Age of Information From Two Strategic Sources Analyzed via Game Theory

Leonardo Badia
Dept. of Information Engineering (DEI), University of Padova, Italy
email: leonardo.badia@unipd.it

***Abstract*—This paper investigates a system with two strategic sources, both being able to update a given information process at the receiver's end, but doing so independently and unbeknownst to each other, and also being aware that they incur a local cost for each update. Thus, the sources should independently make a periodic decision on whether to update or not, weighing the global benefit of decreasing the receiver's age of information versus their individual cost paid. This scenario is analyzed from a game theoretic perspective, showing the existence of three Nash equilibria, with different overall efficiencies. Interestingly, for a wide range of update costs, the efficient equilibria are the ones with most unbalance between the updates from either source. In other words, making use of both sources does not result in an efficient equilibrium. This further enables the evaluation of the Price of Anarchy, quantifying the worst-case scenario inefficiency of selfish management of the sources, under different values of the updating cost.**

***Index Terms*—Age of Information; Game theory; Remote sensing; Price of Anarchy.**

I. Introduction

Many modern implementations of communication networks can be related to the Internet of things (IoT), i.e., an interconnected system of physical objects with the abilities of sensing the environment, analyze and compute data, and communicate with other devices over the Internet, which is expected to be beneficial for many applications in the everyday life [1], [2]. For many reasons, including scalability and ease of implementation in simple devices, these pervasive systems are supposed to employ a distributed management with low complexity algorithms [3]. Hence, the development of solution based on game theory is becoming increasingly popular in such a context [4], [5].

Moreover, it is argued by a relatively recent line of research [6], [7] that in these scenarios, especially in those involving remote sensing, freshness of information is more relevant than the sheer amount of raw data exchanged. Hence, the so-called Age of Information (AoI) may be a performance metric that is interesting to characterize, even more than considering throughput or latency as usually done.

Despite being slightly more complex than other standard metrics, AoI can be quantified analytically (also with closed-form expressions in the simplest cases); thus, it can be included in game theoretic models under proper assumptions. At the same time, it may be interesting to evaluate such a metric from the perspective of distributed devices, independently owned, that therefore act following selfish objectives, as is typical of game theoretic scenarios [8]–[10].

In light of these motivations, the contribution of the present paper is to investigate a scenario consisting of two independent sources, tracking the same underlying process of interest for a receiver, to which they are sending periodic updates with a given probability and incurring an individual cost when doing so. Both sources are equally capable to send an update that refreshes the information at the receiver, but they are also aware that sending two updates at the same time just increases the costs without adding any benefit. This causes them to interact according to a scenario framed as a static game of complete information, where the sources are the players seeking to minimize a combination of the overall AoI achieved by the system, which remains their primary objective, but at the same time also including their individual transmission cost.

To this end, an analytical model is presented for the evaluation of AoI under an uncoordinated but synchronized (over multiple time slots) exchange of updates, where we account for a discrete time axis [6], [11]. This model is employed inside the aforementioned game theoretic scenario so as to identify possible Nash equilibria (NEs), i.e., mutual strategic choices that are taken in a distributed manner but turn out to be unilaterally satisfactory for both players at the same time. This further allows the evaluation of global metric such as the Price of Anarchy (PoA) and the Price of Stability (PoS), namely, the ratio between the global utility of both sources in the best possible scenario versus the worst and best NEs, respectively [12], [13].

From the analysis for one source only, which is immediate to optimize, an extension to the case of two players show that *three* NEs exist for this game, which consist of: (i) a perfectly balanced update frequency between the two sources, and (ii) leaving the burden of the update to only either source (depending on which it is, two different equilibria are achieved). However, the last NEs are actually found to be more efficient than the balanced solution, at least for a wide range of cost parameters. This implies that, from the individual sources' perspective, it would be better if only either of them sends updates, and the other just stays silent, with possible swapping of the roles every now and then.

