Applying Retirement-Planning Strategy to Sensor Networks:

An Integrated Approach to Energy-Aware Medium Access

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Abstract

This report addresses the design of distributed medium access control (MAC) protocols for wireless sensor networks under the performance measure of network lifetime. Integrated in the design of MAC schemes are two key physical layer parameters: the channel state and the residual energy of each sensor. The impact of incorporating these parameters in MAC design on network lifetime is studied. Furthermore, we show that a lifetime-maximizing protocol should dynamically trade off the channel state information (CSI) and the residual energy information (REI) according to the age of the network. Specifically, lifetime-maximizing protocols should be more opportunistic by prioritizing sensors with better channels for transmission when the network is young and more conservative by favoring sensors with more residual energies when the network is old. Following this general design principle, we propose a dynamic protocol for lifetime maximization (DPLM) that exploits both CSI and REI. Analytical results are provided to demonstrate the dynamic property and the asymptotic optimality of DPLM.

Index Terms

Wireless sensor network, distributed protocol, medium access control, opportunistic transmission, network lifetime, energy efficiency, cross-layer design.

I. Introduction

A. An Integrated Approach to Energy-Aware Medium Access

One of the critical operations in wireless sensor networks (WSNs) is the information retrieval process in which sensor measurements are collected by access points (APs) to be used by the end user. In applications that involve mobile APs [1]–[3], a mobile AP initiates a data collection process by broadcasting beacon signals to activate sensors. Activated sensors then transmit, according to a medium access control (MAC) protocol, their measurements directly to the AP through a common wireless channel (see Fig. 1).

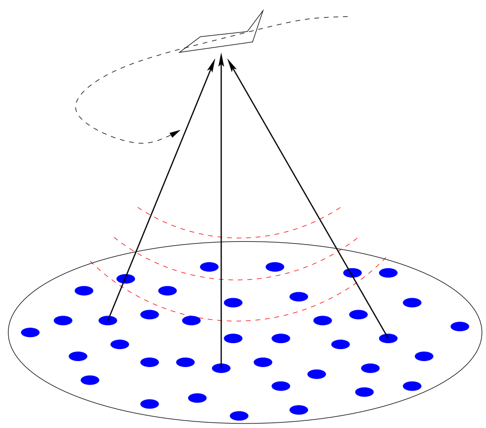


Fig. 1. Sensor network with mobile access point.

In the conventional layered approach, MAC protocols are designed with minimal input from the physical (PHY) layer. The PHY layer is treated as a black box in which nodes are indistinguishable. Starting to gain recognition in the signal processing and the communications societies is the viewpoint that the layered network architecture, fundamental to the success of general purpose communication networks, may in fact be a hindrance to the efficiency of application-specific sensor networks [4]–[6].

In this paper, we take a cross-layer approach to medium access for network lifetime maximization. We demonstrate that to achieve an efficient use of limited energy resources, MAC design should be based upon a PHY layer model that captures diversities among nodes. We show that protocols exploiting dependencies between the MAC and the PHY layers offer improved performance in energy efficiency.

B. Contribution and Organization

Distributed MAC protocols that allow each individual sensor to determine whether it should transmit based on its own state are generally preferred due to their scalability, reduced overhead, and robustness against node failures. In this paper, we focus on the design of distributed MAC protocols. We aim to address the following three issues: (1) what PHY layer parameters should be exploited in MAC design for network lifetime maximization; (2) how to use these parameters in MAC protocols; (3) how to implement MAC protocols that integrate PHY layer parameters in a distributed fashion.

After the problem statement in Section II, we focus on the first issue in Section III. Based on a general formula for network lifetime developed in [7], we identify two key PHY layer parameters that affect the network lifetime: the channel state and the residual energy of each individual sensor. We study the impact of exploiting these two parameters in MAC design on the network lifetime.

In Section IV, we address the second issue. We show that lifetime-maximizing protocols should dynamically trade off the channel state information (CSI) and the residual energy information (REI) according to the age of the network. Specifically, optimal MAC protocols should be more opportunistic by prioritizing sensors with better channels for transmission when the network is young and more conservative by favoring sensors with more residual energy when the network is old. Following this general design principle, we propose a dynamic protocol for lifetime maximization (DPLM) that exploits both CSI and REI. As a consequence of the dynamic nature, DPLM is asymptotically optimal in network lifetime when channel fading is independently and identically distributed (i.i.d.) across transmission slots. That is, the relative performance loss of DPLM as compared to the optimal MAC protocol diminishes with the initial energy of each sensor.

