

Feedback-Aware AoI Policies in Finite-Horizon Multiuser IoT Networks

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Abstract—This work considers finite-horizon status-update systems for real-time IoT monitoring, where multiple devices contend for a shared slotted random-access channel and each device has a strict transmission budget (e.g., due to duty-cycle/energy limits). Unlike a recently proposed single-device perspective, we quantify how cost-effective feedback interacts with multiuser congestion in Age of Information (AoI) optimization. We compare an Offline (OFF) policy that follows a precomputed schedule and requires no feedback, and a Feedback-Aware (FB) policy that combines an optimal single-user dynamic-programming rule with an AoI-aware randomized back-off to mitigate collisions. By means of Monte Carlo simulations, we characterize the operating regimes in terms of network load, channel reliability, and feedback cost. The results show that feedback is not universally beneficial: when feedback is expensive or contention is mild, OFF can be preferable because it preserves transmission opportunities. In contrast, as the network becomes dense and links become more reliable, collisions dominate update failures, and the FB policy yields substantial AoI gains.

Keywords—AoI, IoT, Random Access, Feedback Cost.

I. INTRODUCTION

The problem of transmitting status updates to minimize the age of information (AoI) at a receiver has gained considerable attention in the recent literature [1]. This issue is particularly relevant for real-time Internet of Things (IoT) applications, including precision agriculture and smart farming, where sensors must report soil, crop, and microclimate conditions in a timely manner [2], as well as other monitoring scenarios in which an up-to-date system view enables prompt intervention. AoI is a mathematically tractable metric of information timeliness, suitable for analysis in monitoring and control systems.

However, most AoI optimization studies focus on long-term performance metrics, such as time averages or steady-state distributions [3]–[6]. While analytically convenient, this infinite-horizon perspective abstracts away practical constraints faced by real systems, which often operate over definite and limited horizons due to energy, duty-cycle, or computational limitations. For example, IoT technologies such as LoRaWAN [7] are subject to strict regulatory duty-cycle constraints, effectively bounding the number of transmission opportunities available within a finite observation window. In such regimes,

AoI-optimal strategies may differ substantially from their infinite-horizon counterparts [8].

Another aspect where the prevailing literature may fall short concerns the explicit modeling of feedback and its associated cost. Several finite-horizon AoI optimization frameworks rely on perfect and cost-free feedback [9], [10], implicitly assuming that acknowledgments are available without affecting the resource budget. However, in low-power IoT devices feedback reception is not negligible, as maintaining the receiver active prevents the device from entering low-power sleep states [11]. Under a finite energy budget, allocating resources to feedback may therefore reduce the number of transmissions available for status updates, creating a nontrivial trade-off between adaptivity and resource consumption.

This trade-off has been thoroughly analyzed in recent work by Munari and Badia [12], which characterizes the value of feedback in finite-horizon single-user systems and identifies regimes in which costly feedback is beneficial or detrimental. While this provides a baseline framework, it leaves a critical question unanswered: how do such feedback-driven policies behave in realistic multiuser networks?

Indeed, most practical IoT deployments involve uncoordinated devices contending for a shared medium, where collisions are the primary cause of update failures [13], [14]. Back-off-based mechanisms are a natural control lever for distributed contention regulation, and recent work shows that AoI-aware access and back-off strategies can improve freshness in multiuser systems [15]–[17]. However, these approaches focus on steady-state performance in infinite-horizon systems with persistent transmission opportunities, and do not capture the finite-budget setting considered here.

In this work, we extend the single-user finite-horizon framework from [12] to a more realistic multiuser random-access setting. We investigate how transmission strategies designed for isolated links perform when deployed in shared environments where transmissions are subject to both collisions and channel impairments. Specifically, we study two fundamental approaches: an Offline (OFF) policy, in which devices follow a predetermined transmission schedule and require no feedback, and a Feedback-Aware (FB) policy, which combines a finite-horizon single-user decision rule with an AoI-aware randomized back-off mechanism to mitigate collisions. This formulation enables a systematic investigation of the interplay between feedback cost, which reduces individual transmission resources, and congestion cost, which degrades the effectiveness of those resources in multiuser systems.

