Abstract—In this work, we combine the two notions of timely delivery of information in order to study their interplay: namely, deadline-constrained packet delivery due to latency constraints and freshness of information at the destination. More specifically, we consider a two-user multiple access setup with random-access, in which user 1 is a wireless device with a queue and has external bursty traffic which is deadline-constrained, while user 2 monitors a sensor and transmits status updates to the destination. For this simple, yet meaningful setup, we provide analytical expressions for the throughput and drop probability of user 1, and an analytical expression for the average Age of Information (AoI) of user 2 monitoring the sensor. The relations reveal that there is a trade-off between the average AoI of user 2 and the drop rate of user 1: the lower the average AoI, the higher the drop rate, and vice versa. Simulations corroborate the validity of our theoretical results.

I. INTRODUCTION

With the proliferation of inexpensive devices with impressive sensing, computing, and control capabilities, there has been a rapid increase in Cyber-Physical Systems (CPSs) applications, such as, autonomous vehicles, wireless industrial automation, environmental and health monitoring, to name a few [1], [2]. Such applications, however, accentuate the need for developing efficient algorithms offering timely delivery of information updates. In several occasions, this requires information to arrive at the destination within a certain period of time (deadline-constrained) due to stringent requirements in terms of latency, in others cases it is required to keep the information at the destination as fresh as possible. Information timeliness or freshness at the destination is captured by a new metric, called the Age of Information (AoI) [3], [4]. It was first introduced in [5], and it is defined as the time elapsed since the generation of the status update that was most recently received by a destination.

In this work, we consider a two-user multiple access setup with different traffic characteristics. One user has external bursty traffic which is deadline-constrained, while the other user monitors a sensor and transmits status updates (in the form of packets) to the destination as depicted in Fig. [1]

A. Related Works

Recently, there is an increasing interest on studying the performance of systems with deadline-constrained traffic. The works in [6], [7] consider optimal scheduling schemes for traffic with deadlines. The works [8]–[10], study the performance of random access deadline-constrained wireless networks. In [11], the authors analyze the benefits of scheduling based on exploiting variable transmission times in multi-channel wireless systems with heterogeneous traffic flows. In [12], a joint scheduling-and-power-allocation problem of a downlink cellular system with real-time and non-real-time users. The authors proposed an algorithm that satisfies the hard deadline requirements for the real-time users and stability constraints for the non-real-time ones. In [13], was proposed a dynamic algorithm that solves the problem of minimizing packet drop rate in deadline-constrained traffic by optimizing power allocation under average power consumption constraints.

In [14], was addressed the problem of minimizing the expected weighted sum AoI of a single-hop network with multiple nodes while satisfying minimum throughput requirements from individual nodes. The authors in [15] considered a multicast transmission of a real-time IoT system where the service time of each status update is deadline-constrained. In [16], was introduced a packet deadline as a control mechanism to study its impact on the average AoI for an M/M/1/2 queue. In [17], the AoI in infinite capacity queues with packet deadline was considered.

There is a line of papers that consider the interplay of AoI with throughput or latency. More specifically, in [18], the authors study the performance of a multiple access channel with heterogeneous traffic: one grid-connected node has bursty data arrivals and another node with energy harvesting capabilities sends status updates to a common destination.
the interplay between delay violation probability and average AoI in a two-user wireless multiple access channel with MPR capability was studied. The work in [20] derived optimal status updating policies for a system with a source-destination pair that communicates via a wireless link, whereby the source node is comprised of a queue and serves two traffic flows, one that is AoI sensitive and one that throughput oriented.

To the best of our knowledge, the interaction of deadline-constrained traffic with AoI-oriented traffic has not been studied in the literature.

B. Contributions

In this work, we study the interplay of deadline-constrained traffic and the information freshness in a two-user random access channel with multi-packet reception capabilities. The deadline-constrained user has external bursty traffic modelled by a Bernoulli process, and the incoming packets are stored in its queue. Each packet has a predefined deadline, where if it has not been received by the destination then it is dropped from the system. The second user monitors a sensor, and generates status updates at will in a timeslot. This is the smallest meaningful setup, which is tractable to analyze. The analysis can provide useful insights for in terms of achievable throughput, drop probability, and the average AoI. In order to analyse the performance of the deadline-constrained user we utilize Discrete Time Markov Chains. Furthermore, for the AoI-oriented user, we obtain the average AoI in closed-form expression. We validate the accuracy of our analytical findings with simulations. The results show that there is a trade-off between the average AoI of user 2 and the drop rate of user 1: the lower the average AoI, the higher the drop rate, and vice versa. This is expected, since for reducing either the drop rate or the average AoI, the probability of transmission of the corresponding user should increase, causing interference to the other user, thus reducing the service probability.

