Age of Information Resilience With a Strategic Out-of-Band Relay

Leonardo Badia and Federico Chiariotti
Dept. of Information Engineering (DEI), University of Padova, Italy
email: {leonardo.badia,federico.chiariotti}@unipd.it

***Abstract*—The age of information (AoI) is a metric representing the freshness of the information available at the receiver in a system which involves the exchange of status updates over an error-prone time-slotted channel between a sensing source and a receiver. We consider such a system, with the addition of a relay node that is able to assist the transmission to improve the resilience against failures, and compute the expected AoI over a discrete time-slotted channel when both the sensor and relay are intermittently and independently active. Furthermore, we present a game theoretic formulation of the optimization of the activity rate for both nodes when transmissions are expensive, managing the tradeoff between cost and AoI. The Nash equilibrium (NE) of the resulting game is found to be both efficient from the perspective of the resulting performance and computationally lightweight for a distributed robust control implementation.**

***Index Terms*—Age of Information; Data acquisition; Modeling; Robust communications; Relay.**

I. Introduction

Many sensing applications in the Internet of things (IoT) require to track real-time content, both for monitoring and control. To have an up-to-date picture of the environment, the main requirement for these applications is not throughput, or even latency for individual transmissions, but rather *freshness*: recent data from the sensors should always be available to the monitoring application. Age of information (AoI) is a performance metric that aims to evaluate the freshness of the data updates coming from a remote sensing source [1].

Compared to the aforementioned conventional memoryless metrics such as latency/delay, AoI is better able to characterize not only the performance of the transmission schedule, but also the robustness of the associated network control, and can be connected to the state estimation error as related to the system outage [2], [3]. AoI and related metrics have seen a significant amount of interest from the research community over the past decade, and analytical and experimental studies exist for many schemes and communication technologies [4].

In order to provide reliable performance, several works in the literature have considered coding and automatic repeat request (ARQ) strategies to minimize AoI. The use of repetition in time [5] or over orthogonal communication channels [6] can provide significant reductions of the average and worst-case AoI, but comes at the cost of a higher load on the communication channel. Interestingly, this often comes at the cost of a lower reliability or higher latency for individual packets, as AoI minimization strategies can often involve dropping out-of-date packets [7]. For what concerns the performance improvement that ARQ can provide in terms of AoI [8], [9], it is found to be often better than with error correction coding, as individual updates can be retransmitted only when needed, but requires a feedback channel, which is often costly or even unavailable for low-power IoT nodes.

Energy-limited IoT nodes often have other constraints to consider, such as limited energy or low-bitrate communication channels: in this case, strategies to minimize AoI are often more complex [10] to take into account the additional requirements. Redundant communication schemes increase energy consumption, as the additional transmitted data requires power, so that the consideration of transmission costs is crucial [11]. In general, any redundant solution that can relax either communication or other constraints can be beneficial to the information freshness: as an example, it is possible to consider redundancy in terms of energy [12], using a backup energy source for energy-harvesting nodes.

In this work, we consider a novel scenario, in which a sensor is aided by a relay node [13]: transmissions from the sensor may fail, leading to a higher AoI, but the relay can recover from these failures by retransmitting the message at a higher power, ensuring that it is delivered to the receiver. We analyze the average AoI in this scenario, providing a closed-form evaluation, and define a game theoretic optimization in which transmissions from the node and relay have a cost: the Nash equilibrium (NE) of the game between the sensor and relay represents an easily computable, Pareto efficient solution to the problem of optimizing their activity rate [14]–[16].

The rest of this paper is organized as follows. We start by defining the communication system model in Sec. II. Sec. III presents the analysis, first deriving the AoI in closed form and subsequently introducing the cost model for the sensor and the relay. The analysis of the NE as a possible way to implement a distributed strategic management of the system to increase its resilience is developed in Sec. IV. Sec. V then presents the numerical results, and Sec. VI concludes the paper and presents some possible avenues of future work.

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II. System Model

We consider a sensor and receiver exchanging status updates over a time-slotted wireless channel. We also consider an update-at-will model, where fresh information is always available at the sensor, but transmitting updates has a cost, which will be discussed in the following. As commonly done in the literature [4]–[6], [15], [17], [18], we neglect the propagation delay in the information exchange, so in the following, time instants can be indifferently computed at the transmitter or the receiver side. Thus, the AoI at the receiver in time slot t is given by [1]

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

where $u(t)$ is the time slot index corresponding to the reception of the last update before t, inclusive. So, for the time slots where we perform an update, the AoI is reset to 0, and it linearly grows afterwards.