Our main contributions are summarized as follows:

- We formulate two distinct multiuser transmission strate-

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gies for a finite-horizon, generate-at-will setting, based on extending optimal single-user policies with practical collision mitigation mechanisms.

- We conduct a comprehensive simulation-based study to analyze the performance of these strategies, explicitly characterizing the trade-off between network congestion and feedback cost.
- We identify operating regimes in terms of channel reliability, feedback cost, and network load in which a simple feedback-free offline policy outperforms more sophisticated feedback-aware strategies, and vice versa.

II. SYSTEM MODEL

We consider a finite-horizon multiuser IoT system composed of K devices, indexed by $\{k\}_{k=1}^K$, that share access to a common wireless channel. Time is slotted and the system operates on a finite horizon of n discrete time slots $\{t\}_{t=1}^n$. Devices operate under a generate-at-will model, where a fresh status update can be generated at the moment of transmission, aiming to keep the information available at a central gateway as fresh as possible.

The wireless medium is accessed according to a grant-free slotted random access protocol, similar to slotted ALOHA, without centralized coordination among devices. This access model is widely adopted as a baseline for large-scale IoT and LPWAN deployments due to its low signaling overhead and scalability [18], [19].

A. Transmission Budget and Feedback Cost

Each device is subject to a strict transmission budget over the aforementioned finite horizon of n time slots. Let $\eta \in (0, 1]$ denote the duty cycle, representing the fraction of time slots during which a device is allowed to transmit within the time horizon. In the absence of feedback, the maximum number of transmissions available per device is¹

$$m_{\text{OFF}} = \lfloor \eta n \rfloor. \quad (1)$$

When a feedback mechanism is employed, additional resources are consumed to receive and process acknowledgments. Following [8], [12], feedback is explicitly modeled as a resource-consuming operation. Let $\zeta \geq 0$ denote the normalized feedback cost. In this case, the maximum number of available transmissions is reduced to [8], [12]

$$m_{\text{FB}} = \left\lfloor \frac{m_{\text{OFF}}}{1 + \zeta} \right\rfloor = \left\lfloor \frac{\eta n}{1 + \zeta} \right\rfloor. \quad (2)$$

Despite its simplicity, note that (2) captures the fundamental trade-off between exploiting feedback for improved transmission decisions and preserving transmission opportunities for data updates.

¹Note that such a constraint captures both energy limitations and regulatory restrictions, such as duty-cycle constraints in unlicensed ISM bands. Finite-horizon transmission budgets have been shown to accurately model the operational limits of practical IoT devices [8], [12].

B. Successful Transmission Model

The grant-free model adopted in this work implies that, when device k attempts to transmit a status update in the t -th time slot, the transmission is successfully received by the gateway if and only if two independent conditions are simultaneously satisfied:

- No collision:** device k is the only transmitting device in slot t .
- No channel erasure:** the transmission is not corrupted by channel impairments.

Regarding the channel modeling, we consider for simplicity that fading follows an ON-OFF erasure model, where each transmission is successfully decoded with probability $p \in (0, 1]$, independently across time slots and devices, while erasure occurs with probability $1 - p$. This model is widely used to represent the reliability of low-power wireless links in AoI-oriented analyses [19], [20].

C. Age of Information (AoI)

To quantify the freshness of information at the gateway, we adopt the AoI metric [1]. The instantaneous AoI of device k at time slot t is defined as

$$\Delta_k(t) = t - g_k(t), \quad (3)$$

where $g_k(t)$ denotes the generation time of the most recent update from device k that has been successfully received by the gateway.

In this scenario, the AoI of device k evolves in time as

$$\Delta_k(t+1) = \begin{cases} 1, & \text{if } a_k(t) = 1 \text{ and } \Phi_k(t) = 1 \\ \Delta_k(t) + 1, & \text{otherwise.} \end{cases} \quad (4)$$

where $a_k(t) = 1$ indicates that device k attempts to deliver an update in time slot t , while $\Phi_k(t) \in \{0, 1\}$ is a boolean variable flag with $\Phi_k(t) = 1$ representing the successful transmission of the aforementioned update (no collision nor erasure). On the other hand, $a_k(t) = 0$ indicates absence of transmission (device is silent), while $\Phi_k(t) = 0$ represents a failure (either due to collision or erasure) of the transmission.

