Joint Near-Optimal Age-based Data Transmission and Energy Replenishment Scheduling at Wireless-Powered Network Edge

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***Abstract*—Age of Information (AoI), emerged as a new metric to quantify the data freshness, has attracted increasing interests recently. Most existing works try to optimize the system AoI from the point of data transmission. Unfortunately, at wireless-powered network edge, the charging schedule of the source nodes also needs to be decided besides data transmission. Thus, in this paper, we investigate the joint scheduling problem of data transmission and energy replenishment to optimize the peak AoI at network edge with directional chargers. To the best of our knowledge, this is the first work that considers such two problems simultaneously. Firstly, the theoretical bounds of the peak AoI with respect to the charging latency are derived. Secondly, for the minimum peak AoI scheduling problem with a single charger, an optimal scheduling algorithm is proposed to minimize the charging latency, and then a data transmission scheduling strategy is also given to optimize the peak AoI. The proposed algorithm is proved to have a constant approximation ratio of up to 1.5. When there exist multiple chargers, an approximate algorithm is also proposed to minimize the charging latency and peak AoI. Finally, the simulation results verify the high performance of proposed algorithms in terms of AoI.**

I. Introduction

Wireless Power Transfer (WPT) has become a promising technique to provide a controllable and sustainable energy supply for IoT networks by charging devices via electromagnetic waves [1]–[4]. Due to its convenience and reliability for power provisioning, it has been applied in many application domains [5]–[7]. For example, in the application of structural health monitoring, a system consisting of far-field LoRaWAN battery-free sensing nodes are developed recently with the WPT technique [5]. Moreover, to improve energy transfer efficiency, directional WPT has been introduced as an efficient way to gain the power intensity in a certain direction with energy beamforming. According to [2], employing directional WPT, the rechargeable devices can obtain a performance gain of up to three or more times over that using omnidirectional WPT. Since the electromagnetic waves fade rapidly over distance, the directional WPT model becomes more essential for the far-field applications.

At network edge, Age of Information (AoI) has been introduced as a new metric to quantify the freshness of information recently [8]–[10]. Significant attentions have been paid to it since then, due to the importance of maintaining data freshness in many real-time applications. It is defined as the elapsed time between the present time and the time when the most recent information (stored at the destination) is generated at its source node. Unlike traditional packet-based metrics, such as latency, AoI can naturally characterize the data freshness from the destination's perspective. Considering a typical scenario at network edge, which consists of multiple source nodes (sensing nodes) deployed in a target area and a base station (BS). The source nodes, aimed for different applications, try to sense the ambient environment and transmit the sampled data to the BS. At the BS, the AoI would increase linearly when there are no updates from the source nodes. Due to the limited spectrum bandwidth, only a part of newly generated samples can be forwarded to the BS at each time slot. Thus, how to schedule the data transmissions to minimize the average and peak AoI for the whole network has become a hotspot. Many AoI-based data transmission scheduling algorithms have been proposed recently [14]–[28].

However, at wireless-powered network edge, the charging schedule for the source nodes also needs to be designed besides data transmission. As a result, the scheduling of data transmission and energy replenishment should be designed jointly, which makes the AoI optimization problem more challenging, especially when the directional charging model is exploited to improve energy transfer efficiency. Note that, at a given orientation of the charger, only the source nodes lying in the shape of a sector can be charged, and the harvested energy at each node is also heterogeneous. Without loss of generality, assume the network time is slotted. Then, at each time slot, only a part of the source nodes can be charged and each source node may require different charging time to guarantee its data transmission. Different from the traditional charging scheduling and data transmission scheduling problem, to minimize the system AoI, there exist the following two challenging problems at wireless-powered network edge:

1) How to compute the optimal charging schedule for the

source nodes (*i.e.*, the orientation of the charger at each time slot) considering these nodes' AoI. Note that, under directional charging model, how to exploit the overlapped charging area at different orientations to reduce the charging latency and AoI becomes paramountly important.

2) How to obtain the optimal data transmission decisions for each source node, especially when the source node exploits different sampling models, such as periodical and random sampling model.

Thus, to address the above issues, we investigate the joint scheduling problem of data transmission and energy replenishment for AoI optimization at wireless-powered network edge with directional chargers. Several approximate algorithms are proposed by considering data transmission and energy replenishment simultaneously. The main contribution of this paper is summarized as follows.

- To the best of our knowledge, this is the first work that investigates the joint scheduling problem of data transmission and energy replenishment for AoI optimization. The theoretical bounds of the peak AoI with respect to the charging latency are also derived.
- To minimize the peak AoI with a single directional charger, an approximation algorithm with a constant ratio of up to 1.5 is proposed. In the proposed algorithm, an optimal scheduling algorithm is firstly developed to minimize the charging latency, and then the data transmission strategies for different sampling models are also designed.
- When there exist multiple directional chargers, an approximate algorithm is also proposed to minimize the charging latency and the peak AoI.
- Through extensive simulations, it is shown that the proposed algorithm can reduce the peak AoI by almost a half compared with the baseline methods.

The rest of the paper is organized as follows. Section II surveys the related works. Section III presents the problem formulation. Section IV and V introduce the detailed design and theoretical analysis of the proposed algorithm for single and multiple chargers, respectively. The simulation results are shown in Sections VI. Finally, Section VII concludes the paper.

II. Related Works

The AoI scheduling problem has attracted extensive attentions from researchers. Firstly, AoI was studied for a vehicular network in [9], where the updates are generated periodically and then cached at a first-in-first-out queue at the MAC layer for broadcasting. After that, the AoI under various queueing disciplines are studied by [10]–[13], such as the first-come-first-serve and the last-come-first-serve queues. Considering the single-link wireless network, the authors in [14]–[18] studied the AoI scheduling problem when multiple source nodes share a common channel. When there exist multiple links in the network, the authors in [19], [20] studied the AoI scheduling problem by considering the interference between neighboring links. In [21]–[23], the authors considered a multi-hop network where the messages from the source nodes need to go through several intermediate nodes before reaching the destination. Li et al. [24] studied the single-hop cellular-based network where there exist one base station and multiple source nodes. The theoretical lower bounds of the system's average AoI under three sampling strategies, *i.e,* arbitrary, periodic and per time slot sampling are derived. The AoI scheduling algorithm under 5G network and the network with multi-channels are studied by [25] and [26]. Recently, the authors in [27], [28] studied the peak AoI optimization problem which tries to optimize the maximum AoI. However, these algorithms ignore the energy provisioning problem.

When the source nodes exploit the energy-harvesting model, the AoI scheduling algorithms are studied by [29]–[36]. In [29], the authors considered a system with a single rechargeable source node. Several scheduling policies are proposed when the energy arrival time follows the Poisson point process. The same one-pair network model is also assumed by [30]–[36], where several offline and online scheduling policies are proposed by considering different service time. The authors in [37] considered a two-hop model that there exists an energy-harvesting node between the source and destination. However, all these algorithms assume a simple network model and the energy replenishment process cannot be controlled.

Considering directional charging, the authors in [38] studied the omnidirectional covering problem with directional chargers, which tries to ensure a rechargeable node at an arbitrary position with any orientation can be charged with enough power. Dai et al. [2], [39] investigated the placement problem of directional chargers while the overall charging utility is optimized. The authors in [40], [41] try to schedule the orientations of the chargers to maximize the overall charging utility, and the authors in [1] try to adjust the charging radius adaptively to improve the energy transfer efficiency. Lin et al. [3] studied the charging latency minimization problem when there is a mobile directional charger travelling and stopping at a set of planned locations to charge its surrounding nodes.

