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AoI-Minimal Online Scheduling for Wireless Powered IoT: A Lyapunov Optimization-based Approach

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***Abstract*—This paper investigates the age of information (AoI)-based online scheduling in multi-sensor wireless powered communication networks (WPCNs) for time-sensitive Internet of Things (IoT). Specifically, we consider a typical WPCN model, where a wireless power station (WPS) charges multiple sensor nodes (SNs) by wireless power transfer (WPT), and then the SNs are scheduled in the time domain to transmit their sampled status information with their harvested energy to a mobile edge server (MES) for decision making. For such a system, we first derive a closed-form expression of the successful data transmission probability in Nakagami-m fading channels. To pursue an efficient online scheduling policy that minimizes the Expected Weighted Sum AoI (EWSAoI) of the system, a discrete-time scheduling problem is formulated. As the problem is non-convex with non-explicit expression of the EWSAoI, we propose a Max-Weight policy based on the Lyapunov optimization theory, which schedules the SNs at the beginning of each time in terms of the one-slot conditional Lyapunov Drift. Simulations demonstrate our presented theoretical results and show that our proposed scheduling policy outperforms other baselines such as greedy policy and random round-robin (RR) policy. Especially, when the number of SNs is relatively small, the gain achieved by the proposed policy compared to the greedy policy is considerable. Moreover, some interesting insights are also observed: 1) as the number of SNs increases, the EWSAoI also increases; 2) when the transmit power is relatively small, the larger the number of SNs, the smaller the EWSAoI; 3) the EWSAoI decreases with the increment of transmit power of the WPS and then tends to be flat; 4) the EWSAoI increases with the increment of the distance between the SNs and the MES.**

***Index Terms*—Age of Information (AoI), Nakagami-m fading, wireless powered communication networks (WPCN), Lyapunov optimization, online scheduling policy.**

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I. Introduction

A. Background

In recent years, with the rapid development of the Internet of Things (IoT), a large number of real-time applications, such as vehicle tracking [1], environment monitoring [2], have emerged. In such applications, mobile edge servers (MESs) or central controllers collect data from IoT devices and then track real-time status information through wireless links to perform system control or decision-making. In order to make correct decisions in a timely fashion, the information collected by MESs or central controllers needs to meet high freshness requirements. To characterize the information freshness, a new performance metric, i.e., age of information (AoI), has been proposed in [3], which is defined as the time elapsed since the generation time of the last received update. Since the advent of the concept of AoI, it has attracted lots of interest in wireless communication fields, where some studied the AoI in queueing networks, see e.g., [4] and [5], some applied the AoI to sampling and remote estimation networks, e.g., [6] and [7], some designed the AoI-orientated unnamed aerial vehicle (UAV)-assisted networks, see e.g., [8], [9] and [10], and some others discussed the AoI in caching systems, e.g., [11] and [12]. Since most IoTs are multi-user/sensor systems and different scheduling may yield different AoI performances due to their different channel utilization pattern, designing efficient scheduling policies to improve AoI performance in multi-user/sensor wireless networks is of great importance for IoT and AoI-based scheduling as such has recently been attracting increasing attention [13]–[17].

On the other hand, in many IoT systems, a large number of wireless sensors are deployed to periodically sense and detect states [18]. Due to their small sizes and relatively low manufacturing costs, wireless sensors are usually equipped with limited-capacity batteries. As a result, frequent manual battery replacement/charging is required to maintain the regular operations of the energy-constrained IoT systems, which may be inconvenient and also cause high operational costs, especially in large-scale IoT systems operating in harsh environments. Specifically, for example, SNs in the oil and gas industry, which are often deployed offshore or in the desert; SNs in the agricultural sector, which are often deployed in farmland, far from urban and electrical infrastructure; SNs in field environmental monitoring, which are usually deployed in the wilderness or forest. These practical examples show that frequent manual battery replacement or recharging is not advisable. To handle this issue, energy harvesting (EH) techniques have been considered as effective alternative solutions [19], [20]. Compared with harvesting energy from traditional natural sources such as solar and wind, harvesting energy from radio frequency (RF) signals is more controllable and environment independent [21], [22]. Moreover, RF-based EH has many practical applications, such as smart homes, medical devices, and consumer electronics, etc. Therefore, wireless powered communication network (WPCN) technology with RF-based EH has been regarded as an attractive and promising solution to provide a stable energy supply and extend the life of low-power sensors in various IoT systems.

B. Related Work

In order to design self-sustainable WPCNs for IoT applications, some works have discussed the AoI in WPCNs, see e.g., [23]–[28], thus far. In [23], the average AoI of the WPCN with a first-come-first-served (FCFS) sensor node was investigated in the low SNR region. In [24], the optimal online status update policies were proposed for a wireless power transfer (WPT)-enabled sensor with various battery sizes. In [25], the average AoI for a sensor network with WPT capabilities was minimized. In [26], the uplink average AoI of a unilaterally wireless powered two-way data exchanging network was analyzed and minimized. In [27], the average urgency-aware AoI for an RF-EH enabled network was investigated, where the urgency-aware AoI was characterized by an exponential increase in dissatisfaction with data staleness over time. In [28], the average α-β AoI penalty of WPCN was presented, where a uniform AoI expression was designed and then applied to evaluate the performance of WPCNs.

In all aforementioned existing works [23]–[28], only the single sensor-destination pair WPCN models were investigated. Since in most practical IoT scenarios, multiple sensors have to be powered and scheduled to sense and deliver their collected status update information, some recent works, see e.g., [29]–[32], began to study the AoI-aware user/sensor scheduling in multi-user/sensor WPCNs. In [29], the resource scheduling was designed to maximize the long-term system utility including fairness, throughput, and age-related data processing penalties of wireless powered mobile-edge computing (MEC). In [30], the long-term weighted sum-AoI of the system was minimized, where the WPT and transmission scheduling were jointly optimized. In [31], the long-term average weighted sum of AoI in a multi-user WPCN was minimized, where a deep reinforcement learning (DRL) algorithm was proposed to schedule the users. In [32], an online user scheduling policy was developed to minimize the long-term average AoI, where EH users were scheduled to transmit generated status updates to their intended receivers.

C. Motivations and Contributions

Nevertheless, only the Rayleigh fading channel was discussed for AoI-based multi-sensor WPCNs in the literature, where moreover, the energy and information were delivered separately in different time slots in existing works [29]–[32]. However, in some wireless-powered IoT applications, such as smart agriculture scenarios, line-of-sight (LOS) wireless links may exist. In such cases, the Rayleigh fading model will not be valid any longer due to the existence of LOS links. Significantly, the Nakagami-m fading model reflects the various realistic LOS and non-line-of-sight (NLOS) fading channels experienced in practice. To fill the gap, this paper focuses on designing an AoI-based online scheduling policy for the multi-sensor WPCN by considering the Nakagami-m fading channel model.

