Random-Access Monitoring of Markov Sources: Analytical Characterization of Uncertainty

Houman Asgari*, Giuseppe Cocco‡, Andrea Munari†
* Technical University of Munich (TUM), Germany
‡ Polytechnic University of Catalonia (UPC), Barcelona, Spain
†Institute of Communications and Navigation, German Aerospace Center (DLR), Weßling, Germany
Email: houman.asgari@tum.de, giuseppe.cocco@upc.edu, andrea.munari@dlr.de

***Abstract*—We study the remote monitoring of two-state Markov sources over a shared wireless channel with destructive collisions. System performance is measured in terms of state estimation entropy (SEE) and state estimation error probability (SEEP), which quantify the receiver's uncertainty and decision error regarding the source state, respectively. We consider two transmission policies: a *random* strategy, where nodes access the channel independently of their state, and a *reactive* strategy, where transmissions occur only upon state changes.**

Our main contribution is a simple and explicit analytical characterization of the long-term average SEE and SEEP under both policies using a renewal–reward framework, alternative to the density evolution approach introduced in [1]. For random transmission, both metrics admit closed-form representations as expectations over the geometric steady-state age-of-information distribution. For reactive transmission, we show that estimation uncertainty and error accumulate exclusively through collision events, and derive their long-term averages via a collision-indexed Markov reward recursion.

***Index Terms*—State estimation entropy, random access networks, Markov sources, renewal–reward theory, slotted-ALOHA**

I. Introduction

The remote monitoring of stochastic processes through shared wireless channels is a key application in Internet of Things (IoT) and cyber–physical systems. Typical deployments involve a large number of low-complexity, battery-powered devices that observe an underlying physical process and transmit updates to a common receiver. The need for a reliable estimation of the sensed phenomenon, combined with the strict energy constraints of the devices and the unreliable nature of the communication channel, makes the efficient use of communication resources particularly challenging [2], [3].

In large-scale monitoring systems, grant-based multiple access mechanisms are often impractical due to the coordination signaling overhead, and random access protocols such as ALOHA and its variants are widely adopted in practical systems [4]–[6]. While attractive from an implementation standpoint, these schemes suffer from interference, which fundamentally limits the information conveyable to the receiver. A central challenge in remote monitoring systems is then to quantify how well the receiver can track the state of a monitored process. The age of information (AoI), defined as the time elapsed since the last received update, has emerged as a widely adopted metric for characterizing freshness [7], [8]. While AoI has proven effective for system design and admits elegant analytical characterizations [9]–[11], it is inherently oblivious to the content of updates and the dynamics of the underlying source. In particular, AoI grows at a constant rate even when the monitored process is slowly varying or stays constant for long periods of time, and does not account for the receiver's ability to predict future states based on knowledge of the source model. These limitations become especially pronounced when monitoring sources with memory.

Motivated by this, content-aware metrics have been proposed to better capture the relevance and informativeness of received updates in applications where the source model is known or can be estimated. Among them, State Estimation Entropy (SEE) quantifies the residual uncertainty about the current state of a source at the receiver, taking into account the entire observation history and the source model [1], [12]. Closely related metrics include the state estimation error probability (SEEP), as well as more recent semantic-aware measures such as the Age of Missed Alarm and the Age of False Alarm, which account for the asymmetric costs of different estimation errors [13].

Several recent works have investigated such metrics in networked monitoring systems. In scheduled multi-user settings, optimal sampling and scheduling policies have been proposed to minimize entropy-based uncertainty measures [14], whereas [1], [15] studied the monitoring of multiple two-state Markov sources over a slotted ALOHA channel. These works revealed a fundamental trade-off between AoI and SEE and showed that reactive strategies, where nodes transmit only upon detecting a state change, can substantially reduce estimation uncertainty compared to state-independent transmissions. In turn, [16], [17] highlighted how sampling policies can reduce estimation errors for Markov sources, while [18] studied the impact of packet loss and delay in networked estimation problems.

