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METHODS

# Age of Information Joint Optimization for an Energy Harvesting Network With Erasure Channel

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**ABSTRACT** AoI (Age of Information), a measure of data freshness, is an important consideration in the optimal design of energy harvesting IoT(Internet of Things). Existing AoI studies tend to optimize only for the base station scheduling process or only for the source node update process, and rarely consider the energy constraints and unreliable channels. Therefore, a joint optimization strategy is proposed for an energy harvesting IoT scenario based on heterogeneous source nodes with erasure channels. Based on the energy constraint and channel quality, the base station selects the preferred source node for sample transmission based on the difference in AoI benefit and time cost brought by selecting different source nodes. The source node determines the sample collection moment by taking into account the impact of energy harvesting on the sample collection and transmission, as well as the impact of sample collection on the AoI. Simulation analysis shows that the method can obtain better long-term average AoI in different scenarios than baseline methods.

**INDEX TERMS** Age of information, energy harvesting network, sampling strategy, scheduling strategy, erasure channel.

## I. INTRODUCTION

The data generated by the Internet of Things (IoT) is growing exponentially with the increasing use of IoT in life. In an IoT system, various physical devices can collect and sense various data in the environment through sensors and embedded chips, which are transmitted to base stations (BSs). In some IoT scenarios, BSs must make timely decisions based on the received data samples. Therefore, in such IoT scenarios, BSs are particularly sensitive to the freshness of data. AoI (age of information), a new IoT metric [1], [2], has been used to measure the freshness of data samples in scenarios. AoI optimization can effectively improve the timeliness of information. This is critical for many real-time applications, such as in-vehicle sensor IoT and IoT sensor data monitoring. Optimizing AoI ensures that the BS gets the freshest possible information to make timely decisions or take action.

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In the domain of unmanned aerial vehicles, [3] proposed a deep learning-based AoI optimization method for UAV networks, This method aims to reduce the AoI of UAVs while conserving energy. Reference [4] introduced the concept of AoI into cellular wireless networks and compare the worth of the AoI metric with the value-of-information(VoI) metric. Reference [5] incorporated the concept of AoI into vehicular networks and studying the problem of vehicles' power minimization while ensuring stringent latency and reliability constraints in terms of probabilistic AoI. Unlike traditional latency metrics [6], AoI focuses on the time elapsed from samples generation to the current moment.

In IoT, sensors as source nodes (SNs) are generally passive, and charging or replacing batteries for them is highly inefficient. Configuring the SN with an energy harvester that allows it to receive energy from the environment or the radio frequency(RF) of the BS will effectively solve the energy problem of the SN to extend its lifetime. In the IoT with energy harvesting capability, when the SN samples and transmits samples to the BS are subject to the constraints of energy harvesting rate. This poses a great challenge to minimize the AoI of the whole network.

Existing AoI optimization studies mainly design samples queuing strategies or sampling strategies in terms of the update strategy for the SN to optimize the waiting time of samples, or optimize the transmission interval of samples in terms of the scheduling strategy for the BS. Such studies usually simplify the model at the other aspect. Thus, the possible AoI optimization space at the other aspect tends to be ignored. Meanwhile, most of the existing studies also design optimization strategies from ideal channel scenarios with isomorphic SNs, which deviates significantly from the actual scenarios. Therefore, this paper is dedicated to designing a two-side joint optimization strategy for an energy harvesting AoI scenario with heterogeneous SNs and erasure channel to optimize the overall AoI of the network.

## II. RELATED WORK

SN packet management queuing system is one of the focuses of AoI optimization. Reference [7] studied the average AoI of a random update transport system with a hybrid automatic repeat request (HARQ) feature under the M/G/1/1 queuing model, and comparatively analyzed the optimization effect of the infinite incremental redundancy (IIR) and fixed redundancy (FR) HARQ system for AoI. Reference [8] comparatively studied the average AoI and peak AoI under the First-Come-First-Served (FCFS) GI/GI/1 queue, M/GI/1 queue, and GI/M/1 queue models. Reference [9] investigated the average AoI of the Tandem queue, and evaluated the effect of the number of hops in the transport network on the AoI of the various models. Reference [10] focused on the average AoI and peak AoI of Ber/G/1 queues in discrete-time scenarios and derived their explicit expressions. Such studies mainly start from the arrival model and service model of the samples updating and mostly consider scenarios with one SN and ideal channel. In [11], the AoI optimization in scenarios with multiple heterogeneous sampling sources is considered and a new near-optimal low-complexity scheduling algorithm is provided. In [12], considering the impact of sample squeezing, a preemptive online link resource allocation algorithm based on a greedy strategy is proposed for dynamic channel scenarios. Zhiyuan Jiang et al. proposed a single-packet buffer polling strategy RR-ONE for multi-source single-hop IoT networks and proved that it is the optimal strategy among the arrival-independent renewal strategies in [13]. In [14], based on [13], dynamic terminal scenarios are further considered and an implementation of RR-ONE that can be adapted to dynamic terminals with less overhead is proposed. All the above studies consider the channel to be ideal and do not take into account the energy factor, although the update strategy of the SN and the BS scheduling strategy is considered.

