AoI minimization with Timely-Throughput Constraints over Time-Correlated Wireless Channels

Emmanouil Fountoulakis, Themistoklis Charalambous, Anthony Ephremides, Nikolaos Pappas

***Abstract*—In this work, we consider mixed traffic with time-sensitive users; a deadline-constrained user, and an AoI-oriented user. To develop an efficient scheduling policy, we cast a novel optimization problem formulation for minimizing the average AoI while satisfying the timely throughput constraints. The optimization problem is a Constrained Markov Decision Process (CMDP). We relax the constrained problem to an unconstrained Markov Decision Process (MDP) problem by utilizing Lyapunov optimization theory. The unconstrained problem is solved for each frame by applying backward dynamic programming. Simulation results show that the timely throughput constraints are satisfied while minimizing the average AoI. Also, simulation results show the convergence of the algorithm for different values of the weighted factor and the trade-off between the AoI and the timely throughput.**

I. INTRODUCTION

With the advent of 5G communication networks, the metric of latency plays a vital role in wireless connectivity for addressing the requirements of real-time communications, such as autonomous vehicles, wireless industrial automation, environmental, and health monitoring, to name a few [2], [3]. In real-time communications, information is required to arrive at the destination within a certain period (deadline-constrained) due to stringent requirements in terms of latency, while in other cases, it is required to keep the information at the destination as fresh as possible. The notion of packets with deadlines is connected with the *timely-throughput*, that is *the average number of successful packet deliveries before their deadline expiration* [4]. Age of Information (AoI) can capture the information freshness and it was first introduced in [5]. AoI [6], [7] is defined as *the time elapsed since the generation of the status update that was most recently received by a destination*. Furthermore, time-sensitive applications with different requirements co-exist in the same network and share the same resources. Therefore, it is important to allocate the resources efficiently in order to satisfy the requirements of the heterogeneous traffic.

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An extended version of this work can be found in [1].

Packets with deadlines had been considered in wireless systems almost two decades ago [8]. An extensive survey that provides an overview of the mathematical tools that are used in the area of resource control for delay-sensitive networks can be found in [9]. Recently, there has been a renewed interest in studying the performance of systems with deadline-constrained traffic [10]–[14], especially due to the ongoing automation of traditional manufacturing and industrial practices under the fourth industrial revolution. Packets with deadlines are connected with the notion of *timely throughput*. Timely throughput was first introduced in [4], and it is defined as the average number of successfully delivered packets before their deadlines expiration. In [4], the authors propose an algorithm that satisfies any feasible timely throughput constraint. Furthermore, in [15], the authors analyze the fundamental limits for networks with timely throughput constraints.

Although many works consider the AoI optimization or performance analysis, there are few works that consider AoI optimization in a system with heterogeneous traffic, e.g., [16]–[20]. The work that is closer to our work is [19], where the authors consider a wireless network including AoI-oriented users and deadline-constrained users. The goal is to minimize the average AoI while satisfying the timely throughput constraints. In addition, it is considered that the time is divided into frames and the frames into slots. However, the authors additionally assume that the AoI-oriented user can be scheduled in any time slot within the frame and the value of the AoI remains 1, if the transmission succeeds, during the whole frame. Furthermore, it is assumed that the channel remains fixed during a frame. On the contrary, in our work, we assume that AoI is 1 only when the AoI-oriented user transmits a packet successfully. Furthermore, the channel of a user can change from slot to slot unlike from frame to frame. *These assumptions make the considered problem in our paper fundamentally different and more realistic.*

In this work, we consider two users that send their information over an error-prone channel to a common receiver. The first user is AoI-oriented and the second user has timely throughput requirements. We consider that the channel states are correlated over time. Our goal is to minimize the average AoI while satisfying the timely throughput requirements. The problem is initially formulated as a Constrained Markov Decision Process (CMDP) problem which is known to be a difficult problem to solve and standard approaches, such as the method of Lagrange multipliers, cannot be directly applied. To solve this problem, we first apply tools from Lyapunov optimization theory to

