

Sleep-Wake Sensor Scheduling for Minimizing AoI-Penalty in Industrial Internet of Things

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Abstract—Ensuring data freshness is important for industrial Internet of things (IIoT). In this paper, we consider a typical IIoT application where multiple sensors monitor some time-varying physical processes and report measurements to a central base station through an unreliable wireless channel. In order to save energy, each sensor may switch to sleep mode for a while after successfully transmitting a packet. Since only awake sensors are able to transmit data, we propose a novel function of age of information with penalty (or AoI-penalty) to capture the eagerness of the active sensors to provide fresh information. We formulate a new AoI-penalty minimization problem for scheduling the sensors' transmissions. We theoretically derive a necessary condition for the system's AoI-penalty to converge to a finite value, and further obtain a lower bound of the AoI-penalty. Moreover, we develop a max-weight based scheduling policy and theoretically prove that it is the optimal policy when the network is symmetric and the channel is error-free. Simulation results demonstrate that the proposed policy achieves AoI performance near to the lower bound and that with such sleep-wake sensors, the achieved AoI performance is close to that with non-sleeping sensors but at a much lower energy cost.

Index Terms—Age of information, scheduling, sleep-wake sensors, optimization, penalty, energy, lower bound.

I. INTRODUCTION

INDUSTRIAL Internet of things (IIoT) refers to networks of sensors, controllers, actuators and other devices to monitor and control industrial processes [1], [2]. As an emerging technology, IIoT has found a number of applications in smart factories, environmental monitoring, transportation and so on [3]. IIoT systems usually run in real-time where the freshness of data is of great importance [4], [5].

Consider a typical IIoT consisting of a number of sensors that monitor the dynamic physical process and report the status updates of the process to a base station (BS) for further data analysis, visualization, control and/or decision making. The data freshness can be expressed by Age of Information (AoI), a performance metric that characterizes the time interval from the generation of the latest received information to the current time [6], [7], [8], [9], [10], [11]. Enhancing the

information freshness about the physical process encounters the challenging problem of minimizing the value of AoI. Due to mutual interference on the wireless channels, the sensors should not simultaneously transmit data to the BS, resulting in the problem of sensor scheduling for improving AoI performance. In conventional AoI minimization problems, sensors are often assumed to always remain active and thus can transmit data whenever scheduled [12], [13]. However, this may be unaffordable for commonly battery-powered sensors with limited energy in IIoT [14]. And sometimes it is unnecessary to sample the physical processes all the time when the process status changes slowly. Motivated by duty-cycling sensors that operate in sleep and active alternatively [15], [16], we introduce sleep modes for sensors to save energy.

This paper considers a typical IIoT single-hop application scenario which has been described in the last paragraph. The sensors are programmed to work in a cyclic sleep-wake pattern: For each cycle, the sensor keeps in sleep mode for a fixed sleep time first, and after that, it keeps active until it sends the updates successfully, then, it switches to sleep mode again and a new cycle begins. The higher the emergency of the sensor, the shorter the sleep time is set. Moreover, the sensors in sleep mode are allowed not to collect or send updates, so they are eager to provide fresh updates after they switch to active mode, which naturally leads to that the AoI growth rate of active sensors should be higher than that of the sleeping ones. It also makes sense from the perspective of energy saving: The sensors want to send the data early so that they can switch to sleep mode early to save energy. Hence, we propose a novel AoI-penalty function to capture the eagerness of information from active sensors. Specifically, the new AoI-penalty function grows at different rates, thus offering the system the property of overtaking which means that the AoI-penalty presently with a lower value has a chance to overtake that with a higher value afterwards so that the corresponding sensor can have the opportunity to be scheduled.

On this basis, we investigate the sleep-wake sensor scheduling problem and formulate it as an AoI-penalty optimization problem. We propose a max-weight based scheduling policy to solve the problem. At the beginning of every slot, the policy schedules an active sensor with the highest value of $MW_i(k)$ (equation (21)) to send its updates. It is a light-weighted policy because the time complexity is $\mathcal{O}(M)$ for every decision (M is the number of sensors in the network). Simulation results demonstrate that the AoI-penalty performance of the proposed policy is close to the theoretical lower bound, and that with the sleep-wake sensors, the AoI performance is close to that with

This work was supported in part by the National Natural Science Foundation of China under Grant 92067111, in part by the Outstanding Young Scholarship of Jiangsu Province under Grant BK20180012, in part by the Defense Industrial Technology Development Program and under Grant JCKY202020206B068, and in part by Zhongying Young Scholars Project. The work of Yu Cheng was supported in part by NSF Grants CNS-2008092 and CNS-1816908. (correspondence author: Xianghui Cao)

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non-sleep sensors but at a much lower energy cost. Besides, the results demonstrate that the AoI of the important sensors is lowered down. Our main contributions are summarized as follows:

- We introduce a novel AoI-penalty function for sleep-wake sensors and formulate an AoI-penalty-minimal scheduling problem.
- We analyze the convergence of the attainable AoI-penalty and develop a lower bound of it.
- We prove that the Max-Weight scheduling policy is optimal if the network is symmetric and the channel is error-free, and that it will run in a Round Robin pattern when the network and the channel are symmetric.
- We carry out simulations to evaluate the performance of the proposed policy.

The remainder of the paper is organized as follows. Section II reviews more related work. Section III provides the system model, introduces the AoI-penalty function and formulates the optimization problem. The convergence condition and lower bound of the problem solution are analyzed in Section IV. Section V introduces the max-weight policy and discusses its properties. Section VI demonstrates the simulation results, and finally Section VII concludes the paper.

II. RELATED WORK

Recently, as a metric of data freshness, AoI has attracted increasing attention for the growing demand of real-time data in communication networks. And there are many variants of AoI research. For example, the age of information with priority has been studied. In [17], the updates from the sensors will send to the queue and the arrivals of the updates obey the Poisson Distribution. They model the age process using a stochastic hybrid system for AoI. But they do not consider the energy consumption and the scheduling problem. Similar to [17], there are many studies that optimize AoI with the consideration of queuing theory. For example, to evaluate AoI for single-server queues [6] and queuing system with packet deadlines [18].

Sensor scheduling for minimizing AoI is an important research issue that has been studied in many works [12], [19], [20], [21], [22], [23], [24], [25], [26]. Such a problem is often coupled with sampling for which the commonly considered sampling methods are arbitrary sampling, periodic sampling and per time slot sampling [19]. For these, [19] develops a near-optimal scheduler that decides samples' transmissions to minimize AoI. In particular, with the per time slot sampling, sensors can collect status at the beginning of every slot [12], [20], [21], [22]. In [12], for the sensors under per time slot sampling, several scheduling methods including optimal stationary randomized policy, max-weight policy, drift-plus-penalty policy and whittle's index policy are derived and compared, and the results show that the max-weight and drift-plus-penalty policies outperform the others. In [20], a SQRT-Weight policy is proposed to schedule sensors to transmit their samples in networks with multiple sensors and multi-orthogonal channels. For minimizing a non-linear form of AoI, a weighted directed graph approach is adopted in [21] to

decide sensor scheduling. There have been a few works considering other sampling methods [23], [24]. For example, in [23], considering that packets from different streams randomly arrive, both an optimal stationary randomized policy and a max-weight policy are developed to schedule the packets in three types of queues: first-in-first-out queues, single packets queues and no queues. In order to minimize the age of correlated information in which the information of application will not update until the latest status from the certain set of devices is received, a deep-reinforcement-learning-based approach is developed in [24] to schedule devices. However, the sensors in the above studies keep active all the time, which causes a waste of energy because many sensors in active mode cannot be scheduled due to channel conflict. Thereby, we introduce sleep mode for the sensor to save energy and study the sleep-wake sensor scheduling problem to minimize AoI.

In IIoT, devices, such as battery-powered sensors and energy-harvesting nodes, are energy constrained. Thus, how to achieve AoI minimization while saving energy is a challenging issue. In [27] where the sensors are assumed able to harvest energy with either random battery recharge or incremental recharge, the optimal status update policy to minimize AoI is obtained based on theories of renewal processes. In [28], four power control schemes including online scheduling, offline power control, save-and-transmit and fixed power transmission are considered to minimize both AoI and distortion. In [29], under transmission power constraints, the problem of multi-sensor scheduling is formulated and converted to a single-sensor constrained Markov decision process, and then the scheduling policy is obtained by linear programming.

Aside from power control, sleep modes can be allowed for sensors in order to save their energy [30], [31]. In [30], when waking up from sleep mode, a sensor first performs channel sensing and if it finds the channel busy, it goes back to sleep; otherwise, it transmits packets for status updating. To minimize AoI under the energy constraint, proper sleep time parameters are obtained. However, such a sleep model deprives the sensors of the opportunity to transmit their updates when finding a busy channel (because they will switch to sleep mode afterwards). Moreover, in some cases, it is hard for the sensors to sense whether the channel is busy or not. And the channel sensing needs extra energy consumption. Therefore, in our paper, it is the BS that schedules the sensors to send data, and the problem is formulated into a sleep-wake sensor scheduling model. The work in [31] studies the problem of minimizing the AoI of sleep-wake sensors in wireless sensor-actuator networks and develops a greedy-based scheduling policy. However, only the AoI of sensors in active mode is accounted for. Moreover, compared with [31], we propose a novel AoI-penalty function to characterize the desire for fresh data from sleep-wake sensors in their active mode, while taking into account the sensors' AoI in both active and sleep modes. The AoI-penalty takes energy consumption into account, which helps the system reduce energy consumption, and it helps the BS offer the important sensors more chances to send data.

