Information Freshness in Random Access Networks with Energy Harvesting

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***Abstract*—We consider the age of information (AoI) evaluation in an Aloha-based random access network powered by energy harvesters. We derive a closed-form expression for the average AoI with general energy buffer capacity. The average AoI is then optimized by adjusting the update rate. The results indicate that when the sum of the energy arrival rate of all nodes is greater than or equal to one, the optimal average AoI in the Aloha network is equivalent to that in a network without energy constraints, by setting the update rate to one divided by the total number of nodes. The optimized average AoI then grows linearly with the number of nodes. Otherwise, a degradation of the optimal average AoI emerges, and the update rate should be tuned to be higher than the energy arrival rate.**

***Index Terms*—Age of information, energy harvesting, random access, slotted Aloha.**

I. Introduction

Timeliness is a critical performance metric for Internet of Things (IoT) applications [1], including smart home appliances, remote sensing systems, and environmental detectors. For these applications, if the transmitted information becomes outdated, it can significantly degrade the quality of service and even pose safety risks. To measure timeliness, the age of information (AoI) has been proposed as a new metric [2]. Unlike traditional IoT metrics such as latency or throughput, AoI provides an accurate indication of information freshness from the receiver's perspective, defined as the time elapsed since the last successfully received status update information packet was generated [3] [4].

Many works have explored AoI-oriented network configuration [5]–[19], covering various queuing models [5]–[10], employing random packet generation [9]–[11], controlling packets with deadlines [12], adopting feedback mechanisms [13], implementing retransmission backoff mechanisms to adjust parameters [14], and adapting age-based strategies based on feedback [15]–[19]. However, these works assume that the IoT node always has sufficient energy for transmission. In general, AoI-oriented goals mean the node has to transmit massive fresh information continuously, thereby increasing the energy demand. However, replacing batteries for these set-it-and-forget-it IoT devices becomes highly impractical once the energy is depleted. Consequently, harvesting energy from the environment to power the nodes has emerged as a feasible solution to sustain long-term transmission.

Unlike battery-powered nodes, energy-harvesting nodes may temporarily keep silent during operation to accumulate energy, which can adversely affect AoI performance. Therefore, many previous works have investigated the AoI analysis under energy harvesting constraints [20]–[27] for different battery capacities and AoI-optimal schemes. The above works have focused on point-to-point scenarios, and the AoI analysis in random access networks powered by energy harvesters remains largely unexplored. In IoT networks, nodes are typically deployed densely and compete for channel resources using random access. The AoI degradation and energy cost caused by channel collisions cannot be ignored, which is a significant difference from the point-to-point scenario and merits further investigation.

Recently, the AoI metric in Aloha networks with energy harvesting was evaluated by using a numerical method in [28]. However, there is a lack of a closed-form expression for AoI with general battery capacity. A closed-form analytical expression for the AoI metric in the Aloha network is then required to explore AoI limits, identify the AoI-optimal policy, and help us investigate the differences from the networks without energy constraints. By addressing the above issues, our contributions are summarized as follows:

- We propose an analytical framework to evaluate the AoI performance in a random access network powered by energy harvesting. We derive explicit expressions for the average AoI in Aloha networks with general energy buffer capacity.
- We optimize the average AoI for unit and infinite buffer capacity. The results indicate that when the sum of the energy arrival rate of each node is larger than or equal to one, the Aloha network can achieve the identical optimal average AoI of the network without energy constraints. Otherwise, the performance loss emerges, and the update

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rate should be tuned to be higher than the energy arrival rate. The achieved optimal average AoI becomes worse than the optimal average AoI without energy constraints.
- Our findings suggest that the optimal update rate for an infinite energy buffer capacity case can serve as a tight bound for cases with a finite buffer capacity that is larger than one.

II. System Model

A. Network Configuration and Transmission Protocol

Consider a single-cell Aloha random access energy-aware network comprising n nodes equipped with energy harvesters, all attempting to access a common destination in Fig. 1. The time is slotted into equal-length intervals. We assume that all nodes are synchronized and can initiate a transmission only at the beginning of a time slot, and the transmission of each packet lasts for one slot.

Specifically, we employ the generate-at-will strategy to manage the status updates. Once a node decides to send its update to the destination, it generates a fresh status update before the transmission. With the slotted Aloha protocol, each node samples and transmits a fresh status update with a certain probability q in each time slot when its energy buffer is not empty. We assume that all nodes share the same spectrum, and nodes send their occasional status updates uncoordinated to the destination, which means each node's transmission would cause interference to others. We utilize the collision model to characterize the co-channel interference, which means that if two or more nodes attempt to transmit simultaneously, none of the transmissions will succeed. When a failed node attempts to transmit again, it generates a new status update.