It is sensible to assume that resource limitations limit the rate at which the sensor can transmit updates. We model this limitation as a per-slot probability p: at each time slot, the sensor independently draws a Bernoulli sample, transmitting only if it is equal to 1. We also consider the unreliability of the wireless channel, which may be due to fading and other propagation phenomena or to interference on a shared medium. This is modeled as a packet erasure channel (PEC) with an erasure probability f, which is known to the source.

We consider the presence of a relay node [13], [19], which is known to improve the resilience of the transmission and achieve lower delays. The relay is also randomly and independently active with probability b. When active, the relay is able to capture the information sent by the source and forward it to the receiver via an out-of-band exchange in the case of failure. However, the retransmission performed by the relay is less fresh than the original update, as it is delayed by one additional time slot. In this case, the AoI is reset to 1 instead of 0. This model can also represent a random repetition code [5] with maximal ratio combining (MRC) decoding.

We assume that both the sensor and the relay node are controlled by strategic agents operating with the aim to minimize the AoI at the receiver's side. At the same time, we also consider activity costs for both the sensor and the relay. We leverage and expand analytical results for AoI in the presence of independent random transmissions over a slotted channel. From a performance evaluation perspective, we discuss how our problem can be framed as a potential game [20], whose NE is found to be an efficient tradeoff between achieving fresh information without incurring excessive costs. At the same time, the strategic interaction between the two agents can take place without any explicit exchange of control information, which makes our approach particularly suitable for distributed robust implementations.

We also highlight that our system requires no feedback channel toward the sensor: as transmission is random, and the relay operates independently, the sensor can become active in a given slot, obtain a measurement, transmit its value, and return to sleep mode, without needing to remain awake and receive feedback. As reception may require almost as much power as active transmission [21] for low-power sensors, this can significantly extend the lifetime of the sensor's battery with respect to a scheme relying on feedback.

III. Analysis

We consider a slotted time indexed by integer numbers. A sensor may send updates to a destination following independent and identically distributed (i.i.d) binary variables in each time slot whose probability is p. These updates may be successful or fail, and failures are also i.i.d with probability f. Finally, a relay node may be randomly active during each time slot according to an i.i.d process of probability b; when active, it performs backups of the updates sent by the sensor to the destination, if any, and can reliably send them to the destination. When updates are successful, they are received at the destination without any delay. Conversely, if an update fails but the relay node is active, we assume that the very same update can be delivered to the destination in the following time slot, thanks to an out-of-band transmission. If the update fails but the relay node is inactive, the update is simply lost.

Note that the retransmission by the relay is assumed to be always successful, since it takes place on an orthogonal reliable communication channel, but it would be trivial to include i.i.d failures on this side too, by simply rescaling the value of b. In other words, if the relay node has an i.i.d failure rate h, we can effectively replace b with bh in the following. We first derive a closed-form expression of the expected AoI in this scenario and subsequently discuss the role of the relay and the optimization of its activity.

A. AoI Derivation

Following [22], the expected AoI $\Delta = \mathbb{E}_t[\delta(t)]$ for a sensor with i.i.d updates in each slot whose success rate is ρ can be computed as

$$\Delta = \frac{1}{\rho} - 1\,. \tag{2}$$

If we consider a renewal process whose cycles are defined as periods between successful updates, using the AoI as a reward, we can compute the expected AoI by dividing the expected total reward over a cycle by the average duration of a cycle. If updates happen with probability p and are always successful ($f = 0$), then (2) simply becomes $\Delta = (1-p)/p$. If we include failures, then $\rho = p(1-f)$ and we can write (2) as

$$\Delta = [p(1-f)]^{-1} - 1\,. \tag{3}$$

This last result can also be derived by a different approach. If we define a renewal cycle to be the time between different updates of any kind, successful or not, we need to introduce a bias on the reward due to failures for unsuccessful updates. Following the analysis above, the duration of a cycle is taken as $(1-p)/p$ and the expected reward during each cycle is increased by $(1-f)^{-1}f(1-p)/p^2$ from its original value of $(1-p)^2/p^2$ because of failures.

