Analysis of Age of Information in Slotted ALOHA Networks With Different Strategic Backoff Schemes

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***Abstract*—Status update freshness in slotted ALOHA networks is an important issue for Internet of things scenarios with large number of nodes and uncoordinated access. We compare the age of information of three different implementations of a backoff to counteract collisions due to uncoordinated medium access, where the transmission probability is (i) gradually decreased, (ii) turned to 0 after a collision, or (iii) turned to 0 proactively. We discuss whether these strategies decrease the average AoI of the nodes, and highlight how their efficiency changes with a distributed application in a game theoretic fashion. As a result, the gradual backoff scheme is not recommended, whereas the reactive scheme has an optimal performance inferior to the proactive one, but obtains analogous results at the Nash equilibrium, and can be a candidate for practical implementations.**

***Index Terms*—Age of Information; Medium access control; Random Access Networks; Slotted ALOHA; Game Theory.**

I. Introduction

The Internet of Things (IoT) comprises a copious number of devices interacting to guarantee communication and environment awareness [1], [2]. In remote monitoring, *freshness* of exchanged data is of utmost importance. In this paper, we take it into account by focusing on Age of Information (AoI), a metric that is gaining momentum in recent investigations as more appropriate than delay or throughput to characterize the overall performance of network sensing operations [3]–[6].

Moreover, we put emphasis on systems with strongly *distributed* access, as scalability and dimensionality considerations make it inconvenient to adopt coordination among local IoT nodes. This translates into considering a *random-based* access of low-complexity; indeed, the majority of the real protocols for the IoT are essentially ALOHA-like [7], [8]. Also, while most of the investigations in the literature assume that the individual nodes are aware and can control the AoI of their data [9]–[11], we argue that this is difficult to achieve for pervasive low-complexity sensing nodes, thus we consider access protocols where a stateful optimization of the AoI is too expensive and simpler procedures are adopted, based on limited information available at local nodes [12]–[14].

At the same time, we investigate an individual uncoordinated medium access by means of *game theory* (GT) [15]. An idealized optimal performance of distributed random protocols can only be achieved through a centralized exchange of certain parameters (such as the transmission probability) that may be inapplicable in distributed scenarios. Thus, we explore whether a selfish control by individual nodes, just aimed at maximizing a local objective, is equally performing [16].

Our specific goal is to investigate AoI for random-based (ALOHA-like) access protocols via game theory. Most of the available studies consider a simplified perspective to represent the medium access, in which the nodes only regulate their access probability [2], [17], [18]. This can be appropriate to gain a preliminary understanding of the involved interactions, and show via GT that a distributed access obtains an efficient Nash equilibrium (NE). Yet, the backoff part of the access mechanism is important and should not be neglected as it can be shown to improve the resulting AoI, due to limited collisions and a better access coordination.

Obtaining a proper characterization of backoff is challenging and opens up to different implementations. We compare three models, namely, a gradual, a reactive, and a proactive backoff, all modeled through Markov chains inspired by the classic reference [19]. All of them allow for an analytical representation, where two parameters are employed: the transmission probability p of idle nodes and a parameter a representing the strength of the backoff. We discuss the optimal setup of these parameters toward a utility function that trades the average AoI with the transmission cost. Such a working point can be achieved only through a centralized agreement, thus we discuss whether it can be reached through a fully distributed approach [20], where the nodes act as selfish players in a GT setup with bi-dimensional strategies.

Our main findings are as follows. First of all, we obtain a closed-form expression of the AoI for all three variants of slotted ALOHA with backoff (gradual, reactive, and proactive). We find that the simpler implementation of the backoff with proportionally scaled transmission probability fails to achieve an efficient expected AoI compared to the case without backoff, which is particularly evident in the distributed setup. For the optimal setup, the gains are almost negligible, whereas at the NE the nodes get the same expected transmission probability as without the backoff [21]. Conversely, the reactive and proactive implementations perform better, offering a significant AoI gain. Also, while the proactive backoff is better under an optimum setup, the NEs of the two approaches are almost coinciding; in practice, if the selfish nodes are aware that they

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must perform a proactive backoff, then they transmit more often, which results in lower AoI, but also higher expenditure for transmission. Overall, the reactive and proactive versions can be considered equivalent for a distributed implementation, which is an interesting guideline for practical IoT protocols.