B. Energy Harvesting Model

We assume that the process of energy harvesting obeys a Bernoulli process with probability δ. In each time slot, the energy harvester attempts to harvest energy and checks the amount of energy stored in the energy buffer. Once the energy harvesting process occurs, one unit of energy can be harvested at a time. In addition, it is assumed that the energy buffer is capable of storing a maximum of B units of energy. Once the energy stored in the buffer reaches the upper limit, any additional energy harvested is discarded. Nodes can attempt to transmit a state update only when at least one unit of energy is stored in the buffer. If an energy unit arrives at a node with empty buffer, the node generates a status update until the next time slot, and the transmission decisions occur before the energy arrivals in a time slot. In this paper, we discuss the energy harvesting model by comparing the numerical relationship between the energy arrival rate and the update rate in the following two regimes.

1) Energy-limited regime: We refer to the regime where $\delta < q$ as energy-limited which means that the energy arrival rate is lower than the update rate.

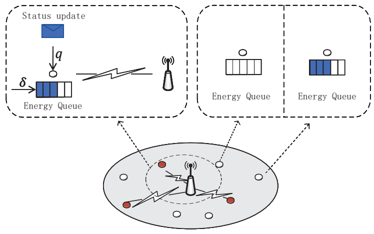


Fig. 1. A simplified illustration of energy harvesting nodes and a common destination in random access cellular networks.

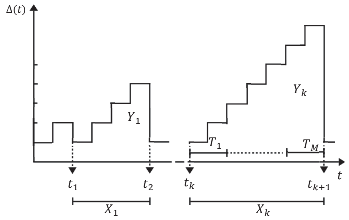


Fig. 2. Evolution of the AoI. t_k denotes the time when the kth update is transmitted successfully. X_k denotes the time between two successful receptions of the status updates. T_k denotes the time between the kth and $(k+1)$th attempted transmissions. Y_k is the area below the AoI step line between t_k and t_{k+1}.

2) Energy-sufficient regime: We refer to the regime where $\delta \geq q$ as energy-sufficient which means that the energy arrival rate is greater than or equal to the update rate.

C. Performance Metric

We focus on the AoI performance in this work. The AoI is defined as *the duration since the generation time of the latest successfully received update until the current time*. The evolution of AoI is illustrated in Fig. 2. The value of AoI increases linearly from one time slot to the next (with an additional value for each time slot) in the event of a transmission failure or the absence of a state update packet. Conversely, the value of AoI decreases to one when a state update packet is successfully transmitted. The mathematical formulation of the evolution of AoI can be expressed as

$$\Delta(t) = \begin{cases} 1 & \text{if transmission successful,} \\ \Delta(t) + 1 & \text{otherwise.} \end{cases} \tag{1}$$

In this paper, we utilize the average AoI as the performance metric, which is defined as follow

$$\bar{\Delta} = \lim_{K \to \infty} \frac{1}{K} \sum_{t=1}^{K} \Delta(t), \tag{2}$$

where K refers to the operation time horizon. In the following, we will present the derivation of the expression of the average AoI constrained by energy harvesting.

III. Average AoI Performance Analysis

Similar to the analysis process of the AoI in [21], we thus derive the average AoI $\bar{\Delta}$ in the random access networks

$$\bar{\Delta} = \frac{\mathbb{E}[T^2]}{2\mathbb{E}[T]} + \frac{\mathbb{E}[T](1-p)}{p} + \frac{1}{2}. \tag{3}$$

From (3), we can observe that the average AoI depends on the probability of successful transmission p, the first and second

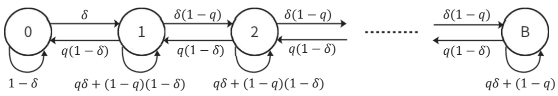


Fig. 3. State transition diagram of energy harvest buffer.

moment of the attempted transmission interval $E[T]$ and $E[T^2]$ respectively. We analyze these three components and derive the closed-form expression of the average AoI.

A. State Characterization of Energy Harvesting

We first analyze the state transition of the energy harvesting system, which helps us derive the probability of successful transmission. The system can be modeled as a multi-dimensional Markov chain, and the states $\mathbf{W} = \{(W_i) \in 0, 1, 2, ...B\}$ indicate the battery status of all nodes in the network, where W_i denotes the state of the number of energy packet in the energy buffer. To simplify the analysis, the stationary approximation can be adopted, where the failure events are modeled as a Bernoulli process with fixed probability.