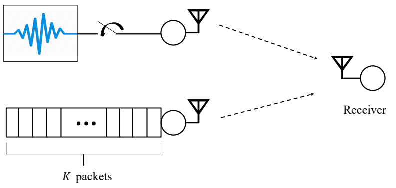


Fig. 1: System with an AoI-oriented user and a deadline-constrained user.

transform the CMDP into a Markov Decision Process (MDP). It is shown that the infinite horizon CMDP can be reduced to an unconstrained weighted stochastic shortest path problem, i.e., a finite-horizon MDP, that is easier to be solved. *We obtain that the optimal decision is not to schedule the AoI only at specific slots of the frame with high probability, e.g., at the beginning or the end of the frame. Instead, it is more beneficial to spread the scheduling time across all the slots within the frame.*

II. System Model

We consider two users transmitting their information in the form of packets to a single receiver over a wireless fading channel, as shown in Fig. 1. Let $i \in \{1,2\}$ denote the i^{th} user of the system. Time is assumed to be slotted, and let $t \in \mathbb{Z}_{\geq 0}$ denote the t^{th} slot, where $t \in \mathbb{Z}_{\geq 0}$ is the set of nonnegative integer numbers. We consider a centralized scheduler that decides every slot to schedule up to one user. Let $u_i(t)$ denote the decision of the scheduler, where

$$u_i(t) = \begin{cases} 1 \text{ , if user } i \text{ is scheduled at time slot } t, \\ 0, \text{ otherwise,} \end{cases} \tag{1}$$

and $\boldsymbol{u}(t) = [u_1(t)\ u_2(t)]^T$. Note that $\sum_i u_i(t) \leq 1, \forall t$. Due to the wireless nature of the channels, we assume that a packet is successfully transmitted from user i to the receiver with some probability. Let $d_i(t)$ denote the successful packet reception of user i, given that $u_i(t) = 1$, where

$$d_i(t) = \begin{cases} 1, \text{ successful packet reception for user } i, \\ 0, \text{ otherwise,} \end{cases} \tag{2}$$

and $\boldsymbol{d}(t) = [d_1(t)\ d_2(t)]^T$.

User 1 is an AoI-oriented user who either samples and transmits fresh information to the receiver or remains silent depending on the scheduling policy. Let $A(t) \in \mathbb{Z}_{>0}$ represent the AoI of user 1 at the receiver. We assume that the value of the AoI is bounded by $A_{\max}$. This assumption is considered for the following two reasons:

1) In practical applications, values of AoI that are larger than a threshold will not provide us additional information about the staleness of the packet, [21]–[23].
2) Assuming unbounded AoI will complicate significantly the solution of the optimization problem without providing additional insights for the performance of the system.

The evolution of the AoI at the receiver is described as

$$A(t+1) = \begin{cases} 1, \text{ successful packet transmission of user } 1, \\ \min\{A_{\max}, A(t)+1\}, \text{ otherwise.} \end{cases} \tag{3}$$

The time average AoI is defined as

$$\bar{A} = \lim_{t\to\infty} \sup \frac{1}{t+1} \sum_{\tau=0}^{t} \mathbb{E}\{A(\tau)\}, \tag{4}$$

where the expectation is with respect to the scheduling policy and the channel randomness. Note that we use a generate-at-will policy. Furthermore, since we do not consider sampling cost, user 1 does not retransmit a packet if the transmission fails. Instead, user 1 samples new information whenever it is scheduled in one of the following slots. We consider that the sampling and transmission process needs one-time slot to be performed.

User 2 is deadline-constrained including packets that must be transmitted within a specific time frame, i.e., before a deadline. More specifically, we consider that K packets arrive to the queue of user 2 every T slots, where $K \leq T$. We consider that a packet needs one slot to be transmitted. The time between two consecutive packet arrivals is a time frame whose length is T time slots. Let $m \in \mathbb{Z}_{\geq 0}$ denote the m^{th} frame, and $t_m = mT$ be the first slot of frame m. The packets must be transmitted before the end of the frame, i.e., T slots after their arrival, otherwise they are dropped.