Some AoI optimization studies for energy harvesting IoT scenarios also exist. In [15], Wu et al. considered a single-source scenario in which energy harvesting sensors continuously monitor the system and send time-stamped state updates to the destination and investigated the SN update strategy for minimizing the long-term average AoI for three battery capacity scenarios, such as infinite, finite, and only one cell, respectively. Arafa et al. [16] extended Jing Yang's results and proved that the optimal update strategy has a multi-threshold structure under a limited battery capacity and an incremental battery recharge model, where the SN updates and transmits samples only when the AoI reaches a threshold. Based on [16] and [17] considered a random battery recharge model. In [18] and [19], the best optimization strategy for AoI is studied under noisy channels with and without feedback, respectively. In [20], Bacinoglu and Uysal-Biyikoglu proposed that the optimal update strategy is a threshold strategy for transmitter-assisted transmission scenarios. Furthermore, Bacinoglu et al. proposed an AoI threshold expression in [21] and stated that minimizing the average AoI is equivalent to solving the optimal threshold problem for the highest energy state. In [22], two schemes (the energy-incentive scheme and price-incentive scheme) are designed, and the variation patterns of AoI gain and energy gain with the distance between the SN and the BS are discussed. In [23], a state update information system consisting of two SNs and a BS is designed, and by proposing the sensor energy harvesting model that can be represented by the Markov chain (MC), the construction method of the transition matrix of the sensor battery energy states as well as the stationary distributions are built. The above studies tend to consider single-source or two-source systems and optimize the AoI unilaterally only from the SNs or the BS.

The contributions of this paper are summarized below:

1) The variation of long-term average AoI is analyzed for an energy harvesting IoT scenario based on heterogeneous SNs with erasure channels.
2) Based on the scheduling process of the BS and the samples updating process of the SN, the AoI is evaluated, and then an AoI minimization strategy that combines the SN sampling strategy and the BS scheduling strategy is proposed.
3) The effectiveness of our method in optimizing the long-term average AoI of the network is verified through simulation experiments.

## III. SYSTEM MODEL

Consider a single-hop wireless network depicted in Fig.1, comprising of $I$ heterogeneous IoT SNs and a BS. Each SN collects sample data that is sensitive to freshness from its respective environment and stores it in its cache, awaiting transmission scheduling by the BS. Each SN can cache a maximum of one sample, and when a new sample arrives, it overwrites the previous one. When the BS schedules a SN for sample transmission, the SN utilizes its energy to transmit the sample. The relationship between the BS and the SNs is characterized by a non-preemptive half-duplex erasure channel, meaning that the BS can only transmit with one SN

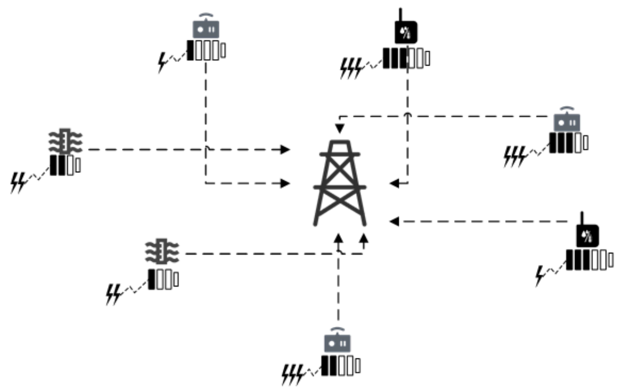

**FIGURE 1.** Schematic diagram of energy harvesting IoT.

at a time, and there is a possibility of transmission failure. In case of transmission failure, the SN retransmits the sample.

The time is discretized into multiple time slots, with each time slot represented by $TTI$. The BS's communication of information and scheduling decisions to the SN is insignificantly small compared to the time required for sample transmission. A SN utilizes a certain number of time slots to transmit a sample to the BS.

The SN is equipped with a battery that has an upper capacity limit and an energy harvester to gather natural energy from the environment. This harvested energy can be utilized for collecting samples or transmitting them. If the SN's battery reaches its full capacity, any additional incoming energy packets are discarded. Once the SN meets the energy condition, it has the flexibility to collect sample or accept scheduling from the BS for transmission at any given time. It's important to note that the energy collection and sample collection processes at the SN on non-orthogonal channels, meaning that the SN cannot simultaneously collect energy and collect or transmit sample.

In this paper, our objective is to minimize the average long-term AoI for the entire network. To achieve this, we explore a joint optimization strategy involving both the BS scheduling and the SN sampling strategy in this IoT scenario.

## IV. AOI MODEL AND PROBLEM DESCRIPTION

Let $S_i$ denote the $i-th$ SN, which is equipped with a battery of capacity $B_i$. The energy harvesting process of $S_i$ can be modeled as a Poisson process, where energy arrives at a rate of $\lambda_i$. Use $E_i(t)$ to represent the amount of energy available to $S_i$ at time slot $t$. Moreover, the energy required for $S_i$ to collect a sample is denoted as $Ec_i$. When $E_i(t) \geq Ec_i$, $S_i$ can collect a new sample at any given time. Additionally, it takes one time slot for each SN to collect a sample.

Using $U_i^s(t)$ to represent the generation time of the cached sample of $S_i$ at time slot $t$, and $A_i^s(t)$ to denote the AoI of the sample cached by $S_i$ at time slot $t$, we have the following relationship:

$$A_i^s(t) = t - U_i^s(t). \tag{1}$$

When the BS has an available transmission channel, it chooses a SN to transmit its cached samples. The transmission delay for each SN may vary due to realistic factors such as transmit power, distance from the BS, sample size, and more. Denote the transmission delay of $S_i$ for transmitting one sample to the BS as $d_i$, and the energy spent by $S_i$ to transmit one sample as $Et_i$. $S_i$ can only receive scheduling from the BS for sample transmission if $E_i(t) \geq Ec_i$.

Let the probability of failure when $S_i$ transmits a sample be $\rho_i$. Since the SN transmits with the BS over a half-duplex channel, when the transmitted sample is lost, the SN receives feedback from the BS only after it has sent the sample in its entirety. When the BS gives feedback that the transmission has failed, the SN collects the energy and retransmits the sample.