Then, we investigate the steady state transition probability, as illustrated in Fig. 3. Specifically, if the buffer is empty (state W_0), a node cannot generate an update. The transition from W_0 to W_1 occurs only through energy harvesting, with a probability of δ; otherwise, the state remains at W_0, with a probability of $1 - \delta$. For cases where a node harvests energy without generating an update, the state transitions from W_i to W_{i+1} (for $i \in 1, 2, \ldots, B-1$), with a probability of $\delta(1-q)$. Conversely, if a node generates an update without harvesting energy, the transition is from W_i to W_{i-1} (for $i \in 1, 2, \ldots, B$), with a probability of $q(1-\delta)$. In scenarios where a node either harvests energy and generates update or does neither, the state W_i (for $i \in 1, 2, \ldots, B$) remains unchanged, with a probability of $q\delta + (1-q)(1-\delta)$.

We assume the steady-state probability of the i-th state is π_i, we can list the steady-state equations as follows

$$\begin{cases} \pi_0 + \pi_1 + ... + \pi_B = 1, \\ (1-\delta)\pi_0 + q(1-\delta)\pi_1 = \pi_0, \\ \delta\pi_0 + (q\delta + (1-q)(1-\delta))\,\pi_1 + q(1-\delta)\pi_2 = \pi_1, \\ \delta(1-q)\pi_1 + (q\delta + (1-q)(1-\delta))\,\pi_2 + q(1-\delta)\pi_3 = \pi_2, \\ ... \\ \delta(1-q)\pi_{B-1} + (q\delta + (1-q))\,\pi_B = \pi_B. \end{cases} \tag{4}$$

Then, the steady-state probability distribution of each state in the discrete-time Markov chain can be derived as

$$\begin{cases} \pi_0 = \dfrac{q-\delta}{q - \delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}, \\ \pi_1 = \dfrac{\delta}{(1-\delta)q}\pi_0, \\ \pi_i = \dfrac{(1-q)\delta}{(1-\delta)q}\pi_{i-1} \qquad i \in \{2, 3, 4, \ldots, B\}. \end{cases} \tag{5}$$

Therefore, the steady-state probability that the energy buffer is empty $\mathbb{P}(E=0)$ and non-empty $\mathbb{P}(E \neq 0)$ are given as

$$\begin{cases} \mathbb{P}(E=0) = \dfrac{q-\delta}{q - \delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}, \\ \mathbb{P}(E \neq 0) = \dfrac{\delta\left(1 - \left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B\right)}{q - \delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}. \end{cases} \tag{6}$$

Particularly, when $\delta = q$, we derive the limits probability of (6) by using the L'Hôpital's rule, that is

$$\begin{cases} \mathbb{P}(E=0) = \dfrac{1-q}{1-q+B}, \\ \mathbb{P}(E \neq 0) = \dfrac{B}{1-q+B}. \end{cases} \tag{7}$$

B. Probability of Successful Transmission

According to the assumption of the collision model, it can be known that at the beginning of a time slot, if $n-1$ nodes decide not to transmit a state update packet, then the network can successfully transmit a state update packet, or else a collision will occur resulting in the loss of all involved state update packets. The potential scenarios for these $n-1$ nodes are as follows: (i) the energy buffer has energy, but the node does not generate a state update packet; (ii) there is no energy in the energy buffer, the node is unable to generate and transmit a state update packet. and the probability of successful transmission can then be given by

$$p = \left(\mathbb{P}(E=0) + \mathbb{P}(E \neq 0) \cdot (1-q)\right)^{n-1}. \tag{8}$$

By substituting (6), (7) into (8), the probability of successful transmission can be derived as

$$p = \begin{cases} \left(1 - \delta q \dfrac{1 - \left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}{q - \delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}\right)^{n-1} & \delta \neq q, \\ \left(1 - \dfrac{qB}{1-q+B}\right)^{n-1} & \delta = q. \end{cases} \tag{9}$$

C. Analysis of $\mathbb{E}[T]$ and $\mathbb{E}[T^2]$

In this part, we derive the expressions of $\mathbb{E}[T]$ and $\mathbb{E}[T^2]$. We assume that the average AoI drops to one after the kth transmission, implying that the energy buffer has at least one unit of energy before the kth transmission. Therefore, two potential events, i.e., Event 1 and 2, may occur before the $(k+1)$th transmission. The detailed analysis is as follows.