The third issued is addressed in Section V. Based on the idea of opportunistic carrier sensing [8], we propose a distributed implementation of MAC protocols that exploit PHY layer parameters. Specifically, we address how to schedule sensors with the desired property using only local information on their PHY layer parameters. Simulation examples are presented in Section VI, and the paper is concluded in Section VII.

C. Related Work

As shown in [9], energy-efficient design can be formulated as an unconstrained or a constrained optimization problem. In the former, the design objective is to either minimize the energy consumption rate or maximize the number of transmitted information bits per Joule under an implicit assumption that each sensor has an infinite amount of energy. Knopp and Humblet [10] showed that the optimal transmission scheme for maximizing the sum capacity under an average power constraint is to enable only the node with the best channel for transmission. It is shown in [8] that this opportunistic (with respect to the channel state) strategy is also optimal in energy efficiency measured in information bits per Joule when the cost in channel acquisition is negligible. Exploiting CSI appears to be the key to the unconstrained energy efficiency [11]–[13].

On the other hand, the constrained formulation of energy-efficient design aims at maximizing the network lifetime under the assumption that each node has a finite amount of energy. In this case, REI plays an important role in the design of lifetime-maximizing protocols. Various energy-aware routing and transmission protocols that exploit REI have been proposed and studied [14]–[19].

Sensor network lifetime has been studied for different network applications. In the extensive list of papers [7], [20]–[23] dealing with lifetime analysis, [7] develops a general law that governs sensor network lifetime for all applications, under any network configuration, and with an arbitrary lifetime definition. In this paper, we obtain general design principles from the lifetime formula given in [7] and develop lifetime-maximizing distributed MAC protocols.

D. Notations

The following notations will be adopted throughout the paper. Vectors are denoted by boldfaced letters. Random variables (RVs) and their realizations are denoted by capital and small letters, respectively. The expectation of an RV X is denoted by $\mathbb{E}[X]$. The n-th largest element of N RVs $\{X_i\}_{i=1}^{N}$ is denoted by $X_{(n)}$. Let $1_{[x]}$ denote the indicator function: $1_{[x]} = 1$ if x is true and 0 otherwise.

II. Problem Statement

A. Network and Radio Model

We consider a demand-driven WSN with N nodes and an AP (see Fig. 1). The AP initiates each data collection in which N_0 ($1 \leq N_0 \leq N$) out of N sensors are chosen to transmit their measurements directly to the AP through a fading channel. The number N_0 of sensors required to be chosen is determined by the underlying application and the QoS requirement of the network. Due to spatial correlation among sensor measurements, we generally have $N_0 \ll N$. The network model described above has application in field estimation. For example, consider a network deployed for estimating a certain parameter in a fixed area. In each data collection, every sensor in the network observes the same parameter with independent observation noise. The AP can thus collect measurements from any N_0 out of N sensors, where the number N_0 of samples is determined by the desired estimation performance (*e.g.*,mean-square-error).

Each sensor's measurement is encoded in a fixed-size packet. We consider bandwidthunlimited applications[1] where the chosen N_0 sensors can transmit their packets simultaneously in a transmission slot using standard multi-access techniques such as frequency division multiple access (FDMA) or code division multiple access (CDMA).

The channels between the AP and the sensors follow a block fading model with block length equal to the transmission slot. That is, the channel realizations remain unchanged over each transmission slot. Let $\mathbf{C} \stackrel{\Delta}{=} (C_1, \ldots, C_N)$, where C_i is the channel gain of sensor i, denote the channel state in a transmission slot. Due to the presence of small-scale fading, channel gain C_i is an RV and its mean $\mathbb{E}[C_i]$ depends on the path loss from sensor i to the AP. The energy $E_{tx}^{(i)}$ required for sensor i to successfully transmit its measurement to the AP in a transmission slot can be modeled by

$$E_{tx}^{(i)} = \mathcal{E}_c + \frac{1}{C_i} \tag{1}$$

where $\mathcal{E}_c$ is the energy consumed in the transmitter circuitry. Note that we have normalized all energy quantities by the received signal energy required to achieve the targeted SNR at the AP. Clearly, the better the channel gain C_i, the less the transmission energy $E_{tx}^{(i)}$.

