Game Theoretic Analysis of Age of Information for Slotted ALOHA Access With Capture

Leonardo Badia, Andrea Zanella, and Michele Zorzi
Department of Information Engineering, University of Padova, Italy
email: {badia,zanella,zorzi}@dei.unipd.it

***Abstract*—A recent line of analysis discusses the age of information as a better performance metric than throughput or delay to evaluate the performance of medium access techniques, especially when applied to remote sensing applications and more in general the Internet of Things. Fully analytical investigations based on game theory have shown how selfish players can behave efficiently in random access systems if they are driven by AoI-based objectives. In this paper, we expand this kind of reasoning to the case of a slotted ALOHA system with capture effect. We present a fully analytical derivation of some notable cases, based on the existing literature, and we highlight the impact of some parameters, specifically the cost coefficient and the capture threshold, towards achieving an efficient allocation that represents an equilibrium point for the network management. It is shown that, when the capture effect is relatively strong, which is easier when the number of terminals is limited, the Nash equilibrium of the system achieves near-optimal performance.**

***Index Terms*—Age of Information; Game theory; Capture effect; Slotted ALOHA; Internet of Things.**

I. Introduction

In many sensing and monitoring applications for remote process control, or hazards detection and prevention, freshness of the data exchanged is more important than their sheer amount [1], [2]. For this reason, the concept of *age of information* (AoI) [3] is gaining momentum in analytical investigations of medium access, to offer a quantitative performance metric beyond standard indicators such as throughput or delay.

An appealing aspect of AoI evaluations is that they can be framed in closed form, along the lines of throughput investigations, but often with unexpected conclusions. This is especially true for systems based on ALOHA-like protocols [4], [5], which are typical whenever the nodes are dense in number, heterogeneous in nature, and limited in their computational and energy resources, as for machine-to-machine communications in the Internet of Things (IoT), where centralized access control becomes impractical. Scenarios of distributed random access can also benefit from investigations based on *game theory*. Such a mathematical tool combines the benefits of modeling the intelligence of the nodes as guided by an individual utility, which is realistic in massive access scenarios, and capturing the system performance to the point of identifying practical solutions for a distributed efficient control.

Some investigations of random access protocols have been performed under the lens of game theory, but mostly focusing on throughput as the main performance metric, whereas until recently, characterizations of the opportunistic behavior of selfish nodes acting under the objective of minimizing the AoI are seldom found in the literature, with few notable exceptions [6]–[8]. In addition, game theoretic investigations have shown that even uncoordinated contention-based access protocols can behave efficiently to some extent, meaning that a relatively efficient Nash equilibrium (NE) can be achieved, when the individual objectives of the players combine their local age of information with a transmission cost term. Most of them, including our own previous work [6], only focus on simple protocols such as slotted ALOHA, which is well known to achieve low access efficiency due to collisions resulting in wasted transmission slots.

However, in [9] we also made a fully analytical investigation of the impact of the so-called *capture effect* on a slotted ALOHA system, that is, the improvement in the probability of successful transmission thanks to the strongest signals surviving collisions and being correctly decoded in spite of the interference of other signals. Notably, that analysis did *not* involve game theory and only considered throughput.

The goal of the present paper is to combine all these elements in an original way, to obtain a game theoretic investigation of a dense network where access is based on slotted ALOHA *with capture effect* and where nodes have the objective of obtaining a low AoI of their data. In fact, the individual goal of the selfish nodes takes also into account a transmission cost, which is needed to attenuate the aggressive behavior of the nodes driven by selfish objectives.

While our investigation is purely analytical and with exact derivations, we will instantiate it for specific cases with the purpose of drawing design guidelines in practical systems. In particular, we will specify it to the sample case of exponential received power values of the terminals, which allows for a simple yet substantial derivation in closed form, where all the relevant parameters are included. We will show how the capture threshold b affects the relationship between the transmission cost c and the system equilibrium, so that the impact of the values of b, c, and also the number of terminals N can be better understood. Also, we can infer a network control by means of a distributed management, where nodes are just incentivized to follow individual objectives. Moreover, the resulting NE is determined, and numerical results show that, when the capture effect is strong enough, also in relationship with a contained number of terminals in the network, the equilibrium performance is very close to that of an optimal allocation from a global standpoint; as a result, network management can be greatly simplified.