When the $S_i$ successfully transmits the latest sample to the BS, the corresponding old sample stored in the BS cache for $S_i$ will be overwritten by the new sample. To represent this, use $z_i(t)$ as an indicator variable that denotes whether $S_i$ successfully transmits a sample to the BS at time slot $t$. Specifically, $z_i(t) = 1$ indicates a successful transmission by $S_i$ at time slot t. Since at most one sample can complete transmission in a time slot, the indicator variable $z_i(t)$ satisfy the following constraints:

$$0 \leq \sum_{i=1}^{I} z_i(t) \leq 1. \tag{2}$$

Use $U_i^b(t)$ to represent the generation time of the sample for $S_i$ in the BS cache at time slot $t$. $U_i^b(t)$ can be determined using equation (3).

$$U_i^b(t) = \begin{cases} U_i^b(t-1), & z_i(t) = 0 \\ U_i^s(t), & z_i(t) = 1. \end{cases} \tag{3}$$

Use $A_i^b(t)$ to denote the AoI of the sample cached by $S_i$ at the BS at time slot $t$. The AoI of the sample cached by BS at time slot t is closely related to the AoI of the sample cached by $S_i$. The value of $A_i^b(t)$ is updated to the AoI of the new sample only when $S_i$ successfully transmits a new sample to the BS. In this case, $A_i^b(t)$ is set to the AoI of the new sample. Otherwise, if $S_i$ does not transmit a new sample, $A_i^b(t)$ increases with time at a rate of 1. Therefore, $A_i^b(t)$ can be calculated using equation (4).

$$A_i^b(t) = t - U_i^b(t) = \begin{cases} A_i^b(t-1) + 1, & z_i(t) = 0 \\ A_i^s(t), & z_i(t) = 1. \end{cases} \tag{4}$$

By substituting equation (1) into equation (4), we can derive the following equation (5).

$$\begin{aligned} A_i^b(t) = [1 - z_i(t)] * \left[A_i^b(t-1) + 1\right] \\ + z_i(t) * \left[t - U_i^s(t)\right]. \end{aligned} \tag{5}$$

Using $\overline{A}(t)$ to denote the average AoI of the samples from $I$ SNs cached by the BS at time slot $t$, we have:

$$\overline{A}(t) = \frac{1}{I}\sum_{i=1}^{I} A_i^b(t), (i \in I). \tag{6}$$

By substituting equation (5) into equation (6), we obtain:

$$\overline{A}(t) = \frac{1}{I}\sum_{i=1}^{I}\{[1 - z_i(t)] * \left[A_i^b(t-1) + 1\right] + z_i(t) * \left[t - U_i^s(t)\right]\}, (i \in I). \tag{7}$$

From equation (7), it can be observed that the variation of $\overline{A}(t)$ is related to $A_i^b(t)$. Only when there is a SN transmitting new sample to the BS, $\overline{A}(t)$ will be updated as a result of this transmission. Otherwise, $\overline{A}(t)$ increases at a rate of 1 per time slot.

Table 1 lists the changes in $S_i$ and the BS AoI when $S_i$ starts transmitting sample at moment t and finishes transmitting sample at moment $t + d_i$. It can be seen that $U_i^s(t)$ remains unchanged at all time, while $U_i^b(t)$ is replaced by the generation time of the new sample at the end of the transmission. $A_i^s(t)$ and $A_i^b(t)$ grows at a rate of rate 1 over time, and at the end of the transmission, the $A_i^b(t)$ is updated to the AoI of the last transmitted sample of $S_i$.

**TABLE 1. Schematic of parameter changes with time.**

| $T$ | $U_i^s(T)$ | $A_i^s(T)$ | $U_i^b(T)$ | $A_i^b(T)$ |
|---|---|---|---|---|
| $t$ | $U_i^s(t)$ | $A_i^s(t)$ | $U_i^b(t)$ | $A_i^b(t)$ |
| $t+1$ | $U_i^s(t)$ | $A_i^s(t)+1$ | $U_i^b(t)$ | $A_i^b(t)+1$ |
| $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ | $\cdots$ |
| $t+d_i-1$ | $U_i^s(t)$ | $A_i^s(t)+d_i-1$ | $U_i^b(t)$ | $A_i^b(t)+d_i-1$ |
| $t+d_i$ | $U_i^s(t)$ | $A_i^s(t)+d_i$ | $U_i^s(t)$ | $A_i^s(t)+d_i$ |

Use $\overline{A^B}$ to denote the long-term average AoI of the BS, which can be calculated by equation (8).

$$\overline{A^B} = \lim_{T\to\infty}\frac{1}{T} * \sum_{t=1}^{T}\overline{A}(t). \tag{8}$$

The optimization objective of this paper is to minimize the $\overline{A^B}$. In the context of BS scheduling, the optimization problem associated with $\overline{A^B}$ involves selecting the appropriate SN for the next transmission when the BS is not engaged.

Fig.2 illustrates the change in AoI for two sample transmissions occurring at the long term $T$ where $x_n$ denotes the start time of the $n-th$ sample transmission from the BS, which is the end point of the $(n-1)-th$ sample transmission.