We consider a typical multi-sensor WPCN, where a WPS can wirelessly power multiple sensor nodes (SNs), and the SNs are scheduled to sample and transmit real-time status information by using their harvested energy. Different from previous works, in this paper, the WPT and data transmission are operated over different frequency bands to realize uninterrupted WPT and RF-based EHs. That is, in our work, the SNs are allowed to harvest and accumulate RF energy continuously to provide a better communication service.

Our goal is to minimize the long-term Expected Weighted Sum AoI (EWSAoI) of the multi-sensor WPCNs by finding an efficient online scheduling policy. The main contributions of this paper are summarized as follows.

- For the considered multi-sensor WPCN, the AoI evolution expression of the data packet collected from each SN over Nakagami-m fading channels is analyzed. Particularly, since the successful data transmission probability implicitly affects the EWSAoI of the WPCN, we first discuss it and derive a closed-form expression for it by using the additivity of the Gamma distribution and the integral operation. Then, the AoI evolution of the system is modeled by utilizing the obtained expression of the successful data transmission probability.
- In order to find an efficient online scheduling policy to minimize the EWSAoI of the system, we formulate a discrete-time scheduling problem to determine which SN should be scheduled at the beginning of a time slot, where the interference among the SNs' information transmission is taken into account.
- As the problem is a typical integer non-linear programming problem with the non-explicit expression of the optimization variable and cannot be solved by using conventional optimization methods, we decompose it into a series of deterministic per-time-slot problems with independent time slots. Then, we propose a Lyapunov optimization-based low-complexity online scheduling policy, i.e., Max-Weight policy, to solve it, which schedules a SN based on the current state of SNs (i.e., the AoI and the harvested energy) in each time slot.
- Simulations demonstrate our presented theoretical results and show that our proposed scheduling policy is able to achieve the lower EWSAoI than some benchmark

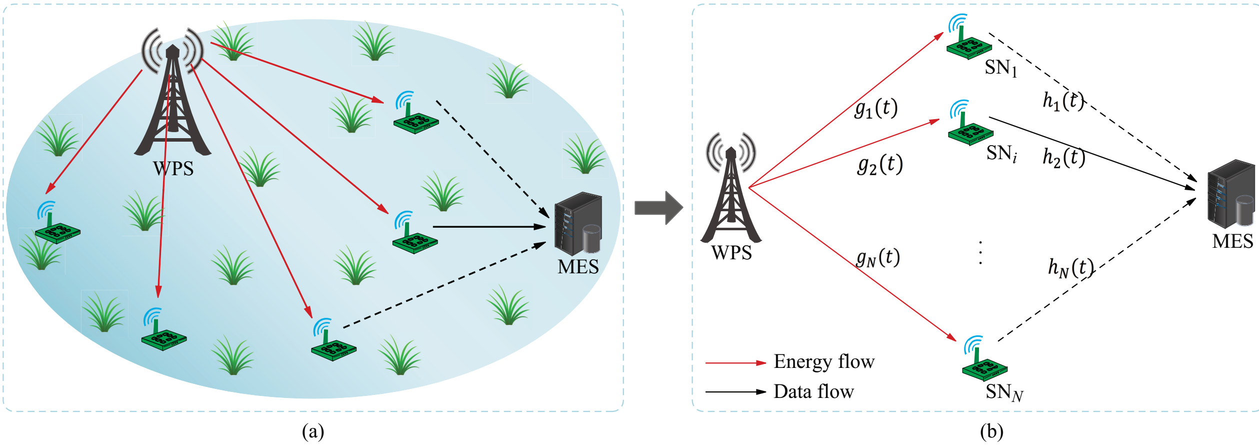

Fig. 1. (a) Typical IoT application scenarios, and (b) System model.

policies, such as greedy policy and random round-robin policy. Especially, when the scale of the system is relatively small, the gain of the proposed policy compared with the greedy policy is considerable. Moreover, the EWSAoI decreases with the increment of transmit power of the WPS, and the value of the EWSAoI decreases slowly and finally tends to be zero. Besides, it is also seen that when the transmit power is relatively small, the larger the number of SNs, the smaller the EWSAoI. Conversely, when the transmit power of the WPS is relatively large, the larger the number of SNs, and the larger the EWSAoI.

The rest of the paper is organized as follows. In Section II, the system model and channel model are presented, and AoI model is described. In Section III, the successful data transmission probability is analyzed and derived. In Section IV, the scheduling problem in the multi-sensor WPSN is formulated, and a low-complexity sub-optimal online scheduling policy is proposed. Some numerical results and analysis are presented in Section V. Finally, Section VI concludes the paper.

II. System Model

A. Network Model

We consider an outdoor intelligent environmental monitoring system consisting of a WPS, a MES, and N SNs indexed by $\mathcal{N} = \{1, 2, \cdots, N\}$, as illustrated in Fig. 1. The MES collects status updates (in data packets) from N SNs via wireless links, where the SNs sample the real-time status information of different physical processes, such as ambient temperature and humidity, and soil acidity. Since the SNs are energy limited, the SNs are powered by the WPS with WPT technology. Specifically, the WPS first broadcasts RF signals to charge the SNs and then the SNs transmit the sampled status information to the MES for computing. It is assumed that the WPS, the SNs, and the MES are all equipped with single antenna due to their small sizes. Since the amount of harvested energy over the wireless link cannot be very large, each SN is equipped with a rechargeable capacity battery to accumulate the harvested energy [33]. We assume that information transmission and energy transfer are operating over orthogonal frequency bands. Thus, the SN is able to harvest and accumulate energy while transmitting the current data packet.

