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Minimizing Age of Information in Energy Harvesting Wireless Sensor Networks

NAOYA HIROSAWA[1], (Graduate Student Member, IEEE), HIROKI IIMORI[2], (Graduate Student Member, IEEE), KOJI ISHIBASHI[1], (Senior Member, IEEE), AND GIUSEPPE THADEU FREITAS DE ABREU[2], (Senior Member, IEEE)

[1]Advanced Wireless and Communication Research Center, The University of Electro-Communications, Tokyo 182-8585, Japan
[2]Department of Electrical and Computer Engineering, Focus Area Mobility, Jacobs University Bremen, 28759 Bremen, Germany

Corresponding author: Naoya Hirosawa (hirosawa@awcc.uec.ac.jp)

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ABSTRACT We consider the uplink of an energy harvesting (EH) wireless sensor network (WSN) where N single-antenna sensors communicate with a common fusion center (FC) with the aim of cooperatively minimizing the overall average age of information (AoI). Specifically, we propose new resource allocation algorithms to minimize the average AoI in an EH-WSNs employing common multiple-access schemes, in particular time-division multiple access (TDMA) and frequency-division multiple access (FDMA). To this end, we take advantage of the convexity of the derived AoI, enabling an optimal resource block assignment, implemented as a greedy algorithm for TDMA systems and in the form of an alternating direction method of multipliers (ADMM) scheme for FDMA systems. The optimality of the greedy resource allocation scheme derived for the TDMA case is obtained by design, whereas that of the ADMM-based method derived for the FDMA case is demonstrated numerically. Simulation results indicate that the choice between TDMA or FDMA depends on the available resources, size of the data packet, and the time of packet observation in the system.

INDEX TERMS Age of information, convex optimization, energy harvesting, wireless sensor networks.

I. INTRODUCTION

Owing to the latest advances in sensing and data transmission technologies, various monitoring services employing wireless sensor networks (WSNs) have been proposed over the years to solve problems in domains such as transportation [2], health [3], and the environment [4], culminating with the notion of digital twins (DTs) [5], [6].

Digital twins are digital representations of physical devices or systems based on data collected in real time, which continuously track physical changes in the devices/systems while forecasting possible future states of the corresponding physical components. Given that a very large number of devices may be connected to feed a DT, the corresponding data must be collected in a distributed and reliable fashion. These requirements can be satisfied by energy harvesting (EH) WSNs, well known for their self-reliance and low-maintenance characteristics.

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Indeed, EH techniques have been well-studied [7]–[12] and matured enough that it can be assumed that the technology will soon become ubiquitous, equipping devices with the capability to convert energy from natural (*i.e.* solar radiation, vibration, and temperature differences) or artificial sources (*i.e.* wireless energy transfer) into electric power required to run sensors. In addition, networking protocols specific for EH-WSNs have also been developed [13]–[17], which contribute to the reliability of such systems.

However, a problem associated with the latter paradigm that has received comparatively less attention is the "*freshness*" issue or the age of information (AoI) of messages collected and distributed by EH-WSNs. Indeed, protocols for EH-WSNs have so far largely focused on energy and data arrival processes, without addressing the fact that, in practice, data collected by EH-WSNs may be outdated, which affects their suitability to DT applications. Thus, a new concept is needed to ensure the freshness of information in such time-bound data-oriented systems, as argued *e.g.* in [18], [19].

As noted in [18], [19], AoI can be defined as the time elapsed from the moment the information is generated and captured by the sensor, until it is received by the destination, which, in the case of our application of interest can be considered as the FC. Interestingly, as reported in [20]–[24], the optimal strategy that minimizes AoI is different from conventional data rate maximization and delay minimization strategies, motivating the design of new WSN optimization approaches for DT applications in which freshness of information is fundamental.

However, similar to data rate and delay, AoI is also impacted by the presence of multiple users – or in the context of WSNs, multiple sensors – that compete for the same frequency and time resources, which must therefore be properly allocated or scheduled. Considering this issue, resource allocation schemes aimed at minimizing AoI in time-division multiple access (TDMA) and frequency-division multiple access (FDMA) systems have been studied in [25]–[29]. In addition, the characterization of AoI has been studied for random access networks in [30] and for carrier sense multiple access (CSMA) networks with distributed scheduling in [31]. We remark, however, that the scenarios considered in the aforementioned works are not constrained by the possibility of battery outage or random energy arrival processes, as faced by maintenance-free EH-WSNs. In turn, EH-oriented AoI minimization problems have been previously investigated in [32]–[37], but for a unidirectional communication scenario in which a single EH-sensor node (SN) continuously sends status updates to a single FC.

Considering that practical DT-WSN scenarios rely on multiple SNs communicating with a common FC, we argue that in order to address the DT case, contributions such as those of [32]–[37] need to be generalized, in particular toward the design of optimal resource allocation handling multiple SNs, aimed at minimizing the average AoI under battery-constrained conditions. To the best of our knowledge, no mechanism to minimize the AoI in DT EH-WSNs has been proposed thus far. In this study, we therefore investigate a system with N EH-SNs that simultaneously communicates with a common FC, proposing novel resource allocation algorithms both in TDMA and FDMA modes to minimize the corresponding average aggregate AoI.

The remainder of this article is organized as follows. The system model is described in Section II, while the convexity analysis and mathematical expression for AoI in the case of sensor network systems with one SN and one FC are presented in Section III-A. In Section III-B, we consider a more general scenario where N SNs send data to a common FC, proposing new radio resource allocation algorithms for both TDMA and FDMA scenarios. The numerical results of the proposed algorithms are shown in Section IV, and the conclusions are presented in Section V.

NOTATION

Vectors and scalars are denoted by bold and standard fonts, such as in $\mathbf{x}$ and x, respectively. The absolute value and ceiling functions are respectively denoted by $|x|$ and $\lceil x \rceil \triangleq \min\{n \in \mathbb{Z} \mid n \geq x\}$. Sets of natural, real, and complex numbers are respectively denoted by $\mathbb{Z}$, $\mathbb{R}$ and $\mathbb{C}$. Finally, the fact that a random variable x follows the complex Gaussian distribution with mean μ and variance σ^2 is expressed as $x \sim \mathcal{C}(\mu, \sigma^2)$.

II. SYSTEM MODEL

Consider the uplink of a WSN consisting of N single-antenna SNs sending status updates to one common FC, as shown in Fig. 1, such that each SN is subjected to limited power harvested from environmental sources such as solar radiation, vibration, and radio frequency waves. It is assumed that the length of an uplink packet transmitted by an i-th SN is denoted by D_i [bits], where $i \in \{1, 2, \ldots, N\}$ denotes the node index, and all the harvested energy (no loss) is stored in a supercapacitor embedded in each SN. For the sake of simplicity but without loss of generality, we assume that the initial amount of energy stored in each supercapacitor is 0 [J]. Denoting the average harvested power at the i-th SN by E_i [W], the amount of energy available after $k_i \in \mathbb{Z}^+$ normalized unit time samples can be expressed as $k_i E_i$ [J]. Furthermore, assuming that we adopt uniform power allocation over $n_i \in \mathbb{Z}^+$ transmission time slots, the transmitted power at each time slot can be described as $k_i E_i / n_i$ [W]. In turn, the communication channel from the i-th SN to the FC is modeled as a flat fading channel with gains h_i, subjected to zero mean additive white Gaussian noise (AWGN) characterized by a noise power spectral density N_0 [W/Hz], with a total system bandwidth of B_{total} [Hz].

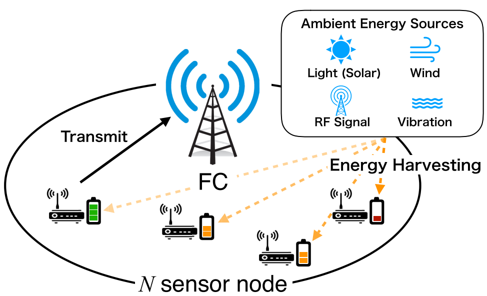


FIGURE 1. EH-WSNs model with *N* single-antenna sensor nodes (SNs) transmitting status update information to a common fusion center (FC). Each SN is equipped with an EH power source and aims to cooperatively minimize the overall average AoI.