1) Event 1: If only one energy packet is stored in the energy buffer before the kth attempted transmission, and no energy arrives in this time slot. The remaining energy after the kth attempted transmission can not support subsequent transmissions. Then, nodes are temporarily silent to accumulate energy. The corresponding probability is then given by

$$\Pr\{\text{Event } 1\} = \frac{(1-\delta)\pi_1}{\mathbb{P}(E>0)} = \frac{\frac{\delta}{q} - \left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}{1 - \left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}. \tag{10}$$

2) Event 2: If more than one energy packet is stored in the energy buffer before the kth attempted transmission, then the transmitter can support subsequent transmissions. The corresponding probability is then given by

$$\Pr\{\text{Event } 2\} = 1 - \frac{(1-\delta)\pi_1}{\mathbb{P}(E>0)} = \frac{1-\frac{\delta}{q}}{1-\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}. \tag{11}$$

Therefore, the expression of $\mathbb{E}[T]$ can be given by

$$\begin{aligned}
\mathbb{E}[T] =& \Pr\{\text{Event } 1\}\sum_{k=2}^{\infty} k \sum_{l=1}^{k-1}(1-\delta)^{l-1}\delta(1-q)^{k-l-1}q \\
&+ \Pr\{\text{Event } 2\}\sum_{k=1}^{\infty} k(1-q)^{k-1}q \\
=& \frac{1-\frac{\delta}{q}}{1-(\frac{(1-q)\delta}{(1-\delta)q})^B}\left(\frac{\delta+q}{\delta q}\right) + \frac{\frac{\delta}{q}-(\frac{(1-q)\delta}{(1-\delta)q})^B}{1-(\frac{(1-q)\delta}{(1-\delta)q})^B}\frac{1}{q},
\end{aligned} \tag{12}$$

and the expression of $\mathbb{E}[T^2]$ can be given by

$$\begin{aligned}
\mathbb{E}[T^2] =& \Pr\{\text{Event } 1\}\sum_{k=2}^{\infty} k^2 \sum_{l=1}^{k-1}(1-\delta)^{l-1}\delta(1-q)^{k-l-1}q \\
&+ \Pr\{\text{Event } 2\}\sum_{k=1}^{\infty} k^2(1-q)^{k-1}q \\
=& \frac{1-\frac{\delta}{q}}{1-(\frac{(1-q)\delta}{(1-\delta)q})^B}\left(\frac{2-q}{q^2}+\frac{2-\delta}{\delta^2}+\frac{2}{\delta q}\right) + \frac{\frac{\delta}{q}-(\frac{(1-q)\delta}{(1-\delta)q})^B}{1-(\frac{(1-q)\delta}{(1-\delta)q})^B}\frac{2-q}{q^2}.
\end{aligned} \tag{13}$$

D. Average AoI Analysis

By combining (3), (9), (12) and (13), the closed-form of the average AoI $\bar{\Delta}$ can be presented as the following theorem.

Theorem 1. *The average AoI $\bar{\Delta}$ in an energy-harvesting-powered random access network can be expressed as*

$$\bar{\Delta} = \begin{cases} \dfrac{q-\delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}{\delta q\left(1-\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B\right)\left(1-\delta q\dfrac{1-\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}{q-\delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}\right)^{n-1}} \\ \quad -\dfrac{(q-\delta)^2\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B}{\delta q\left(1-\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B\right)\left(q-\delta\left(\frac{(1-q)\delta}{(1-\delta)q}\right)^B\right)} & \delta \neq q, \\ \dfrac{1-q+B}{qB\left(1-\frac{qB}{1-q+B}\right)^{n-1}} - \dfrac{1-q}{qB} + \dfrac{1-q}{q(1-q+B)} & \delta = q. \end{cases} \tag{14}$$

The following corollary considers the infinite energy buffer capacity case, i.e., $\lim_{B\to\infty}\bar{\Delta}$, as shown below.

Corollary 1. *When the energy buffer capacity $B\to\infty$, in the energy-limited regime i.e., $\delta < q$, the average AoI in (14) can be expressed as*

$$\lim_{B\to\infty}\bar{\Delta} = \frac{1}{\delta(1-\delta)^{n-1}}. \tag{15}$$

In the energy-sufficient regime, i.e., $\delta \geq q$, the average AoI can be expressed as

$$\lim_{B\to\infty}\bar{\Delta} = \frac{1}{q(1-q)^{n-1}}. \tag{16}$$

Corollary 1 indicates that when the energy buffer capacity is relatively large, the energy arrival rate dominates the average AoI in the energy-limited regime due to the energy constraint.