The system is operated in a discrete-time manner, where the time is equally slotted, with $t \in \{1, 2, \cdots, T\}$ denoting the slot index and T_s being the length of each time slot. To avoid inter-sensor interference, at most one SN is allowed to be scheduled to transmit data in each time slot. If a SN is not scheduled in a time slot, it will only harvest energy, and not sample and not transmit data in the slot in order to save energy. It is assumed that each SN has a data buffer with one packet-length buffer size. At the beginning of time slot t, the SN who is scheduled will sample a new data packet and replace the old undelivered one stored in its data buffer.[1]

Let $a_i(t) \in \{0, 1\}$ denote the scheduling indicator of the system at the beginning of time slot t, where $i \in \{1, 2, \cdots, N\}$. If $a_i(t) = 1$, SN i is scheduled and transmits its sampled data packet in time slot t. Otherwise, if $a_i(t) = 0$, SN i is not scheduled and does not sample and transmit data packet. As at most one SN is scheduled in each time slot, it satisfies that

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

B. Channel Model

To be general, we consider both the large-scale path loss and the small-scale fading effects. Let d_{wi} and d_{im} be the distance between the WPS and SN i and between SN i and the MES. The log-distance path loss model is adopted, so the large-scale channel gain between WPS and SN i and between SN i and the MES can be expressed as $\zeta d_{wi}^{-\kappa}$ and $\zeta d_{im}^{-\kappa}$, respectively, where ζ is a constant and κ is the path loss factor.

[1]Since SNs can be passive sensors, the energy consumed by them to generate data packets is much less than that for packet transmission [34] and ignored here with the similarly treatment as in [25] and [26]. Moreover, since the sensed and generated data packets are usually short, it can be assumed that generating data packet also consumes a little bit of time, so ignored as in [25], [26]. Therefore, this paper ignores the time and energy costs of generating data packets at the SNs, which may be taken into account in the future.

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Let $g_i(t)$ and $h_i(t)$ denote the small-scale channel coefficients of the links from the WPS to SN i and from SN i to the MES in time slot t, respectively. Block fading channel model is employed and the interval of T_s is less than the channel coherence time, so channel coefficients are regarded to be static within each time slot but they may change from one slot to the next randomly following independent Nakagami-m distribution. As a result, the fading channel power gains $|g_i|^2$ and $|h_i|^2$ follow the Gamma distribution with means power u_i and v_i, respectively. Thus, the probability density function (PDF) of $|g_i|^2$ and $|h_i|^2$ can be respectively expressed by [35]

$$f_{|g_i|^2}(x) = \frac{\lambda_i^{m_i}}{\Gamma(m_i)} x^{m_i-1} e^{-\lambda_i x}, \tag{2}$$

and

$$f_{|h_i|^2}(x) = \frac{\beta_i^{n_i}}{\Gamma(n_i)} x^{n_i-1} e^{-\beta_i x}, \tag{3}$$

with $\lambda_i = m_i/u_i$ and $\beta_i = n_i/v_i$ being the ratio parameter, and m_i and n_i representing the Nakagami-m fading factors. Assuming that both m_i and n_i are integers, the cumulative distribution function (CDF) of $|g_i|^2$ and $|h_i|^2$ are expressed as

$$F_{|g_i|^2}(x) = 1 - e^{-\lambda_i x} \sum_{k=0}^{m_i-1} \frac{(\lambda_i x)^k}{k!}, \tag{4}$$

and

$$F_{|h_i|^2}(x) = 1 - e^{-\beta_i x} \sum_{k=0}^{n_i-1} \frac{(\beta_i x)^k}{k!}, \tag{5}$$

respectively.

C. Energy Harvesting Model

The WPS keeps broadcasting RF signals to charge the SNs with a fixed transmit power P_w over the downlink energy transfer channel. The linear EH model is employed[2], so the amount of energy harvested by SN i from the WPS within time slot t is given by

$$e_i(t) = \eta P_w |g_i(t)|^2 \zeta d_{wi}^{-\kappa} T_s, \tag{6}$$

where $\eta \in (0, 1)$ is the energy conversion efficiency.

To improve the successful data transmission probability, SN i uses all accumulated energy in its battery to transmit the packet if it is scheduled at time slot t.[3] Let $E_i(t)$ denote the available energy of SN i at the beginning of time slot t. Suppose K time slots has elapsed since SN i was last scheduled and transmitted a data packet, $E_i(t)$ can be expressed by

$$\begin{aligned} E_i(t) = E_i^{(K)}(t) &= \sum_{n=1}^{K} e_i(n) \\ &= \sum_{n=1}^{K} \eta P_w |g_i(n)|^2 \zeta d_{wi}^{-\kappa} T_s \\ &= \xi_i \sum_{n=1}^{K} |g_i(n)|^2, \end{aligned} \tag{7}$$

where $\xi_i = \eta P_w \zeta d_{wi}^{-\kappa} T_s$.

Initially, SNs have no harvested energy, so at the beginning of the 1st time slot, one have that

$$E_i(1) = 0, \quad \forall i \in \{1, 2, \cdots, N\}.$$

D. The Long-Term Expected Weighted Sum AoI

AoI, defined as the time elapsed since SN generates the last received data packet, is employed to measure the timeliness of the sampled data. Thus, the AoI of the data collected by SN i at the t-th time slot is given by

$$\Delta_i(t) = (t - U_i(t)) T_s, \tag{8}$$

where $U_i(t)$ is the time slot index denoting the generation time of SN i's latest data packet received by the MES.

Let $b_i(t)$ denote the binary variable that indicates whether a packet from SN i has been successfully delivered to the MES in time slot t. Specifically, $b_i(t) = 1$ indicates that the data packet from SN i has been successfully delivered to the MES in time slot t, and $b_i(t) = 0$ indicates that the data packet from SN i was not delivered successfully in time slot t. Let D_i denote the size of the data packet sampled by SN i and $c_i(t)$ denote the amount of data that can be delivered within time slot t. Since only when $c_i(t) \geq D_i$, the MES can successfully receive the data packet from SN i, the probability that the data packet of SN i at time slot t is successfully received can be expressed by

$$p_i(t) = \Pr\{c_i(t) \geq D_i\}. \tag{9}$$

As the data packet from SN i can be successfully received by the MES only when $c_i(t) \geq D_i$, the probability of $b_i(t) = 1$ is equal to the probability of $c_i(t) \geq D_i$. Thereby, one have that

$$\begin{cases} \Pr\{b_i(t) = 1\} = p_i(t), & \text{if } a_i(t) = 1; \\ \Pr\{b_i(t) = 0\} = 1 - p_i(t), & \text{if } a_i(t) = 1; \\ \Pr\{b_i(t) = 0\} = 1, & \text{if } a_i(t) = 0. \end{cases} \tag{10}$$

Particularly, if the MES successfully receives a new data packet of SN i during time slot t, the AoI of the data packet collected from SN i is reset to T_s, i.e., $\Delta_i(t+1) = T_s$. If the MES does not receive a new data packet of SN i during time slot t, the AoI of the data packet collected from SN i increases T_s, i.e., $\Delta_i(t+1) = \Delta_i(t) + T_s$. Without loss of generality, in this paper, we assume that the initial AoI of all SNs is

[2] Although the non-linear EH model is more general and actual, it is also more challenging to analyze. As a result, many recent works have still adopted the linear EH model to study the basic performance of networks. Moreover, it is noted that the linear EH model is also meaningful in most cases. Especially, when the input energy is relatively small or the distance between the WPS and the sensor is not very short, the EH circuit may still work in the linear region [21], [36]. Thus, similar to many existing works, see, e.g., [25] and [26], the linear EH model is adopted in our work to analyze the performance of the multi-sensor WPCN system.