III. Problem Definition

A. Network Model and Charging Model

Consider a wireless-powered network, which consists of a BS equipped with a directional charger, and a set of rechargeable source nodes randomly deployed around the BS, denoted by $S = \{s_1, s_2, ..., s_n\}$. Except for receiving the sampled data from the source nodes, the BS is also responsible for charging them to satisfy the energy requirement for their transmissions. Each source node can transmit its sampled data only after it has been charged enough energy. Note that, in this paper, we mainly focus on the energy for data transmission (the energy for sampling, which is much smaller or just comes from another source, is omitted here).

To charge the source nodes, the directional wireless charger is employed here to improve energy transfer efficiency for the far-field source nodes. Under directional charging model, according to [2], the charger with a given orientation $\overrightarrow{o_i}$ can only charge a part of source nodes, *i.e.*, the nodes lying in the shape of a sector with angle ϕ and radius R. For example, as

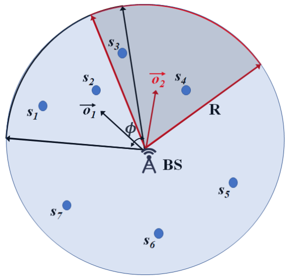


Fig. 1. An example of wireless-powered network edge.

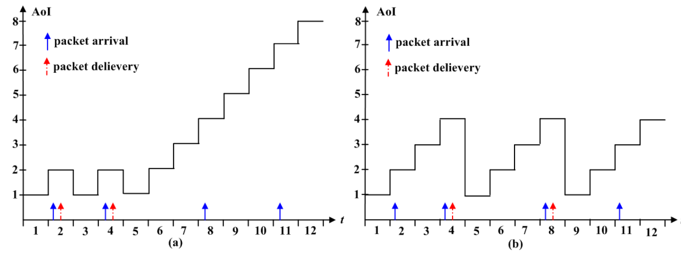


Fig. 2. An example of AoI scheduling.

in Fig.1, when the directional charger is at orientation $\overrightarrow{o_1}$, only the source nodes s_1, s_2, and s_3 can be charged.

Let $\Gamma(\overrightarrow{o_i})$ denote the set of source nodes lying in the charging area of the directional charger at orientation $\overrightarrow{o_i}$. For example, as in Fig.1, we can have $\Gamma(\overrightarrow{o_1}) = \{s_1, s_2, s_3\}$ and $\Gamma(\overrightarrow{o_2}) = \{s_3, s_4\}$. Then, the charging power received by source node s_i can be computed by the following equation [2]:

$$P(s_i, \overrightarrow{o_i}) = \begin{cases} \frac{\alpha}{(d(BS, s_i)+\beta)^2}, & if\ s_i \in \Gamma(\overrightarrow{o_i}) \\ 0, & otherwise \end{cases}$$

where α and β denote two constants related to the surrounding environment and the hardware parameters of the directional charger, and $d(BS, s_i)$ is the Euclidean distance between the BS and the source node s_i. One should note that, for any two different orientations $\overrightarrow{o_i}$ and $\overrightarrow{o_j}$, their covered source nodes may be overlapped, *i.e.*, $\Gamma(\overrightarrow{o_i}) \cap \Gamma(\overrightarrow{o_j}) \neq \emptyset$. Note that, under such model, how to exploit the overlapped area of different orientations is upmost important for directional charging.

In addition, if $\Gamma(\overrightarrow{o_i}) \subseteq \Gamma(\overrightarrow{o_j})$ $(i \neq j)$, we call $\overrightarrow{o_i}$ a redundant orientation, which can be just removed. Assume there are in total m $(m \leq n)$ non-redundant orientations for the directional charger, *i.e.*, $\overrightarrow{o_1}$, $\overrightarrow{o_2}$,...,$\overrightarrow{o_m}$, and $\Gamma(\overrightarrow{o_i}) \nsubseteq \Gamma(\overrightarrow{o_j})$ $(1 \leq i, j \leq m\ \&\ i \neq j)$. Obviously, for all these orientations, one can have $\cup_{i=1}^{m} \Gamma(\overrightarrow{o_i}) = \{s_1, s_2, ..., s_n\}$.

As for each source node s_i, let e_i be the consumed energy for transmitting one unit data, and L_i denote the size of its sampled data. Then, if it wants to transmit its sampled data to the BS at time slot k (which means it has been charged enough energy at the beginning of the k-th time slot), then it must satisfy $\sum_{t=1}^{k-1} P(s_i, \overrightarrow{o(t)}) \cdot \tau \geq e_i \cdot L_i$. Note that, the network time is assumed to be divided into time slots with fixed length τ [20], [42], [43], and $\overrightarrow{o(t)}$ denotes the orientation of the wireless charger at time slot t, *i.e.*, $\overrightarrow{o(t)} \in \{\overrightarrow{o_1}, \overrightarrow{o_2}, ..., \overrightarrow{o_m}\}$.

B. AoI Model

For the BS, it maintains the most recent sample received from each source node s_i. Once it receives a new sample from a source node s_i, the old one will be replaced. At time slot t, let $U_{s_i}(t)$ denote the generation time of the newest sample at source node s_i, and let $U^B_{s_i}(t)$ denote the generation time of s_i's newest sample stored at the BS. Note that $U^B_{s_i}(t)$ is not always equal to $U_{s_i}(t)$. They are equal if there is no new sample arrived at s_i after it transmits its newest sample to BS.

To guarantee the data-freshness of the whole network, we adopt AoI in designing the scheduling algorithm in this paper. Assume $A_{s_i}(t)$ denote the AoI of s_i at time slot t, which is defined as the number of time slots elapsed up to time slot t since the generation time of the most recent sample. Note that, we also use time slot as the unit of AoI and assume the length of a time slot is much longer than the transmission time as in [20] (According to [44], the amount of harvested power using a micro-energy harvester is three to six orders of magnitude lower, thus we mainly consider the charging time here and assume the bandwidth is enough). Then, the AoI of s_i at time slot t $(t \geq 1)$, *i.e.*, $A_{s_i}(t)$, can be calculated as $A_{s_i}(t) = t - U^B_{s_i}(t)$. Actually, $A_{s_i}(t)$ is a zigzag-like function which grows linearly until the source node sends a freshest sample to the BS. At the beginning, $U^B_{s_i}(1)$ is just set to be 0 for each source node.

Denote $x_i(t) \in \{0, 1\}$ as the transmission decision for source node s_i, which means whether it is scheduled to transmit its sample at time slot t. Note that, the source node can hold its transmission after been charged till the scheduled transmission time. If $x_i(t) = 1$, then at the next time slot $t+1$, the AoI value will drop to $t+1-U^B_{s_i}(t+1)$. In addition, since the source node only sends the newest sample to be BS, thus, one can have $U^B_{s_i}(t+1) = U_{s_i}(t)$, which means $A_{s_i}(t+1) = t+1-U^B_{s_i}(t+1) = t+1-U_{s_i}(t)$. Thus, the AoI of s_i, at time $t+1$, *i.e.*, $A_{s_i}(t+1)$, can be updated as:

$$A_{s_i}(t+1) = \begin{cases} t+1-U_{s_i}(t), & if\ x_i(t) = 1 \\ A_{s_i}(t)+1, & otherwise \end{cases}$$

Note that, if s_i transmits a sample which also arrives at time t (it means $U_{s_i}(t) = t$ here), then the AoI value at time $t+1$ will drop to 1.

For example, as in Fig. 2, it shows the AoI of source node s_i in the first 12 time slots. Assume s_i has sampled 4 packets (as the blue arrow) and has been charged enough energy for transmitting two packets at time 1. If one schedules the transmission of the first two samples at time 2 and 4 as shown in Fig.2(a), the AoI of the source node s_i drops to 1 at the beginning of time 3 and 5, respectively. But the peak AoI value reaches 8. However, if one let source node s_i transmit the samples at time 4 and 8, respectively, then the peak AoI of s_i drops to 4, which is shown in Fig.2(b).