Another aspect of the system model that is fundamental to the analysis of the AoI of distributed systems is the time of origin of information, relative to the timestamp of transmitted packets. To elaborate, analyses of AoI can be found in the literature; they are based on two distinct timing conditions, namely, a *distributed* model in which each SN has its own time origin, as adopted *e.g.* [28], and a *concurrent* model in which a common time origin is shared by all SNs as adopted for instance in [29], [32].

Both these models are valid as they address distinct applications. For example, the distributed model employed in [28] is better suited to applications such as the monitoring of structures (*e.g.* bridges, tunnels, and towers), in which multiple sensors are installed on the same structure, so that an update indicating a status deterioration at any of the SNs indicates a deterioration of the structure itself. In turn, the concurrent model adopted *e.g.* in [29], [32], which is also more commonly utilized, addresses applications such as DT, in which different pieces of information collected by different SNs contribute to composing a larger whole, *e.g.* the digital twin of a given system.

Having made this remark, in this article, we focus on the latter (more prevalent) concurrent timing approach, in which the multi-access scheme employed has also a greater impact, especially in the context of EH networks, as it affects both the time SNs must wait from the moment data is collected until they can transmit in the case of TDMA schemes, as well as the time available for EH nodes to gather sufficient energy to transmit, in the case of an FDMA scheme.

III. AoI MINIMIZATION PROBLEM OVER MULTIPLE-ACCESS CHANNELS

A. PRELIMINARY: SINGLE SN-FC LINK

For the sake of completeness and clarity of exposition, we first consider a simple scenario in which a single SN communicates with the FC, as studied in [32]. Then, the capacity of the corresponding channel for a fixed h can be written as

$$C \triangleq B\log_2\left(1+|h|^2\frac{kE}{nBN_0}\right), \tag{1}$$

where B is the bandwidth assigned to the SN.

We observe that the SN can successfully transfer its data D to the FC if and only if the total information communicated at best at the rate C over the transmission time n, exceeds D. In other words, the following condition must be satisfied in order for the delivery to be successful

$$D \le nC. \tag{2}$$

Following related literature [19], [32], the AoI P of the node is the reward over the total elapsed time, including the harvesting time k and the data transmission time n, *i.e.*

$$P \triangleq \frac{1}{2}(k+n)^2. \tag{3}$$

Given the above, we now consider the AoI minimization problem subject to the throughput requirement given in the inequality (2), namely

$$\underset{k,n}{\text{minimize}} \;\; P, \tag{4a}$$
$$\text{subject to} \;\; D \le nC. \tag{4b}$$

Substituting (1) into (2) and expressing the harvesting time k that satisfies the constraint of inequality (2), we obtain

$$k \ge \left\lceil \frac{nBN_0}{|h|^2E}\left(2^{\frac{D}{nB}}-1\right)\right\rceil, \tag{5}$$

such that the minimum harvesting time k as a function of the transmission time n can be obtained from the lower bound of the latter inequality, *i.e.*,

$$k(n) = \frac{nBN_0}{|h|^2E}\left(2^{\frac{D}{nB}}-1\right). \tag{6}$$

By combining equations (3) and (6), the AoI can be expressed as a function of n, namely

$$f(n) = \frac{1}{2}(k(n)+n)^2. \tag{7}$$

Owing to the relaxation in equation (6), the function $f(n)$ in equation (7) can be considered as a lower bound of the AoI P, such that the constrained optimization problem in equation (4) is an equivalent unconstrained problem

$$\underset{n}{\text{minimize}} \;\; f(n). \tag{8}$$

Although k and n are treated as real numbers in the above section, we shall hereafter limit these quantities to positive integer (*i.e.*, natural) values to accommodate for the discrete nature of packetized TDMA networks as well as of synchronous FDMA schemes. Since the solution of equation (8) is generally not integer, the desired solution of the problem will be taken as a projection of the solution n^* of (8) onto the feasible set, namely, $(\lceil n^*\rceil, \lceil k(n^*)\rceil)$.

A comparison between the average AoI achievable with continuous versus discrete times is shown in Fig. 2. To be more specific, the figure exhibits plots of $\mathbb{E}[f(n)]$ with $f(n)$ as in equation (7), respectively with $n \in \mathbb{R}$ and $k(n)$ as in equation (6) averaged over multiple realizations of h, and with the transmission and harvesting times projected to their closest upper-bounding integers $(\lceil n^*\rceil, \lceil k(n^*)\rceil)$. It can be seen that a fundamental penalty is paid for the discretization of time required by synchronous access schemes such as TDMA and FDMA, which increases with the transmission time n.

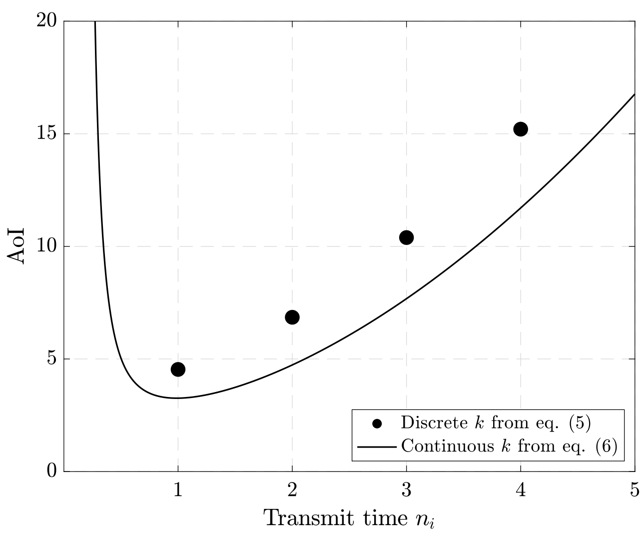


FIGURE 2. Average AoI with continuous and discrete transmission and harvesting times, for a single-SN system with $D = 1$ [Mbit], $E = 1.0$ [mW], and base SNR $\triangleq \frac{\mathbb{E}[|h|^2]}{BN_0} = 30$ [dB].

We emphasize also that such a penalty does not include the possible sub-optimality incurred by projecting the real-valued solution of the problem in equation (8) onto $\mathbb{N}$, as opposed to solving the problem directly over $\mathbb{N}$, which however is NP-hard.

To conclude this subsection, we address the solution of the AoI minimization problem given by equation (7), which is facilitated by the following two results.

Proposition 1: With $E > 0$, $D > 0$, $B > 0$, $N_0 > 0$, $|h|^2 > 0$, $\beta \triangleq BN_0/E$, and $\gamma \triangleq D/B$, the AoI $f(n)$ given by equation (7) is convex with respect to n.

Proof: See Appendix A. ■

Proposition 2: For $\gamma > 0$ and $\beta > 0$, the unique solution n^* of the minimization problem described by equation (8) can be obtained by solving the implicit equation

$$\frac{\beta}{|h|^2}\left(2^{\frac{\gamma}{n}} - 1\right) - \frac{\beta\gamma\log(2)}{|h|^2 n}2^{\frac{\gamma}{n}} + 1 = 0. \tag{9}$$

Proof: See Appendix B. ■

Finally, we introduce the main result of this subsection, in the form of the following Proposition.

Proposition 3: For $\gamma > 0$ and $\beta > 0$, the solution of equation (9), *i.e.*, the transmission time n^* that minimizes the AoI in the single SN-FC link, is bounded by

$$n_L^* \triangleq \frac{\gamma}{\log_2\left(e - 1 + \frac{|h|^2}{\beta}\right)} \leq \underbrace{n^* \leq \gamma\log 2}_{\forall\, |h|^2 > \beta} \triangleq n_U^*, \tag{10}$$

where we emphasize that the condition $|h|^2 > \beta$ is only required for the upper-bounding relation to hold.

Proof: See Appendix C. ■

B. GENERALIZATION: MULTIPLE SNs-FC LINKS

Taking advantage of the formulation presented above, we now consider a more general scenario where N SNs simultaneously transmit, with the help of either a TDMA or an FDMA scheme, to a common FC, proposing two corresponding resource allocation schemes optimized to minimize the mean AoI of both systems.