Denote the area of the graph enclosed by the $overset-A(T)$ curve with the horizontal coordinate on the time interval

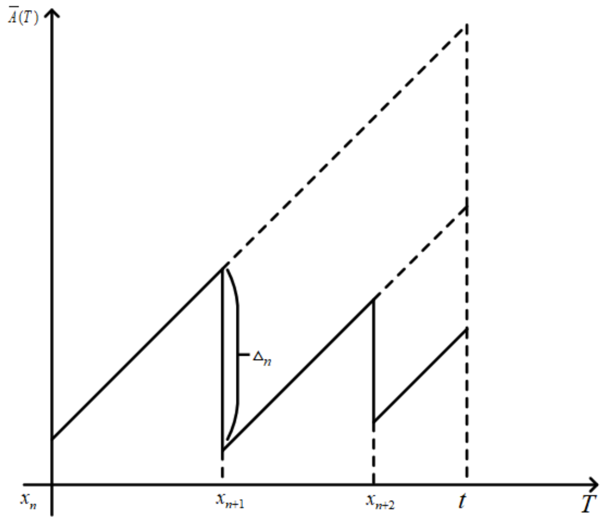


**FIGURE 2. Schematic diagram of AoI.**

$[x_n, t]$ as $S_{x_n}^t$. If no new sample arrive during the interval $[x_n, t]$, $S_{x_n}^t$ can be computed using equation (9).

$$S_{x_n}^t = \left[2\overline{A}(x_n) + t\right] * t/2. \tag{9}$$

When a new sample arrives at the moment $x_{n+1}$, the average AoI $\overline{A}(x_{n+1})$ is less than $\overline{A}(x_n)+(x_{n+1}-x_n)$ because the fresh sample's AoI is updated. We can use $\Delta_n$ to represent the reduction in $\overline{A}(x_{n+1})$ caused by the transmission of the $n-th$ sample. From Fig.2, it can be observed that $\Delta_n$ can be calculated using equation (10).

$$\Delta_n = \overline{A}(x_n) + (x_{n+1} - x_n) - \overline{A}(x_{n+1}). \tag{10}$$

Assuming that only one transmission occurred in the interval $[x_n, t]$, $S_{x_n}^t$ can be determined by equation (11).

$$S_{x_n}^t = \left[t/2 * \left(2\overline{A}(x_n) + t\right)\right] - \Delta_n * [t + (x_{n+1} - x_n)]. \tag{11}$$

Further observation of Fig.2 shows that $S_{x_n}^t$ decreases further if a second sample arrival occurs in the interval $[x_n, t]$. Thus, the optimization problem of $\overline{A^B}$ can be transformed into a minimization problem of $S_0^T$ when $T$ is long enough.

The meaning of the symbols used in this paper is shown in the Table 2.

## V. DESIGN OF THE JOINT OPTIMIZATION STRATEGY

### A. BS SCHEDULING STRATEGY

The value of $S_0^T$ is primarily influenced by two factors: the gain $\Delta_n$ resulting from sample transmission and the transmission delay $x_{n+1} - x_n$. A larger $\Delta_n$ or a smaller $x_{n+1} - x_n$ are both advantageous for optimizing $S_0^T$.

In accordance with equation (7), the change in $\Delta_n$ is solely related to the update of the AoI by the SN that completes the sample transmission. We can use $\Delta_i^n$ to represent the

**TABLE 2.** Symbol table.

| | |
|---|---|
| $TTI$ | time slot |
| $S_i$ | the $i-th$ SN |
| $B_i$ | battery capacity of the $i-th$ SN |
| $\lambda_i$ | energy arrival rate of $S_i$ |
| $E_i(t)$ | the amount of energy available to $S_i$ at time slot $t$ |
| $Ec_i$ | the energy required for $S_i$ to collect a sample |
| $Et_i$ | the energy spent by $S_i$ to transmit one sample |
| $d_i$ | the transmission delay of $S_i$ |
| $\rho_i$ | the probability of failure when $S_i$ transmits a sample |
| $z_i(t)$ | an indicator variable that denotes whether $S_i$ successfully transmits a sample to the BS at time slot $t$ |
| $U_i^s(t)$ | the generation time of the cached sample of $S_i$ at time slot $t$ |
| $A_i^s(t)$ | the AoI of the sample cached by $S_i$ at time slot $t$ |
| $U_i^b(t)$ | the generation time of the sample for $S_i$ in the BS cache at time slot $t$ |
| $A_i^b(t)$ | the AoI of the sample cached by $S_i$ at the BS at time slot $t$ |
| $\overline{A}(t)$ | the average AoI of the samples from $I$ SNs cached by the BS at time slot $t$ |
| $\overline{A}^B$ | the long-term average AoI of the BS |
| $x_n$ | the start time of the $n-th$ sample transmission |
| $S_{x_n}^t$ | the area of the graph enclosed by the $overset{-}A(T)$ curve with the horizontal coordinate on the time interval $[x_n, t]$ |
| $\Delta_i^n$ | the value by which $A_i^b(x_{n+1})$ changes when $S_i$ is chosen for the $n-th$ sample transmission |
| $\omega_i$ | The time to wait for the energy to be collected to initiate the next transmission after a failed transmission of $S_i$ |
| $\mathbb{E}(x_n)$ | expected start time of the nth transmission |
| $\pi_n^i$ | sampling feasible time interval for the $i-th$ transmission $S_i$ |
| $l_n^i$ | The left endpoint of this interval |
| $r_n^i$ | The right endpoint of this interval |
| $C_n^i$ | the sampling time point of $S_i$ during the $n-th$ transmission |

value by which $A_i^b(x_{n+1})$ changes when $S_i$ is chosen for the $n-th$ sample transmission. This change can be calculated using equation (12).

$$\Delta_i^n = A_i^b(x_n) - A_i^s(t) = A_i^b(x_n) - x_n + U_i^s(t). \tag{12}$$

It is indeed advantageous for AoI optimization to select the SN with a larger $\Delta_i^n$ for transmission. Considering the possibility of failure during sample transmission between the SN and the BS, the expectation value $\mathbb{E}(x_{n+1} - x_n)$ is used instead of the sample transmission delay. Choosing the SN that minimizes $\mathbb{E}(x_{n+1} - x_n)$ for transmission can be beneficial for AoI optimization. Therefore, the scheduling strategy of the BS can be designed as follows: when the BS is idle, it selects the SN that maximizes $\Delta_i^n - \mathbb{E}(x_{n+1} - x_n)$ for transmission.

