AoI Minimization Data Collection Scheduling for Battery-Free Wireless Sensor Networks

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Abstract—Age of Information (AoI) is a new metric for measuring the freshness of sensory data in wireless sensor networks. The Battery-Free Wireless Sensor Network (BF-WSN) is proposed to break through the lifetime limitation of battery-powered wireless sensor networks. However, the emerging BF-WSN also brings challenges to the minimization of AoI, on account of its energy characteristics. In this paper, we investigate the AoI minimization data collection scheduling problem for BF-WSNs. The off-the-shelf works for the AoI minimization data collection scheduling problem either focus on simple networks with no more than three nodes or assume that battery-free sensor nodes have specific energy harvesting process, such as Bernoulli process and Poisson process. Different from these works, we first consider the AoI minimization data collection scheduling for one-hop BF-WSNs with multiple battery-free sensor nodes transmitting their sensory data to the sink node, where the energy harvesting processes of battery-free sensor nodes are non-specific. We propose the optimal offline algorithm and the online algorithm for the problem, respectively. The optimality of the offline algorithm and the competitive ratio of the online algorithm are theoretical proved and analyzed. Numerical results are provided to verify the performances of the proposed algorithms.

Index Terms—Age of information, battery-free wireless sensor networks, data collection scheduling.

1 Introduction

Age of Information (AoI) is a new metric for measuring the freshness of sensory data in wireless sensor networks. AoI was first proposed in [1] [2] and has been receiving increasing attention since. AoI characterizes the freshness of sensory data from the destination's perspective and is defined as the time that elapsed since the last received sensory data was generated. Different from traditional packet-centric metrics, such as delay and throughput, AoI is a destination-centric metric. An increasing number of applications in wireless sensor networks require time-sensitive sensory data to improve the quality of service. What's more, stale sensory data is of little value to these applications. Therefore, plenty of works have been devoted to investigating the AoI minimization data collection scheduling problem in wireless sensor networks.

Energy supply is the major limitation in wireless sensor networks and restricts its wide applications to a certain extend. The energy supply in wireless sensor networks mainly relies on batteries equipped in sensors, which have limited battery capacity. Replacing batteries is necessary for network sustainability. However, it is difficult or even infeasible to replace batteries in many applications. To break through this limitation, the Battery-Free Wireless Sensor Network (BF-WSN) emerges in recent years. BF-WSNs are composed of battery-free sensor nodes, which can harvest energy from the sustainable power sources in their ambient environments instead of batteries, such as solar power [3] [4], wind power [5], and Radio Frequency (RF) signal power [6] [7], etc. To store the harvested energy, battery-free sensor nodes are equipped with capacitors which can be recharged infinitely.

Despite the sustainable energy supply from power sources in the ambient environments, the energy supply in BF-WSNs is uncontrollable and insufficient for continuous working. Therefore, the energy constraint is a major concern for the AoI minimization data collection scheduling problem in BF-WSNs. A few recent works start to investigate the AoI minimization data collection scheduling problem under an energy harvesting setting [8]–[17]. Most of the works only consider the simple scenario, where the network only consists of one battery-free sensor node transmitting its sensory data to one sink node. However, the methods proposed by these works are inapplicable to networks with multiple battery-free sensor nodes transmitting their sensory data to one sink node since the inevitable interference among transmissions is not considered in these methods. Besides, some existing works are proposed based on the assumption that the energy harvesting process of a battery-free sensor node follows a Bernoulli process [8] [9] or a Poisson process [10]–[13]. However, the scheduling algorithms proposed by these works may be infeasible for BF-WSNs with other energy harvesting processes.

In this paper, we solve the above problems and investigate the AoI minimization data collection scheduling

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problem in one-hop BF-WSNs. Transmission interference among multiple battery-free sensor nodes is considered in the data collection scheduling. We propose data collection scheduling algorithms for BF-WSNs with non-specific energy harvesting processes. The main contributions of this paper are as follows.

1) The problem of AoI Minimization Scheduling (AMS) to generate data collection schedules with minimum weighted sum of average peak ages for one-hop BF-WSNs, is formally defined.
2) An optimal offline algorithm is proposed for the offline version of the AMS problem, provided that the sink node has the global knowledge of the future energy profiles of all battery-free sensor nodes. The optimality of the offline algorithm is proved.
3) An online algorithm is proposed for the online version of the AMS problem, provided that the network has no knowledge of the future energy profiles of battery-free sensor nodes. The competitive ratio of the online algorithm is theoretically analyzed.
4) Numerical results are provided to evaluate the performances of the proposed algorithms.

The organization of this paper is as follows. In Section 2, we discuss the related works. Section 3 provides the formal definition of the AoI Minimization Scheduling (AMS) problem. The optimal offline algorithm and the online algorithm are proposed and analyzed in Section 4 and 5, respectively. In Section 6, numerical results are presented to verify the performances of the proposed algorithms. Finally, Section 7 concludes the paper.

2 Related Works

Age of Information (AoI) was first proposed in [1] [2], and has been receiving increasing attention since [18]–[20]. Plenty of works have been proposed to optimize AoI for data collection scheduling in wireless sensor networks [8]–[12], [14]–[17], [21]–[26], including battery-powered wireless sensor networks and battery-free wireless sensor networks.

2.1 Battery-Powered Wireless Sensor Networks

The works in [21]–[26] investigated the AoI optimization data collection scheduling problem in battery-powered wireless sensor networks. The work in [21] investigated to minimize the average age penalty of the status update packets transmitted by a single source node. It formulated the average age penalty minimization problem as a constrained semi-Markov decision process with an uncountable state space and proposed algorithms for the problem to find the optimal status update policy. The works in [22] and [23] investigated to optimize AoI in single-hop wireless sensor networks, where a number of sources transmitting their packets to one destination. The work in [22] considered the unreliable wireless channel, and proposed algorithms to minimize the expected weighted sum AoI of the network while satisfying both interference and throughput constraints. The work in [23] considered two optimization objectives, i.e., minimizing the total average peak age and the total average age of the sources. The work in [24] considered the scheduling for a mobile agent collecting data from multiple sources. It designed the trajectory for the mobile agent to minimize peak AoI and average AoI of the network. The work in [25] studied the minimum age transmission scheduling problem for multiple sender-receiver pairs. The authors proposed a randomized 2.733-approximation algorithm and a dynamic-programming-based exact algorithm to minimize the total age of all receivers at all time indices. The work in [26] investigated to minimize the peak age and average age in wireless sensor networks with multiple source-destination links. The authors considered two types of sources, i.e., active sources and buffered sources, and proposed scheduling policies for them. However, these works are not applicable to battery-free wireless sensor networks any more, on account of the energy characteristics of battery-free sensor nodes.

2.2 Battery-Free Wireless Sensor Networks

A few recent works have been proposed to investigate the AoI minimization data collection scheduling problem under an energy harvesting setting [8]–[12], [14]–[17]. These works considered the AoI minimization data collection scheduling problem in simple networks, which consists no more than three nodes. Most of the works assume that battery-free sensor nodes have specific energy harvesting process, such as the Bernoulli process and the Poisson process. Therefore, these works can be divided into two categories according to the energy harvesting process applied in these works.

The first category of works considered the BF-WSNs with battery-free sensor nodes having specific energy harvesting process. The work in [8] considered the transmission between one battery-free sensor node and one sink node and assumed that the energy harvesting process of the battery-free sensor node followed a Bernoulli process. The authors studied the AoI minimization scheduling problem for networks with an erasure channel. The work in [9] considered a more complex network with two source nodes and one common destination, where one source node is battery-free and the other one is battery-powered. The energy harvesting process of the battery-free sensor node is also assumed to follow the Bernoulli process. The authors investigated to minimize the delay and AoI in a multiple access channel. The following works considered the transmission between one battery-free sensor node and one sink node and assumed that the energy harvesting process of the battery-free sensor node followed a Poisson process. The authors in [17] considered the optimal online policies to minimize the long-term average AoI under three scenarios, i.e., the battery size of the source node is infinite, finite, and one unit only, respectively. The work in [10] studied to minimize the long term average AoI at the destination. It proved that the optimal policy was a renewal policy. The works in [11] [12] investigated to minimize the long-term average AoI for networks with noisy channel. An average-cost reinforcement learning algorithm was proposed in [14] to minimize the expected average AoI. Although assuming the specific energy harvesting process of battery-free sensor nodes can help to get better theoretical results. The assumption of battery-free sensor nodes with specific energy harvesting process may be invalid in most cases.

The second category of works considered the BF-WSNs with battery-free sensor nodes having non-specific energy harvesting process. The work in [15] first proposed an offline policy to minimize both the average AoI and the peak AoI for a simple network with one pair of transmitter-receiver. Then, it proposed a threshold policy to minimize the average AoI for the online problem, which achieved performance close to the offline policy. The work in [16] also considered the transmission between one battery-free sensor node and one sink node. The authors studied to minimize the average AoI for networks where the transmission delay was the function of the energy consumption for transmission. They formulated the problem under different scenarios and characterized the corresponding optimal solutions.