[3] For the considered system, on the one hand, due to the small transmit power and the long wireless charging distance, the amount of energy harvested by each SN in each time slot is very small. On the other hand, in order to achieve the goal of minimizing the average AoI, the energy harvested by SNs over a period of time will be consumed, and it is difficult for the battery to be fully charged. Therefore, in our work, SN i uses all accumulated energy in its battery to transmit the packet if it is scheduled at time slot t. Moreover, the available energy at each SN can be intelligently harnessed using DRL methods, which we will take into account in future work.

equal to T_s, i.e., $\Delta_i(1) = T_s, \forall i$. With such an observation, the evolution of $\Delta_i(t)$ is described by

$$\Delta_i(t+1) = \begin{cases} T_s, & \text{if } b_i(t) = 1; \\ \Delta_i(t) + T_s, & \text{otherwise.} \end{cases} \tag{11}$$

Then the average AoI of SN i at the MES over T time slots can be captured by $\mathbb{E}\big[\sum_{t=1}^{T} \Delta_i(t)\big]/T$, where $\mathbb{E}(\cdot)$ is the expectation operation. Thus, the long-term EWSAoI of the entire network is given by

$$\bar{\Delta} = \lim_{T\to\infty} \frac{1}{NT} \mathbb{E}\Big[\sum_{t=1}^{T}\sum_{i=1}^{N} \alpha_i \Delta_i(t)\Big], \tag{12}$$

where $\alpha_i > 0$ is the predefined weight of SN i measuring the importance of SN i's status update.

III. Successful Data Transmission Probability

Since the evolution of AoI depends the probability that the data packet of SN i is successfully received by MES at time slot t, we first derive an explicit expression of the successful data transmission probability in this section.

Let $P_i(t)$ represent the available transmit power of SN i at time slot t. Following (7), one have that

$$P_i(t) = \frac{E_i^{(K)}(t)}{T_s} = \frac{\xi_i \sum_{n=1}^{K} |g_i(n)|^2}{T_s}. \tag{13}$$

Thus, if SN i is scheduled to perform information transmission in time slot t, according to Shannons formula, the amount of data that can be delivered within time slot t is given by

$$c_i(t) = T_s W \log_2\Big(1 + \frac{P_i(t)|h_i(t)|^2\zeta}{N_0 d_{im}^{\kappa}}\Big), \tag{14}$$

where W denotes the communication bandwidth and N_0 represents the noise power at the MES.

Proposition 1. *In the considered multi-sensor WPCN system, assuming SN i has uninterruptedly harvested energy over K slots before time slot t over a Nakagami-m fading channel, the successful data transmission probability of SN i at time slot t is*

$$p_i(t) = \frac{2}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i\beta_i F_i)^{\frac{n_i+k}{2}}}{k!} K_{n_i-k}(2\sqrt{\lambda_i\beta_i F_i}), \tag{15}$$

where $F_i = \frac{R_i T_s}{\xi_i}$ with $R_i = (2^{\frac{D_i}{T_s W}} - 1) N_0 d_{im}^{\kappa}/\zeta$.

Proof. According to (9) and (14), one have that

$$\begin{aligned} p_i(t) =& \Pr\Big\{T_s W \log_2\Big(1 + \frac{P_i(t)|h_i(t)|^2\zeta}{N_0 d_{im}^{\kappa}}\Big) \geq D_i\Big\} \\ =& \Pr\{P_i(t)|h_i(t)|^2 \geq R_i\}, \end{aligned} \tag{16}$$

where $R_i = (2^{\frac{D_i}{T_s W}} - 1) N_0 d_{im}^{\kappa}/\zeta$. By applying the representation of $P_i(t)$ in (13), (16) can be re-expressed by

$$\begin{aligned} p_i(t) &= \Pr\Bigg\{\frac{\xi_i\Big(\sum_{n=1}^{K}|g_i(n)|^2\Big)|h_i(t)|^2}{T_s} \geq R_i\Bigg\} \\ &= \Pr\Big\{\Big(\sum_{n=1}^{K}|g_i(n)|^2\Big)|h_i(t)|^2 \geq F_i\Big\}, \end{aligned} \tag{17}$$

where $F_i = \frac{R_i T_s}{\xi_i}$.

For convenience, we define $X_i = \sum_{n=1}^{K}|g_i(n)|^2$ and $Y_i = |h_i(t)|^2$, and $Z_i = X_i Y_i$. According to the additivity of the gamma distribution, the PDF and CDF of X_i can be expressed as [35]

$$f_{X_i}(x) = \frac{\lambda_i^{m_i K}}{\Gamma(m_i K)} x^{m_i K-1} e^{-\lambda_i x}, \tag{18}$$

and

$$F_{X_i}(x) = 1 - e^{-\lambda_i x} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i x)^k}{k!}. \tag{19}$$

Thus, the CDF of Z_i can be expressed as

$$F_{Z_i}(z) = \int_0^\infty F_{X_i}\Big(\frac{z}{y}\Big) f_{Y_i}(y) dy. \tag{20}$$

Then, we obtain Eq. (21), which can be found at the top of the next page.

Using the following equation,

$$\int_0^\infty x^n e^{-ax} dx = \frac{\Gamma(n+1)}{a^{n+1}}, n > -1, a > 0, \tag{22}$$

we can show $I_1 = 1$.