In a sense, this finding is unfavorable for distributed architectures aimed at remote sensing, where multiple sources work independently. Even with the only inefficiencies coming from lack of coordination among multiple sources, the system is working at a more desirable equilibrium, at least from the sources' own point of view, if only either of them sends updates. However, some remarks mitigate this conclusion. First of all, the update probability for the balanced solution is found to be very close to the optimal value, especially for increasing costs. Also, the AoI achieved at the balanced equilibrium is better than when only one source is active, so the system manager might try to push the system toward this operating point, which is more efficient from the receiver's perspective. Moreover, this may prompt further investigations for low-cost signaling exchange among the sources that would allow to harmonize their updates and therefore avoid inefficiencies from the lack of coordination.

The rest of this paper is organized as follows. Section II reviews related work in the area. Section III presents the game theoretic model and develops the analysis. Section IV shows some numerical results. Finally, Section V gives the conclusions.

II. Related Work and Contribution of the Paper

In the literature, there are several approaches framing the network exchange of data coming from independent multiple sources as a game. The general idea is to use game theory to characterize a distributed management of such sources, and possibly evaluate its efficiency [5], [11], [14]. In these papers, the objective of the nodes is generally assessed in terms of data amount and/or quality versus their cost of transmission.

Also, a relevant point is whether to consider a homogeneous network structure, consisting of many nodes acting in identical but uncoordinated fashion, or just a limited number of them (usually two). The former methodology would be more consistent with the pervasive nature of IoT systems, but requires specific approaches such as mean-field games or minority games, as argued in [15]. In reality, one contribution of the present paper is to highlight the potential inefficiencies (or at least the lack of interest for some nodes in participating in an equilibrium outcome that is inefficient for them) of symmetrical solutions. In order to keep the investigation simple and allow for a fully analytical derivation, the analysis considers two sources as players in a standard game, although one can argue that the main conclusions can promptly be extended, at least in principle, to a higher number of sources.

Notably, the most common application of game theory to data exchange in IoT systems is possibly that of security [4], [16], [17], also sometimes framed as a jamming problem [18]–[21], with an adversarial setup between the legitimate network nodes and some attackers. This is also a very relevant aspect of IoT scenarios, and is possibly easy to integrate as something akin to a zero-sum game [12]. However, the analysis of the present paper just considers a uniform structure of the network with the same objective for all the nodes, and the end goal is to achieve an efficient coordination, which all the sources would be interested in.

Instead, in this paper the specific focus is on the AoI as the performance metric; given the relatively recent idea of using information freshness as an important performance metric in remote sensing [6], there are only a handful of papers using a similar objective. For example, [8] considers AoI but for a ultra-dense IoT system, which prompts the game theoretic analysis through mean-field games, as opposed to considering the detailed behavior (but just for a pair of sources) as done here.

Another relevant paper is [9], where multiple nodes are interested in tracking different processes and compete over a shared channel to get the lowest AoI. A related game is considered in [10], where two transmitter/receiver pairs are trying to exchange updates over a wireless channel but they cause interference to each other, which degrades the quality of the update. These papers are more similar to the analysis presented here, but in all these cases multiple sources are considered to be *competitive* and tracking different processes. Up to the author's knowledge, this is the first paper attempting at characterizing sources that are neither explicitly collaborating nor competing, they just share the same global objective of sending timely updates but with a selfish interest (as is typical of game theory) in saving their individual cost.

Thus, the present paper presents an original contribution in that a game theoretic evaluation of AoI, already itself rarely addressed aside from the most recent literature, is framed in the management of individual sources that try to minimize the *same* AoI, with the only selfish component of their utility being their individual cost.

In this spirit, the conclusions reached by the analysis, where it is found that it might be more convenient in some cases for the sources to be inactive and leave only one of them to update, are detrimental to the overall goal of network collaboration. As a consequence, for the sake of a more efficient distributed management, some form of coordination, even through elementary signaling, ought to be introduced. On the other hand, the AoI value clearly benefits from a balanced usage of both sources, so that the network manager and/or the receiver might be interested in promoting this specific outcome, possibly compensating the individual sources for their efforts.

III. System Model

A system with two sources S_1 and S_2 and one receiver R is considered. Both sources are tracking an underlying process of interest for R, and they are capable to send updates about it. The receiver is interested in getting an information status about the process that is as fresh as possible. This is quantified through the AoI metric δ, defined as the difference between the current time value and the last update from either source [9], [22].