However, the networks in practice are more complex. In networks with multiple battery-free sensor nodes transmitting their sensory data to one sink node, the interference among these transmissions are inevitable. Since the above works did not consider interference among the simultaneous transmissions of multiple sensor nodes, they are not applicable for complex networks any more. Therefore, in this paper, we investigate the AoI minimization data collection scheduling problem in BF-WSNs with multiple battery-free sensor nodes having non-specific energy harvesting processes.

3 Problem Definition

3.1 System Model

In this paper, we consider a one-hop Battery-Free Wireless Sensor Network (BF-WSN) with one sink node, v_0, collecting time-sensitive sensory data from n battery-free sensor nodes, $V = \{v_1, v_2, \cdots, v_n\}$. We adopt a discrete-time system in this paper, where time is slotted into equal time slots and the length of each time slot is the time consumption for a battery-free sensor node generating and transmitting one sensory data packet to the sink node. We consider the scheduling for the network in T time slots and index the time slots by $1, 2, \cdots, T$. Without loss of generality, we assume that $T = mn + 1$, where $m \in \mathbb{N}$ and $m > n$ in general. In each time slot, the sink node can only receive one data packet from a single battery-free sensor node for transmission interference. We use an indicator $s_i(t)$ ($i = 1, 2, \cdots, n$) to denote the wireless channel assignment in time slot t. When $s_i(t) = 1$, the wireless channel is assigned to battery-free sensor node v_i in time slot t for transmitting its sensory data packet to the sink node, and $s_i(t) = 0$ otherwise. Due to the transmission interference, the indicators in time slot t satisfy that

$$\sum_{i=1}^{n} s_i(t) \leq 1, \quad \forall t \in \{1, 2, \cdots, T\}. \tag{1}$$

Besides, we assume that the wireless channel in the BF-WSN is reliable [13] [17] [25], thus each sensory data packet transmitted by a battery-free sensor node v_i in time slot t can be successfully received by the sink node if $s_i(t) = 1$ and $\sum_{j=1}^{n} s_j(t) \leq 1$. In the future works, we will consider a more realistic wireless channel setting, i.e., erasure wireless channel [8] [15] [18] [22], where each transmission in the wireless channel may fail with a certain probability.

3.2 Energy Model

Battery-free sensor nodes harvest energy from power sources in their ambient environment, such as solar power, wind power, and RF signal power, etc. The amount of energy harvested by an individual battery-free sensor node varies with time. Besides, the amount of energy harvested by different battery-free sensor nodes in the same time slot may be different. We use $E_i^H(t)$ to denote the energy harvested by battery-free sensor node v_i in time slot t. Without loss of generality, we assume that $E_i^H(0) = 0$. Plenty of works have been devoted to constructing energy prediction models for battery-free sensor nodes harvesting energy from different power sources [27]–[35]. However, the accuracy of these energy prediction models cannot be guaranteed. In general, $E_i^H(t)$ cannot be estimated precisely before time slot t.

We use $E_i^C(t)$ to denote the amount of energy consumed by battery-free sensor node v_i in time slot t. We say that a battery-free sensor node v_i is in active state in time slot t if v_i generates a sensory data packet and transmits it to the sink node in time slot t. Otherwise, we say that v_i is in idle state in time slot t. All battery-free sensor nodes have the uniform energy consumption for generating and transmitting a sensory data packet, denoted by e_s. We assume that the energy consumption of a battery-free sensor node in idle state is negligible. Therefore, the energy consumption of $v_i \in V$ in time slot t is,

$$E_i^C(t) = \begin{cases} e_s, & \text{if } v_i \text{ is in active state,} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Then, we use $E_i(t)$ to denote the energy stored in v_i at the beginning of time slot t, where

$$E_i(t) = E_i(t-1) + E_i^H(t-1) - E_i^C(t-1). \tag{3}$$

We use an indicator $f_i(t)$ to denote whether $v_i \in V$ has enough energy for generating and transmitting a sensory data packet at the beginning of time slot t, i.e.,

$$f_i(t) = \begin{cases} 1, & \text{if } E_i(t) \geq e_s, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

3.3 Problem Statement

Age of Information (AoI) is a destination-centric measurement for the freshness of information that received by the sink node. We use $a_i(t)$ to denote the AoI with respect to battery-free sensor node v_i in time slot t, which is the time that elapsed since the generation of the sensory data packet that was most recently transmitted from v_i to the sink node, i.e.,

$$a_i(t) = t - u_i(t), \tag{5}$$

where $u_i(t)$ is the generation time of the freshest sensory data packet received by the sink node from battery-free sensor node v_i. We consider the generate-at-will model similar to [11] [21]. That is, each battery-free sensor node can generate its sensory data packet at any time by its own will and transmit the generated sensory data packet to the sink node instantly. As Fig.1 shows, the AoI $a_i(t)$ drops to 1 if a new sensory data packet is transmitted from v_i to the sink node in time slot $(t-1)$, and increases linearly in time otherwise. That is,

$$a_i(t+1) = \begin{cases} 1, & \text{if } s_i(t)f_i(t) = 1, \\ a_i(t)+1, & \text{otherwise.} \end{cases} \quad (6)$$

For simplicity, and without loss of generality, we assume tl

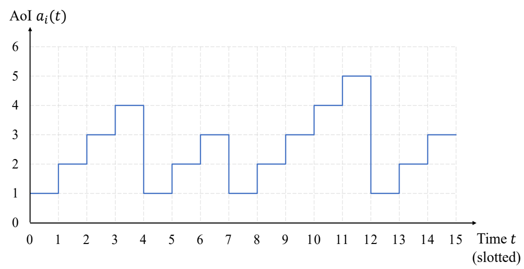

Fig. 1: The AoI for a battery-free sensor node.

In this paper, we consider the weighted sum of average peak ages as the age metric, which is a common age metric in wireless sensor networks [24] [26] [36]. Different from the delay metric and the throughput metric, the age metric has higher demands. Specifically, the minimum delay problem only cares for the delay of data packets transmitted from the source to the destination and the minimum throughput problem only cares for the times of successful transmissions from the source to the destination. But the minimum AoI problem also cares for how regularly the successful transmissions with low delay happen. To achieve a good age performance for data collection in wireless sensor networks, it requires to collect data with low delay regularly [18].

From Fig.1, we can see that the peak age with respect to battery-free sensor node v_i is achieved just before a new sensory data packet is successfully received by the sink node from v_i. Besides, the last peak age with respect to battery-free sensor node v_i in T time slots is achieved in the last time slot T. A battery-free sensor node v_i can generate a sensory data packet and transmit it to the sink node in time slot t only when the wireless channel is assigned to v_i in time slot t and the energy stored in v_i at the beginning of time slot t is no less than e_s, i.e., $s_i(t)f_i(t) = 1$. Otherwise, battery-free sensor node v_i keeps idle in time slot t.

Therefore, the average peak age with respect to v_i in T time slots is defined as,

$$\overline{\Delta_i^P} = \frac{\sum_{t=1}^{T} s_i(t)f_i(t)a_i(t)}{\sum_{t=1}^{T} s_i(t)f_i(t)}. \quad (7)$$

For simplicity of exposition, we set $s_i(T)f_i(T) = 1, \forall v_i \in V$. Therefore, the weighted sum of average peak ages in the BF-WSN is defined as,

$$\overline{\Delta^P} = \sum_{i=1}^{n} w_i \overline{\Delta_i^P}, \quad (8)$$

where $w_i > 0$ is the weight of battery-free sensor node v_i and $\sum_{i=1}^{n} w_i = 1$. The weights of battery-free sensor nodes represent their different demands for the information of freshness.

A data collection scheduling policy for the one-hop BF-WSN in T time slots can be denoted as a sequence $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$, where $\pi(t) \in \{0, 1, \cdots, n\}$. $\pi(t) = 0$ means that no battery-free sensor node transmits its sensory data packet to the sink node in time slot t, otherwise, battery-free sensor node $v_{\pi(t)}$ generates a sensory data packet and transmits it to the sink node in time slot t. In this paper, we study the data collection scheduling problem in one-hop BF-WSNs to minimize the weighted sum of average peak ages, called AoI Minimization Scheduling (AMS) problem. The AMS problem can be formulated as follows.

Input:

1) $V = \{v_1, v_2, \cdots, v_n\}$, the set of battery-free sensor nodes in a one-hop BF-WSN,
2) T, the number of time slots, where $T = mn + 1$ and $m > n$ in general,
3) $E_i(1)$ $(i = 1, \cdots, n)$, the initial energy stored in battery-free sensor node v_i,
4) $E_i^H(t)$ $(i = 1, \cdots, n$ and $t = 1, \cdots, T)$, the amount of energy harvested by v_i in time slot t,
5) e_s, the amount of energy consumed by each battery-free sensor node to generate and transmit one sensory data packet.

