Energy-Efficient Detection Using Ordered Transmissions in Energy Harvesting WSNs

Sai Kiran Pallapothu and Neelesh B. Mehta, *Senior Member, IEEE*

***Abstract*—We propose a novel energy-efficient ordered transmissions scheme for Bayesian hypothesis testing in energy harvesting (EH) wireless sensor networks (WSNs), in which the EH nodes harvest energy from the environment and can replenish their batteries. The proposed scheme exploits the distributed timer scheme to ensure that the nodes transmit their readings to the fusion node in the decreasing order of their log likelihood ratios without any node knowing the readings of any other node. It addresses the new problem of missing transmissions that arises in EH WSNs because the energy harvested by the nodes is random. We show how the disruption caused in the sequence of ordered transmissions by these missing transmissions can be tackled. The proposed scheme not only reduces the number of transmissions, but also reduces the error probability compared to the conventional unordered scheme in which all the sensor nodes attempt to transmit in a pre-determined order. This is unlike several energy-efficient techniques that reduce the number of transmissions but increase the error probability.**

***Index Terms*—Energy harvesting, WSN, energy-efficiency, ordered transmissions, detection.**

I. Introduction

Wireless sensor networks (WSNs) are finding increasing applications in environmental monitoring, industrial automation, surveillance and security, smart homes, and intelligent transportation [1]–[3]. They consist of several sensor nodes that probe the environment and report their sensed data to a fusion node (FN), which processes the data and estimates parameters or detects outcomes [1]–[3]. To be able to do so, a sensor node requires energy, which is typically provided by a pre-charged battery. However, over time, the sensor node dies because the energy stored in its battery gets depleted.

Several techniques such as censoring [4], [5], on-off keying [6], duty cycling or sleep scheduling [7], [8], and clustering [9], [10] have been proposed to improve the energy-efficiency of the sensor nodes and improve the lifetime of the WSN. However, this also entails an unwelcome degradation in the performance of the WSN.

A notable exception is the ordered transmissions scheme (OTS), which can improve the energy-efficiency without any decrease in performance [11]–[13]. It works as follows for Bayesian hypothesis testing. Each sensor node sets a timer that is inversely proportional to the absolute value of its log-likelihood ratio (LLR). The sensor node transmits its LLR to the FN as soon as its timer expires. This ensures – in a distributed manner – that the nodes transmit in the decreasing order of the absolute values of their LLRs. Every time the FN receives an LLR, it decides upon a hypothesis or allows the nodes to further decrement their timers. Once it decides, it stops the sensor nodes from making any further transmissions. It provably reduces the number of transmissions by at least 50% without any increase in the error rate [11].

Sai Kiran Pallapothu and Neelesh B. Mehta are with the Dept. of Electrical Communication Eng. (ECE), Indian Institute of Science (IISc), Bangalore, India. (Emails: saikiranpallapothu@gmail.com, neeleshbmehta@gmail.com)

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A. *Focus and Contributions*

In this paper, we present a novel energy harvesting (EH)-aware ordered transmissions scheme (EH-OTS) for a WSN that consists of EH sensor nodes. The EH nodes are fundamentally different because they do not permanently die once they drain their battery energy. Instead, they can replenish their batteries by harvesting energy from green renewable sources such as solar, thermal, vibrational, electromagnetic, or mechanical [14]. The potential of an infinite lifetime makes EH WSNs very appealing [14].

In these networks, a critical new issue arises due to the randomness in the energy harvested. Now, the sensor nodes can occasionally have insufficient energy to transmit. As a result, they cannot transmit their sensed data to the FN. These missing transmissions disrupt the sequence of transmissions that the aforementioned ordered transmissions scheme exploits and can render it ineffective. We make the following contributions to address this challenge.

We propose a new scheme called EH-OTS. In it, each EH sensor node sets a timer and transmits a measurement packet to the FN when its timer expires. For Gaussian statistics, we first show that it is sufficient for the measurement packet to contain a non-negative metric that is an affine function of the LLR. The timer is a monotonically non-increasing function of its metric [15], [16]. This ensures that the timer of a node with a larger LLR expires before the timers of nodes with smaller LLRs. Thus, the nodes transmit in the decreasing order of their LLRs – even though no node, including FN, knows the LLR of any other node a priori.