Specifically relevant to this paper is the work in [1], where the authors model the interaction between the source dynamics

The work of G. Cocco is supported by the Ramon y Cajal fellowship program, grant RYC2021-033908-I, and by grant PID2022-137099NB-C41 both funded by MCIN/AEI/10.13039/501100011033/FEDER, the European Union "NextGenerationEU" Recovery Plan for Europe.

A. Munari would like to thank the Federal Ministry of Research, Technology, and Space (BMFTR) for supporting the xG-RIC project as part of the research program Communication Systems "Souverän. Digital. Vernetzt." (grant number 16KIS2429K).

and the channel outcomes through hidden Markov models and evaluate the SEE numerically by means of quantized density evolution, which tracks the distribution of the a posteriori log-likelihood ratio across time. While accurate, the iterative nature of the analysis falls short in highlighting some important structural properties that govern the long-term behavior of the system. Taking the lead from this observation, we elaborate further on remote monitoring over slotted ALOHA channels, leveraging the renewal structure inherent to random access systems to derive closed-form expressions for the long-term average SEE *and* the SEEP. Under random transmission, we show that uncertainty growth is entirely driven by the time elapsed since the last successful reception, leading to a simple expectation over the geometric age distribution for both performance metrics. Under reactive transmission, we reveal a markedly different behavior: estimation uncertainty and, correspondingly, the SEEP accumulate exclusively through collision events, while idle slots preserve the receiver's knowledge of the source state. This structure leads naturally to a collision-indexed Markov–reward formulation, which captures both entropy-based and error-based performance metrics within a unified framework. Monte Carlo simulations validate the analysis and illustrate how reactive strategies can substantially mitigate the SEE by selectively suppressing unnecessary transmissions.

II. System Model and Preliminaries

We consider a wireless uplink system with M statistically independent sources (nodes), each with an associated transmitter, and communicating with a common receiver over a shared channel. Time is slotted and perfectly synchronized across nodes. Each source evolves as a two-state, time-homogeneous Markov chain with symmetric transition probabilities $q_{01} = q_{10} = q$. Given the symmetry of the problem, we address the state estimation at the receiver for an arbitrary *reference source*, denoting its state at time n by X_n.

Nodes transmit update packets over the shared channel following slotted ALOHA [19]. Accordingly, at every slot each node accesses the channel independently, and packets carry the current state of the transmitting source. We adopt a collision channel model. If exactly one packet is transmitted in a slot, the receiver identifies the transmitting node and decodes its state. Instead, concurrent transmissions result in a destructive collision from which no packet is recovered. The receiver detects collisions but cannot determine which or how many nodes were involved. No feedback is provided by the receiver, and retransmissions are not considered. The channel output in slot n is denoted with $Y_n \in \{\mathsf{S}, \mathsf{I}, \mathsf{C}\}$, where S denotes successful reception of the reference source; I indicates that the reference source did not transmit (idle slot or single transmission from another source); and C denotes a collision. The sequence of observations up to time n is written as $Y^n := [Y_0, \dots, Y_n]$.

For our study, we focus on two transmission strategies:

- *Random transmission*: each source transmits in every slot with probability $\alpha \in (0,1)$, independently of its state. The reference source is thus successfully decoded when it is the sole transmitter, i.e., with probability
$$\omega = \alpha(1-\alpha)^{M-1}. \tag{1}$$
In the following, we set $\alpha = 1/M$, which maximizes the throughput of slotted ALOHA and ensures that the random transmission policy operates at its optimal point for the considered metrics [1].
- *Reactive transmission*: a node transmits if and only if its state changes, so that channel outcomes are directly linked to the underlying source dynamics. Leaning on the independence of the processes, the probability that the reference source is successfully decoded, i.e., that it toggles while all other sources remain silent, is given by
$$\omega = q(1-q)^{M-1}. \tag{2}$$

A. State Estimation Entropy

The receiver keeps track of the observed sequence of channel outputs Y^n. Accordingly, its uncertainty about X_n given the specific realization y^n is quantified by

$$H_n := H(X_n \mid Y^n = y^n). \tag{3}$$

Clearly, the successful reception of a packet by the reference source reveals its state exactly and yields $H_n = 0$. The subsequent evolution of H_n depends on the adopted transmission policy. Our performance metric is the *state estimation entropy*

$$H_\infty = \lim_{N\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} H_n, \tag{4}$$

which coincides with the steady-state expectation of H_n under the hypothesis of ergodic sources [1].