TABLE I: DEFINITION OF KEY NOTATIONS

Notation	Definition
M	Number of sensors in the network
K	Number of slots. Slot index is $k \in \{1, 2, \dots, K\}$
T_i	Sleep time of sensor i
$u_i(k)$	Indicator function shows whether sensor i is scheduled at the beginning of slot k
p_i	Probability of successful transmission from sensor i
$d_i(k)$	Indicator function shows whether the samples collected at the beginning of slot k by sensor i is received by the BS
$\mathbb{E}[\cdot]$	Expectation operator
$U_i(k)$	The generation time of the freshest data the BS receives from sensor i by the end of slot k
$j_i(k)$	The active time of sensor i at the beginning of slot k
$\Delta_i(k)$	The value of the AoI-penalty associated with sensor i at the beginning of slot k
w_i	The growth rate of AoI-penalty when sensor i is active
Δ_i^k	The area under the AoI-penalty $\Delta_i(k)$ curve for slot k
Δ_i^*	The optimal expected sum of AoI-penalty in (7)
L_B	The lower bound of the optimization problem (7)
$I_i[m]$	The number of slots between the $(m-1)$ th and m th updates delivered by sensor i
$\overline{\mathbb{M}}[\mathbf{x}]$	The mean of a set of values \mathbf{x}

III. SYSTEM MODEL

Consider that M sensors monitor some physical processes and send measurements of the processes' states through an unreliable wireless channel to a BS. Ideally, all the sensors can send real-time measurements to the BS such that the processes' information at the BS is kept fresh all the time. However, practically there are some constraints on such an ideal model. Firstly, simultaneous transmissions may collide with each other due to co-channel interference. In this paper, we assume that at most one sensor can be scheduled at a time to transmit measurement data to the BS. Secondly, the wireless channel is lossy even though only one sensor transmits data. In addition, for energy-constrained sensors typical in IIoT, they are allowed to sleep to save energy. Specifically, once a data packet of sensor i is successfully received by the BS, the sensor is assumed to switch to sleep mode for a fixed period of sleep time T_i . The sleep time can be set in accordance with the physical processes and the importance of sensors, e.g., the sleep time of the sensor is set smaller when the physical process changes faster and the corresponding sensor's data is more important. Compared with the duty cycling sensors, the sleep-wake sensors in this paper have more chances to provide fresh information. Because the sleep-wake sensors will sleep for a period of time only after the fresh data has been received by the BS. When the sensors are in sleep mode, the BS has the fresh data from the sensors, and it avoids the energy consumption that the sensors remain active when it cannot be scheduled due to channel conflict. However, the duty cycling sensors may still sleep when the data from them is stale because they cycle into sleep mode. The main notations used throughout this paper are summarized in Table I.

Let the time be slotted with slot index $k \in \{1, 2, \dots, K\}$. For convenience, we set the length of each slot to 1 and assume that T_i is an integer for any i . We assume that the transmission delay for each sensor at any time is no more than one slot. At the beginning of each slot, the BS makes scheduling decisions, and at the end of each slot, the corresponding

sensors which are scheduled will get deliveries of feedback to inform them whether their data is successfully received by the BS or not. Let $u_i(k) \in \{0, 1\}$ denote the choice of the BS at time k such that $u_i(k) = 1$ means sensor i is selected to transmit measurement data of its monitored process taken at the beginning of slot k , and $u_i(k) = 0$ means otherwise. As aforementioned, at most one sensor can be scheduled to transmit data, i.e., $\forall k$,

$$\sum_{i=1}^M u_i(k) \leq 1. \quad (1)$$

We assume that a data transmission from sensor i will be successfully received by the BS with probability $p_i \in (0, 1]$ due to the lossy wireless channel. The channel is assumed to be stable and p_i does not change over time. Let $d_i(k) = 1$ denote that the BS successfully receives (by the end of slot k) the data from sensor i sent at that slot and $d_i(k) = 0$ denotes otherwise. Therefore,

$$\mathbb{E}[d_i(k)] = p_i \mathbb{E}[u_i(k)]. \quad (2)$$

Denote by $U_i(k)$ the generation time of the freshest data the BS receives from sensor i by the end of slot k . Since the transmission delay is no more than 1, we have

$$U_i(k) = \begin{cases} U_i(k-1), & \text{if } d_i(k) = 0, \\ k, & \text{if } d_i(k) = 1. \end{cases} \quad (3)$$

A. Age of Information with Penalty

From the perspective of the BS, by conventional definition, the AoI associated with sensor i at the beginning of slot k is $k - U_i(k-1)$. Obviously, the AoI grows at a fixed rate (i.e., 1) when the BS does not receive fresher data from that sensor. AoI also can indicate the desire for fresh information. As a sleeping sensor is allowed not to transmit data, once it wakes up, it is eager to send its fresh data to the BS. If the sensor stays in active mode for a longer time, it not only means the sensor's information at the BS stales, but more energy of the sensor is wasted for being active. Thus, it is reasonable that active sensors that have been in active mode for a long time are more eager to provide fresh information than those who have just woken up. Therefore, we propose an *AoI-penalty* function to represent the property mentioned above, which makes the sensors that stay in active mode for a long time easier to be scheduled [7], [32], [33]. Specifically, we set the growth rate of the AoI of sensor i as 1 and $w_i > 1$ when it is in sleep mode and active mode, respectively. For our system model, sensors are more eager to transmit information when they switch to active mode. Because they can provide fresh data when they are active and they can switch to sleep mode early to save energy if they send the data out early. And, the more urgent the sensor is (smaller T_i), the more eager it is to send data in active mode, because smaller T_i means the corresponding physical process is more important and changes faster. As a consequence, w_i and T_i should be negatively correlated and w_i should be greater than 1 but not too large. In addition, sensors with the same value of T_i have the same value of w_i . An example of the setting of w_i is provided in (25). In

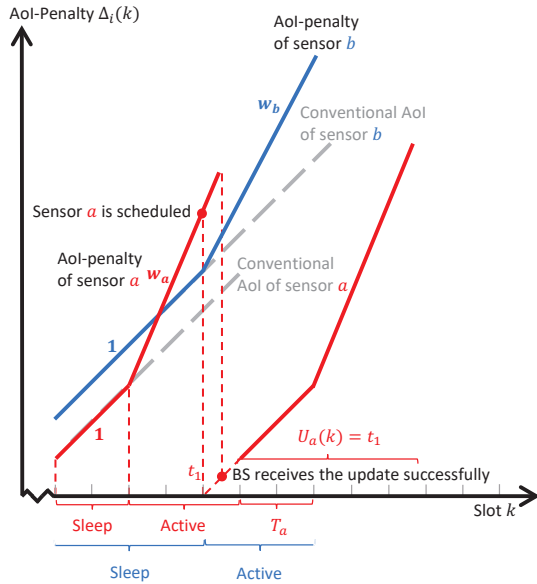


Fig. 1: Example of AoI-penalty.

addition, the AoI-penalty function as introduced above brings new properties that traditional AoI does not have:

- As shown in Fig. 1, consider that the BS schedules the sensor with the highest value of AoI at each time. With different growth rates, the AoI of sensor a is allowed to overtake that of sensor b , thus granting a the chance to be scheduled afterwards. This overtaking property prevents the BS from scheduling the sensors that just wake up after a long sleep time rather than the sensors with short sleep time which have stayed in active mode for a long time.
- According to our definition, the sleep time can reflect the importance of sensors. The setting of AoI-penalty may offer the sensors with shorter sleep time (more important sensors) more chances to send their information due to the higher value of w_i .
- The sensors in active mode may be in sampling, transmitting data or waiting, which consumes more energy than being in sleeping mode. In this sense, the proposed AoI-penalty function reflects the energy consumption of sleep-wake sensors. Optimizing AoI-penalty will also optimize energy consumption.

Upon successfully receiving the data from sensor i , the BS resets w_i as 1 for the time period from the data reception time to the end of the corresponding slot.

B. Optimization Problem

Let $j_i(k)$ indicate the number of slots that the sensor i has stayed in active mode since it waked up from last sleep mode, at the beginning of slot k . In particular, let $j_i(k) = -1$ if sensor i is in sleep mode during slot k , then we have

$$j_i(k) = \begin{cases} k - Q_i(k-1), & \text{if } k \geq Q_i(k-1), \\ -1, & \text{otherwise,} \end{cases} \quad (4)$$

where $Q_i(k) = U_i(k) + T_i + 1$.

Let Π be the set all feasible scheduling policies. Denote by $\pi \in \Pi$ an arbitrary admissible policy. At the beginning of slot k , policy π be either keeping idle or selecting a sensor in active mode to transmit update. Let $\Delta_i(k)$ represent the AoI-penalty of sensor i at the beginning of slot k .

$$\Delta_i(k+1) = \begin{cases} 1, & \text{if } d_i(k) = 1, \\ \Delta_i(k) + 1, & \text{if } d_i(k) = 0 \text{ and } j_i(k) = -1, \\ \Delta_i(k) + w_i, & \text{if } d_i(k) = 0 \text{ and } j_i(k) \geq 0. \end{cases} \quad (5)$$

We adopt the Expected Sum of AoI-penalty to characterizes the freshness of the information of the entire network when the BS employs policy π

$$\Delta^\pi = \frac{1}{KM} \mathbb{E} \left[\sum_{k=1}^K \sum_{i=1}^M \Delta_i(k) \mid \vec{\Delta}(1), \vec{U}(0) \right], \quad (6)$$

where $\vec{\Delta}(1) = [\Delta_1(1) \ \Delta_2(1) \ \cdots \ \Delta_M(1)]^T$ and $\vec{U}(0) = [U_1(0) \ U_2(0) \ \cdots \ U_M(0)]^T$ are the vectors which indicate the initial state of the network. We assume that $\Delta_i(1) = 1$ and $U_i(0) = 0, \forall i$, and omit $\vec{\Delta}(1)$ and $\vec{U}(0)$ henceforth.