To this end, we first define the mean conditional[1] AoI minimization problem associated with a scenario with N SNs, which can be expressed as

$$\underset{\boldsymbol{n}}{\text{minimize}}\ \frac{1}{N}\sum_{i=1}^{N} f(n_i), \tag{11}$$

where $\boldsymbol{n} \triangleq \{n_1, n_2, \ldots, n_N\}$.

1) TIME DIVISION MULTIPLE ACCESS SYSTEMS

To avoid interference among the N SNs, in a TDMA scheme the entire bandwidth available in the system B_{total} is assigned to a single SN during its transmission time interval n_i. In other words, we have

$$B_i = B, \ \forall\,. \tag{12}$$

[1] Here, the term mean refers to the average taken over the multiple SNs, while the term condition refers to the fact that the channel gains h are assumed to be constant.

For the sake of simplicity, it shall also be assumed hereafter that all SNs are subjected to the same conditions, such that the average harvested energy E and the amount of data to be transmitted D are the same for all SNs.

Finally, under a TDMA scheme, only one SN is allowed to transmit during its allocated time, which can be expressed by the constraint

$$\sum_{i=1}^{N} \mathbb{1}_i(t) \leq 1, \tag{13}$$

where $\mathbb{1}_i(t)$ is an indicator function that takes the value 1 at $k_i < t \leq (k_i + n_i)$ and 0 elsewhere.

Taking into account the above constraints, the resource allocation problem to minimize the average AoI in TDMA can be formulated as

$$\underset{\boldsymbol{n}}{\text{minimize}}\ \frac{1}{N}\sum_{i=1}^{N} f(n_i), \tag{14a}$$

$$\text{subject to}\ \sum_{i=1}^{N} \mathbb{1}_i(t) \leq 1, \quad \forall\, 0 \leq t \leq k_N + n_N. \tag{14b}$$

In order to gain insight on how to solve the problem described above in a general setting, we first consider a particular case with only two SNs, labeled SN_1 and SN_2. Following our notation, the optimal transmission times associated with these two SNs will be denoted n_1^* and n_2^*, respectively, with their corresponding minimum energy harvesting times, obtained from equation (6), denoted accordingly by $k(n_1^*)$ and $k(n_2^*)$.

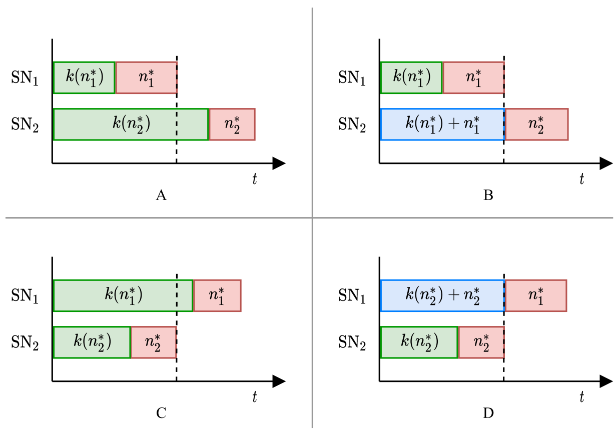


FIGURE 3. Illustration of the four allocation arrangements in a TDMA-based EH-WSN with two SNs and one FC.

Referring to Figure 3, it is evident that in this case, the problem of minimizing the mean conditional AoI reduces to determining which of the two nodes shall transmit first, a decision which is informed by whether the time taken by the first node to complete its harvesting-and-transmission cycle is sufficient to enable the second node to harvest enough energy for its own transmission.

In other words, the optimal time allocation is fundamentally driven by the tests $k(n_2^*) \gtrless k(n_1^*) + n_1^*$ and

$k(n_1^*) \gtrless k(n_2^*) + n_2^*$, with the best strategy being given by the one in which the SN second to transmit has enough time to harvest all the required energy during the transmission of the first node, such that its transmission can start immediately after the first.

To elaborate further, following the illustration in Figure 3, there are four distinct cases to be considered, namely:

$$\bar{f}_A(n_1^*, n_2^*) = \frac{1}{2}\left(k(n_1^*) + n_1^*\right)^2 + \frac{1}{2}\left(k(n_2^*) + n_2^*\right)^2, \tag{15a}$$

$$\bar{f}_B(n_1^*, n_2^*) = \frac{1}{2}\left(k(n_1^*) + n_1^*\right)^2 + \frac{1}{2}\left(k(n_1^*) + n_1^* + n_2^*\right)^2, \tag{15b}$$

$$\bar{f}_C(n_1^*, n_2^*) = \frac{1}{2}\left(k(n_2^*) + n_2^*\right)^2 + \frac{1}{2}\left(k(n_1^*) + n_1^*\right)^2, \tag{15c}$$

$$\bar{f}_D(n_1^*, n_2^*) = \frac{1}{2}\left(k(n_2^*) + n_2^*\right)^2 + \frac{1}{2}\left(k(n_2^*) + n_2^* + n_1^*\right)^2, \tag{15d}$$

where $\bar{f}(n_1, n_2) \triangleq \frac{f(n_1)+f(n_2)}{2}$ and the indices A, B, C and D represent the four distinct possibilities as illustrated.

It can be seen that the cases A and C, with corresponding mean conditional AoI given by (15a) and (15c), respectively, are inefficient because they cause the channel to remain idle after the first to transmit SN completes its cycle, while SN second to transmit harvests the required energy for its own transmission. It follows therefore that the optimum allocation strategy in this particular setting of two SN lays in between the cases B and D. Furthermore, it is evident that the optimum choice between these two options is governed by the test

$$\bar{f}_B \underset{\mathrm{SN}_1 \rightarrow \mathrm{SN}_2}{\overset{\mathrm{SN}_2 \rightarrow \mathrm{SN}_1}{\gtrless}} \bar{f}_D, \tag{16}$$

which, if stated in words, signifies that the transmission order SN_2 followed by SN_1 is optimal if $\bar{f}_B > \bar{f}_D$, whereas the order SN_1 followed by SN_2 is optimal if $\bar{f}_B < \bar{f}_D$.

In light of the above, we consider the following results.

Proposition 4: For $\gamma > 0$ and $\beta > 0$,

$$|h_1|^2 > |h_2|^2 \implies n_{1L}^* < n_{2L}^*, \tag{17a}$$

$$n_{1U}^* = n_{2U}^*. \tag{17b}$$

Proof: See Appendix D. ■

Proposition 5: For $\gamma > 0$ and $\beta > 0$,

$$|h_1|^2 > |h_2|^2 \implies k(n_{1L}^*; h_1) < k(n_{2L}^*; h_2), \tag{18a}$$

$$|h_1|^2 > |h_2|^2 > \beta \implies k(n_{1U}^*; h_1) < k(n_{2U}^*; h_2), \tag{18b}$$

where the bounding quantities (n_{1L}^*, n_{1U}^*) are as defined in Proposition 3 and its proof.

Proof: See Appendix E. ■

Proposition 6: For $\gamma > 0$ and $\beta > 0$,

$$\bar{f}_B(n_{1L}^*, n_{2L}^*) < \bar{f}_D(n_{1L}^*, n_{2L}^*), \tag{19a}$$

$$\bar{f}_B(n_{1U}^*, n_{2U}^*) < \bar{f}_D(n_{1U}^*, n_{2U}^*). \tag{19b}$$

Proof: See Appendix F. ■

We remark that setting $|h_1|^2 > |h_2|^2$ is without loss of generality as it amounts merely to ordering the SNs. Although a closed-form expression of the optimum transmission times n_1^* and n_2^* cannot be obtained, Proposition 6 in fact establishes that, given knowledge of $|h_1|^2$ and $|h_2|^2$ only, the wisest TDMA allocation strategy in a system with two SNs is a "*greedy*" scheme in which the SN with the strongest channel gain precedes the other SN, since under such a strategy both the lower and upper bounds on the mean AoI $\bar{f}_B(n_1^*, n_2^*)$ are inferior to those of the alternative "*Robin Hood*" (the weaker SN first) strategy of allocating times the other way around.