The problem of calculating $\mathbb{E}(x_{n+1} - x_n)$ is considered below. The time $\omega_i$ to wait for the energy to be collected to initiate the next transmission after a failed transmission of $S_i$ can be calculated by equation (13).

$$\omega_i = Et_i/\lambda_i. \tag{13}$$

When the transmission from $S_i$ fails $M$ times, the calculation of $\mathbb{E}(x_{n+1} - x_n)$ can be performed using equation (14).

$$\begin{aligned}\mathbb{E}(x_{n+1} - x_n) &= \lim_{M\to\infty}\sum_{m=0}^{M} m * \rho_i^m * (d_i + \omega_i) + d_i \\ &= \frac{\rho_i}{(1-\rho_i)^2} * (d_i + \omega_i) + d_i \\ &= \frac{\rho_i}{(1-\rho_i)^2} * (d_i + Et_i/\lambda_i) + d_i.\end{aligned} \tag{14}$$

Thus, the following equation (15) can be obtained.

$$\begin{aligned}\Delta_i^n - \mathbb{E}(x_{n+1} - x_n) &= \left[A_i^b(x_n) - x_n + U_i^s(t)\right] \\ &\quad - \left[\frac{\rho_i}{(1-\rho_i)^2} * \left(d_i + \frac{Et_i}{\lambda_i}\right) + d_i\right].\end{aligned} \tag{15}$$

### *B. SN SAMPLING POLICY*

From equation (15), it can be observed that the magnitude of $\Delta_i^n$ on the left-hand side of the equation depends on the sampling strategy of the SNs. Specifically, the closer $U_i^s(x_n)$ is to $x_n$ at the moment $x_n$, the larger the value of $\Delta_i^n$ will be. Therefore, even after specifying the BS scheduling strategy, it is still possible to reduce the value of $\overline{A}^B$ by optimizing the sampling strategy of SNs. Considering the definition of AoI, in order to minimize the AoI of the sample cached by the SN before transmission, the SN should collect the sample as late as possible before accepting the BS's scheduling. However, the sample collection is constrained by the available energy, and the potential energy waste after the battery is full should also be taken into account during the sampling strategy optimization.

Under the assumption that the energy harvesting process of $S_i$ follows a Poisson process with a rate of $\lambda_i$, the energy expectation of $S_i$ after $k$ time intervals at time t can be computed using equation (16). The sampling strategy of the SN is then designed based on this energy expectation.

$$E_i(t+k) = E_i(t) + \lambda_i * k. \tag{16}$$

When the BS initiates the $n-th$ transmission and the current selection is $S_j$, all SNs consider the completion of this transmission as the desired time point for the BS to start the $(n+1)-th$ transmission. This desired time point, denoted as $\mathbb{E}(x_{n+1})$, can be expressed using equation (17).

$$\mathbb{E}(x_{n+1}) = x_n + d_j. \tag{17}$$

To ensure that the SN can provide fresh samples at the moment $\mathbb{E}(x_{n+1})$, it should collect the fresh samples within the interval $[x_n, \mathbb{E}(x_{n+1})]$ and gather the necessary energy for transmitting the samples in advance. This is done to prevent the samples from being unable to be sent due to insufficient energy. The energy constraint imposed on $S_i$ within the interval $[x_n, \mathbb{E}(x_{n+1})]$ can be calculated as in equation (18) based on the energy required for collecting and transmitting the samples.

$$E_i(x_n) \geq Ec_i + Et_i - (\mathbb{E}(x_{n+1}) - x_n - 1) * \lambda_i. \tag{18}$$

When $S_i$ satisfies the energy constraints specified in equation (18), it means that $S_i$ can gather sufficient energy to collect and transmit fresh sample within the interval $[x_n, \mathbb{E}(x_{n+1})]$. In other words, the energy available to $S_i$ is capable of meeting the requirements for both sample collection and transmission during that interval.

To determine the sampling time point for $S_i$, it is essential to establish the feasible time interval for sampling during the

$n-th$ sample transmission. This interval is denoted as $\pi_n^i$. The left endpoint of this interval, represented as $l_n^i$, signifies the earliest possible time point for $S_i$ to be sampled in the context of the $n-th$ sample transmission from the BS. It indicates the starting time of the feasible sampling interval for $S_i$.

For $S_i$ that satisfies the constraints, $l_n^i$ corresponds to the moment when the energy within the interval $[x_n, \mathbb{E}(x_{n+1})]$ first meets the condition for sampling energy. Thus, $l_n^i$ can be determined using equation (19).

$$l_n^i = x_n + \frac{Ec_i - E_i(x_n)}{\lambda_i}. \tag{19}$$

According to the definition of AoI, the later $S_i$ is sampled in the interval $\pi_n^i$, the fresher the sample is. The right endpoint of $\pi_n^i$ is denoted as $r_n^i$. Since sampling a sample requires 1 time slot, $S_i$ should start sampling at the latest at the moment $\mathbb{E}(x_{n+1}) - 1$ in order to complete the sample collection at the moment $\mathbb{E}(x_{n+1})$. However, for the SN $S_i$ with a battery capacity less than $Ec_i + Et_i$, and satisfying the energy constraint (18), if the energy is not used for sampling and instead remains unused when the battery is full, any newly arrived energy packets will be discarded because there is no space to store them. This results in energy wastage. Consequently, there may not be enough time to collect the energy required for transmitting the sample before $\mathbb{E}(x_{n+1}) - 1$. Therefore, for $S_i$ with $B_i < Ec_i + Et_i$, $r_n^i$ can be calculated using equation (20).

$$r_n^i = \mathbb{E}(x_{n+1}) - \frac{(Et_i - B_i + Ec_i)}{\lambda_i} - 1. \tag{20}$$