However, in case an EH node does not have sufficient energy in its battery to transmit the measurement packet, it sends a low energy pilot signal. Thus, even though the FN does not get to know the metric of this EH node, it knows that a transmission is missing. For this novel model, in which some ordered metrics can be missing, we propose new decision rules to be used at the FN for Bayesian hypothesis testing.

Given the probability that an EH node has insufficient energy to transmit, we present two key new findings. First, EH-OTS improves the energy-efficiency of the WSN by reducing the average number of sensor nodes that transmit. Second, it

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also yields a lower probability of error, which is defined as the probability that a wrong hypothesis is detected, compared to the unordered transmission scheme (UTS), in which all sensor nodes with sufficient energy attempt to transmit in a pre-determined order that does not depend on their LLRs. This is noteworthy because the technique in [11] reduces the number of transmissions, but not the probability of error.

Lastly, we present Monte Carlo simulation results for an EH WSN in which the energy harvesting and energy storage processes are explicitly modeled. These together with the transmission scheme determine the probability that a node cannot transmit. We observe that the proposed scheme again markedly reduces the probability of error compared to sequential detection [17, Chp. III.D] and UTS.

While EH-OTS seems similar to sequential detection [17], there are several fundamental differences. In sequential detection, the transmissions by the sensor nodes are not ordered as a function of their measurements. Secondly, while calculating the decision thresholds used by sequential detection, it is typically assumed that the number of sensor nodes is sufficiently large and that the FN can wait for a sufficient number of measurements to make a decision that achieves the desired performance. On the other hand, EH-OTS can be designed for any given number of EH sensor nodes.

B. Organization and Notations

This paper is organized as follows. Section II describes the system model. In Section III, we propose new decision rules for ordered transmissions with missing measurements. Numerical results are presented in Section IV, and are followed by our conclusions in Section V.

Notation: $\Pr(\cdot)$ denotes probability. The probability density function (PDF) and cumulative distribution function (CDF) of a random variable (RV) X are denoted by $f_X(\cdot)$ and $F_X(\cdot)$, respectively. The PDF and CDF of X conditioned on a hypothesis H_h are denoted by $f_X(\cdot|H_h)$ and $F_X(\cdot|H_h)$, respectively.

II. System Model

Consider a WSN consisting of N EH sensor nodes and an FN. Time is divided into measurement rounds. At the beginning of each round, sensor node i makes a measurement y_i, for $1 \leq i \leq N$. Within each round, the FN collects measurements from some or all of the sensor nodes and makes a decision about the hypothesis, as explained below.

A. Measurement Model

For ease of exposition and to gain insights, we present the notation and our scheme below for Gaussian statistics [18], [19]. In a round, the measurement y_i by sensor i is given as follows for two hypotheses H_0 and H_1:

$$y_i = \begin{cases} s_i + n_i, & \text{under hypothesis } H_1, \\ n_i, & \text{under hypothesis } H_0. \end{cases} \quad (1)$$

Here, s_i is the random signal component with mean 0 and variance σ_s^2 that is present under H_1 and is absent under H_0, and n_i is the measurement noise with mean 0 and variance σ_n^2. The signal components $s_1, \ldots, s_N$ are independent and identically distributed (i.i.d.) RVs. Furthermore, $n_1, \ldots, n_N$ are i.i.d. RVs, and are mutually independent of $s_1, \ldots, s_N$.

We shall assume that the absolute values of the measurements are bounded above by a threshold τ, i.e., $|y_i| \leq \tau$. In practice, this is a mild assumption since the measurements inevitably saturate. When τ is sufficiently large (but finite), the probability of the event $y_i > \tau$ is negligible. The technical reason for this assumption is explained in Section III-B. Hence, the PDFs of the measurement $y_i \in [-\tau, \tau]$ conditioned on the two hypotheses are given by

$$f_{Y_i}(y_i|H_0) = \frac{1}{\sqrt{2\pi}\sigma_n \left(1 - 2Q\left(\frac{\tau}{\sigma_n}\right)\right)} \exp\left(-\frac{y_i^2}{2\sigma_n^2}\right), \quad (2)$$

$$f_{Y_i}(y_i|H_1) = \frac{1}{\sqrt{2\pi}\sigma_1 \left(1 - 2Q\left(\frac{\tau}{\sigma_1}\right)\right)} \exp\left(-\frac{y_i^2}{2\sigma_1^2}\right), \quad (3)$$

where $\sigma_1 = \sqrt{\sigma_s^2 + \sigma_n^2}$ and $Q(\cdot)$ denotes the Gaussian Q-function [20].