B. State Estimation Rule

Based on the observation history, the receiver computes the posterior distribution $P(X_n{=}x \,|\, y^n)$. The maximum a posteriori (MAP) state estimate $\hat{X}_n$ is

$$\hat{X}_n = \arg\max_{x\in\{0,1\}} P(X_n = x \mid y^n) \tag{5}$$

and the corresponding instantaneous SEEP is

$$P_{\mathrm{e},n} = \mathsf{P}\left(\hat{X}_n \neq X_n \mid Y^n = y^n\right). \tag{6}$$

C. Renewal–Reward Framework

We recall a standard result from renewal theory that will be used to characterize long-term averages.

Theorem 1 (Renewal–Reward Theorem [20, Chp. 3])**.** *Let $\{T_k\}_{k\geq 1}$ be a renewal process with renewal epochs $T_k = \sum_{i=1}^{k} \Delta_i$, where $\{\Delta_i\}_{i\geq 1}$ are i.i.d. nonnegative inter-renewal times with $\mathbb{E}[\Delta_i] < \infty$. Let $\{R_i\}_{i\geq 1}$ be a sequence of random rewards such that the pairs $\{(\Delta_i, R_i)\}_{i\geq 1}$ are i.i.d. and $\mathbb{E}[|R_1|] < \infty$. Define the cumulative reward process*

$$R(t) = \sum_{i=1}^{N(t)} R_i, \tag{7}$$

where $N(t) = \max\{k : T_k \le t\}$. *Then*

$$\lim_{t\to\infty} \frac{R(t)}{t} = \frac{\mathbb{E}[R_1]}{\mathbb{E}[\Delta_1]}, \qquad \text{a.s. and in mean.} \tag{8}$$

In our system, a renewal occurs whenever a successful transmission reveals the source state, starting a new estimation cycle. The inter-renewal time Δ_i is the random number of slots between two successes and R_i denotes the cumulative estimation uncertainty accrued during that cycle.

III. State Estimation Under Random Transmission

Under random transmission, only successful receptions (S) convey information about the reference source. The receiver's estimation of the reference source state evolves solely through Markov prediction between successive updates, which occur independently across slots with probability ω, defined in (1).

Let T_k denote the k-th successful decoding time. The inter-arrival times $\Delta_k = T_k - T_{k-1}$ are i.i.d. geometric random variables with parameter ω, inducing a renewal structure. At T_k, the receiver learns X_{T_k} exactly and $H_{T_k} = 0$. For $n \in [T_k, T_{k+1})$, let us define the quantity $a = n - T_k$. Since observations in this interval are uninformative, the receiver's belief is obtained by a-step Markov prediction from X_{T_k}, and hence H_n depends only on a. Note that a corresponds to the age of information between consecutive receptions.

Define $\lambda \triangleq 1-2q \in [0,1)$. After a slots without update, the probability that the source remains in the last decoded state is

$$\mathsf{P}(X_n = X_{T_k} \mid y^n) = \mathsf{P}(X_{T_k+a} = X_{T_k} \mid X_{T_k}) = \frac{1+\lambda^a}{2}, \tag{9}$$

which yields the instantaneous SEE at age a,

$$H_{T_k+a} = h_2\left(\frac{1+\lambda^a}{2}\right), \tag{10}$$

where $h_2(p)$ denotes the binary entropy function.