For the analysis, a discrete time axis divided into slots of same duration, also referred to in the following as *update epochs*, is considered; the resulting AoI at each time instant is computed as an integer value. For example, we assume that $\delta = 0$ for any epoch where an update from either source is received. More in general, if s_1 and s_2 provide their respective updates at time slots $\boldsymbol{\tau}_1 = \{\dots, \tau_1^{(1)}, \tau_1^{(2)}, \dots, \tau_1^{(n)}, \dots\}$ and $\boldsymbol{\tau}_2 = \{\dots, \tau_2^{(1)}, \tau_2^{(2)}, \dots, \tau_2^{(n)}, \dots\}$, the value of δ at time slot t is

$$\delta(t) = t - \max\left(\{\tau \leq t\} \cap (\boldsymbol{\tau}_1 \cup \boldsymbol{\tau}_2)\right) . \tag{1}$$

TABLE I
OUTCOME OF THE INTERACTIONS AT EACH UPDATE EPOCHS

		source S_2	
		update	**idle**
source S_1	**update**	$\delta(t) \leftarrow 0$ S_1&S_2 pay c	$\delta(t) \leftarrow 0$ S_1 pays c
	idle	$\delta(t) \leftarrow 0$ S_2 pays c	$\delta(t) \leftarrow \delta(t-1)+1$ no cost paid

At each time slot, the sources decide, in a random fashion and independent of each other, whether to access the resource and therefore perform an update, or stay idle. If a source decides to update the information at the receiver, it is also requested to pay a cost term, denoted as c. For each of the possible four outcomes, we are able to determine the evolution of $\delta(t)$ from the previous value $\delta(t-1)$, and the associated updating costs paid by the sources. A schematic representation is given in Table I. Notably, the information at R is updated in 3 cases out of 4, the only exception being when neither source decides to update, in which case $\delta(t)$ increases by one but no cost is paid. While the table is hinting at a *normal form* representation of a game [12], [13], in this specific case the strategic choices are better modeled as continuous values, namely, the probabilities of performing an update.

For the sake of simplicity, it is assumed that there is no signaling from R to the sources, so S_1 and S_2 just choose by themselves to update with an independent and identically distributed (i.i.d.) probability value, denoted as p_1 and p_2, respectively, over different time slots. This is consistent with a sensing scenario in which there is no way to adopt more sophisticated strategies, which would make sense if R is capable of actively sending requests to the sources; in which case, for example, R can push for an update with higher probability, e.g., if the AoI is becoming very large. However, our scenario allows for a fully analytical development that is consistent with other similar investigations [6], [23]. Moreover, whenever a source decides to update, its sent data are always received successfully. This means that updates never fail; it would be possible to extend this analysis to the case of non-guaranteed decoding of the update, as per [22], or unreliable feedback from the sources [24], or even potential collisions and interferences among the sources [10], but all of these extensions would only marginally affect the essence of the analysis, and are therefore left for future work.

As pointed out in the previous section, one major difference with the existing literature is that we consider two independent sources that are just lacking coordination but are not themselves competing. Indeed, they just try to update the same receiver, so it would make sense for them to obtain a lower AoI as part of their objectives. On the other hand, they are also aware of the inherent inefficiency of their lack of information exchange, which can sometimes lead to sending two updates at the same time.

For this reason, the introduction of a cost term does not only make sense in order to correctly characterize the physical nature of the devices (according to this aspect, c can be related to energy consumption or data processing costs to obtain and transmit an update information packet) but also as an externality introduced to somehow limit aggressive updates from the sources at every single epoch [13]. In particular, as will be clearer from the subsequent analytical formalization, $c \geq 1$ must be imposed for the problem to be physically sensible; otherwise, both sources will consider the updating cost not to be enough of a burden to refrain from always updating.

