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Opportunistic Carrier Sensing for Energy-Efficient Information Retrieval in Sensor Networks

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We consider distributed information retrieval for sensor networks with cluster heads or mobile access points. The performance metric used in the design is energy efficiency defined as the ratio of the average number of bits reliably retrieved by the access point to the total amount of energy consumed. A distributed opportunistic transmission protocol is proposed using a combination of carrier sensing and backoff strategy that incorporates channel state information (CSI) of individual sensors. By selecting a set of sensors with the best channel states to transmit, the proposed protocol achieves the upper bound on energy efficiency when the signal propagation delay is negligible. For networks with substantial propagation delays, a backoff function optimized for energy efficiency is proposed. The design of this backoff function utilizes properties of extreme statistics and is shown to have mild performance loss in practical scenarios. We also demonstrate that opportunistic strategies that use CSI may not be optimal when channel acquisition at individual sensors consumes substantial energy. We show further that there is an optimal sensor density for which the opportunistic information retrieval is the most energy efficient. This observation leads to the design of the optimal sensor duty cycle.

Keywords and phrases: sensor networks, distributed information retrieval, opportunistic transmission, energy efficiency.

1. INTRODUCTION

A key component in the design of sensor networks is the process by which information is retrieved from sensors. In an ad hoc sensor network with cluster heads/gateway nodes, sensors send their packets to their cluster heads using a certain transmission protocol [1, 2, 3]. For sensor networks with mobile access [4, 5], data are collected directly by the mobile access points (see Figure 1). In both cases, a population of sensors (those in the same coverage area of an access point) must share a common wireless channel. Thus, an information retrieval protocol that determines which sensors should transmit and the rates of transmissions needs to be designed for efficient channel utilization.

Distributed information retrieval allows each sensor, by itself, to determine whether it should transmit and the rate of transmission. One such example is ALOHA in which each sensor flips a coin (possibly biased by its channel state) to determine whether it should transmit [6, 7]. Another example is a fixed TDMA schedule by which each sensor transmits in a predetermined time slot. A centralized protocol, in contrast, requires the scheduling by the access point. A particularly relevant technique is the so-called opportunistic scheduling [8, 9] by which the access point determines which sensor should transmit according to the channel states of the sensors. In this paper, we are interested in distributed information retrieval which, in the context of sensor networks, has many advantages: less overhead, more robust against node failures, and possibly more energy efficient.

1.1. Energy-efficient opportunistic transmission

By opportunistic transmission we mean that the information retrieval protocol utilizes the channel state information (CSI). Specifically, suppose that the channel states of a set of activated sensors are obtained. An opportunistic transmission protocol chooses, according to some criterion, a subset of activated sensors to transmit and determines their transmission rates. Knopp and Humblet [8] showed that, to maximize the sum capacity under the average power constraint, the opportunistic transmission that allows a single user with

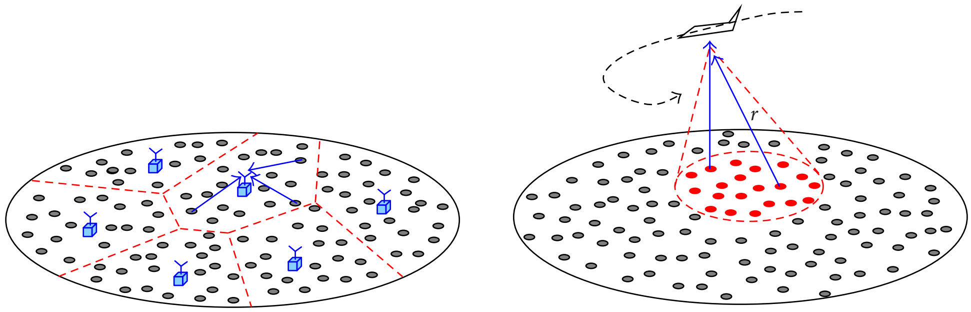

FIGURE 1: Information retrieval in sensor networks.

the best channel to transmit is optimal. Other opportunistic schemes include [6, 7, 9, 10, 11, 12, 13] and the references therein.

The idea of opportunistic information retrieval, at the first glance, is appealing for sensor networks where energy consumption is of primary concern. If the channel realization of a sensor is favorable, the sensor can transmit at a lower power level for the same rate or at a higher rate using the same power. If the sensor has a poor channel, on the other hand, it is better that the sensor saves the energy by not transmitting (and not creating interference to others). What is missing in this line of argument, however, is the cost of obtaining channel states and the cost of determining opportunistic scheduling. If it takes a considerable amount of energy to estimate the channel at each sensor and if determining the set of sensors with the best channels requires additional communications among sensors, it is no longer obvious that an opportunistic information retrieval is more energy efficient than a strategy—for example, using a predetermined schedule—that does not require the channel state information.

It is necessary at this point to specify the performance metric used in the design of information retrieval protocols. For sensor networks, we use energy efficiency (bits/Joule) defined by the ratio of the expected total number of bits reliably received at the access point and the total energy consumed. Here we will include both the energy radiated at the transmitting antenna and the energy consumed in listening, computation, and channel acquisition (when an opportunistic strategy is used). For sensor networks, it has been widely recognized that energy consumption beyond transmission can be substantial [3, 4, 14].

Using energy efficiency as the metric, we aim to address the following questions. If channel acquisition consumes energy, is opportunistic transmission strategy optimal? What would be an energy-efficient *distributed* opportunistic information retrieval? What network parameters affect the energy efficiency? Can these parameters be designed optimally?

While it is debatable whether the information theoretic metric of energy efficiency is appropriate for sensor networks, our goal is to gain insights into the above fundamental questions. It should also be emphasized that the distributed opportunistic protocol developed in this paper applies also to noninformation theoretic metrics such as throughput and throughput per unit cost.