The rest of this paper is arranged as follows. In Sec. II, we discuss the literature concerning AoI, ALOHA-like access with backoff, and game theory. Sec. III presents the analytical framework, detailing three implementations of the backoff procedure and solving all of them. In Sec. IV, we present the numerical results. Finally, Sec. V concludes the paper.

II. Related Work

The representation of random access protocols via (approximately) Markov states is indebted to the influential model in [19], although we consider a model with fewer states to enable a closed-form derivation of the NE, and different twists on the implementation of the backoff.

An important reference to our contribution is also [22] that studies ALOHA implementations for delay-constrained communications. However, our study diverges significantly from that analysis, which does not consider AoI nor GT approaches, and whose ALOHA schemes vary in the information available to the nodes. For example, they consider dynamic values of the transmission probability p, and machine learning capabilities to train its setup. Similarly, sophisticated deep reinforcement learning approaches are used by ALOHA nodes in [23]. Conversely, we aim at simple IoT nodes, for which the setup of parameters such as p and also the backoff is static and based on considerations not involving any artificial intelligence. Yet, we take a game theoretic stance in that the nodes are strategic, so they are not deprived of any rational decision-making capability, but they approach a lightweight challenge that is more appropriate for elementary IoT devices.

More related to AoI for random access networks, [9] investigates the information freshness of slotted ALOHA or carrier sense multiple access, performing an AoI minimization. Their queueing-like approach uses the offered traffic λ as a parameter, whereas we consider a backlogged traffic with variable transmission probability. Also, they do not consider a backoff nor they investigate the NE.

Many references consider a more powerful AoI optimization where an ALOHA-like protocol is explicitly designed with the purpose of achieving information freshness. For example, [10], [11], [17] consider a variant of a slotted ALOHA subject to an age threshold that must be exceeded for the node to attempt transmission. With different analytical results, these papers show that efficient AoI values can be obtained without deteriorating the rest of the network performance and also present efficient methods to compute the age threshold. Our approach is different as we do not seek for theoretical modifications of the protocol, but rather we investigate possible off-the-shelf implementations, where the slack of the optimization is in the parameter setup of an already established protocol, which is likely to be more viable in pervasive IoT implementations.

Our approach does not require to know the instantaneous AoI that, while certainly theoretically possible, may open up additional challenges related to a cross-layer optimization. Indeed, even a not-so-smart node is in principle able to track the AoI at the destination while checking for collisions, but in a realistic network this would require an interaction between the application and the data link layers. In the end, a precise tracking of the AoI likely requires a feedback from the receiver that causes additional power consumption and may increase the collision probability if performed in-band. For example, [12] discusses why it can be convenient to perform a less invasive stateless optimization, as we do here.

Our analysis is also similar to [24] in that we attempt a bi-dimensional optimization of slotted ALOHA parameters, one of which (the transmission probability) is the same, and the other somehow represents the persistence of the distributed nodes. That reference considers the number of transmission attempts, whereas we use a general parameter representing the backoff intensity. Other differences are that they investigate peak AoI, a trait shared with [25], whereas we consider the average AoI; also, there is no game theoretic investigation from the perspective of a distributed implementation, as the one we present here.

A game theoretic analysis of a slotted ALOHA network is relevant as it is the quintessential setup in which nodes act without any coordination, as argued in [26], [27] for throughput considerations. Thus, it is also interesting to characterize the AoI under this lens. In this sense, our analysis also mirrors the approach of [20] that investigates whether such an optimization can be achieved by means of decentralized actions by individual nodes, as we do. However, our perspective is different, as we specifically consider definite implementations that are achievable in practical IoT setups, instead of a general scenario where multiple nodes share a common channel, which is a much wider space to explore (indeed, they use a multi-armed bandit, whereas our optimizations are in closed-form).

Although the use of GT for evaluating AoI is already present in the seminal reference [5] for multiple queueing sources, further developments are actually circumscribed to relatively few contributions. For example, [28] considers a game played by multiple nodes with the objective of AoI minimization, but the medium access is not specifically on slotted ALOHA. In [29], GT is used to study the AoI of competing sources over an interference channel. Also [30] studies the minimization of AoI in a slotted random medium access via GT but the game is played by virtual network agents focusing on either throughput or AoI, so it is more of a comparison of objectives rather than a way to achieve distributed control.