II. SYSTEM MODEL

We consider two users transmitting their information in form of packets over a wireless fading channel to a receiver as shown in Fig. 1. Time is assumed to be slotted. Let \( t \in \mathbb{Z}_+ \) denote the \( t \)th slot.

At each time slot \( t \), a packet arrives to the queue of user 1 with arrival probability \( \lambda \). Each packet of user 1 has a deadline. We consider that each packet deadline expires in \( d \) slots since the time of arrival. Therefore, the packet must be successfully transmitted within \( d \) slots; otherwise, it is dropped and discarded from the system. User 1 attempts for transmission (given that its queue is non-empty) with probability \( q_1 \) at each time slot.

User 2, at each time slot, samples “fresh” information and attempts to transmit it in form of a packet with probability \( q_2 \). We consider that the procedures of sampling together with transmission take one time slot.

AoI represents how “fresh” is the information from the perspective of the receiver. Let \( A(t) \) be a strictly positive integer that depicts the AoI associated with user 1 at the receiver. The AoI evolution at the receiver is written as

\[
A(t + 1) = \begin{cases} 
1, & \text{successful packet reception,} \\
A(t) + 1, & \text{otherwise.}
\end{cases}
\] (1)

A. Physical Layer Model

We consider that a packet from user \( i \) is successfully transmitted to the receiver if and only if the Signal-To-Interference-and-Noise Ration (SINR) is above a certain threshold \( \gamma_i \), i.e., \( \text{SINR}_i \geq \gamma_i \). Let \( P_{tx,i} \) be the transmit power of user \( i \), and \( r_i \) be the distance between user \( i \) and the receiver. The received power, when user \( i \) transmits, is \( P_{rx,i} = h_i r_i^\alpha \), where \( h_i \) is a random variable (RV) representing small-scale fading and \( s_i \) is the received power factor. Under Rayleigh fading, \( h_i \) is exponentially distributed [21]. The received power factor \( s_i \) is given by \( s_i = \frac{P_{tx,i} r_i^\alpha}{\gamma_i} \), where \( \alpha \) is the path loss exponent. When only user \( i \) transmits, the success transmission probability for user \( i \) is given by

\[
P_{s/i} = \exp \left( -\frac{\gamma_i \eta}{v_i s_i} \right),
\] (2)

where \( v_i \) is the parameter of the Rayleigh fading RV (i.e., \( h_i \sim \text{Rayleigh}(v_i) \)), and \( \eta \) is the noise power at the receiver. When both users transmit, the successful transmission probability for user \( i \) is given by [22, Theorem 1]

\[
P_{s/i,j} = \exp \left( -\frac{\gamma_i \eta}{v_i s_i} \right) \left( 1 + \frac{v_j s_j}{v_i s_i} \right)^{-1},
\] (3)

where \( j = i \mod 2 + 1 \).

Then, the service probability for user 1 is

\[
\mu_1 = q_1 (1 - q_2) P_{1/1} + q_1 q_2 P_{1/1.2} = q_1 \left[ (1 - q_2) P_{1/1} + q_2 P_{1/1.2} \right],
\] (4)

and for user 2 is

\[
\mu_2 = q_2 (1 - q_1 P\{Q > 0\}) P_{2/2} + q_2 q_1 (\text{Pr}\{Q > 0\} P_{2/2,1}) = q_2 \left[ (1 - q_1 P\{Q > 0\}) P_{2/2} + q_1 (\text{Pr}\{Q > 0\} P_{2/2,1}) \right].
\] (5)

respectively. Then, the average success probability for user 1 and user 2 is

\[
p_1 = (1 - q_2) P_{1/1} + q_2 P_{1/1.2},
\] (6)

and

\[
p_2 = (1 - q_1 P\{Q > 0\}) P_{2/2} + q_1 (\text{Pr}\{Q > 0\} P_{2/2,1}),
\] (7)

respectively.

\( ^{1}\text{We would like to emphasize that the analysis presented in this work is more general and it can be applied to other channel cases as long as we can obtain the values for the success probabilities.} \)
A conversation or argument about average AoI analysis.

In this section, we provide the analysis for average AoI of user 1 at the receiver. Let $T_i$ be the time between two consecutive attempted transmissions. Let $S_k$ be the number of time slots between the $k^{th}$ and $(k+1)^{th}$ successful packet reception from user 1 and $M$ the number of attempted transmissions between successful receptions $k$ and $(k+1)$. Note that $M$ is a RV. In Fig. 2, we illustrate an example of AoI evolution.