Moreover, by utilizing the fact [[37], 3.471.9], I_2 is further given by

$$\begin{aligned} I_2 &= \int_0^\infty \Bigg[e^{-\lambda_i \frac{z}{y}} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i \frac{z}{y})^k}{k!}\Bigg] \Bigg[\frac{\beta_i^{n_i}}{\Gamma(n_i)} y^{n_i-1} e^{-\beta_i y}\Bigg] dy \\ &= \frac{\beta_i^{n_i}}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i z)^k}{k!} \int_0^\infty e^{-\lambda_i \frac{z}{y} - \beta_i y} y^{n_i-k-1} dy \\ &= \frac{2\beta_i^{n_i}}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i z)^k}{k!} \Big(\frac{\lambda_i z}{\beta_i}\Big)^{\frac{n_i-k}{2}} K_{n_i-k}\Big(2\sqrt{\lambda_i\beta_i z}\Big) \\ &= \frac{2}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i\beta_i z)^{\frac{n_i+k}{2}}}{k!} K_{n_i-k}(2\sqrt{\lambda_i\beta_i z}), \end{aligned} \tag{23}$$

where K_v is the v-th order modified Bessel function of the second kind. According to (21), (22) and (23), the CDF of Z_i can be written as

$$F_{Z_i}(z) = 1 - \frac{2}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i\beta_i z)^{\frac{n_i+k}{2}}}{k!} K_{n_i-k}(2\sqrt{\lambda_i\beta_i z}). \tag{24}$$

Therefore, we obtain

$$\begin{aligned} p_i(t) =& \Pr\Big\{Z_i \geq F_i\Big\} = 1 - F_{Z_i}(F_i) \\ =& \frac{2}{\Gamma(n_i)} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i\beta_i F_i)^{\frac{n_i+k}{2}}}{k!} K_{n_i-k}(2\sqrt{\lambda_i\beta_i F_i}). \end{aligned} \tag{25}$$

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$$
\begin{aligned}
F_{Z_i}(z) &= \int_0^\infty \left[1 - e^{-\lambda_i \frac{z}{y}} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i \frac{z}{y})^k}{k!}\right] \left[\frac{\beta_i^{n_i}}{\Gamma(n_i)} y^{n_i-1} e^{-\beta_i y}\right] dy \\
&= \underbrace{\int_0^\infty \left[\frac{\beta_i^{n_i}}{\Gamma(n_i)} y^{n_i-1} e^{-\beta_i y}\right] dy}_{I_1} - \underbrace{\int_0^\infty \left[e^{-\lambda_i \frac{z}{y}} \sum_{k=0}^{m_i K-1} \frac{(\lambda_i \frac{z}{y})^k}{k!}\right] \left[\frac{\beta_i^{n_i}}{\Gamma(n_i)} y^{n_i-1} e^{-\beta_i y}\right] dy}_{I_2} .
\end{aligned} \tag{21}
$$

IV. Problem Formulation and Solution

A. Problem Formulation

The goal is to develop a low-complexity online scheduling policy such that the long-term EWSAoI of the system could be minimized. We denote the scheduling policy $\boldsymbol{\pi}$ as a sequence of actions $\boldsymbol{\pi} = (\boldsymbol{a}^\pi(1), \boldsymbol{a}^\pi(2), \cdots, \boldsymbol{a}^\pi(t), \cdots) \in \Pi$, where $\boldsymbol{a}^\pi(t) = (a_1^\pi(t), a_2^\pi(t), \cdots, a_N^\pi(t))$ and Π denotes the set of all feasible scheduling policies, with $a_i^\pi(t)$ being the scheduling indicator of the system on SN i at the beginning of time slot t with policy $\boldsymbol{\pi}$. Specifically, $a_i^\pi(t) = 1$ indicates that SN i is scheduled and $a_i^\pi(t) = 0$ indicates that SN i is not scheduled. Then, the scheduling problem formulation can be mathematically expressed by

$$
\mathbf{P_1}: \min_{\pi \in \Pi} \lim_{T \to \infty} \frac{1}{NT} \mathbb{E}\left[\sum_{t=1}^{T} \sum_{i=1}^{N} \alpha_i \Delta_i^\pi(t)\right] \tag{26a}
$$

$$
\text{s.t. } a_i^\pi(t) \in \{0,1\},\ i \in \{1,2,\cdots,N\},\ \forall t, \tag{26b}
$$

$$
\sum\nolimits_{i=1}^{N} a_i^\pi(t) \le 1,\ \forall t, \tag{26c}
$$

where $\Delta_i^\pi(t)$ is AoI of SN i at the MES in time slot t with policy $\boldsymbol{\pi}$. The constraint (26c) follows the fact that at most one SN is scheduled in each time slot to transmit data packet. Since $E_i(1) = 0$ for $i \in \{1,2,\cdots,N\}$, no SN is scheduled to transmit data packet in the first time slot. That is, $\boldsymbol{a}^\pi(1) = 0$.

B. Problem Transformation

Problem $\mathbf{P_1}$ is a typical integer non-linear programming (INLP) problem with the non-explicit expression of the objective function, so it is difficult to solve it directly. As is known, Lyapunov method is able to make an online decision with autonomous learning, we propose a low-complexity suboptimal online scheduling policy based on Lyapunov function, which is also referred to as the Max-Weight Policy in the sequel.

The Lyapunov optimization method does not require any predictive information of random variables in the decision-making process and is able to gradually optimize the decision at each time period according to the changes of the external environment [38], [39]. In addition, the Lyapunov optimization algorithm has low complexity, which can effectively ensure the rapidity of AoI-based task scheduling decisions. Accordingly, we decompose the original scheduling problem into a series of scheduling problems to minimize the one-slot conditional Lyapunov Drift in each time slot.

Following the goal of minimizing EWSAoI, we first define a quadratic Lyapunov function in terms of the weighted AoI, i.e.,

$$
L(\boldsymbol{\Delta}(t)) = \frac{1}{2} \sum_{i=1}^{N} \alpha_i \Delta_i^2(t), \tag{27}
$$

where $\boldsymbol{\Delta}(t)$ is a state vector at time slot t with $\boldsymbol{\Delta}(t) = [\Delta_1(t), \Delta_2(t), \cdots, \Delta_N(t)]$.

Then, the one-slot conditional Lyapunov Drift is defined as

$$
\delta(\boldsymbol{\Delta}(t)) = \mathbb{E}[L(\boldsymbol{\Delta}(t+1)) - L(\boldsymbol{\Delta}(t)) | \boldsymbol{\Delta}(t)], \tag{28}
$$

where $\delta(\boldsymbol{\Delta}(t))$ actually represents the expected growth of $L(\boldsymbol{\Delta}(t))$ from time slot t to the next slot $(t+1)$.

Therefore, the scheduling decisions for time slot t can be obtained by solving the following Problem $\mathbf{P_2}$,

$$
\mathbf{P_2}: \quad \min_{\boldsymbol{a}^\pi(t)} \ \delta(\boldsymbol{\Delta}(t)) \tag{29a}
$$

$$
\text{s.t. } a_i^\pi(t) \in \{0,1\}, \tag{29b}
$$

$$
\sum\nolimits_{i=1}^{N} a_i^\pi(t) \le 1. \tag{29c}
$$

C. Online Scheduling Policy

According to (11), the dynamic evolution of the AoI of SN i can be given by

$$
\Delta_i(t+1) = b_i^\pi(t) \cdot T_s + \big(1 - b_i^\pi(t)\big) \cdot \big(\Delta_i(t) + T_s\big), \tag{30}
$$

where $b_i^\pi(t) \in \{0,1\}$ indicates whether a data packet from SN i with policy $\boldsymbol{\pi}$ has been successfully delivered to the MES in time slot t.