Furthermore, the impossibility to be certain of the optimality of the greedy allocation does *not* detract from the overall optimality of the TDMA strategy described, because the optimality of the initial choice can be easily verified (and if necessary reverted) by solving equation (9) via a simple bisection algorithm, which is only made more efficient given the assured bounds offered in Propositions 4 and 5.

Next, we consider a more general setting, where N SNs communicate with the FC through a TDMA scheme. In this case, referring to Figure 3, it is evident that since all SNs stay in EH mode while the greedily-selected SNs transmit, after a sufficiently large number of SNs have transmitted the order of the remaining SNs is irrelevant to optimality.

In other words, the uncertainty of the channel power-based greedy selection between any pair of SNs $(i, i+1)$ decreases with i. Taking all the above into consideration, an optimal TDMA strategy to minimize the average AoI can be obtained for the general system with N SNs, by repeating the pair-wise greedy-selection described above.

In summary, the optimal TDMA strategy is therefore:

1) Sort the indices SNs in descending order of channel power, such that $|h_1|^2 > \cdots > |h_N|^2$;
2) Set $i = 1$ and solve equation (9) via bisection using the bounds in inequalities (17) only for two strongest SNs, obtaining n_i^* and n_{i+1}^*;
3) If and only if all remaining nodes have not harvested enough energy, and $\bar{f}_B(n_1^*, n_2^*) > \bar{f}_D(n_1^*, n_2^*)$, swap the indices $n_1^* \leftrightarrow n_2^*$;
4) Allocate n_i^*, and remove i index from the list $\boldsymbol{N}$;
5) Repeat steps 2 to 4 until there is only one SN left, which is allocated last.

The pseudocode corresponding to the TDMA allocation procedure described above that minimizes the mean AoI of an EH-WSNs with N-SNs is shown in Algorithm 1.

2) FREQUENCY DIVISION MULTIPLE ACCESS SYSTEMS

In contrast to the TDMA scheme, in an FDMA system, SNs can transmit data to the FC and in an orthogonal manner, at the expense of a reduction in the bandwidth B_i used by each SN, which is a fraction of the total available bandwidth B_{total}. In this case, the mean AoI minimization problem can be written as

$$\underset{\boldsymbol{n},\, \boldsymbol{B}}{\text{minimize}} \quad \frac{1}{N}\sum_{i=1}^{N} f(n_i, B_i), \tag{20a}$$

Algorithm 1 Greedily-Initialized TDMA AoI Minimizer

Inputs: $E > 0$, $D > 0$, $B > 0$, $N_0 > 0$ and $|h_i|^2 > 0$, with $i \in \boldsymbol{N} \triangleq \{1, \ldots, N\}$. **Outputs:** Optimal transmission time $\boldsymbol{n}^* \in \mathbb{R}^+$ and optimal harvested time $\boldsymbol{k}^* \in \mathbb{R}^+$.

Initialization:
Set loop counter $i = 1$.
Set initial transmission times $\boldsymbol{n} \gg 1$.
Set initial harvesting times $\boldsymbol{k} = 0$.
Sort SN indices $\boldsymbol{N}$ such that $|h_1|^2 > \cdots > |h_N|^2$.
Core Procedure:
while $|\boldsymbol{N}| \geq 2$ **do**
  Find the optimal n_i^* and n_{i+1}^* by solving (25c).
  if $\bar{f}_B(n_i^*, n_{i+1}^*) > \bar{f}_D(n_i^*, n_{i+1}^*)$ **then**
    Swap indices i and $i+1$
  end if
  if $i \geq 2$ and (14b) is not satisfied **then**
    Update $k(n_i) = k(n_{i-1}) + n_{i-1}$
  end if
  Update $\boldsymbol{N} \leftarrow \boldsymbol{N} \setminus i$
  Append $\boldsymbol{n}^*$ with n_i and $\boldsymbol{k}^*$ with $k(n_i)$
  Update $i \leftarrow i + 1$.
end while

$$\text{subject to } \; B_{\text{total}} - \sum_{i=1}^{N} B_i = 0, \tag{20b}$$

where $\boldsymbol{B} \triangleq \{B_1, B_2, \ldots, B_N\}$.

Since the objective function given (20a) involves a coupled expression of the optimization variables $\boldsymbol{n}$ and $\boldsymbol{B}$, as shown in (6) and (7), it is difficult to solve the above optimization analytically and globally. Therefore, we resort to an alternating optimization framework where (20) is divided into optimization problems (I) and (II) as follows.

(I) Optimization problem for bandwidth allocation $\boldsymbol{B}$

$$\underset{\boldsymbol{B}}{\text{minimize}} \; \frac{1}{N}\sum_{i=1}^{N} f(B_i|n_i), \tag{21a}$$

$$\text{subject to } \; B_{\text{total}} - \sum_{i=1}^{N} B_i = 0. \tag{21b}$$

(II) Optimization problem for transmission time allocation $\boldsymbol{n}$

$$\underset{\boldsymbol{n}}{\text{minimize}} \; \frac{1}{N}\sum_{i=1}^{N} f(n_i|B_i). \tag{22}$$

Next, consider the following result.

Proposition 7: For $E_i > 0$, $|h_i|^2 > 0$, $N_0 > 0$, $D_i > 0$ and $n_i > 0$, the function $f(B_i|n_i)$ is convex with respect to B_i.

Proof: Please see Appendix G. ∎

The convexity of $f(B_i|n_i)$ established by Proposition 7 implies that problem (21) can be efficiently solved via the alternating direction method of multipliers (ADMM) [38].

More specifically, following [38], [39], convex problems of the form described in (21) can be solved by successive iterations of the following steps:

$$\boldsymbol{B} \leftarrow \underset{\boldsymbol{B}}{\text{argmin}} \, L_\rho(\boldsymbol{B}, B_{\text{total}}, u), \tag{23a}$$

$$\theta \leftarrow \left(B_{\text{total}} - \sum_{i=1}^{N} B_i\right), \tag{23b}$$

$$u \leftarrow u + \theta, \tag{23c}$$

where $\theta \in \mathbb{R}$ is an auxiliary variable, u is the scaled dual variable, and $L_\rho(\boldsymbol{B}, B_{\text{total}}, u)$ is the associated augmented Lagrangian of the problem, which, for a penalty parameter $\rho > 0$, is given by

$$L_\rho(\boldsymbol{B}, B_{\text{total}}, u) = \sum_{i=1}^{N} f(B_i|n_i) + \frac{\rho}{2}\left(B_{\text{total}} - \sum_{i=1}^{N} B_i + u\right)^2 + \frac{\rho}{2}u^2. \tag{24}$$

Similarly, the convexity of $f(n_i|B_i)$ with respect to n_i established by Proposition 1, together with the bounds on its minimizer established by Proposition 3, enables the efficient solution of problem (22) via the bisection method (BM). Altogether, using these two techniques, the optimum bandwidth and transmit time allocation problem (20) can be obtained by solving equations (21) and (22) alternately. A pseudocode summarizing the method described above is given in Algorithm 2.

Algorithm 2 ADMM - BM AoI Minimizer

Inputs: $E_i > 0$, $|h_i|^2 > 0$, $N_0 > 0$, $B_{\text{total}} > 0$, $B_i > 0$, $D_i > 0$, $n_i > 0$, $i \in \boldsymbol{N} \triangleq \{1, \ldots, N\}$, convergence range ε, and number of iterations for outer and inner loops $s_{\text{out}}^{\max}$ and $s_{\text{in}}^{\max}$. **Outputs:** Optimal transmission times $\boldsymbol{n}^* \in \mathbb{R}^+$ and optimal bandwidths $\boldsymbol{B}^* \in \mathbb{R}^+$.