We assume all devices start with a synchronized initial age $\Delta_k(0) = 0$, $k = 1, \dots, K$, corresponding to a status update available at $t = 0$; this choice does not affect the steady-state comparison across policies, since $n \gg 1$.

The network average AoI in the finite horizon is then

$$\bar{\Delta} = \frac{1}{nK} \sum_{k=1}^K \sum_{t=1}^n \Delta_k(t). \quad (5)$$

III. TRANSMISSION PROTOCOLS

Following [8], [12], we analyze two distinct finite-horizon single-user transmission strategies adapted to a multiuser scenario with shared-channel contention. The first is an offline (OFF) policy that operates without feedback and follows a precomputed transmission schedule. The second is a feedback-aware (FB) policy, where devices adapt their transmission decisions based on their instantaneous AoI and employ a contention back-off mechanism to mitigate collisions.

A. Offline (OFF) Policy

The OFF policy is a non-reactive scheduling strategy in which transmission decisions are fully determined prior to system operation and remain independent of both channel realizations and feedback.

1) *Scheduling Construction*: In the single-device setting of [12], the offline policy is obtained by optimizing a sequence of inter-update intervals $\mathbf{y} = [y_0, y_1, \dots, y_{m_{\text{OFF}}}]$ that partitions the time horizon n , i.e., $\sum_{\ell=0}^{m_{\text{OFF}}} y_\ell = n$. The expected average AoI can be expressed in closed form as a function of $\mathbf{y}$. The optimal schedule $\mathbf{y}^*$ is then obtained by solving

$$\min_{\mathbf{y}} \bar{\Delta}(\mathbf{y}) \quad \text{s.t.} \quad \sum_{\ell=0}^{m_{\text{OFF}}} y_\ell = n, \quad (6)$$

which, after continuous relaxation, leads to a system of linear equations derived from the first-order optimality conditions.

Finally, the nominal transmission instants are given by

$$\tau_\ell = \sum_{i=0}^{\ell-1} y_i^*, \quad \ell = 1, \dots, m_{\text{OFF}}. \quad (7)$$

2) *Multiuser Extension*: In the multiuser setting, we do not presume any coordination between devices. Consequently, to maintain the structure of the optimal single-user schedule, each device independently introduces a random time offset in the transmit instants from (7). Specifically, each user k draws an offset $o_k(t) \sim \mathcal{U}[0, [y_0^*]]$, which shifts its transmission pattern over time. The resulting transmission set is

$$\mathcal{T}_k(t) = \{\tau_{k,1} + o_k(t), \dots, \tau_{k,m_{\text{OFF}}} + o_k(t)\}. \quad (8)$$

This randomization serves two purposes: (i) preserve the optimal spacing between transmissions derived for the single-user case, and (ii) reduce systematic collisions by desynchronizing users. Consequently, the transmission decision of user k in slot t is given by

$$a_k(t) = \begin{cases} 1, & \text{if } t \in \mathcal{T}_k, \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

It is important to note that, due to the lack of feedback, users do not adapt their schedules based on past successes or failures. As a result, the OFF policy may incur redundant transmissions or missed opportunities, especially in dense networks or unreliable channels, which motivates the comparison with feedback-aware strategies.

B. Feedback-Aware (FB) Policy with AoI-Aware Back-Off

The FB policy proposed in this work extends the optimal single-user finite-horizon strategy from [8], [12] by enabling each device to react to its local AoI state while incorporating a random back-off mechanism to alleviate contention in the multiuser scenario.

1) *State Representation and Policy Structure*: The state of device k at time t is defined as

$$\mathbf{s}_k(t) = (\Delta_k(t), m_k(t), w_k(t)), \quad (10)$$

where $\Delta_k(t)$ is the instantaneous AoI, $m_k(t)$ is the remaining number of transmissions, and $w_k(t)$ is a back-off counter.