Thus, within each renewal cycle the entropy can be seen as a deterministic "reward" trajectory, starting with $H_{T_k} = 0$ and converging to 1 bit as $a \to \infty$. The cumulative entropy accrued during the k-th renewal cycle is therefore given by

$$\sum_{a=0}^{\Delta_k - 1} H_{T_k+a}.$$

By the renewal–reward theorem, the long-term average state estimation entropy is given by

$$H_\infty = \frac{\mathbb{E}\left[\sum_{a=0}^{\Delta_k-1} H_{T_k+a}\right]}{\mathbb{E}[\Delta_k]}. \tag{11}$$

Using the geometric distribution of Δ_k, we have

$$\begin{aligned}\mathbb{E}\left[\sum_{a=0}^{\Delta_k-1} H_{T_k+a}\right] &= \sum_{a=0}^{\infty} \mathsf{P}(\Delta_k > a)\, H_{T_k+a} \\ &= \sum_{a=0}^{\infty} (1-\omega)^a\, H_{T_k+a}. \end{aligned} \tag{12}$$

Substituting into (11) and recalling (10) yields

$$H_\infty = \omega \sum_{a=0}^{\infty} (1-\omega)^a h_2\left(\frac{1+\lambda^a}{2}\right). \tag{13}$$

Under random transmission, for $n = T_k + a$ with $a \ge 0$, the posterior distribution $\mathsf{P}(X_n = \cdot \mid Y^n)$ depends only on the age term a. As a result, the instantaneous SEEP depends only on a and is given by

$$P_{\mathrm{e}}(a) = \frac{1-\lambda^a}{2}. \tag{14}$$

As in the entropy analysis, the sequence $\{T_k\}$ induces a renewal structure, and the SEEP within each renewal cycle follows a deterministic trajectory indexed by the age a, starting from $P_{\mathrm{e}}(0) = 0$ and converging to $1/2$ as $a \to \infty$. The long-term average SEEP is obtained by averaging this trajectory over the stationary age distribution, which is geometric with parameter ω. By the renewal–reward theorem, the asymptotic SEEP is therefore

$$P_{\mathrm{e},\infty} = \omega \sum_{a=0}^{\infty} (1-\omega)^a \frac{1-\lambda^a}{2}. \tag{15}$$

IV. State Estimation Under Reactive Transmission

We now analyze the SEE under the reactive transmission policy. Unlike the random case, channel observations are coupled to the source dynamics and can convey information about its state even without a successful decoding. In particular, $Y_n = \mathsf{I}$ indicates that the reference source did not transmit and therefore did not change state, whereas collision (C) indicates that at least two nodes toggled; since the reference source may or may not be among them, some uncertainty remains.

Let T_k denote the time of the k-th successful decoding of the reference source. We focus on slots within the renewal cycle, i.e., $T_k \le n < T_{k+1}$, and define the collision counter

$$J_n \triangleq \sum_{\ell=T_k+1}^{n} \mathbf{1}\{Y_\ell = \mathsf{C}\}. \tag{16}$$

The collision count defines a Markov chain within each renewal cycle. Within a cycle, idle slots leave the entropy unchanged, collision slots increase the collision count j, and the cycle terminates at the next successful decoding. Fig. 1 depicts the embedded Markov chain of the collision count within a cycle: I yields a self-loop, C moves to $j+1$, and S terminates the cycle and resets to $j = 0$. Since I implies no toggle of the reference source's state, the posterior depends on the observation history only through the collision count J_n. Accordingly, we define the belief after j collisions as

$$b_j \triangleq \mathsf{P}(X_n = X_{T_k} \mid J_n = j), \qquad j \ge 0, \tag{17}$$

with initial condition $b_0 = 1$. Define the corresponding collision-indexed entropy level

$$\mathcal{H}_j \triangleq h_2(b_j). \tag{18}$$

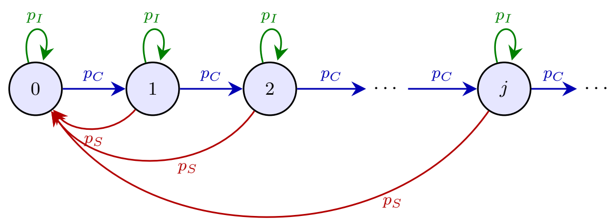

Fig. 1. Embedded Markov chain of the collision count j within a renewal cycle under reactive transmission.