Output: $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$, where $\pi(t) \in \{0, 1, \cdots, n\}$, the data collection schedule for battery-free sensor nodes of the one-hop BF-WSN in T time slots to minimize the weighted sum of average peak ages, $\overline{\Delta^P}$.

4 THE OFFLINE ALGORITHM

In this section, we first consider the offline version of the AoI Minimization Scheduling (OFF-AMS) problem, provided that the sink node has the global knowledge of the energy profiles of all battery-free sensor nodes in the following T time slots. A large number of works have been devoted to building energy prediction models for battery-free sensor nodes harvesting energy from solar power [27]–[29], wind power [30] [31], and RF signal power [32]–[35]. When the accuracy of these energy prediction models is guaranteed, it is possible for the sink node to get the global knowledge of the energy profiles of all battery-free sensor nodes in the following T time slots. We devise an optimal offline algorithm, called the Large Age Revenue First (LARF) algorithm, for the OFF-AMS problem.

4.1 The LARF Algorithm

Before the description of the offline algorithm, we first introduce the following definitions.

Definition 1 (Maximum number of transmissions)**.** *The maximum number of transmissions for a battery-free sensor node v_i is defined as $H_i = \lfloor \frac{E_i(1)+\sum_{t=1}^{T-1} E_i^H(t)}{e_s} \rfloor$. That is, battery-free sensor node v_i can transmit at most H_i data packets to the sink node in the following T time slots for energy constraint.*

Definition 2 (Energy profile)**.** *The energy profile for a battery-free sensor node v_i in the following T time slots is defined as a sequence of H_i time slots, $\mathcal{P}_i = \{\tau_i(1), \tau_i(2), \cdots, \tau_i(H_i)\}$, where $\tau_i(j)$ $(j = 1, \cdots, H_i)$ is the earliest time slot that v_i can transmit its j-th data packet for energy constraint. And $\tau_i(j)$ is defined as*

$$\tau_i(j) = \min\{\tau + 1 | E_i(1) + \sum_{t=0}^{\tau} E_i^H(t) \geq je_s, 0 \leq \tau < T\}.$$

Definition 3 (Number of successful transmissions)**.** *The number of successful transmissions for a battery-free sensor node v_i in schedule $\boldsymbol{\pi} = \{\pi(1), \cdots, \pi(T)\}$ is defined as $C_i = \sum_{t=1}^{T-1} s_i(t)f_i(t) = \sum_{t=1}^{T-1} \mathbb{1}_{\pi(t)=i}$, where the indicator $\mathbb{1}_{\pi(t)=i}$ equals to 1 if $\pi(t) = i$ holds, and 0 otherwise. By definition, $C_i \leq H_i$. Besides, $\sum_{t=1}^{T} s_i(t)f_i(t) = C_i + 1$, since $s_i(T)f_i(T) = 1$.*

According to the property of the peak age, we have the following lemma.

Lemma 1. *For any schedule $\boldsymbol{\pi} = \{\pi(1), \cdots, \pi(T)\}$, the sum of peak ages for battery-free sensor node v_i in T time slots is T, i.e., $\sum_{t=1}^{T} s_i(t)f_i(t)a_i(t) = T$, where $i = 1, \cdots, n$.*

Proof. We assume that $s_i(t)f_i(t) = 1$ when $t = t_1, t_2, \cdots, t_k$ in schedule $\boldsymbol{\pi}$, where $1 \leq t_1 < \cdots < t_k = T$. Therefore, we have that $\sum_{t=1}^{T} s_i(t)f_i(t)a_i(t) = \sum_{j=1}^{k} a_i(t_j)$. According to the definition of AoI in (6), we have $a_i(t_j + 1) = 1$, and $a_i(t_{j+1}) = a_i(t_j + 1) + (t_{j+1} - (t_j + 1)) = t_{j+1} - t_j$, for any $j = 1, \cdots, k-1$. Besides, $a_i(t_1) = a_i(0) + t_1 = t_1$. As a consequence, we have $\sum_{t=1}^{T} s_i(t)f_i(t)a_i(t) = \sum_{j=1}^{k} a_i(t_j) = t_1 + \sum_{j=1}^{k-1}(t_{j+1} - t_j) = t_k = T$. This completes the proof. □

Therefore, the average peak age with respect to battery-free sensor node v_i in T time slots is rewritten as $\overline{\Delta_i^P} = \frac{T}{C_i+1}$. Then, the mathematical formulation of the OFF-AMS problem is as follows.

$$
\begin{aligned}
\min_{\boldsymbol{\pi}} \quad & \overline{\Delta^P} = \sum_{i=1}^{n} w_i \overline{\Delta_i^P} = \sum_{i=1}^{n} \frac{w_i T}{C_i + 1} \qquad (9)\\
\text{s.t.} \quad & s_i(t) \in \{0, 1\}, \quad t = 1, \cdots, T, i = 1, \cdots, n,\\
& \sum_{i=1}^{n} s_i(t) \leq 1, \quad t = 1, \cdots, T,\\
& \sum_{t=1}^{\tau_i(j)-1} \mathbb{1}_{\pi(t)=i} < j, \quad j = 1, \cdots, H_i, i = 1, \cdots, n,
\end{aligned}
$$

where $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$ and $\pi(t) = \sum_{i=1}^{n} i \cdot s_i(t)f_i(t)$. According to (9), the objective function of the OFF-AMS problem only depends on the number of successful transmissions of battery-free sensor nodes in T time slots, C_i $(i = 1, \cdots, n)$. Therefore, we define the *age revenue*s with respect to the successful transmissions of battery-free sensor nodes as follows.

Definition 4 (Age revenue)**.** *The age revenue with respect to the j-th successful transmission of battery-free sensor node v_i is defined as the reduction of the weighted sum of average peak ages $\overline{\Delta^P}$ after the j-th $(j = 1, \cdots, H_i)$ successful transmission of v_i, i.e.,*

$$
R_i(j) = \frac{w_i T}{(j-1)+1} - \frac{w_i T}{j+1} = \frac{w_i T}{j(j+1)}. \qquad (10)
$$

Theorem 1. *For a battery-free sensor node v_i, its age revenues satisfy that $R_i(1) > R_i(2) > \cdots > R_i(H_i)$.*

Proof. According to the definition of age revenue, $\forall 1 \leq j < k \leq H_i$, $R_i(j) - R_i(k) = \frac{w_i T}{j(j+1)} - \frac{w_i T}{k(k+1)} > 0$. This finishes our proof. □

By virtue of the *age revenue*s of successful transmissions of all battery-free sensor nodes, we propose a greedy algorithm, the Large Age Revenue First (LARF) algorithm, for the OFF-AMS problem. In the LARF algorithm, the wireless channel assignment is initialized as $s_i(t) = 0$ for $i = 1, \cdots, n$, and $t = 1, \cdots, T$. Accordingly, the data collection schedule is initialized as $\pi(t) = 0$ for $t = 1, \cdots, T$. The LARF algorithm is presented in Algorithm 1, which consists of the following three steps.

Step 1. Calculate the age revenue with respect to each successful transmission of each battery-free sensor node by (10). There are at most H_i age revenues for battery-free sensor node v_i $(i = 1, \cdots, n)$, i.e., $R_i(1), R_i(2), \cdots, R_i(H_i)$.

Step 2. Sort all $K = \sum_{i=1}^{n} H_i$ age revenues in non-ascending order. Without loss of generality, we place the ordered age revenues into a queue $\mathcal{Q}$.

Step 3. The age revenues are extracted from queue $\mathcal{Q}$ one by one to calculate the data collection schedule for the network in T time slots. Without loss of generality, we assume that the k-th age revenue extracted from queue $\mathcal{Q}$ is $R_i(j)$. As a consequence, we assign the wireless channel to the j-th transmission of battery-free sensor node v_i as follows. There are two cases.

1) If $\{t | \tau_i(j) \leq t < T, \pi(t) = 0\} \neq \emptyset$, we set $\tau = \min\{t | \tau_i(j) \leq t < T, \pi(t) = 0\}$. Then, the wireless channel is assigned to the j-th transmission of battery-free sensor node v_i in time slot τ, i.e., $s_i(\tau) = 1$. Since $E_i(1) + \sum_{t=0}^{\tau-1} E_i^H(t) \geq E_i(1) + \sum_{t=0}^{\tau_i(j)-1} E_i^H(t) \geq je_s$ and $\sum_{t=0}^{\tau-1} E_i^C(t) = (j-1)e_s$, we have that $E_i(\tau) \geq e_s$, i.e., $f_i(\tau) = 1$. Therefore, v_i is scheduled to generate and transmit its j-th data packet to the sink node in time slot τ, i.e., $\pi(\tau) = i$.
2) Otherwise, no interference-free wireless channel is available for the j-th transmission of v_i.

After the above three steps, the data collection schedule for the network in the following T time slots is generated, i.e., $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$.