In other words, this correspond to comparing two different approaches that must give the same result. In the former, we consider cycles only between transitions where the AoI returns to 0 (successful updates), which gives (3). Alternatively, we can obtain the same equation by considering cycles between updates of any kind (successful or unsuccessful), which gives the same linear increase of the AoI, but reduces the duration of a cycle. The initial value of the AoI may also be non-zero, which happens if the previous update is not successful. This means that we compute Δ as the sum of $p^{-1}-1$ and a bias β due to previous failures, equal to f times a geometric number of slots until reaching a success, with probability $p(1-f)$, averaging over the number of slots, which leads to:

$$\Delta = p^{-1} - 1 + \sum_{j=0}^{+\infty} (j+1) f p (1-f)(1-p+fp)^j \,. \quad (4)$$

Clearly, the result of the summation in (4) is the same as in (3) as trivially verifiable. However, we can use this method to account for the relay by adjusting the bias.

In this case, the bias due to failed updates is different and can be computed through three different terms. In the following, for notational convenience, we will set $q = 1-b$, representing the probability that the backup is inactive.Note that all three terms require that the update from the intended source fails, so we always have a coefficient f. The terms are then as follows:

1) If the backup is active for the update, the bias is simply equal to 1. This happens with probability $x_1 = f(1-q)$;
2) If the backup is inactive, which happens with probability q, and the last successful update from the sensor was $j+1$ slots ago, the bias is the same in the computation of (4). In this case, the probability of the bias being equal to $j+1$ is $x_2(j) = pq(1-f)(1-p+fpq)^j$, as we must consider both the case of no transmission and of a failed transmission without backup;
3) If the last successful update $j+1$ slots ago was from the relay, i.e., the transmission of the sensor failed, but the relay retransmitted it correctly, the bias is $j+2$; this happens with probability $x_3(j) = pf^2 q(1-q)(1-p+fpq)^j$.

Combining the three terms, we find that the bias is in this case equal to

$$\begin{aligned}\beta =& x_1 + \sum_{j=0}^{+\infty} \Big[x_2(j)(j+1) + x_3(j)(j+2)\Big] \\ =& f(1-q) + pfq \sum_{j=0}^{+\infty} \Big\{(1-p+fpq)^j \Big[(j+1)(1-f) \\ &+ (j+2)f(1-q)\Big]\Big\} = \frac{f(p+q-pq)}{p(1-fq)} \,.\end{aligned} \quad (5)$$

After some algebra and including the bias in the total computation by adding it to $p^{-1}-1$ as per (4), we get

$$\Delta = \frac{1-p(1-f)}{p(1-fq)} . \quad (6)$$

We remark that the effect of the backup at the relay node is localized in the addition of a q term in the denominator to the result for the system without a relay as given in (3). Naturally, the result of (6) implies that when $q = 1$, i.e., the relay never performs a backup, the expected AoI Δ is the same as derived in (3). On the other hand, when $q = 0$, i.e., the relay is always active, we get $\Delta = p^{-1} - 1 + f$, which is consistent with failures causing a fixed increase of 1 in the AoI, since the relay is always delivering the update, but introduces a delay of 1 slot, thus increasing the expected AoI by f.

B. Node Activity Optimization

Similar to [22], [23], we investigate the optimization of the activation probability of the sensor, assuming it incurs a cost c every time it sends an update. This implies that the expected cost paid by the source is cp, which is compared with the expected AoI. Since they are both objectives to minimize, the utility function of the source can be described as

$$u_{\mathrm{S}}(p,b) = -\Delta - cp \,, \quad (7)$$

following the standard convention that the utility represents an objective to maximize instead [24].

This cost term can model the expenditure of a finite resource by the sensor (e.g., energy in a battery-powered or energy-harvesting sensor), but also the use of the shared wireless medium and of the resources of the relay. From a network control perspective, trivial situations when the sensor constantly sends updates represent a waste of bandwidth. Thus, the cost can be seen as a way to regulate the sensor activity as the result of a tradeoff between transmitting as sparsely as possible and minimizing the AoI. We also remark that $u_{\mathrm{S}}(p,b)$, coherently with the usual requirements of utility theory, is written as a function of both p and b, the dependence on b being through Δ that is a function of both parameters, reminding that $q = 1-b$. This means that we can account for the beneficial impact that the relay node and its backups have on the AoI, which in turn allows to transmit more often, in spite of this causing an increased cost cp.