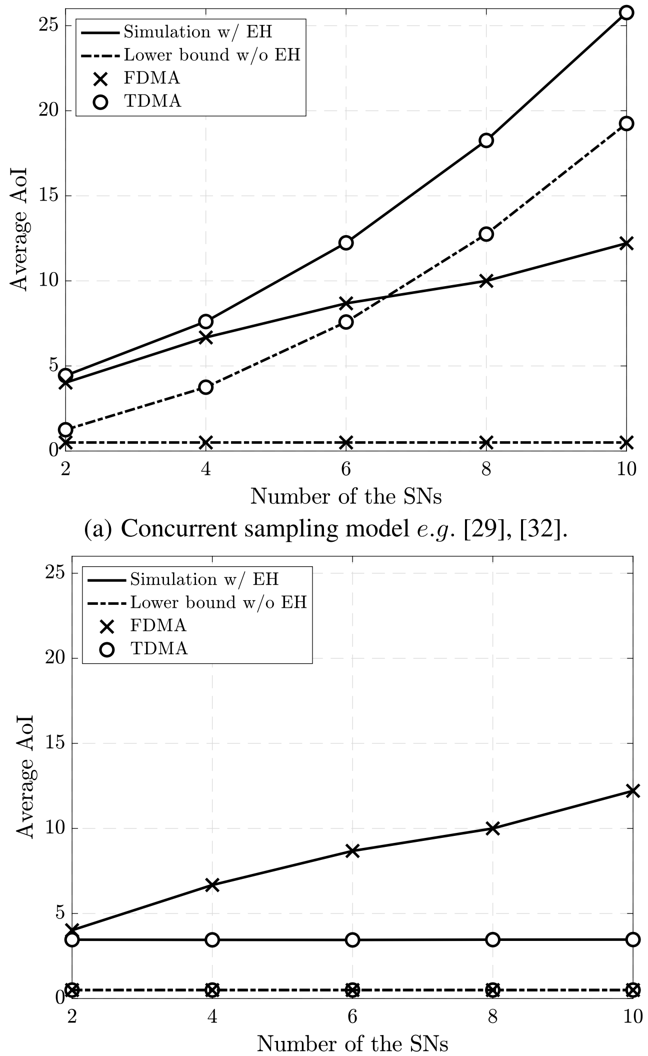
Initialize outer loop counter to $s_{\text{out}} = 1$.
Set initial transmission time $\boldsymbol{n}^{s_{\text{out}}} \gg 1$ and $\theta \gg 1$.
while $s_{\text{out}} \leq s_{\text{out}}^{\max}$ and $|\boldsymbol{n}^{s_{\text{out}}} - \boldsymbol{n}^{s_{\text{out}}-1}| > \varepsilon$ **do**
  Initialize the inner loop counter to $s_{\text{in}} = 1$.
  while $s_{\text{in}} \leq s_{\text{in}}^{\max}$ and $\theta > \varepsilon$. **do**
    Update $B_i^{s_{\text{in}}}$, $\theta^{s_{\text{in}}}$ and $u^{s_{\text{in}}}$ via equation (23).
    Update $s_{\text{in}} \leftarrow s_{\text{in}} + 1$.
  end while
  Find the $\boldsymbol{n}^{s_{\text{out}}}$ by solving (9).
  Update $s_{\text{out}} \leftarrow s_{\text{out}} + 1$.
end while
$\boldsymbol{n}^* = \boldsymbol{n}^{s_{\text{out}}}$ and $\boldsymbol{B}^* = \boldsymbol{B}^{s_{\text{in}}}$.

IV. NUMERICAL RESULTS

In this section, we present numerical results that build on the analysis and algorithms developed above to reveal the impact of EH, as well as of TDMA and FDMA multiple-access strategies, on the optimized AoI of WSNs. To this end, we first evaluate the performance of the proposed optimization algorithms in terms of the average AoI values in TDMA and FDMA scenarios and over fading channels.

Following a related study [11], [40], we set the total bandwidth and noise power spectrum density of the system to $B_{\text{total}} = 1$ [MHz] and $N_0 = 10^{-17}$ [mW/Hz], respectively, and assume that h_i follows independent and identically distributed (i.i.d.) Gaussian distributions (Rayleigh fading channel) with the SNs and the FC separated by a distance of 1 [km] and the path loss for that distance set to 100 [dB]. Finally, the volume of information transmitted is set to $D_i = 1$ [Mbit], and the average EH rate (*i.e.*, the expected EH power) is set to $E_i = 1.0$ [mW] for all SNs.

Fig. 4 shows the average AoI performance, as a function of the number of SNs in the system, achieved by Algorithms 1 and 2 in such a scenario with TDMA and FDMA. More specifically, Fig. 4(a) shows results for the concurrent case of *e.g.* in [29], [32], when the sensed information is obtained simultaneously by all SNs and them transmitted after the SNs the required energy is harvested.



(a) Concurrent sampling model $e.g.$ [29], [32].

(b) Distributed sampling model $e.g.$ [28].

FIGURE 4. Average AoI as a function of the number of SNs in TDMA and FDMA with i.i.d. Rayleigh channels.

The figure shows also results obtained without the EH constraint, which can be taken as a lower bound on the average AoI, since no additional time is required to wait for the SNs to energize before transmitting.

It can be seen that in this case FDMA outperforms TDMA, although only mildly so in systems of small size. This is because, in TDMA schemes, the SNs must wait not only for their own EH cycles but also for preceding SNs complete their transmissions, before they themselves can transmit.

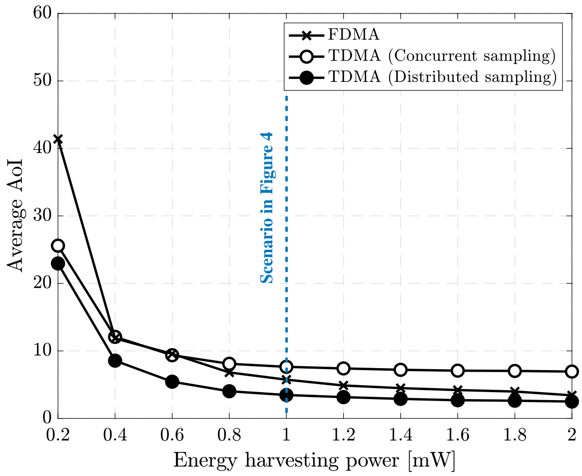
It is also found, however, that FDMA schemes exhibit a wider gap between the AoIs achieved with and without EH constraints, which increases as the size of the system grows. In contrast, the "EH penalty" paid by the TDMA scheme is significantly smaller and less dependent on the size of the system. To understand this result, recall that indeed in a TDMA system, the time consumed by EH cycles is only of relevance in the allocation of the first SNs to transmit, since all other SNs allocated later slots will, with great likelihood, have already harvested enough energy to carry out their transmissions by the time their allocated slots come due.

Next, Fig. 4(b) compares the average AoI obtained under a distributed sampling model such as that assumed *e.g.* in [28], showing results entirely opposite to those of Fig. 4(a). In this case, it is found that TDMA is superior to FDMA, with the difference between these two access schemes becoming increasingly significant as the number of SNs grows. Indeed, we note that an FDMA scheme in a strict sense – namely, in which SNs are allocated their own dedicated bands within which to transmit – is too "static" to comport the required dynamics of varying EH and sampling times faced in a WSN operating under a distributed sampling paradigm. It is this feature that makes the FDMA approach less flexible,[2] as observed both in Figs. 4(a) and 4(b).

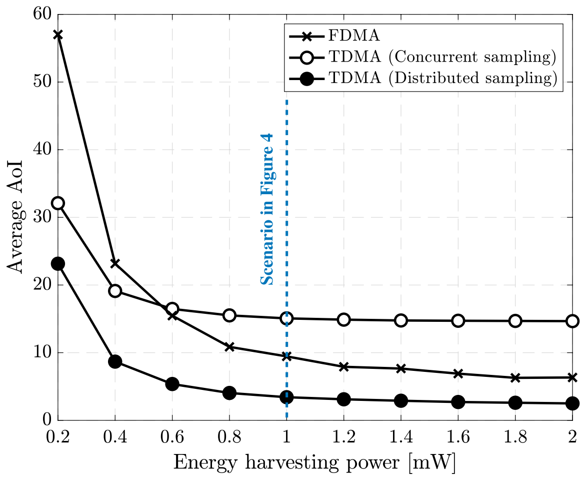
The findings observed above are confirmed and made more evident in the results shown in Figure 5, in which the average AoI of the optimized TDMA and FDMA schemes, both under concurrent and distributed sampling and as functions of the EH power, are compared for systems with $N = 4$ and $N = 7$ SNs, with the remaining parameters identical to those of Figure 4. It is found that under the distributed sampling model TDMA maintains, compared to FDMA, a lower AoI value regardless of the amount of EH power available or the number of SNs in the system, with the gap only growing with N, as already verified also in Figure 4.