**Proposition 1.** The average AoI, $ar{A}$, is given by

$$\bar{A} = \frac{1}{q_2 p_2},$$

where $q_2$ is the probability with which user 2 attempts to transmit and $p_2$ is the average success probability and it is given in (7).

**Proof.** $S_k$ can be written as

$$S_k = \sum_{i=1}^{m_k} T_i,$$

where $m_k$ is the realization of RV $M$ between the $k^{th}$ and $(k+1)^{th}$ successful packet reception from user 1. Note that $S_k$ is a stationary process. Therefore, $\mathbb{E}[S_k] = \mathbb{E}[S]$, and $\mathbb{E}[S_k^2] = \mathbb{E}[S^2]$, for any $k$. Then, the average AoI is calculated as

$$\bar{A} = \lim_{N \to \infty} \frac{\sum_{k=1}^{N} S_k}{\sum_{k=1}^{N} S_k} = \lim_{N \to \infty} \frac{\sum_{k=1}^{N} \frac{S_k^2 + S_k}{2}}{\sum_{k=1}^{N} S_k} = \frac{\mathbb{E}[S^2]}{2\mathbb{E}[S]} + \frac{1}{2}. \quad (10)$$

We can write $\mathbb{E}[S]$ as

$$\mathbb{E}[S] = \sum_{m=1}^{\infty} m \mathbb{E}[T] (1 - p_2)^{m-1} p_2 = \mathbb{E}[T] \sum_{m=1}^{\infty} m (1 - p_2)^{m} \frac{p_2}{1 - p_2} = \frac{\mathbb{E}[T]}{p_2}. \quad (11)$$

In order to calculate $\mathbb{E}[S^2]$, we utilize that

$$S_k^2 = \left( \sum_{i=1}^{m_k} T_i \right)^2 = \sum_{i=1}^{m_k} T_i^2 + \sum_{i=1}^{m_k} \sum_{j \neq i} T_i T_j. \quad (12)$$

Taking the conditional expected value of $S^2$, we obtain

$$\mathbb{E}[S^2 | M = m] = m \mathbb{E}[T^2] + m(m - 1) (\mathbb{E}[T])^2, \quad (13)$$

and therefore,

$$\mathbb{E}[S^2] = \sum_{m=1}^{\infty} \mathbb{E}[S^2 | M = m] (1 - p_2)^{m-1} p_2$$

$$= \mathbb{E}[T^2] + \frac{2(1 - p_2) (\mathbb{E}[T])^2}{p_2^2}, \quad (14)$$

where (a) follows by utilizing that $\sum_{k=1}^{\infty} k^2 r^{k-1} = \frac{r+1}{(1-r)^3}$, $r < 1$ and $\sum_{k=1}^{\infty} i c^k = \frac{e}{(1-c)^3}$, $|c| < 1$. In addition, we need to derive $\mathbb{E}[T]$ and $\mathbb{E}[T^2]$.

$$\mathbb{E}[T] = \sum_{k=1}^{\infty} k \Pr\{T = k\} = \sum_{k=1}^{\infty} k (1 - q_2)^k q_2 (a) = \frac{1}{q_2}, \quad (15)$$

where (a) follows by utilizing $\sum_{i=1}^{\infty} ic^k = \frac{e}{(1-c)^3}$, $|c| < 1$.

$$\mathbb{E}[T^2] = \sum_{k=1}^{\infty} k^2 \Pr\{T = k\} = \sum_{k=1}^{\infty} k^2 (1 - q_2)^k q_2 (b) = 2 - \frac{q_2}{q_2}, \quad (16)$$

where (b) following by utilizing $\sum_{k=1}^{\infty} k^2 r^{k-1} = \frac{r+1}{(1-r)^3}$, $r < 1$. Substituting (15) and (16) into (11) and (14), and after algebraic manipulations, we conclude that

$$\bar{A} = \frac{1}{q_2 p_2}. \quad (17)$$

The proof is completed. □

**IV. PACKET DROP RATE OF USER 1**

In this section, we provide the expression for the drop rate for user 1. We consider that if a packet from user 1 is not successfully transmitted because of channel errors, we have the option to retransmit it. In particular, we retransmit the packet until its successful transmission or its deadline expiration. Therefore, the maximum number of retransmissions is $d - 1$.