In the LARF algorithm, the j-th transmission of battery-free sensor node v_i is scheduled in time slot $\tau = \min\{t | \tau_i(j) \leq t < T, \pi(t) = 0\}$, if $\{t | \tau_i(j) \leq t < T, \pi(t) = 0\} \neq \emptyset$. That means the j-th transmission of battery-free sensor node v_i is scheduled in the earliest possible time slot which satisfies both energy constraint and interference constraint, i.e., battery-free sensor node v_i is scheduled to transmit its data packet as regular and timely as possible subjecting to its weight.

Algorithm 1: LARF Algorithm

```
Input: V, energy profiles P_i = {τ_i(1), ···, τ_i(H_i)}
       (i = 1, ···, n), weights w_i (i = 1, ···, n), T, e_s.
Output: Data collection schedule, π = {π(1), π(2), ···, π(T)}.
for i = 1 to n do
    for j = 1 to H_i do
        Caculate age revenue by R_i(j) = w_i T / (j(j+1));
Sort age revenues in non-ascending order and push them in
queue Q;
while Q ≠ ∅ do
    Extract the maximum age revenue from queue Q, which is
    assumed as R_i(j);
    if {t | τ_i(j) ≤ t < T, π(t) = 0} ≠ ∅ then
        τ = min{t | τ_i(j) ≤ t < T, π(t) = 0};
        s_i(τ) = 1; f_i(τ) = 1; π(τ) = i;
return π = {π(1), π(2), ···, π(T)}.
```

4.2 The Optimality of the LARF Algorithm

In this section, we prove that the OFF-AMS problem can be formulated in terms of finding a maximum-weight independent subset in a weighted matroid. Since matroids exhibit the greedy-choice property and the optimal-substructure property [37], the optimal solution of the OFF-AMS problem can be produced by a greedy algorithm. Therefore, we can prove the optimality of the proposed greedy algorithm, the LARF algorithm.

The OFF-AMS problem can be formulated as follows. There are totally $K = \sum_{i=1}^{n} H_i$ possible transmissions corresponding to n battery-free sensor nodes in T time slots. The set of all transmissions are denoted by $S = \{a_{i,j} | i = 1, \cdots, n, \text{ and } j = 1, \cdots, H_i\}$, where $a_{i,j}$ denotes the j-th transmission of battery-free sensor node v_i. Transmission $a_{i,j}$ has an earliest start time $\tau_i(j)$ according to the energy profile of v_i in Definition 2. Transmission $a_{i,j}$ in a schedule is *valid* if it is scheduled after its earliest start time $\tau_i(j)$. Otherwise, this transmission is *fake* since it violates the energy constraint. And a *valid* transmission $a_{i,j}$ can bring an age revenue $R_i(j)$. The OFF-AMS problem is equivalent to find a schedule for all transmissions that maximize the total age revenues brought by *valid* transmissions.

We say that a set of transmissions A is independent if there exists a schedule for these transmissions such that all transmissions are *valid*. Let $\mathcal{I}$ denote the set of all independent sets of transmissions. Besides, for $t = 1, \cdots, T$, we apply $N_t(A)$ to denote the number of transmissions in independent set A whose earliest start time is later than or equal to t. Note that $N_T(A) = 0$ for any independent set A. Then, we have the following lemma.

Lemma 2. *For any set of transmissions, denoted by A, the following statements are equivalent.*

(1) A is an independent set.
(2) For any $t = 1, \cdots, T$, we have $N_t(A) \leq T - t$.
(3) If the transmissions in A are sorted in monotonically decreasing order of their earliest start times, and can be scheduled in time slot $T-1, T-2, \cdots, T-|A|$, respectively, then all transmissions in A are valid.

Proof. The proof consists of three steps.

- We prove that (1) implies (2) with its contrapositive. If $N_t(A) > T - t$ for some t, then there is no way to schedule more than $T - t$ transmissions in $T - t$ time slots. Therefore, A is not independent.
- (2) implies that there are at most $T - t$ transmissions, which should be scheduled in the last $T - t$ time slots for any t. Therefore, (3) claims.
- (3) trivially implies (1).

This completes the proof. □

Based on Lemma 2, we prove the following theorem.

Theorem 2. *If S is a set of $K = \sum_{i=1}^{n} H_i$ transmissions with earliest start times, and $\mathcal{I}$ is the set of all independent sets of transmissions, then the corresponding system $(S, \mathcal{I})$ is a matroid.*

Proof. We have to prove that $(S, \mathcal{I})$ satisfies the three properties of matroid.

1) By definition, transmission set S is a finite set.
2) We will prove that $\mathcal{I}$ is nonempty and hereditary. It is clear that $\mathcal{I}$ is nonempty. Next, we prove that $\mathcal{I}$ is hereditary, i.e., if $A \in \mathcal{I}$ and $B \subseteq A$, then $B \in \mathcal{I}$. Since $B \subseteq A$, we have $N_t(B) \leq N_t(A)$ for any $t = 1, \cdots, T$. Based on Lemma 2, we have $N_t(B) \leq N_t(A) \leq T - t$ for $t = 1, \cdots, T$, then B is independent and $B \in \mathcal{I}$.
3) We will prove that $(S, \mathcal{I})$ satisfies the exchange property, i.e., if $A \in \mathcal{I}$, $B \in \mathcal{I}$, and $|A| < |B|$, then there exists a transmission $x \in B - A$ such that $A \cup \{x\} \in \mathcal{I}$. Since $|B| > |A|$, there must exist a time slot k satisfying that $N_k(B) > N_k(A), \forall 1 \leq t \leq k$. Therefore, we have that there is at least one transmission $x \in B - A$ whose earliest start time is time slot k. We will prove that $A \cup \{x\} \in \mathcal{I}$. According to Lemma 2, we have that $N_t(A) \leq T - t$ and $N_t(B) \leq T - t$ for $1 \leq t \leq T$ since $A \in \mathcal{I}$ and $B \in \mathcal{I}$. There are two cases.
   - For $1 \leq t \leq k$, $N_t(A \cup \{x\}) = N_t(A) + 1 \leq N_t(B) \leq T - t$.
   - For $k < t \leq T$, $N_t(A \cup \{x\}) = N_t(A) \leq T - t$.

   That is, for any $t = 1, \cdots, T$, $N_t(A \cup \{x\}) \leq T - t$, then $A \cup \{x\}$ is independent based on Lemma 2 and $A \cup \{x\} \in \mathcal{I}$.

In consequence, $(S, \mathcal{I})$ is a matroid. □

Theorem 3. *The LARF algorithm is an optimal solution for the OFF-AMS problem.*

Proof. Based on Theorem 2, we have proved that the OFF-AMS problem can be formulated as finding a maximum-weighted independent subset in a weighted matroid. Therefore, the greedy algorithm can produce the optimal solution for the OFF-AMS problem. In the LARF algorithm, line 7 checks whether the j-th transmission of battery-free sensor node v_i with maximum age revenue is valid. If so, the wireless channel is assigned to this transmission in time slot τ, i.e., transmission $a_{i,j}$ is added to the independent set A. Otherwise, this transmission is discarded. Therefore, the independence of set A is always maintained in the **while** loop (line 5 to line 9 in the LARF algorithm). Therefore, each transmission in the independent set A with maximum sum of age revenues are allowed to occupy the wireless channel in a unique time slot. As a consequence, the LARF algorithm produces an optimal schedule for the OFF-AMS problem. □

5 The Online Algorithm

In this section, we consider the online version of the AoI Minimization Scheduling (ON-AMS) problem, provided that the network has no knowledge of the energy profiles of battery-free sensor nodes in the following T time slots. Furthermore, even the battery-free sensor node itself has no knowledge of its own future energy profile. As a consequence, an online data collection scheduling algorithm is required to adjust the data collection scheduling in time adapting to the current energy status of each battery-free sensor node. Each battery-free sensor node has to transmit an update packet containing its current energy status to the sink node at the beginning of a time slot so that the sink node can generate the data collection scheduling in this time slot according to the current energy status of each battery-free sensor node. However, the frequent transmissions of update packets will introduce extra energy consumption and channel occupancy, which will affect the performance of data collection in BF-WSNs. Therefore, we devise an online data collection scheduling algorithm for the ON-AMS problem, which can generate data collection schedules cooperatively by the sink node and all battery-free sensor nodes in a BF-WSN.

5.1 The ORR Algorithm

The proposed online algorithm is named as the Opportunistic Round-Robin (ORR) algorithm. As its name indicates, the wireless channel is assigned to battery-free sensor nodes in a round robin manner. Round robin is a common method applied in scheduling of battery-powered wireless sensor networks [18] [38] [39]. Meanwhile, each battery-free sensor node decides whether to generate and transmit its data packet to the sink node in the time slot based on its energy status. The ORR algorithm is presented in Algorithm 2.