Under a concurrent sampling model, however, it is again found that FDMA can outperform TDMA, as long as the EH power available and/or the number of SNs in the system are/is sufficiently large. All in all, the results of Fig. 5 points for a localized optimality of FDMA, that is, under certain

[2]One can argue that an FDMA scheme with dynamically allocated bands would resolve this limitation. That would, however, require that the FC is aware of the instantaneous data volumes D_i of all SNs, which would be impractical.

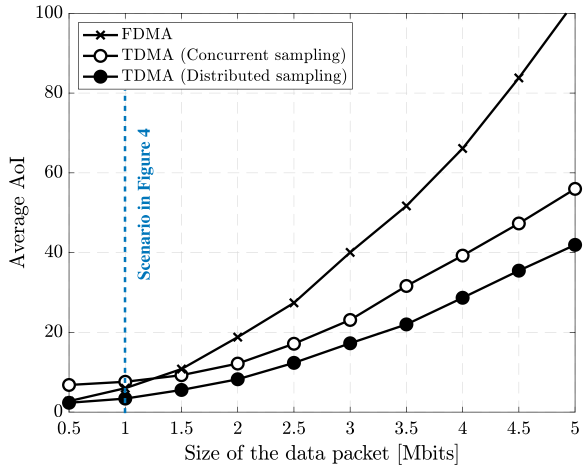


(a) Number of SNs: $N = 4$.

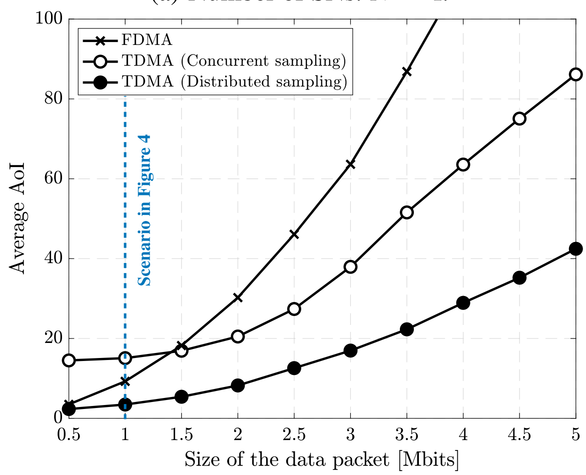


(b) Number of SNs: $N = 7$.

FIGURE 5. Average AoI as a function of EH power in TDMA and FDMA systems.



(a) Number of SNs: $N = 4$.



(b) Number of SNs: $N = 7$.

FIGURE 6. Average AoI as a function of the size of data packets in TDMA and FDMA systems.

conditions, but an overall greater robustness TDMA schemes, with respect to the sampling model, system size, and available EH power.

This conclusion is only made clearer by the results of Fig. 6, where the average AoI achieved by the optimized TDMA- and FDMA-based EH wireless sensor networks, plotted as functions of the size of data packets, with $E_i = 1.0$[mW], both under concurrent and distributed sampling are compared, for systems with $N = 4$ and $N = 7$ SNs, with the remaining parameters identical to those of Figure 4. Noticing that an increase of the data volume D_i, with the EH power kept fixed, amounts to making the EH constraint more stringent, it is non-surprising that it is found that under such conditions the FDMA approach proves increasingly inadequate as the D_i grows.

It can therefore be reasonably concluded, with all relevant parameters taken into account jointly, that TDMA is a more robust multi-access scheme than FDMA for EH-WSNs, with the remark that punctually, depending on specific conditions, the FDMA might be a better choice.

However, we also reemphasize that it might be possible to extend the work carried out here to jointly optimize time and frequency allocations, building an overall robust and optimum scheme for EH-WSNs. This will be pursued in future work.

V. CONCLUSION

In this study, we considered the uplink of a WSN where N SNs equipped with EH power supplies transmit their data to a common FC, aiming to create a maintenance-free wireless communication system.

Taking into account TDMA and FDMA as possible multiple-access schemes, we have reformulated the AoI minimization problems for both scenarios, analyzing their optimality conditions. Furthermore, we proposed novel resource allocation algorithms for these two schemes to solve the formulated optimization problems by leveraging the aforementioned analyses. From the simulation results and previous study in [28], it is necessary to choose TDMA or FDMA separately depending on available resources, size of the data packet, and the time of packet observation in the system.

APPENDIX A
PROOF OF PROPOSITION 1

In this appendix, we prove that equation (7) is convex with respect to the number of time slots n assigned to a given SN by demonstrating that its second derivative is strictly positive under feasible parameter setups.

Indeed, differentiating equation $f(n)$ with respect to n yields the first-order derivative as follows.

$$\frac{\mathrm{d}}{\mathrm{d}n} f(n) = g_1(n) \times g_2(n), \tag{25a}$$

with

$$g_1(n) \triangleq \frac{\beta n}{|h|^2}\left(2^{\frac{\gamma}{n}} - 1\right) + n, \tag{25b}$$

$$g_2(n) \triangleq \frac{\beta}{|h|^2}\left(2^{\frac{\gamma}{n}} - 1\right) - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}} \log 2^{\frac{\gamma}{n}} + 1, \tag{25c}$$

where the auxiliary parameters $\beta \triangleq BN_0/E$ and $\gamma \triangleq D/B$ were introduced in order to simplify the expressions.

Next, taking the second derivative of $f(n)$ yields

$$\frac{\mathrm{d}^2 f(n)}{\mathrm{d}n^2} = \frac{\mathrm{d}}{\mathrm{d}n}(g_1(n) \times g_2(n)) = \overbrace{\left(g_2(n)\right)^2}^{\geq 0} \times \left(\frac{\beta}{|h|^2}\big(\underbrace{2^{\frac{\gamma}{n}} - 1}_{\geq 0}\big) + 1\right) \frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}} (\log 2^{\frac{\gamma}{n}})^2, \tag{26}$$

where, since $\beta > 0,\ \gamma > 0,\ |h|^2 > 0,\ n > 0$, it follows that $\frac{\mathrm{d}^2 f(n)}{\mathrm{d}n^2} > 0$, completing the proof. ■

APPENDIX B
PROOF OF PROPOSITION 2

Since $f(n)$ is a convex function with respect to n, it possesses a unique minimizer in $n \in [0, \infty)$ located at the point where its first-order derivative is equal to 0. In turn, as per equation (25), the minimizer of $f(n)$ must be a root of either $g_1(n)$ or $g_2(n)$, with the other bounded at that point.

Suffice it therefore to show that only the function $g_2(n)$ has a root in $n \in [0, \infty)$. To this end, let us first examine the following limits of $g_1(n)$

$$\lim_{n \to +0} g_1(n) = \lim_{n \to +0} \underbrace{\frac{\beta n}{|h|^2}(2^{\frac{\gamma}{n}} - 1)}_{\to +\infty} + \underbrace{n}_{\to +0} = +\infty, \tag{27a}$$

$$\lim_{n \to +\infty} g_1(n) = \lim_{n \to +\infty} \underbrace{\frac{\beta n}{|h|^2}(2^{\frac{\gamma}{n}} - 1)}_{\to +\infty} + \underbrace{n}_{\to +\infty} = +\infty, \tag{27b}$$

which combined with the fact that the term $(2^{\gamma/n} - 1) \geq 0$, implies that $g_1(n)$ is strictly positive in $n \in \mathbb{R}$, and bounded within the interval limits.