One can see, the AoI of source node s_i is not only related to its charged energy, but also its transmission decision. Thus, to guarantee the data freshness, one not only needs to compute the charging plan for the source nodes smartly, but also be very careful to schedule packet delivery of each source node.

As in [27], [28], we mainly focus on the peak AoI of the source nodes in this paper. Let $A^{peak}_{s_i}$ denote the peak AoI of source node s_i during a period from 1 to $\mathcal{T}$ ($\mathcal{T}$ >> 1), which can be calculated as :

$$A^{peak}_{s_i} = max\{A_{s_i}(t), \forall 1 \leq t \leq \mathcal{T}\}$$

For all the source nodes, let A^{peak} denote the peak AoI for the whole network, which can be calculated as:

$$A^{peak} = max\{A^{peak}_{s_i}, \forall 1 \leq i \leq n\}$$

To guarantee the data-freshness, we try to minimize the peak AoI for all the source nodes in the network, which is called the Minimum Peak AoI Scheduling problem.

In this paper, we will first study the Minimum Peak AoI Scheduling problem with a Single charger (MPAS-S). And then, we will introduce the algorithms for the Minimum Peak AoI Scheduling problem with Multiple chargers (MPAS-M).

C. Problem Formulation

In the following, we will introduce the formal definition of the MPAS-S problem. Note that, in this paper, we also consider three sampling models as in [24] : 1) Sampling by time slot, 2) Sampling with period T_i, and 3) Sampling randomly.

Input:

1) A set of source nodes $S = \{s_1, s_2, ..., s_n\}$, and a BS;
2) All the m orientations of the charger, *i.e.*, $\overrightarrow{o_1}$,$\overrightarrow{o_2}$,...,$\overrightarrow{o_m}$, and the covered source nodes at each orientation $\overrightarrow{o_i}$, *i.e.*, $\Gamma(\overrightarrow{o_i})$;
3) For each source node s_i, the energy consumption for transmitting unit data e_i and the size of sample data L_i;
4) The sampling model for each source node s_i.

Output:

1) The charging decision, $\overrightarrow{o(t)}$ ($t = 1, 2, ..., \mathcal{T}$);
2) The data transmission decision, $x_i(t)$ ($t = 1, 2, ..., \mathcal{T}$).

while the peak AoI of the whole network A^{peak} is minimized.

Since $\mathcal{T}$ is a much large value, the searching space of $\overrightarrow{o(t)}$ and $x_i(t)$ would be extremely large. In the following, we will introduce an age-based scheduling algorithm which considers data transmission and energy replenishment simultaneously.

IV. The Joint Scheduling Algorithm with Single Charger

A. Theoretical Bound of the Peak AoI

Before introducing the detailed algorithm, we will first present some interesting properties of the theoretical bound of the peak AoI with respect to different sampling models.

Let $\mathcal{A}_{opt}$ denote the optimal peak AoI under the optimal charging and data transmission plan, and Υ_{opt} denote the optimal charging latency of the whole network, *i.e.*, the required charging time for each node to transmit at least once.

Firstly, considering the sampling by time slot model (which can be also seen as sampling with $T_i = 1$ for each source node s_i), it can be easily verified that $\mathcal{A}_{opt}$ is just equal to $\Upsilon_{opt} + 1$, which is shown in Theorem 1.

Theorem 1. *If $T_i = 1$ for each source node s_i ($1 \leq i \leq n$), then $\mathcal{A}_{opt} = \Upsilon_{opt} + 1$.*

Secondly, when the sampling period $T_i > 1$, the upper bound of the peak AoI can be proved to be at most $\Upsilon_{opt} + T_{max}$, where $T_{max} = max\{T_i, 1 \leq i \leq n\}$.

Theorem 2. *If $T_i > 1$ for each source node s_i ($1 \leq i \leq n$), then $\Upsilon_{opt} + 1 \leq \mathcal{A}_{opt} \leq \Upsilon_{opt} + T_{max}$.*

The proof is omitted here due to space limitation. Note that, in this case, the optimal peak AoI can also be equal to $\Upsilon_{opt} + 1$ by designing the charging order and transmission order carefully, considering nodes' sampling period.

Consider a special case that the sampling period of each source node is larger than Υ_{opt}. Then the peak AoI will just be T_{max}, which is shown in Theorem 3. This is very interesting, because the optimal peak AoI may even drop when the sampling period increases.

Theorem 3. *If $T_i > \Upsilon_{opt}$ for each source node s_i ($1 \leq i \leq n$), then $\mathcal{A}_{opt} = T_{max}$.*

Proof: Let the sampling period of source node s_i be the largest, *i.e.*, $T_i = T_{max}$. Firstly, since the BS can update the sample by at least T_{max} time, one can have $\mathcal{A}_{opt} \geq T_{max}$. Secondly, since $T_i > \Upsilon_{opt}$, which means source node s_i must have been charged enough energy during a sampling period. In this case, one can just let the source nodes transmit when a new sample arrives, *i.e.*, t, and the peak AoI will be at most T_{max} at time t and will drop to 1 at time $t + 1$. Therefore, the optimal peak AoI is T_{max}. ■

Thirdly, under random sampling model, we can also obtain the same result as in Theorem 2, which is shown in Theorem 4. Note that, under random sampling model, even when $D_{max} > \Upsilon_{opt}$, one cannot obtain $\mathcal{A}_{opt} = D_{max}$ here.

Theorem 4. *Let $D_{max} > 1$ denote the maximum duration between two samples, then $\Upsilon_{opt} + 1 \leq \mathcal{A}_{opt} \leq \Upsilon_{opt} + D_{max}$.*

According to the above analysis, one can find that, to obtain the optimal peak AoI, the optimal charging latency should be obtained firstly, which is also non-trivial.

Thus, in the following, we will first introduce a method to obtain the optimal charging latency, and then design a data transmission schedule with an approximation ratio up to 1.5.

B. Optimizing the Charging Latency

To obtain the optimal charging latency Υ_{opt}, we first transform the charging latency minimization problem to a new kind of geometric set cover problem, *i.e.*, circle set cover problem.

Let $r(s_i) = \left\lceil \frac{e_i \cdot L_i \cdot (d(B,s_i)+\beta)^2}{\alpha * \tau} \right\rceil$ denote the minimum number of time slots that s_i needs to be charged for transmitting its sample. Then, the charging latency minimization problem can be seen as the problem of using the minimum number of sets from $\{\Gamma(\overrightarrow{o_1}), \Gamma(\overrightarrow{o_2}), ..., \Gamma(\overrightarrow{o_m})\}$ to cover each source nodes' request $r(s_i)$. Note that, each set $\Gamma(\overrightarrow{o_i})$ can be used multiple times and each source node s_i needs to be covered by at least $r(s_i)$ times here. For simplicity, let $\mathcal{R} = \{r(s_1), r(s_2), ..., r(s_n)\}$ denote the covering requirements of all the source nodes. As one can see, since all the sets constitute a circle, thus, we call such problem the *Circle Set Cover* problem.

Considering the example in Fig. 1, assume there are six orientations, that is $\Gamma(\overrightarrow{o_1}) = \{s_1, s_2, s_3\}$, $\Gamma(\overrightarrow{o_2}) = \{s_3, s_4\}$, $\Gamma(\overrightarrow{o_3}) = \{s_4, s_5\}$, $\Gamma(\overrightarrow{o_4}) = \{s_5, s_6\}$, $\Gamma(\overrightarrow{o_5}) = \{s_6, s_7\}$, $\Gamma(\overrightarrow{o_6}) = \{s_7, s_1\}$, and the required charged number of time slots for the source nodes is set to be $\mathcal{R} = \{2, 1, 3, 4, 2, 2, 4\}$.