Finally, [18], [21], [31] have a similar approach to what presented here but with many important differences, most notably, they do not consider a backoff component in the medium access, which is our key contribution, and they all perform a single variable optimization in the access probability as opposed to the multi-dimensional search of the present paper, to obtain the optimal working point as well as the NE.

III. System Model

We consider a discrete time axis divided into slots. Our representation of slotted ALOHA examines competing access by N backlogged nodes that always have a packet to transmit; also, in the age computations, they all have separate AoI values and always have fresh information available (generate-at-will model), and we neglect the transmission delay. All of these are common assumptions for this kind of analysis [3], [4].

In each slot, the nodes independently access the channel. Collisions ensue when the number of accessing nodes is greater than 1. To limit their impact, a backoff phase is kept into consideration, differently from most existing contributions where medium access is abstracted by considering an independent and identically distributed (i.i.d) probability p of transmission in each slot [17], [21], [27]. In our analysis instead, nodes alternate between an *idle* phase and a *backoff* phase, which can be seen as states of a Markov chain [19].

We consider the following schemes for the transition between these two phases. In all cases, we set that during the idle phase, nodes transmit with i.i.d probability whose value is set to p, but the scheme differ on what happens in the backoff.
Gradual backoff (GR-backoff): inspired by [25], this scheme assumes that colliding nodes transit to the backoff phase, where they transmit with probability ap, with $a \leq 1$ being a re-scaling factor. A node exits the backoff state and goes back to idle after performing a successful transmission.
Reactively silent backoff (RS-backoff): in this case, the node still enters the backoff state after a collision, but instead of reducing the transmission probability, it remains silent for a random number of slots. This is obtained by setting $a \leq 1$ as the probability of exiting backoff and going back to idle.
Proactively silent backoff (PS-backoff): the previous scheme is modified as nodes go to the backoff state after each transmission, not just after collision. Similar to the reactive scheme, we set a parameter $a \leq 1$ with analogous meaning.

All the proposed backoff schemes can approximate the state of a node with a discrete time Markov chain whose states are 0 and 1 corresponding to idle and backoff, respectively. Note that in reality the state transitions are not exactly memoryless, as they depend on the joint choices of all nodes to determine collisions. Yet, this results in an acceptable approximation under large N (e.g., $N \geq 10$) as discussed in [19].

The individual choices of the values of p and a for node i are denoted as p_i and a_i, respectively. This is just meant to emphasize that the nodes are choosing their own parameters independently of each other. However, symmetry considerations will lead to an optimal global choice, as well as a NE condition, where these two parameters have the same value for all the nodes in the network [21].

If π_{0i} and π_{1i} are the steady state probabilities that node i is in state 0 or 1, respectively, we have that the expected transmission probability of node i in the RS-backoff and PS-backoff schemes is $t_i = \pi_{0i} p_i$, while in the GR-backoff scheme can be computed as $t_i = \pi_{0i} p_i + \pi_{1i} a_i p_i$.

We intend to use these expressions of t_i from the perspective of different nodes, to compute the collision probability. That

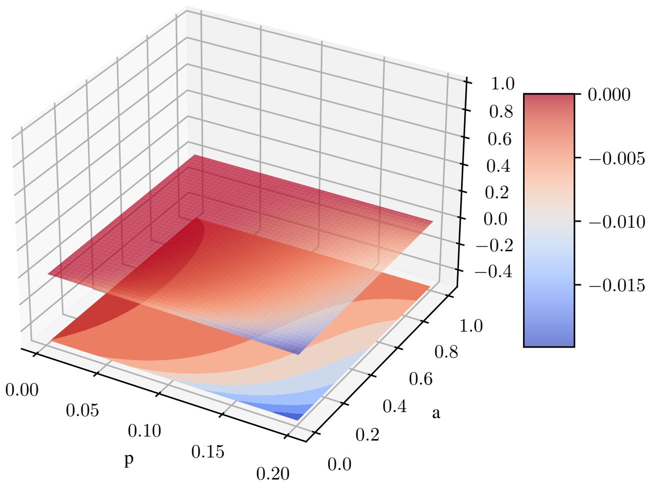

Fig. 1. Difference of the transmission probability under the approximation of the two-state Markov chain and the exact formula, $N = 10$ nodes.