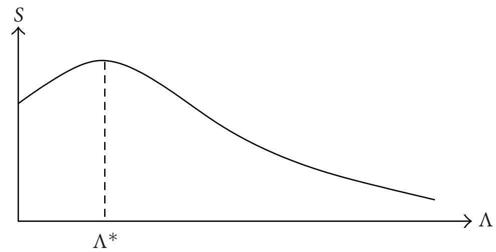

FIGURE 2: Energy-efficiency characteristics.

1.2. Summary of results

The contribution of this paper is twofold. First, we demonstrate that when the cost of channel acquisition is small as compared to the energy consumed in transmission, the opportunistic transmission is optimal. However, when the average number of activated sensors exceeds a certain threshold, the opportunistic strategy looses its optimality; its energy efficiency approaches zero as the average number of activated sensors approaches infinity. Figure 2 illustrates the generic characteristics of the energy efficiency of the opportunistic transmission where Λ denotes the average number of activated sensors. When Λ is small, the gain in sum capacity due to the use of the best channel dominates the increase in energy consumption. As Λ increases beyond a certain value, the energy cost for acquiring the channel state of every activated sensor overrides the improvement in sum capacity. It is thus critical that the average number Λ of activated sensors be optimized. In Section 5, we study possible schemes of controlling Λ by the design of the sensor duty cycle.

Second, we propose opportunistic carrier sensing—a distributed protocol that achieves a performance upper bound assumed by the centralized opportunistic transmission. The key idea is to incorporate local CSI into the backoff strategy of carrier sensing. Specifically, a decreasing function is used to map the channel state to the backoff time. Each sensor, after measuring its channel, generates the backoff time according to this backoff function. When the propagation delay is negligible, the decreasing property of the backoff function ensures that the sensor with the best channel state seizes the channel. To minimize the performance loss caused by propagation delay, the backoff function is constructed to balance the energy consumed in carrier sensing and the energy wasted in collision. This protocol also provides a distributed solution to the general problem of finding the maximum/minimum.

1.3. Related work

The metric of energy efficiency considered in this paper can be traced back to capacity per unit cost [15, 16]. For sensor networks, such a metric captures important design tradeoffs. However, the literature on using this metric for sensor networks is scarce. Our results explicitly include energy consumed in channel acquisition and listening.

The idea of using CSI was sparked by the work of Knopp and Humblet [8]. Exploiting CSI induces multiuser diversity as the performance increases with the number of users [9, 10]. Throughput optimal scheduling for downlink over time-varying channels by a central controller has been considered in [17, 18], all assuming the knowledge of the channel states at no cost. Decentralized power allocation based on channel states was investigated by Telatar and Shamai under the metric of sum capacity [12]. Viswanath et al. [19] have shown the asymptotic optimality of a decentralized power control scheme for a multiaccess fading channel that uses CDMA with an optimal receiver. The effect of decentralized power control on the sum capacity of CDMA with linear receivers and single-user decoders was studied by Shamai and Verdú in [20]. All the work along this line uses rate, not the energy efficiency, as the performance metric. Using channel state information in random access has been considered in [6, 7, 21]. Qin and Berry, in particular, aimed to schedule the sensor with the best channel to transmit by a distributed protocol—channel-aware ALOHA [7]. The throughput of channel-aware ALOHA, however, is limited by the efficiency of the conventional ALOHA protocol.

1.4. Organization of the paper

In Section 2, we state the network model. The performance of the opportunistic transmission is addressed in Section 3 where we obtain a performance upper bound and characterize the optimal number of transmitting sensors in the opportunistic transmission. In Section 4, we propose opportunistic carrier sensing. A backoff function is constructed and its robustness to propagation delay is demonstrated. In Section 5, we focus on the optimality of the opportunistic transmission. Optimal sensor activation schemes are discussed. Section 6 concludes the paper.

2. THE NETWORK MODEL

2.1. The sensor network

We assume that the sensor nodes form a two-dimensional Poisson field[1] with mean λ. The number M of active sensors that share the wireless channel to an access point is thus a Poisson random variable with mean $\Lambda = a\lambda$ where a denotes the coverage area of the mobile access point or the size of the cluster, that is,

$$P[M = m] = \frac{e^{-\Lambda} m^{\Lambda}}{m!}. \quad (1)$$

For a sensor network with mobile access, we consider a single access point. For a sensor network under the structure of clusters, we focus on the information retrieval within one cluster. We assume that there is no interference among adjacent clusters (which can be achieved by, for example, assigning different frequencies to adjacent clusters) and the sensors within the cluster transmit directly to the cluster head as considered in [3]. Thus, information retrieval for a sensor network with mobile access or cluster heads can be modeled as a many-to-one communication problem. Aiming at providing insights to fundamental questions on opportunistic transmission, we further assume that sensors within the coverage area of the mobile access point or the same cluster can hear each other's transmission.

2.2. The wireless fading channel

The physical channel between an active sensor and the access point is subject to flat Rayleigh fading with a block length of T seconds, which is also the length of transmission slot. The channel is thus constant within each slot and varies independently from slot to slot.

Consider the first slot where n nodes transmit simultaneously. The received signal $y(t)$ at the access point can be written as

$$y(t) = \sum_{i=1}^{n} h_i x_i(t) + n(t), \quad 0 \le t \le T, \quad (2)$$

where h_i is the channel fading process experienced by sensor i, $n(t)$ the white Gaussian noise with power spectrum density $N_0/2$, and $x_i(t)$ the transmitted signal with fixed power P_{out}. We point out that the power constraint used here is different from the long-term average power constraint considered in [8]. We assume that sensors can only transmit at a fixed power level P_{out} and do not have the capability of allocating power over time. Define

$$\rho \triangleq \frac{P_{\text{out}}}{WN_0}. \quad (3)$$

Let

$$\gamma_i \triangleq |h_i|^2 \sim \exp(\overline{\gamma}_i) \quad (4)$$

denote the channel gain from sensor i to the access point. Under independent Rayleigh fading, γ_i is exponentially distributed with mean $\overline{\gamma}_i$. The average received SNR of sensor i is thus given by $\rho\overline{\gamma}_i$.