For the circle set cover problem, when choosing the set, one must take the overlapped nodes and nodes' covering requirements into account. In the following, we will first introduce a dynamic programming based algorithm for the circle set cover problem. It mainly works as follows.

1) Dynamic Programming Based Algorithm: Firstly, sort the orientations of the charger, *i.e.*, $\overrightarrow{o_1}, \overrightarrow{o_2}, ..., \overrightarrow{o_m}$, in the clockwise order. Let $\overrightarrow{o_1}$ be the first orientation. In addition, denote $prev(\overrightarrow{o_i})$ and $next(\overrightarrow{o_i})$ as the previous and next orientations of $\overrightarrow{o_i}$, respectively, *i.e.*, $prev(\overrightarrow{o_1}) = \overrightarrow{o_m}$ and $next(\overrightarrow{o_m}) = \overrightarrow{o_1}$.

One can find that, for any set $\Gamma(\overrightarrow{o_i})$, it can be used at most $k^i_{max} = max\{r(s_j), \forall s_j \in \Gamma(\overrightarrow{o_i})\}$ times in the optimal result. And once if $\Gamma(\overrightarrow{o_i})$ is used by k $(k \le k^i_{max})$ times, then the covering requirement can be updated by $r(s_j) = max\{r(s_j) - k, 0\}$ for any source node s_j in $\Gamma(\overrightarrow{o_i})$.

Let $\mathcal{L}(i, m, \mathcal{R})$ denote the minimum latency when using the orientations from $\overrightarrow{o_i}$ to $\overrightarrow{o_m}$ to satisfy the covering requirement $\mathcal{R}$. Then, we can obtain the dynamic programming equation:

$$\mathcal{L}(i, m, \mathcal{R}) = min\{k + \mathcal{L}(i + 1, m, \mathcal{R}^k), 0 \le k \le k^i_{max}\}$$

where $\mathcal{R}^k$ denotes the covering requirement after using set $\Gamma(\overrightarrow{o_i})$ by k times. As for the last orientation $\overrightarrow{o_m}$, one can have:

$$\mathcal{L}(m, m, \mathcal{R}) = \begin{cases} \infty, & if\ \exists r(s_j) > 0\ and\ s_j \notin \Gamma(\overrightarrow{o_m}) \\ max\{r(s_j), \forall s_j \in \Gamma(\overrightarrow{o_m})\}, & otherwise \end{cases}$$

Note that, if there exists a source node not being covered, *i.e.*, $\exists r(s_j) > 0$ *and* $s_j \notin \Gamma(\overrightarrow{o_m})$, it means we cannot satisfy the covering requirement at this time, then set $\mathcal{L}(m, m, \mathcal{R}) = \infty$.

The optimal result can be obtained by calculating $\mathcal{L}(1, m, \mathcal{R})$. However, the time complexity of the above dynamic programming algorithm is exponential with the number of sets, *i.e.*, $O(m^{r_{max}+1})$, where $r_{max} = max\{r(s_j), 1 \le j \le n\}$.

2) Polynomial Optimal Algorithm: Next, we will introduce an efficient polynomial algorithm. The main trick is that if we can transfer the Circle Set Cover problem to a problem which we named as the Line Set Cover problem, then we can solve it greedily. Note that, in the line set cover problem, all the sets can be sorted in a line as shown in Fig.3.

Assume $\Gamma(\overrightarrow{o_1})$, $\Gamma(\overrightarrow{o_2})$,..., $\Gamma(\overrightarrow{o_m})$ forms a line set cover problem. Let κ_i denote the optimal number for set $\Gamma(\overrightarrow{o_i})$. Then, the greedy algorithm for the line set cover problem works as follows. Without loss of generality, let $\Gamma(\overrightarrow{o_1})$ be the first set. First, for each orientation $\overrightarrow{o_i}$ from $\overrightarrow{o_1}$ to $\overrightarrow{o_{m-1}}$, do :

- Let $\chi(\overrightarrow{o_i}) = \Gamma(\overrightarrow{o_i}) - \Gamma(\overrightarrow{o_{i+1}})$ denote the set of source nodes only in $\Gamma(\overrightarrow{o_i})$ and not in $\Gamma(\overrightarrow{o_{i+1}})$.
- Set $\kappa_i = max\{r(s_j), \forall s_j \in \chi(\overrightarrow{o_i})\}$.
- For any source node s_j in $\Gamma(\overrightarrow{o_i})$, update its covering requirement by $r(s_j) = max\{r(s_j) - \kappa_i, 0\}$.

Second, for the last set $\overrightarrow{o_m}$, set $\kappa_m = max\{r(s_j), \forall s_j \in \Gamma(\overrightarrow{o_m})\}$.

With the above greedy algorithm, we will introduce the detailed optimal algorithm for the circle set cover problem.

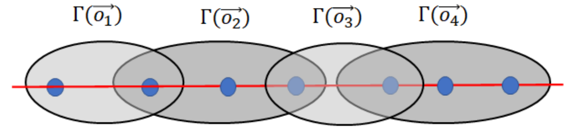


Fig. 3. An example of the line set cover problem.

Before that, some notations are introduced. Let $[\overrightarrow{o_l}, \overrightarrow{o_k}]$ denote the set of orientations from $\overrightarrow{o_l}$ to $\overrightarrow{o_k}$ in the clockwise order. W.L.O.G, assume $k > l$. Let $\Gamma([\overrightarrow{o_l}, \overrightarrow{o_k}]) = \cup^k_{i=l}\Gamma(\overrightarrow{o_i})$ denote the union of all the source nodes from $\Gamma(\overrightarrow{o_l})$ to $\Gamma(\overrightarrow{o_k})$.

Definition 1 (Orientation Cut). For any orientation $\overrightarrow{o_i}$, if $\Gamma(\overrightarrow{o_i}) \cap \Gamma(prev(\overrightarrow{o_i})) = \emptyset$, then we call $\overrightarrow{o_i}$ an orientation cut, which means there is no overlapped source nodes between $\Gamma(\overrightarrow{o_i})$ and $\Gamma(prev(\overrightarrow{o_i}))$.

Notice that, if there exists an orientation cut $\overrightarrow{o_i}$, then we can just transform the circle set cover problem to a line set cover problem, *i.e.*, sort $\overrightarrow{o_i}$ to $prev(\overrightarrow{o_i})$ in the clockwise order.

However, there may not exist such an orientation cut in many scenarios. To handle such scenario, we introduce the definition of orientation collection cut.

Definition 2 (Orientation Collection Cut). For a collection of orientations $[\overrightarrow{o_l}, \overrightarrow{o_k}]$, if $\Gamma(prev(\overrightarrow{o_l})) \cap \Gamma(next(\overrightarrow{o_k})) = \emptyset$, then we call $[\overrightarrow{o_l}, \overrightarrow{o_k}]$ an orientation collection cut.

Actually, it means that we can divide the whole sets into two parts with an orientation collection cut $[\overrightarrow{o_l}, \overrightarrow{o_k}]$: the sets in $[\overrightarrow{o_l}, \overrightarrow{o_k}]$ and the sets in $[next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})]$. One can find that the second part forms a line set cover problem. Then, we only need to find the optimal result for $[\overrightarrow{o_l}, \overrightarrow{o_k}]$. Note that, l may equal to k. The detailed method works as follows.

Firstly, let $\Lambda([\overrightarrow{o_l}, \overrightarrow{o_k}]) = \Gamma([\overrightarrow{o_l}, \overrightarrow{o_k}]) - \Gamma([next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})])$ denote the set of source nodes only in $\Gamma([\overrightarrow{o_l}, \overrightarrow{o_k}])$.