The control action is governed by the composite policy μ_{FB} , such that $a_k(t) = \mu_{\text{FB}}(\mathbf{s}_k(t))$:

$$a_k(t) = \begin{cases} 1 \text{ (transmit)}, & w_k(t) = 0, m_k(t) > 0, \\ & \text{and } \mu_{\text{DP}}(\Delta_k(t), m_k(t)) = 1, \\ 0 \text{ (wait)}, & \text{otherwise,} \end{cases} \quad (11)$$

where $\mu_{\text{DP}}(\cdot)$ denotes the optimal single-user decision rule obtained via dynamic programming [12], derived from a finite-horizon Markov decision process (MDP).

In this MDP, the system state at slot t is given by $x(t) = (\Delta(t), m(t))$, where $\Delta(t)$ denotes the instantaneous AoI at the receiver and $m(t)$ is the number of remaining transmission opportunities. At each slot, the device selects a binary control action indicating whether to transmit or remain idle. The system then evolves according to the channel success probability p : a successful transmission resets the AoI to zero, whereas an unsuccessful transmission leads to an AoI increase.

The objective is to minimize the cumulative AoI over the finite horizon. Following [12], the optimal policy is obtained via backward dynamic programming as the control policy that minimizes the expected cumulative AoI. At each state, the decision is made by comparing the expected cost of transmitting versus remaining idle, selecting the action with the lowest cost-to-go, which yields the decision rule $\mu_{\text{DP}}(\Delta(t), m(t))$.

Remark 1: $\mu_{\text{DP}}(\cdot)$ is obtained from the single-user MDP with channel success probability p , which does not account for collisions. In the multiuser setting, the effective success probability of an attempt is $p_{\text{eff}} = p \cdot \Pr[\text{no collision}] \leq p$, of which μ_{DP} has no visibility. Thus, μ_{FB} is a heuristic composition of an optimal single-user rule with a decoupled collision-mitigation layer, rather than a jointly optimal multiuser policy.

2) *State Transition Dynamics*: Let $\mathcal{A}(t)$ denote the set of devices attempting transmission in slot t . The state $\mathbf{s}_k$ evolution of device k follows:

1) **Successful transmission** ($a_k(t) = 1$ and $\Phi_k(t) = 1$)

$$\begin{cases} \Delta_k(t+1) = 1 & \text{(AoI resets)} \\ m_k(t+1) = m_k(t) - 1 & \text{(attempts decrease)} \\ w_k(t+1) = 0 & \text{(back-off counter resets)} \end{cases} \quad (12)$$

2) **Idle slot** ($a_k(t) = 0$)

$$\begin{cases} \Delta_k(t+1) = \Delta_k(t) + 1 & \text{(AoI increases)} \\ m_k(t+1) = m_k(t) & \text{(attempts unchanged)} \\ w_k(t+1) = \max(0, w_k(t) - 1) & \text{(back-off decreases)} \end{cases} \quad (13)$$

3) **Failed transmission** ($a_k(t) = 1$ and $\Phi_k(t) = 0$)

$$\begin{cases} \Delta_k(t+1) = \Delta_k(t) + 1 & \text{(AoI increases)} \\ m_k(t+1) = m_k(t) - 1 & \text{(attempts decrease)} \\ w_k(t+1) \sim \mathcal{U}\{0, W_k(t)\} & \text{(drawn back-off counter),} \end{cases} \quad (14)$$

where $W_k(t)$ represents the contention window, which we propose to be adapted according to the instantaneous AoI of device k as

$$W_k(t) = \max \left(1, W_{\text{max}} - \left\lfloor \frac{\Delta_k(t)}{S} \right\rfloor \right), \quad (15)$$