[1] As shown in [22], the difference (in terms of network connectivity) between a Poisson field and a uniformly distributed random field is negligible when the number of nodes is large. For the simplicity of the analysis, we assume a Poisson distributed sensor network.

2.3. The energy consumption model

In each slot, energy consumed by active sensors may come from three operations: transmission, reception, and scheduling.

Let E_r and E_t denote, respectively, total energy consumed in receiving and transmitting in one slot. We have [14]

$$E_r = \mathbb{E}\left[P_{\text{rx}}\sum_{i=1}^{M} T_{\text{rx}}(i)\right], \tag{5}$$

$$E_t = \mathbb{E}\left[P_{\text{tx}}\sum_{i=1}^{M} T_{\text{tx}}(i)\right], \tag{6}$$

where the expectation is with respect to M, $T_{\text{rx}}(i)$, and $T_{\text{tx}}(i)$ are the average reception and transmission time of node i, P_{rx} is the sensor's receiver circuitry power, P_{tx} is the power consumed in transmission which consists of transmitter circuitry power and antenna output power P_{out}.

In the distributed opportunistic transmission, active sensors perform synchronization and channel acquisition using a beacon signal broadcast by the access point[2] and determine who should transmit and at what rate. The expected total cost E_c of scheduling transmissions based on the channel states of the active sensors is lower bounded by

$$E_c \geq \Lambda e_c, \tag{7}$$

where e_c is the amount of energy consumed by one sensor in estimating its channel state from the beacon signal. This lower bound holds for both centralized and distributed implementations of the opportunistic transmission. It is achieved when the active sensors, each with access only to its own channel state, can determine the set of transmitting sensors at no cost. We show in Section 4 that when the propagation delay among active sensors is negligible, the scheduling cost of the proposed opportunistic protocol achieves the lower bound given in (7).

3. OPPORTUNISTIC TRANSMISSION FOR ENERGY EFFICIENCY

In this section, we address the performance of the opportunistic transmission under the metric of energy efficiency. As a performance measure, energy efficiency is first defined and the underlying coding scheme specified. We then obtain an upper bound on the performance of the opportunistic transmission and characterize the optimal number of transmitting sensors.

3.1. Sum capacity and coding scheme

Given that the channel fading process h_i is independent among sensors, and strictly stationary and ergodic, the sum capacity achieved by an information retrieval protocol which enables n sensors in each slot is given by [23]

$$R = W\mathbb{E}\left[\log\left(1+\rho\sum_{i=1}^{n}\gamma_i\right)\right], \tag{8}$$

where W is the transmission bandwidth and the expectation is over the fading process γ_i (see (4)). To achieve this rate, the CSI is used in decoding. The information rate is constant over time and each codeword sees a large number of channel realizations.

An alternative coding scheme is to use different transmission rates according to the channel states of the transmitting sensors. In this case, each codeword experiences only one channel realization, resulting in a smaller coding delay. When the block length T is sufficiently large, the achievable sum rate averaged over time can be approximated by (8). Note that using a variable information rate in each slot requires the CSI in both encoding and decoding. If more than one sensor is enabled for transmission, each transmitting sensor must know not only its own channel state, but also the channel states of other simultaneously transmitting sensors in order to determine the rate of transmission. In Section 4, we show that with the proposed opportunistic carrier sensing, each transmitting sensor obtains the channel states of other sensors at no extra cost. The proposed protocol is thus applicable to both coding schemes. Without loss of generality, we assume, for the rest of the paper, this alternative coding scheme which uses variable information rate. We point out that under this coding scheme, (8) is only an approximation to the achievable sum rate. A more rigorous formulation is to use error exponents [15].

3.2. n-TDMA

As a benchmark, we first give an expression of energy efficiency for a predetermined scheduling where n sensors are scheduled for transmission in each slot. At the beginning of each slot, n sensors wake up, measure their channel states, and transmit. Referred to as n-TDMA, this scheme with optimal n has the energy efficiency

$$S_{\text{TDMA}} = \max_{n}\frac{WT\mathbb{E}\left[\log\left(1+\rho\sum_{i=1}^{n}\gamma_i\right)\right]}{ne_c+nTP_{\text{tx}}}, \tag{9}$$

where expectation[3] is over M and $\{\gamma_i\}_{i=1}^{n}$. Since $n \ll \Lambda$ in general, we have ignored the rare event of $M < n$. The above optimization can be obtained numerically.

3.3. Opportunistic transmission

3.3.1. A performance upper bound

With the opportunistic strategy, n sensors with the best channels are enabled for transmission in each slot. Let $\gamma_M^{(i)}$ denote

[2]We assume reciprocity. The channel gain from a sensor to the access point is the same as that from the access point to the sensor.

[3]To be precise, the numerator of (9) should be written as $WT\mathbb{E}_M\{\mathbb{E}_{\gamma^{(i)}}[\log(1+\rho\sum_{i=1}^{\min\{n,m\}}\gamma_m^{(i)})|M=m]\}$.

the ith best channel gain among M sensors. The energy efficiency of the opportunistic strategy with optimal n is

$$S_{\text{opt}} = \max_n \frac{WT\mathbb{E}\left[\log\left(1+\rho\sum_{i=1}^{n}\gamma_M^{(i)}\right)\right]}{E_c + nTP_{\text{tx}}}, \quad (10)$$

where expectation is over M and $\{\gamma_M^{(i)}\}_{i=1}^{n}$. Using the lower bound on E_c given in (7), we obtain a performance upper bound for the opportunistic strategy:

$$S_{\text{opt}} \leq \max_n \frac{WT\mathbb{E}\left[\log\left(1+\rho\sum_{i=1}^{n}\gamma_M^{(i)}\right)\right]}{\Lambda e_c + nTP_{\text{tx}}}. \quad (11)$$

3.3.2. The optimal number of transmitting sensors

Since the performance upper bound given in (11) is achieved by the opportunistic carrier sensing proposed in Section 4, we can use this upper bound to study the optimal number n^* of transmitting sensors and the optimality of the opportunistic transmission.