We denote by $f_m(t)$ the time interval between the beginning of the current frame and slot t, i.e., $f_m(t) = t - mT$. Let $Q(t)$ denote the number of packets that are in the queue of user 2 in time slot t. The evolution of the queue is described as

$$Q(t+1) = \max\{Q(t) - d_2(t), 0\}\mathbf{1}_{\{f_m(t)\neq 0\}} + K\mathbf{1}_{\{f_m(t)=0\}}, \forall t. \tag{5}$$

The *timely throughput* measures the average number of successful deliveries, i.e., the packets delivered before the deadline [4], [15]. In this work, we are interested in ensuring *frame-based timely throughput* above a threshold, for user 2, defined as

$$\lim_{M\to\infty} \frac{1}{M+1} \sum_{m=0}^{M} \left(\sum_{\tau=mT}^{(m+1)T-1} \mathbb{E}\{d_2(\tau)\} \right). \tag{6}$$

Our motivation for defining *per frame average timely throughput* is that it is not only important to serve as many packets as possible, but also to keep high QoS for every frame. In other words, to ensure a high average number of successful packets delivery before their deadline expiration, i.e., before the end of the frame.

The channel of each user i is assumed to be a time-correlated fading channel and each one evolves as a two-state Gilbert-Elliot model. The evolution of the channel states can be modeled as a Markov chain. Let $h_i(t)$ denote the channel state of user i at time slot t, which is modeled as a Markov chain with two states, and let $\mathbf{h}(t) = [h_1(t)\ h_2(t)]^T$. "Bad" state represents deep fading of the channel and any transmission will fail. "Good" state represents mild fading of the channel and any transmission will succeed. The channel transition probabilities are given by $\Pr\{h_i(t+1) = 1|h_i(t) = 1\} = p_{11,i}$, $\Pr\{h_i(t+1) = 1|h_i(t) = 0\} = p_{01,i}$. We consider delayed channel sensing for both users. More specifically, the channel state for each user i is known at the receiver only at the end of each slot.

III. Problem Formulation

Definition 1 (Scheduling Policy). *A scheduling policy ω is a (possibly randomized) rule of scheduling user i at each time slot t. Policy ω takes into account only the information of state of the system at time slot t, which consists of the delayed information of the channel state, queue length of user 2, value of the AoI of user 1. Since we consider random channels, the outcome of a scheduling decision is a random variable. A policy ω specifies a probability distribution $\mathbf{u}^\omega(t)$, where $u_i^\omega(t)$ is the probability of scheduling user i at time slot t given the system state. The set of all policies is denoted by Ω.*

In this work, our target is to find a policy ω that solves the following optimization problem

$$\min \quad \bar{A}^\omega \tag{7a}$$

$$\text{s. t.} \quad \lim_{M\to\infty} \inf \frac{1}{M+1} \sum_{m=0}^{M} \left(\sum_{\tau=mT}^{(m+1)T-1} \mathbb{E}\left\{d_2^\omega(\tau)\right\} \right) \geq q, \tag{7b}$$

where q, $0 \leq q \leq K$, is the minimum per frame average timely throughput requirements of user 2, and π is the scheduling policy.

Definition 2 (Feasible Region of Timely-Throughput Requirements). *Consider the set of all policies Ω, and denote by $\bar{q}^\omega$ the timely-throughput that is achieved by applying policy ω. Then, the feasible region of timely throughput requirements, denoted by Γ, is $\Gamma = \cup_{\omega\in\Omega}\left\{q \in [0, K] | q \leq \bar{q}^\omega\right\}$.*

A. Slackness Assumptions

The problem in (7) is a CMDP with state $s(t) = (A(t), Q(t), \mathbf{h}(t))$. Under mild assumptions (such as the state space and the action space being finite) the MDP has an optimal stationary policy that chooses $\mathbf{u}(t)$ as a stationary and possibly randomized function of the state $s(t)$ only [24]. Note that the system experiences regular renewals, i.e., at the beginning of each frame a batch of K packets arrive at the queue while the remaining packets from the previous frame has been discarded. Therefore, the performance of any $s(t)$-only policy can be characterized by ratios of expectations over one renewal time [25]. Thus, we make the following assumption.