Next, consider the limits of $g_2(n)$, namely

$$\begin{aligned}\lim_{n \to +0} g_2(n) &= \lim_{n \to +0} \frac{\beta}{|h|^2}\left(2^{\frac{\gamma}{n}} - 1\right) - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}} \log 2^{\frac{\gamma}{n}} + 1 \\ &= \lim_{n \to +0} \underbrace{\frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}}}_{\to +\infty} \underbrace{\left(1 - \log 2^{\frac{\gamma}{n}}\right)}_{\to -\infty} - \frac{\beta}{|h|^2} + 1 = -\infty,\end{aligned} \tag{28a}$$

and

$$\lim_{n \to +\infty} g_2(n) = \lim_{n \to +\infty} \frac{\beta}{|h|^2} \underbrace{\left[\left(2^{\frac{\gamma}{n}} - 1\right) - 2^{\frac{\gamma}{n}} \log 2^{\frac{\gamma}{n}}\right]}_{\to +0} + 1 = 1, \tag{28b}$$

which indicate that $g_2(n)$ possesses at least one root in the interval $n \in [0, \infty)$.

Finally, differentiating (25c) with respect to n yields

$$\frac{\mathrm{d}}{\mathrm{d}n} g_2(n;\, h) = \frac{\beta \gamma^2 \log^2(2)}{|h|^2 n^3} 2^{\frac{\gamma}{n}} > 0, \tag{29}$$

where the last inequality follows from the fact that for $E > 0,\ D > 0,\ B > 0,\ N_0 > 0$ and $|h|^2 > 0$, which in turn implies that $\beta \triangleq BN_0/E > 0$ and $\gamma \triangleq D/B > 0$.

Altogether, equations (28a), (28b) and (29) imply that the function $g_2(n;\, h)$ is monotonically increasing function from $-\infty$ to 1 and therefore has a single root in $n \in \mathbb{R}$, completing the proof. ■

APPENDIX C
Proof of Proposition 3

Our objective is to obtain upper and lower bounds to the solution of the equation

$$\overbrace{1 - \frac{\beta}{|h|^2} + \frac{\beta}{|h|^2}\left(2 - \log 2^{\frac{\gamma}{n}}\right) 2^{\frac{\gamma}{n}} - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}}}^{g_2(n;h) \triangleq} = 0, \tag{30}$$

where we have rewritten the function $g_2(n;\, h)$ defined in equation (25c), in a manner that will prove convenient in the sequel.

Next, consider the following bound

$$(2 - \log 2^{\frac{\gamma}{n}}) 2^{\frac{\gamma}{n}} \leq e, \tag{31}$$

which is easily proved by defining $g_3(x) \triangleq (2 - \log x)x$ with $x \triangleq 2^{\frac{\gamma}{n}}$ and observing that

$$\left.\frac{d}{dx} g_3(x)\right|_{x=e} = 0, \tag{32a}$$

$$\frac{d^2}{dx^2} g_3(x) = -\frac{1}{x} < 0, \ \forall x \geq 0, \tag{32b}$$

from which it follows immediately that the maximum value of $g_3(x)$ is achieved at the point $x = 2^{\frac{\gamma}{n}} = e$, and given by

$$g_3(e) = (2 - \log e)e = e. \tag{33}$$

Using inequality (31) in equation (30) readily yields the following functional upper bound to $g_2(n;\, h)$,

$$g_{2U}(n;\, h) \triangleq 1 + \frac{\beta}{|h|^2}(e - 1) - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{n}}. \tag{34}$$

It is obvious that the upper-bounding function $g_{2U}(n;\, h)$ is strictly ascending monotonic on n, such that due to the strictly ascending monotonicity of $g_2(n;\, h)$ itself, proved in

Appendix B, it follows immediately that the root the $g_{2U}(n;h)$ is a lower bound on the root of $g_2(n;h)$, that is

$$g_{2U}(n_L;h)=0 \implies n_L^* = \frac{\gamma}{\log_2\left(\frac{|h|^2}{\beta}+e-1\right)} \le n^*. \tag{35}$$

Finally, we note that at the point $2^{\frac{\gamma}{n}} = e$, where the equality $g_{2U}(n;h) = g_2(n;h)$ holds, we have

$$g_{2U}(n;h) = 1 - \frac{\beta}{|h|^2} > 0, \quad \forall\, |h|^2 > \beta, \tag{36}$$

such that, again due to the monotonically ascending behaviors of both functions, it follows that as long as the condition $|h|^2 > \beta$ is satisfied, we have

$$g_{2U}(n_U;h) = g_2(n_U;h) \implies n_U^* = \gamma \log 2 \ge n^*, \tag{37}$$

which concludes the proof. ■

APPENDIX D
PROOF OF PROPOSITION 4

Recall that the lower-bound n_L^* on the optimal transmission time that minimizes the AoI of a given SN is the root of the upper-bounding function $g_{2U}(n;h)$, defined in equation (34), of the function $g_2(n;h)$, defined in equation (30).

Directly introducing the condition $|h_1|^2 > |h_2|^2$, and the equivalent relation $|h_2|^2 = |h_1|^2 - \eta$, with $\eta \in \mathbb{R}^+$, the difference between $g_{2U}(n;h_1)$ and $g_{2U}(n;h_2)$ yields

$$\begin{aligned} d(n;h_1,h_2) &\triangleq g_{2U}(n;h_1) - g_{2U}(n;h_2) \\ &= \frac{\eta\beta}{|h_1|^2|h_2|^2}\left(2^{\frac{\gamma}{n}}+1-e\right), \end{aligned} \tag{38}$$

which is obviously monotonically decreasing on n.

The latter fact, together with the trivial limits

$$\lim_{n\to+0} d(n;h_1,h_2) = +\infty, \tag{39a}$$

$$\lim_{n\to+\infty} d(n;h_1,h_2) = +0, \tag{39b}$$

implicates that $d(n;h_1,h_2) > 0$ in $n \in \mathbb{R}^+$, and consequently that $g_{2U}(n;h_1) > g_{2U}(n;h_2)$.

However, since $g_{2U}(n;h_1)$ and $g_{2U}(n;h_2)$ are themselves monotonically ascending functions, the above also implicates that the root n_{1L}^* of $g_{2U}(n;h_1)$ is smaller than the root n_{2L}^* of $g_{2U}(n;h_2)$, which proves inequality (17a).

Finally, we can observe from inequality (37) that the upper-bounding transmission time n_U^* is independent of $|h|^2$, such that equation (17b) follows trivially, concluding the proof. ■

APPENDIX E
PROOF OF PROPOSITION 5

Substituting the expression for the lower bound n_L^* given in inequality (35) into equation (6) we have

$$k(n_L^*;h) = \frac{\gamma}{|h|^2}\frac{|h|^2+\beta(e-2)}{\log_2\left(\frac{|h|^2}{\beta}+e-1\right)}. \tag{40}$$

In order to prove implication (18a), it is sufficing to verify that for $|h_1|^2 > |h_2|^2 > \beta$

$$\begin{aligned} &k(n_{2L}^*;h_2) - k(n_{1L}^*;h_1) \\ &= \frac{\gamma}{|h_2|^2}\frac{|h_2|^2+\beta(e-2)}{\log_2\left(\frac{|h_2|^2}{\beta}+e-1\right)} - \frac{\gamma}{|h_1|^2}\frac{|h_1|^2+\beta(e-2)}{\log_2\left(\frac{|h_1|^2}{\beta}+e-1\right)} \\ &= \underbrace{\frac{\gamma\log_2\left(\frac{|h_1|^2+\beta(e-1)}{|h_2|^2+\beta(e-1)}\right)}{\log_2\left(\frac{|h_1|^2}{\beta}+e-1\right)\log_2\left(\frac{|h_2|^2}{\beta}+e-1\right)}}_{\ge 0} + \frac{\beta\gamma(e-2)}{|h_1|^2|h_2|^2} \\ &\quad\times \underbrace{\frac{|h_1|^2\log\left(\frac{|h_1|^2}{\beta}+e-1\right) - |h_2|^2\log\left(\frac{|h_2|^2}{\beta}+e-1\right)}{\log_2\left(\frac{|h_1|^2}{\beta}+e-1\right)\log_2\left(\frac{|h_2|^2}{\beta}+e-1\right)}}_{\ge 0} \ge 0. \end{aligned} \tag{41}$$