Substituting (30) into (27) and then substituting the updated (27) into (28), the expression of the one-slot conditional Lyapunov Drift can be given by

$$
\begin{aligned}
\delta(\boldsymbol{\Delta}(t)) = & \underbrace{-\frac{1}{2} \sum_{i=1}^{N} \mathbb{E}\Big[b_i^\pi(t) | \boldsymbol{\Delta}(t)\Big] \alpha_i \Delta_i(t) \big(\Delta_i(t) + 2T_s\big)}_{\text{term 1}} \\
& + \underbrace{\sum_{i=1}^{N} \alpha_i \Delta_i(t) T_s + \frac{1}{2} \sum_{i=1}^{N} \alpha_i T_s^2}_{\text{term 2}} .
\end{aligned} \tag{31}
$$

One can see that policy π is only related to the first term of (31), i.e., term 1. In order to efficiently solve Problem $\mathbf{P_2}$ that aims to minimize $\delta(\boldsymbol{\Delta}(t))$, the scheduling policy $\boldsymbol{\pi}$ should maximize

$$
\sum_{i=1}^{N} \mathbb{E}\Big[b_i^\pi(t) | \boldsymbol{\Delta}(t)\Big] \underbrace{\alpha_i \Delta_i(t) \big(\Delta_i(t) + 2T_s\big)}_{w_i(t)}, \forall t.
$$

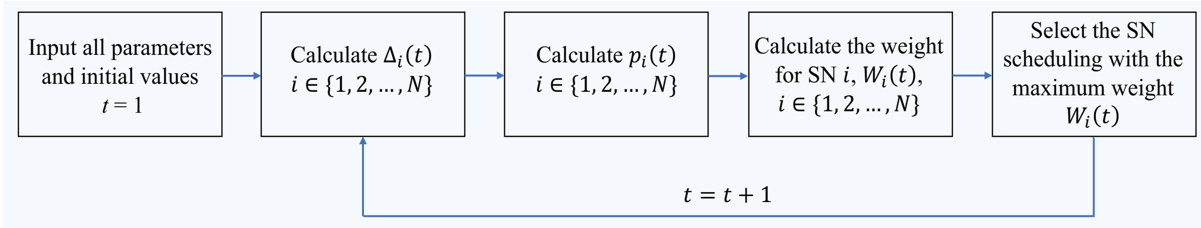

Fig. 2. The corresponding workflow for all process chains.

That is, for SN i, if it is with the largest value of $w_i(t)$ among all SNs, its corresponding $b_i(t)$ approaches to 1. Moreover, as $b_i(t)$ depends on $\mathbf{\Delta}(t)$ through $a_i(t)$, one have that

$$\mathbb{E}[b_i(t)|\mathbf{\Delta}(t)] = \mathbb{E}[b_i(t)|a_i(t)].$$

According to (10), we have that

$$\mathbb{E}[b_i(t)|a_i(t)] = p_i(t)a_i(t). \tag{32}$$

Based on the analysis above, to minimize $\delta(\mathbf{\Delta}(t))$, the SN with the largest value of $W_i(t) = p_i(t)w(t)$ should be scheduled. Thus, the optimal solution to Problem $\mathbf{P_2}$ can be expressed by,

$$a_i^\pi(t) = \begin{cases} 1, & \text{if } i = \arg\max\limits_{i\in\mathcal{N}} W_i(t); \\ 0, & \text{otherwise.} \end{cases} \tag{33}$$

That is, the SN with the largest $W_i(t)$ will be scheduled. So, our presented scheduling policy is called Max-Weight Policy. Particularly, if there are two or more SNs with the same largest $W_i(t)$ in time slot t, one can be arbitrarily selected. For clarity, the details of the presented Max-Weight Policy is summarized in Algorithm 1.

Algorithm 1 The Presented Max-Weight Scheduling Policy.

Input: The distances d_{wi} and d_{im}, fading channel parameters, the number of time slots elapsed since SN i last transmitted data packet in time slot t, $\forall i \in \{1,2,\cdots,N\}$.

1: Observe the AoI of SN i at the MES in time slot t.
2: Calculate the probability of successful transmission for SN i, i.e., $p_i(t)$;
3: Calculate the weight for SN i. The expression of weight is given by

$$W_i(t) = p_i(t)\alpha_i\Delta_i(t)\big(\Delta_i(t) + 2T_s\big);$$

4: Select the SN with the maximum weight $W_{i^*}(t)$, $i^* = \arg\max\limits_{i\in\mathcal{N}} W_i(t)$. Therefore, we get

$$a_i^\pi(t) = \begin{cases} 1, & \text{if } i = i^*; \\ 0, & \text{otherwise.} \end{cases}$$

Output: The optimal $\boldsymbol{a}^\pi(t)$.

The corresponding workflow for all process chains is shown in Fig. 2.

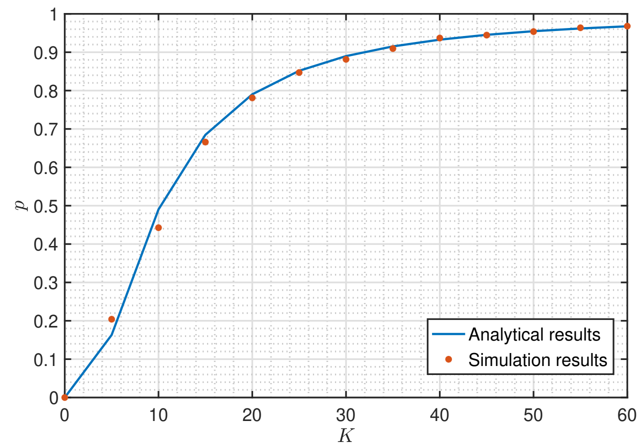

Fig. 3. The successful data transmission probability p versus the number of slot time K.

D. Complexity Analysis

In time slot t, the weight of each SN needs to be calculated, so the time complexity of each slot of Max-Weight Policy is $O(N)$. As problem $\mathbf{P_2}$ has to be solved for each time slot, the complexity of the Max-weight policy over time T is about $T \cdot O(N)$.