It has been shown by Knopp and Humblet [8] that the optimal transmission scheme for maximizing sum capacity under a long-term average power constraint is to enable only one sensor (the one with the best channel) to transmit. Under the metric of energy efficiency with a fixed transmission power, however, allowing more than one transmission may be optimal when the cost in channel acquisition becomes substantial.

Proposition 1. *For a fixed slot length T, transmission power P_{tx}, and the channel acquisition cost e_c, the optimal number n^* of transmitting sensors for the opportunistic transmission is given by*

$$n^* = 1 \quad \text{if } \Lambda < \frac{TP_{\text{tx}}(2C_1 - C_2)}{e_c(C_2 - C_1)}, \qquad n^* > 1 \quad \text{otherwise}, \quad (12)$$

where $C_n = WT\mathbb{E}[\log(1+\rho\sum_{i=1}^{n}\gamma_M^{(i)})]$.

For the proof of Proposition 1, see Appendix A.

In Figure 3, we plot the energy efficiency of the opportunistic transmission for different numbers n of transmitting sensors. In Figure 3a, the average number Λ of active sensors is 500 while, in Figure 3b, it is set to 5 000. We can see that n^* increases from 1 to 2 when Λ increases. The intuition behind this is that the cost in channel acquisition dominates when $\Lambda = 5\,000$; allowing one more transmission improves the sum rate without inducing significant increase in energy consumption. The performance of n-TDMA is also plotted in Figure 3 for comparison. For this simulation setup, the optimal number of transmitting sensors for n-TDMA equals 1. We observe that the opportunistic transmission is inferior to the simple predetermined scheduling at $\Lambda = 5\,000$. Indeed, we show in Section 5 that the opportunistic transmission strategy looses its optimality when Λ exceeds a threshold.

4. OPPORTUNISTIC CARRIER SENSING

In this section, we propose opportunistic carrier sensing, a distributed protocol whose performance approaches to the upper bound of the opportunistic strategy given in (11). We first present the basic idea of the opportunistic carrier sensing under the assumption of negligible propagation delay among active sensors. In Section 4.2, we study the design of the backoff function to minimize the performance loss caused by propagation delay.

4.1. The basic idea

We now present the basic idea of the opportunistic carrier sensing by considering an idealistic scenario. We assume that the transmission of one sensor is immediately detected by other active sensors. In the next subsection, we discuss how to circumvent the propagation delay among active sensors.

The key idea of opportunistic carrier sensing is to exploit CSI in the backoff strategy of carrier sensing. First consider $n^* = 1$, that is, in each slot, only the sensor with the best channel transmits. After each active sensor measures its channel gain γ_i using the beacon of the access point, it chooses a backoff τ based on a predetermined function $f(\gamma)$ which maps the channel state to a backoff time and then listens to the channel. A sensor will transmit with its chosen backoff delay if and only if no one transmits before its backoff time expires. If $f(\gamma)$ is chosen to be a strictly decreasing function of γ as shown in Figure 4, this opportunistic carrier sensing will ensure that only the sensor with the best channel transmits. Under the idealistic scenario where the transmission of one sensor is immediately detected by other active sensors, $f(\gamma)$ can be any decreasing function with range $[0, \tau_{\max}]$, where $\tau_{\max}$ is the maximum backoff. Since $\tau_{\max}$ can be chosen as any positive number, the time required for each sensor listening to the channel can be arbitrarily short. Hence, energy consumed in each slot comes only from each sensor estimating its own channel state (the lower bound on E_c given in (7)) and the transmission by one sensor; opportunistic carrier sensing thus achieves the performance upper bound of the opportunistic strategy.

We now consider $n^* > 1$. If the energy detector of each sensor is sensitive enough to distinguish the number of simultaneous transmissions, the opportunistic carrier sensing protocol stated above can be directly applied—a sensor transmits with its chosen backoff if and only if the number of transmissions at that time instant is smaller than n^*. Note that by observing the time instant τ at which the number of simultaneous transmissions increases (energy-level jumps) and mapping this time instant back to the channel gain using $\gamma = f^{-1}(\tau)$, a sensor obtains the channel states of other transmitting sensors and can thus determine its transmission rate. Note that the channel gain of a transmitting sensor is learned by measuring the backoff of the transmission, not the signal strength.

If, however, sensors can not obtain the number of simultaneous transmissions, we generalize the protocol as follows. We partition each slot into two segments: carrier sensing and information transmission (see Figure 5). During the carrier