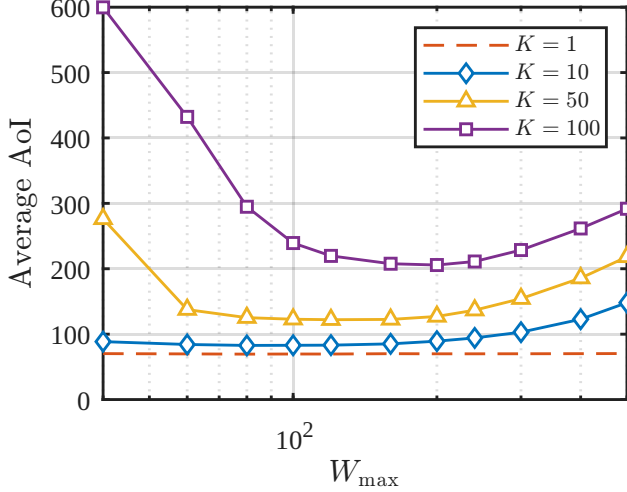


Fig. 1: Average AoI as a function of the maximum contention window size $W_{\max}$, for different numbers of users K , under the FB policy with feedback cost $\zeta = 0.25$.

in which $W_{\max}$ is the maximum contention window size, and S is a scaling parameter.

The parameter $W_{\max}$ sets the baseline contention level, while the AoI-dependent term $\Delta_k(t)$ enables dynamic prioritization of stale users. The scaling factor S is critical in finite-horizon systems: without it ($S = 1$), the window shrinks too fast, causing simultaneous aggressiveness and higher collision probability in dense regimes; for large $W_{\max}$, access becomes overly conservative, delaying transmissions and preventing full use of the transmission budget within the finite horizon. S smooths this transition, balancing collision avoidance with timely updates.

IV. NUMERICAL RESULTS

We evaluate the AoI performance of the proposed transmission policies via Monte Carlo simulations. For each parameter configuration, we estimate $\mathbb{E}[\bar{\Delta}]$ by averaging (5) over 10^3 independent simulation runs of a finite time horizon with $n = 1600$ slots [12]. Moreover, unless otherwise stated, we consider a duty cycle $\eta = 0.01$ and a channel success probability $p = 0.9$, which jointly define a representative operating point that highlights the trade-offs between transmission opportunities, feedback cost, and network congestion.

For each configuration (K, m, p, ζ) , the pair $(W_{\max}, S)$ used by the FB policy is obtained via an exhaustive two-dimensional grid search: $W_{\max}$ is swept over a range centered on K , and S over $\{2, 4, \dots, 20\}$; for each candidate pair, the average AoI is estimated over 10^3 runs, and the minimizing pair is retained.

First, Fig. 1 shows the average AoI as a function of the maximum contention window size $W_{\max}$ under the FB policy, for different numbers of users K and fixed feedback cost $\zeta = 0.25$. For each value of $W_{\max}$, the scaling parameter is independently optimized.

The results exhibit a clear non-monotonic behavior. For small $W_{\max}$, the system operates in an aggressive access regime, leading to frequent collisions and high AoI, especially

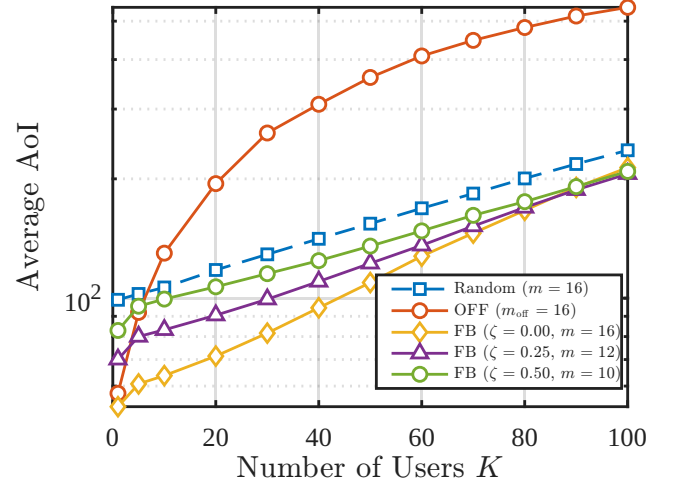


Fig. 2: Average AoI as a function of the number of active devices K , for a baseline random scheme, OFF and FB policies, the latter under different feedback-cost regimes.

for large K . As $W_{\max}$ increases, the backoff mechanism becomes more effective at spreading transmissions over time, reducing collisions and significantly improving AoI.