E. Average AoI Optimization

Theorem 1 indicates that the average AoI is influenced by the update rate q, which can be adjusted. Consequently, it is of great importance to explore how to properly tune the update rate. We then establish the following optimization problem

$$\begin{aligned} \bar{\Delta}^* = &\min_{\{q\}}\ \bar{\Delta} \\ \text{s.t.}\ \ & q\in(0,1]. \end{aligned} \tag{17}$$

The complex form of $\bar{\Delta}$ makes it difficult to give a general expression of the optimal update rate. As an alternative approach, we consider $B=1$ to represent the small buffer capacity case and $B\to\infty$ to represent the large buffer capacity case to obtain insight. The problem (17) can be transformed into

$$\bar{\Delta}^*_{B=1} = \min_{\{q\}}\ \bar{\Delta}_{B=1}, \tag{18}$$

and

$$\bar{\Delta}^*_{B=\infty} = \min_{\{q\}}\ \bar{\Delta}_{B=\infty}. \tag{19}$$

The following theorems present the solution of (18) and (19).

Theorem 2. *When the energy buffer capacity $B=1$, the corresponding optimal average AoI $\bar{\Delta}^*_{B=1}$ is achieved when the update rate q is tuned to be*

$$q^*_{B=1} = \min\left\{\frac{\delta(\mathrm{e}^{z_0}-1)}{\delta\mathrm{e}^{z_0}-2\delta-\mathrm{e}^{z_0}+1}, 1\right\}, \tag{20}$$

where $z_0\in(\ln(1-\delta), 0)$ is the solution of the equation

$$zn - \ln\left(\frac{\delta^2(n\mathrm{e}^z-n+1)}{(1-\delta)(\mathrm{e}^z-1)^2}\right) = 0. \tag{21}$$

Theorem 3. *When the energy buffer capacity $B\to\infty$, the corresponding optimal average AoI $\bar{\Delta}^*_{B\to\infty}$ is given by*

$$\bar{\Delta}^*_{B\to\infty} = \begin{cases} n\left(1+\dfrac{1}{n-1}\right)^{n-1} & n\delta\geq 1, \\ \dfrac{1}{\delta(1-\delta)^{n-1}} & \textit{otherwise}, \end{cases} \tag{22}$$

which is achieved when the update rate q is tuned to be

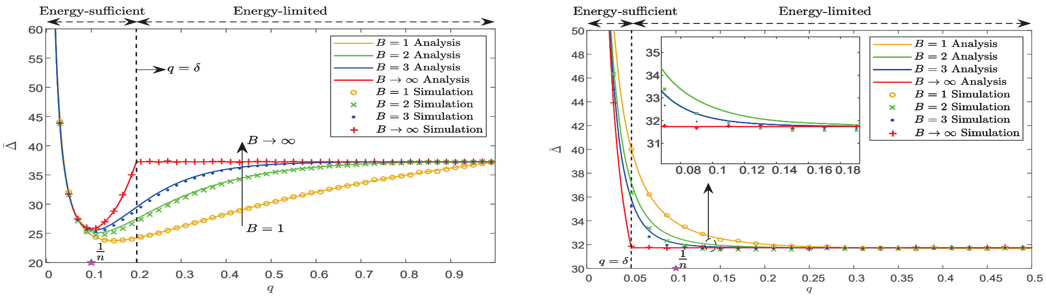
$$q^*_{B\to\infty} = \min\left\{\frac{1}{n}, \delta\right\}. \tag{23}$$

The above theorems can be obtained from theorem 1 and corollary 1 straightforwardly, and the proof omitted here due to limited space. In the following part, we will present that Theorem 2 and 3 can serve as bounds for (17) by comparing them with results obtained through numerical methods.