Then, we can build an AoI-penalty optimization-scheduling problem:

$$\min_{\pi \in \Pi} \lim_{K \rightarrow +\infty} \frac{1}{KM} \mathbb{E} \left[\sum_{k=1}^K \sum_{i=1}^M \Delta_i(k) \right] \quad (7a)$$

$$\text{s.t.} \quad \begin{cases} u_i(k)j_i(k) \geq 0, & \forall k, \forall i; \\ u_i(k) = \{0, 1\}, & \forall k, \forall i; \\ \sum_{i=1}^M u_i(k) \leq 1, & \forall k, \end{cases} \quad (7b)$$

Let Δ^* denote the optimal expected sum of AoI-penalty. There are three constraints in (7): the first constraint ensures that the selected sensor is in active mode, the second one means a scheduling choice, while the last one ensures that at most one sensor is scheduled in a slot.

IV. PROBLEM ANALYSIS

A. Convergence Condition

Firstly, we analyze the convergence of Δ^π when $K \rightarrow \infty$ so that we can narrow the search range of the scheduling policies. A convergence analysis shows the condition the scheduling policy π needs to meet if this policy makes Δ^π converge to a finite value.

Theorem 1 (Necessary Condition for Convergence). If a scheduling policy π makes Δ^π converge to a finite value as $K \rightarrow +\infty$, it should satisfy the following condition: $\forall t' \in [1, +\infty)$ and $\forall i \in \{1, 2, \dots, M\}$,

$$\Pr \left(\sum_{k=t'}^{\infty} u_i(k) \geq 1 \right) = 1. \quad (8)$$

Proof: The proof is shown in Appendix A. ■

Theorem 1 reveals that the system will not appear as follows: with a positive probability, starting from a certain time slot, at least one sensor keeps idle all the time. According to Theorem 1, the scheduling policies should satisfy the necessary condition. Beyond that, Theorem 1 helps us prove some theorems in the following part.

Algorithm 1: Obtaining the Lower Bound

Input: input parameters M, T_i, p_i, w, ζ

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1 if  $T_i \equiv 0$  then
2    $\bar{M}[I_i] \leftarrow \frac{1}{p_i}, \forall i$ 
3   if the second part of (14b) is not satisfied then
4      $L_B \leftarrow \frac{w^0 (\sum_{i=1}^M \sqrt{1/p_i})^2}{2M} + \frac{2-w^0}{2}$ 
5   else
6      $L_B \leftarrow \sum_{i=1}^M f(\bar{M}[I_i])/M$ 
7   end
8 else
9    $\lambda \leftarrow 0;$ 
10   $\bar{M}[I_i] \leftarrow \max \left\{ T_i + \frac{1}{p_i}, \sqrt{\frac{(w_i-1)(T_i+T_i^2)}{w_i}} \right\}, \forall i$ 
11  if the second part of (14b) is not satisfied then
12     $u \leftarrow \min\{w_1, w_2, \dots, w_M\}/(2M), l \leftarrow 0$ 
13    repeat
14       $\lambda \leftarrow (l+u)/2$ 
15       $\bar{M}[I_i] \leftarrow \max \left\{ T_i + \frac{1}{p_i}, \sqrt{\frac{(w_i-1)(T_i+T_i^2)}{w_i-2M\lambda}} \right\}, \forall i$ 
16      if  $\sum_{i=1}^M \bar{M}[I_i] \geq \left( \sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2$  then
17         $u \leftarrow \lambda$ 
18      else
19         $l \leftarrow \lambda$ 
20      end
21    until  $u-l \leq \zeta;$ 
22  end
23   $L_B \leftarrow \sum_{i=1}^M f(\bar{M}[I_i])/M$ 
24 end
25 return  $L_B$ 

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B. Lower Bound of the Performance

Assume that there is an admissible policy π that meets all the constraints in (7b) and ensures each sensor will be scheduled during a finite time interval (Theorem 1). Denote by Ω the sample space of the network and by $\omega \in \Omega$ the sample path associated with policy π for the time-horizon of K slots. For this sample path, let $D_i(K) = \sum_{k=1}^K d_i(k)$ be the total updates received by the BS during the K slots, and $I_i[m]$ be the inter-delivery time associated with the deliveries of the updates come from sensor i , i.e., $I_i[m]$ is the number of slots between the $(m-1)$ th and m th updates delivered by sensor i . Let R_i be the number of remaining slots after the last delivery of update by sensor i . Then we can denote time-horizon K as follows:

$$K = \sum_{m=1}^{D_i(k)} I_i[m] + R_i, \quad \forall i \in \{1, 2, \dots, M\}, \quad (9)$$

where $I_i[m] \geq T_i + 1$, because sensor i is able to be scheduled only when it is in active mode. We use the operator $\bar{M}[\mathbf{x}]$ to represent the mean of a set of values \mathbf{x} . With such a definition,

let the mean of $I_i[m]$ and $I_i^2[m]$ be

$$\bar{M}[I_i] = \lim_{K \rightarrow +\infty} \frac{1}{D_i(K)} \sum_{m=1}^{D_i(K)} I_i[m] \quad (10)$$

$$\bar{M}[I_i^2] = \lim_{K \rightarrow +\infty} \frac{1}{D_i(K)} \sum_{m=1}^{D_i(K)} I_i^2[m]. \quad (11)$$

Below we obtain a lower bound of the optimal solution.

Lemma 1. The optimal AoI-penalty of (7) meets the following:

$$\Delta^* \geq \frac{1}{M} \sum_{i=1}^M f(\bar{M}[I_i]), \quad (12)$$

where

$$f(\bar{M}[I_i]) = \frac{w_i \bar{M}[I_i]}{2} + \frac{(w_i-1)(T_i+T_i^2)}{2\bar{M}[I_i]} + \frac{2T_i - 2w_i T_i + 2 - w_i}{2}. \quad (13)$$

Proof: The proof is supplied in Appendix B. ■

Lemma 2. A lower bound L_B of the optimization problem (7) can be obtained by solving

$$L_B = \min_{\bar{M}[I_i]} \frac{1}{M} \sum_{i=1}^M f(\bar{M}[I_i]) \quad (14a)$$

$$s.t. \quad \begin{cases} \bar{M}[I_i] \geq T_i + \frac{1}{p_i}, \forall i; \\ \sum_{i=1}^M \bar{M}[I_i] \geq \left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2. \end{cases} \quad (14b)$$

Proof: The proof is offered in Appendix C. ■

Theorem 2 (The lower bound). L_B can be obtained by solving problem (14) with Algorithm 1. The w^0 in Algorithm 1 is the value of w when the sleep time T is 0.

Proof: The proof is provided in Appendix D. ■

Notice that ζ in Algorithm 1 is the parameter which influences the accuracy of the solution, and the value of it should be small. Theoretically, we have obtained the lower bound of the optimization problem in (7), which can help us analyze the performance of scheduling policies.

V. MAX-WEIGHT POLICY

It is difficult to obtain the optimal low-complexity solution to (7) because of its the real-time scheduling decisions, randomness, infinite states, infinite time-horizon and the property of non-convex ($u_i(k) \in \{0, 1\}$ makes the feasible set non-convex). In [12], [13], [31], [29], the optimal low-complexity solutions are also difficult to obtain for similar problems. Max-Weight policy and Drift-Plus-Penalty policy have better performance in [12]. Therefore, in this section, we adopt the light-weighted scheduling policy: Max-Weight policy. It minimizes the drift of a Lyapunov Function of the system state during every slot and it meets the condition in Theorem 1. Compared with [12], [13], this paper takes into account the sleep mode and non-linear AoI, which makes it challenging to analyze the system's performance.

In this section, we introduce the proposed policy (or the MW policy for short) based on the concept of max-weight which has been used to deal with AoI scheduling problem in [12], [13]. Using concepts from Lyapunov Optimization [34], the MW policy can be obtained by minimizing the drift of a Lyapunov Function of the system state during every slot. The state of the system during every slot is

$$S_k = \left\{ \Delta_i(k), j_i(k) \right\}_{i=1}^M. \quad (15)$$

For every slot, define the quadratic Lyapunov function as:

$$L(S_k) = \frac{1}{2} \sum_{i=1}^M \Delta_i^2(k). \quad (16)$$

which indicates the AoI-penalty of the system during slot k . Obviously, we can calculate $L(S_k)$ by the system state during slot k . We define Lyapunov Drift which describes the expected change in function $L(S_k)$ from one slot to the next slot

$$G(S_k) = \mathbb{E}[L(S_{k+1}) - L(S_k) | S_k]. \quad (17)$$

Consequently, if we want to lower down the value of system AoI-penalty in (6), we need to keep $L(S_k)$ small by reducing $G(S_k)$ for every slot. Substituting (16) into (17), we can get

$$G(S_k) = \frac{1}{2} \sum_{i=1}^M \mathbb{E}[(\Delta_i^2(k+1) - \Delta_i^2(k) | S_k)]. \quad (18)$$

Sensor i can be scheduled at the beginning of slot k only when it is in active mode, i.e., $j_i(k) \geq 0$ or $\Delta_i(k) \geq T_i + 1$. Therefore, we just discuss the case where sensors are active.

$$\begin{aligned} \mathbb{E}[\Delta_i^2(k+1) | S_k] &= (\Delta_i(k) + w_i)^2 (1 - p_i \mathbb{E}[u_i(k) | S_k]) \\ &\quad + p_i \mathbb{E}[u_i(k) | S_k]. \end{aligned} \quad (19)$$

Manipulating (19) yields that

$$\begin{aligned} &\mathbb{E}[\Delta_i^2(k+1) - \Delta_i^2(k) | S_k] \\ &= -p_i \mathbb{E}[u_i(k) | S_k] [(\Delta_i(k) + w_i)^2 - 1] + w_i(2\Delta_i(k) + w_i). \end{aligned} \quad (20)$$

In order to reduce $G(S_k)$ during every slot, we need to determine the value of $\{u_i(k)\}_{i=1}^M$ at the beginning of every slot. We should consider (18) and (20) to determine the value of $u_i(k)$. Notice that only the first term of (20) can be affected by the choice of $u_i(k)$ of active sensors. So, we extract the first term of (20), remove $u_i(k)$ and minus sign

$$MW_i(k) = p_i [(\Delta_i(k) + w_i)^2 - 1]. \quad (21)$$

Remark 1. In order to minimize (18), the MW policy selects the active sensor with the highest $MW_i(k)$ to transmit the update at the beginning of each slot k . In addition, the policy is set to select the one with the smallest serial number to break the tie if two or more sensors have the same value of $MW_i(k)$.