In the same spirit, we can write that the relay node also incurs a cost for every time slot it is active, and we denote it as a coefficient k. In expectation, the average cost is then kb and the utility of the relay node can be assumed to be

$$u_{\mathrm{R}}(p,b) = -\Delta - kb \,, \quad (8)$$

since the relay is also interested in minimizing the AoI. Finally, we can also define a *system welfare* that can analogously represent the utility of the whole system, as

$$w(p,b) = -\Delta - cp - kb \,. \quad (9)$$

The system welfare $w(p,b)$ is actually slightly different from the *total utility* $u_{\mathrm{S}}(p,b) + u_{\mathrm{R}}(p,b) = -2\Delta - cp - kb$ since a factor 2 is missing. The choice of defining it in this way is justified by remarking that the maximal welfare can be achieved by a NE of the system, where the sensor and the relay nodes are individually managed by a distributed control. The derivation of this NE and its analytical implications is developed in the next section.

IV. Game Theoretic Analysis

We treat the sensor and the relay as two rational agents S and R playing a *static game of complete information* with continuously valued actions p and b, both of which fall in $[0, 1]$. These agents follow their respective utilities $u_{\mathrm{S}}(p, b)$ and $u_{\mathrm{R}}(p, b)$. This game structure implies that values p and b (we equivalently use $q = 1 - b$ in the following for notational convenience) are determined by each agent independently and unbeknownst of each other, which would fulfill the typical requirements of IoT systems to minimize the signaling between nodes and also offers improved robustness against wrong or missing exchanges [16]. As remarked above, the sensor does not require reception capabilities to determine the strategy, only knowledge of the erasure probability f and of the cost parameters c and k.

The NE condition can be derived as

$$\frac{\partial u_{\mathrm{S}}(p, b)}{\partial p} = 0 \,, \quad \frac{\partial u_{\mathrm{R}}(p, b)}{\partial b} = 0 \,, \tag{10}$$

which implies

$$\frac{\partial \Delta}{\partial p} = -c \,, \quad \frac{\partial \Delta}{\partial b} = -k \,, \tag{11}$$

and also shows that $w(p, b)$ is a potential function of a proper potential game [20]. This entails that this game has a NE that can be found in a computationally efficient way that translates into a distributed system management, through the procedure known as *fictitious play* [25], [26], which in essence corresponds to each node working independently to locally maximize its own utility function without the need of coordinating with the other node.

An analytical evaluation of the conditions that an NE satisfies can be derived by combining (6) with (11). This results in the following system of equations:

$$\begin{cases} p = & \sqrt{\dfrac{1}{c(1 - fq)}} \\ q = & \dfrac{1}{f} - \sqrt{\dfrac{1 - p(1 - f)}{fkp}} \end{cases} \,, \tag{12}$$

where we used the artifice $q = 1 - b$ and therefore we actually rewrote the second condition of (11) as $\partial \Delta / \partial q = k$.

However, p and q must fall within $[0, 1]$, thus we must also verify the border conditions. For the sensor node, a simple way to guarantee that is to impose $c \geq 1$, which also makes sense if compared with a strategic case without relays [22]. The condition is more complicated for the relay and it can actually serve to derive particular working regimes, such as the relay being always active or inactive.

It turns out that the behavior of the relay node ultimately depends on the numerical value of k (as is also intuitive). The higher the value of k, the lower the probability of an active relay becomes, but when this value goes outside the interval $[0, 1]$ it simply means that the NE is found at a border condition for the choice of b (or q, equivalently). The condition