Assumption 1: There exists a policy $\omega \in \Omega$, that satisfies the following, over any renewal frame:

$$\frac{\mathbb{E}\left[\sum_{\tau=mT}^{(m+1)T-1} A^{\omega_1}(\tau)\right]}{T} = \bar{A}_{\text{opt}}, \tag{8}$$

$$q - \mathbb{E}\left[\sum_{\tau=mT}^{(m+1)T-1} d_2^{\omega_1}(\tau)\right] \leq 0, \tag{9}$$

where $A^{\omega_1}(\tau)$, and $d_2^{\omega_1}(\tau)$, are the values of $A(t)$ and $d_2(t)$ obtained by applying policy ω_1, and $\bar{A}_{\text{opt}}$ is the optimal value of the time average AoI. Note that Assumption 1 is mild and holds whenever problem (7) is feasible, i.e., $\forall q \in \Gamma$. We now make a stronger assumption guaranteeing that the constraint in (7b) is met with ϵ-slackness. In the following assumption, we focus only on the satisfaction of the constraints. This assumption is related to standard "Slater-type" assumptions in optimization theory [26].

Assumption 2: There exists a value $\epsilon > 0$ and a policy $\omega_2 \in \Omega$ policy that satisfies the following over any renewal frame:

$$\frac{q - \mathbb{E}\left[\sum_{\tau=mT}^{(m+1)T-1} d_2^{\omega_2}(\tau)\right]}{T} \leq -\epsilon, \tag{10}$$

where $d_2^{\omega_2}(\tau)$ is the value of $d_2(\tau)$ obtained by applying policy ω_2. In the next section, we describe our proposed dynamic control algorithm.

IV. Dynamic Control Algorithm

Before describing our proposed algorithm that solves (7), let us recall some basic definitions. The Lyapunov function and the Lyapunov drift are denoted by $L(\mathbf{q}(t))$ and $\Delta(L(\mathbf{q}(t))) \triangleq \mathbb{E}\left\{L(\mathbf{q}(t+1)) - L(\mathbf{q}(t))|\mathbf{q}(t)\right\}$, respectively.

Definition 3 (Strong Stabilitity). *A discrete time process $Q(t)$ is strongly strable if:* $\lim\sup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\left\{|Q(\tau)|\right\} \leq \infty$.

We define a virtual queue $Z(t)$ represent the constraint in (7b), where $Z(0) = 0$. We update the value of the virtual queue as $Z(t+1) = \max\left[Z(t) - d_2(t), 0\right] + \frac{q}{T}$. Process $Z(t)$ can be seen as a queue with "service rate" $\bar{d}_2$ and "arrival rate" $\frac{q}{T}$. We will show that the average constraint in (7b) is transformed into a queue stability problem.

Definition 1. A discrete time process $Q(t)$ is rate stable if $\lim_{t\to\infty} \frac{Q(t)}{t} = 0$ with probability 1.

Lemma 1. *If $Z(t)$ is rate stable, then the constraint in* (7b) *is satisfied.*

Proof. Please see the proof of Lemma 1 in [1]. □

A. Lyapunov Drift

We define the following quadratic Lyapunov function as

$$L(Z(t)) \triangleq \frac{1}{2} Z^2(t). \tag{11}$$

We define the *frame-based Lyapunov drift* as

$$\Delta(Z(t_m)) \triangleq \mathbb{E}\left[L(Z(t_m+T)) - L(Z(t_m))|Z(t_m)\right], \quad (12)$$

where $t_m = mT$ is the starting slot of the m^{th} frame.

Lemma 2. *Under any policy $\mathbf{u}(\tau)$ for all slots during a renewal frame $\tau \in \{t_m, \ldots, t_m+T-1\}$, we have*

$$\Delta(Z(t_m)) \leq B + \mathbb{E}\left[G(t_m)|Z(t_m)\right], \quad (13)$$

where $G(t_m)$ is defined as

$$G(t_m) \triangleq Z(t_m) \sum_{\tau=t_m}^{t_m+T-1} (q - d_2(\tau)), \quad (14)$$

and B is a finite constant defined as $B \triangleq \frac{Tq^2+T(T-1)}{2}$.