An example of the detailed operations of the MW policy is illustrated in Figure 2. Assume that there are two sensors in the network. The parameters are: $T_1 = 3$, $T_2 = 4$, $p_1 > p_2$ and $w_1 > w_2$. At the beginning, the two sensors are in sleep mode, and the BS cannot schedule any of them to send data. Then, sensor 1 and sensor 2 switch to active mode successively. The BS schedules sensor 1 to send data because the value of MW_1

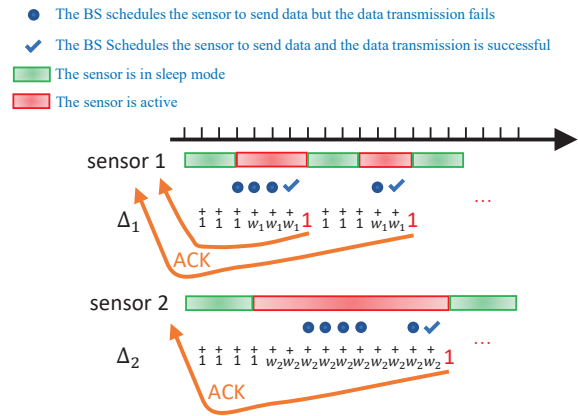


Fig. 2: An example of the operation of the MW policy.

is higher. When sensor 1 sends the data successfully, it will receive an acknowledgement from the BS, and then sensor 1 switches into sleep mode (the BS knows sensor 1 will sleep for 3 slots). After that, the BS begins to schedule sensor 2 because it is still active. Assume that the transmission fails all the time and sensor 1 switches into active mode again (the BS knows sensor 1 will be active at that time). Moreover, we assume that the value of MW_1 overtakes MW_2 . Then the BS stops scheduling sensor 2 and begins to schedule sensor 1. The later operation process can be seen in Figure 2.

A. Performance Analysis

From (21), we can find that if one sensor is idle from a certain slot, there is at least one sensor's transmission fails all the time. However, p_i is greater than 0 for all i . The probability of such an event will not be a positive number. Therefore, we can obtain Remark 2.

Remark 2. The MW policy meets the necessary condition in Theorem 1.

Assume that the network is symmetric (all the sensors adopt the same sleep times $T_i \equiv T$ so that $w_i \equiv w$) and the channel is symmetric ($p_i \equiv p$). At the beginning of slot k , MW schedules sensor i because the value of $\Delta_i(k) + w$ is the highest among the active sensors. Assume this transmission fails and we can get $\Delta_i(k+1) = \Delta_i(k) + w$. The growth rates of AoI-penalty of other sensors are not greater than sensor i . According to (21) and $p_i \equiv p$, we have the following remark.

Remark 3. When the network and the channel are symmetric, once a sensor is scheduled, MW does not switch scheduling decisions until the sensor transmits the update successfully.

The following theorem reveals a special working pattern for MW when the network and the channel are symmetric.

Theorem 3 (Round Robin Pattern). When the network is symmetric, the necessary and sufficient condition of the MW policy generates the Round Robin pattern (the sensors transmit data in the order $1, 2, \dots, M, 1, 2, \dots, M, 1, 2, \dots$) is that the channel is symmetric.

Proof: The proof is provided in Appendix E. ■

In fact, when the network and channel are symmetric, MW schedules one active sensor with the highest value of $\Delta_i(k)$ to transmit the update to the BS at the beginning of each slot k , which is the greedy policy in [13].

Remark 4. The MW policy will degenerate into the Greedy policy if the network and the channel are symmetric.

According to Theorem 3, we can get the following corollary.

Corollary 1. MW generates a Round Robin pattern when the network is symmetric and the channel is error-free ($p_i \equiv 1$).

Then, we can get some properties of MW when the network is symmetric and the channel is error-free.

Corollary 2. For a symmetric network and an error-free channel, as $K \rightarrow \infty$, the expected sum of AoI-penalty under MW becomes

$$\Delta^{MW} = \begin{cases} \frac{T}{2} + 1, & \text{if } M < T + 1, \\ f(M), & \text{if } M \geq T + 1, \end{cases} \quad (22)$$

where $f(\cdot)$ has been defined in (13).

Proof: According to Corollary 1, each sensor is in cycle mode after slot $T + M$. If $M < T + 1$ and $k \geq T + M + 1$, the change rule of the value of AoI-penalty for all the sensors during one transmission cycle is $\{1, 2, \dots, T + 1\}$. In addition, if $M \geq T + 1$, the change rule of the value of AoI-penalty for all the sensors during one transmission cycle is $\{1, 2, \dots, T + 1, T + 1 + w, \dots, T + 1 + (M - T - 1)w\}$. According to the renewal processes, we can get (22) by the strong law of large numbers [35]. ■

Next, we prove that MW is optimal when the network is symmetric and the channel is error-free.

Theorem 4 (Optimality of Max-Weight Policy). If the network is symmetric and the channel is error-free, as $K \rightarrow \infty$, the MW policy attains the minimum expected sum of AoI-penalty in (6) among all the admissible policies and it is the solution to the optimization problem in (7). Furthermore, the corresponding optimal AoI-penalty is

$$\Delta^* = \begin{cases} \frac{T}{2} + 1, & \text{if } M < T + 1, \\ f(M), & \text{if } M \geq T + 1, \end{cases} \quad (23)$$

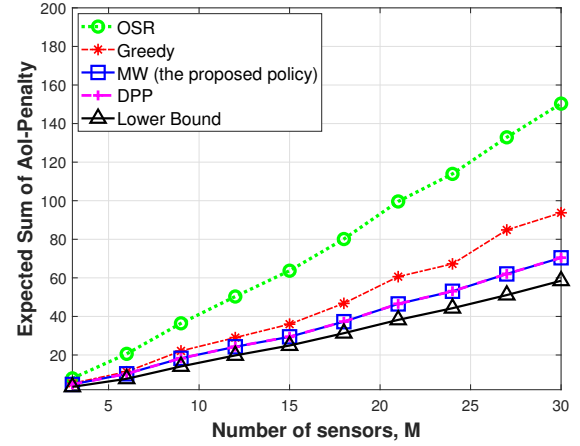
Proof: The proof is provided in Appendix F. ■

In addition, according to the operation process in Section V, we can get Remark 5.

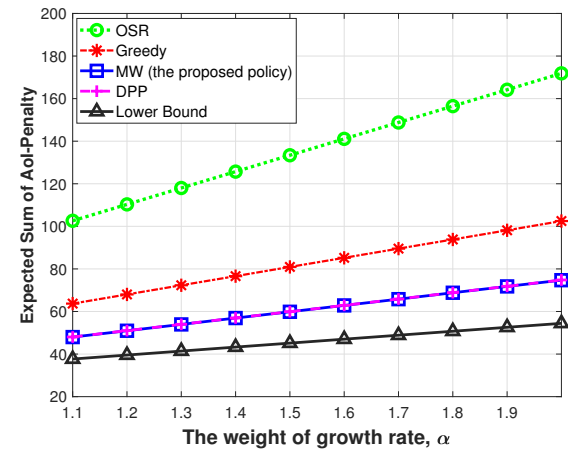
Remark 5. The MW policy needs to calculate the value of $\{MW_i(k)\}_{i=1}^M$ for every decision, so the time complexity of it is $\mathcal{O}(M)$.

B. Discussions

Based on the proposed MW policy, the scheduling decisions are made by the BS in a centralized manner at every slot. In order to make the decisions, the BS needs to know the current $\{\Delta_i\}_{i=1}^M$ and the working modes of the sensors. Fortunately, for each sensor i , by the definition of AoI in (5), $\Delta_i(k)$ is known by the BS, so is the working mode of sensor i . Therefore, during each slot, the BS can make the scheduling decision by himself, given the parameters $\{T_i\}_{i=1}^M$ and $\{p_i\}_{i=1}^M$. Specifically, the initial state of each sensor is



(a) Comparison under different numbers of sensors M



(b) Comparison under different weight α

Fig. 3: Performance comparisons of different policies.

assumed to be $\Delta_i(1) = 1$ and $U_i(0) = 0$. Given the BS the parameters $\{T_i\}_{i=1}^M$, it can calculate $\{w_i\}_{i=1}^M$ by the definition of the penalty function such as in (25). Each sensor will sleep for a fixed time T_i after successfully sending a data packet to the BS, and then keeps active until it is scheduled by the BS and successfully sends its current packet. Therefore, the BS also knows the working modes of the sensors during every slot.

In this paper, we assume that the number of sensors in the system is a constant. However, our method can be easily extended to the cases with sensors join/leave the networks. Take that a new sensor joins the network for example. Upon finishing the necessary association processes with the BS, the sensor sends its sleep time, say T_i , to the BS. And the BS evaluates the channel quality in terms of p_i . Then, the BS can make scheduling decisions based on our proposed method with the new sensor accounted.