Let c_{uv} be the cost incurred if hypothesis H_u is chosen when hypothesis H_v is true, and let p be the prior probability of the hypothesis H_1.

B. Modeling Impact of EH

An EH node does not transmit if it does not have enough energy in its battery. We first model this using a transmission miss probability ρ. Thereafter, in Section IV-A, we also model the dependency of ρ on the transmission scheme itself.

C. Proposed Scheme EH-OTS

Before presenting the proposed scheme, we first revisit the LLR-based Bayesian hypothesis test, which provably minimizes the probability of error [17]. We show that it can be equivalently written in terms of a metric that is non-negative. We shall exploit this result in designing EH-OTS.

Lemma 1. *Let $\Theta_i = y_i^2$. The optimal detection test that minimizes the probability of error is given by*

$$\sum_{i=1}^{N} \Theta_i \underset{H_0}{\overset{H_1}{\gtrless}} \lambda, \quad (4)$$

where $\lambda = \frac{2\sigma_n^2\sigma_1^2}{\sigma_s^2}\left[a + N\ln\left(\frac{\sigma_1}{\sigma_n}\right) + N\ln\left(\frac{1-2Q(\tau/\sigma_1)}{1-2Q(\tau/\sigma_n)}\right)\right]$ *and* $a = \ln\left(\frac{(c_{10}-c_{00})(1-p)}{(c_{01}-c_{11})p}\right)$.

Proof: The proof is relegated to Appendix A. ■

We shall henceforth refer to Θ_i as the *metric* of sensor node i. From the appendix, it can be seen that it is an affine function of the LLR. Using order statistics notation [21], let $[i]$ denote the index of the sensor node with the i^{th} largest value of Θ_i, for $1 \leq i \leq N$. Hence, $\Theta_{[1]} > \Theta_{[2]} > \cdots > \Theta_{[N]}$. The above test in (4) is then equivalent to

$$\sum_{i=1}^{N} \Theta_{[i]} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda. \quad (5)$$

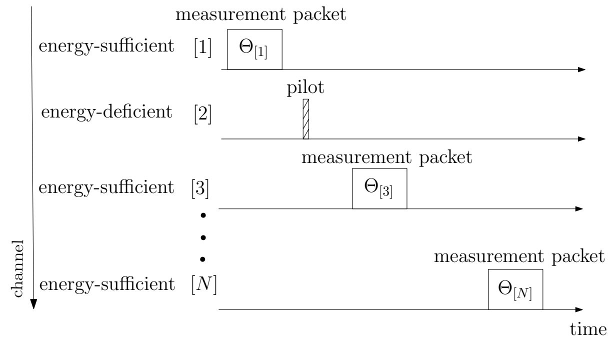

Fig. 1. Energy-sufficient and energy-deficient nodes transmitting measurement packets and pilot signals, respectively, in the order of their metrics as per the timer scheme. In the illustration, EH sensor node [2] is energy-deficient and misses its transmission.

A sensor node can transmit its metric to the FN, which requires an energy E_{tx}, only if the energy stored in its battery at the beginning of the round exceeds E_{tx}. In such a case, we say that the sensor node is *energy-sufficient* in that round. Else, we say that it is *energy-deficient*.

With non-negative metrics, the proposed scheme is as follows. A sensor node i sets its timer as a monotonically non-increasing function of its metric Θ_i [15], [16]. When the timer expires, the sensor node transmits a packet to the FN if it is energy-sufficient. The packet contains the metric Θ_i as its data. Else, if the node is energy-deficient, it sends a low-energy pilot signal to the FN, which consumes an energy qE_{tx}. While a measurement packet contains a header and tail to indicate the start and end of the packet, synchronization and training fields, and the metric [2], [3], a pilot signal is a small burst of energy that need not carry any information. Hence, $q \ll 1$.[1] The sensor nodes transmit over orthogonal channels so that the measurement packets or pilot signals transmitted by different sensor nodes do not collide [11]. The FN senses all the channels. The transmission model is illustrated in Figure 1.