V. Simulation Results

In this section, simulation results are provided to validate the proposed scheduling policy and demonstrate the AoI performance of the considered multi-sensor system under the proposed scheduling policy.

According to [14], [25], [30], the simulation parameters are set as fellow. The transmit power of the WPS is $P_w = 0.1$ W, and the energy conversion efficiency is $\eta = 0.7$. The system bandwidth is $W = 0.1$ MHz, and the noise power at the receiver is set as $N_0 = -60$ dBm. The time slot length is set as $T_s = 1$ s, and the size of data packet is $D = 3000$ bits. The distances between the WPS and SN i and between SN i and the MES are set as $d_{wi} = d_{im} \in \{12, 16\}$ meters. The large-scale path loss factor is set as $\kappa = 2$, and constant ζ is set as 10^{-3}. For the Nakagami-m small-scale fading channel, m_i and n_i are set to be 2 for $\forall i$, and the ratio parameter λ_1 and β_i are set to be 1 for $\forall i$. Generally, to highlight the different importance of each SN, the weight of SN i is $\alpha_i = (N+1-i)/N$, $\forall i \in \{1,2,\cdots,N\}$.

First, to verify the correctness of the theoretical analysis results of successful data transmission probability, Fig. 3 is

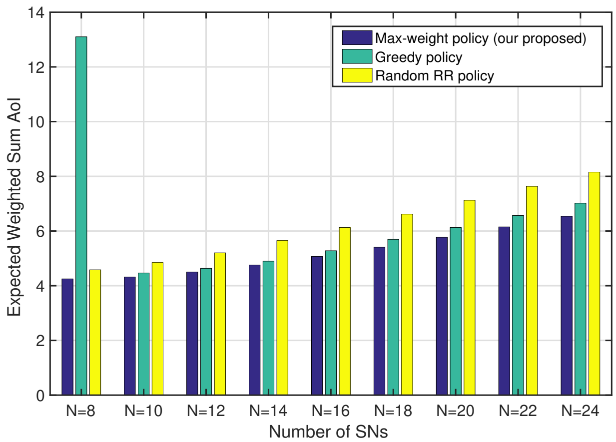

Fig. 4. The EWSAoI versus the number of SNs under three different policies.

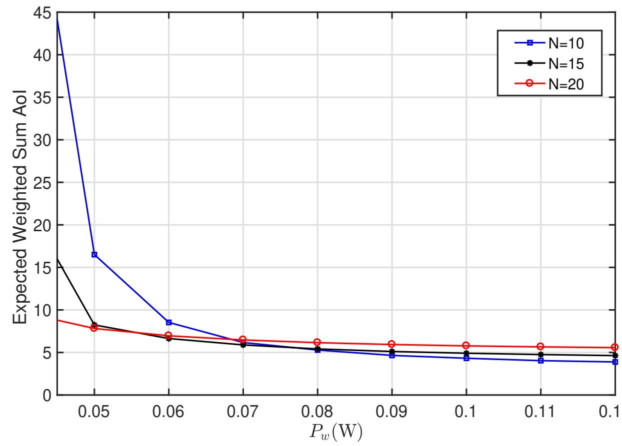

Fig. 6. The EWSAoI versus the transmit power P_w under different N.

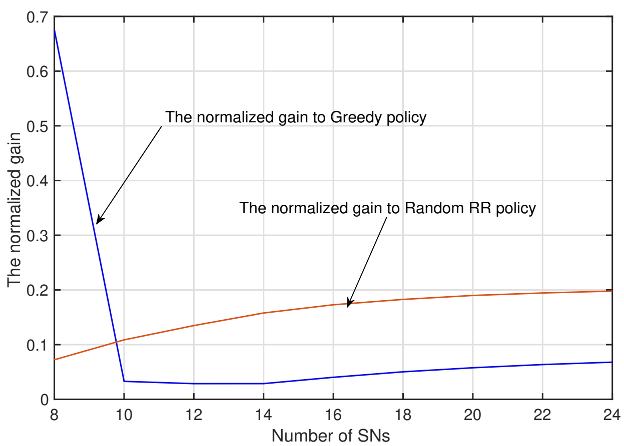

Fig. 5. The normalized gain of the EWSAoI achieved by the Max-weight policy to the EWSAoI achieved by the benchmark policies.

shown. It can be seen that the analytical results and the simulation results match well, which validates our obtained theoretical results. The simulation results are obtained by the Monte Carlo simulation up to $5 * 10^5$ realizations. The successful data transmission probability p increases with the increase of K, while the increment decreases gradually. The reason is that with the increase of K, the energy harvested by the sensor increases, so the transmitted power increases, but according to Shannon's theory, the transmission rate will not continue to increase.

For comparison, the *greedy policy* and *random round-robin (RR) policy* are simulated as the benchmark policies. In the greedy policy, the SN with the highest expected AoI is scheduled in each time slot. In the random round-robin policy, N time slots are a frame, and the channel in each frame is allocated to each sensor for scheduling in a random cycle.

Fig. 4 shows the EWSAoI versus the number of SNs under three scheduling policies. It is seen that compared with the random RR policy, the EWSAoI achieved by our proposed policy and the greedy policy are much smaller when N is greater than 10. When the number of SNs is relatively small, the gain of the proposed policy compared with the greedy policy is more obvious. For the greedy policy, the SN with the highest EWSAoI is scheduled in each time slot. This policy may have the same SN continuously scheduled when the number of SNs is relatively small. However, the scale of the WPCNs are often not too large, so our proposed scheduling policy is more efficient. It can also be seen that as the number of SNs increases, the EWSAoI also increases (except under the greedy policy). The reason may be that as the number of SNs increases, the effect on EWSAoI of increasing the time interval at which each SN is scheduled is greater than the effect on EWSAoI of increasing transmit power.

In order to clearly observe the benefits brought by our proposed Max-weight policy, Fig. 5 plots the normalized gain of the EWSAoI achieved by the Max-weight policy to the EWSAoI achieved by the greedy policy and that by the random RR policy, respectively. The result shows that when $N = 8$, the normalized gain to greedy policy and random RR policy are about 67.6% and 7.2%, respectively.