VI. SIMULATION RESULTS

In this section, we compare the performance of the proposed policy with three other scheduling policies: Greedy policy, Optimal Stationary Randomized policy (OSR) and Drift-Plus-

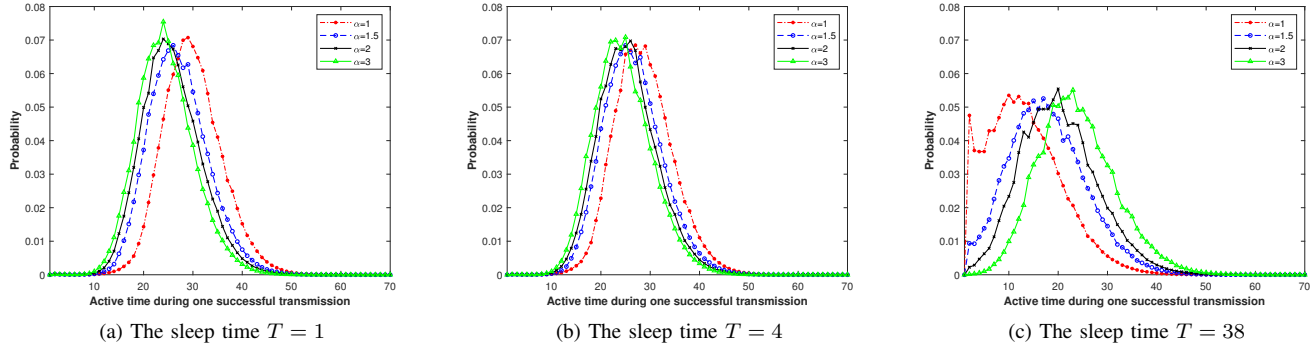


Fig. 4: The probability distribution of active time of the sensors with different emergency during one successful transmission.

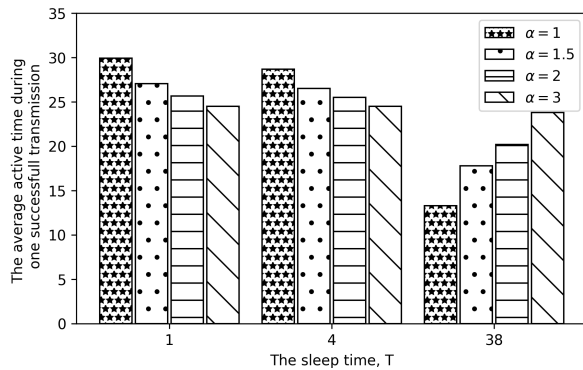


Fig. 5: The average active time with different emergency and different α during one successful transmission.

Penalty policy (DPP). Different from [12], Stationary Randomized policy in this paper schedules a sensor i with a fixed probability $\beta_i \in (0, 1]$ if the sensor is in active mode. According to the renewal process, we can derive a closed-form expression for (6) under Stationary Randomized Policy. Then, we can obtain the Optimal Stationary Randomized Policy OSR by using nonlinear optimization techniques. Given space limitations, we do not show how to solve the problem, but we will adopt OSR in simulations. The DPP policy adds a penalty term to the MW policy, and in our simulations the penalty is set as

$$\frac{1}{2} \sum_{i=1}^M \ln \left(\frac{T_{max}}{T_i} \right) \mathbb{E}[(\Delta_i(k+1) | S_k)], \quad (24)$$

in the sense that sensors with short sleep time may gain more chances to be scheduled.

We evaluate the performance of these policies in terms of the expected sum of AoI-penalty as given in (6). Then, we use simulations to study the characteristics of our AoI-penalty function from the perspective of active time and the AoI of each sensor. Lastly, we compare the performance in AoI and energy consumption between the sleep-wake sensors in this paper and the non-sleeping sensors such as in [12], [13], [29].

The setting of w_i in the simulation is:

$$w_i = \begin{cases} \alpha \left(1 + \frac{1-e^{-T_{max}/T_i}}{1+e^{-T_{max}/T_i}} \right), & \text{if } T_i \neq 0, \\ 2\alpha, & \text{if } T_i = 0. \end{cases} \quad (25)$$

where $T_{max} = \max\{T_1, T_2, \dots, T_M\}$. The weight $\alpha \geq 1$ represents how much the sensor is eager to send data in its active mode compared to the sleep mode. Above shows that w_i and T_i are negatively correlated and $1 \leq \alpha < w_i < 2\alpha$ ($T_i \neq 0$). The default parameter settings are: $M = 20$, $K = 10^5$, $\alpha = 1$, $p_i = i/M$, w_i is set as in (25). The sleep time T_i is randomly generated within $[1, 2M]$.

Fig. 3a shows the results of an average of 2000 simulations with fixed $K = 10^5$ and $\alpha = 1$, which shows simulation results with different $M \in \{3, 6, \dots, 30\}$. Fig. 3b shows the results of an average of 2000 simulations with fixed $M = 20$ and $K = 10^5$, which shows simulation results with different $\alpha \in \{1.1, 1.2, 1.3, \dots, 2.0\}$. From Fig. 3a and Fig. 3b, we can find the MW policy and DPP policy have better AoI performance in our simulations than OSR policy and Greedy policy. The result of the MW policy and DPP policy are close to the lower bound. The performance of DPP and MW are similar because they only differ in the penalty term. Notice that the reason why OSR policy performs worst is that it wastes a lot of opportunities to schedule sensors.

Next, we do some simulations on the performance of the sensors of high and low emergency, respectively, where the differences in sensors' emergency are achieved by setting different sleep time periods. Fig. 4 demonstrates the distribution of the active time of three sensors of different emergency under the MW policy, where $p \equiv 0.5$, $K = 10^5$ and $M = 20$. Fig. 5 demonstrates the average active time of the sensors in Fig. 4. Fig. 4a and the left part in Fig. 5 represent the sensor with the highest emergency ($T = 1$), where we can see that the larger α is, the shorter the average active time of the sensor is. And most of the active time is between 20 and 50 slots. Fig. 4b and the middle part in Fig. 5 reflect the performance of the sensor with the second highest emergency ($T = 4$), and its performance is similar to that of the sensor with the highest emergency. In contrast, as shown in Fig. 4c and the right part in Fig. 5, the average active time of the sensor with the lowest emergency ($T = 38$) indicates that the larger α is, the larger the average active time of the sensor is. This is

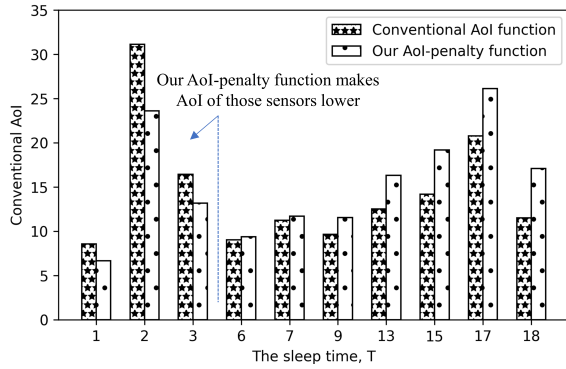


Fig. 6: Under different AoI model, the conventional AoI performance of each sensor.

because the AoI-penalty function and the MW policy offer the important sensors more chances to send data but at the cost that the scheduling opportunities of unimportant sensors are sacrificed. The larger the value of α is, the more obvious the above property is.

In order to figure out whether our AoI-penalty function helps important sensors offer fresh information, we do further simulations. Fig. 6 shows the conventional AoI performance of each sensors, where $K = 10^5$, $M = 10$, $\alpha = 3$ and the MW policy is adopted. In order to make AoI comparable, the AoI in Fig. 6 is conventional while our model operates in AoI-penalty function. The conventional AoI grows at a fixed rate of 1 when no fresh information is provided [12]. The conventional AoI of the three sensors with shorter sleep time ($T = 1, 2, 3$) is lower in our AoI-penalty function, which demonstrates our AoI-penalty function sacrifices the AoI of the sensors with larger sleep time to provide smaller AoI for the sensors with smaller sleep time. Therefore, our AoI-penalty can provide fresh information for the important sensors (the sensors with smaller sleep time).

Then, in order to figure out whether sleep mode can help sensors strike a balance between fresh samples and energy conservation, we simulate two groups of sensors and compare the performance of AoI and energy consumption. The sensors in the first group are equipped with sleep mode while the sensors in the second group do not have sleep time and are non-sleeping. In order to make AoI comparable, the AoI in Fig. 7 is conventional while our model operates in sleep-wake and AoI-penalty function. Same to [36], we set the power consumption in sleeping, active and transmitting data modes as $15 \mu\text{W}$, 13.5 mW and 24.75 mW , respectively. Fig. 7 shows the results of an average of 2000 simulations with $\alpha = 1$ and $K = 10^5$ under the MW policy. As shown, the AoI performance of the sensors equipped with sleep mode is quite close to the non-sleeping sensors while the sleep-wake sensors can save a lot of energy.