Within the renewal cycle ($T_k \leq n < T_{k+1}$), the time-indexed entropy satisfies $H_n = \mathcal{H}_{J_n}$. Let

$$\phi \triangleq \mathsf{P}(\text{reference toggled} \mid Y_n = \mathsf{C}) \tag{19}$$

denote the conditional probability that the reference source was among the colliding transmitters in a collision slot.

Let $K \sim \text{Binomial}(M, q)$ be the number of transmitting nodes. Conditioning on the collision event $\{K \geq 2\}$, we have

$$\phi = \frac{q\big(1-(1-q)^{M-1}\big)}{1-(1-q)^M - Mq(1-q)^{M-1}}. \tag{20}$$

For a given b_j, if the reference did not change state, then $\{X_n = X_{T_k}\}$, while if it toggles state $\{X_n = \overline{X}_{T_k}\}$, $\overline{X}_{T_k}$ being the complementary state. Therefore:

$$b_{j+1} = (1-\phi)\, b_j + \phi\,(1-b_j) = \phi + (1-2\phi)\, b_j, \tag{21}$$

which yields the closed form

$$b_j = \frac{1}{2} + \frac{1}{2}(1-2\phi)^j, \tag{22}$$

converging to $\frac{1}{2}$ as $j \to \infty$. Substituting into (18) we have

$$\mathcal{H}_j = h_2\left(\frac{1}{2} + \frac{1}{2}(1-2\phi)^j\right). \tag{23}$$

Cycle Structure and Average SEE: As in Sec. III, the times $\{T_k\}$ are regeneration points. Define the slot-outcome probabilities for the reference source as

$$p_{\text{s}} \triangleq \mathsf{P}(Y_n = \mathsf{S}) = q(1-q)^{M-1}, \tag{24}$$

$$p_{\text{c}} \triangleq \mathsf{P}(Y_n = \mathsf{C}) = 1-(1-q)^M - Mq(1-q)^{M-1}, \tag{25}$$

$$p_{\text{i}} \triangleq \mathsf{P}(Y_n = \mathsf{I}) = 1 - p_{\text{s}} - p_{\text{c}}. \tag{26}$$

Let R_j be the expected total entropy accumulated from the current slot until the end of the cycle, conditioned on a given collision count j. Grouping the I slots before the next non-I outcome yields the recursion

$$R_j = p_{\text{s}} \cdot 0 \;+\; p_{\text{i}}\big(\mathcal{H}_j + R_j\big) \;+\; p_{\text{c}}\big(\mathcal{H}_{j+1} + R_{j+1}\big). \tag{27}$$

Rearranging (27) for R_j gives

$$R_j = \frac{p_{\text{i}}\mathcal{H}_j + p_{\text{c}}\mathcal{H}_{j+1}}{p_{\text{s}} + p_{\text{c}}} + \frac{p_{\text{c}}}{p_{\text{s}} + p_{\text{c}}} R_{j+1}. \tag{28}$$

Setting

$$\eta \triangleq \frac{p_{\text{c}}}{p_{\text{s}} + p_{\text{c}}}, \qquad \beta_j \triangleq \frac{p_{\text{i}}\mathcal{H}_j + p_{\text{c}}\mathcal{H}_{j+1}}{p_{\text{s}} + p_{\text{c}}},$$

(28) becomes $R_j = \beta_j + \eta R_{j+1}$. Iterating we obtain

$$R_0 = \beta_0 + \eta R_1 = \beta_0 + \eta\beta_1 + \eta^2 R_2 = \cdots = \sum_{j=0}^{N-1} \eta^j \beta_j + \eta^N R_N.$$