Therefore, the feasible sampling interval $\pi_n^i$ for $S_i$, which satisfies the energy constraints (18), within the interval $[x_n, \mathbb{E}(x_{n+1})]$, can be expressed as:

$$\pi_n^i = \begin{cases} \left[x_n + \dfrac{[Ec_i - E_i(x_n)]}{\lambda_i}, \mathbb{E}(x_{n+1}) - 1\right], \\ \qquad B_i \geq Ec_i + Et_i \\ \left[x_n + \dfrac{[Ec_i - E_i(x_n)]}{\lambda_i}, \mathbb{E}(x_{n+1}) - \dfrac{(Et_i - B_i + Ec_i)}{\lambda_i} - 1\right], \\ \qquad B_i < Ec_i + Et_i. \end{cases} \tag{21}$$

According to the definition of AoI, the SN should choose the latest time point, which corresponds to the right endpoint of the interval, for sampling. Denote the sampling time point of $S_i$ during the $n-th$ transmission as $C_n^i$, which can be expressed as:

$$C_n^i = \begin{cases} \mathbb{E}(x_{n+1}) - 1, & B_i \geq Ec_i + Et_i \\ \mathbb{E}(x_{n+1}) - \dfrac{(Et_i - B_i + Ec_i)}{\lambda_i} - 1, & B_i < Ec_i + EEt_i. \end{cases} \tag{22}$$

For $S_i$ that does not satisfy the energy constraints (18), it is necessary to collect the sample when the battery is full. This ensures that the excessively outdated samples in the cache are updated, and it helps maintain a high energy level to compete for the next transmission. In this case, $C_n^i$ can be determined using equation (23).

$$C_n^i = \{t | E_i(t) = B_i, x_n \leq t \leq \mathbb{E}(x_{n+1})\}. \tag{23}$$

Therefore, based on the energy constraint (18), the SN adopts a half-cycle half-threshold sampling strategy. This means that when the energy constraints are satisfied, the SN collects sample according to the threshold determined by equation (22). On the other hand, when the energy constraints are not satisfied, the SN collects sample according to the time points determined by equation (23). This strategy allows for efficient sample collection while considering the energy limitations of the SN.

In summary, based on the aforementioned SN sampling strategy and BS scheduling policy, this paper proposes a joint optimization strategy algorithm in erasure channels(JOSEC). In the event of an idle BS channel with multiple SNs requiring sample uploads, the BS selects SNs with smaller $\Delta_i^n - \mathbb{E}(x_{n+1} - x_n)$ values for transmission. This choice aims to strike a balance between minimizing transmission delays and achieving superior AoI optimization effects. The SNs utilize the BS's broadcast to predict the next available idle time of the BS channel. Subsequently, based on SNs own energy conditions, SNs proactively collect samples in advance, enabling to compete for sample uploads during the next idle period of the BS channel.

Diverging from conventional algorithms that solely prioritize AoI optimization, JOSEC takes into account not only the AoI but also factors such as transmission delay, energy levels, and sample erasure probability for each SN. While scheduling a SN with a larger AoI to transmit new samples may be advantageous for reducing the average AoI at the BS, neglecting the time cost of transmission might result in the suboptimal selection. The JOSEC algorithm effectively mitigates this by considering both AoI and transmission time costs, ensuring a more comprehensive optimization outcome when compared to algorithms solely focusing on AoI.

To describe our algorithm, we utilize the notation $F(t)$ to denote the index of the SN to which the sample being transmitted by the BS at time t belongs. When $F(t) = 0$, it indicates that the channel of the BS is idle. Additionally, we employ $Bc(t)$ to represent the transmission completion prediction time of the BS's broadcast at time t, and $St_i(t)$ to denote the sampling time point computed by $S_i$ using the JOSEC algorithm.

The specific process is shown in Algorithm 1.

## VI. RESULTS AND DISCUSSION

The simulation is run on a PC with 64-bit Windows 11 operating system with Intel (R) Core (TM) i7-7700HQ, CPU 2.81GHz and 16gb of RAM. The experimental code is written in Java 17.

### A. SCENARIO SETUP AND BASELINE METHODOLOGY

This experiment simulated the scenario of multiple SNs and a single BS transmitting in an erasure channel within an energy

**Algorithm 1** JOSEC

Enter *TTI* $t$.
if($F(t) == 0$)
    BS Select the SN with the largestwith the largest $\Delta_i^n - \mathbb{E}(x_{n+1} - x_n)$ for sample uploading.
    $F(t) = i$
    Broadcast $Bc(t)$.
else
    Resume the incomplete transmission.
end if
for(SNs)
    Collect energy and update status
    Set $St_i(t) = C_n^i$ based on the $Bc(t)$.
    if($St_I(t) == t$)
        Collect samples.
    end if
Enter the next *TTI*.

harvesting IoT context. To demonstrate the optimality of the proposed algorithm in this paper, simulations were conducted across various time scales, different numbers of source nodes in the IoT network, varying energy harvesting rates, diverse channel erasure probabilities, and different battery capacity sizes. The data presented in this paper represents the average values obtained from 100 simulation runs over a time span of 10,000 time slots. This approach was adopted to eliminate the impact of incidental factors and ensure the validity of the experimental data.

In order to increase the realism of the experimental scenario, a SN library containing 100 SNs is generated with randomly assigned values for various indicators. In a realistic scenario, the energy consumption of communication between SNs and the BS depends on factors such as transmission distance, transmission rate, and packet size. Additionally, differences in sensor types, operating modes, communication protocols, and data volume sizes among different SNs lead to variations in the sizes of data sample packets. To simulate this diversity and uncertainty, we randomly assign values to the indicators of the SNs in the library. Specifically, the battery size of each SN is randomly set between 10 and 15 units of capacitance size. The energy consumed for collecting and transmitting samples is randomly distributed between 5 and 10 energy units. The energy collection rate is randomly assigned between 3 and 5 energy units. The transmission delay is randomized between 2 and 5 *TTI*s.