However, beyond an intermediate region, further increases in $W_{\max}$ degrade performance. Large contention windows introduce excessive waiting times, resulting in underutilization of the channel. Moreover, excessively large $W_{\max}$ may prevent users from fully exploiting their available transmission budget, as previously discussed, since prolonged backoff intervals can delay or even suppress scheduled transmissions within the finite horizon.

Fig. 2 shows the average AoI versus the number of active devices K , comparing the OFF and FB policies under different feedback costs, as well as a Random scheme. In the latter, each device randomly (uniformly) selects m_{OFF} transmission instants over the horizon. The FB policy employs optimized parameters $(W_{\max}, S)$ for each K . As expected, the AoI increases with K for all schemes due to higher collision probability. The OFF policy degrades the most, as its deterministic scheduling leads to persistent collisions, while the Random scheme offers better scalability but remains non-adaptive.

The FB policy achieves the best performance for small and moderate K , leveraging both AoI-aware scheduling and optimized contention control. As K increases, however, the FB curves cluster, indicating a contention-limited regime where collision effects dominate and additional transmission opportunities bring limited gains. In this regime, a nonzero feedback cost ζ can slightly improve performance by implicitly reducing channel access aggressiveness.

The interplay between feedback cost and success probability is further illustrated in Fig. 3, which presents a regime map that identifies the operating regions where the OFF or FB policy yields lower AoI for two fixed numbers of users $K \in \{10, 30\}$. As network density increases from $K = 10$ to $K = 30$ users, the FB policy's capacity to mitigate collisions becomes so critical that it outperforms the OFF policy across a much wider range of feedback costs and poorer channel conditions. The

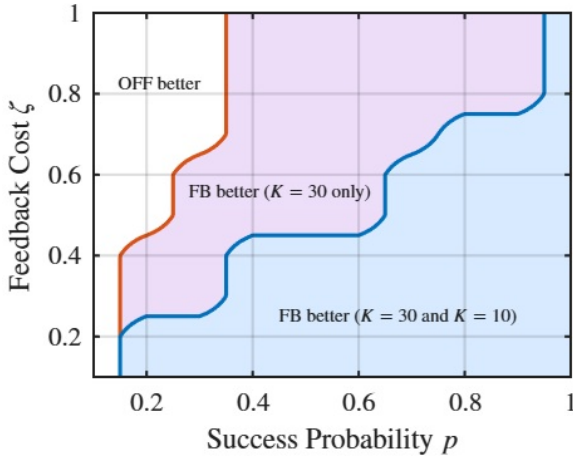


Fig. 3: Operating regions where OFF or FB policies achieve lower AoI as a function of the channel success probability p and feedback cost ζ , for $K = 10$ and $K = 30$.

figure also shows that when the feedback cost ζ is sufficiently high, the OFF policy becomes preferable despite its lack of adaptivity. In this regime, the reduction in the number of available transmissions caused by feedback exceeds the benefits of AoI-aware scheduling and collision mitigation.

Conversely, for low to moderate feedback costs, the FB policy achieves lower AoI, especially as the channel success probability increases. This behavior highlights an important difference between single-user and multiuser systems. While higher channel reliability reduces the need for feedback in isolated scenarios, in multiuser networks it amplifies the impact of congestion. As fading-induced losses decrease, collisions become the dominant source of update failures, increasing the value of feedback-driven back-off mechanisms.

V. CONCLUSION

We study two multiuser transmission strategies extending a single-user finite-horizon AoI framework: a pre-planned Offline policy requiring no feedback, and a Feedback-Aware policy combining a single-user DP rule with AoI-aware back-off. Numerical results show that feedback is not always beneficial: its value depends on network density and feedback cost, favoring OFF in sparse or costly-feedback regimes and FB in dense networks where collisions dominate AoI performance. Overall, AoI-optimal strategies for isolated devices do not directly carry over to multiuser settings, making explicit modeling of feedback cost and congestion essential for scalable, low-latency IoT. Future works include deriving μ_{DP} jointly with the contention process and obtaining closed-form expressions for $(W_{\max}, S)$, since obtaining it via exhaustive grid search might not be scalable to large deployments.

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