Secondly, for each source node $s_j \in \Lambda([\overrightarrow{o_l}, \overrightarrow{o_k}])$, if it only belongs to a certain set $\Gamma(\overrightarrow{o_i})$ $(s_j \notin \Gamma(\overrightarrow{o_x}), \forall x \ne i)$, then at least $r(s_j)$ of $\Gamma(\overrightarrow{o_i})$ are required. Let $\Lambda(\overrightarrow{o_i})$ denote the set of such source nodes only in $\Gamma(\overrightarrow{o_i})$. Set $\kappa'_i = max\{r(s_j), s_j \in \Lambda(\overrightarrow{o_i})\}$ (Note that, κ'_i is not the final result for set $\Gamma(\overrightarrow{o_i})$). After that, for any source node s_j in $\Gamma(\overrightarrow{o_i})$, the covering requirement can be updated by $r(s_j) = max\{r(s_j) - \kappa'_i, 0\}$.

Thirdly, for all the source nodes in $\Lambda([\overrightarrow{o_l}, \overrightarrow{o_k}])$, find all the feasible solutions, *i.e.*, $(\kappa_l, \kappa_{l+1}, ..., \kappa_k)$, and put them in a set X. Then, for each feasible solution in X, do:

- Update the covering requirement for the source nodes in $\Gamma([next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})])$ with $\kappa_l, \kappa_{l+1}, ..., \kappa_k$;
- Employ the above greedy algorithm for the source nodes in $\Gamma([next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})])$;
- Calculate the total latency $\mathcal{L} = \sum^m_{j=1} \kappa_j + \sum^k_{j=l} \kappa'_j$, where $\sum^k_{j=l} \kappa'_j$ denotes the result in the second step.

Finally, the one with minimum latency will be chosen, and the corresponding value κ_j for each set will be obtained. One can find that, to further reduce the computation time, one can choose the orientation collection cut $[\overrightarrow{o_l}, \overrightarrow{o_k}]$, which has the minimum value $\prod^k_{i=l} r(\Gamma(\overrightarrow{o_i}))$, where $r(\Gamma(\overrightarrow{o_i})) = max\{r(s_j), s_j \in \Gamma(\overrightarrow{o_i})\ \&\ s_j \notin \Lambda(\overrightarrow{o_i})\}$ denotes the maximum number times of set $\Gamma(\overrightarrow{o_i})$ can be used in the third step.

Algorithm 1: The Optimal Algorithm for the Circle Set Cover Problem

Input: The group of sets $\Gamma(\overrightarrow{o_i})$ $(1 \leq i \leq m)$, and the covering requirement $\mathcal{R} = \{r(s_1), r(s_2), ..., r(s_n)\}$;
Output: The optimal value $\kappa_1, \kappa_2, ..., \kappa_m$;

Function `Circle_Set_Cover_Scheduling`($[\overrightarrow{o_1}, \overrightarrow{o_m}], \mathcal{R}$)
  Sort all the orientations in the clockwise order;
  if *there exist an orientation cut* $\overrightarrow{o_i}$ **then**
    Exploit the Line_Set_Cover_Scheduling($[\overrightarrow{o_i}, prev(\overrightarrow{o_i})], \mathcal{R}$);
  else
    Let the collection collection cut $[\overrightarrow{o_l}, \overrightarrow{o_k}]$ be the one with the minimum value $\prod_{i=l}^{k} r(\Gamma(\overrightarrow{o_i}))$;
    for $\forall \overrightarrow{o_t} \in [\overrightarrow{o_l}, \overrightarrow{o_k}]$ **do**
      Let $\Lambda(\overrightarrow{o_t})$ denote the set of source nodes only in $\Gamma(\overrightarrow{o_t})$;
      Set $\kappa'_t = max\{r(s_j), s_j \in \Lambda(\overrightarrow{o_t})\}$;
      For each source node s_j in $\Gamma(\overrightarrow{o_t})$, updated its requirement by $r(s_j) = max\{r(s_j) - \kappa'_t, 0\}$;
    Calculate all the feasible solutions for $\Lambda([\overrightarrow{o_l}, \overrightarrow{o_k}])$ and put them in a set X;
    for $\forall(\kappa_l, \kappa_{l+1}, ..., \kappa_k) \in X$ **do**
      Update the covering requirements for the source nodes in $\Gamma([next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})])$ with $\kappa_l, \kappa_{l+1}, ..., \kappa_k$;
      Line_Set_Cover_Scheduling($[next(\overrightarrow{o_k}), prev(\overrightarrow{o_l})], \mathcal{R}$);
      Calculate the total latency $\mathcal{L} = \sum_{j=1}^{m} \kappa_j + \sum_{j=l}^{k} \kappa'_j$;
    Find the one with minimum latency $\mathcal{L}$, and the corresponding value κ_j for each set;
  return $\kappa_1, \kappa_2, ..., \kappa_m$;

Function `Line_Set_Cover_Scheduling`($[\overrightarrow{o_l}, \overrightarrow{o_k}], \mathcal{R}$)
  $\overrightarrow{o_t} \leftarrow \overrightarrow{o_l}$;
  for $x = 1$ *to* $|[\overrightarrow{o_l}, \overrightarrow{o_k}]| - 1$ **do**
    $\chi(\overrightarrow{o_t}) \leftarrow \Gamma(\overrightarrow{o_t}) - \Gamma(next(\overrightarrow{o_t}))$;
    $\kappa_t = max\{r(s_k), \forall s_k \in \chi(\overrightarrow{o_t})\}$;
    for $s_j \in \Gamma(\overrightarrow{o_t})$ **do**
      $r(s_j) = max\{r(s_j) - \kappa_t, 0\}$;
    $\overrightarrow{o_t} \leftarrow next(\overrightarrow{o_t})$;
  Set $\kappa_k = max\{r(s_j), \forall s_j \in \Gamma(\overrightarrow{o_k})\}$;
  return $\kappa_l, \kappa_{l+1}, ..., \kappa_k$;

Now, the complete algorithm is introduced, which is shown in Algorithm 1. Let p denote the number of orientations in the collection $[\overrightarrow{o_l}, \overrightarrow{o_k}]$ and $\delta = max\{|\Gamma(\overrightarrow{o_i})|, 1 \leq i \leq m\}$. Then, the time complexity of Algorithm 1 is at most $O(p^{r_{max}+1} \cdot m \cdot \delta)$. Since p is generally a much small number, then the proposed algorithm is polynomial. For the example in Fig.1, one can find that $[\overrightarrow{o_1}]$ is an orientation collection cut (it includes one orientation), and the optimal result is computed as $\{1, 2, 2, 0, 2, 2\}$ for all the 6 orientations, which takes 9 time slots in total.

C. Data Transmission Scheduling Algorithm

After obtaining the optimal charging latency, we choose to charge the source nodes periodically with the obtained result. Note that, once a source node has been charged enough energy, how to design the data transmission strategy is also much important for the AoI optimization problem.

In the following, we will consider the random sampling model firstly. Under such model, one simplest way is let the node which has been charged enough energy just transmit its newest sample without any waiting, which is called the Transmitting without Waiting (TW) strategy. Although it would not incur any waiting time for the AoI, it may result in a node transmits a sample whose generation time is quite old.

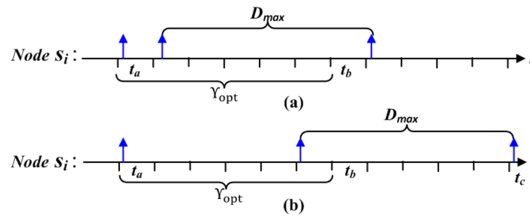


Fig. 4. The example of peak AoI scheduling, where the blue arrow denotes the packet arrival time.