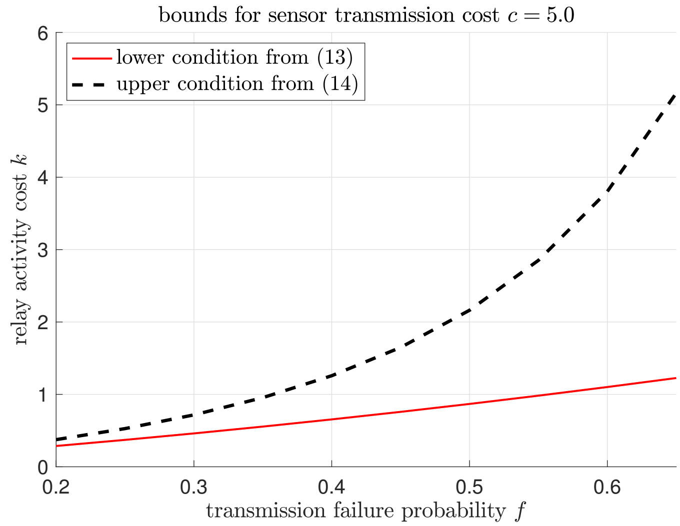

Fig. 1. Lower and upper bounds on k for the relay activity to fall inside $[0, 1]$, vs. transmission failure probability f, for sensor transmission cost $c = 5$.

for the relay node being always active (i.e., $q = 0$) can be found by forcing $q \leq 0$ in (12), which gives

$$k \leq f\sqrt{c} - f(1 - f) \tag{13}$$

whereas the same approach for $q \geq 1$ determines the range of k for which the relay is always inactive, i.e.,

$$k \geq \frac{f(\sqrt{c} - \sqrt{1 - f})}{(1 - f)^{1.5}} \,. \tag{14}$$

The NE condition can be computed by first verifying if either of these bounds holds, in which case, q is immediately determined and p is derived accordingly as the best strategic choice for the sensor, i.e., $p = (c)^{-0.5}$ or $p = (c(1-f))^{-0.5}$ if the strategic relay is always active and inactive, respectively. Instead, if $f\big(\sqrt{c} - (1 - f)\big) \leq k \leq f\big(\sqrt{c} - \sqrt{1 - f}\big)/(1 - f)^{1.5}$, then the NE is found in an inner point of $[0, 1]$ for both strategic choices of the agents.

Fig. 1 can offer some further numerical insight on the actual values involved. In particular, we highlight that the two conditions converge to a very narrow range when the probability of transmission failure f is low. For $f \to 0$, both conditions tend to 0. In this case the relay is always inactive if its cost is not 0, and any activity probability is equivalent if it is: indeed, there is no need for a relay to assist an error-free communication. As f increases, the value of k lingers around values that are much lower than c. This is also justified by the remark that, while the relay retransmission is always free from errors, it introduces a further latency. Thus, it is convenient only if its associated cost k is generally lower than the sensor transmission cost c (at least for values of f that are not excessively large). When f increases, the gap between the two conditions widens and we get a significant range of values for k within which the NE is found outside the border conditions for b.

In the case p and b both fall in inner points of $[0, 1]$, their numerical values can be immediately found by a recursive

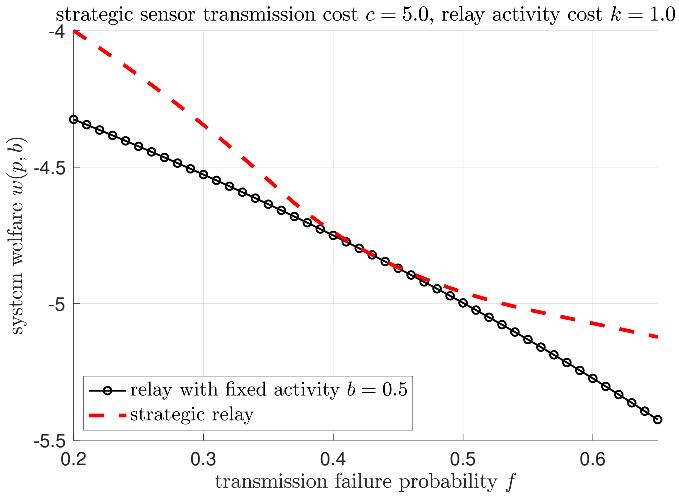

Fig. 2. Comparison of a relay with fixed activity probability $b = 0.5$ and a strategic sensor. System welfare $w(p, b)$ vs. transmission failure probability f, for sensor transmission cost $c = 5$ and relay activity cost $k = 1$.

