 5, pp. 4878–4889, 2024.

[13] K. Saurav and R. Vaze, "Game of ages in a distributed network," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1240–1249, May 2021.

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

[15] A. E. Kalør and P. Popovski, "Minimizing the age of information from sensors with common observations," *IEEE Wireless Commun. Lett.*, vol. 8, no. 5, pp. 1390–1393, 2019.

[16] B. Zhou and W. Saad, "Age of information in ultra-dense IoT systems: Performance and mean-field game analysis," *arXiv preprint arXiv:2006.15756*, 2020.

[17] J. Tong, L. Fu, and Z. Han, "Age-of-information oriented scheduling for multichannel IoT systems with correlated sources," *IEEE Trans. Wireless Commun.*, vol. 21, no. 11, pp. 9775–9790, 2022.

[18] Q. He, G. Dán, and V. Fodor, "Joint assignment and scheduling for minimizing age of correlated information," *IEEE/ACM Trans. Netw.*, vol. 27, no. 5, pp. 1887–1900, 2019.

[19] A. Zancanaro, G. Cisotto, and L. Badia, "Modeling value of information in remote sensing from correlated sources," *Comp. Commun.*, vol. 203, pp. 289–297, 2023.

[20] V. Tripathi and E. Modiano, "Optimizing age of information with correlated sources," in *Proc. ACM MobiHoc*, 2022, pp. 41–50.

[21] L. Badia, "Age of information from two strategic sources analyzed via game theory," in *Proc. Int. Wkshp Comp. Aided Model. Design Commun. Links Netw. (CAMAD)*, 2021, pp. 1–6.

[22] M. Li, "Generalized Lagrange multiplier method and KKT conditions with an application to distributed optimization," *IEEE Trans. Circuits Syst. II*, vol. 66, no. 2, pp. 252–256, 2018.

[23] A. Buratto, A. Mora, A. Bujari, and L. Badia, "Game theoretic analysis of AoI efficiency for participatory and federated data ecosystems," in *Proc. IEEE ICC Workshops*, 2023, pp. 1301–1306.

[24] R. Ginevičius and A. Krivka, "Application of game theory for duopoly market analysis," *J. Business Econ. Manag.*, vol. 9, no. 3, pp. 207–217, 2008.

[25] G. D. Nguyen, S. Kompella, C. Kam, J. E. Wieselthier, and A. Ephremides, "Information freshness over an interference channel: A game theoretic view," in *Proc. IEEE Infocom*, 2018, pp. 908–916.

[26] L. Badia and A. Munari, "A game theoretic approach to age of information in modern random access systems," in *Proc. IEEE Globecom Wkshps*, 2021, pp. 1–6.

[27] S. Banerjee and S. Ulukus, "The freshness game: Timely communications in the presence of an adversary," *IEEE/ACM Trans. Netw.*, vol. 32, no. 5, pp. 4067–4084, 2024.

[28] M. K. C. Shisher, H. Qin, L. Yang, F. Yan, and Y. Sun, "The age of correlated features in supervised learning based forecasting," in *Proc. IEEE Infocom Workshops*, 2021, pp. 1–8.

[29] A. A. Al-Habob, O. A. Dobre, and H. V. Poor, "Age- and correlation-aware information gathering," *IEEE Wireless Commun. Lett.*, vol. 11, no. 2, pp. 273–277, Feb. 2022.

[30] B. Buyukates, M. Bastopcu, and S. Ulukus, "Version age of information in clustered gossip networks," *IEEE J. Sel. Areas Inf. Th.*, vol. 3, no. 1, pp. 85–97, 2022.

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

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

[33] M. Taghouti, A. K. Chorppath, T. Waurick, and F. H. P. Fitzek, "Practical compressed sensing and network coding for intelligent distributed communication networks," in *Proc. IEEE IWCMC*, 2018, pp. 962–968.