For example, as in Fig.4(a), assume node s_i is charged enough energy at time t_a and t_b respectively, and D_{max} denotes the largest sampling interval. Assume it transmits the freshest sample at time t_a first. In this case, the AoI value would drop to 1 at time $t_a + 1$. At the next ready time t_b (the time that it has been charged enough energy), under the TW strategy, it will transmit the freshest sample arrives at time $t_a + 1$. Then, the AoI value will only drop to Υ_{opt} at time $t_b + 1$, and at the next ready time after t_b, the peak AoI will reach $2\Upsilon_{opt} - 1$, although the optimal peak AoI is only $\Upsilon_{opt} + 1$ in this case.

In addition, if one lets the source nodes transmit the message only when they arrive a new sample, which is called the Transmit when a new sample Arrives (TA) strategy, then the peak AoI for Fig.4(a) will be just $\Upsilon_{opt} + 1$ (D_{max} equals to Υ_{opt} here). But one cannot just exploit the TA strategy here. Considering the example in Fig.4(b), if it only transmits the message at time t_a and time t_c, then the peak AoI will also be $2\Upsilon_{opt} - 1$ at time t_c, which is also a much larger value.

Thus, to reduce the peak AoI value, we will introduce a threshold-based data transmission strategy here, by combining the above two strategies. It mainly works as follows.

Firstly, let $\Delta_{s_i}(t)$ denote the duration between the present time t and the generation time of the freshest sample for source node s_i, which can be calculated by $\Delta_{s_i}(t) = t - U_{s_i}(t)$.

Secondly, for any source node s_i, if it has not been charged enough energy at time t, then it just waits for being charged ready. Otherwise, at time slot t, it does as follows:

1) If $A_{s_i}(t) \leq \Upsilon_{opt}$, transmit the freshest sample only if $D_{max} = 1$, Otherwise, continue to wait.
2) Else if $\Upsilon_{opt} < A_{s_i}(t) \leq 3\Upsilon_{opt}/2$ and $\Delta_{s_i}(t) \leq \Upsilon_{opt}/2$, transmit the freshest sample as in TW.
3) Else if $\Upsilon_{opt} < A_{s_i}(t) \leq 3\Upsilon_{opt}/2$ and $\Delta_{s_i}(t) > \Upsilon_{opt}/2$, transmit when a new sample arrives as in TA.
4) If $A_{s_i}(t) > 3\Upsilon_{opt}/2$, just transmit the freshest sample.

With the above strategy, it can return the peak AoI at most $1.5\mathcal{A}_{opt}$, which will be analyzed lately. As for the example shown in Fig.4(a) and Fig.4(b), it will both return the peak AoI of $\Upsilon_{opt} + 1$ in two cases.

As for the periodical sampling model, same as in the above analysis, we can just replace $\Upsilon_{opt}/2$ by $T_i/2$ in the above four conditions, *i.e.*, $\Delta_{s_i}(t) \leq T_i/2$ in the 2nd condition. In addition,

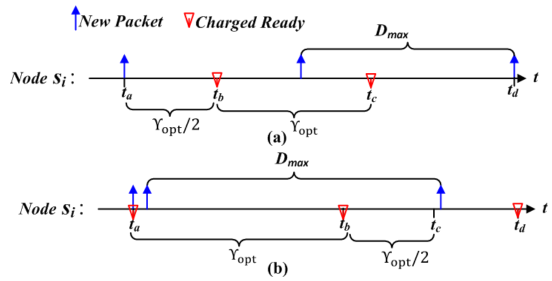


Fig. 5. The example of peak AoI analysis.

if $T_i > \Upsilon_{opt}$, one can just employ the TA strategy here.

Now, the Joint Age-based Data transmission and Energy replenishment (JADE) scheduling algorithm is completed.

D. Performance Analysis

Let the peak AoI value of the proposed method be $\mathcal{A}$. In the following, we will first analyze the approximation ratio of JADE under the random sampling model.

Lemma 1. *If $1 \leq D_{max} \leq \Upsilon_{opt}$, the peak AoI of the proposed algorithm under random sampling model is at most* $3\Upsilon_{opt}/2+1$.

Proof: We will prove $\mathcal{A} \leq 3\Upsilon_{opt}/2 + 1$ when $1 \leq D_{max} \leq \Upsilon_{opt}$ by contradiction. Without loss of generality, let the source node with the largest peak AoI be s_i and assume its peak AoI is at least $3\Upsilon_{opt}/2+2$. Let its peak AoI be obtained at time t, then one can find that the last sample is at time $t-3\Upsilon_{opt}/2-2$. In addition, since the charging latency is at most Υ_{opt}, then it can be charged ready at time $t-\Upsilon_{opt}/2-1$. At such time, if it decides to transmit, then the peak AoI at time t will be less than $3\Upsilon_{opt}/2$ (Since $1 \leq D_{max} \leq \Upsilon_{opt}$), which is a contradiction. If it decides to wait, it can wait at most $\Upsilon_{opt}/2$, implying that it transmits before t and its peak AoI is obtained before t, which is a contradiction. Thus, one can have $\mathcal{A} \leq 3\Upsilon_{opt}/2 + 1$. ■

Lemma 2. *If $D_{max} > \Upsilon_{opt}$, the peak AoI of the proposed algorithm under random sampling model is at most $max\{D_{max} + \Upsilon_{opt}/2 + 1, 3\Upsilon_{opt}/2 + 1\}$.*

It can be proved by considering the following two extreme cases. First, consider an extreme case as in Fig.5(a), where source node s_i has been charged ready at time t_b and transmits a newest sample whose generation time is t_a. At time t_c, if it decides to transmit a packet, then its peak AoI is at most $max\{3\Upsilon_{opt}/2 + 1, D_{max}\}$. If it decides to wait, its peak AoI is also at most $3\Upsilon_{opt}/2 + 1$ since it will just transmit when its AoI reaches $3\Upsilon_{opt}/2$. Note that, when node s_i chooses to wait at time t_b, we can also have the same result. Additionally, consider another extreme case as in Fig.5(b), node s_i waits its peak AoI reaches $3\Upsilon_{opt}/2$ at time t_b, while the newest sample still does not arrive. At this time, its peak AoI will be $D_{max} + \Upsilon_{opt}/2+1$ at the next ready time at t_d. Note that, if the sample arrives earlier, a much smaller peak AoI will be obtained.

Since $\mathcal{A}_{opt} \geq max\{\Upsilon_{opt} + 1, D_{max}\}$, then we can conclude that the approximation ratio of the proposed JADE algorithm is at most 1.5, which is shown in the following Theorem 5.

Theorem 5. *Under the random sampling model, the approximation ratio of the proposed JADE algorithm is at most* 1.5.

As for the periodical sampling model, we can prove that, $\mathcal{A} \leq max\{\Upsilon_{opt}+T_{max}/2+1, 3\Upsilon_{opt}/2+1\}$ when $1 \leq T_{max} \leq \Upsilon_{opt}$, and $\mathcal{A} = T_{max}$ when $T_i > \Upsilon_{opt}$ $(1 \leq i \leq n)$. The proof is omitted here. It means it has an approximation ratio of at most 1.5 in the first case and can reach optimum in the second case.

Theorem 6. *If $1 \leq T_{max} \leq \Upsilon_{opt}$, the peak AoI of the proposed algorithm is at most $max\{\Upsilon_{opt} + T_{max}/2 + 1, 3\Upsilon_{opt}/2 + 1\}$.*

Theorem 7. *If $T_i > \Upsilon_{opt}$ for each source node s_i $(1 \leq i \leq n)$, the peak AoI of the proposed algorithm is at most T_{max}.*

V. AoI Scheduling with Multiple Wireless Chargers

Since one charger's covering area is usually limited, which may not cover the whole network, thus, we consider a more general scenario where there exist multiple directional wireless chargers deployed in the target area in this section.

