Minimizing Age of Information in Energy Harvesting Wireless Sensor Networks

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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.

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 $\lceil x \rceil$. 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 $\mu$ and variance $\sigma^2$ 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 $k_iE_i$ [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 $k_iE_i/n_i$ [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 $B_{\text{total}}$ [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.](image-url)
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

$$C \triangleq B \log_2 \left( 1 + \frac{k E}{n B N_0} \right),$$

(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

$$D \leq nC.$$  

(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.

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

(3)

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

$$\text{minimize } P,$$  

subject to $D \leq nC$.  

(4a)

(4b)

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

$$k \geq \left\lceil \frac{n B N_0}{|h|^2 E} \left( 2^{\frac{D}{n B N_0}} - 1 \right) \right\rceil,$$  

(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.,

$$k(n) = \frac{n B N_0}{|h|^2 E} \left( 2^{\frac{D}{n B N_0}} - 1 \right).$$  

(6)

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

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

(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

$$\text{minimize } f(n).$$  

(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](image-url)

**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 $\triangleq \frac{2D}{BN_0} = 30$ [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

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

**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 \( \beta \geq \beta^* \), the solution of equation (9), i.e., the transmission time \( n^* \) that minimizes the AoI in the single SN-FC link, is bounded by

\[
n^*_1 \triangleq \frac{\gamma}{\log(2) \left( e - 1 + \frac{|h|^2}{\beta^*} \right) \geq n^* \leq \gamma \log 2 \triangleq n^*_1, 
\]

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

\[
\text{minimize} \quad \frac{1}{N} \sum_{i=1}^{N} f(n_i), 
\]

where \( n \triangleq \{n_1, n_2, \ldots, n_N\} \).

1) TIME DIVISION MULTIPLE ACCESS SYSTEMS

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

\[
B_i = B, \quad \forall. 
\]

\(^1\) 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

\[
\sum_{i=1}^{N} \mathbb{I}(t) \leq 1, 
\]

where \( \mathbb{I}(t) \) 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

\[
\text{minimize} \quad \frac{1}{N} \sum_{i=1}^{N} f(n_i), 
\]

subject to

\[
\sum_{i=1}^{N} \mathbb{I}(t) \leq 1, \quad \forall 0 \leq t \leq k_N + n_N. 
\]

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](image-url)

**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 \( k(n^*_2) \geq k(n^*_1) + n^*_1 \) and...
which, if stated in words, signifies that the transmission order

there are four distinct cases to be considered, namely:

To elaborate further, following the illustration in Figure 3,

are inefficient because they cause the channel to remain

where

Proposition 3 and its proof.

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 optim-
ality 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 > |h_2|^2, \ldots > |h_N|^2.

2) Set \( i = 1 \) and solve equation (9) via bisection using the
bounds in inequalities (17) only for two strongest SNs,

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 \( N \);

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 \( B_t \) used by each SN,
which is a fraction of the total available bandwidth \( B_{\text{total}} \).

In this case, the mean AoI minimization problem can be written as

\[
\text{minimize } n, B \quad \frac{1}{N} \sum_{i=1}^{N} f(n_i, B_i),
\]

(20a)
Algorithm 1 Greedily-Initialized TDMA AoI Minimizer

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

**Initialization:**
1. Set loop counter $i = 1$.
2. Set initial transmission times $n \gg 1$.
3. Set initial harvesting times $k = 0$.
4. Sort SN indices $N$ such that $|h_1|^2 > \cdots > |h_N|^2$.

**Core Procedure:**
5: while $|N| \geq 2$ do
6:   Find the optimal $n^*_i$ and $n^*_i$ by solving (25c).
7:   if $f_B(n^*_i, n^*_i) > f_D(n^*_i, n^*_i)$ then
8:       Swap indices $i$ and $i+1$.
9:   end if
10:  if $i \geq 2$ and (14b) is not satisfied then
11:     Update $k(n_i) = k(n_{i-1}) + n_{i-1}$
12:   end if
13:  Update $N \leftarrow N \setminus i$
14:  Append $n^*$ with $n_i$ and $k^*$ with $k(n_i)$
15:  Update $i \leftarrow i + 1$.
16: end while

subject to $B_{\text{total}} - \sum_{i=1}^{N} B_i = 0$, \hspace{1cm} (20b)

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

Since the objective function given (20a) involves a coupled expression of the optimization variables $n$ and $B$, 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 $B$

$$\begin{align*}
\min_B & \quad \frac{1}{N} \sum_{i=1}^{N} f(B_i|n_i), \\
\text{subject to} & \quad B_{\text{total}} - \sum_{i=1}^{N} B_i = 0.
\end{align*}$$

(II) Optimization problem for transmission time allocation $n$

$$\begin{align*}
\min_n & \quad \frac{1}{N} \sum_{i=1}^{N} f(n_i|B_i).
\end{align*}$$