Fig. 6 describes that the EWSAoI versus the transmit power of the WPS P_w under different numbers of SNs. In the simulations, the EWSAoI is obtained by the proposed Max-wight policy. It is observed that the EWSAoI decreases with the increment of transmit power P_w and then tends to be flat, because higher P_w makes the battery charge faster and thus increases the transmit power of the SN. Furthermore, due to Shannon's capacity theorem, the data transmission rate of the SN cannot increase infinitely, so as P_w increases, the amount of EWSAoI decrease slowly tends to zero. Interestingly, we have also observed that when the transmit power P_w is relatively small, the larger the number of SNs, the smaller the EWSAoI. Conversely, when the transmit power P_w is relatively large, the larger the number of SNs, and the larger the EWSAoI. The reason is that when the transmission power is small, the probability of successful transmission is small. When the number of SNs increases, the time interval for each SN to be scheduled increases, which increases the time for harvesting energy, thereby increasing the probability of successful transmission.

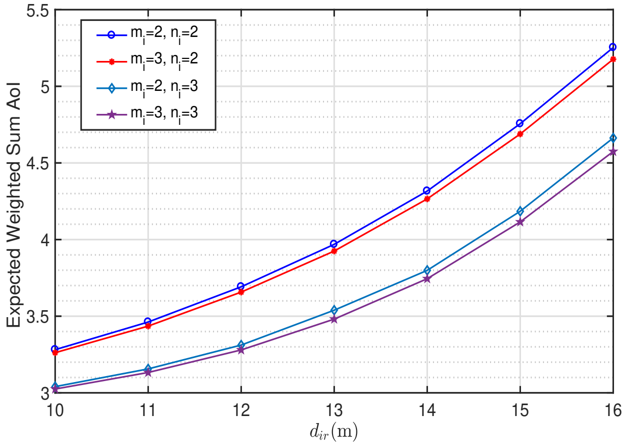

Fig. 7. The EWSAoI versus the distance between SNs and the MES under different channel parameters.

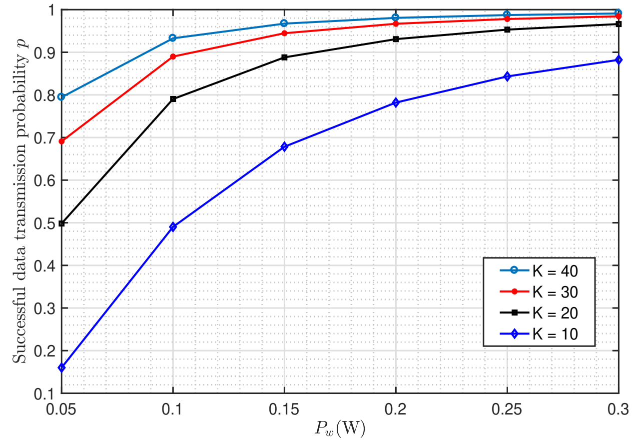

Fig. 9. The successful data transmission probability p versus the transmit power P_w under different K.

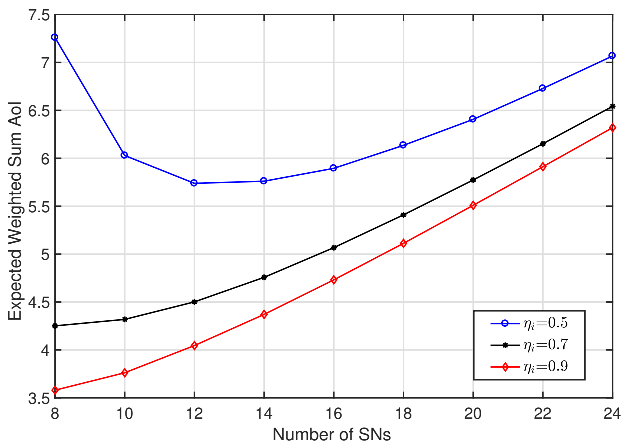

Fig. 8. The EWSAoI versus the number of SNs under different energy conversion efficiency η.

Fig. 7 displays that the EWSAoI versus the distance between the SNs and the MES under different shape parameters of Nakagami-m channels m_i and n_i. In the simulations, the EWSAoI is obtained by the proposed Max-wight policy, and d_{wi} is set as 16 m, $\forall i$. One can see that the EWSAoI increases with the increment of the distance between the SNs and the MES. The reason is that in order to obtain more energy, the longer the distance, the more time is required. It can also be seen that when the transmission channel fading model is close to Rayleigh fading (i.e., m_i and n_i are close to 1), the AoI performance of the system is worst. This is because the probability of successful data transmission decreases, so the EWSAoI increases. It can also be seen that the change of parameter values of the data transmission channel has a greater impact on the EWSAoI.

Fig. 8 shows the EWSAoI versus the number of SNs under different energy transmission efficiency η. It can be seen that the larger η is, the smaller EWSAoI is, because the larger η is, the more energy harvested by SNs, and thus the greater the transmit power. However, in practice, the energy conversion efficiency is generally small, so the value of the energy conversion efficiency should be set reasonably. In particular, it can be seen from the figure that when $\eta = 0.5$, the EWSAoI of the system with 8 SNs is greater than the EWSAoI of the system with 10 SNs, and the EWSAoI of the system with 10 SNs is greater than the EWSAoI of the system with 12 SNs. This is because the energy harvesting interval of the SN is small and the energy conversion efficiency is small, so the harvested energy is small and the data transmission always fails. Therefore, the EWSAoI is relatively large. This observation in Fig. 8 is useful when considering a IoT system design. It indicates that the proposed system analysis approach is a useful tool, especially for the SN number is not too big.

To evaluate the effect of the transmit power on the successful transmission probability. Fig. 9 illustrates the successful data transmission probability p versus the transmit power P_w under different K. It can be observed that as the transmit power P_w increases, the successful transmission probability grows logarithmically. Additionally, the larger K is, the greater the successful transmission probability becomes. This is because the larger K is, the more energy is harvested by SNs.

VI. Conclusion

This paper studied the online scheduling policy for multi-sensor WPCNs to minimize the EWSAoI of the system, in which a WPS charges multiple SNs by WPT, and then SNs are scheduled to transmit their sampled real-time status information to the MES for decision making. For such a system, we first analyzed the successful data transmission probability and derived a closed-form expression for it over Nakagami-m fading channels. Next, to pursue an efficient online scheduling policy that minimizes the long-term EWSAoI of the system, we formulated a discrete-time scheduling problem for scheduling the SNs at the beginning of each time. Then, an efficient online scheduling policy, i.e., Max-Weight policy, was proposed based on Lyapunov optimization theory. Simulations verify our presented theoretical results and show that our proposed policy outperforms other benchmark policies such as greedy policy and random RR policy. Especially, when the scale of the system is relatively small, the gain of the proposed policy compared with the greedy policy is considerable, which indicates that a simple and flexible system design is more attractive in the viewpoint of power supply and sensing data freshness for IoT.

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