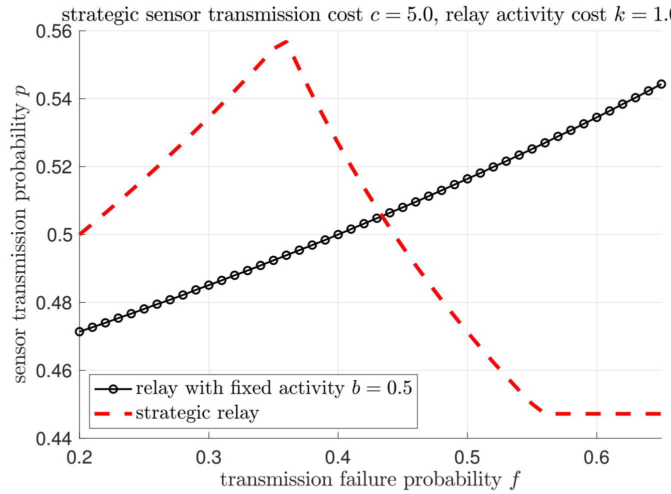

Fig. 3. Comparison of a relay with fixed activity probability $b = 0.5$ and a strategic sensor. Sensor transmission probability p vs. transmission failure probability f, for sensor transmission cost $c = 5$ and relay activity cost $k = 1$.

approach, where an initial value $p = p^{(0)}$ can be set and then used to solve (12) to derive any $q^{(i)}$ from $p^{(i)}$ and then $p^{(i+1)}$ from $q^{(i)}$. Actually, this procedure would correspond to the practical game theoretic technique known as *fictitious play*, where each player computes the best response to the current belief about the other player's move, and, assuming the other player is rational as well, updates the belief accordingly [25]. Especially, this procedure works in our specific case as the game possesses a potential function (the welfare $w(p, b)$) and this even guarantees the uniqueness of the NE. Practical instances of fictitious play for the problem at hand show that even considering $p^{(0)} = 0$, numerical convergence of the procedure under a very fine-graned precision is guaranteed already after few iterations (usually fewer than 10). The fact that the NE is computable through simple operations is particularly relevant in light of possible protocol implementations on real IoT devices with limited processing capabilities.

V. Numerical Results

We evaluate the resulting analytical framework and the system performance at the NE for the sensor and the relay being strategic agents that are driven by (7) and (8), respectively. In other words, they both try to minimize the AoI but at the same time they want to limit their individual costs. In the following, the value of the sensor transmission cost c is always taken equal to 5, whereas different values of the relay activation cost k are considered. All the results have been confirmed by Monte Carlo simulation.

Fig. 2 highlights the effect of a strategic behavior by the relay node, as we compare the resulting system welfare $w(p, b)$ for two scenarios, *both* of which consider a strategic sensor (i.e., the sensor tries to optimize its own objective). However, in the former case, the relay is active with a fixed probability $b = 0.5$, regardless of the cost, while in the latter the relay is also strategic and a NE can be computed through fictitious play. Naturally, the NE achieves a better system welfare thanks to the strategic interaction between sensor and relay. The two curves only coincide when $b = 0.5$ actually happens to be the best strategic choice for the relay.

It is worth noting that considering a strategic relay changes not only the behavior of the relay itself, but also that of the sensor, since the latter behaves as a rational agent that can exploit the more efficient performance of the system. This is visible in Fig. 3, which plots the sensor transmission probability p as a function of the transmission failure probability f. When the relay node has a fixed activity pattern, the sensor can only exploit its intervention to a limited extent. For example, as f increases, the sensor is forced to be more active to compensate for the increased failures; however, it is limited by its own cost, leading to an increased AoI.

Conversely, the trend of the sensor transmission probability when the relay is strategic (and the sensor is aware of that) is much more interesting. We can notice that, for low values of f, the sensor is sending updates more often; this happens because the strategic relay is always inactive, as its intervention is deemed to be less convenient – however, this still results in a better system welfare. As we will see in the following results, the strategic relay becomes active only for f approximately greater than 0.36 and from this point on, the value of p decreases sharply, until reaching a floor when the relay is always active at around $f = 0.57$. From this point on, both the sensor and the relay keep a fixed activity rate, with that of the relay being $b = 1$.