As mentioned, the timer scheme ensures that the nodes transmit in the decreasing order of their metrics, even though no node knows the metric of any other node a priori. Every time the FN receives a measurement packet, it employs the decision rules, which we present in Section III, to decide between H_0 and H_1. If it senses a pilot signal, it does not get to know the metric but it does know that a sensor node has missed its turn to transmit. It then waits for the next measurement packet or it makes a decision if no more sensor nodes are left to transmit.

Once the FN has made a decision, it broadcasts a control signal to all the sensor nodes to halt their timers for the rest of the round. Else, the nodes continue to decrement their timers. The process starts afresh at the beginning of every round.

[1]We assume that a sensor node maintains an energy reserve so that it can transmit pilot signals even if it is energy-deficient for several measurement rounds. The capacity of this energy reserve will be small since $q \ll 1$. For example, even a storage capacity of wE_{tx}, for $w \geq 1$, is sufficient to support $w/q \gg 1$ pilot transmissions.

III. New Decision Rules

We first revisit the design rules for the case in which all the sensor nodes are energy-sufficient and there are no missed transmissions. While this scenario has been considered in [11], the decision rules that we derive are novel and different. This is because, as per Lemma 1, the metric Θ_i of sensor node i is an affine, non-negative function of its LLR L_i. This is unlike [11], in which the metric is the absolute value of LLR, and, thus, lacks information about the sign of the LLR. We then derive new decision rules when there are missing transmissions.

A. No Missing Transmissions

Let the first k ordered metrics $\Theta_{[1]}, \Theta_{[2]}, \ldots, \Theta_{[k]}$, for $1 \leq k \leq N$, be available at the FN due to the use of the aforementioned timer scheme. Then, as derived in Appendix B, the new decision rules are as follows:

$$\text{Decide } H_1 \text{ if} : \sum_{i=1}^{k} \Theta_{[i]} > \lambda, \tag{6}$$

$$\text{Decide } H_0 \text{ if} : \sum_{i=1}^{k} \Theta_{[i]} < \lambda - (N-k)\Theta_{[k]}. \tag{7}$$

Notably, the appendix also shows that doing so leads to the same decision as having all the N metrics at the FN. If neither (6) nor (7) is satisfied, then the FN waits for the next transmission, which will be by node $[k+1]$. It can be shown that after all the N nodes transmit, either (6) or (7) will always hold. Hence, the FN will always make a decision.

B. With Missing Transmissions

Consider the general case where the FN has received the metric from sensor node $[k]$, for $1 \leq k \leq N$, and the sensor nodes $[m_1], [m_2], \ldots, [m_j]$, for $1 \leq j < k$, are energy-deficient and have, thus, missed their transmissions. Let p_l be the largest integer that is less than m_l such that the sensor node $[p_l]$ is energy-sufficient. If all the sensor nodes $[1], \ldots, [m_l]$ are energy-deficient, then $p_l \triangleq 0$. Similarly, let n_l be the smallest integer that is greater than m_l such that the sensor node $[n_l]$ is energy-sufficient. If all the sensor nodes $[m_l], [m_l+1], \ldots, [N]$ are energy-deficient, then $n_l \triangleq N+1$. Further, we define $\Theta_{[0]} \triangleq \tau^2$ and $\Theta_{[N+1]} \triangleq 0$. Since $|y_i| \leq \tau$, it follows that $\Theta_i \leq \tau^2 = \Theta_{[0]}$, for all $1 \leq i \leq N$.

The following key result, which is derived in Appendix C, provides a compact representation of the new decision rules for the scenario with missing transmissions:

$$\text{Decide } H_1 \text{ if} : \sum_{i=1, i \notin \{m_1,\ldots,m_j\}}^{k} \Theta_{[i]} > \lambda - \sum_{l=1}^{j} \Theta_{[n_l]}, \tag{8}$$

$$\text{Decide } H_0 \text{ if} : \sum_{i=1, i \notin \{m_1,\ldots,m_j\}}^{k} \Theta_{[i]} < \lambda - \sum_{l=1}^{j} \Theta_{[p_l]} - (N-k)\Theta_{[k]}. \tag{9}$$

Notably, we see from the derivation in the appendix that if either (8) or (9) holds, then the decision is the same as

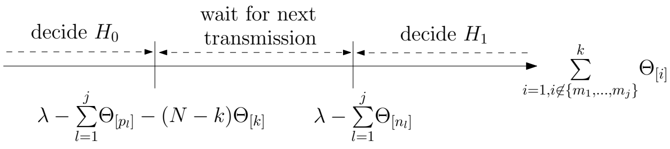

Fig. 2. The decision regions when j sensor nodes $[m_1], [m_2], \ldots, [m_j]$ missed their transmissions and the most recent metric is received by the FN from sensor node $[k]$.

that based on knowing all the N metrics, including even the missed ones! If neither (8) nor (9) is satisfied, the FN waits for the next transmission by the node $[k+1]$. The decision rules are illustrated in Figure 2.