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:

$$\begin{align*}
B & \leftarrow \arg \min_B L_\rho(B, B_{\text{total}}, u), \\
\theta & \leftarrow \left( B_{\text{total}} - \sum_{i=1}^{N} B_i \right), \\
u & \leftarrow u + \theta,
\end{align*}$$

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

$$L_\rho(B, B_{\text{total}}, u) = \sum_{i=1}^{N} f(B_i|n_i) + \frac{\rho}{2} \left( B_{\text{total}} - \sum_{i=1}^{N} B_i + u \right)^2 + \frac{\rho}{2} u^2.$$  \hspace{1cm} (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:** $E_i \geq 0$, $|h_i|^2 > 0$, $N_0 > 0$, $B_{\text{total}} > 0$, $B_i > 0$, $D_i > 0$, $n_i > 0$, $\epsilon \in N \triangleq \{1, \ldots, N\}$, convergence range $\epsilon$, and number of iterations for outer and inner loops $s^\text{max}$ and $s^\text{in}$.

**Outputs:** Optimal transmission times $n^* \in \mathbb{R}^+$ and optimal bandwidths $B^* \in \mathbb{R}^+$.

1: Initialize outer loop counter to $s^\text{out} = 1$.
2: Set initial transmission time $n^\text{out} \gg 1$ and $\theta \gg 1$.
3: while $s^\text{out} \leq s^\text{max}$ and $|n^\text{out} - n^\text{out-1}| > \epsilon$ do
4: Initialize the inner loop counter to $s^\text{in} = 1$.
5: while $s^\text{in} \leq s^\text{max}$ and $\theta > \epsilon$ do
6: Update $B_i^{\text{in}}$, $\theta^{\text{in}}$ and $u^{\text{in}}$ via equation (23).
7: Update $s^\text{in} \leftarrow s^\text{in} + 1.$
8: end while
9: Find the $n^\text{out}$ by solving (9).
10: Update $s^\text{out} \leftarrow s^\text{out} + 1$.
11: end while

12: $n^* = n^\text{out}$ and $B^* = B^{\text{in}}$.

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 in 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 then transmitted after the SNs the required energy is harvested.

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, 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 point for a localized optimality of FDMA, that is, under certain conditions, a 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.

---

**FIGURE 4.** Average AoI as a function of the number of SNs in TDMA and FDMA with i.i.d. Rayleigh channels.
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 \( E_i = 1.0 \text{[mW]} \), 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.

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.
yields the first-order derivative as follows.

\[
\frac{d}{dn}f(n) = g_1(n) \times g_2(n),
\]

(25a)

with

\[
g_1(n) \triangleq \frac{\beta n}{|h|^2} (2^{\frac{\gamma}{2}} - 1) + n,
\]

(25b)

\[
g_2(n) \triangleq \frac{\beta}{|h|^2} (2^{\frac{\gamma}{2}} - 1) - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{2}} \log 2^{\frac{\gamma}{2}} + 1,
\]

(25c)

where the auxiliary parameters \( \beta \triangleq B N_0/E \) and \( \gamma \triangleq D/B \) were introduced in order to simplify the expressions.

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

\[
\frac{d^2 f(n)}{dn^2} = \frac{d}{dn} (g_1(n) \times g_2(n)) = (g_2(n))^2 \times \left( \frac{\beta}{|h|^2} (2^{\frac{\gamma}{2}} - 1) + 1 \right) \frac{\beta}{|h|^2} 2^{\frac{\gamma}{2}} (\log 2^{\frac{\gamma}{2}})^2,
\]

(26)

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

**APPENDIX C**

**Proof of Proposition 3**

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

\[
1 - \frac{\beta}{|h|^2} + \frac{\beta}{|h|^2} (2 - \log 2^{\frac{\gamma}{2}}) 2^{\frac{\gamma}{2}} - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{2}} = 0,
\]

(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

\[
(2 - \log 2^{\frac{\gamma}{2}}) 2^{\frac{\gamma}{2}} \leq e,
\]

(31)

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

\[
\frac{d}{dx} g_3(x) \bigg|_{x=\bar{x}} = 0,
\]

(32a)

\[
\frac{d^2}{dx^2} g_3(x) = -\frac{1}{\bar{x}} < 0, \; \forall x \geq 0,
\]

(32b)

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

\[
g_3(e) = (2 - \log e)e = e.
\]

(33)

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

\[
g_{2U}(n; h) \triangleq 1 + \frac{\beta}{|h|^2} (e - 1) - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{2}}.
\]

(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

\[
\lim_{n \to +\infty} g_2(n) = \lim_{n \to +\infty} \frac{\beta}{|h|^2} \left( \frac{2^{\frac{\gamma}{2}} - 1}{2^{\frac{\gamma}{2}}} - \frac{\beta}{|h|^2} 2^{\frac{\gamma}{2}} \log 2^{\frac{\gamma}{2}} \right) + 1 = 1,
\]