VII. CONCLUSION

In this paper, the sensors can work in sleep-wake mode to save energy and enhance lifetime. We design an AoI-penalty function to express the need for fresh information of active

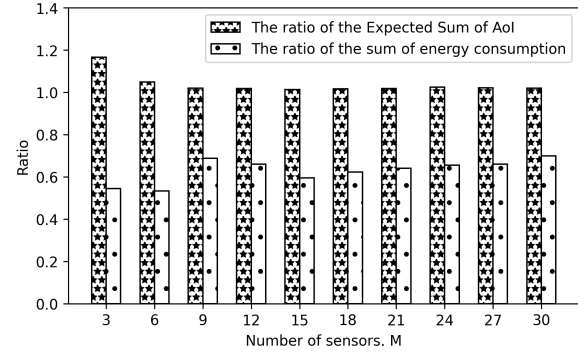


Fig. 7: Performance comparison of AoI and energy consumption between sleep-wake and non-sleeping sensors.

sensors and establish an AoI-penalty optimization-scheduling problem. Then we introduce a max-weight based scheduling policy and prove that it is the optimal policy when the network is symmetric and the channel is error-free. In addition, the MW policy will operate in a Round Robin pattern when the network and the channel are symmetric. In the simulation results, the AoI-penalty performance of the MW policy is close to the lower bound. It is also found that the penalty function lowers down the AoI of the important sensors. In addition, the simulation result shows that sleep-wake sensors in this paper can save a lot of energy and provide a good AoI performance. In our future work, we will optimize AoI with joint analysis of dynamic sleep time and scheduling policies when the sensors are equipped with limited energy.

APPENDIX A PROOF OF THEOREM 1

Under a scheduling policy π , let $\beta > 0$ be the probability of the following event: $\exists i', k' \in \mathbb{N}^+$, sensor i' is no longer scheduled after slot k' . When the event occurs as $K \rightarrow +\infty$, we assume the value of Δ^π still can converge to a finite value. Then we adopt reduction to absurdity.

Without loss of generality, we can assume the last time the BS receives the update from sensor i' is the end of slot $k' - 1$. Then we can get $U_{i'}(k) = U_{i'}(k' - 1) = k' - 1$ when $k \geq k'$. According to (6), we can get

$$\begin{aligned} \Delta^\pi &\geq \frac{\beta}{K} \sum_{k=1}^K \sum_{i=1}^M \Delta_i(k) \\ &= \frac{\beta}{K} \left(\sum_{k=1}^K \sum_{\substack{i=1 \\ i \neq i'}}^M \Delta_i(k) + \sum_{k=1}^{k'-1} \Delta_{i'}(k) + \sum_{k=k'}^K \Delta_{i'}(k) \right). \end{aligned} \quad (26)$$

Extracting the last term of the above equation and applying the formula of the sum of arithmetic progression, we have

$$\begin{aligned} &\frac{\beta}{K} \sum_{k=k'}^K \Delta_{i'}(k) \\ &= \frac{\beta[T_{i'}^2 + T_{i'}]}{2K} + \frac{\beta[j_{i'}(K) + 1][2T_{i'} + 2 + w_{i'}j_{i'}(K)]}{2K}. \end{aligned} \quad (27)$$

The second term of (27) is infinite as $K \rightarrow \infty$ because the order of K on the molecule is higher. In addition, the first two terms of (26) are non-negative and hence $\Delta^\pi \rightarrow \infty$ as $K \rightarrow \infty$, which conflicts with the hypothesis.

APPENDIX B PROOF OF LEMMA 1

Within each $I_i[m]$ interval, the initial value of $\Delta_i(k)$ is 1, the value of $\Delta_i(k)$ grows 1 every slot when sensor i is in sleep mode and grows w_i every slot when sensor i is in active mode. According to the limit we have mentioned, the value of R_i is finite even when $K \rightarrow +\infty$. Therefore, the sum of $\Delta_i(k)$ during the remaining time is finite and its influence on the value of (6) can be ignored when $K \rightarrow +\infty$. Then, the time-average AoI-penalty of sensor i when $K \rightarrow +\infty$ can be written as

$$\begin{aligned} & \lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{k=1}^K \Delta_i(k) \\ &= \lim_{K \rightarrow +\infty} \sum_{m=1}^{D_i(K)} \frac{T_i^2 + T_i}{2K} \\ &+ \lim_{K \rightarrow +\infty} \sum_{m=1}^{D_i(K)} \frac{(I_i[m] - T_i)(2T_i + 2 + w_i(I_i[m] - T_i - 1))}{2K} \\ &= \lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{m=1}^{D_i(K)} \left(\frac{w_i}{2} I_i^2[m] + \frac{2T_i - 2w_i T_i + 2 - w_i}{2} I_i[m] \right) \\ &+ \lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{m=1}^{D_i(K)} \frac{(w_i - 1)(T_i + T_i^2)}{2} \end{aligned} \quad (28)$$

Combining (9) and (10) yields

$$\lim_{K \rightarrow +\infty} \frac{K}{D_i(K)} = \overline{\mathbb{M}}[I_i] + \lim_{K \rightarrow +\infty} \frac{R_i}{D_i(K)}. \quad (29)$$

According to Theorem 1, the policy π we adopt makes $D_i(K) \rightarrow +\infty$ when $K \rightarrow +\infty$. Substituting (29) into (28) and applying the limit of R_i yield that

$$\begin{aligned} & \lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{k=1}^K \Delta_i(k) \\ &= \lim_{K \rightarrow +\infty} \frac{D_i(K)}{K} \frac{1}{D_i(K)} \sum_{m=1}^{D_i(K)} \frac{w_i}{2} I_i^2[m] \\ &+ \lim_{K \rightarrow +\infty} \frac{D_i(K)}{K} \frac{1}{D_i(K)} \sum_{m=1}^{D_i(K)} \frac{2T_i - 2w_i T_i + 2 - w_i}{2} I_i[m] \\ &+ \lim_{K \rightarrow +\infty} \frac{D_i(K)}{K} \frac{1}{D_i(K)} \sum_{m=1}^{D_i(K)} \frac{(w_i - 1)(T_i + T_i^2)}{2} \\ &= \frac{w_i \overline{\mathbb{M}}[I_i^2]}{2 \overline{\mathbb{M}}[I_i]} + \frac{2T_i - 2w_i T_i + 2 - w_i}{2} + \frac{(w_i - 1)(T_i + T_i^2)}{2 \overline{\mathbb{M}}[I_i]} \\ &\geq \frac{w_i \overline{\mathbb{M}}[I_i]}{2} + \frac{(w_i - 1)(T_i + T_i^2)}{2 \overline{\mathbb{M}}[I_i]} + \frac{2T_i - 2w_i T_i + 2 - w_i}{2} \\ &\triangleq f(\overline{\mathbb{M}}[I_i]). \end{aligned} \quad (30)$$

where the above inequality applies Jensen's inequality. Taking the derivative of $f(\overline{\mathbb{M}}[I_i])$ with respect to $\overline{\mathbb{M}}[I_i]$, we can see that $f(\overline{\mathbb{M}}[I_i])$ is monotonically increasing when

$$\overline{\mathbb{M}}[I_i] \geq \sqrt{T_i^2 + T_i - T_i^2/w_i - T_i/w_i}. \quad (31)$$

As mentioned above: $I_i[m] \geq T_i + 1$, therefore,

$$\overline{\mathbb{M}}[I_i] \geq T_i + 1 > \sqrt{T_i^2 + T_i - T_i^2/w_i - T_i/w_i}, \quad (32)$$

which leads to that $f(\overline{\mathbb{M}}[I_i]) \geq f(T_i + 1) > 0$. Since $\lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{k=1}^K \Delta_i(k)$ is positive for all the admissible policies and all the sample path, by Fatou's lemma we can obtain $\lim_{K \rightarrow +\infty} \mathbb{E}[\frac{1}{K} \sum_{k=1}^K \Delta_i(k)] \geq \mathbb{E}[\lim_{K \rightarrow +\infty} \frac{1}{K} \sum_{k=1}^K \Delta_i(k)]$.

As a consequence, from (7a), we can get $\Delta^* \geq \frac{1}{M} \sum_{i=1}^M \mathbb{E}[f(\overline{\mathbb{M}}[I_i])]$. Then, by removing the expectation operation due to the strong law of large numbers, inequality (12) is acquired.

APPENDIX C PROOF OF LEMMA 2

Assume that the policy π schedules sensor i once it switches to active mode and does not schedule other active sensors unless the sensor i that is being scheduled has successfully transmitted its update to the BS. Then the number of times sensor i is scheduled during a successful transmission interval is a geometric random variable. The behavior above leads to the lower bound of $\overline{\mathbb{M}}[I_i]$:

$$\overline{\mathbb{M}}[I_i] \geq T_i + \frac{1}{p_i}. \quad (33)$$

Let $\Upsilon_i(K)$ represent the number of times the sensor i is scheduled up to and including slot K . Because the BS allows at most one sensor to be scheduled per slot, we can get

$$\sum_{i=1}^M \Upsilon_i(K) = \sum_{k=1}^K \sum_{i=1}^M u_i(k) \leq K. \quad (34)$$

With the strong law of large numbers, we know

$$\lim_{K \rightarrow +\infty} \frac{D_i(K)}{\Upsilon_i(K)} = p_i. \quad (35)$$

Combining (29), (34) and (35)

$$\begin{aligned} \sum_{i=1}^M \overline{\mathbb{M}}[I_i] &= \lim_{K \rightarrow +\infty} \sum_{i=1}^M \frac{K}{D_i(K)} \\ &\geq \lim_{K \rightarrow +\infty} \left(\sum_{i=1}^M \Upsilon_i(K) \right) \left(\sum_{i=1}^M \frac{1}{D_i(K)} \right) \\ &\stackrel{(a)}{\geq} \lim_{K \rightarrow +\infty} \left(\sum_{i=1}^M \sqrt{\frac{\Upsilon_i(K)}{D_i(K)}} \right)^2 \\ &= \left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2, \end{aligned} \quad (36)$$

where (a) adopts Cauchy-Schwarz inequality. Combining the constrains with Lemma 1, Lemma 2 can be proved.