Since $\mathcal{H}_j \leq 1$ for all j, the sequence $\{R_j\}$ is bounded, and $\eta^N R_N \to 0$ as $N \to \infty$. Hence

$$R_0 = \sum_{j=0}^{\infty} \eta^j \beta_j. \tag{29}$$

Splitting β_j and re-indexing the second sum we have

$$\begin{aligned} R_0 &= \frac{1}{p_{\text{s}} + p_{\text{c}}}\left(p_{\text{i}} \sum_{j=0}^{\infty} \eta^j \mathcal{H}_j + p_{\text{c}} \sum_{j=0}^{\infty} \eta^j \mathcal{H}_{j+1}\right) \\ &= \frac{1}{p_{\text{s}} + p_{\text{c}}}\left(p_{\text{i}} + \frac{p_{\text{c}}}{\eta}\right) \sum_{j=0}^{\infty} \eta^j \mathcal{H}_j, \end{aligned} \tag{30}$$

where we used $\mathcal{H}_0 = 0$. Substituting $p_{\text{c}}/\eta = p_{\text{s}} + p_{\text{c}}$ and $p_{\text{i}} + p_{\text{s}} + p_{\text{c}} = 1$ yields

$$R_0 = \frac{1}{p_{\text{s}} + p_{\text{c}}} \sum_{j=0}^{\infty} \eta^j \mathcal{H}_j. \tag{31}$$

The cycle length is geometrically distributed with parameter p_{s}, so $\mathbb{E}[\Delta] = 1/p_{\text{s}}$. By the renewal–reward theorem we have

$$H_\infty = (1-\eta) \sum_{j=0}^{\infty} \eta^j \mathcal{H}_j. \tag{32}$$

Within a renewal cycle, the posterior depends on the observation history only through the collision count J_n. Hence, conditioned on $J_n = j$, the MAP error probability depends solely on the belief b_j, and is given by

$$\begin{aligned} P_{\text{e}}^{(j)} &= \mathsf{P}\Big(\hat{X}_n \neq X_n \mid J_n = j\Big) \\ &= 1 - \max\{b_j,\, 1-b_j\}. \end{aligned} \tag{33}$$

The belief admits the closed form in (22), yielding

$$P_{\text{e}}^{(j)} = \frac{1}{2}\big(1 - |1-2\phi|^j\big), \tag{34}$$

which increases monotonically with the number of collisions and converges to $1/2$, corresponding to complete uncertainty.

Long-term average SEEP: Using the same arguments adopted for the entropy analysis, the asymptotic SEEP is

$$P_{\text{e},\infty} = \sum_{j=0}^{\infty} \mathsf{P}(J = j)\, P_{\text{e}}^{(j)}, \tag{35}$$

which reduces to a geometric law with parameter $1-\eta$

$$P_{\text{e},\infty} = (1-\eta) \sum_{j=0}^{\infty} \eta^j P_{\text{e}}^{(j)}. \tag{36}$$

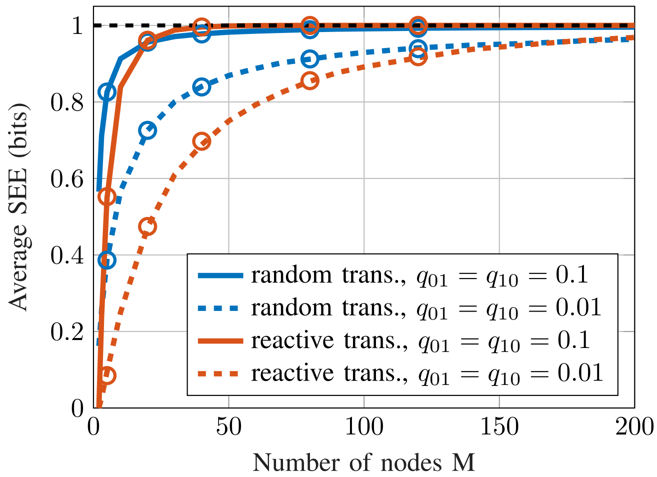

Fig. 2. Average state estimation entropy versus number of nodes M. Lines denote analytical results, whereas markers show Monte Carlo simulations.