is, the success probability of node i when transmitting in a given slot depends on the probability that all other nodes $j \neq i$ do not transmit as well. Due to the dependent behavior of nodes related to collisions, using t_j in that case is not entirely accurate, yet in practice this can be shown to be a generally robust approximation. We verified this assertion by comparing the exact transmission probability computed on a larger Markov chain where the number of nodes in backoff is precisely kept into account, which can be solved for the steady state probabilities that an individual node is in state 0. Fig. 1 plots the difference between the transmission probability of the GR-backoff case calculated with the approximation and the one with the exact formula, for N=10 nodes. The approximation slightly underestimates the transmission probability, but the difference is negligible when the values of interest of p and a are considered, as will be clear from the results of Sec. IV. Analogous results hold for the RS-backoff and PS-backoff schemes; actually, for the PS-backoff, the expression of t_i is exact as all nodes behave independently.

A. Age of Information

For GR-backoff, the AoI δ_i of user i is on average [21]

$$\mathbb{E}\left[\delta_i^{\mathrm{GR}}\right] = \frac{1}{t_i \prod_{j \neq i} (1 - t_j)} - 1 \,, \tag{1}$$

a result derived by applying the renewal reward theorem [32].

Similar to [18], [26], we consider a cost paid by each node every time it transmits, even if the transmission ends up in a collision, through a coefficient c, whose value can be connected to physical aspects such as energy consumption or just be a shadow price meant to limit the aggressiveness of nodes [27], [33]. Thus, we define the utility of node i as

$$u_i(\boldsymbol{t}) = -\,\mathbb{E}\left[\delta_i\right](\boldsymbol{t}) - c t_i = -\frac{1}{t_i \prod_{j \neq i} (1 - t_j)} + 1 - c t_i \,, \tag{2}$$

meant as an objective that node i seeks to maximize, hence the negative sign, since i would like to minimize both AoI and transmission cost. Vector $\boldsymbol{t} = (t_1, t_2, \ldots, t_N)$ collects the N transmission probabilities; for symmetry reasons, its best global choice is a symmetrical vector $\boldsymbol{t^*} = (t^*, t^*, \ldots, t^*)$. The same symmetry will be found for the NEs in Sec. III-B.

In the PS-backoff scheme, the computation of the expected AoI is less straightforward as nodes do not transmit in the backoff state. We can exploit that the expected AoI can be expressed as the ratio of second and first order moments of the (discrete) inter-update time [34]. We notice that nodes transmit in cycles longer than a single slot consisting of a backoff phase and a period in the idle state before attempting transmission. We approximate the duration of this cycle with its average $k_i = \frac{1}{a_i} + \frac{1}{p_i}$, and we denote with ξ the number of times this cycle is repeated. We also define $z = \prod_{j \neq i}^{N} (1 - t_j)$ as the probability that every node $j \neq i$ stays silent when i attempts transmission. Then, the expected AoI takes the form

$$\mathbb{E}\left[\delta_i^{\mathrm{PS}}\right] = \frac{\sum_{\xi=1}^{\infty} k_i \left(\xi - 1\right) \frac{k_i \xi}{2} z \left(1 - z\right)^{\xi - 1}}{\sum_{\xi=0}^{\infty} k_i \left(\xi + 1\right) z \left(1 - z\right)^{\xi}} \tag{3}$$

that after some algebra reduces to

$$\mathbb{E}\left[\delta_i^{\mathrm{PS}}\right] = \frac{k_i}{z} - \frac{k_i}{2} - \frac{1}{2}\,. \tag{4}$$

Once again, this is an approximated expression due to k_i being an average value, but we ran simulations to verify its accuracy and compared the difference in AoI between simulations and (4) in Fig. 2. Even though some values have a noticeable gap, the difference flattens around 0 for the optimal values, showing that our approximation is acceptable. We will further argue that this is not an issue for the NE either. It follows that we can set a utility for the PS-backoff as well, akin to (2), as the opposite of the sum of expected AoI and transmission cost.