Initially, the wireless channel assignment and energy indicators are initialized as $s_i(t) = 0$ and $f_i(t) = 0$ for $i = 1, \cdots, n$ and $t = 1, \cdots, T$ (line 3). Accordingly, the data collection schedule is initialized as $\pi(t) = 0$, for $t = 1, \cdots, T$ (line 4). For any battery-free sensor node $v_i \in V$, it will generate and transmit its sensory data packet in time slot t, if and only if the wireless channel is assigned to v_i in time slot t and the energy stored in v_i at the beginning of time slot t is no less than e_s, i.e., $s_i(t) = 1$ and $f_i(t) = 1$. Therefore, the ORR algorithm consists of three steps. In the first step, the sink node decides the wireless channel assignment $s_i(t)$ in a round robin manner, where $i = 1, \cdots, n$ and $t = 1, \cdots, T$. In the second step, each battery-free sensor node $v_i \in V$ decides the energy indicator $f_i(t)$ according to its stored energy, where $t = 1, \cdots, T$. In the third step, the data collection schedule is generated based on $s_i(t)$ and $f_i(t)$, where $i = 1, \cdots, n$ and $t = 1, \cdots, T$. In this way, the data collection schedule is cooperatively derived by the sink node and all battery-free sensor nodes.

Step 1. Assign the wireless channel to battery-free sensor nodes in a round robin manner (line 7-8). For all $t = 1, \cdots, T$, the wireless channel is assigned to the battery-free sensor node v_i in time slot t, where $i = t \pmod n$. That is, $s_i(t) = 1$ if $i = t \pmod n$.

Step 2. Calculate the energy indicator of each battery-free sensor node based on its energy status (line 9-10). In time slot t, each battery-free sensor node $v_i \in V$ checks its stored energy $E_i(t)$. According to (4), $f_i(t) = 1$ if $E_i(t) \geq e_s$.

Step 3. Generate the online data collection schedule cooperatively by $s_i(t)$ and $f_i(t)$ (line 11-15). Each battery-free sensor node $v_i \in V$ generates and transmits its sensory data packet in time slot t if the wireless channel is assigned to v_i in time slot t and the energy stored in v_i at the beginning of time slot t is no less than e_s, i.e., $\pi(t) = i$ if $s_i(t) = 1$ and $f_i(t) = 1$.

After the above three steps, the online data collection schedule for the network in T time slots is generated cooperatively by the sink node and all battery-free sensor nodes.

In the ORR algorithm, the wireless channel is assigned to all battery-free sensor nodes in a round robin manner. That means if battery-free sensor node v_i has accumulated enough energy for its j-th transmission in time slot t, then the j-th transmission of battery-free sensor node v_i is scheduled no latter than time slot $t + n$, i.e., battery-free sensor node v_i is scheduled to transmit its sensory data packet as regular and timely as possible.

Algorithm 2: ORR Algorithm

Input: V, the harvested energy $E_i^H(t)$ $(i = 1, \cdots, n$, $t = 1, \cdots, T)$, e_s.
Output: Data collection schedule, $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$.

1 **for** $t = 1$ *to* T **do**
2   **for** $i = 1$ *to* n **do**
3     $s_i(t) = 0$; $f_i(t) = 0$;
4   $\pi(t) = 0$;
5 **for** $t = 1$ *to* T **do**
6   **for** $i = 1$ *to* n **do**
7   **if** $i = t \pmod n$ **then**
8       $s_i(t) = 1$;
9   **if** $E_i(t) \geq e_s$ **then**
10       $f_i(t) = 1$;
11   **if** $s_i(t) = 1$ *and* $f_i(t) = 1$ **then**
12       $\pi(t) = i$;
13       $E_i(t+1) = E_i(t) + E_i^H(t) - e_s$;
14   **else**
15       $E_i(t+1) = E_i(t) + E_i^H(t)$;
16 **return** $\boldsymbol{\pi} = \{\pi(1), \pi(2), \cdots, \pi(T)\}$.

5.2 The Competitive Ratio of the ORR Algorithm

In this section, we analyze the competitive ratio of the ORR algorithm. Given a BF-WSN with n battery-free sensor nodes, the energy profiles of them in T time slots are denoted by $\mathcal{P}_1, \cdots, \mathcal{P}_n$, where $\mathcal{P}_i = \{\tau_i(1), \cdots, \tau_i(H_i)\}$ is defined in Definition 2. We use $\boldsymbol{\pi}_{off} = \{\pi_{off}(1), \cdots, \pi_{off}(T)\}$ to denote the optimal schedule for the OFF-AMS problem. Then, the weighted sum of average peak ages of schedule $\boldsymbol{\pi}_{off}$ is $\overline{\Delta_{off}^P} = \sum_{i=1}^{n} \frac{w_i T}{C_i^{off}+1}$, where $C_i^{off} = \sum_{t=1}^{T-1} \mathbb{1}_{\pi_{off}(t)=i}$. Due to the energy constraint of battery-free sensor node v_i, we have that $C_i^{off} \leq H_i$ for $i = 1, \cdots, n$. We use $\boldsymbol{\pi}_{on} = \{\pi_{on}(1), \cdots, \pi_{on}(T)\}$ to denote the schedule derived by the proposed ORR algorithm. Then, the weighted sum of average peak ages of schedule $\boldsymbol{\pi}_{on}$ is $\overline{\Delta_{on}^P} = \sum_{i=1}^{n} \frac{w_i T}{C_i^{on}+1}$, where $C_i^{on} = \sum_{t=1}^{T-1} \mathbb{1}_{\pi_{on}(t)=i}$. Therefore, the competitive ratio of the ORR algorithm is denoted as R, satisfying that

$$\overline{\Delta_{on}^P} \leq R \cdot \overline{\Delta_{off}^P}. \tag{11}$$

Before analyzing the competitive ratio of the ORR algorithm, we first introduce the following definitions.

Definition 5 (Minimum/Maximum Blanking Period)**.** *The minimum/maximum blanking period for n battery-free sensor nodes with energy profiles $\mathcal{P}_i = \{\tau_i(1), \cdots, \tau_i(H_i)\}$ $(i = 1, \cdots, n)$ in T time slots is defined as $\Delta\tau_{min} = \min\{\tau_i(j) - \tau_i(j-1) | 1 \leq i \leq n, 1 \leq j \leq H_i + 1\}$ or $\Delta\tau_{max} = \max\{\tau_i(j) - \tau_i(j-1) | 1 \leq i \leq n, 1 \leq j \leq H_i + 1\}$, where $\tau_i(j)$ is the earliest time slot for battery-free sensor node v_i to transmit its j-th data packet for $j = 1, \cdots, H_i$, and we define $\tau_i(0) = 0$ and $\tau_i(H_i + 1) = T$.*

Based on the definitions of the minimum blanking period $\Delta\tau_{min}$ and the maximum blanking period $\Delta\tau_{max}$, we analyze the competitive ratio of the ORR algorithm in the following cases.

Theorem 4. *When the maximum blanking period for n battery-free sensor nodes in T time slots satisfies that $\Delta\tau_{max} \le n$, the competitive ratio of the ORR algorithm is $R = w_{max}(n + (n+1)/m)$, i.e., $\overline{\Delta^P_{on}} \le (w_{max}(n + (n+1)/m))\overline{\Delta^P_{off}}$, where $w_{max} = \max\{w_i | 1 \le i \le n\} \le 1$ and $T = mn + 1$.*

Proof. By Definition 1 and Definition 2, the energy profile of battery-free sensor node v_i is $\mathcal{P}_i = \{\tau_i(1), \cdots, \tau_i(H_i)\}$, where $\tau_i(j)$ is the earliest time slot that v_i can transmit its j-th data packet and H_i is the maximum number of transmissions for v_i. Since $\tau_i(j) - \tau_i(j-1) \le \Delta\tau_{max} \le n$ for any $i = 1, \cdots, n$ and $j = 1, \cdots, H_i + 1$, we have that each battery-free sensor node can harvest at least e_s energy every n time slots based on Definition 2. Then, by the description of the ORR algorithm, we have that for $k = 1, \cdots, m-1$, $s_i(kn+i) = 1$ and $E_i(kn+i) \ge e_s$, i.e., $s_i(kn+i) = 1$ and $f_i(kn+i) = 1$. Therefore, we have $\pi_{on}(kn+i) = i$, for $k = 1, \cdots, m-1$. Therefore, we have that $C_i^{on} \ge m-1$ and

$$\overline{\Delta^P_{on}} = \sum_{i=1}^{n} \frac{w_i T}{C_i^{on} + 1} \le \sum_{i=1}^{n} \frac{w_i T}{(m-1)+1} = \frac{T}{m}. \tag{12}$$

Due to the transmission interference, it is known that $\sum_{i=1}^{n} C_i^{off} \le T$. Therefore, the following inequation holds

$$\begin{aligned} \overline{\Delta^P_{off}} &= \sum_{i=1}^{n} \frac{w_i T}{C_i^{off} + 1} \overset{(a)}{\ge} \frac{T}{\sum_{i=1}^{n} w_i (C_i^{off} + 1)} \\ &\ge \frac{T}{w_{max}\sum_{i=1}^{n}(C_i^{off} + 1)} \ge \frac{T}{w_{max}(T+n)}, \end{aligned} \tag{13}$$

where step (a) follows from the weighted Jensen's inequality and $w_{max} = \max\{w_i | 1 \le i \le n\} \le 1$.