To explore these differences in a more general way, we consider the NE for different values of the relay activation cost k, and we evaluate different metrics of interest. We start by considering the expected AoI, which is displayed in Fig. 4. While it is intuitive that the AoI generally increases with f, we can see that the presence of the relay twists this trend in an interesting way. In particular, the AoI transitions between two increasing trends, from a higher one corresponding to a

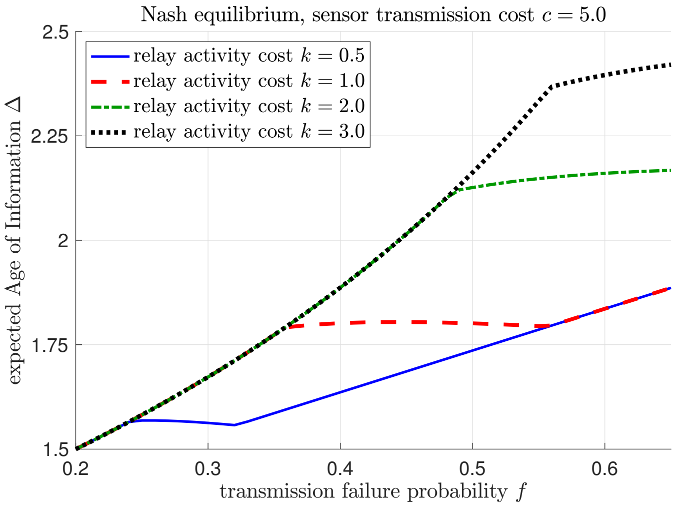

Fig. 4. Expected age of information Δ at the NE as a function of transmission failure probability f, for different values of the relay activity cost k and sensor transmission cost $c = 5$.

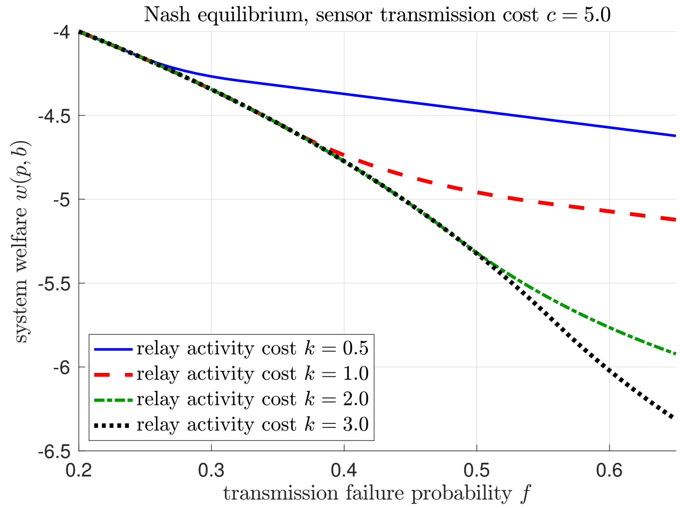

Fig. 5. Welfare $w(p, b)$ at the NE as a function of transmission failure probability f, for different values of the relay activity cost k and sensor transmission cost $c = 5$.

strategic relay that is always inactive as its activation cost is too high, to a lower one where the relay is always active. These correspond to the limit conditions found in the previous section. The higher the cost, the longer the transition between the two trends and also the higher the value of f for which it takes place. Remarkably, this transition is plateau-like but not exactly, as we can notice some counterintuitive trends (for example, the expected AoI for $k = 0.5$ has a minimum that is also an angular point for $f \approx 0.32$). This happens because the system welfare $w(p, b)$, which is the common objective of the strategic nodes at the NE, does not consist of the AoI alone, but it also includes the costs that the nodes incur. Since higher values of f must be contrasted by a higher activity by the nodes, the total welfare is still decreasing in f even though the expected AoI might be locally decreasing as well.

This is confirmed by Fig. 5, which shows the system welfare $w(p, b)$, i.e., the real objective of the strategic agents, as a function of f. Here, the curves do not exhibit any angular point, but just a generally decreasing trend as f increases; however, the descent is slower when the relay node intervenes – which happens only at high values of f if the cost k is high.

Figs. 6 and 7 report the behavior of the strategic nodes, showing the sensor transmission probability p and the relay node activity probability b, respectively. These results simply generalize the trends already highlighted for the specific case in Fig. 3. In particular, the relay transitions from being always inactive if f is relatively low, as the sensor can achieve a low AoI on its own, to being always active when f is high. Naturally, a higher value of k makes the relay more reluctant to intervene, increasing both the minimum f at which the relay is always active and the range of values of f for which the solution is an inner point.