The RS-backoff scheme can be analyzed with a similar explicit AoI computation. In this case, the backoff phase is counted only once per cycle, thus it is taken out of the summation of (3). Some tedious algebra gets

$$\mathbb{E}\left[\delta_i^{\mathrm{RS}}\right] = \frac{\frac{1 - p_i}{p_i^2} \frac{z}{2} + \frac{-k_i^2 z^3 - k_i^2 z + 2k_i^2 - k_i z^3 + k_i z}{2z^2}}{\frac{1}{p_i} z + \frac{k_i \left(1 - z^2\right)}{z}} \tag{5}$$

which is again an approximate expression, since we replaced the term inside summation with its expectation. However, similar evaluations through simulation confirm the appropriateness of our approach, thus we can use a utility as per (2).

B. Game Theoretic Analysis

From a GT standpoint, the NE results from a one-sided optimization of the utility, i.e., each player looks for a *best response* to the unchanged moves of the others. Without loss of generality, we focus on player 1. A NE must satisfy

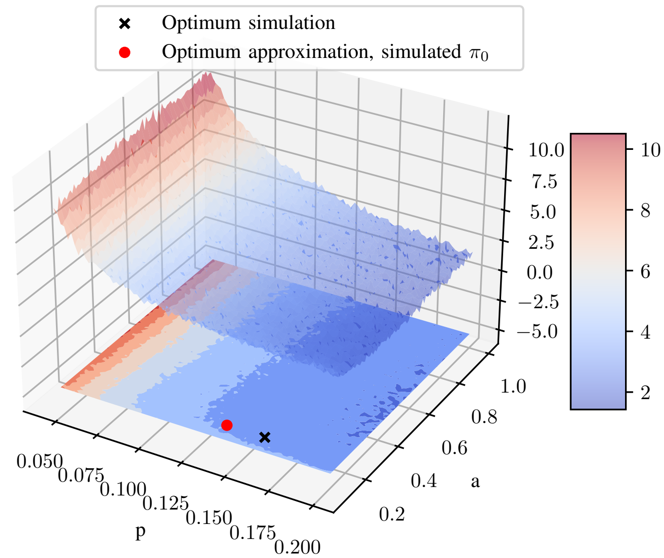

Fig. 2. AoI difference between analysis (with an approximation for the k_i term) and simulation. The analysis underestimates the AoI but the difference in the metric values is almost negligible around the optimal points.

$$\nabla u_1 \left(\boldsymbol{t}\right) = \mathbf{0} \tag{6}$$

which is to say that the partial derivatives of the utility with respect to p_1 and a_1 are equal to 0. For the gradual backoff scheme, the partial derivative of the utility in a_1 (the one in p_1 is structurally the same) can be written as

$$\frac{\partial u_1 \left(\boldsymbol{t}\right)}{\partial a_1} = \frac{\partial t_1}{\partial a_1} \left(\frac{1}{t_1^2 \prod_{j=2}^{N} \left(1 - t_j\right)} - c \right) = 0 \tag{7}$$

and the derivatives can be obtained either numerically or in closed form with the chain rule.

By replacing the index 1 with that of a generic player, the expression can be evaluated for all the nodes. However, symmetry considerations and the fact that t must be a probability value in $[0, 1]$ lead to $t_1 = t_2 = \ldots = t_N = t$. Thus, we can solve a system of differential equations in t to obtain the NE, which can again be done by numerical means.

We remark that for small values of the cost parameter c there is no efficient solution to the system, which means that the only NE is in a *catastrophic equilibrium* where $p = a = 1$ (and thus $t = 1$) for all the nodes. For sufficiently high costs, another more efficient NE appears, as is argued in [18]. For the GR-backoff scheme, this happens when c is bigger than a threshold γ^{GR} that can be written as

$$\gamma^{\mathrm{GR}} = \frac{\left(N + 1\right)^{N+1}}{4 \left(N - 1\right)^{N-1}} \tag{8}$$

which is the same value found in [21].