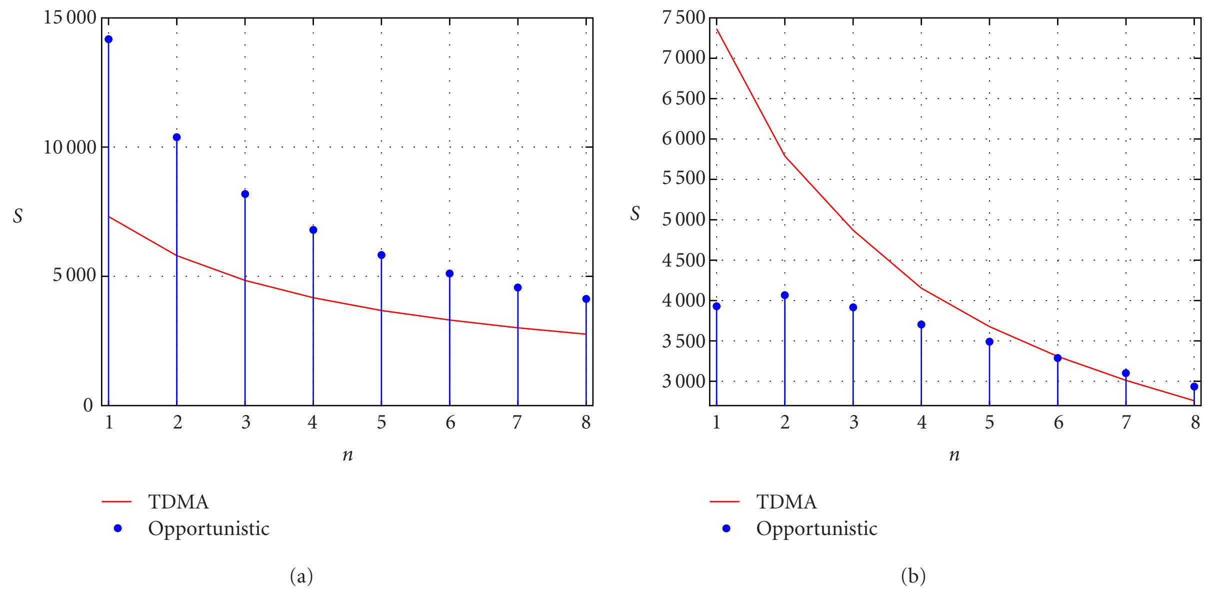

FIGURE 3: The optimal number n^* of transmitting sensors ($W = 1\,\text{kHz}$, $\rho\overline{\gamma_i} = 3\,\text{dB}$, $T = 0.01$ second, $P_{tx} = 0.181\,\text{W}$, $e_c = 1.8\,\text{nJ}$): (a) $\Lambda = 500$ and (b) $\Lambda = 5\,000$.

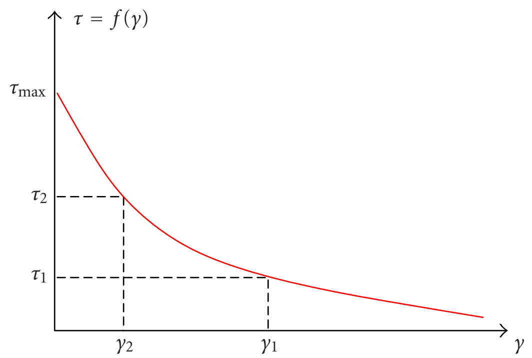

FIGURE 4: Opportunistic carrier sensing.

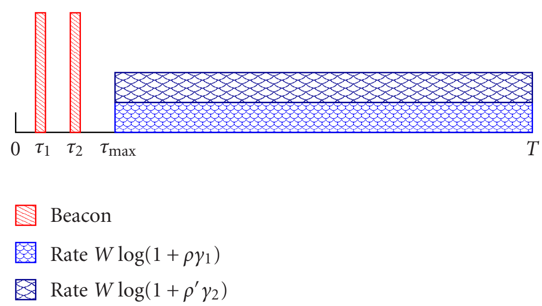

FIGURE 5: Opportunistic carrier sensing for $n^* = 2$.

sensing period, sensors transmit, with backoff delay determined by $f(\gamma)$, a beacon signal with short duration. A sensor transmits a beacon if and only if the number of received beacon signals is smaller than n^*. By measuring the time instant at which each beacon signal is transmitted, those n^* sensors with the best channels can also obtain all n^* channel states from $f^{-1}(\tau)$ and thus encode their messages accordingly. Shown in Figure 5 is an example with $n^* = 2$. During the carrier sensing segment $[0, \tau_{\max}]$, two beacon signals are transmitted at τ_1 and τ_2 by two sensors with the best channel gains. Based on τ_1, τ_2, and $f^{-1}(\tau)$, these two sensors obtain each other's channel state (see Figure 4). They then encode their messages for transmissions in the second segment of the slot. One possible encoding scheme, as shown in Figure 5, is based on the idea of successive decoding. The sensor with the higher channel gain γ_1 encodes its message at rate $W\log(1+\rho\gamma_1)$ as if it was the only transmitting node. The other sensor with channel gain γ_2 encodes its message by treating the transmission from the sensor with channel γ_1 as noise. It transmits at rate $W\log(1+\rho'\gamma_1)$ where

$$\rho' = \frac{P_{\text{out}}}{N_0 W + P_{\text{out}}\gamma_1}. \tag{13}$$

We point out that the idea of opportunistic carrier sensing provides a distributed solution to the general problem of finding maximum/minimum. By substituting the channel gain γ with, for example, the temperature measured by each sensor, the distance of each sensor to a particular location, or the residual energy of each sensor, we can retrieve information of interest (the highest/lowest temperature, the measurement closest/farthest to a location) from sensors of interest (those with the highest energy level or those with the best channel gain) in a distributed and energy-efficient fashion.

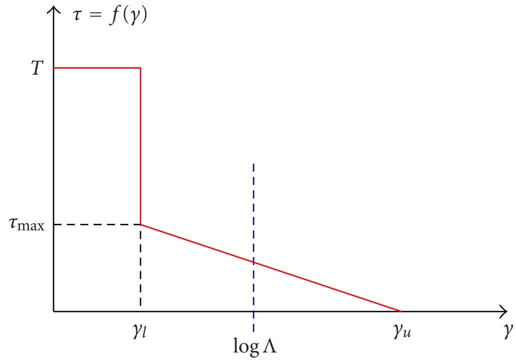

Figure 6: Backoff function under significant propagation delay.