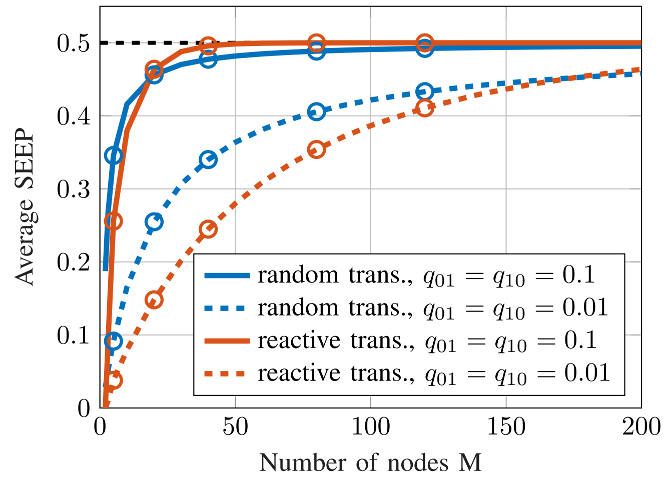

Fig. 3. Average state estimation error probability versus number of nodes M. Lines represent analytical results, while markers show Monte Carlo simulations.

V. Simulation Results and Discussion

We validate the analytical results on the average SEE derived in Secs. III and IV via Monte Carlo simulations, and compare random and reactive transmission policies under different channel loads. The SEE is estimated by time-averaging the instantaneous conditional entropy $H(X_n \mid Y^n)$ over long horizons. We investigate how the average SEE scales with the number of contending nodes M. Results are shown for two values, $q = 0.1$ and $q = 0.01$, corresponding to moderately fast and slow source dynamics, respectively.

Fig. 2 shows the average SEE as a function of M under both transmission strategies. The plots confirm the correctness of the derived expressions. As expected, the SEE increases with the number of nodes due to stronger channel contention, which reduces the frequency of informative observations at the receiver. For both access policies, slower source dynamics ($q_0 = 0.01$) lead to a lower SEE, since state transitions are rarer and missed updates are less detrimental.

A clear performance gap can be observed between the two strategies. Reactive transmission yields a lower SEE under low and moderate channel loads, but a crossover occurs as M increases, after which random transmission becomes preferable. This behavior is due to the fact that, under reactive access, successful updates occur with probability $p_s = q(1-q)^{M-1}$, which decays exponentially with M, whereas under random access the update rate can be sustained by tuning the access probability. In the extreme case $M = 2$, reactive transmission enables perfect tracking of the reference source, resulting in zero SEE. It is worth noting that the crossover occurs when the SEE is already close to one for both policies, i.e., when the receiver has almost no information about the source. This corresponds to a heavily overloaded regime where reliable monitoring is no longer feasible, so the performance difference is of limited practical relevance. The SEEP (Fig. 3) exhibits a similar behavior. Reactive transmission outperforms random access at low and moderate loads, since even collisions and idle slots convey information. As M increases, a crossover appears, and random transmission becomes preferable.

The crossover occurs earlier for faster dynamics ($q = 0.1$), while it is shifted to larger M for slower sources ($q = 0.01$). In the high-load regime, the SEEP under reactive transmission approaches $1/2$ more rapidly due to the vanishing success probability, whereas random transmission maintains a lower error probability by sustaining a higher effective update rate.

VI. Conclusions

We studied remote monitoring of two-state Markov sources over a slotted ALOHA channel and provided an explicit analytical characterization of the long-term average SEE and SEEP under both random and reactive transmission policies. In contrast to density evolution approaches, the analysis is based on the renewal structure induced by successful updates. It yields closed-form expressions that clarify how source dynamics and channel randomness affect these metrics.

For random transmission, both metrics reduce to simple expectations over the geometric steady-state age distribution. For reactive transmission, we characterize a different structure: estimation uncertainty and error accumulate exclusively through collision events. This leads to a collision-indexed Markov–reward recursion that captures both SEE and SEEP within a unified framework. The analysis shows that reactive transmission outperforms at low and moderate loads, while a crossover occurs at high load due to the vanishing probability of successful updates, which is confirmed by simulations.

Future work includes extending the analysis to more general source models such as time-inhomogeneous Markov processes, as well as investigating hybrid transmission strategies that combine random and reactive access mechanisms.

Acknowledgment

The authors would like to thank Gerhard Kramer for helpful discussions and feedback on this work.