The rest of this paper is organized as follows. In Section II, we discuss the previous contributions on the subjects of game theory and random access with multi-packet reception, and explain how the contribution of the present paper fills a gap in the related literature. Also, we summarize the key ingredients, based on existing results, of our analysis. These elements are developed in Section III for our analysis, where we first discuss the AoI evaluation with capture effect, and then apply game theory to derive the possible NEs of the resulting systems and their connection to the technical parameters. We will further instantiate this to the specific case of exponential SNR so as to show numerical results in Section IV. Finally, we will conclude the paper in Section V.

II. Background

A. Related work

Several papers in the literature apply game theory to network systems, in particular the most common reference scenario is for security issues in adversarial contexts at the different layers of the protocol stack, such as denial-of-service or jamming [10], [11]; in [12], this is applied to an AoI-based scenario. There is also a line of research for medium access seen as a game played by selfish agents, where ALOHA-like techniques are a reference case investigated by many classic references [13]–[15]; however, these papers mostly consider throughput-based objectives for the players, since the popularity of AoI as a performance metric is relatively recent. From a game theoretic standpoint, one can generally conclude that the NE of such systems is less efficient than a globally optimum operating point [16]. However, in a recent contribution [6], we prove that this conclusion is mitigated for systems where the players aim at minimizing their AoI, since when the cost parameter is above a given threshold, a better NE arises. Moreover, the main criterion adopted in these contributions to represent the medium access is just that collisions result in lost packets, and the so-called *capture effect* is rarely considered. Our contribution in the present paper is to extend this kind of investigations to this case, leveraging the analysis presented in [9].

We also note that there has been a recent flourishing of papers focusing on AoI evaluations, especially for remote sensing in IoT. While slotted ALOHA is already considered in [3] as a reference scenario, and there have been some recent investigations along this line [17], [18], the field is relatively unexplored for what concerns datalink layer aspects such as modeling the medium access and/or the capture effect. At the same time, it is also still uncommon to find AoI employed within the utility functions of game theoretic approaches. A notable reference is [19], where the authors consider a game based on AoI, but the access model is just based on an abstract assumption that collisions lead to losing the packets. Another relevant paper is [20], where two transmitter/receiver pairs share access over an interference channel, but the end goal is related to the achievable capacity at the physical layer, without specific considerations on medium access control.

B. Summary of Preliminary Results

We now highlight the starting point of our analysis, to better frame the contribution of the present paper. In [6], we applied game theory to AoI in slotted ALOHA. For random-based medium access, the AoI follows from all nodes' transmission probabilities $\mathbf{t} = (t_1, t_2, \dots, t_N)$, chosen independently by the nodes seen as distributed agents. Thus, a standard minimization of the AoI can be derived, where symmetry reasons imply $t_j = t$ for all $j \in \{1, \dots, N\}$.

The essence of a game theoretic perspective is that, instead of achieving a minimization for all t_j's, an individual player, say terminal 1, is put under the spotlight, and the minimization of its AoI is done over t_1 only, leaving the other values $t_2, \dots t_N$ unchanged. For symmetry reasons, it is sensible that this once again results in an equilibrium where all t_j's are equal, but to a different value than before. As a result, we are led to another operating point, in general more aggressive than the optimal one since nodes are driven by their selfish objective - a very well established game theoretic principle known as *the tragedy of the commons* [21].

However, in a game theoretic analysis it is often customary to introduce a cost term that the nodes pay to access the channel [15], [22]. This can be connected with some practical motivation, such as energy expenditure within the terminals, or simply to control their access. As a result, the transmission probabilities of the individual nodes can be controlled, to the point that a better NE arises when the cost is above a given threshold, which can be computed analytically [6].

However, due to the inefficiency of slotted ALOHA, it is generally required to introduce a high cost to control the NE when the number of terminals is large. A more realistic characterization of the medium access will possibly lead to a better equilibrium without introducing too high transmission costs. For this reason, in the present analysis we resort to our previous characterization of the capture effect in random medium access presented in [9]. That paper proposes several closed-form derivations of how to represent multi-packet reception capabilities of the terminals. We just take some sample approaches to address this point, but the analysis is general and can be extended to any scenario presented in the paper.