First, a scenario with only one source is considered. From the analytical framing of this case, it will be easy to derive the game structure when two sources exist as players in a game. If a source sends random updates with probability p, the expected AoI of the receiver can be computed as [22]

$$\mathbb{E}[\delta_j](p) = \frac{1}{p} - 1 \tag{2}$$

and if a cost term for sending an update is considered, proportional to p through a cost coefficient c, the total expenditure of the source is promptly derived as

$$K(p) = \frac{1}{p} - 1 + cp\ . \tag{3}$$

Now, the cost-optimal solution for the source is to always send updates at each slot if $c \leq 1$, in which case the AoI is constantly 0. The problem becomes more interesting if $c > 1$, since in this case we can find the optimal update probability as $p^* = \sqrt{1/c}$. Note that this value does not optimize the AoI per se, but rather the linear combination of (3) where the update cost is also considered, so it is optimal from the perspective of the source. This is important since a game theoretic approach further extends this situation to the case of *two* sources, each one of them being interested in selfishly maximizing its own individual objective.

For two sources, we can represent the problem by defining a *static game of complete information* [12], denoted as $\mathcal{G} = (\mathcal{N}, \mathcal{A}, \mathcal{U})$ as follows. The set of players $\mathcal{N}$ is set as $\mathcal{N} = \{S_1, S_2\}$; being passive and not sending any feedback whatsoever, R is not a player in the game. The action set $\mathcal{A}$ is defined for both players as their update probability (denoted as p_1 and p_2, respectively) taking values in $[0, 1]$. In other words, the sources decide, independently of each other, the probability to which their own updates are sent. Finally, the payoff functions in set $\mathcal{U}$, also called utilities, are symmetrically defined along the lines of (3), with the following differences: (i) the utilities are functions of both p_1 and p_2, as is meaningful in any game-theoretic interaction; (ii) equation (3) represents cost values to be minimized; in game theory, it is more common to seek for utilities to be maximized, which be achieved by taking $u(p_1, p_2) = -K(p_1, p_2)$. Thus, by remarking that the expected AoI is now a function of both strategic choices of S_1 and S_2 and can be computed as

$$\mathbb{E}[\delta_j](p_1, p_2) = \frac{1}{p_1 + p_2 - p_1 p_2} - 1 \tag{4}$$

we can define

$$\begin{aligned} u_1(p_1,p_2) &= -K_1(p_1,p_2) = -\frac{1}{p_1+p_2-p_1p_2}+1-cp_1 \\ u_2(p_1,p_2) &= -K_2(p_1,p_2) = -\frac{1}{p_1+p_2-p_1p_2}+1-cp_2 \end{aligned} . \quad (5)$$

The term p_1p_2 in the denominator reflects the inefficiency of the two uncoordinated sources: if S_1 and S_2 were able to avoid overlapping updates, e.g., by signalling a preemption request to each other, the overall system utility would be higher, and could be computed as

$$u_{\max}(p_1,p_2) = -\frac{1}{p_1+p_2}+1-c(p_1+p_2) . \quad (6)$$

Note that in this case it would be indifferent how the total update probability p_1+p_2 is split into the contributions from either source. A balanced solution to (6), where $p_1=p_2$, could simply be derived by substituting p with $2p$ in (3), thereby achieving an update probability $p^{**}=0.5$ for $1\le c\le 2$ and $p^{**}=(2c)^{-1/2}$ when $c\ge 2$.

Also, further conditions are imposed in that the details of the scenario and the utility functions followed by each player are *common knowledge* among them. In such a game, the players look for playing a *best response* to their beliefs on the other player's move and NEs are computed as the strategical choices where these conditions met, i.e., both players play a best response to each other [12].

Theorem 1. *Game $\mathcal{G}=(\mathcal{N},\mathcal{A},\mathcal{U})$ as defined above, has only one NE where the two players choose their actions such that $0<p_1,p_2<1$, and in this case $p_1=p_2$.*

Proof. The theorem can be directly proven by setting the first order derivatives $\mathrm{d}u_1/\mathrm{d}p_1$ and $\mathrm{d}u_2/\mathrm{d}p_2$ as 0. This result in the following condition on p_1 for S_1, if p_2 is assumed given:

$$p_1 = \frac{\sqrt{\dfrac{1-p_2}{c}}-p_2}{1-p_2} \quad (7)$$

and similarly for S_2 with a reversal of p_1 and p_2. Notably, (7) implies that with $p_2=0$ the solution for p_1 is the same as when only one source is present. By imposing the same conditions of (7) on p_1 and p_2 it is immediate to derive that it must hold $p_1=p_2=p_b$, and p_b can be found as the only real solution that falls within $[0,1]$ of the fourth degree equation

$$1-p-c(2p-p^2)^2=0 , \quad (8)$$

which can be easily computed by numerical means. □

Theorem 2. *Game $\mathcal{G}=(\mathcal{N},\mathcal{A},\mathcal{U})$ also has two further NEs, consisting of the choice of update probability 0 by either source, while the other chooses it according to the single-source scenario.*