APPENDIX D
PROOF OF THEOREM 2

Consider an arbitrary $i \in \{1, \dots, M\}$. For the case: $T_i \equiv 0$, the second term in $f(\overline{M}[I_i])$ is equal to zero and we can get

$$\frac{1}{M} \sum_{i=1}^M f(\overline{M}[I_i]) = \sum_{i=1}^M \frac{w_i \overline{M}[I_i]}{2M} + \sum_{i=1}^M \frac{2 - w_i}{2M}. \quad (37)$$

The problem can be solved through linear programming. Firstly, let $\overline{M}[I_i] = 1/p_i, \forall i$. If the second part of (14b) can be satisfied, we substitute $\overline{M}[I_i] = 1/p_i$ into (14a) and get the value of L_B . However, if (14b) cannot be satisfied, we substitute the equation below into (14a) and get the value of L_B .

$$\sum_{i=1}^M \overline{M}[I_i] = \left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2. \quad (38)$$

This process is realized from line 1-7 in Algorithm 1.

For other cases, we can analyze the KKT conditions to get L_B . Let $\{\gamma_i\}_{i=1}^M$ be the KKT multipliers associated with the relaxation of the first part of (14b) and λ be the KKT multipliers associated with the relaxation of the second part of (14b). Then, for $\lambda \geq 0$ and $\gamma_i \geq 0$, we can define

$$\begin{aligned} \mathcal{L}(\overline{M}[I_i], \lambda, \gamma_i) = & \frac{1}{M} \sum_{i=1}^M f(\overline{M}[I_i]) \\ & + \sum_{i=1}^M \gamma_i \left(T_i + \frac{1}{p_i} - \overline{M}[I_i] \right) \\ & + \lambda \left[\left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2 - \sum_{i=1}^M \overline{M}[I_i] \right], \end{aligned} \quad (39)$$

otherwise, we can define $\mathcal{L}(\overline{M}[I_i], \lambda, \gamma_i) = +\infty$. So, we can obtain the KKT conditions.

- 1) The Stationarity is $\nabla_{\overline{M}[I_i]} \mathcal{L}(\overline{M}[I_i], \lambda, \gamma_i) = 0$;
- 2) The first Complementary Slackness is $\gamma_i \left(T_i + \frac{1}{p_i} - \overline{M}[I_i] \right) = 0$;
- 3) The second Complementary Slackness is $\lambda \left[\left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2 - \sum_{i=1}^M \overline{M}[I_i] \right] = 0$;
- 4) The Primal Feasibilities are $\overline{M}[I_i] \geq T_i + \frac{1}{p_i}$ and $\sum_{i=1}^M \overline{M}[I_i] \geq \left(\sum_{i=1}^M \sqrt{\frac{1}{p_i}} \right)^2$;
- 5) The Dual Feasibilities are $\gamma_i \geq 0, \forall i$ and $\lambda \geq 0$.

In order to get stationarity, $\nabla_{\overline{M}[I_i]} \mathcal{L}(\overline{M}[I_i], \lambda, \gamma_i) = 0$, we need to calculate the partial derivative of $\mathcal{L}(\overline{M}[I_i], \lambda, \gamma_i)$ with respect to $\overline{M}[I_i]$

$$\overline{M}[I_i] = \sqrt{\frac{(w_i - 1)(T_i + T_i^2)}{w_i - 2M\gamma_i - 2M\lambda}}. \quad (40)$$

According to (40) and the KKT conditions, firstly, we assume that $\lambda = 0$, so the solution is

$$\overline{M}[I_i] = \max \left\{ T_i + \frac{1}{p_i}, \sqrt{\frac{(w_i - 1)(T_i + T_i^2)}{w_i}} \right\}, \quad (41)$$

if the solution cannot meet the constraint of the second part of (14b), we can get $\lambda \neq 0$. If $\lambda \neq 0$, the solution is

$$\overline{M}[I_i] = \max \left\{ T_i + \frac{1}{p_i}, \sqrt{\frac{(w_i - 1)(T_i + T_i^2)}{w_i - 2M\lambda}} \right\}, \quad (42)$$

where the solution should meet the constraint, 3) of KKT conditions. In this case, we need to find the solution of λ . The line 8-24 in Algorithm 1 adopts bisection method to get the solution of λ . Algorithm 1 can get the value of L_B by finding the optimal $\{\overline{M}[I_i]\}_{i=1}^M$.

APPENDIX E
PROOF OF THEOREM 3

Firstly, we prove the necessary condition. Reorder the sensor index $\{i\}$ in descending order of p_i . At the beginning, all the sensors are in sleep mode. Then, during slot $T + 1$, all the sensors switch to active mode and the MW policy selects the active sensor with highest value of $MW_i(T + 1)$ to transmit update. Manipulating (21), we have

$$MW_i(k) = p_i \Delta_i^2(k) + 2p_i w \Delta_i(k) + p_i (w^2 - 1). \quad (43)$$

From Fig. 8, during slot $T + 1$, we can know sensor 1 is scheduled because the value of p_1 is highest among all the active sensors. Let $n_{i,j}$ represent the number of scheduling required for the j th successful transmission of sensor i . During slot $T + 1 + n_{1,1}$, the BS begins to schedule sensor 2. However, from slot $2T + 1 + n_{1,1}$ to $2T + 1 + n_{1,1} + n_{x,1} + \dots + n_{M,1} - 1$, sensor 1 is in active mode again, which is shown in Fig. 8. Notice that x is the sensor that is being scheduled during slot $2T + 1 + n_{1,1}$. Although sensor x may have been scheduled several times before slot $2T + 1 + n_{1,1}$, it has no effect on the following derivation. From slot $2T + 1 + n_{1,1}$ to $2T + 1 + n_{1,1} + n_{x,1} + \dots + n_{M,1} - 1$, if sensor M has not finished its transmission task, we should keep $MW_1(k) < MW_M(k)$ during the time interval so that the scheduling order is $(1, 2, \dots, M)$. As a consequence, for $z \in \{0, 1, 2, \dots, n_{x,1} + \dots + n_{M,1} - 1\}$, we obtain the following inequality:

$$p_1 [(T + 1 + zw)^2 - 1] < p_M [(T + 1 + (T + n_{1,1} + z)w)^2 - 1]. \quad (44)$$

Later, sensor 1 will be scheduled again. However, from slot $3T + 1 + n_{1,1} + n_{x,1} + \dots + n_{M,1} + n_{1,2}$ to $3T + 1 + n_{1,1} + n_{x,1} + \dots + n_{M,1} + n_{1,2} + n_{y,2} + \dots + n_{M,2} - 1$, sensor 1 is in active mode again, which is shown in Fig. 8. The meaning of sensor y is like sensor x . Therefore, similar to the derivation in the previous paragraph, for $z \in \{0, 1, 2, \dots, n_{y,2} + \dots + n_{M,2} - 1\}$, we obtain the following inequality:

$$p_1 [(T + 1 + zw)^2 - 1] < p_M [(T + 1 + (n_{1,2} + z)w)^2 - 1]. \quad (45)$$

Then the system goes into a cycle and the scheduling order is $(1, 2, \dots, M, 1, 2, \dots)$.

From (44), (45), $n_{1,1} \geq 1$ and $n_{1,2} \geq 1$, we can get

$$\frac{p_1}{p_M} < \frac{[T + 1 + (v + 1)w]^2 - 1}{[T + 1 + vw]^2 - 1}, \quad (46)$$

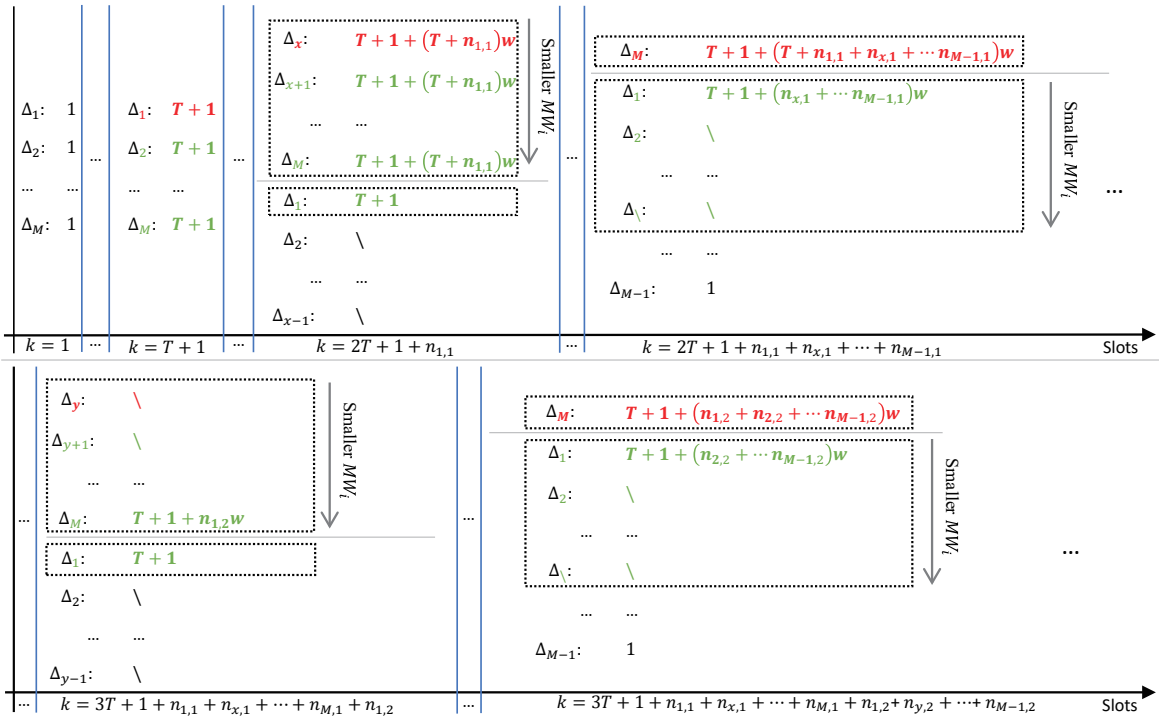


Fig. 8: The evolution of AoI-penalty under the MW policy, where the network is symmetric.

where $v \geq 0$. We can deduce that the right side of the inequality (46) decreases as v increases. We have

$$\frac{p_1}{p_M} < \lim_{v \rightarrow +\infty} \frac{[T+1+(v+1)w]^2 - 1}{[T+1+vw]^2 - 1}. \quad (47)$$

Combining with $p_1 \geq p_M$, we can get

$$\frac{p_1}{p_M} = 1. \quad (48)$$

Moreover, p_1 and p_M is the highest and lowest value among all the p_i , respectively. As a consequence, we can get $p_i \equiv p$. Notice that we have ignored the situation that BS is idle, because it is obvious that the scheduling order still is $(1, 2, \dots, M, 1, 2, \dots)$ in such a situation.