Starting from such existing work by the authors, the present paper evolves the analysis in a novel manner achieving new, original results. Our contribution can be summarized as follows. First, we give an analytical derivation of the AoI when the capture effect is present, which, to the best of our knowledge, is not available in the present literature. Moreover, we apply game theory as detailed above, focusing on the transmission probability of a specific terminal, chosen so as to optimize its *individual* objective (a linear combination of its AoI and paid cost). The resulting NE is then discussed and quantified, highlighting the role played by key parameters.

III. Mathematical Analysis

We consider a network of N terminals that are synchronized on a discrete (slotted) time reference. The terminals share a common transmission channel which is used to send identical-sized packets towards a single receiver (sink). The time slot is hence assumed to be equal to the packet transmission time, and transmissions can only occur according to the slot pattern. We further assume that, during each time slot, terminal i is actively transmitting with probability t_i, independent of all the other nodes, and the packet transmitted always contain up-to-date information. Thus, the AoI of the data sent by a specific terminal is separately counted at the sink, and whenever a packet transmission is successful, that AoI value is set to 0, otherwise it is increased by 1 at each time slot.

Now, denote with $q_i(j)$ the probability that a packet sent by a transmitting node i is *captured* in the presence of j competing transmitters, including node i itself. Notably, $q_i(1) = 1$, when i is the only transmitter, while, for a regular slotted ALOHA system without capture, $q_i(j) = 0$ if $j > 1$. Thus, the individual success probability ρ_i of a given terminal i can be determined as the joint instance of two separate events: (i) terminal i transmits; and (ii), out of all combined transmission patterns of the other $N-1$ terminals, i's transmission is captured. If, without loss of generality, we focus on terminal 1, whose transmission probability is t_1, and assume for symmetry reasons that all other terminals have the same transmission probability t, i.e., $t_2 = t_3 = \ldots = t_N = t$,[1] the probability of successful transmission of terminal 1 is

$$\rho_1 = t_1 \sum_{j=1}^{N} \binom{N-1}{j-1} t^{j-1}(1-t)^{N-j}\, q_1(j)\,. \qquad (1)$$

By expanding the analysis of [9], several ways to compute $q_1(j)$ can be found. For the sake of simplicity, we consider one specific case of exponentially distributed received power terms, which allows for an immediate derivation reported next. Other similar considerations can be made for the other scenarios of multi-packet reception capabilities of the sink node discussed in that paper, possibly including techniques such as successive interference cancelation.

A. The case of exponential received powers

One simple way to model $q_1(j)$ is to assume that terminal 1's packet is captured if its received power is higher than a given fraction of the sum of all other received powers from active terminals. If we denote the received powers of the j active terminals as $P_1, P_2, \ldots, P_j$, where P_1 is the received power of the terminal of interest, i.e., terminal 1, we can write $q_1(j) = \Pr[P_1 > b \sum_{h=2}^{j} P_h]$, where the key parameter b is the *capture threshold*. The reader can refer to [9] for a more in-depth discussion on the value of b. Here, we treat it like an adjustable parameter whose role in determining the AoI will be explored next.

The expression above simplifies to a neat exact derivation if the received powers of all active terminals are independent and identically distributed (i.i.d.) following an exponential distribution with parameter λ, i.e., $P_h \sim \mathrm{Exp}(\lambda)$, i.i.d., that is, the probability density function (pdf) of all received powers is $f_{P_h}(x) = \lambda e^{-\lambda x}\, \mathbb{1}(x)$, with $\mathbb{1}(x)$ being a unit step. From this assumption, it promptly follows that, for $j>1$, $q_1(j) = \Pr[P_1 > b\, Q_{j-1}]$, where $Q_k \sim \mathrm{Erlang}(k, \lambda)$ is a random variable with Erlang distribution of index k and parameter λ.

From known properties of the Erlang distribution, we get

$$\Pr[P_1 > b\, Q_{j-1}] = \mathbb{E}_{Q_{j-1}}\left[e^{-b\lambda Q_{j-1}}\right] = \frac{1}{(1+b)^{j-1}} \qquad (2)$$

since $\mathbb{E}_{Q_k}[e^{aQ_k}] = (1 - a/\lambda)^{-k}$.