(28b)
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
\[ g_{2U}(n_L; h) = 0 \implies n_L^* = \frac{\log_2 \left( \frac{|h|^2}{\beta} + e - 1 \right)}{\gamma} \leq n^*. \quad (35) \]

Finally, we note that at the point $2^{\frac{2}{\gamma}} = e$, where the equality $g_{2U}(n; h) = g_2(n; h)$ holds, we have
\[ g_{2U}(n; h) = 1 - \frac{\beta}{|h|^2} > 0, \quad \forall |h|^2 > \beta, \quad (36) \]
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
\[ g_{2U}(n_U; h) = g_2(n_U; h) \implies n_U^* = \gamma \log_2 2 \geq n^*, \quad (37) \]
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
\[ d(n; h_1, h_2) = g_{2U}(n; h_1) - g_{2U}(n; h_2) = \frac{n \beta}{|h_1|^2|h_2|^2} \left( 2^{\frac{2}{\gamma}} + 1 - e \right), \quad (38) \]
which is obviously monotonically decreasing on $n$.

The latter fact, together with the trivial limits
\[ \lim_{n \to +0} d(n; h_1, h_2) = +\infty, \quad (39a) \]
\[ \lim_{n \to +\infty} d(n; h_1, h_2) = +0, \quad (39b) \]
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 $n^*_1$ of $g_{2U}(n; h_1)$ is smaller than the root $n^*_2$ 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
\[ k(n_L^*; h) = \frac{\gamma}{|h|^2} \frac{|h|^2 + \beta(e - 2)}{\log_2 \left( \frac{|h|^2}{\beta} + e - 1 \right)}. \quad (40) \]

In order to prove implication (18a), it is sufficeing to verify that for $|h_1|^2 > |h_2|^2 > \beta$
\begin{align*}
&k(n_1^*; h_2) - k(n_2^*; 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)} \\
&= \frac{\gamma}{|h_2|^2} \log_2 \left( \frac{|h_2|^2}{|h_1|^2} + \beta(e - 1) \right) + \frac{\beta \gamma(e - 2)}{\log_2 \left( \frac{|h_2|^2}{|h_1|^2} + e - 1 \right)} \\
&\quad \times \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_2|^2}{\beta} + e - 1 \right) \log_2 \left( \frac{|h_2|^2}{\beta} + e-1 \right)} \geq 0.
\end{align*}

(41)

In turn, substituting the expression for the upper bound $n_U^*$ given in inequality (37) into equation (6) yields
\[ k(n_U^*; h) = \frac{\beta \gamma(e - 1)}{|h|^2}, \quad (42) \]
from which it follows trivially that $k(n_1^*; h_1) < k(n_2^*; h_2)$ 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
\begin{align*}
\tilde{f}_D(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, \quad (43a) \\
\tilde{f}_D(n_1^*, n_2^*) &= \frac{1}{2} \left( k(n_1^*) + n_2^* \right)^2 + \frac{1}{2} \left( k(n_2^*) + n_1^* \right)^2, \quad (43b)
\end{align*}

First, with respect to inequality (19a), it is readily found from these equations that
\begin{align*}
\tilde{f}_D(n_1^*, n_2^*) \geq & \frac{1}{2} \left( k(n_1^*) + n_2^* \right)^2 + \frac{1}{2} \left( k(n_2^*) + n_1^* \right)^2 \\
&\quad - \frac{1}{2} \left( k(n_1^*) + n_1^* \right)^2 - \frac{1}{2} \left( k(n_1^*) + n_1^* \right)^2 \geq 0,
\end{align*}

(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{align*}
\tilde{f}_D(n_1^*, n_2^*) - &\tilde{f}_D(n_1^*, n_2^*) \\
= &\frac{1}{2} \left( k(n_1^*) + n_2^* \right)^2 + \frac{1}{2} \left( k(n_2^*) + n_2^* \right)^2 \\
&\quad - \frac{1}{2} \left( k(n_1^*) + n_1^* \right)^2 - \frac{1}{2} \left( k(n_1^*) + n_1^* \right)^2 \geq 0.
\end{align*}

(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

\[
\frac{d}{dB_i} f(B_i|n_i) = \left( \alpha_i B_i n_i \left( 2^{\frac{D_i}{B_i}} - 1 \right) + n_i \right) \times \left( \alpha_i n_i \left( 2^{\frac{D_i}{B_i}} - 1 \right) - \alpha_i 2^{\frac{D_i}{B_i}} \log 2 \right),
\]

where we have implicitly defined \( \alpha_i \equiv N_i/[h_i]^2 E_i \).

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

\[
\frac{d^2}{dB_i^2} f(B_i|n_i) = \left( \alpha_i 2^{\frac{D_i}{B_i}} \left( n_i - \log 2 \right) + n_i + 1 \right)^2 \times \alpha_i 2^{\frac{D_i}{B_i}} \log 2 \left( ^2 n_i + \log ^2 B_i \right).
\]

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

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