Proof. Please see Appendix A in [1]. □

B. Frame-Based Drift-Plus Penalty Algorithm

In order to provide a solution to the optimization problem in (7), we implement a policy over the course of the frame to minimize the following expression

$$\min_{\mathbf{u}(t)} \mathbb{E}\left[G(t_m) + V\sum_{\tau=t_m}^{t_m+T-1} A(\tau)|Z(t_m)\right], \quad (15)$$

where the expectation is with respect to the policy and the randomness of the channel. The problem in (15) is a *stochastic shortest path problem* which usually is solved approximately [24]. In the next subsection, we analyze the performance of the algorithm under the assumption that we have a policy that can approximate (15).

C. Approximation Theorem

Assumption 3: For constants, $C \geq 0$, $\delta \geq 0$, define a (C,δ) - approximation of (15) to be a policy for choosing $\mathbf{u}(t)$ over a frame $\tau \in \{t_m, \ldots, t_m+T-1\}$ such that

$$\mathbb{E}\left[G(t_m) + V\sum_{\tau=t_m}^{t_m+T-1} A(\tau)|Z(t_m)\right] \leq \mathbb{E}\left[G^{\text{opt}}(t_m) + V\sum_{\tau=t_m}^{t_m+T-1} A_{\text{opt}}(\tau)|Z(t_m)\right] + C + \delta Z(t_m) + V\delta, \quad (16)$$

where A_{opt} and G_{opt} are the optimal values.

Theorem 1. *Suppose that Assumptions 1, 2, hold for a given $\epsilon > 0$, and suppose we use a (C,δ)-approximation every frame so that Assumption 3 holds. If $\epsilon > \frac{\delta}{T}$, then constraint* (7b) *is satisfied and*

$$\lim_{R\to\infty} \sup \frac{1}{R}\sum_{r=0}^{R} \mathbb{E}\left[Z(t_m)\right] \leq \frac{B + C + V(T\bar{A}_{opt} + \delta)}{\epsilon T - \delta} \quad (17)$$

and

$$\lim_{t\to\infty} \sup \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}\left[A(\tau)\right] \leq \frac{B}{VT} + \gamma(A_{\max} - 1) + (1-\gamma)A_{opt} + \frac{C}{VT} + \frac{\delta}{T}, \quad (18)$$

where $\gamma = \frac{\delta}{\epsilon T}$.

Proof. Please see Appendix C in [1]. □

V. Solution of the MDP

The problem in (15) is an MDP problem. Let $\mathcal{A} = \{1, 2, \ldots, A_{\max}\}$ denote the set of possible values of AoI of user 1. Furthermore, let $\mathcal{Q} = \{0, 1, 2, \ldots, L\}$ be the set of possible values of the queue of user 2. Then, $\mathcal{A}(t) \in \mathcal{A}$, and $Q(t) \in \mathcal{Q}$. A transmission policy $\mathbf{u}(t)$ specifies the decision rules every time slot t. Note that the described MDP problem is a finite-horizon problem. We solve the optimization problem at every frame. At the beginning of each frame, we know the channel conditions of the previous slot for each users, the state of the queue (it is always L packets at the beginning of the frame), and the value of the AoI of user 1.

The next state depends on both the scheduler's decision and the channel states. Note that we schedule user 2 only if it has remaining packets in its queue, and recall that at the end of frame m, we drop all the remaining packets, if there is any.

A. Transition Probabilities

The system state in time slot t is described by $s(t) = (A(t), Q(t), \mathbf{h}(t))$. The transition probabilities are described in Table I.

B. Backward dynamic programming algorithm

Initially, we drop the frame indices and take $t \in \{0, 1, \ldots, T-1\}$. As a first step, we consider that the transmission error probabilities are fixed, i.e., the channels are i.i.d over the slots. In our system model, we take an action in time slot t, and we observe the cost in time slot $t+1$. If we transmit a packet, it will successfully be transmitted with some probability. We know whether the transmission is successful or not at the end of the slot due to ACK/NACK. Below we define the costs for the different channel models. The instantaneous cost at time slot t is defined in Table II, where $\hat{C}_{t+1}(s(t), \mathbf{u}(t), W_{t+1}|s(t), \mathbf{u}(t), \mathbf{h}(t)$ is the cost received in time slot t. The Bellman's equation is described below

$$V_t(s(t)) = \min_{\mathbf{u}(t)} \mathbb{E}\left\{\hat{C}_{t+1}(s(t+1), W_{t+1}|s(t), \mathbf{u}(t))\right\} = \min_{\mathbf{u}(t)} \left(C_t(s(t), \mathbf{u}(t)) + \gamma \sum_{s'\in\mathcal{S}} \Pr(s(t+1) = s'|s(t), \mathbf{u}(t))V_{t+1}(s')\right), \quad (21)$$

where $0 < \gamma < 1$.