Combine (12) and (13), we have that

$$\frac{\overline{\Delta^P_{on}}}{\overline{\Delta^P_{off}}} \le \frac{w_{max}(T+n)}{m} = w_{max}(n + (n+1)/m). \tag{14}$$

This completes the proof. □

Theorem 5. *When the minimum blanking period for n battery-free sensor nodes in T time slots satisfies that $\Delta\tau_{min} \ge n$, the competitive ratio of the ORR algorithm is $R = 1$.*

Proof. By Definition 1 and Definition 2, the energy profile of battery-free sensor node v_i is $\mathcal{P}_i = \{\tau_i(1), \cdots, \tau_i(H_i)\}$, where $\tau_i(j)$ is the earliest time slot that v_i can transmit its j-th data packet and H_i is the maximum number of transmissions for v_i. Since $\tau_i(j) - \tau_i(j-1) \ge \Delta\tau_{min} \ge n$ for any $i = 1, \cdots, n$ and $j = 1, \cdots, H_i+1$, we have that it consumes at least n time slots for each battery-free sensor node to harvest e_s energy. According to the description of the ORR algorithm, for any $j = 2, \cdots, H_i + 1$, there must exist a time slot $t = z_j n + i$ ($z_j \in \{1, \cdots, m-1\}$) in time interval $[\tau_i(j-1), \tau_i(j))$, where $E_i(z_j n+i) \ge e_s$ and $s_i(z_j n+i) = 1$, i.e., $f_i(z_j n + i) = 1$ and $s_i(z_j n + i) = 1$. Therefore, we have $\pi_{on}(z_j n+i) = i$. That is, in the ORR algorithm, each battery-free sensor node v_i must be scheduled once in time interval $[\tau_i(j-1), \tau_i(j))$ for $j = 2, \cdots, H_i + 1$. Therefore, we have that $C_i^{on} = H_i$.

Since $C_i^{off} \le H_i$ for the energy constraint of each battery-free sensor node v_i, we have that

$$\frac{\overline{\Delta^P_{on}}}{\overline{\Delta^P_{off}}} = \frac{\sum_{i=1}^{n} \frac{w_i T}{C_i^{on}+1}}{\sum_{i=1}^{n} \frac{w_i T}{C_i^{off}+1}} \le \frac{\sum_{i=1}^{n} \frac{w_i T}{H_i+1}}{\sum_{i=1}^{n} \frac{w_i T}{H_i+1}} = 1. \tag{15}$$

This finishes our proof. □

Theorem 6. *When the minimum blanking period and the maximum blanking period for n battery-free sensor nodes in T time slots satisfy that $\Delta\tau_{min} < n < \Delta\tau_{max}$ and $\frac{n}{k} \le \Delta\tau_{min} < \frac{n}{k-1}$, the competitive ratio of the ORR algorithm is $R = k$, i.e., $\overline{\Delta^P_{on}} \le k\overline{\Delta^P_{off}}$, where $k = 2, \cdots, n$.*

Proof. By Definition 1 and Definition 2, the energy profile of battery-free sensor node v_i is $\mathcal{P}_i = \{\tau_i(1), \cdots, \tau_i(H_i)\}$, where $\tau_i(j)$ is the earliest time slot that v_i can transmit its j-th data packet and H_i is the maximum number of transmissions for v_i. For any $k = 2, \cdots, n$, we prove that the competitive ratio of the ORR algorithm is $R = k$ if $\frac{n}{k} \le \Delta\tau_{min} < \frac{n}{k-1}$. There are two cases.

1) If $H_i < k$, there must exist a $1 \le j \le H_i + 1$ satisfying that $\tau_i(j) - \tau_i(j-1) > n$. According to the description of the ORR algorithm, there must exist a time slot $t = zn+i$ ($z \in \{1, \cdots, m-1\}$) in time interval $[1, T)$, where $E_i(zn+i) \ge e_s$ and $s_i(zn+i) = 1$, i.e., $f_i(zn+i) = 1$ and $s_i(zn+i) = 1$. Therefore, we have $\pi_{on}(zn+i) = i$. That is, each battery-free sensor node is scheduled at least once in time interval $[1, T)$. Therefore, we have that $C_i^{on} \ge 1$. Since $C_i^{off} \le H_i < k$ for the energy constraint of each battery-free sensor node v_i, we have that

$$\frac{\overline{\Delta^P_{on}}}{\overline{\Delta^P_{off}}} = \frac{\sum_{i=1}^{n} \frac{w_i T}{C_i^{on}+1}}{\sum_{i=1}^{n} \frac{w_i T}{C_i^{off}+1}} \le \frac{\sum_{i=1}^{n} \frac{w_i T}{2}}{\sum_{i=1}^{n} \frac{w_i T}{k+1}} \overset{(b)}{\le} k, \tag{16}$$

where step (b) is true since $k \ge 2$.

2) If $H_i \ge k$, we have that $\lfloor \frac{H_i}{k} \rfloor \ge 1$. Since $\tau_i(j) - \tau_i(j-1) \ge \Delta\tau_{min} \ge \frac{n}{k}$ for any $i = 1, \cdots, n$ and $j = 1, \cdots, H_i + 1$, we have that $\tau_i(lk+1) - \tau_i((l-1)k+1) \ge k \cdot (\frac{n}{k}) = n$ for any $l = 1, \cdots, \lfloor \frac{H_i}{k} \rfloor$. According to the description of the ORR algorithm, for any $l = 1, \cdots, \lfloor \frac{H_i}{k} \rfloor$, there must exist a time slot $t = z_l n + i$ ($z_l = \{1, \cdots, m-1\}$) in time interval $[\tau_i((l-1)k+1), \tau_i(lk+1))$, where $E_i(z_l n + i) \ge e_s$ and $s_i(z_l n + i) = 1$, i.e., $f_i(z_l n + i) = 1$ and $s_i(z_l n+i) = 1$. Therefore, we have that $\pi_{on}(z_l n+i) = i$. That is, in the ORR algorithm, each battery-free sensor node v_i is scheduled at least once in time interval $[\tau_i((l-1)k+1), \tau_i(lk+1))$ for $l = 1, \cdots, \lfloor \frac{H_i}{k} \rfloor$. Therefore, we have that $C_i^{on} \ge \lfloor \frac{H_i}{k} \rfloor$. Since $C_i^{off} \le H_i$ for the energy constraint of each battery-free sensor node v_i, we have that

$$\frac{\overline{\Delta^P_{on}}}{\overline{\Delta^P_{off}}} = \frac{\sum_{i=1}^{n} \frac{w_i T}{C_i^{on}+1}}{\sum_{i=1}^{n} \frac{w_i T}{C_i^{off}+1}} \le \frac{\sum_{i=1}^{n} \frac{w_i T}{\lfloor \frac{H_i}{k} \rfloor + 1}}{\sum_{i=1}^{n} \frac{w_i T}{H_i+1}} \overset{(c)}{\le} k, \tag{17}$$

where the step (c) is true since

$$k(\lfloor \frac{H_i}{k} \rfloor + 1) \ge k(\frac{H_i - (k-1)}{k} + 1) = H_i + 1. \tag{18}$$

This finishes our proof. □

6 Numerical Results

In this section, we evaluate the performances of the proposed LARF algorithm and ORR algorithm. In the experiments, the sink node directly collects sensory data packets

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from all n battery-free sensor nodes in a one-hop BF-WSN, where the network size varies from $n = 5$ to $n = 55$ with a step of 5. The total number of time slots for data collection scheduling is set as $T = 2101$. We compare the proposed LARF algorithm and ORR algorithm with the following two algorithms.

- **The MAX_FIRST algorithm:** In the MAX_FIRST algorithm, the wireless channel is always assigned to the battery-free sensor node with the maximum AoI in any time slot t, i.e., if $a_i(t) \geq a_j(t), \forall v_j \in V$, then $s_i(t) = 1$. If more than one battery-free sensor node have the maximum AoI, the algorithm can break the tie with their IDs. The MAX_FIRST algorithm assumes that all battery-free sensor nodes have the knowledge of the maximum AoI of all battery-free sensor nodes. However, the truth is that only the sink node has the knowledge of the maximum AoI of all battery-free sensor nodes. It requires more time consumption for the sink node to broadcast the wireless channel assignment $s_i(t) = 1$ in each time slot t, which is counterproductive to minimize AoI.
- **The RANDOM algorithm:** In the RANDOM algorithm, each battery-free sensor node v_i satisfying $E_i(t) \geq e_s$ competes for the wireless channel in time slot t with a probability of $\frac{1}{n}$. That is, if a battery-free sensor node has accumulated enough energy to transmit its sensory data packet to the sink node, it will transmit its sensory data packet with a probability of $\frac{1}{n}$. However, if there are more than one battery-free sensor node competing the wireless channel in the same time slot, all transmissions will fail due to transmission interference.