We use a Discrete Time Markov Chain to model the system. In particular, the states of the Markov chain represent the waiting time of the packet that is in the head of the queue. The number of states of the Markov chain is equal to $d + 1$. In Fig. 3, we depict an example of a Markov chain for a system with $d = 3$. The system is in state 0 if there is no packet waiting in the queue. It transits to state 1 after the arrival of a packet. The system transits to the next state if the packet is not successfully transmitted. It remains in the current state if we have an arrival and a successful transmission in the same time...
slot. We observe that when the system is in state 3, i.e., we have only one chance (slot) to transmit the packet before its expiration, the system transition depends only on the events of new arrivals and not on the service probability $\mu_1$. The reason is that we will remove the packet from the queue either by serving or dropping it. Therefore, the Markov chain, when it is in state 3, is affected only by the recent packet arrival, if there is any.

The transition probability matrix (row stochastic) of the Markov chain in Fig. 1 is shown below:

$$P = \begin{bmatrix}
\lambda & \lambda & 0 & 0 \\
\mu_1 \lambda & \mu_1 \lambda & \bar{\mu}_1 & 0 \\
\mu_1 \lambda^2 & \mu_1 \lambda \bar{\lambda} & \mu_1 \lambda & \bar{\mu}_1 \\
\bar{\lambda} & \bar{\lambda}^2 & \bar{\lambda} \bar{\lambda} & \bar{\lambda}
\end{bmatrix}.$$

In general, the transition matrix of a Markov chain with $d + 1$ states has the form

$$P = \begin{bmatrix}
\lambda & \lambda & \cdots & \lambda & 0 & 0 \\
\mu_1 \lambda & \mu_1 \lambda & \cdots & \mu_1 \lambda & \bar{\mu}_1 & \cdots \\
\mu_1 \lambda^2 & \mu_1 \lambda \bar{\lambda} & \cdots & \mu_1 \lambda \bar{\lambda} & \mu_1 \lambda & \cdots \\
\vdots & \vdots & \ddots & \vdots & \vdots & \ddots \\
\mu_1 \lambda^{d-1} & \mu_1 \lambda \bar{\lambda}^{d-2} & \cdots & \mu_1 \lambda \bar{\lambda}^{d-2} & \mu_1 \lambda & \cdots & \bar{\lambda} & \bar{\lambda}
\end{bmatrix}.$$

We denote by $\pi = [\pi_0, \pi_1, \ldots, \pi_d]$ the steady state distribution of the Markov chain. To derive $\pi$, we solve the following linear system of equations

$$\pi P = \pi, \; \pi \mathbf{1} = 1.$$  \hspace{1cm} (18)

We observe from (18) that $\pi$ is an eigenvector of $P$. After applying eigenvalue decomposition (EVD) we obtain the eigenvectors and eigenvalues of matrix $P$. We find the eigenvector that corresponds to the eigenvalue that is equal to 1. We normalize the elements of the eigenvector and we obtain $\pi$. Then, we calculate the drop rate as

$$D = \pi_d \bar{\mu}_1.$$  \hspace{1cm} (19)

In addition, we calculate the probability the queue of user 1 to be non empty; $Pr\{ Q > 0 \} = 1 - \pi_0$. Therefore, all the terms in (7) are now known and the average AoI can be computed.

V. SIMULATION AND NUMERICAL RESULTS

In this section, we provide results that show the interplay between the packet drop rate of user 1 and average AoI of user 2 at the receiver. We consider that the users are located at distance $r_i = 50$ m from the receiver. The receiver noise power is $\eta = -100$ dbm and the path loss exponent $\alpha = 4$. We consider that the SINR$_i$ threshold is the same for both users, $\gamma_1 = \gamma_2 = \gamma$. Recall that, $\gamma_2$, affects the sampling of a new status update for user 2. We provide results for different scenarios to observe: i) average AoI and drop rate in the symmetric users scenario; ii) interplay between average AoI and packet drop rate; iii) impact of interference on the drop rate and the AoI.

A. Symmetric users scenario

In the symmetric users scenario, both users transmit with power $P_1 = P_2 = 5$ mW. The SINR threshold for both users, $\gamma$, is equal to 0 dbm. In Fig. 4 we provide results for the average AoI for user 2 and the drop rate for user 1 for different values of the attempt transmission probabilities.

For simplicity of exposition, given a probability of an event, denoted by $p$, we denote the probability of its complementary event by $\bar{p} = 1 - p$.  

$^3$Both users transmit with the same power and same access probability, $q_1 = q_2$.  

Fig. 3: Markov chain, for which the deadline of packets is equal to 3 time slots, i.e., $d = 3$.