In turn, substituting the expression for the upper bound n_U^* given in inequality (37) into equation (6) yields

$$k(n_U^*;h) = \frac{\beta\gamma}{|h|^2}(e-1), \tag{42}$$

from what it follows trivially that $k(n_{1U}^*;h_1) < k(n_{2L}^*;h_2)$ for $|h_1|^2 > |h_2|^2$, which completes the proof. ■

APPENDIX F
PROOF OF PROPOSITION 6

For convenience, let us first reproduce equations (15b) and (15d), namely

$$\bar{f}_B(n_1^*,n_2^*) = \tfrac{1}{2}\left(k(n_1^*)+n_1^*\right)^2 + \tfrac{1}{2}\left(k(n_1^*)+n_1^*+n_2^*\right)^2, \tag{43a}$$

$$\bar{f}_D(n_1^*,n_2^*) = \tfrac{1}{2}\left(k(n_2^*)+n_2^*\right)^2 + \tfrac{1}{2}\left(k(n_2^*)+n_2^*+n_1^*\right)^2, \tag{43b}$$

First, with respect to inequality (19a), it is readily found from these equations that

$$\begin{aligned} &\bar{f}_D(n_{1L}^*,n_{2L}^*) - \bar{f}_B(n_{1L}^*,n_{2L}^*) \\ &= \frac{1}{2}\left\{k(n_{2L}^*)+n_{2L}^*\right\}^2 + \frac{1}{2}\left\{k(n_{2L}^*)+n_{2L}^*+n_{1L}^*\right\}^2 \\ &\quad - \frac{1}{2}\left\{k(n_{1L}^*)+n_{1L}^*\right\}^2 - \frac{1}{2}\left\{k(n_{1L}^*)+n_{1L}^*+n_{2L}^*\right\}^2 \ge 0, \end{aligned} \tag{44}$$

where the last inequality follows directly from inequality (17a) in Proposition 4 and inequality (18a) in Proposition 5.

As for inequality (19b), we again observe that

$$\begin{aligned} &\bar{f}_D(n_{1U}^*,n_{2U}^*) - \bar{f}_B(n_{1U}^*,n_{2U}^*) \\ &= \frac{1}{2}\left\{k(n_{2U}^*)+n_{2U}^*\right\}^2 + \frac{1}{2}\left\{k(n_{2U}^*)+n_{2U}^*+n_{1U}^*\right\}^2 \\ &\quad - \frac{1}{2}\left\{k(n_{1U}^*)+n_{1U}^*\right\}^2 - \frac{1}{2}\left\{k(n_{1U}^*)+n_{1U}^*+n_{2U}^*\right\}^2 \ge 0, \end{aligned} \tag{45}$$

where the last inequality follows from equality (17b) in Proposition 4 and inequality (18b) in Proposition 5, concluding the proof. ■

APPENDIX G
PROOF OF PROPOSITION 7

Differentiating $f(B_i|n_i)$, we obtain

$$\frac{\mathrm{d}}{\mathrm{d}B_i}f(B_i|n_i) = \left(\alpha_i B_i n_i\left(2^{\frac{D_i}{B_i n_i}}-1\right)+n_i\right) \times\left(\alpha_i n_i\left(2^{\frac{D_i}{B_i n_i}}-1\right)-\alpha_i 2^{\frac{D_i}{B_i n_i}}\log 2^{\frac{D_i}{B_i}}\right), \tag{46}$$

where we have implicitly defined $\alpha_i \triangleq N_0/|h_i|^2\, E_i$.

In turn, the second derivative of $f(B_i|n_i)$ is

$$\frac{\mathrm{d}^2}{\mathrm{d}B_i^2}f(B_i|n_i) = \left(\alpha_i 2^{\frac{D_i}{Bn_i}}\left(n_i-\log 2^{\frac{D_i}{Bn_i}}\right)+\alpha_i n_i+1\right)^2 \times\alpha_i 2^{\frac{D_i}{B_i n_i}}\log 2^{\frac{D_i}{B_i}}\left(\frac{2n_i}{B_i}+\log 2^{\frac{D_i}{B_i}}\right) \tag{47}$$

From the latter equation, it is evident that for $\alpha_i > 0,\ D_i > 0,\ n_i > 0,\ n_i > 0$, we have $\mathrm{d}^2 f(B_i|n_i)/\mathrm{d}B_i^2 > 0$, which indicates that $f(B_i|n_i)$ is strictly convex with respect to B_i concluding the proof. ■

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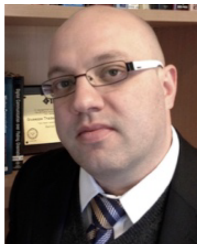
NAOYA HIROSAWA (Graduate Student Member, IEEE) received the B.E. degree in engineering from The University of Electro-Communications, Tokyo, Japan, in 2019, where he is currently pursuing the M.E. degree. His current research interests are energy harvesting and age of information.

HIROKI IIMORI (Graduate Student Member, IEEE) received the B.Eng. degree in electrical and electronic engineering and the M.Eng. degree (Hons.) in advanced electrical, electronic and computer systems from Ritsumeikan University, Kyoto, Japan, in 2017 and 2019, respectively. He is currently pursuing the Ph.D. degree with a focus on electrical engineering and computer science with Jacobs University Bremen, Germany. He received the YKK Doctoral Fellowship from the Yoshida Scholarship Foundation, in 2019. His research interests include optimization theory, wireless communications, and signal processing.

KOJI ISHIBASHI (Senior Member, IEEE) received the B.E. and M.E. degrees in engineering from The University of Electro-Communications, Tokyo, Japan, in 2002 and 2004, respectively, and the Ph.D. degree in engineering from Yokohama National University, Yokohama, Japan, in 2007. From 2007 to 2012, he was an Assistant Professor with the Department of Electrical and Electronic Engineering, Shizuoka University, Hamamatsu, Japan. Since 2012, he has been with the Advanced Wireless and Communication Research Center, The University of Electro-Communications, where he is currently an Associate Professor. From 2010 to 2012, he was a Visiting Scholar with the School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA. His current research interests include energy harvesting communications, wireless power transfer, grant-free access, MIMO systems, signal processing, and information theory.



GIUSEPPE THADEU FREITAS DE ABREU (Senior Member, IEEE) received the B.Eng. degree in electrical engineering and the Latu Sensu degree (specialization) in telecommunications engineering from the Universidade Federal da Bahia, Salvador, Brazil, in 1996 and 1997, respectively, and the M.Eng. and Ph.D. degrees in physics, electrical and computer engineering from the Yokohama National University, Japan, in 2001 and 2004, respectively. He received the Uenohara Award by The University of Tokyo, in 2000, for his Graduate work. From 2004 to 2006, he was a Postdoctoral Fellow in statistical signal processing and communications theory with the Department of Electrical and Information Engineering, University of Oulu, Finland, where he was an Adjunct Professor (Docent) from 2006 to 2011. Since 2011, he has been a Professor of electrical engineering with Jacobs University Bremen, Bremen, Germany. From 2015 to 2018, he was simultaneously a Professor of electrical engineering from Ritsumeikan University, Japan. His research interests span a wide range of topics within communications and signal processing, including communications theory, estimation theory, statistical modeling, wireless localization, cognitive radio, wireless security, MIMO systems, energy harvesting networks, random networks, connected vehicle networks, and many other topics. He co-authored articles short listed for Best Paper Award at the Asilomar Conference on Signals Systems and Computers in 2009, 2012, and 2014. He was co-recipient of the Best Paper Award at the Workshop on Positioning Navigation and Communications in 2012 and 2014. He was a recipient of the prestigious JSPS, Heiwa Nakajima, and NICT fellowships in 2010, 2013, and 2015, respectively. He served as Associate Editor for the IEEE Transactions on Wireless Communications from 2009 to 2014 and the IEEE Transactions on Communications from 2015 to 2017. He is currently an Executive Editor of the IEEE Transactions on Wireless Communications.