Proof. This follows from the previous theorem as, beyond the maximal points inside $[0,1]$, also the extreme values must be considered, and (p_1,p_2) being chosen as $(0,c^{-1/2})$ or $(c^{-1/2},0)$ give maximum conditions according to (7). □

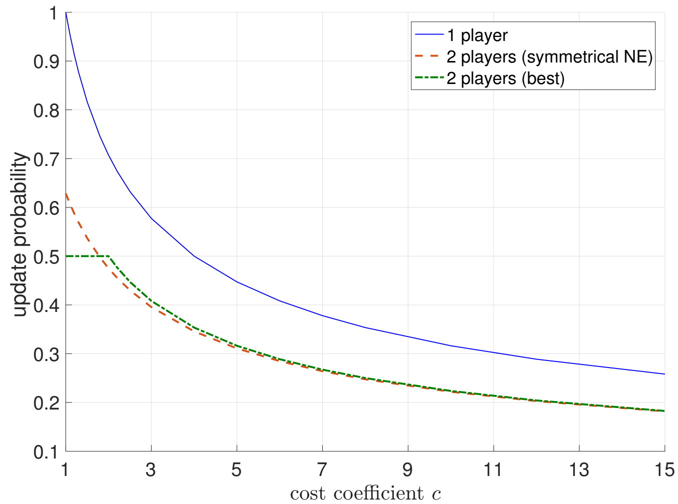

Fig. 1. Update probability p as a function of the transmission cost c, chosen according to different NEs or with a globally optimal choice.

To sum up, the game has *three* NEs, two of which can be dubbed as *lazy* NEs, since they just correspond to using only one source, while the other never updates, and one is instead a *balanced* NE, where both sources update independently with the same probability p_b. Surprisingly, the overall system efficiency computed as $u_1(p_1,p_2)+u_2(p_1,p_2)$ is superior at the two lazy NEs than the balanced NE if the condition $c<\gamma$ holds, where $\gamma\approx 10.67$ (found via numerical means). It is important to notice that this does not mean a lower AoI for the lazy NEs, since the sources' utilities are also computed including the cost term. However, it implies that a distributed management, where individual nodes are solely acting following their individual utilities, can achieve a better efficiency if some of the sources do not send any update.

For comparison purposes, in the following section we will evaluate the PoA and PoS, whose respective definitions are

$$\begin{aligned} PoA &= \frac{u_{\max}(p^{**},p^{**})}{\min\big(u_1(p_b,p_b)+u_2(p_b,p_b),u_1(p^*,0)+u_2(p^*,0)\big)} \\ PoS &= \frac{u_{\max}(p^{**},p^{**})}{\max\big(u_1(p_b,p_b)+u_2(p_b,p_b),u_1(p^*,0)+u_2(p^*,0)\big)} , \end{aligned} \quad (9)$$

where the optimal allocation at the numerator is compared versus the worst (respectively, best) NE at the denominator, with the possible choices for the NE being the symmetrical NE or either of the lazy NEs that give the same total utility.

IV. Numerical Evaluations

We present some evaluations to better visualize in numerical terms the conclusions of the previous section. To this end, we consider a system with two sources S_1 and S_2 sending updates to a receiver R with probability p_1 and p_2, respectively. The sources have a cost c for sending an update, and their utility is the global AoI achieved, also accounting for the updates from the other source, plus their individual update cost as per (5).