With missed transmissions, the scenario in which the FN has not made a decision and no more energy-sufficient nodes exist to transmit their metrics can occur. The FN can detect such a scenario by waiting until the maximum allowed selection time $T_{\max}$ that was budgeted for the timer scheme. In such a scenario, the FN decides the hypothesis based on the available $N-j$ metrics in a manner similar to UTS [17]. Specifically, it decides H_1 if

$$\sum_{i=1, i \notin \{m_1, \ldots, m_j\}}^{N} \Theta_{[i]} > \lambda - \frac{2j\sigma_n^2\sigma_1^2}{\sigma_s^2} \ln\left(\frac{\sigma_1}{\sigma_n}\right) - \frac{2j\sigma_n^2\sigma_1^2}{\sigma_s^2} \ln\left(\frac{1-2Q\left(\tau/\sigma_1\right)}{1-2Q\left(\tau/\sigma_n\right)}\right), \quad (10)$$

and H_0, otherwise. In the extreme case in which all the N transmissions are missed, the above decision rules do not apply. Instead, the FN just declares the hypothesis that has a higher prior probability as its decision.

To understand the above rule better, consider the example in which only one transmission is missed, i.e., $j = 1$. Then, the decision rules become

$$\text{Decide } H_1 \text{ if}: \sum_{i=1, i \neq m_1}^{k} \Theta_{[i]} > \lambda - \Theta_{[m_1+1]}, \quad (11)$$

$$\text{Decide } H_0 \text{ if}: \sum_{i=1, i \neq m_1}^{k} \Theta_{[i]} < \lambda - (N-k)\Theta_{[k]} - \Theta_{[m_1-1]}. \quad (12)$$

If $m_1 = N$, then the decision rule for H_1 gets modified as $\sum_{i=1}^{N-1} \Theta_{[i]} > \lambda$, since $\Theta_{[N+1]} = 0$. If $m_1 = 1$, then the decision rule for H_0 gets modified as $\sum_{i=2}^{k} \Theta_{[i]} < \lambda - (N-k)\Theta_{[k]} - \Theta_{[0]}$.[2]

IV. Numerical Results

We now present Monte Carlo simulation results for benchmarking the performance of EH-OTS. We first specify the probability ρ that a node is energy-deficient, and evaluate the average number of transmissions and the probability of error as a function of ρ. Thereafter, in Section IV-A, we present results when the energy harvesting and energy storage processes are explicitly modeled. These together with the transmission scheme determine ρ.

[2]Without the bound $\Theta_{[1]} \leq \Theta_{[0]} = \tau^2$, we see from (12) that $\lambda - (N-k)\Theta_{[k]} - \Theta_{[0]}$ is $-\infty$. As a result, the FN cannot make an early decision about H_0. As discussed, this bound is a mild assumption in practice.

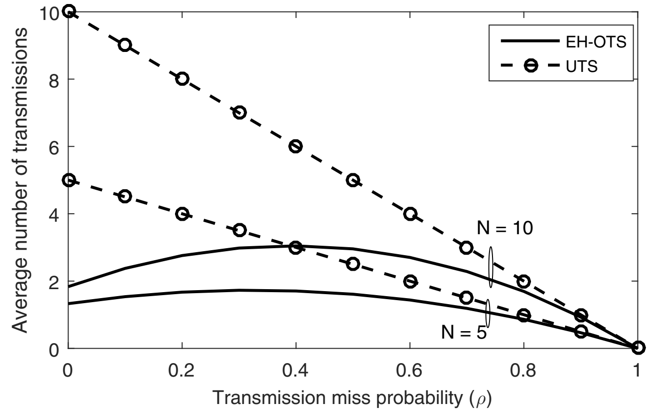

Fig. 3. Comparison of the average number of transmissions as a function of the transmission miss probability ρ for different values of N.