According to the analysis in Section 5.2, the energy profiles of battery-free sensor nodes will affect the performance of algorithms in minimizing AoI of data collection in BF-WSNs. In the experiments, we consider two general energy harvesting processes for battery-free sensor nodes in BF-WSNs, i.e., the Poisson energy harvesting process [17] [13] and the constant-rate energy harvesting process [40] [32]. It is worth noting that the proposed algorithms also apply to the data collection scheduling in BF-WSNs with other energy harvesting processes. In the experiments, the variation of rate λ in Poisson energy harvesting process and mean μ and standard deviation σ in Normal distribution that the constant energy harvesting rate follows in constant-rate energy harvesting process can only affect the average blanking period instead of the minimum/maximum blanking period in Definition 5. Therefore, the numerical results are not segregated into scenarios stated in Theorem 4, Theorem 5 and Theorem 6. However, both the parameter λ in Poisson energy harvesting process and the parameters μ and σ in constant-rate energy harvesting process are chosen according to the well known cases [17] [13] [40] [32]. Therefore, the numerical results presented in this section reveals the results for the well known cases. It is worth noting that the proposed algorithms also apply to other parameters in Poisson energy harvesting process or constant-rate energy harvesting process.

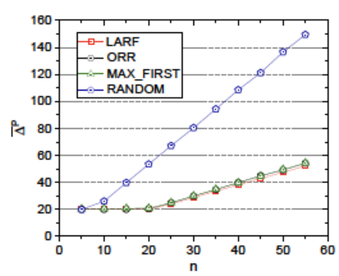
We evaluate the performances of the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm in terms of the weighted sum of average peak ages and the average age of data collection in BF-WSNs, i.e., $\overline{\Delta^P}$ and $\overline{\Delta}$, where $\overline{\Delta^P}$ is calculated by (8) and $\overline{\Delta} = \sum_{i=1}^{n} w_i \frac{\sum_{t=1}^{T} a_i(t)}{T}$. The weights of all battery-free sensor nodes are chosen as follows. We randomly divide the battery-free sensor nodes into 5 groups. The battery-free sensor nodes in the same group have the same weight. And the difference of the sum weights of battery-free sensor nodes in two adjacent group is 0.05. It is worth noting that the proposed algorithms also apply to other diverse weights chosen methods.

6.1 Algorithm Performance in BF-WSNs with Poisson Energy Harvesting Process

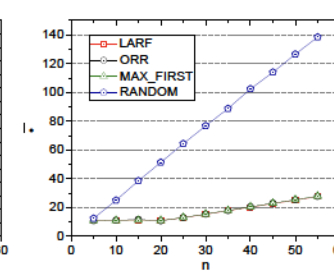
We first evaluate the performances of algorithms in BF-WSNs with Poisson energy harvesting process [17] [13]. That is, the energy harvested by a battery-free senor node in a time slot arrive in units according to a Poisson process with rate λ. The impact of the network size n and the energy profiles of battery-free sensor nodes, represented by λ, on the performances of the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm are evaluated, respectively.

6.1.1 The Impact of Network Size

First, we evaluate the weighted sum of average peak ages and average age of data collection in BF-WSNs as network size n increases from 5 to 55. The energy harvested by a battery-free sensor node in a time slot arrive in units according to a Poisson process with rate $\lambda = 0.05 \times e_s$, where e_s is the energy consumption for a battery-free sensor node to generate and transmit one sensory data packet. Fig.2 presents the numerical results, where each data point in the figures is the average result produced by running algorithms on 100 BF-WSNs.



(a) The impact of n on $\overline{\Delta^P}$.



(b) The impact of n on $\overline{\Delta}$.

Fig. 2: The impact of n on the performances of algorithms in BF-WSNs with Poisson energy harvesting process.

Fig.2 (a) shows the weighted sum of average peak ages $\overline{\Delta^P}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. The numerical results reveal the following facts. First, the weighted sum of average peak ages $\overline{\Delta^P}$ increases with the increase of n. Second, the performance of the proposed online ORR algorithm is close to the optimal offline LARF algorithm regardless of the network size. Third, the

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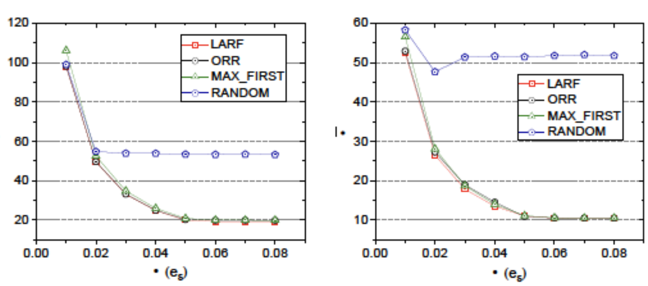
proposed LARF algorithm and ORR algorithm can significantly increase the freshness of sensory data packets collected by the sink node. Although the MAX_FIRST algorithm has similar performance with the proposed algorithms, the MAX_FIRST algorithm is not feasible in fact since battery-free sensor nodes can not have the knowledge of real-time maximum AoI of the network. Fourth, the weighted sum of average peak ages $\overline{\Delta^P}$ produced by the proposed LARF algorithm and ORR algorithm increases sharply after $n \geq e_s/\lambda = 20$. The reasons are as follows. When $n < e_s/\lambda$, the expectation of the energy harvested by a battery-free sensor node in n time slots is $n\lambda < e_s$. Therefore, the energy constraint is the major constraint for reducing $\overline{\Delta^P}$. However, after $n \geq e_s/\lambda$, the expectation of the energy harvested by a battery-free sensor node in n time slots is larger than e_s. That means the probability of a battery-free sensor node to harvest at least e_s energy in n time slots increases with the increase of n. Meanwhile, the increase of n leads the increased competitions among battery-free sensor nodes for the common wireless channel and the transmission interference becomes the main constraint in reducing $\overline{\Delta^P}$ when $n \geq e_s/\lambda$. Therefore, when $n \geq e_s/\lambda$, $\overline{\Delta^P}$ increases sharply with the increase of n.

Fig.2 (b) shows the average age $\overline{\Delta}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. Surprisingly, the proposed LARF algorithm and ORR algorithm also have good performance in reducing the average age of data collection in BF-WSNs.

6.1.2 The Impact of Energy Profile

Next, we evaluate the weighted sum of average peak ages and average age of data collection in BF-WSNs as the Poisson parameter λ increases from $0.01 \times e_s$ to $0.08 \times e_s$, where e_s is the energy consumption for a battery-free sensor node to generate and transmit one sensory data packet. We set the network size as $n = 20$. Fig.3 shows the numerical results, where each data point in the figures is the average result produced by running algorithms on 100 BF-WSNs.



(a) The impact of λ on $\overline{\Delta^P}$. (b) The impact of λ on $\overline{\Delta}$.

Fig. 3: The impact of λ on the performances of algorithms in BF-WSNs with Poisson energy harvesting process.

Fig.3 (a) shows the weighted sum of average peak ages $\overline{\Delta^P}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. It can be observed from the figure that the weighted sum of average peak ages $\overline{\Delta^P}$ produced by all algorithms decreases with the increase of λ. It reveals the fact that the energy harvesting ability of battery-free sensor nodes has a powerful influence on the freshness of sensory data collected by the sink node in BF-WSNs. But the proposed LARF algorithm and ORR algorithm can significantly increase the data freshness of data collection in BF-WSNs no matter what the energy profiles of battery-free sensor nodes are. In the experiments, the MAX_FIRST algorithm has similar performance with the proposed algorithms, but it is not feasible in fact since the assumption that all battery-free sensor nodes have the knowledge of real-time maximum AoI of the network is invalid in BF-WSNs. What's more, the figure presents that the performance of the online ORR algorithm is similar to the offline optimal LARF algorithm, which verifies that the online ORR algorithm has a low competitive ratio. Specifically, the weighted sum of average peak ages $\overline{\Delta^P}$ produced by the proposed LARF algorithm and ORR algorithm decreases sharply before $\lambda < e_s/n = 0.05 \times e_s$. The reason is that the expectation of the energy harvested by a battery-free sensor node in n time slots is $n\lambda < e_s$ before $\lambda < e_s/n$. Therefore, the energy constraint is the major constraint for the transmissions of battery-free sensor nodes when $\lambda < e_s/n$ while the transmission interference constraint is the major constraint when $\lambda \geq e_s/n$.

Fig.3 (b) presents the average age $\overline{\Delta}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. The figure reveals the fact that the proposed LARF algorithm and ORR algorithm can also reduce the average age of data collection in BF-WSNs.