REFERENCES

[1] G. Cocco, A. Munari, and G. Liva, "Remote monitoring of two-state Markov sources via random access channels: An information freshness vs. state estimation entropy perspective," *IEEE J. Sel. Topics Inf. Theory.*, vol. 4, pp. 651–666, 2023.

[2] J. Ding, M. Nemati, C. Ranaweera, and J. Choi, "IoT connectivity technologies and applications: A survey," *IEEE Access*, vol. 8, pp. 67 646–67 673, 2020.

[3] Z. Qadir, K. N. Le, N. Saeed, and H. S. Munawar, "Towards 6G Internet of Things: Recent advances, use cases, and open challenges," *ICT Express*, vol. 9, no. 3, pp. 296–312, 2023.

[4] LoRa Alliance, "The LoRa Alliance Wide Area Networks for Internet of Things," www.lora-alliance.org.

[5] Sigfox, "SIGFOX: The Global Communications Service Provider for the Internet of Things," www.sigfox.com.

[6] A. Munari, S. Cioni, H. Krishnamurthy, B. Shrestha, A. Sengupta, E. Recayte, and A. Rico-Alvariño, "Contention-based early data transmission for 3GPP IoT over non-terrestrial networks," *IEEE Comm. Standards Magazine*, 2026.

[7] R. Yates and S. Kaul, "The age of information: Real-time status updating by multiple sources," *IEEE Trans. Inf. Theory*, vol. 65, no. 3, pp. 1807–1827, 2019.

[8] R. Yates, Y. Sun, R. Brown, S. Kaul, E. Modiano, and S. Ulukus, "Age of information: An introduction and survey," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1183–1210, 2021.

[9] S. Kaul, M. Gruteser, V. Rai, and J. Kenney, "Minimizing age of information in vehicular networks," in *Proc. IEEE SECON*, June 2011.

[10] S. Kaul, R. Yates, and M. Gruteser, "Real-time status: How often should one update?" in *Proc. IEEE INFOCOM*, Mar. 2012.

[11] R. Yates and S. Kaul, "Status updates over unreliable multiaccess channels," in *Proc. IEEE ISIT*, Jun. 2017.

[12] M. Rezaeian, B. Vo, and J. Evans, "The optimal observability of partially observable Markov decision processes: Discrete state space," *IEEE Trans. Autom. Control*, vol. 55, no. 12, pp. 2793–2798, 2010.

[13] J. Luo and N. Pappas, "Exploiting data significance in remote estimation of discrete-state Markov sources," *arXiv preprint arXiv:2406.18270*, 2024.

[14] G. Chen, S. C. Liew, and Y. Shao, "Uncertainty-of-information scheduling: A restless multiarmed bandit framework," *IEEE Trans. Inf. Theory*, vol. 68, no. 9, pp. 6151–6173, 2022.

[15] G. Cocco, A. Munari, and G. Liva, "State estimation entropy for two-state Markov sources in slotted ALOHA random access channels," in *Proc. IEEE Info. Theo. Workshop (ITW)*, France, Apr. 2023.

[16] M. Salimnejad, M. Kountouris, and N. Pappas, "State-aware real-time tracking and remote reconstruction of a Markov source," *Journal of Communications and Networks*, vol. 25, no. 5, pp. 657–669, 2023.

[17] N. Akar and S. Ulukus, "Timely monitoring of Markov chains under sampling rate constraints," in *Proc. IEEE ICC*, Denver, CO, USA, June 2024, pp. 189–194.

[18] T. Soleymani, J. Baras, and K. Johansson, "State estimation over delayed and lossy channels: An encoder-decoder synthesis," *IEEE Transactions on Automatic Control*, vol. 69, pp. 1568–1583, 2023.

[19] N. Abramson, "The throughput of packet broadcasting channels," *IEEE Trans. Commun.*, vol. COM-25, no. 1, pp. 117–128, 1977.

[20] S. M. Ross, *Stochastic Processes*, 2nd ed. New York: John Wiley & Sons, 1996.