We simulate the system for a duration of 10^6 rounds. We consider the uniform cost model with $c_{uv} = 1$, if $u \neq v$, and $c_{uv} = 0$, if $u = v$ [11], [17]. We set $\Pr(H_1) = 0.1$, $\sigma_n^2 = 1$, and $\tau = 3\sqrt{\sigma_s^2 + \sigma_n^2}$. The signal-to-noise ratio (SNR) σ_s^2/σ_n^2 is set as 10 dB.

Figure 3 plots the average number of transmissions for EH-OTS and UTS as a function of ρ for different numbers of sensor nodes N. We note that EH-OTS for the special case of $\rho = 0$ reduces to the scheme in [11]. As ρ increases from 0 to 0.4, the average number of transmissions of EH-OTS increases initially. This is because a missed metric will typically require the transmission of multiple subsequent metrics, as they are smaller. As ρ increases further beyond 0.4, the average number of transmissions decreases due to the lack of energy-sufficient nodes. It eventually becomes 0 at $\rho = 1$, since no nodes transmit. For UTS, the average number of transmissions is equal to $N(1-\rho)$. It also eventually becomes 0 at $\rho = 1$. For any $\rho < 1$ and any N, the average number of transmissions is smaller for EH-OTS. For example, at $\rho = 0$, EH-OTS requires 72% and 80% fewer transmissions on average than UTS for $N = 5$ and 10, respectively.

Figure 4 plots the probability of error as a function of ρ for EH-OTS and UTS for different N. For both schemes, it increases as ρ increases and approaches $\Pr(H_1)$. This is because fewer metrics are available at the FN to make a decision about the hypothesis. The probability of error for the two schemes is the same for $\rho = 0$ and for $\rho = 1$. This is because at $\rho = 0$, a node will be energy-sufficient in both schemes. Therefore, it will transmit every time its timer expires. At $\rho = 1$, no node will transmit and the probability of error for both schemes is $\Pr(H_1) = 0.1$. Notably, for all $0 < \rho < 1$ and for all N, the probability of error for EH-OTS is less than that of UTS. This is because, with ordering, the FN can exploit information about the range in which the missing metrics lie. We note that this behavior does not occur in [11], and shows a surprising double-benefit of ordering.

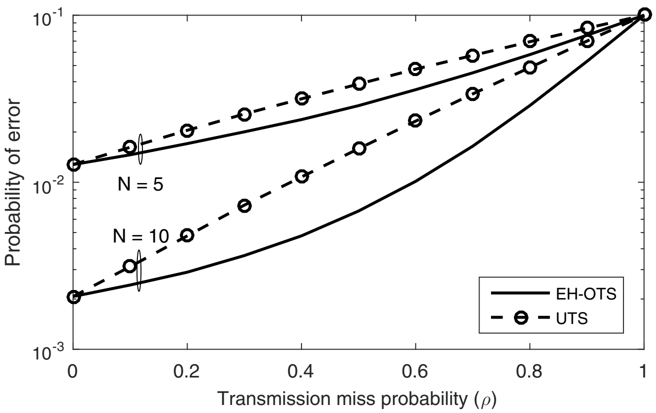

Fig. 4. Comparison of the probability of error as a function of the transmission miss probability ρ for different values of N.

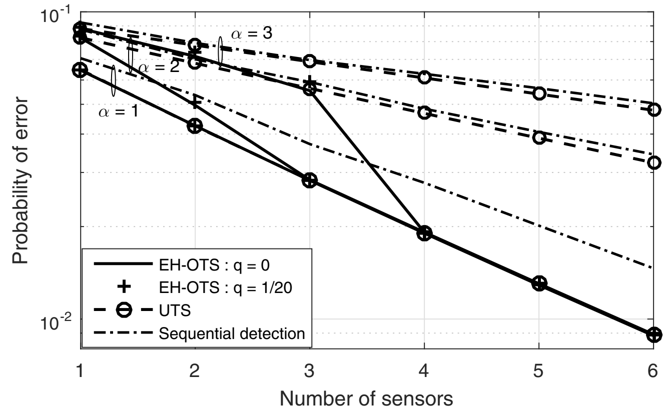

Fig. 5. Performance benchmarking: Probability of error of EH-OTS, UTS, and sequential detection for an EH WSN as a function of N for different α.

A. Simulation of EH WSN Without Explicitly Specifying ρ

We now present results from a more comprehensive simulation model in which the physically intuitive energy harvesting and storage models are specified. We no longer fix ρ, which depends on the statistics of the energies harvested and consumed; the latter depends on the transmission scheme itself.