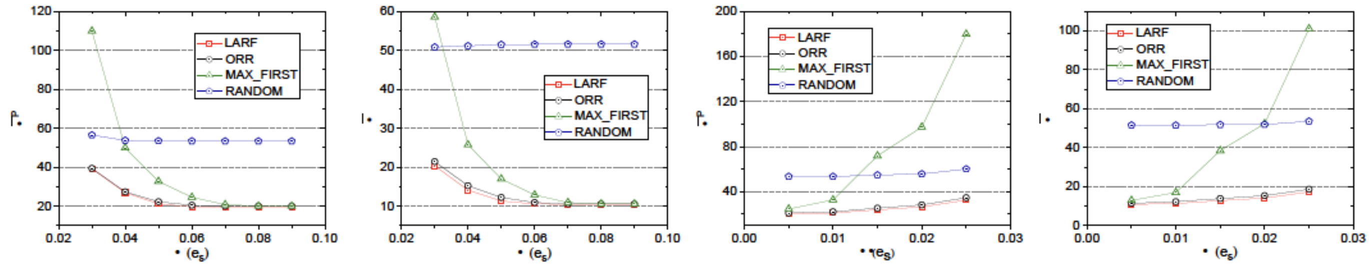
6.2 Algorithm Performance in BF-WSNs with Constant-Rate Energy Harvesting Process

We then evaluate the performances of algorithms in BF-WSNs with constant-rate energy harvesting process. Each battery-free sensor node v_i has a constant energy harvesting rate r_i in T time slots. We assume that r_i follows the Normal distribution with mean μ and standard deviation σ, i.e., $r_i \sim \mathcal{N}(\mu, \sigma^2)$, $\forall v_i \in V$. The impact of network size n and energy profiles of battery-free sensor nodes, represented by μ and σ, on the performances of the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm are evaluated, respectively.

6.2.1 The Impact of Network Size

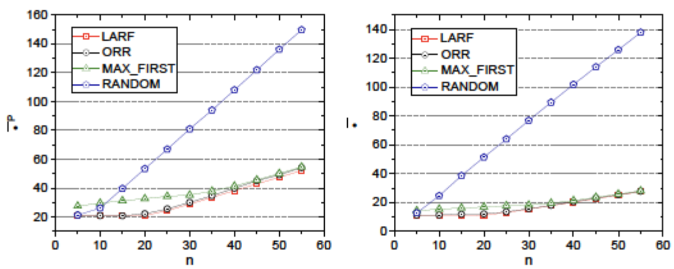
First, we evaluate the weighted sum of average peak ages and average age of data collection in BF-WSNs as the network size n increases from 5 to 40. The energy harvesting rate of each battery-free sensor node follows the Normal distribution with mean $\mu = 0.05 \times e_s$ and standard deviation $\sigma = 0.01 \times e_s$, where e_s is the energy consumption for a battery-free sensor node to generate and transmit one sensory data packet. Fig.4 presents the numerical results, where each data point in the figures is the average result produced by running algorithms on 100 BF-WSNs.

Fig.4 (a) presents the weighted sum of average peak ages $\overline{\Delta^P}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm, and the RANDOM algorithm, respectively. We can observe from Fig.4 (a) that the impact of n on the performances of these algorithms running in BF-WSNs with constant-rate energy harvesting process is



(a) The impact of μ on $\overline{\Delta^P}$. (b) The impact of μ on $\overline{\Delta}$. (c) The impact of σ on $\overline{\Delta^P}$. (d) The impact of σ on $\overline{\Delta}$.

Fig. 5: The impact of energy profile on the performances of algorithms in BF-WSNs with constant-rate energy harvesting process.



(a) The impact of n on $\overline{\Delta^P}$. (b) The impact of n on $\overline{\Delta}$.

Fig. 4: The impact of n on the performances of algorithms in BF-WSNs with constant-rate energy harvesting process.

similar to that in BF-WSNs with Poisson energy harvesting process. First, the weighted sum of average peak ages $\overline{\Delta^P}$ increases with the growth of n. Second, the proposed online ORR algorithm has similar performance with the proposed optimal offline algorithm no matter what the network size is, which verifies that the proposed online ORR algorithm has a low competitive ratio. Third, the proposed ORR algorithm and LARF algorithm can produce lower $\overline{\Delta^P}$ than the RANDOM algorithm and the MAX_FIRST algorithm. Although the MAX_FIRST algorithm has similar performance with the proposed algorithms, it is not feasible in fact since the assumption that all battery-free sensor nodes have the knowledge of real-time maximum AoI of the network fails in BF-WSNs. Finally, the $\overline{\Delta^P}$ produced by the LARF algorithm and the ORR algorithm increases sharply after $n \geq e_s/\mu = 20$. The reasons are as follows. When $n < e_s/\mu$, it indicates that the expectation $\mathbb{E}(r_i) = \mu < e_s/n$. Therefore, the energy constraint is the major constraint for reducing $\overline{\Delta^P}$ and there is little transmission interference among battery-free sensor nodes. When $n \geq e_s/\mu$, however, since the probability of a battery-free sensor node to harvest at least e_s energy in n time slots increases with the increase of n, the energy constraint is no longer the major constraint for reducing $\overline{\Delta^P}$. Instead, the transmission interference constraint becomes the major constraint for reducing $\overline{\Delta^P}$ since the increase of n incurs the increased competitions among battery-free sensor nodes for the common wireless channel. Therefore, $\overline{\Delta^P}$ increases sharply after $n \geq e_s/\mu = 20$.

Fig.4 (b) presents the average age $\overline{\Delta}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. The figure reveals that the proposed LARF algorithm and ORR algorithm can also reduce the average age of data collection in BF-WSNs, which verifies the good performance of the proposed algorithms in increasing data freshness for data collection in BF-WSNs.

6.2.2 The Impact of Energy Profile

Next, we evaluate the impact of energy profiles of battery-free sensor nodes on the weighted sum of average peak ages and average age of data collection in BF-WSNs. We set the network size as $n = 20$. Since the energy harvesting rates of battery-free sensor nodes follow the Normal distribution with mean μ and standard deviation σ, we evaluate the impact of μ and σ, respectively. Fig.5 shows the numerical results, where each data point in the figures is the average result produced by running algorithms on 100 BF-WSNs.

We first evaluate the weighted sum of average peak ages and average age of data collection in BF-WSNs as mean μ increases from $0.03 \times e_s$ to $0.09 \times e_s$, where e_s is the energy consumption for a battery-free sensor node to generate and transmit one sensory data packet. We set standard deviation as $\sigma = 0.01 \times e_s$. The experiment results are presented in Fig.5 (a) and (b). Fig.5 (a) shows that the weighted sum of average peak ages $\overline{\Delta^P}$ produced by all algorithms decreases with the increase of μ. It can also be observed from the figure that the proposed LARF algorithm and ORR algorithm has better performance than the other two algorithms. Besides, the performance of the proposed online ORR algorithm is close to the performance of the optimal offline LARF algorithm. Specifically, the weighted sum of average peak ages $\overline{\Delta^P}$ produced by the proposed algorithms decreases sharply after $\mu < e_s/n = 0.05 \times e_s$. As mentioned before, energy is the major constraint for reducing $\overline{\Delta^P}$ when $\mu < e_s/n$. Therefore, the increase of the expectation $\mathbb{E}(r_i) = \mu$ will reduce $\overline{\Delta^P}$ sharply when $\mu < e_s/n$. Fig.5 (b) presents the average age $\overline{\Delta}$ achieved by the LARF algorithm, the ORR algorithm, the MAX_FIRST algorithm and the RANDOM algorithm, respectively. It reveals the fact that the proposed LARF algorithm and ORR algorithm can also reduce the average age of data collection in BF-WSNs.

We also evaluate the weighted sum of average peak ages and average age of data collection in BF-WSNs as standard deviation σ increases from $0.005 \times e_s$ to $0.025 \times e_s$, where e_s is the energy consumption for a battery-free sensor node to generate and transmit one sensory data packet. We set mean as $\mu = 0.05 \times e_s$. The experiment results are presented in Fig.5 (c) and (d). Intuitively, both the weighted sum of average peak ages $\overline{\Delta^P}$ and the average age $\overline{\Delta}$ increase with the increase of σ. The standard deviation σ represents the differences among the energy harvesting rates of battery-free sensor nodes in a BF-WSN. Therefore, the figures reveal that the larger differences among energy harvesting rates of battery-free sensor nodes in a BF-WSN will reduce the data freshness of data collection in the network. Similar to the above experiment results, the proposed LARF algorithm and ORR algorithm can always increase the data freshness of data collection in BF-WSNs.

7 Conclusion

In this paper, we investigate the AoI minimization data collection scheduling problem in one-hop BF-WSNs with multiple battery-free sensor nodes having non-specific energy harvesting processes. We propose the optimal offline LAEF algorithm and the online ORR algorithm, where the optimality of the offline algorithm and the competitive ratio of the online algorithm are theoretically proved and analyzed. Finally, numerical results are provided to verify the performances of the proposed algorithms. The numerical results reveal that the proposed LARF algorithm and ORR algorithm can significantly improve the data freshness of data collection in BF-WSNs.

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