Fig. 4: Symmetric case. $P_1 = P_2 = 5$ mW. $\gamma = 0$ dbm, $\lambda = 0.8$, $d = 5$.  

(a) Average AoI of user 2 at the receiver.

(b) Packet drop rate of user 1.
We observe that as we increase $q_1$, $q_2$, we obtain a better performance for both average AoI and drop rate. However, we see that for values greater than 0.7, the average AoI saturates to a value close to 2. The reason is that as we increase $q_2$ the system performance depends mostly on the successful transmission probability. Therefore, after a certain value of $q_2$, we do not achieve better performance. On the other hand, the performance increases for user 1, i.e., in terms the packet drop rate. In this case, the gradually increasing of $q_1$ affects the performance of the drop rate because, for user 1, we have the chance to retransmit the same packet.

### B. Interplay between average AoI and packet drop rate

In Fig. 5 we obtain each value of AoI and drop rate by changing the value of $q_2$. In particular, we consider the values $0.1, 0.2, \ldots, 1$. For the simplicity of presentation, we show only the analytical results for a simulation setup with $10^6$ slots.

In Fig. 5a we obtain the interplay between the two performance metrics for different values of $\gamma$. As it is expected, we observe that for higher values of $\gamma$, the performance in terms AoI and drop rate decreases. Furthermore, it is shown that as we increase $q_1$, the average AoI dramatically decreases. It is interesting one to observe that for $\gamma = -5$ dbm, the impact of increasing $q_1$ on the average AoI is higher than the case with $\gamma = 5$ dbm. Furthermore, we observe that for $\gamma = 5$ dbm the drop rate increases significantly as we increase $q_2$. The reason is that for high values of the SINR threshold the receiver is sensitive in terms of interference and the probability to have an error in transmission increases.

In Fig. 5b we obtain different value of our performance metrics by changing the values of the access probability of user 1, $q_1$. We observe that for higher values of $q_1$ the higher the value of the average AoI. Furthermore, we obtain that for high values $q_2$ the average AoI is close to the values for which $q_1$ is lower. However, the drop rate significantly decreases for high values of $q_1$. Therefore, one can observe that a good trade-off between AoI and drop rate is achieved when $q_1$ and $q_2$ have high values.

In Fig. 5c we provide results of average AoI and drop rate for different value of $\lambda$. We observe that for $\lambda = 0.2$ the drop rate is not affected significantly by the value of $q_2$. The reason is that $0.2$ is much smaller than the access probability, $q_1 = 0.5$. However, as we increase the value of $\lambda$, we obtain that the drop rate increases significantly as we increase $q_2$. In particular, for $\lambda = 0.8$, the drop rate takes values from $0.4$ to $0.55$ for $q_2 = 0.4$ to $0.8$. On the other hand for $\lambda = 0.2$, the drop rate takes values from $0.3$ to $0.5$ for $q_2 = 0.4$ to $0.8$.

### C. The impact of interference on drop rate and average AoI

In this set up, the SINR threshold, $\gamma$, is equal to 5 dbm, the transmit power of user 1, $P_1$, is equal to 10 mW, and the transmit power of user 2, $P_2$, is equal to 5 mW. Our goal is to observe for which cases it is not optimal to increase the access probabilities more than a certain point for both the drop rate and average AoI. As shown in Fig. 6a, the user with lowest transmission power, i.e., user 1, is affected significantly by the values of $q_1$ and $q_2$. In particular, we observe for values greater than 0.6 the average AoI increases. This is because the interference from user 1 increases significantly as we increase $q_2$ and therefore, the service rate for user 1 starts decreasing again. User 1 is also affected by higher values of $q_1$ and $q_2$. 

![Graph](image-url)
However, it is shown, in Fig. 6b, that user 2 is less sensitive in interference than user 2 because user 1 has a higher transmit power.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

In this work, we studied the interplay of deadline-constrained packet delivery and freshness of information at the destination. More specifically, we considered a two-user multiple access setup with random access, in which user 1 is a wireless device with a queue and has external bursty traffic which is deadline-constrained, while user 2 monitors a sensor and transmits status updates to the destination. We provided analytical expressions for the throughput and drop probability of user 1, and an analytical expression for the average AoI of user 2. We demonstrated that there exists a trade-off between the average AoI of user 2 and the drop rate of user 1. Our analytical findings are validated through simulations.

From our results it is evident that the probability of accessing the channel affects the performance of individual users as well as that of the overall system. Ongoing work focuses on optimizing these probabilities. Furthermore, larger and more general setups will be considered.

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