Each EH sensor node harvests energy E_h with probability p_h at the beginning of each round and harvests no energy with probability $(1 - p_h)$ [22]. The node stores the harvested energy in its battery for transmitting data or pilots to the FN in the current or future measurement rounds. The batteries are assumed to have unlimited capacity [19]. Let $\alpha = E_{\text{tx}}/(p_h E_h)$ denote the ratio of the energy E_{tx} required to transmit a measurement packet to the average energy harvested $p_h E_h$ in a round. Equivalently, a sensor node requires the energy harvested in α rounds to transmit one measurement packet to the FN, on average. As mentioned, the energy required to transmit a pilot signal is equal to qE_{tx}, where $q \ll 1$.

We simulate the system for a duration of 10^6 measurement rounds, and track the evolution of the battery energy in each node. As above, we set $c_{01} = c_{10} = 1$ and $c_{00} = c_{11} = 0$. Furthermore, $E_h = 1$, $p_h = 0.5$, $\Pr(H_1) = 0.1$, $\sigma_n^2 = 1$, $\tau = 3\sqrt{\sigma_s^2 + \sigma_n^2}$, and SNR $= 10$ dB. Before the first round, zero energy is stored in the batteries of all the sensor nodes.

Figure 5 plots the probability of error as a function of N for $\alpha = 1$, 2, and 3 for EH-OTS, UTS, and sequential detection.[3] Results are shown for the case when the pilot energy is negligible ($q = 0$) and when it is not ($q = 1/20$).

When $q = 0$: For $\alpha = 1$, all the sensor nodes are energy-sufficient with probability 1, since the energy harvested in a round is the same as that required by a transmission. Therefore, the probability of error of EH-OTS and UTS is the same. However, for $\alpha = 2$ and 3, the probability of error of EH-OTS is markedly lower than that of UTS and sequential detection. For example, for $N = 4$, it is lower than that of UTS by a factor of 2.44 and 3.19 for $\alpha = 2$ and 3, respectively. The reason behind this is the fewer transmissions that occur in EH-OTS because of the information it exploits about the range in which the missing metrics lie. Also note that the probability of error for EH-OTS for $N \geq 3$ when $\alpha = 2$ and for $N \geq 4$ when $\alpha = 3$ is the same as that for $\alpha = 1$. This is because the nodes become energy-sufficient with probability 1 in this regime.

When $q = 1/20$: There is a marginal increase in the probability of error of EH-OTS for $N \leq 2$ when $\alpha = 2$ and for $N \leq 3$ when $\alpha = 3$. This is because the probability that a node becomes energy-deficient marginally increases as it spends some of its energy in transmitting pilots. As N increases, the probability of error of both schemes decreases monotonically as there are fewer missing transmissions.

V. Conclusions and Future Work

We proposed a novel ordered transmissions scheme for an EH WSN, in which some sensor nodes were unable to transmit due to lack of sufficient energy. For the same transmission miss probability, we saw that the new decision rules that we derived not only reduced the average number of sensor nodes that transmitted but also the probability of error, compared to the conventional unordered transmissions scheme. For an EH WSN, it achieved a markedly lower probability of error than the unordered transmissions scheme and sequential detection.

Interesting avenues for future work include modeling the effect of deep channel fades, which can also cause the transmissions from the sensor nodes to not be decodable at the FN, and adapting the transmit power as a function of the channel gain between the sensor node and the FN to improve the energy-efficiency further.

Appendix

A. Proof of Detection Test

Let $L_i = \ln\left(f_{Y_i}(y_i|H_1)/f_{Y_i}(y_i|H_0)\right)$ denote the LLR of sensor node i. Substituting the conditional PDFs of y_i in (2)

[3]For sequential detection, the thresholds are chosen as per [17, Chp. III.D]. In order to ensure a fair comparison, the target false alarm and missed detection probabilities are set to be the same as those observed for EH-OTS. In case no more energy-sufficient EH nodes remain and a decision is yet to be made, then the FN decides the hypothesis along the lines of UTS.

and (3) and simplifying, we get

$$L_i = \ln\left(\frac{\sigma_n}{\sigma_1}\right) + \ln\left(\frac{1-2Q\left(\tau/\sigma_n\right)}{1-2Q\left(\tau/\sigma_1\right)}\right) + \frac{y_i^2}{2}\frac{\sigma_s^2}{\sigma_1^2\sigma_n^2}. \quad (13)$$