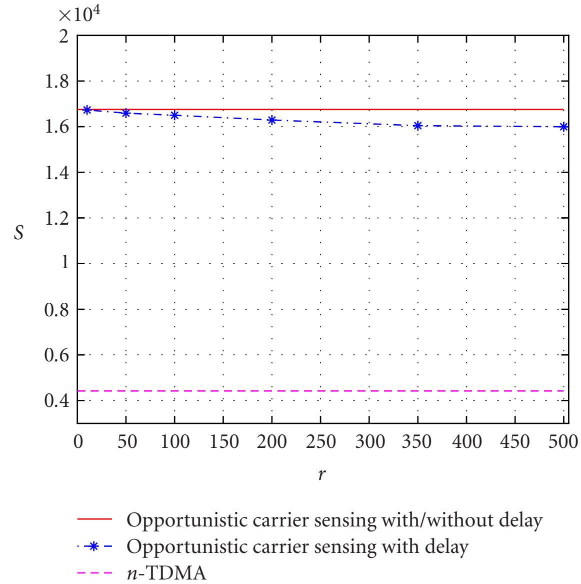

Figure 7: Performance of opportunistic carrier sensing under significant delay ($\Lambda = 100$, $W = 1$ kHz, $\rho\overline{\gamma}_i = 3$ dB, $T = 0.01$ second, $P_{tx} = 0.181$ W, $P_{rx} = 0.18$ W, $e_c = 1.8$ nJ).

4.2. Backoff design under significant delay

We now generalize the basic idea of opportunistic carrier sensing to scenarios with significant delay which may include both the propagation delay and the time spent in the detection of transmissions. Without loss of generality, we focus on the case of $n^* = 1$.

In the idealistic case considered in the previous subsection, energy consumed in carrier sensing is negligible due to the arbitrarily small carrier sensing time τ_{max}. Furthermore, using any decreasing function as the backoff function $f(\gamma)$ avoids collision, an event where several nodes transmit simultaneously while no information is received at the access point. When there is substantial delay, however, collision and energy consumed by carrier sensing[4] are inevitable. To maintain the optimal performance achieved under the idealistic scenario, $f(\gamma)$ needs to be designed judiciously to minimize both the occurrence of collision and the energy consumed in carrier sensing. Unfortunately, these are two conflicting objectives. On one hand, choosing a larger τ_{max} makes it more likely to map channel gains to well-separated backoff times, thus reducing collisions. On the other hand, a larger τ_{max} results in less transmission time and more energy consumption of carrier sensing.

To balance the tradeoff between collision and energy consumption of carrier sensing, we propose $f(\gamma)$ as illustrated in Figure 6. This backoff scheme is a linear function on a finite interval $[\gamma_l, \gamma_u)$ where the channel gain is mapped to a backoff time in $(0, \tau_{max}]$. Sensors with channel gains greater than γ_u transmit without backoff ($\tau = 0$) while sensors with channel gains smaller than γ_l turn off their radios until next slot ($\tau = T$), without even participating in the carrier sensing process.

The proposed backoff function is completely determined by γ_l, γ_u, and τ_{max}. The choice of a finite γ_u allows better resolution among highly likely channel realizations. The option of a nonzero γ_l avoids the listening cost of sensors whose channels are unlikely to be the best. For a relatively large Λ, a large percentage of active sensors can be freed of carrier sensing cost with a carefully chosen γ_l. The maximum backoff time τ_{max} is chosen to balance collision and energy consumption of carrier sensing. It is jointly optimized with γ_l and γ_u to maximize energy efficiency:

$$\{\gamma_l^*, \gamma_u^*, \tau_{max}^*\} = \arg\max S(\gamma_l, \gamma_u, \tau_{max}). \tag{14}$$

The optimal $\{\gamma_l^*, \gamma_u^*, \tau_{max}^*\}$ can be obtained via numerical evaluation or simulations. To narrow the search range of γ_l and γ_u, asymptotic extreme-order statistics given in Lemma 1 (see Section 5.1) can be exploited. For a relatively large Λ, the best channel gain $\gamma^{(1)}$ is on the order of $\log\Lambda$.

We now consider a simulation example to evaluate the performance of opportunistic carrier sensing with the backoff function $f(\gamma)$ given in Figure 6 using numerically optimized parameters $\{\gamma_l^*, \gamma_u^*, \tau_{max}^*\}$. We focus on information retrieval by a mobile access point and model the coverage area of the mobile access point as a disk with radius r (see Figure 1). The maximum propagation delay β is then given by

$$\beta = \frac{2r}{v_l}, \tag{15}$$

where v_l is the speed of light.[5] Shown in Figure 7 is the energy efficiency of opportunistic carrier sensing as a function of the radius r of the coverage area which determines the maximum propagation delay. Compared with the performance in the ideal scenario (no propagation delay), the performance of opportunistic carrier sensing degrades gracefully with

[4]Listening to the channel requires the receiver being turned on, which consumes energy as given in (5).

[5]We have ignored the delay in the detection of transmission at sensor nodes. It can be easily accommodated by adding a constant to the propagation delay.

propagation delay. Even with a coverage radius of 500 meters, the performance degradation due to propagation delay is less than 5%.

5. OPTIMAL SENSOR ACTIVATION

In this section, we demonstrate that the energy efficiency of the opportunistic transmission vanishes as the number Λ of active sensors approaches infinity. Possible schemes for optimizing the number of active sensors are discussed.

5.1. Tradeoff between sum capacity and energy consumption

Since the extreme value of i.i.d. samples increases with the sample size, it is easy to show that the sum capacity achieved by n sensors with the best channels increases with Λ. Unfortunately, larger Λ also leads to higher energy consumption in channel acquisition (see (7)). Proposition 2 shows that the gain in sum capacity does not always justify the cost in obtaining the channel states.

Proposition 2. *For a fixed slot length T, transmission power P_{tx}, and the channel acquisition cost $e_c > 0$,*

$$\lim_{\Lambda\to\infty} S_{opt} = 0. \tag{16}$$

A direct consequence of Proposition 2 is that, as summarized in Corollary 1, the opportunistic strategy looses its optimality when Λ exceeds a threshold.