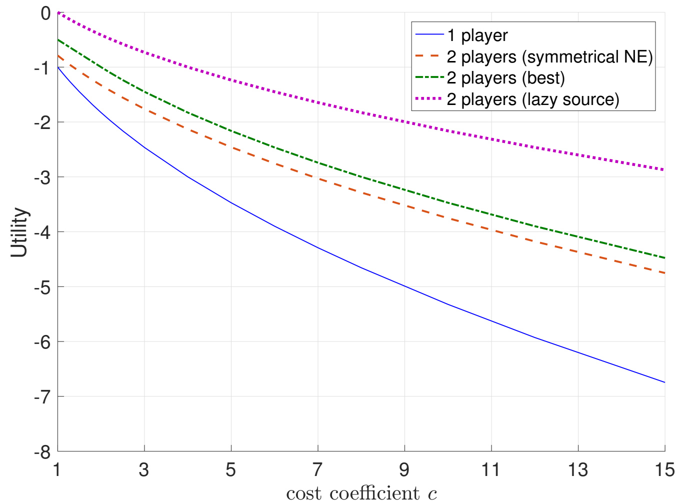

Fig. 2. Resulting utility of each source, as a function of the transmission cost c, at different NEs or a globally optimal choice.

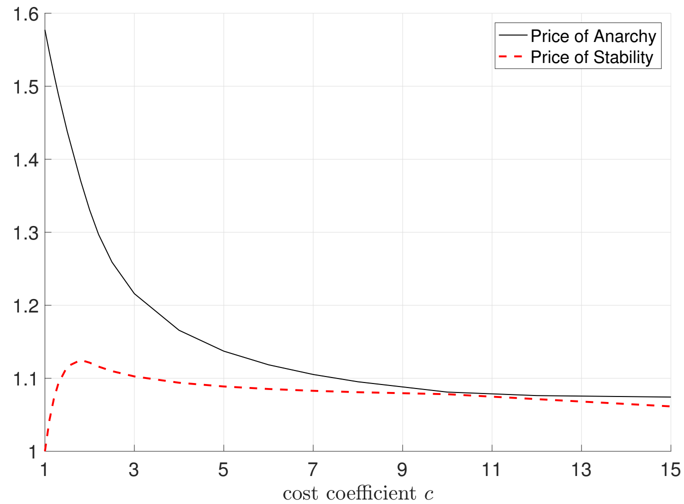

Fig. 3. Price of Anarchy and Price of Stability, as functions of the transmission cost c.

The compared scenarios in the results are: (i) the case with only one source, making its update decision so as to minimize its global cost according to (3), i.e., $p^* = c^{-1/2}$; incidentally, this also works for the *lazy* NEs, where one of the two sources never sends updates, so it chooses an update probability equal to 0, and consequently the other one also plays according to (3) as though it was the only source in the system; (ii) the symmetrical NE of two sources, both choosing a balanced probability value $p_1 = p_2 = p_b$ according to (8); and finally (iii) the best allocation with two sources, assuming they are perfectly coordinated and therefore maximizing (6), as p^{**}.

Fig. 1 reports the update probability of the sources under these different conditions, i.e., the three plots show p^*, p_b, and p^{**}. Notably, after a plateau of 0.5 for $c \leq 2$, the values of p^{**} and p_b become quite similar for higher costs, and are basically indistinguishable for $c > 5$. This follows from the update probability being decreasing in c, so that the absence of the product p_1p_2 in the denominator of (6) does not change the maximizing value. However, the two probability values being comparable does not lead to the same total utility, as will be shown in the following results.

Fig. 2 compares the utilities of the individual sources. For the balanced NE, both S_1 and S_2 get the same utility. In the lazy NEs, they obtain different values, with the value of the source never sending updates displayed as "lazy source," also being the highest curve, since it benefits from the other source's updating but pays no cost, whereas the other source gets the same utility as the only player in the scenario with one source.

From this figure one can appreciate the counterintuitive result that the total utility in the case of a lazy NE (which is the sum of the highest and lowest curves) is better than twice the total utility in the balanced case, and closer to the best achievable total utility under perfect coordination. In other words, the welfare of a system with a lazy source is closer to the optimum than a balanced one, albeit clearly less fair.

This is further confirmed by Fig. 3, where the PoA and PoS are computed, according to (9). The PoS is around 1 for values of c close to 1 since both the lazy NE (the best one in this case) and the optimal choice of p correspond to updating at every time slot, which gives an AoI close to 0 and the only contribution to the utility being the cost paid to update.