Finally, we highlight that the two figures have parallel trends: if $b = 0$, the sensor activity increases with f, while it is stable if $b = 1$. On the other hand, the sensor activity decreases

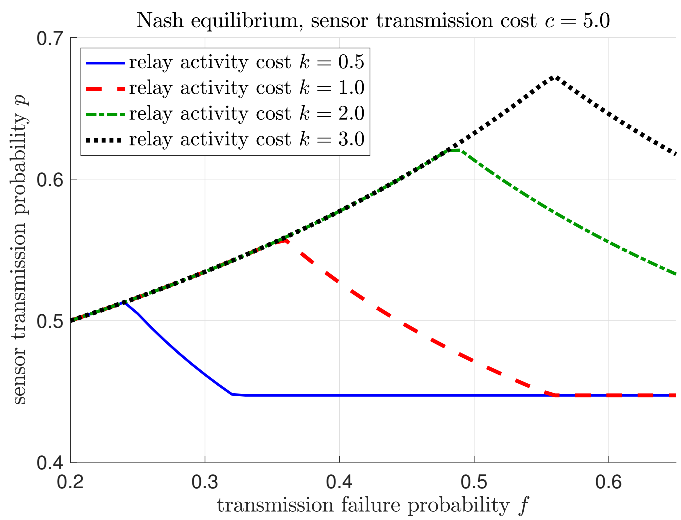

Fig. 6. Source transmission probability (at the NE) as a function of transmission failure probability f, for different values of the relay activity cost k and sensor transmission cost $c = 5$.

if f increases and the solution is an inner point of $[0, 1]$: this is because the relay activity cost is smaller, so that the relay gradually takes up more of the burden of compensating for transmission failures, until it reaches $b = 1$ and all packets are retransmitted.

VI. Conclusions

We studied a scenario of status updates between a sensor and receiver over an error-prone slotted channel, considering the presence of a relay node that, when active, can recover failures in the subsequent slot. We leveraged a closed-form analytical computation of the AoI as a function of the involved parameters, to derive a game theoretic representation of the interaction between the sensor and the relay as strategic agents driven by a common potential, consisting of the expected AoI

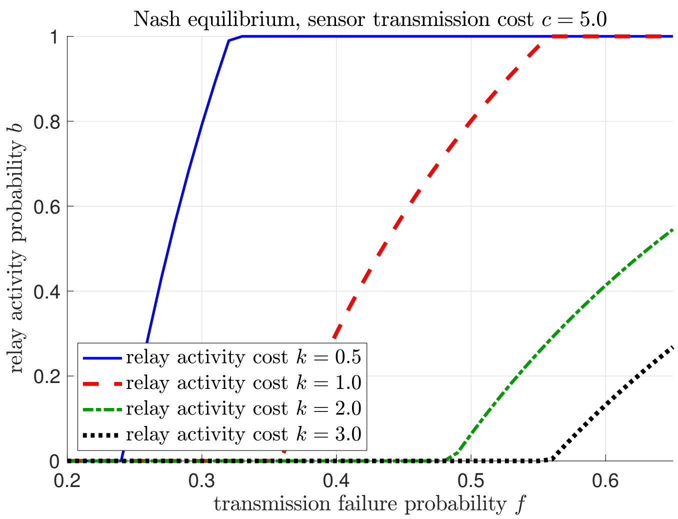

Fig. 7. Relay activity probability (at the NE) as a function of transmission failure probability f, for different values of the relay activity cost k and sensor transmission cost $c = 5$.

and the involved costs, that they evaluate according to their individual benefit.

We showed that such an approach is able to derive an efficient system working point, and is able to do so without any signaling exchange but just through local computation at each node. Thus, our proposed approach can be generalized to a framework for practical implementations in IoT scenarios, for any context where additional nodes can intervene to assist failure in the status updates exchange and thereby improving system reliability [5], [21]. Also, it may serve to design practical protocols for the assisting nodes, as well as identifying theoretical conditions for their introduction, e.g., avoiding their implementation if it does not meet significant benefits.

Future extensions may consider different models for the activity of the nodes other than i.i.d activation probabilities, e.g., stateful optimizations can be performed [27], and the same for the failure rate of the channel [28], as well as the data generation process [29], or including an underlying process that correlate all of them [15], such as the energy harvesting pattern [12].

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