Corollary 1. *There exists $\Lambda_0 < \infty$ such that $S_{opt} < S_{TDMA}$ when $\Lambda > \Lambda_0$.*

The proof (see Appendix B) of Proposition 2 is based on the following result on asymptotic extreme-order statistics [24].

Lemma 1. *Let $X_1, X_2, \ldots$ be i.i.d. random variables with continuous distribution function $F(x)$. Let x_0 denote the upper boundary, possibly $+\infty$, of the distribution: $x_0 \triangleq \sup\{x : F(x) < 1\}$. If there exists a function $R(t)$ such that for all x,*

$$\lim_{t\to x_0} \frac{1-F(t+xR(t))}{1-F(t)} = e^{-x}, \tag{17}$$

then

$$\frac{X_m^{(1)} - a_m}{b_m} \xrightarrow{d} \exp\{-e^{-x}\}, \tag{18}$$

where $X_m^{(1)} = \max_{i\le m} X_i$, $1-F(a_m) = 1/m$, $b_m = R(a_m)$, and $\xrightarrow{d}$ denotes convergence in distribution.

Common fading distributions such as Rayleigh and Ricean satisfy the assumptions of Lemma 1. For Rayleigh fading considered in this paper, we have $a_m = \log m$ and $b_m = 1$, that is,

$$X_m^{(1)} - \log m \xrightarrow{d} \exp\{-e^{-x}\}. \tag{19}$$

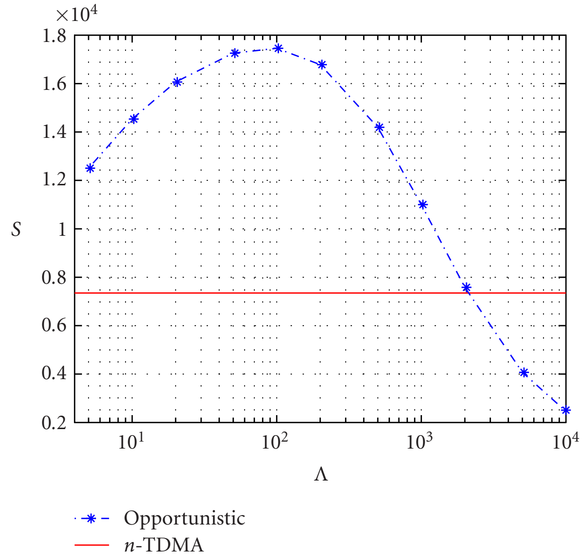

FIGURE 8: Tradeoff between sum capacity and energy consumption ($W = 1$ kHz, $\rho\bar{\gamma}_i = 3$ dB, $T = 0.01$ second, $P_{tx} = 0.181$ W, $e_c = 1.8$ nJ).

Shown in Figure 8 are simulation results on the energy efficiency of the opportunistic transmission as compared to the predetermined scheduling. Since both the sum rate and the energy consumption of n-TDMA are independent of Λ, the energy efficiency is constant over Λ. For the opportunistic strategy, the energy efficiency increases with Λ when Λ is relatively small. In this region, the energy consumption is dominated by transmission; the increase in the cost of channel acquisition does not significantly affect the total energy expenditure. The energy efficiency thus improves as the sum capacity increases with Λ. When Λ increases beyond 100 where the cost in channel acquisition contributes more than 10% of the total energy expenditure, the increase in energy consumption overrides the improvement in sum rate; the energy efficiency starts to decrease. Eventually, the gain in sum capacity achieved by exploiting CSI can no longer justify the cost in obtaining CSI, and the opportunistic strategy is inferior to the predetermined scheduling.

5.2. The optimal number of active sensors

As shown in Figure 8, the performance of the opportunistic transmission depends on the average number of active sensors's. To achieve the best performance of the opportunistic strategy, the average number Λ of active sensors should be carefully chosen.

The average number of active sensors can be controlled via the sensor duty cycle or the size of the coverage area of the mobile access point (or the cluster). Assume that each sensor with probability p wakes up independently to detect the beacon signal of the access point. For a coverage area of size a, the average number of active sensors is given by $\Lambda = ap\lambda$, where λ is the node density defined in Section 2. The average number of active sensors can thus be controlled by varying either a or the duty cycle p.

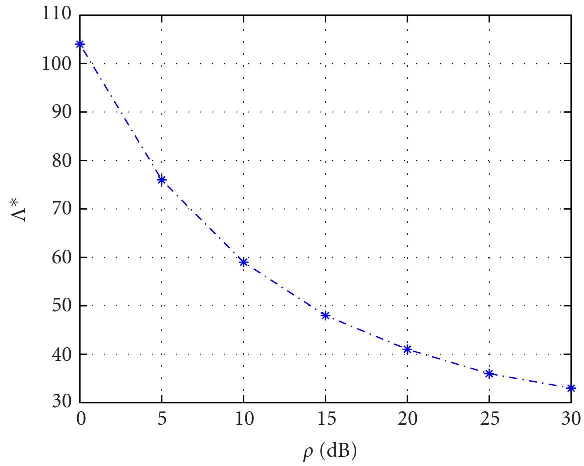

Figure 9: The optimal number of active sensors ($W = 1$ kHz, $T = 0.01$ second, $P_{tx} = 0.181$ W, $e_c = 1.8$ nJ).

In Figure 9, we plot the optimal average number Λ^* of the active sensors as a function of the average SNR. Without loss of generality, we normalize $\overline{\gamma}_i$ to 1. The average received SNR is thus given by ρ. We observe that Λ^* is a decreasing function of ρ. The reason for this is that the larger the average SNR, the smaller the impact of $\gamma^{(1)}$ on the sum rate (see (10)). Thus, the threshold beyond which the channel acquisition cost overrides the gain in sum rate decreases with ρ, resulting in decreasing Λ^*.

6. CONCLUSION

In this paper, we focus on distributed information retrieval in wireless sensor networks. Energy efficiency is introduced as the performance metric. Measured in bits per Joule, this metric captures a major design constraint—energy—of sensor networks.