In order to evaluate our method (JOSEC,denoted as M1), the following three baseline methods were chosen:

1) The SN sampling strategy use our half-cycle half-threshold sampling strategy and replace the BS scheduling strategy with a greedy strategy that selects the largest AoI value for the BS cache (Denoted as M2).
2) The BS scheduling strategy use our scheduling strategy based on the greedy strategy and replace the SN sampling strategy with a full energy sampling strategy. (Denoted as M3).
3) The RRONE algorithm from literature [14] is used, where the SN retains the latest samples and the BS is polled for scheduling (Denoted as M4).

Among the mentioned baseline methods, M2 and M3 are considered as ablation comparisons. They individually study the optimization effects of the BS scheduling strategy and the SN updating strategy of the proposed algorithm, respectively. The M4 method is the most available method under ideal channel conditions without energy constraints, and a comparison with the M4 method shows the optimization of our method under unreliable channels with energy constraints. By considering different aspects and variations in these baseline methods, we aim to provide a comprehensive evaluation of the proposed algorithm and its optimization effects in various scenarios, including energy-constrained environments and erasure channels commonly found in IoT applications.

### B. EFFECT OF DURATION

Fig.3 presents the results of experiments conducted to analyze the variation of the long-term average AoI at the BS over a duration of $5\times10^4$ *TTI*s. The experiments involve selecting 50 SNs from the SN library. The observations from Fig.3 indicate that, after an initialization period, the long-term average AoI of the BS for all methods reaches a stable value. Furthermore, the AoI of the BS achieved by our method (M1) outperforms the other three algorithms significantly.

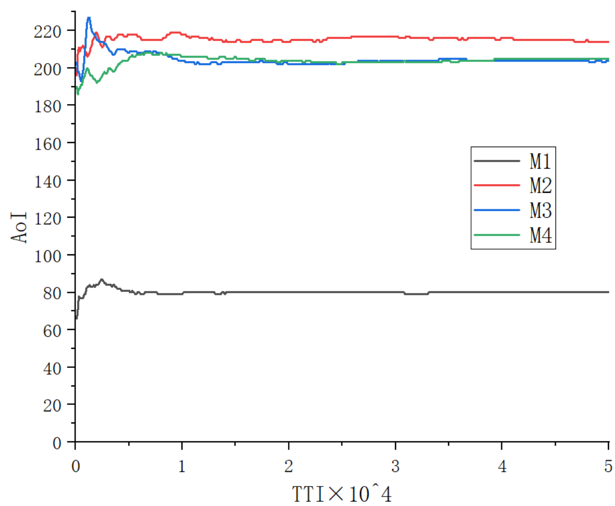


**FIGURE 3.** Variation of AoI with 50 SNs at long period of time.

M2 has the worst effect. Because it does not consider the influence of channel quality and energy constraints, nor does it consider whether the SN cache sample is too old. M3 uses our SN optimization strategy and achieves better results than M2. However, it uses the BS scheduling strategy based on polling so as to achieves lower effect than M1. The above experimental results and analysis show that it is necessary to jointly optimize the SN sampling strategy and the BS scheduling strategy. The results shown in Fig.3 also show that our method is superior to the existing method (M4).

### C. EFFECT OF NUMBER OF SNS

Fig.4 displays the long-term average variation of AoI at the BS. The variation is observed as the number of SNs increases from 10 to 100 with a step of size 10. As can be seen from Fig.4, for different number of SNs, the AoI obtained by our method is better than the other three methods. Moreover, as the number of SNs increases, the advantage of our method becomes more obvious. Therefore, it can be considered that our method is more suitable for large-scale energy harvesting IoT.

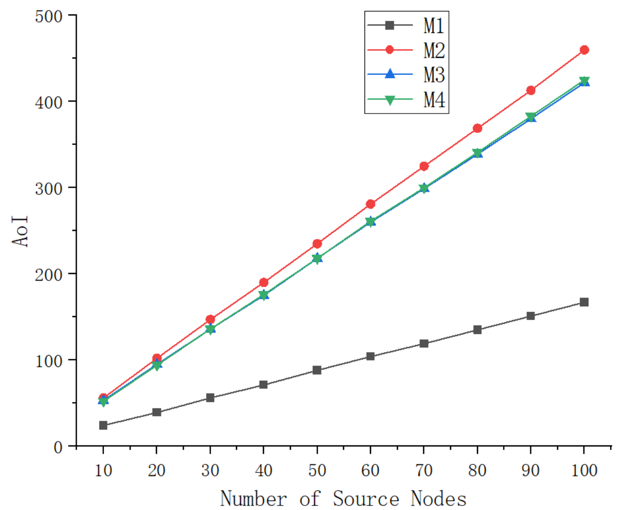


**FIGURE 4.** Variation of AoI with difference in number of SNs.

### D. EFFECT OF ENERGY HARVESTING RATE

Fig.5 also randomly selects 50 SNs from the SN library and examines the variation of AoI under different SN energy collection rates ranging from 1 to 15. The experimental results show that our method is superior to the other three methods regardless of the energy harvesting rate. Meanwhile, for all methods, AoI tends to be stable as the energy harvesting rate increases. This shows that the influence of energy constraint on AoI optimization is significantly reduced when the energy collection rate is high.