Hence, putting $k = j-1$ in (1), we can write ρ_1 as

$$\rho_1 = t_1 \left[(1-t)^{N-1} + \sum_{k=1}^{N-1} \binom{N-1}{k} \frac{t^k (1-t)^{N-1-k}}{(1+b)^k}\right] \qquad (3)$$

which reduces to $$\rho_1 = t_1 \left(\frac{1+b(1-t)}{1+b}\right)^{N-1}\,. \qquad (4)$$

B. AoI evaluation and game theoretic formulation

The derivation of ρ_1 above is particularly useful as it immediately reflects into the AoI evaluation. Since we are considering a discrete time axis, the average AoI of the ith terminal, denoted as Δ_i, can be written as [6]

$$\Delta_i = \rho_i^{-1} - 1\,. \qquad (5)$$

In particular, if we are interested in a symmetric centralized optimal solution to minimize the AoI of all the terminals, we can set $t_1 = t$ and find the minimum of Δ_i over t. This can be easily done by setting the first derivative in t to 0, but we can actually remark that the problem is relatively trivial since minimizing the AoI just corresponds to maximizing the success probability ρ_1, which is an obvious consequence of the terminals choosing their transmission probabilities independently of one another.

A game theoretic perspective becomes instead more interesting, and is made relatively simple by the separation found in (4) between t_1 (the value of choice for the terminal of interest) and t, i.e., the transmission probability of every other terminal. In a game theoretic analysis, we can consider the N terminals as the players of a static game of complete information [23], where they set their action as their transmission probability, chosen independently and unbeknownst to each other.

However, if we set the payoffs of the players as their AoI values (or better, we ought to set the utility of the ith terminal as $u_i = -\Delta_i$, since the AoI is to be minimized, while u_i is to be maximized), the resulting sheer minimization of the AoI from the perspective of a selfish terminal will lead to a catastrophic NE. In fact, whatever the choice of the other terminals, it is always convenient for the terminal of interest to aggressively transmit with probability 1 [14]. Symmetry considerations imply that all terminals do the same and we get a NE where everyone transmits in every slot, and the resulting AoI is $\Delta_i = (1+b)^{N-1}$ for all terminals.

[1] Clearly, we look into fully symmetric solutions for which also $t_1 = t$. Yet, we keep the notations separate in order to distinguish between terminal 1, on which we focus, and all other terminals. This distinction will become useful when dealing with the game theoretic part of the analysis.

The common solution in game theoretic approaches is the introduction of a cost incurred by each individual node i, proportional to its transmission probability t_i through a constant c [11], [15], [16]. Such a cost term can be either related to actual physical phenomena, such as the energy consumption of the terminal when transmitting, or just introduced for the sake of limiting persistent access by the terminals. This will actually prompt a further discussion in the following.

For the purpose of a game theoretic analysis, we define the *utility* of the ith player as the value that terminal i seeks to maximize, defined as

$$u_i(\mathbf{t}) = -\Delta_i - c\,t_i = -\frac{1}{\rho_i} + 1 - c\,t_i \tag{6}$$

where the negative sign has the same explanation as above (all terminals actually seek to *minimize* AoI and/or transmission cost) and the individual utilities are defined to be functions of the *entire* array of transmission probabilities, $\mathbf{t} = (t_1, \dots, t_N)$, which happens through Δ_i and thus through ρ_i.

The utilities defined in (6) can be employed in two ways. On the one hand, symmetry reasons lead to assuming that all t_i's are equal, i.e., $\mathbf{t} = (t, t, \dots, t)$ and under this condition an optimal t can be found, such that the utilities are maximized. The numerical derivation of such a maximum is immediate by setting the first-order derivative $\mathrm{d}u_i/\mathrm{d}t = 0$. This corresponds to a fully coordinated working point, which is often deemed to be impractical in a game theoretic spirit, as individual selfish players may have an incentive to deviate.

On the other hand, we can also explore a unilateral maximization of the utility of a player of interest, say, terminal 1, while the moves of the others are kept unchanged. This requires to separate the transmission probability t_1 of such a terminal, while all the others can be assumed to use transmission probability t. Note that in the end, also t_1 will be set equal to this very value, but only after taking the first order derivative, which is now $\mathrm{d}u_i/\mathrm{d}t_1$, and setting it equal to 0. In game theoretic terms, this is the NE condition since each player chooses a *best response* to the moves of the others.