We can solve the recursions in (21) by applying backward dynamic programming. We denote by $\mathcal{S}$ the set with all possible states. The idea of the algorithm is quite simple. The algorithm runs over the duration of each frame starting at the last slot, i.e., the T^{th} of each frame. We initialize the value

$$
P_{s_t \to s_{t+1}} = \begin{cases} p_{11,1}, \text{if } \mathbf{u}(t) = [1\ 0]^T, h_1(t) = 1, \text{ and } s(t+1) = (1, Q(t), (1, x)), \\ 1 - p_{11,1}, \text{ if } \mathbf{u}(t) = [1\ 0]^T, h_1(t) = 1, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t), (0, x)), \\ p_{01,1}, \text{ if } \mathbf{u}(t) = [1\ 0]^T, h_1(t) = 0, \text{ and } s(t+1) = (1, Q(t), (1, x)), \\ 1 - p_{01,1}, \text{ if } \mathbf{u}(t) = [1\ 0]^T, h_1(t) = 0, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t), (0, x)), \\ p_{11,2}, \text{if } \mathbf{u}(t) = [0\ 1]^T, h_2(t) = 1, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t)-1, (x, 1)), \\ 1 - p_{11,2}, \text{ if } \mathbf{u}(t) = [0\ 1]^T, h_2(t) = 1, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t), (x, 0)), \\ p_{01,2}, \text{ if } \mathbf{u}(t) = [0\ 1]^T, h_2(t) = 0, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t)-1, (x, 1)), \\ 1 - p_{01,2}, \text{ if } \mathbf{u}(t) = [0\ 1]^T, h_2(t) = 0, \text{ and } s(t+1) = (\min\{A(t)+1, A_{\max}\}, Q(t), (x, 0)), \end{cases} \tag{19}
$$

TABLE I: Transition probabilities. x is used to show that the value of the corresponding element does not affect the state transition.

$$
C_t(s(t), \mathbf{u}(t)) = \mathbb{E}\left\{\hat{C}_{t+1}(s(t+1), W_{t+1}|s(t), \mathbf{u}(t))\right\} = \begin{cases} Zq + V(p_{11,1} + (1-p_{11,1})\min\{A(t)+1, A_{\max}\}), \text{ if } u_1(t) = 1 \text{ and } h_1(t) = 1, \\ Zq + V(p_{01,1} + (1-p_{01,1})\min\{A(t)+1, A_{\max}\}), \text{ if } u_1(t) = 1 \text{ and } h_1(t) = 0, \\ Z(q - p_{11,2}) + V(\min\{A(t)+1, A_{\max}\}), \text{ if } u_2(t) = 1 \text{ and } h_2(t) = 1, \\ Z(q - p_{01,2}) + V(\min\{A(t)+1, A_{\max}\}), \text{ if } u_2(t) = 1 \text{ and } h_2(t) = 0, \end{cases} \tag{20}
$$

TABLE II: Instantaneous cost.

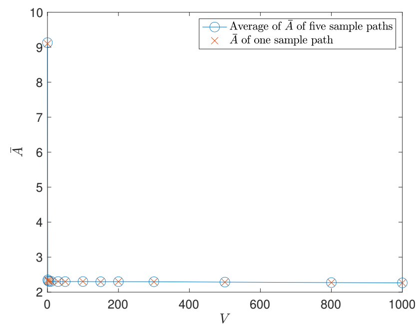
of being at each state at the last slot, and then, we calculate the value of each state at every time slot by going backward. This algorithm is standard and well known in the literature [27].