To obtain the NE in the reactively and proactively silent backoff, we use the same procedure of GR-backoff, i.e., we differentiate the utility through the chain rule and find the NE numerically. Also these schemes have threshold cost values

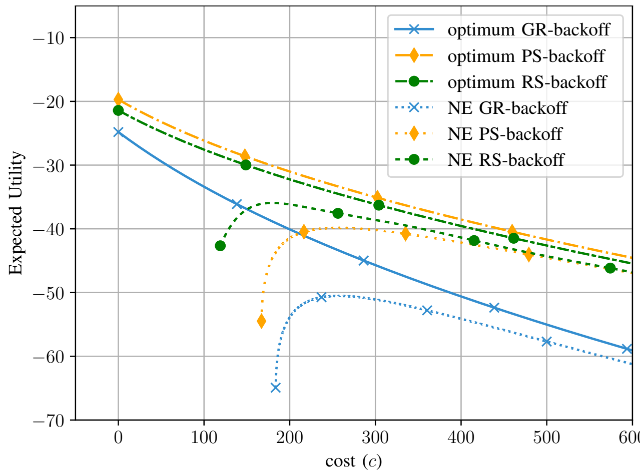

Fig. 3. Utility with the globally optimal choice of the parameters and at the NE in the considered backoff schemes, $N = 10$ nodes.

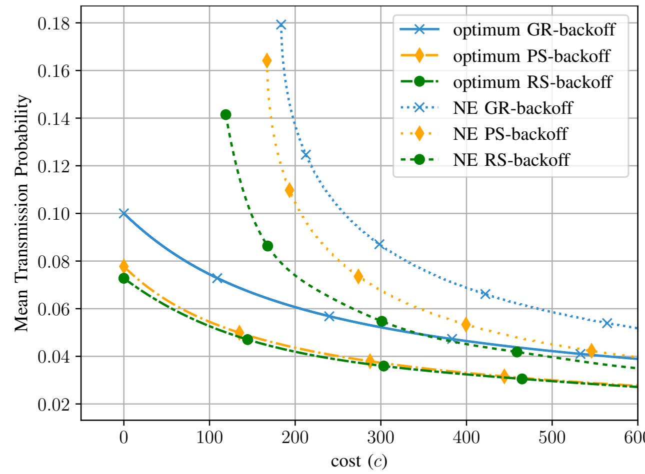

Fig. 5. Mean transmission probability with the globally optimal choice of the parameters and at the NE in the considered backoff schemes, $N = 10$ nodes.

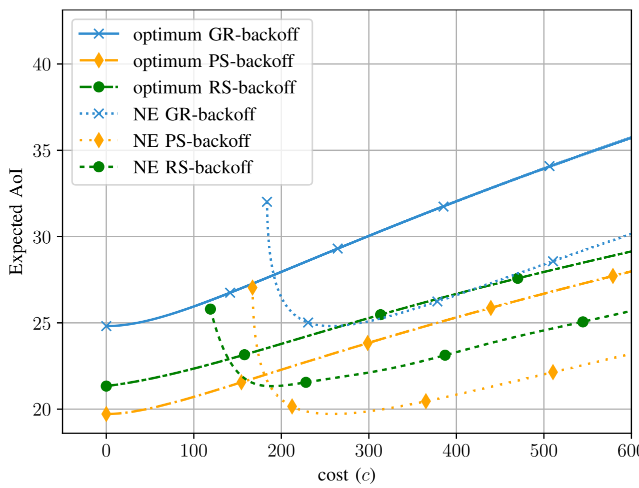

Fig. 4. AoI with the globally optimal choice of the parameters and at the NE in the considered backoff schemes, $N = 10$ nodes.