IV. Simulation Results and Discussion

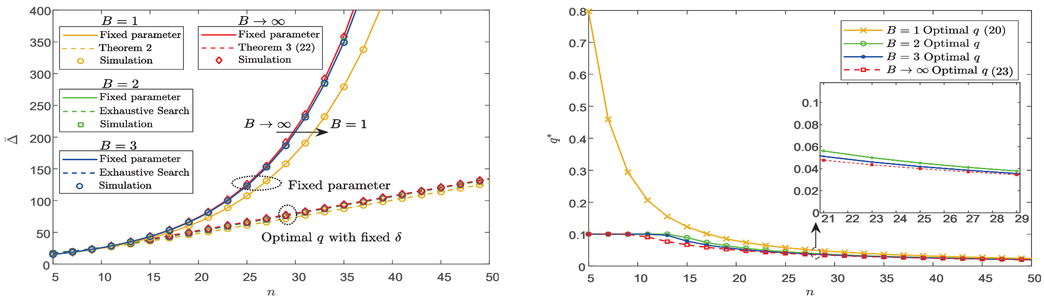
This section presents the simulation results to verify the preceding theoretical analysis. The simulation setting is identical to the system model in Section II. Each simulation is carried out for 10^8 time slots. The average AoI $\bar{\Delta}$ is obtained by calculating the ratio of the sum of the AoI of each node to the total number of time slots 10^8 and nodes n.

1) Analysis of $\bar{\Delta}$ versus q when $n\delta\geq 1$: Initially, Fig. 4 depicts the average AoI $\bar{\Delta}$ as a function of the update rate q. The close alignment between simulation and theoretical



(a) (b)

Fig. 4. (a) The average AoI $\bar{\Delta}$ versus the update rate q with fixed network size $n = 10$, fixed energy arrival rate $\delta = 0.2$ when $n\delta \geq 1$. (b) The average AoI $\bar{\Delta}$ versus the update rate q with fixed network size $n = 10$, fixed energy arrival rate $\delta = 0.05$ when $n\delta < 1$.



(a) (b)

Fig. 5. (a) The average AoI $\bar{\Delta}$ in fixed parameter, δ=0.1, q=0.5 versus individual optimal tuning the update rate with fixed δ=0.1. (b) The optimal update rate with fixed δ=0.1 versus the network size n.

analysis validates our analysis. Furthermore, when $n\delta \geq 1$, Fig. 4(a) presents the Aloha network powered by energy harvesters can achieve the optimal average AoI as the slotted Aloha without energy constrained, by properly tuning the update rate. Additionally, the average AoI can benefit from the smaller energy buffer capacity due to its function in controlling concurrency when the energy arrival rate is large.

2) Analysis of $\bar{\Delta}$ versus q when $n\delta < 1$: Fig. 4(b) depicts the average AoI $\bar{\Delta}$ as a function of the update rate q when $n\delta < 1$. In this case, the average AoI is constrained by the lower energy arrival rate. In this case, the update rate should be adjusted, and larger than the energy arrival rate to obtain a relatively good performance. Moreover, the average AoI can benefit from the larger energy buffer capacity in this case, and different from the case of $n\delta \geq 1$. Combining the observations of Fig. 4(a) and Fig. 4(b), we can see the average AoI can be optimized by properly tuning the update rate.

3) Average AoI performance gain: To further investigate the gain of the AoI optimization, we compare the fixed update rate scheme with the proposed optimized scheme in Fig. 5(a). This figure presents the average AoI as a function of the network size n with various energy buffer capacities. With a fixed update rate, the average AoI rises sharply as the network size n increases. Due to more nodes competing with the transmission node tends to increase channel collision. Then, delivering new update packets to the destination becomes more challenging, contributing to the increase in the average AoI.

When we adjust the update rate according to the proposed scheme, the pogain is significant with optimal tuning of the update rate. The optimal average AoI exhibits linear growth with the number of nodes rather than exponential growth.

4) Comparison of the optimal configuration: Then, Fig. 5(b) shows the optimal update rate for different buffer capacities, specifically when $B \in \{1, 2, 3, \infty\}$. The optimal update rate for a general buffer capacity is bounded by the rates for $B = 1$ and $B = \infty$, and the gaps are quickly diminished when n is increased, and close to the optimal update rate $q^*_{B\to\infty}$. The results indicate the $q^*_{B\to\infty} = \min\left\{\frac{1}{n}, \delta\right\}$ can be a tight approximation for optimal update rate for $B > 1$, and the sub-optimal average AoI for general $B > 1$ can be obtained by combining the Theorem 1 and the optimal update rate $q^*_{B\to\infty}$.

V. Conclusion

We derive a closed-form expression for the average AoI with general energy buffer capacity, which is then optimized by adjusting the update rate. The results indicate that when the sum of the energy arrival rate of all nodes is greater than or equal to one and the energy buffer capacity is relatively larger, the optimal average AoI in the Aloha-based random access network powered by energy harvesters is (approximately) equivalent to that without energy constraints, by setting the update rate to one divided by the total number of nodes.

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