Then, we can prove the sufficient condition. Lower AoI-penalty will lead to lower value of (43) when $p_i \equiv p$. According to Remark 3, the scheduling order is $(1, 2, \dots, M, 1, 2, \dots)$ when the network and channel are symmetric.

APPENDIX F PROOF OF THEOREM 4

Denote by $\mathbb{I}_i(\cdot)$ the indicator function in the sense that $\mathbb{I}_i(s) = 1$ if $i \notin s$ and $\mathbb{I}_i(s) = 0$ otherwise. Let \hat{s}_k be the sensor that is scheduled during slot k and transmits the update successfully, and let \hat{c}_k be the set of sensors that is in sleep mode during slot k . Let $\vec{\mathbb{I}}(\cdot) = [\mathbb{I}_1(\cdot) \mathbb{I}_2(\cdot) \dots \mathbb{I}_M(\cdot)]^T$ and let $\vec{\Delta}(k) \odot \vec{\mathbb{I}}(\cdot)$ be the entry-wise product of vectors $\vec{\Delta}(k)$ and $\vec{\mathbb{I}}(\cdot)$. Then, $\vec{\Delta}(k)$ evolves as

$$\vec{\Delta}(k+1) = \vec{\Delta}(k) \odot \vec{\mathbb{I}}(\hat{s}_k) + (w-1)\vec{\mathbb{I}}(\hat{s}_k \cup \hat{c}_k) + \vec{1}, \quad (49)$$

where $\vec{1}$ is the unity column vector with length M .

Then, we can get that $\vec{\Delta}(k+1)$ can be expressed as a function of $\vec{\Delta}(1)$, $\{\hat{s}_j\}_{j=1}^k$ and $\{\hat{c}_j\}_{j=1}^k$

$$\begin{aligned} \vec{\Delta}(k+1) &= \vec{\Delta}(1) \odot \vec{\mathbb{I}}\left(\bigcup_{j=1}^k \hat{s}_j\right) + \sum_{a=1}^k (w-1)\vec{\mathbb{I}}\left(\bigcup_{j=a}^k \hat{s}_j \cup \hat{c}_a\right) \\ &\quad + \sum_{a=2}^k \vec{\mathbb{I}}\left(\bigcup_{j=a}^k \hat{s}_j\right) + \vec{1} \end{aligned} \quad (50)$$

We prove (50) by induction. Substituting $k=1$ into (50) and we can get (49). Then, assume that (50) holds for k . For step $k+1$, substituting $\vec{\Delta}(k)$ of the form (50) into (49) yields that

$$\begin{aligned} \vec{\Delta}(k+1) &= \vec{\Delta}(k) \odot \vec{\mathbb{I}}(\hat{s}_k) + (w-1)\vec{\mathbb{I}}(\hat{s}_k \cup \hat{c}_k) + \vec{1} \\ &= \left[\vec{\Delta}(1) \odot \vec{\mathbb{I}}\left(\bigcup_{j=1}^{k-1} \hat{s}_j\right) + \sum_{a=1}^{k-1} (w-1)\vec{\mathbb{I}}\left(\bigcup_{j=a}^{k-1} \hat{s}_j \cup \hat{c}_a\right) \right. \\ &\quad \left. + \sum_{a=2}^{k-1} \vec{\mathbb{I}}\left(\bigcup_{j=a}^{k-1} \hat{s}_j\right) + \vec{1} \right] \odot \vec{\mathbb{I}}(\hat{s}_k) + (w-1)\vec{\mathbb{I}}(\hat{s}_k \cup \hat{c}_k) + \vec{1} \\ &= \vec{\Delta}(1) \odot \vec{\mathbb{I}}\left(\bigcup_{j=1}^k \hat{s}_j\right) + \sum_{a=1}^k (w-1)\vec{\mathbb{I}}\left(\bigcup_{j=a}^k \hat{s}_j \cup \hat{c}_a\right) \\ &\quad + \sum_{a=2}^k \vec{\mathbb{I}}\left(\bigcup_{j=a}^k \hat{s}_j\right) + \vec{1}, \end{aligned} \quad (51)$$

which is identical to the expression in (50). By induction, we know that (50) holds for all $k \geq 1$.

Then we can get

$$\begin{aligned}
 & \sum_{i=1}^M \Delta_i(k) \\
 = & \sum_{i=1}^M \left[\Delta_i(1) \mathbb{I}_i \left(\bigcup_{j=1}^{k-1} \hat{s}_j \right) + \sum_{a=1}^{k-1} (w-1) \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \cup \hat{c}_a \right) \right. \\
 & \left. + \sum_{a=2}^{k-1} \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \right) + 1 \right] \\
 = & \sum_{i=1}^M \Delta_i(1) \mathbb{I}_i \left(\bigcup_{j=1}^{k-1} \hat{s}_j \right) + \sum_{i=1}^M \sum_{a=1}^{k-1} (w-1) \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \cup \hat{c}_a \right) \\
 & + \sum_{i=1}^M \sum_{a=2}^{k-1} \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \right) + M. \tag{52}
 \end{aligned}$$

All the admissible policies cannot schedule any sensors when $k \leq T$ because they are in sleep mode during that time. Therefore, the value of (52) is same for all the admissible policies when $k \leq T + 1$. Below we prove the theorem by considering two complementary cases, i.e., $M < T + 1$ and $M \geq T + 1$.

1) For the case $M < T + 1$, when $k \geq T + M + 1$, we can know the change rule of the value of AoI-penalty for all the sensors during one transmission cycle is $\{1, 2, \dots, T + 1\}$, which is the optimal change rule for all sensors. From Corollary 2, we can get

$$\Delta^* = \Delta^{MW} = \frac{T}{2} + 1 \tag{53}$$

2) For the another case $M \geq T + 1$, according to the proof of Theorem 3, there always exist one sensor that is scheduled at the beginning of each slot when $T + 1 \leq k$, and the order is $(1, 2, \dots, M, 1, 2, \dots)$. Therefore, the MW policy maximizes the number of deliveries and for every $\pi \in \Pi$ and we have

$$\left| \bigcup_{j=1}^k \hat{s}_j^{MW} \right| \geq \left| \bigcup_{j=1}^k \hat{s}_j^\pi \right|, \tag{54}$$

where $|s|$ means the number of the elements of set s and MW represents the MW policy. In addition, we can get

$$\left| \bigcup_{j=a}^k \hat{s}_j^{MW} \right| \geq \left| \bigcup_{j=a}^k \hat{s}_j^\pi \right|, \quad a \in \{1, 2, \dots, k\}. \tag{55}$$

Also, the MW policy maximizes the number of the sensors that are in sleep mode. If the intersection of $\bigcup_{j=a}^k \hat{s}_j^{MW}$ and \hat{c}_a is a empty set, the MW policy maximizes the number of elements of the union of them. If the intersection of $\bigcup_{j=a}^k \hat{s}_j^{MW}$ and \hat{c}_a is not a empty set, the number of elements is M , which is the maximum admissible value. So we can know

$$\left| \bigcup_{j=a}^k \hat{s}_j^{MW} \cup \hat{c}_a^{MW} \right| \geq \left| \bigcup_{j=a}^k \hat{s}_j^\pi \cup \hat{c}_a^\pi \right|, \quad a \in \{1, 2, \dots, k\}. \tag{56}$$

Equation (54) shows the MW policy minimizes the first term in R.H.S. of (52). The last term in RHS of (52) is constant. The second term in RHS of (52) can be written as

$$\begin{aligned}
 & \sum_{i=1}^M \sum_{a=1}^{k-1} (w-1) \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \cup \hat{c}_a \right) \\
 = & \sum_{a=1}^{k-1} (w-1) \left[M - \left| \bigcup_{j=a}^{k-1} \hat{s}_j \cup \hat{c}_a \right| \right], \tag{57}
 \end{aligned}$$

and the third term in RHS of (52) can be written as

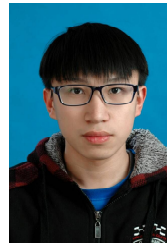
$$\sum_{i=1}^M \sum_{a=2}^{k-1} \mathbb{I}_i \left(\bigcup_{j=a}^{k-1} \hat{s}_j \right) = \sum_{a=2}^{k-1} \left[M - \left| \bigcup_{j=a}^{k-1} \hat{s}_j \right| \right]. \tag{58}$$

According to (55)-(58), the MW policy minimizes (52) in every slot k in this case. From Corollary 2, we can get $\Delta^* = \Delta^{MW} = f(M)$ which completes the proof.

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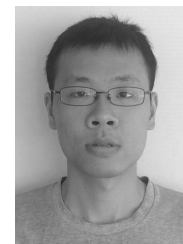
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