Assume there are q $(q > 1)$ directional chargers in the area, which are denoted by $C^1, C^2, ..., C^q$, respectively. Let $\overrightarrow{o^j(t)}$ $(1 \leq j \leq q)$ denote the orientation of the j-th charger at time slot t. For each charger C^j, let the number of orientations of charger C^j be m_j, *i.e.*, $\overrightarrow{o^j_1}, \overrightarrow{o^j_2}, ..., \overrightarrow{o^j_{m_j}}$. Similarly, denote $\Gamma(\overrightarrow{o^j(t)})$ as the set of source nodes that can be charged by charger C^j at orientation $\overrightarrow{o^j(t)}$. Note that, under this scenario, a source node may be charged by several chargers simultaneously. According to [2], the received power of source node s_i at time t, *i.e.*, $P(s_i, t)$, can be calculated as $P(s_i, t) = \sum_{j=1}^{q} P(s_i, \overrightarrow{o^j(t)})$.

Although the MPAS-M problem becomes more challenging under this scenario, fortunately, we find that the theoretical bounds for the peak AoI still hold. Thus, in the following, we will study the charging latency minimization problem with multiple directional chargers firstly.

Note that, one cannot just use the above $r(s_i)$ to compute the charging time slots for source node s_i here. Therefore, we set $r(s_i) = e_i \cdot L_i$ to be the required energy by source node s_i.

Let $t^j(k)$ denote the number of time slots that charger C^j stayed at its k-th orientation. Then, for charger C^j, its latency can be calculated as $\sum_{k=1}^{m_j} t^j(k)$. As for the whole network, the charging latency minimization problem can be formulated as:

$$Minimize\ max_{1\leq j\leq q}\{\sum_{k=1}^{m_j} t^j(k)\}$$

$$subject\ to: \sum_{j=1}^{q}\sum_{k=1}^{m_j} t^j(k)\cdot P(s_i, \overrightarrow{o^j(k)}) \geq r(s_i), 1 \leq i \leq n;$$

$$t^j(k) \in \{0, 1, 2, ..., \}, 1 \leq j \leq q, 1 \leq k \leq m_j.$$

It can be proved to be NP-hard by transforming a special case of such problem to the Geometric Multi-Set Multi-Cover problem [45] and the proof is omitted here.

Theorem 8. *The charging latency minimization problem with multiple wireless chargers is NP-hard.*

In the following, we will introduce a constant approximation algorithm for it.

Firstly, since brute force all the possible orientations to find an optimal strategy is much costing, here, we transform the above problem to an LP problem where $t^j(k)$ can be relaxed as a real number. Let $\tilde{t^j(k)}$ be the optimal value obtained by the LP solver. One can see $\tilde{t^j(k)}$ includes two parts: the integer part, denote by $\lfloor \tilde{t^j(k)} \rfloor$, and the fractional part, denoted by $\hat{t^j(k)}$.

Secondly, set $t^j(k) = \lfloor \tilde{t^j(k)} \rfloor$. Update the covering requirement for each source node in $\Gamma(\overrightarrow{o^j_k})$. For the fractional part, if $\hat{t^j(k)} > 1/2$ and there exists a node $s_i \in \Gamma(\overrightarrow{o^j_k})\&r(s_i) > P(s_i, \overrightarrow{o^j_k})/2$, then update $t^j(k)$ by $t^j(k) + 1$, and update the covering requirement for each source node in $\Gamma(\overrightarrow{o^j_k})$.

Thirdly, sort all the chargers according to their latency in the non-decreasing order. For each charger from C_1 to C_q, find a set of orientations that can cover the whole circle, denoted by O^j. Since each orientation can cover a sector with angle ϕ, then there are at most $\lceil 2\pi/\phi \rceil$ such orientations. Then, for each charger from C_1 to C_q, do as follows:

- For the j-th charger, find an orientation from O^j which can cover most uncover nodes (*i.e.*,$r(s_i) > 0$), let such orientation be o^j_k.
- Update $t^j(k)$ by $t^j(k) + 1$, and then update the covering requirements for the uncover nodes.

The above steps continue until there is no nodes with $r(s_i) > 0$.

Let $\mathcal{L}_{opt}$ denote the optimal charging latency, and f be the maximum number of sets that includes a same node in a charger. Then we can have the following theorem.

Theorem 9. *The proposed algorithm has a latency bound of* $2\mathcal{L}_{opt} + c$, *where* $c = \lceil f/2 \rceil \cdot 2\pi/\phi$ *is a constant.*

Proof: Let $\mathcal{L}$ denote the charging latency obtained by the proposed algorithm. Firstly, one can see $\mathcal{L}_{opt} \geq \sum_{k=1}^{m_j} \tilde{t^j(k)}$. In the proposed algorithm, one can have $\mathcal{L} = \sum_{k=1}^{m_j} \lfloor \tilde{t^j(k)} \rfloor$ at the first. For the fractional part, if $\lfloor \tilde{t^j(k)} \rfloor \geq 1$, then one can see, $t^j(k) = \lfloor \tilde{t^j(k)} \rfloor + 1 \leq 2\tilde{t^j(k)}$. In addition, if $\hat{t^j(k)} \geq 1/2$, then $t^j(k) \leq 2\tilde{t^j(k)}$. And if $\hat{t^j(k)} < 1/2$, for each charger, at most $\lceil f/2 \rceil \cdot 2\pi/\phi$ time slots are required. Then, the total latency of the proposed algorithm is at most $\mathcal{L} \leq \sum_{k=1}^{m_j} 2\tilde{t^j(k)} + \lceil f/2 \rceil \cdot 2\pi/\phi \leq 2\mathcal{L}_{opt} + \lceil f/2 \rceil \cdot 2\pi/\phi = 2\mathcal{L}_{opt} + c$. ■

After obtaining the charging latency, then one can just exploit the above threshold-based transmission strategy.

Theorem 10. *The peak AoI of the proposed algorithm under random sampling model is at most* $max\{D_{max} + \Upsilon_{opt} + (c + 1)/2, 3\Upsilon_{opt} + (3c + 1)/2\}$.

VI. Simulation Results

In this section, we evaluate the performance of the proposed algorithms through extensive simulations. Note that, in the simulations, the proposed algorithms under different data transmission strategies, *i.e.*, the TW and TA strategy, are also evaluated, denoted by JADE-TW and JADE-TA, respectively. Additionally, the following baseline algorithms are evaluated:

First, two heuristic AoI scheduling methods are exploited as baseline, where we greedily choose the transmission nodes and the orientations at each time slot. In the first method, we let the node with maximum AoI being charged, which is denoted by Greedy-AoI. In the second method, we prior choose the orientation which can cover the largest sum of AoI values. This method is denoted by Greedy-Charge.

Second, the existing AoI based transmission schedule [24], *i.e.*, Juventas, is also compared in the experiments, where we first choose the nodes need to be transmitted as in [24], and then schedule the charger's orientation to charge such node.

Third, for the scenario with multiple chargers, we first exploit the optimal charging schedules obtained by CPLEX with three data transmission strategies as the lower bound. They are denoted by Optimal-TW, and Optimal-TA, Optimal-TT (the one with threshold). In addition, we also exploit the Greedy-Charge scheduling method as the baseline here, where we choose the orientation of each charger greedily.