VI. Simulation Results

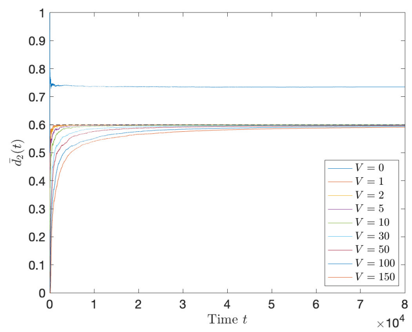
In this section, we provide results to study the performance of our proposed algorithm in terms of the average value of the AoI and the convergence regarding the timely throughput requirements. We investigate how different values of the weight factor V can affect both the value of AoI and the convergence of the algorithm. For the following results, we consider that $p_{11,1} = p_{11,2} = 0.9$, and $p_{01,1} = p_{01,2} = 0.6$. The length of the frame, T, is 20 time slots, and the number of arrived packets at the beginning of every frame, K, is equal to 15 packets. We consider that the maximum value of the AoI, $A_{\text{max}} = 20$. The timely throughput requirements are $q = 12$ packets/frame or $q/T = 0.6$ packet/slot. We run each experiment for 0.5×10^6 time slots, and we use MATLAB environment to perform our simulations.

In Fig. 2, we provide the average value of AoI for different values of V as well as the convergence of the timely throughput constraints. In Fig. 2a, we compare the average value of AoI of five sample paths with that of one sample-path. We observe that the values are quite close to each other. Therefore, the algorithm offers high performance regarding robustness. Furthermore, it is shown that the AoI reaches its minimum value even for small values of V. We see that for values of V larger than 5 the change of the value of the average AoI is negligible. In Fig. 2b, we see that for large values of V, for example, $V = 150$, the algorithm needs long time to stabilize the virtual queue because the value of the virtual queue becomes larger than the term of AoI after many slots.

In Fig. 3, we provide results that show the scheduling time percentage per slot within a frame for each user. In Fig. 3a, we observe that for $V = 10$, the scheduling time for user 1 is spread within the frame. That means that the percentage of scheduling time does not change significantly from slot to slot. On the other hand, for larger values of V, we observe that the percentage of the scheduling time for user 1 changes from slot to slot, especially after the 10$^{\text{th}}$ slot and for $V = 100$ because the AoI is multiplied by a large weight and if the value of AoI starts increasing as time passes by the corresponding term becomes quite large. Therefore, the scheduler schedules the

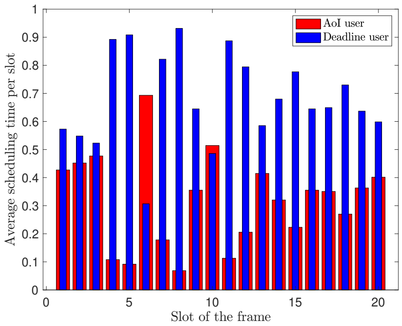


(a) Average AoI for different values of weight factor V.

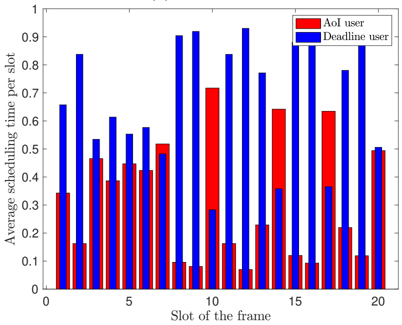


(b) Convergence of the timely throughput constraints.

Fig. 2



(a) $V = 10$.



(b) $V = 100$.

Fig. 3: Scheduling time percentage per slot within a frame.

user 1 in order to minimize the objective function.

VII. Conclusion

In this work, we considered a wireless network consisting of time-critical users with different requirements under uncertain environments. We studied how an AoI-oriented user and a deadline-constrained user can share the same resources to satisfy their requirements. To this end, we formulated a stochastic optimization problem for minimizing the average AoI while satisfying the timely-throughput constraints which is a CMDP problem. In order to solve the problem, we utilized tools from Lyapunov optimization and MDP. With this approach, we reduced the CMDP to an unconstrained weighted stochastic shortest path problem. We implemented backward dynamic programming to solve the unconstrained problem. Simulation results showed that the timely-throughput constraint is satisfied while minimizing the average AoI. Furthermore, we provided the trade-off between the minimum value of AoI and the convergence of the average constraint.

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