Noting that the expression (1) of ρ_1 can be rearranged as $\rho_1 = t_1 K_1$ where

$$K_1 = \sum_{j=1}^{N} \binom{N-1}{j-1} t^{j-1}(1-t)^{N-j}\, q_1(j) \tag{7}$$

does not depend on t_1, we can elaborate the NE condition $\mathrm{d}u_i/\mathrm{d}t_1 = 0$ into

$$\frac{1}{\rho_1^2}\frac{\mathrm{d}\rho_1}{\mathrm{d}t_1} - c = 0 \quad \Rightarrow \rho_1 t_1 = \frac{1}{c}\,. \tag{8}$$

Now, we can also set $t_1 = t$ and look for NE solutions in t of the resulting equation $\rho_1 t - 1/c = 0$.

Depending on the value of c, there are different cases. If c is too low, the equation has no solutions and the only NE is found in $t = 1$ for all terminals. As c increases, we observe a threshold phenomenon [6], i.e., another NE arises when $c > \gamma$, with γ being a proper threshold value, for which different conditions can be formalized depending on the expression of ρ_1 and the resulting equation.

C. Discussion on the NE structure for the sample case

If we consider the case of exponentially distributed received powers, (4) will lead to an $(N{+}1)$th degree equation

$$t^2\left(\frac{1+b(1-t)}{1+b}\right)^{N-1} = \frac{1}{c} \tag{9}$$

whose solutions in t, if valid as probability values, represent NEs for the system. Indeed, the NE condition (9) obtains t between 0 and 1 only for sufficiently high c. It can be proven that there exists a value γ such that if $c > \gamma$, there is another NE beyond the catastrophic one, which leads to a more efficient coordination among the terminals despite them following individual objectives. While γ depends on several factors (including the capture model and the number of terminals), its existence is guaranteed by the above reasoning.

We can point out an important structural property of γ following (9). If we denote $A(t) = t^2(1+b(1-t))/(1+b)^{N-1}$, we observe that if

$$\frac{\mathrm{d}A(t)}{\mathrm{d}t}(1^-) > 0 \quad \Rightarrow b(N-1) < 2\,, \tag{10}$$

then $A(t)$ is always increasing in $[0, 1]$ and its maximum is in $(1+b)^{1-N}$, which gives a precise expression for γ. In other words, if $b(N-1) < 2$, i.e., b and/or N are low, we need $c > \gamma = (1+b)^{N-1}$ for a better NE to exist. Conversely, if (10) is not verified, the value of γ further increases; the capture effect is weak, and a high cost is required [6].

IV. Numerical Results

We show some practical evaluations of the equations derived in the previous analysis to draw some quantitative conclusions. We consider N terminals as players in a simultaneous-move game following individual utilities that are a linear combination of their negative AoI and their negative transmission cost, with coefficient $c = \tilde{c}N$, and whose strategic choices are their individual transmission probability values. Their received power values are i.i.d. exponentially distributed, and medium access is slotted ALOHA with capture threshold b. A successfully captured transmission sends the AoI of a terminal back to 0. We consider symmetric solutions where the transmission probability is the same for all terminals. The results are always shown as functions of the normalized transmission cost $\tilde{c}$, for the number of users $N \in \{10, 100\}$, and considering two different capture thresholds, i.e., $b = 0.02$ and $b = 0.2$. According to [9], the former represents a strong capture effect, whereas the latter has a more limited extent, yet it still significantly improves over standard slotted ALOHA. We also note that the case $b = 0.2$, $N = 100$ does not meet condition (10), while all the others do.

In Figs. 1–2, we report the resulting transmission probabilities of the terminals computed either at the NE (when available) or for the optimal centralized case. We remark that t at the NE is meaningful only if $c > \gamma$ and overall an increasing cost significantly lowers the transmission probability of both cases. For $b = 0.02$ the NE and optimal curves are very close, while for $b = 0.2$ there is still some gap. This implies that a