We examine the performance of the opportunistic transmission which exploits CSI for transmission scheduling. Taking into account energy consumed in channel acquisition, we demonstrate that sum-rate improvement achieved by opportunistic transmission does not always justify the cost in channel acquisition; there exists a threshold of the average number of activated sensor nodes beyond which the opportunistic strategy looses its optimality. Sensor activation schemes are discussed to optimize the energy efficiency of the opportunistic transmission.

We propose a distributed opportunistic transmission protocol that achieves the performance upper bound assumed by the centralized opportunistic scheduler. Referred to as opportunistic carrier sensing, the proposed protocol incorporates CSI into the backoff strategy of carrier sensing. A backoff function which maps channel state to backoff time is constructed for scenarios with substantial propagation delay. The performance of opportunistic carrier sensing with the proposed backoff function degrades gracefully with propagation delay. The proposed protocol also provides a distributed solution to the general problem of finding the maximum/minimum.

A number of issues are not addressed in this paper. We have used the information theoretic metric of energy efficiency that implicitly assumes that data from different sensors are independent. For applications in which data are highly correlated, distributed compression techniques may be necessary [25]. Fairness in transmission is another issue that needs to be considered in practice. For sensor networks with mobile access points or networks with randomly rotated cluster heads, the probability of transmission can be made uniform. For networks with fixed cluster heads, sensors closer to the cluster head tend to have stronger channel, thus transmit more often. This, however, can be easily equalized by using the normalized channel gain in the backoff strategy.

APPENDICES

A. PROOF OF PROPOSITION 1

Let S_n denote the energy efficiency of the opportunistic strategy which enables n sensors with the best channels in each slot. We have

$$S_n = \frac{C_n}{\Lambda e_c + nTP_{tx}}. \tag{A.1}$$

To prove Proposition 1, we need to show that for $\Lambda < TP_{tx}(2C_1 - C_2)/e_c(C_2 - C_1)$, $S_1 \geq S_n$ for all n. Since

$$\begin{aligned} \frac{C_1}{\Lambda e_c + TP_{tx}} &\geq \frac{C_n}{\Lambda e_c + nTP_{tx}} \\ &\Longrightarrow \Lambda e_c(C_n - C_1) \\ &\leq TP_{tx}(nC_1 - C_n), \end{aligned} \tag{A.2}$$

we only need to show that there exists $\Lambda > 0$ that satisfies (A.2). This reduces to the positiveness of $nC_1 - C_n$ which follows directly from the concavity of the logarithm function.

B. PROOF OF PROPOSITION 2

Let $S_{opt}(m)$ denote the energy efficiency of the opportunistic transmission where exactly m sensors are active in each slot. We first show, based on Lemma 1, that $\lim_{m\to\infty} S_{opt}(m) = 0$:

$$\lim_{m\to\infty} S_{opt}(m) = \lim_{m\to\infty} \max_{1\leq n\leq m} \frac{\mathbb{E}\left[WT\log\left(1+\rho\sum_{i=1}^{n}\gamma_m^{(i)}\right)\right]}{me_c + nTP_{tx}} \tag{B.1}$$

$$\leq \lim_{m\to\infty} \frac{\mathbb{E}\left[WT\log\left(1+m\rho\gamma_m^{(1)}\right)\right]}{me_c} \tag{B.2}$$

$$\leq \lim_{m\to\infty} \frac{WT\log\left(1+m\rho\mathbb{E}\left[\gamma_m^{(1)}\right]\right)}{me_c} \tag{B.3}$$

$$\leq \lim_{m\to\infty} \frac{WT\log\left(1+m^2\rho\right)}{me_c} \tag{B.4}$$

$$= 0, \tag{B.5}$$

where $\gamma_m^{(i)}$ denotes the ith-order statistics over m samples; the expectations in (B.1) and (B.2) are with respect to $\{\gamma_m^{(i)}\}_{i=1}^n$ and $\gamma_m^{(1)}$, respectively. Jensen's inequality is used to obtain (B.3), and Lemma 1, which shows that $\gamma_m^{(1)} \sim \log(m) < m$, for large m, is used to obtain (B.4). Combining (B.5) and the fact that $S_{\text{opt}}(m) > 0$ for all m, we conclude that $\lim_{m\to\infty} S_{\text{opt}}(m) = 0$. Thus,

$$\forall \epsilon > 0, \quad \exists M_0 > 0, \quad \text{s.t. } S_{\text{opt}}(m) < \epsilon \quad \forall m > M_0. \tag{B.6}$$

That $S_{\text{opt}}(m)$ vanishes with m also implies that

$$\exists \overline{S} < \infty, \quad \text{s.t. } S_{\text{opt}}(m) < \overline{S} \quad \forall m. \tag{B.7}$$

It is easy to show that for Poisson distributed random variable M,

$$\lim_{\Lambda\to\infty} P[M \le M_0] = \lim_{\Lambda\to\infty} \frac{\sum_{i=1}^{M_0}(\Lambda)^i/i!}{e^{\Lambda}} = 0. \tag{B.8}$$

Thus, for ϵ and M_0 given in (B.6), we have

$$\exists M_1 > 0, \quad \text{s.t. } P[M \le M_0] < \epsilon \quad \forall \Lambda > M_1. \tag{B.9}$$

Combining (B.6), (B.7), and (B.9), we have, for $\Lambda > M_1$,

$$\begin{aligned} S_{\text{opt}} &= \sum_{m=1}^{\infty} P[M = m] S_{\text{opt}}(m) \\ &= \sum_{m=1}^{M_0} P[M = m] S_{\text{opt}}(m) + \sum_{m=M_0+1}^{\infty} P[M = m] S_{\text{opt}}(m) \\ &< \epsilon \overline{S} + \epsilon. \end{aligned} \tag{B.10}$$

We thus obtain Proposition 2 from the arbitrariness of ϵ.

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