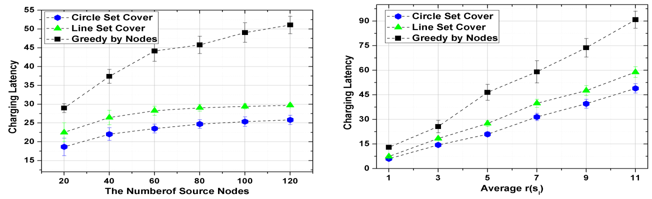
In the simulations, we mainly focus on the charging latency and peak AoI performance of the proposed algorithms under various network models, where we randomly deploy 100 nodes in a 100m×100m field. As in [2], the parameters are set $\alpha = 10000$, $\beta = 40$, $R = 40$, and the length of a time slot is set 10. The length of the data size is set from 10 to 100 and the energy for transmitting unit data are set 4, which means the number of required charging time slots, *i.e.*, $r(s_i)$, is ranging from 1 to 15 in the experiments. In addition, the sampling period of each source node is generated randomly to test a wide range of configurations. In all the simulations, each plotted point represents the average of 100 executions.

A. AoI and Latency with Single Wireless Charger

In this group of experiments, we first evaluate the charging latency of the proposed methods with single charger, and then the peak AoI value under different number of source nodes (*i.e.*, n), charging time slot ($r(s_i)$), and sampling models.

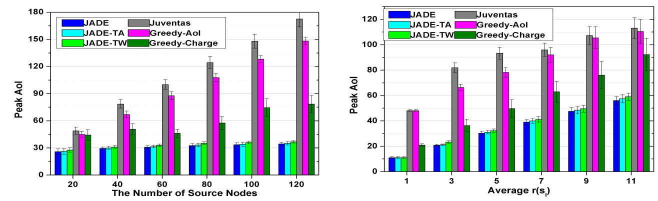
Fig.6 compares the charging latency of the proposed methods as a function of n and $r(s_i)$. To demonstrate the performance of the proposed algorithms, we first employ the Line Set Cover scheduling algorithm as the baseline (where we just choose the set from the first orientation to the last one). In addition, a greedy algorithm which charges the nodes one by one (denoted by Greedy by Nodes) is also evaluated. The first observation from Fig.6 is that the charging latency of the proposed algorithms is much less than that of the two baseline algorithms in all the scenarios. Especially, compared to the Greedy by Nodes method, the charging latency is reduced by almost a half. This demonstrates the importance of considering the overlapped charging orientations for directional charging.

Fig.7 evaluates the peak AoI of the proposed methods under different n and $r(s_i)$. As one can see in Fig.7(a), the peak AoI of the proposed methods under different data transmission strategies is much less than the one of the existing Juventas and the Greedy-AoI, Greedy-Charge algorithms. Compared to other methods, the Juventas method performs the worst. This is because it prefers to schedule the nodes which can be fast charged. But, in the directional charging model, these nodes can be simultaneously charged when scheduling other nodes.



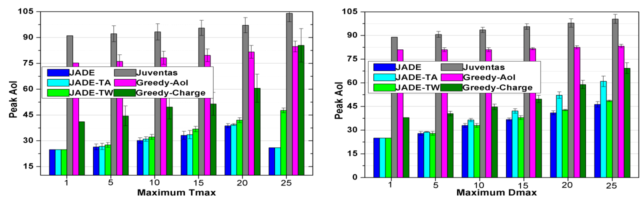
(a) Number of Source Nodes (b) Average Required Charging Time

Fig. 6. Charging latency.



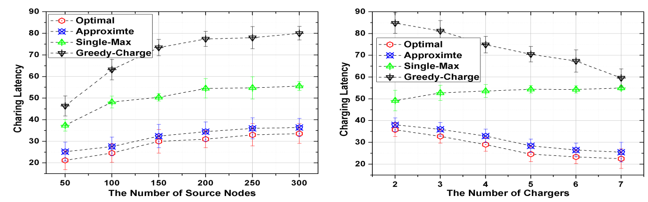
(a) Number of Source Nodes (b) Average Required Charging Time

Fig. 7. Peak AoI.



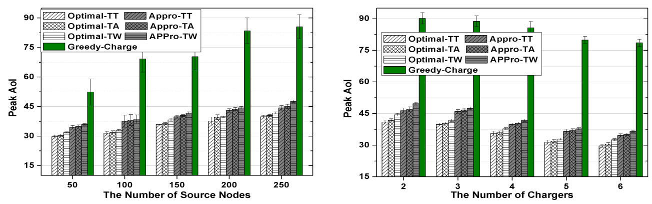
(a) Periodical Sampling Model (b) Random Sampling Model

Fig. 8. Peak AoI.



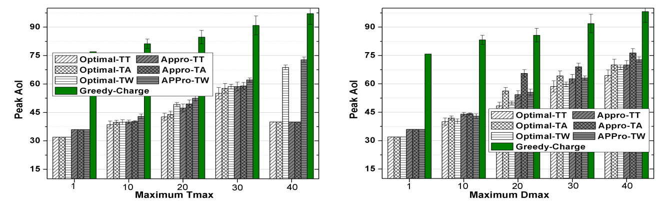
(a) Number of Source Nodes (b) Number of Wireless Chargers

Fig. 9. Charging Latency.



(a) Number of Source Nodes (b) Number of Wireless Chargers

Fig. 10. Peak AoI.



(a) Periodical Sampling Model (b) Random Sampling Model

Fig. 11. Peak AoI.

This is also why the Greedy-Charge algorithm performs much better than the Juventas and Greedy-AoI algorithms.

Fig.8 presents the peak AoI of the proposed methods under different sampling models. The periodical sampling model is evaluated as in Fig.8(a). As one can see, when $T_i = 1$, the peak AoI of each method is fixed. This is because it is just equal to the charging latency (we fix the source nodes' position and data size here). Additionally, one can find that the proposed threshold-based method (JADE) performs much better in all scenarios, while the TW method performs much worse when $T_{max} > \Upsilon_{opt}$ (as in Fig.8(a)) and the TA method performs much worse under the random sampling model (as in Fig.8(b)).

B. AoI and Latency with Multiple Wireless Chargers

Next, we evaluate the performance of the proposed algorithm when there exist multiple wireless chargers.

Fig.9 presents the charging latency of the proposed algorithms for different n and q values. Firstly, compared to the Greedy-Charge method, the latency of the proposed approximate method can be reduced by almost 60%. The latency of Greedy-Charge is even larger than the maximum latency calculated by each charger independently (denote by Single-Max). Compared to the optimal method, the performance of the approximate method is very close.

Fig.10 compares the peak AoI of the proposed algorithms for different n and q values. One can see that, in both scenarios, the peak AoI of the proposed approximate method (*i.e.*, Appro.) is much less than the one of Greedy-Charge. This is mainly due to the proposed method not only can obtain a much small charging latency, but also can improve the peak AoI by the TT transmission strategy (the one with threshold).

Fig.11 compares the peak AoI of the proposed algorithms under different sampling models. An interesting observation is that, when we set nodes' sampling period to be 40, which exceeds the charging latency, the peak AoI of the TT and TA transmission strategy drops in Fig.11(a), while other methods still grow. This is because they can return the optimal result T_{max} in this case. Note that, the TW strategy cannot return the optimal result here. Additionally, different from the periodical scenario, the AoI of all methods still increase under the random sampling model as in Fig.11(b). This is because the sampling duration can range from 1 to D_{max} in this case.

VII. Conclusions

In this paper, the joint scheduling problem of data transmission and energy replenishment for AoI optimization is introduced for the first time. The theoretical bounds of the peak AoI with respect to the charging latency are derived. For the minimum peak AoI scheduling problem with a single charger, an approximation algorithm with a ratio of up to 1.5 is proposed. When there are multiple chargers, an approximate algorithm is also designed. The simulation results verify the high performance of the proposed algorithms.

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