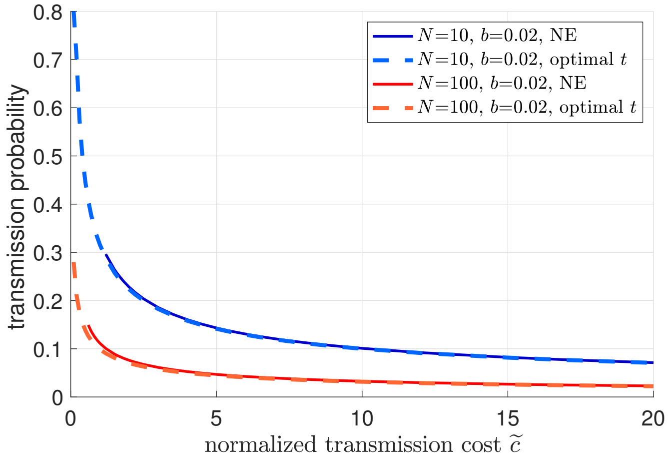

Fig. 1. Transmission probability t as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup, for capture threshold $b = 0.02$.

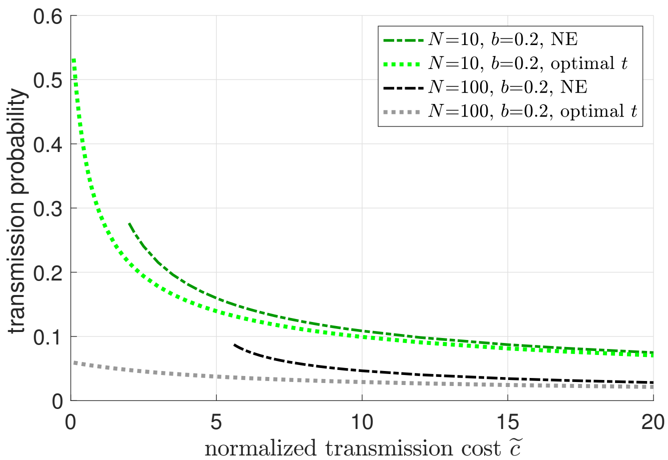

Fig. 2. Transmission probability t as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup, for capture threshold $b = 0.2$.

strong capture effect causes that even a decentralized system is able to work at near-optimal NEs.

However, this also hints that the value of c deserves a technical discussion on its physical nature. Due to the need for a sufficiently high c, the near-optimality of the NE is achieved only if the persistence of selfish terminals is somehow limited. At the same time, it is convenient that c is not too high, since this would result in a very low transmission probability (and, as will be shown next, high AoI). This suggests that if c goes beyond being just a technical parameter, like the energy expenditure, and can be set with some slack, a proper regulation is key to obtain an efficient management.

In Figs. 3–4, we report the resulting values of the system throughput, for $N = 10$ and $N = 100$ terminals, respectively. These plots are straightforward extensions of the previous results on the transmission probabilities, yet they show that the system throughput at NE is even closer to the optimal case, given that we have a sort of compensation between a slightly higher t, resulting in more collisions but also a better chance of being captured. Also, the throughput rapidly decreases in

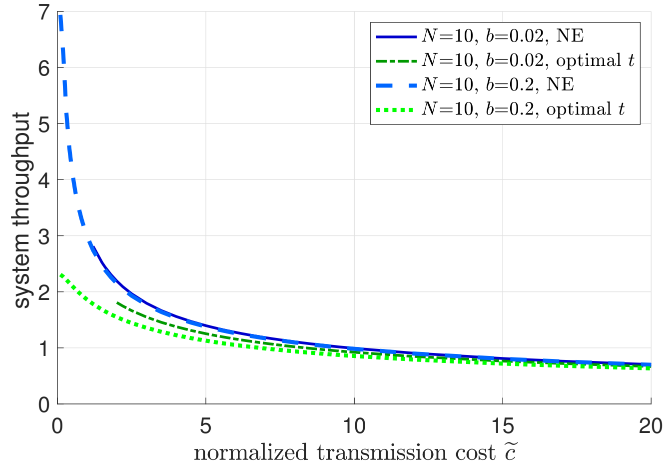

Fig. 3. System throughput, as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup, for $N = 10$ terminals.