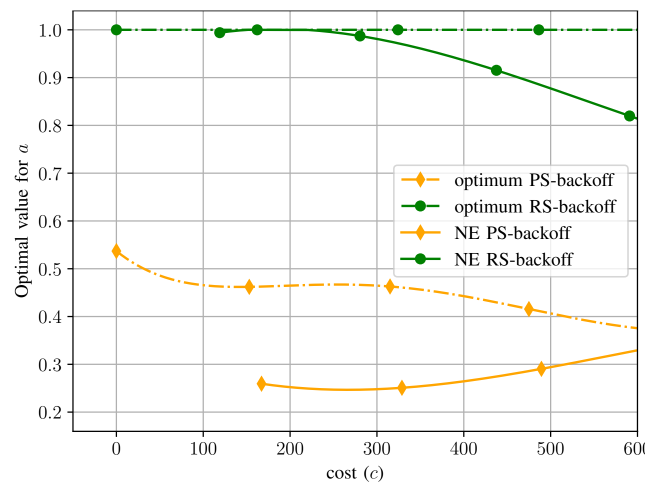

Fig. 6. Optimal values for the parameter a in PS-backoff and RS-backoff, $N = 10$ nodes.

γ^{PS} and γ^{RS}, for PS-backoff and RS-backoff, respectively, so that another NE emerges if $c > \gamma$. It holds experimentally that $\gamma^{\mathrm{GR}} > \gamma^{\mathrm{PS}} > \gamma^{\mathrm{RS}}$. To sum up, for sufficiently high values of c there exists a non-catastrophic NE for all backoff schemes where the transmission probability is non-unitary, which can be regarded as the convergence point of a distributed choice of strategic nodes following a local utility maximization.

IV. Results

We evaluate the formulas of Sec. III to gain visual insight of their implications. All plots consider $N = 10$ nodes. Also, for the sake of visual clarity, we omit the comparison with a basic slotted ALOHA protocol without backoff, as we found out that GR-backoff achieves very similar results, with improvements of the AoI that are never beyond 1%.

Fig. 3 shows the utility values obtained by the different methods. For all the backoff implementations it is evident that the NE is significantly worse than optimal at low costs, but it converges toward an optimal assignment as the cost increases. It is notable that RS-backoff has a worse optimum than PS-backoff, but the NE of the latter is slightly worse, meaning that there is a local strategic advantage in choosing not to proactively backing off after every transmission.

Fig. 4 shows the expected AoI obtained by the different methods. The implications are similar, even in light of the approximations about the AoI, as the general trend of the curves suggests that the proactively and reactively silent schemes are always better than GR-backoff. As already noted in Fig. 3, the NEs tend to approach the global optimum when parameter c is sufficiently large. The NE of RS-backoff obtains better values for the metric with respect to the optimum of PS-backoff for almost all the considered transmission cost values reinforcing the previous assertion that it is beneficial for selfish nodes to take a more competitive stance and choose the RS-backoff scheme when the cost is high enough.

Fig. 5 shows the mean transmission probabilities obtained by the various implementations of the backoff profiles with respect to the transmission cost. As can be noted, the NEs start from large values but quickly fall down towards the global optimum probabilities. It is interesting that the PS-backoff and RS-backoff solutions tend to have lower values for the transmission probability when compared with GR-backoff, but at the same time they achieve better values for the AoI. This suggests that going silent is ultimately better for the AoI than gradually decreasing the transmission probability, a result which is in line with the findings for more complex schemes such as the threshold-ALOHA of [10], [11].

Fig. 6 displays the value of a for PS-backoff and RS-backoff, which is the reciprocal of the average duration of the backoff. Interestingly, in RS-backoff the optimal value is always 1 independently of the cost, which is an indication that, for what concerns AoI minimization, it is important to return to transmission as soon as possible, while at the same time performing a short backoff to locally decrease collisions (in our discrete time setup, the minimal value for such a backoff is indeed one slot). This aggressive behaviour results in worse values for the AoI and a slightly lower transmission probability. Conversely, in PS-backoff where each transmission attempt causes to enter the backoff state, the optimal choice for a is slightly below 0.5. For what concerns the NEs, PS-backoff and RS-backoff exhibit opposite trends and both of them eventually converge to $a = 0.5$ for large enough costs.

V. Conclusions

We presented a game theoretic analysis of AoI for a slotted ALOHA system with explicit inclusion of three different ways of implementing the backoff phase. We gave a closed-form derivation of the optimal working points and the NEs. We discussed the resulting impact on the system performance, showing that a gradual decrease of the transmission probability is unable to improve the AoI-related performance compared to the scheme without backoff. Conversely, reactive and proactive backoffs are effective; while the proactive scheme is slightly better for a centralized control, they are equivalent from a distributed perspective.

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