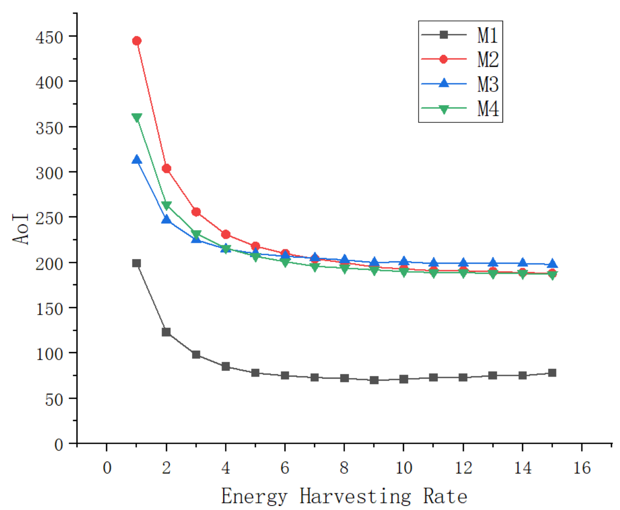


**FIGURE 5.** Variation of AoI with difference in energy harvesting rate.

With the increase in energy harvesting rate, the energy constraints on sample collection and transmission at the SNs are reduced. When the energy harvesting rate at the SNs is sufficiently high to mitigate the impact of energy limitations on sample collection and transmission behavior, the M1 method enables each SN to provide fresh samples in the next transmission. Additionally, the BS can select, disregarding energy constraints, the SN that offers the best AoI optimization effect for transmission, resulting in the optimal performance.

In the M2 method, although each SN can provide fresh samples in the next transmission, the BS only greedily selects the next transmission SN based on the AoI value, neglecting the influence of channel erasures. Under the condition of no energy constraints, this approach approximates a round-robin schedule, which falls short in terms of optimization effectiveness.

In the M3 and M4 methods, the sampling strategy of the SNs leads to frequent sampling at high energy harvesting rates. However, due to the absence of prediction regarding the start time of the next transmission, many SNs are in a state of sampling or energy harvesting when the BS schedules the transmission of SNs. Consequently, they are not included in the scheduling process, and the BS can only select SNs with suboptimal optimization effects for transmission. As a result, the optimization effectiveness is inferior to that of the M1 method.

### E. EFFECT OF ERASURE RATE

Fig.6 illustrates the variation of the long-term average AoI for the four methods in the scenario of 50 SNs under different erasure probability channels. As observed in Fig.6, the AoI by the proposed method surpasses the other three methods across all erasure probability channels. Moreover, the higher the erasure probability, the better the optimization of our method.

### F. EFFECT OF BATTERY SIZE

Fig.7 illustrates the variation of the long-term average AoI for the four methods in the scenario of 50 SNs under different battery size. As observed in Fig.7, the size of the battery has a small effect on the AoI, except for M4 because the sampling strategy does not take into account the case where the battery capacity is smaller than the energy required to collect and transmit the samples, so the AoI also reaches stabilization when the size of the battery in the M4 control group is larger than the energy required to collect and transmit the samples.

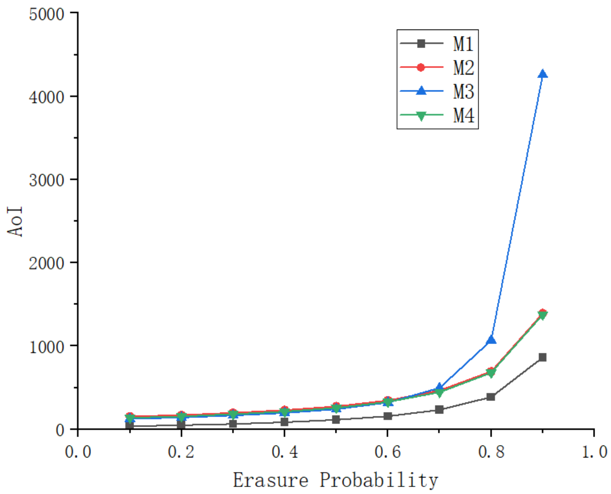


**FIGURE 6.** Variation of AoI with difference in erasure probability.

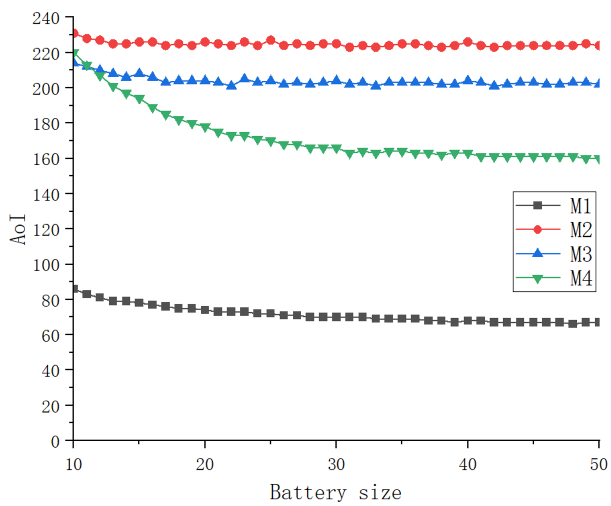


**FIGURE 7.** Variation of AoI with difference in battery size.

Therefore, the size of the battery causes little impact on the study of AoI in the scenarios of this paper

In summary, our presented method consistently exhibits superior AoI performance compared to the other methods, regardless of the erasure probability, and the performance gap widens with higher erasure probabilities.

## VII. CONCLUSION

Energy harvesting IoT is widely used, and AoI optimization is an important means to improve the freshness of data. This paper proposes an AoI minimization strategy combining SN sampling and BS scheduling. This strategy allows the SN to be heterogeneous and the channel between the SN and the BS to be unreliable. Simulation results show that the strategy can effectively optimize the long-term average AoI of the network with different numbers of SNs, different energy collection rates, and different channel quality.

In the future, we plan to extend the relevant research to multi-hop networks and incorporate the service life of networks into the optimization goals.

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