Moreover, it is interesting to notice that, at low values of c, the PoA, determined by the symmetrical NE versus the optimal management, is significantly higher than 1 despite the choices of the update probability in the two cases being almost identical. Therefore, this is inherently due to the loss of efficiency in the lack of coordination of the sources that are sometimes sending redundant updates. Also, the figure highlights that the PoS and the PoA become identical for $c = \gamma$, after which the relationship between the NEs actually is subverted, with the balanced NE becoming now the globally efficient one.

Actually, this does not look like a very striking difference in that for all values of $c > 7$ all the three NEs get a similar performance, which is between 6% and 11% worse than the optimally coordinated updates. Indeed, the symmetrical NE becomes even more efficient as the cost increases beyond what shown in the figure, but at the same time the AoI at the receiver is very high as the update probability becomes very low.

Finally, Fig. 4 reports the AoI achieved by the different source management techniques. It is especially highlighted that the AoI is generally lower for the symmetrical NE, albeit the lazy NE gets a lower AoI around 0 for values of the cost term c close to 1. This means that, for higher cost values, the lazy NEs do not outperform a balanced solution in terms of AoI. However, since the ultimate objective of the individual sources also include the cost for sending an update, the redundancy in the overlapping updates cause the total utility to be lower as shown in Fig. 2.

Still, from the perspective of a system manager, this can be a point to favor the balanced NE over other allocations, due to

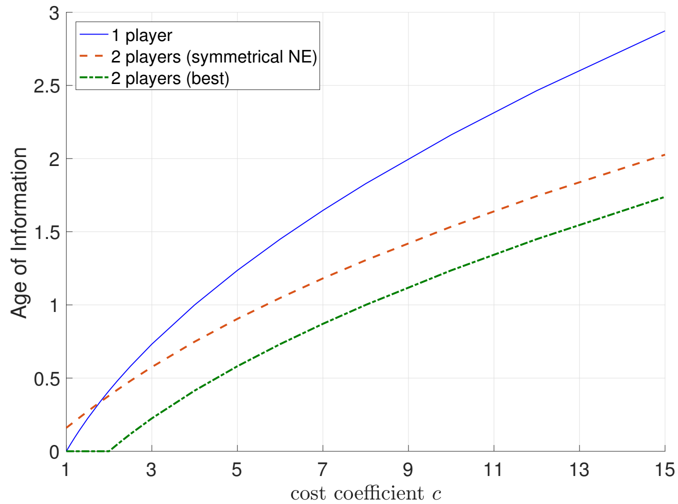

Fig. 4. Expected AoI, as a function of the transmission cost c, for different NEs or with a globally optimal choice.

its ability to achieve a lower AoI; as for the selfish perspective of the individual sources, they are still reaching a NE anyways, so even according to the game theoretic formulation, they do not want to deviate from that choice.

V. Conclusions and Future Work

A game theoretic analysis of a system with two sources operating under AoI-based utilities, also including an individual transmission cost term, was presented. It was shown that the equilibria where the system makes an unbalanced use of the sources (actually, limiting the updates to one source only) might sometimes turn out to be more efficient than the one where both sources are sending updates with the same frequency. Notably, the efficiency is to be meant from the sources perspective, since the AoI obtained by a balanced equilibrium is still shown to be lower.

Nevertheless, this result is apparently limiting the usefulness of having multiple distributed sources acting in an uncoordinated fashion. Remarkably, this result was derived under the condition that multiple source updating at the same time do not cause any efficiency loss beyond their redundancy, for example, multiple updates are always in agreement and/or never collide at the physical layer, in which case the resulting equilibrium will likely be even worse.

However, it must be reminded that in the analyzed system there is no way for the sources to get any feedback or additional information on the operation of the other source and/or the receiver status. Clearly, this result can also be interpreted as the need for some simpler coordination from the involved parties, even in the form of exchanging short messages, e.g., to update the sources, solicit an update, and/or fairly share the burden of the updates as done in the optimal scenario used for comparison.