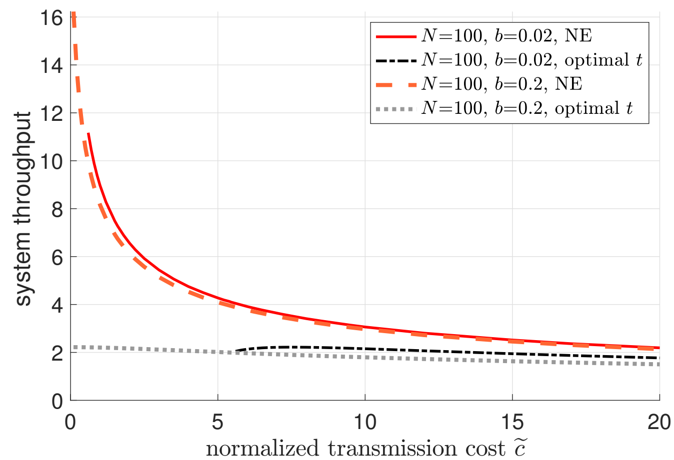

Fig. 4. System throughput, as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup, for $N = 100$ terminals.

$\widetilde{c}$, except when $b = 0.2$, $N = 100$, for which it is already low anyway (the capture threshold is too low for so many users).

Fig. 5 shows the resulting expected AoI. Notably, this is *not* the objective of the players, since they actually try to minimize a utility combining AoI and transmission cost, which is instead shown in Fig. 6. At any rate, we notice that in all the resulting plots the optimal management and the NE are almost indistinguishable, with the only exception of the case $b = 0.2$ and $N = 100$, which is when (10) is violated. Overall, we conjecture that the efficiency of the NE is related to its threshold structure and the actual value of the threshold, which is an issue that certainly deserves to be explored in future work. From a quantitative standpoint, we can say that the system-wide optimization can be replaced by a distributed setup through an NE, which is especially true when N and/or b are low enough, i.e., the capture effect is stronger.

V. Conclusions

We presented a game theoretic analysis of a large number of nodes sharing access following a slotted ALOHA

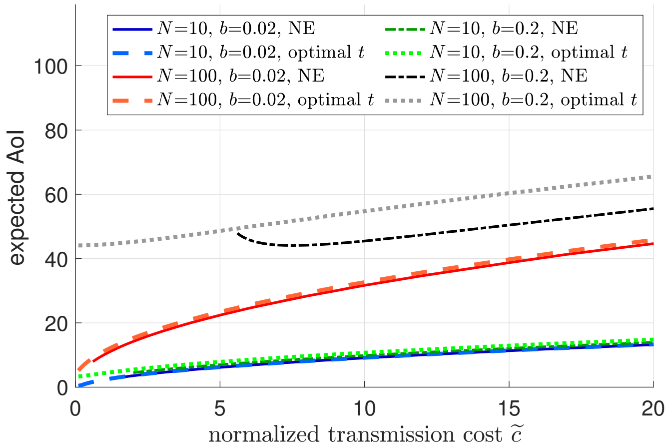

Fig. 5. Expected AoI, as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup.

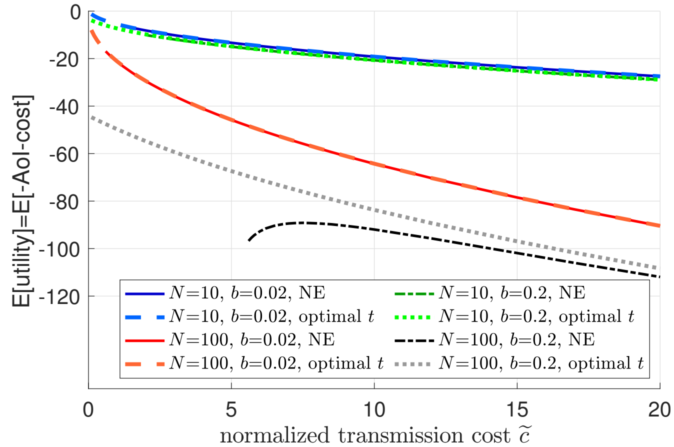

Fig. 6. AoI-based utility of each terminal, as a function of the normalized transmission cost $\widetilde{c}$, at the NE or with an optimal setup.

protocol with capture effect, with their individual objectives being related to minimizing their AoI and also comprising a transmission cost. Based on previous analytical formulations of the AoI for a random access system, we showed that our framework is able to set an AoI-efficient working point, doing so in a distributed fashion where nodes act without coordination and driven by selfish objectives. This translates the system-wide optimization to a more practical approach based on individual actions of each nodes.