For Bayesian hypothesis testing with prior probability $p = \Pr(H_1)$ and costs c_{00}, c_{01}, c_{10}, and c_{11}, the optimal detection test that minimizes the probability of error is given by [17]

$$\sum_{i=1}^{N} L_i \underset{H_0}{\overset{H_1}{\gtrless}} \ln\left(\frac{(c_{10}-c_{00})(1-p)}{(c_{01}-c_{11})p}\right). \quad (14)$$

Substituting (13) in (14) and rearranging terms yields (4).

B. Decision Rules When No Transmission is Missed

From (5), the test for deciding hypothesis H_1 is $\sum_{i=1}^{N}\Theta_{[i]} > \lambda$. Splitting this summation in terms of the received metrics $\Theta_{[1]},\ldots,\Theta_{[k]}$ and the yet-to-be received metrics $\Theta_{[k+1]},\ldots,\Theta_{[N]}$, we get

$$\sum_{i=1}^{k}\Theta_{[i]} + \sum_{i=k+1}^{N}\Theta_{[i]} > \lambda. \quad (15)$$

Since $\Theta_{[i]} < \Theta_{[k]}$, for $i > k$, we get

$$\sum_{i=1}^{k}\Theta_{[i]} + (N-k)\Theta_{[k]} > \lambda. \quad (16)$$

Rearranging terms, we get $\sum_{i=1}^{k}\Theta_{[i]} > \lambda - (N-k)\Theta_{[k]}$.

Similarly, the test for hypothesis H_0 is $\sum_{i=1}^{N}\Theta_{[i]} < \lambda$. Using $\Theta_{[i]} \geq 0$, we get $\sum_{i=1}^{k}\Theta_{[i]} < \lambda$.

Therefore, if $\sum_{i=1}^{k}\Theta_{[i]} > \lambda$, the FN decides H_1. Else, if $\sum_{i=1}^{k}\Theta_{[i]} < \lambda-(N-k)\Theta_{[k]}$, the FN decides H_0. Otherwise, it awaits the next transmission. We also see that this leads to the same decision as having the metrics of all the N nodes.

C. Decision Rules When Multiple Transmissions are Missed

Let transmissions of j sensor nodes $[m_1],[m_2],\ldots,[m_j]$ be missed, where $1 \leq m_1 < \cdots < m_j < k \leq N$. From (5), the test for deciding hypothesis H_1 is $\sum_{i=1}^{N}\Theta_{[i]} > \lambda$. Splitting this summation in terms of the received, missed, and yet-to-be received metrics, we get

$$\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} + \sum_{l=1}^{j}\Theta_{[m_l]} + \sum_{i=k+1}^{N}\Theta_{[i]} > \lambda. \quad (17)$$

Since $\Theta_{[m_l]} < \Theta_{[p_l]}$, for $1 \leq l \leq j$, and $\Theta_{[i]} < \Theta_{[k]}$, for $k < i \leq N$, it follows that

$$\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} + \sum_{l=1}^{j}\Theta_{[p_l]} + (N-k)\Theta_{[k]} > \lambda. \quad (18)$$

Rearranging terms, we get $\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} > \lambda - \sum_{l=1}^{j}\Theta_{[p_l]}-(N-k)\Theta_{[k]}$. Similarly, the test for hypothesis H_0 is $\sum_{i=1}^{N}\Theta_{[i]} < \lambda$. Using $\Theta_{[m_l]} > \Theta_{[n_l]}$, for $1 \leq l \leq j$, and $\Theta_{[i]} > 0$, we get $\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} < \lambda - \sum_{l=1}^{j}\Theta_{[n_l]}$.

Therefore, if $\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} > \lambda - \sum_{l=1}^{j}\Theta_{[n_l]}$, the FN decides H_1. Else, if $\sum_{i=1, i\notin\{m_1,\ldots,m_j\}}^{k}\Theta_{[i]} < \lambda - \sum_{l=1}^{j}\Theta_{[p_l]} - (N-k)\Theta_{[k]}$, the FN decides H_0. Otherwise, it awaits the next transmission. If $k \leq N$, we see that this leads to the same decision as having the metrics of all the N nodes.

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