To sum up, the results found justify the need for at least a minimal cooperation among the nodes to achieve AoI-efficient updating schemes from multiple sources. Not doing so would result in a suboptimal management of the AoI, which, albeit still limited in its inefficiency (the PoA is overall bounded) does not justify the introduction of multiple sources as the best NEs might often be achieved by only using one of them.

References

[1] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of things for smart cities," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 22–32, 2014.

[2] G. Cisotto and S. Pupolin, "Evolution of ICT for the improvement of quality of life," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 33, no. 5-6, pp. 6–12, 2018.

[3] B. Cao, Y. Li, L. Zhang, L. Zhang, S. Mumtaz, Z. Zhou, and M. Peng, "When Internet of things meets blockchain: Challenges in distributed consensus," *IEEE Netw.*, vol. 33, no. 6, pp. 133–139, 2019.

[4] H. Wu and W. Wang, "A game theory based collaborative security detection method for Internet of things systems," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 6, pp. 1432–1445, 2018.

[5] V. S. Dasari, B. Kantarci, M. Pouryazdan, L. Foschini, and M. Girolami, "Game theory in mobile crowdsensing: A comprehensive survey," *Sensors*, vol. 20, no. 7, p. 2055, 2020.

[6] 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, 2021.

[7] C. Kam, S. Kompella, G. D. Nguyen, J. E. Wieselthier, and A. Ephremides, "On the age of information with packet deadlines," *IEEE Trans. Inf. Theory*, vol. 64, no. 9, pp. 6419–6428, 2018.

[8] 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.

[9] K. Saurav and R. Vaze, "Game of ages," in *Proc. IEEE Infocom Wkshps*, 2020, pp. 942–947.

[10] 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.

[11] A. V. Guglielmi and L. Badia, "Bayesian game analysis of a queueing system with multiple candidate servers," in *Proc. IEEE CAMAD*, 2015, pp. 85–90.

[12] S. Tadelis, *Game theory: an introduction*. Princeton univ. press, 2013.

[13] A. B. MacKenzie and L. A. DaSilva, "Game theory for wireless engineers," *Synth. Lect. Commun.*, vol. 1, no. 1, pp. 1–86, 2006.

[14] A. Zappone, S. Buzzi, E. Jorswieck, and M. Meo, "A survey on game-theoretic approaches to energy-efficient relay-assisted communications," in *Proc. IEEE TIWDC*, 2013, pp. 1–6.

[15] P. Semasinghe, S. Maghsudi, and E. Hossain, "Game theoretic mechanisms for resource management in massive wireless IoT systems," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 121–127, 2017.

[16] R. Rani, S. Kumar, and U. Dohare, "Trust evaluation for light weight security in sensor enabled Internet of things: Game theory oriented approach," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8421–8432, 2019.

[17] H. Sedjelmaci, S. M. Senouci, and T. Taleb, "An accurate security game for low-resource IoT devices," *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 9381–9393, 2017.

[18] N. Namvar, W. Saad, N. Bahadori, and B. Kelley, "Jamming in the Internet of things: A game-theoretic perspective," in *Proc. IEEE Globecom*, 2016, pp. 1–6.

[19] L. Badia and F. Gringoli, "A game of one/two strategic friendly jammers versus a malicious strategic node," *IEEE Netw. Lett.*, vol. 1, no. 1, pp. 6–9, 2019.

[20] A. Gouissem, K. Abualsaud, E. Yaacoub, T. Khattab, and M. Guizani, "Game theory for anti-jamming strategy in multi-channel slow fading IoT networks," *IEEE Internet Things J.*, 2021.

[21] V. Vadori, M. Scalabrin, A. V. Guglielmi, and L. Badia, "Jamming in underwater sensor networks as a bayesian zero-sum game with position uncertainty," in *Proc. IEEE GLOBECOM*, 2015, pp. 1–6.

[22] R. D. Yates and S. K. Kaul, "Status updates over unreliable multiaccess channels," in *Proc. IEEE ISIT*, 2017, pp. 331–335.

[23] 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.

[24] L. Badia, "On the effect of feedback errors in Markov models for SR ARQ packet delays," in *Proc. IEEE Globecom*, Dec. 2009, pp. 1–6.