Future work may consider an expanded game theoretic formulation where the strategic choices of the nodes are more complex than just setting their transmission probability, possibly considering some sort of feedback from the receiver and an overall planning ahead over multiple update epochs. Even for these scenarios, game theory can be the proper instrument to set a self-enforcing distributed management of nodes with minimal supervision from the network manager, which appear to be a desirable choice for future IoT implementations.

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References

[1] B. Zhou and W. Saad, "Minimum age of information in the internet of things with non-uniform status packet sizes," *IEEE Trans. Wireless Commun.*, vol. 19, no. 3, pp. 1933–1947, Mar. 2019.

[2] 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, Sep. 2018.

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

[4] A. Munari, "Modern random access: an age of information perspective on irregular repetition slotted ALOHA," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 3572–3585, Jun. 2021.

[5] I. Leyva-Mayorga, C. Stefanovic, P. Popovski, V. Pla, and J. Martinez-Bauset, "Random access for machine-type communications," *Wiley 5G Ref: The Essential 5G Reference Online*, pp. 1–21, 2019.

[6] L. Badia, "Impact of transmission cost on age of information at nash equilibrium in slotted ALOHA," *IEEE Netw. Lett.*, 2021, early access.

[7] I. Kadota, E. Uysal-Biyikoglu, R. Singh, and E. Modiano, "Minimizing the age of information in broadcast wireless networks," in *Proc. Allerton Conference, IEEE*, 2016, pp. 844–851.

[8] R. Talak, S. Karaman, and E. Modiano, "Distributed scheduling algorithms for optimizing information freshness in wireless networks," in *Proc. IEEE SPAWC*, 2018, pp. 1–5.

[9] A. Zanella and M. Zorzi, "Theoretical analysis of the capture probability in wireless systems with multiple packet reception capabilities," *IEEE Trans. Commun.*, vol. 60, no. 4, pp. 1058–1071, Apr. 2012.

[10] F. Jameel, S. Wyne, G. Kaddoum, and T. Q. Duong, "A comprehensive survey on cooperative relaying and jamming strategies for physical layer security," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2734–2771, thirdquarter 2018.

[11] 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, Mar. 2019.

[12] Y. Yang, X. Wei, R. Xu, L. Peng, and L. Liu, "Game-based channel access for AoI-oriented data transmission under dynamic attack," *IEEE Internet Things J.*, 2021, early access.

[13] Y. Cho and F. A. Tobagi, "Cooperative and non-cooperative ALOHA games with channel capture," in *Proc. IEEE Globecom*, 2008, pp. 1–6.

[14] L. Chen, T. Cui, S. H. Low, and J. C. Doyle, "A game-theoretic model for medium access control," in *Proc. WICON*, 2007.

[15] A. MacKenzie and S. Wicker, "Selfish users in ALOHA: a game-theoretic approach," in *Proc. IEEE VTC Fall*, vol. 3, 2001, pp. 1354–1357.

[16] G. Tan and J. Guttag, "The 802.11 MAC protocol leads to inefficient equilibria," in *Proc. IEEE Infocom*, vol. 1, 2005, pp. 1–11.

[17] D. C. Atabay, E. Uysal, and O. Kaya, "Improving age of information in random access channels," in *Proc. IEEE Infocom Wkshps*, 2020, pp. 912–917.

[18] H. H. Yang, A. Arafa, T. Q. Quek, and H. V. Poor, "Age of information in random access networks: A spatiotemporal study," in *Proc. IEEE Globecom*, 2020, pp. 1–6.

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

[20] 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.

[21] L. Prospero, R. Costa, and L. Badia, "Resource sharing in the Internet of Things and selfish behaviors of the agents," *IEEE Trans. Circuits Syst. II*, vol. 68, no. 12, pp. 3488–3492, Dec. 2021.

[22] R. T. Ma, V. Misra, and D. Rubenstein, "An analysis of generalized slotted-ALOHA protocols," *IEEE/ACM Trans. Netw.*, vol. 17, no. 3, pp. 936–949, 2008.

[23] A. B. MacKenzie and L. A. DaSilva, *Game theory for wireless engineers*, ser. Synth. Lect. Commun. Morgan & Claypool, 2006, vol. 1, no. 1.