B. Lifetime Definition

We assume that each sensor is powered by a non-rechargeable battery with initial energy $\mathcal{E}_0$. Let $\mathbf{E} \stackrel{\Delta}{=} (E_1, \ldots, E_N)$, where E_i is the residual energy of sensor i, denote the network energy profile at the beginning of a transmission slot. Note that residual energy E_i is an RV depending on the channel realizations of sensor i when it was chosen for transmission.

At the beginning of a transmission slot, a sensor can be in one of the following four states: dead, ineligible, inactive, and active. A sensor is considered *dead* if its residual energy drops below the transmitter circuitry consumption, *i.e.*, $E_i \leq \mathcal{E}_c$. In other words, it does not have enough energy for transmission under any channel condition. A living sensor is considered

[1] Bandwidth-limited applications where only one sensor can transmit in each transmission slot have been considered in [24].

ineligible if it has already successfully transmitted its packet to the AP in one of the previous transmission slots of the current data collection. An eligible sensor is considered *inactive* if it does not have enough residual energy for the current transmission, *i.e.*, $\mathcal{E}_c \leq E_i < E_{tx}^{(i)}$. An eligible sensor is considered *active* if it has sufficient residual energy for the current transmission, *i.e.*, $E_i \geq E_{tx}^{(i)} = \mathcal{E}_c + \frac{1}{C_i}$.

Recall that the AP needs to collect measurements from N_0 sensors in each data collection. If there are more than or equal to N_0 active sensors in the first transmission slot of a data collection, the AP will choose N_0 sensors for transmission[2] and then completes this data collection. Otherwise, the AP has to initiate a new transmission slot to collect the remaining measurements until total N_0 measurements are collected. In this case, a complete data collection may consist of multiple transmission slots. We define network lifetime L as the number of complete data collections until the number of dead sensors in the network reaches a certain threshold N_T ($1 \leq N_T \leq N$).

At the end of network lifetime, the total energy E_w left in the network is wasted. The wasted energy can be written as

$$E_w = \sum_{i=1}^{N} E_i(L), \tag{2}$$

where L is the number of data collections completed during the network lifetime, and $E_i(L)$ is the network energy profile at the end of the L-th data collection.

Realizing that sensors experience different channel fading and have different residual energies, we seek the answer to the following question: which set of sensors should transmit in each transmission slot so that the network lifetime is maximized.

III. Two Key PHY Layer Parameters: CSI and REI

In this section, we address the first issue: what PHY layer parameters should be exploited in MAC design for network lifetime maximization. Using the law of lifetime developed in

[2] We assume that an active sensor must transmit its packet to the AP if it is chosen.

[7], we identify two key PHY layer parameters that affect the network lifetime: the channel state and the residual energy. We then study the individual impact of exploiting CSI and REI in MAC design on the network lifetime.

A. A General Formula for Network Lifetime

In [7], we have obtained a general formula for the expected network lifetime $\mathbb{E}[L]$ which holds independently of the underlying network model including network architecture, data collection initiation, lifetime definition, channel fading characteristics, and energy consumption model. Applying this lifetime formula to the current network setting, we obtain the expected network lifetime as

$$\mathbb{E}[L] = \frac{N\mathcal{E}_0 - \mathbb{E}[E_w]}{\mathbb{E}[E_{tx}]} \tag{3}$$

where $\mathbb{E}[E_w]$ is the expected wasted energy over the whole network (see (2)) and $\mathbb{E}[E_{tx}]$ is the total expected energy consumed in a randomly chosen data collection[3]. Note that $\mathbb{E}[E_{tx}]$ includes the energy consumed by all N_0 chosen sensors in the randomly chosen data collection.

From (3), we find that reducing $\mathbb{E}[E_{tx}]$ and $\mathbb{E}[E_w]$ leads to prolonged network lifetime. This observation will help us to identify the key PHY layer parameters that affect the network lifetime.

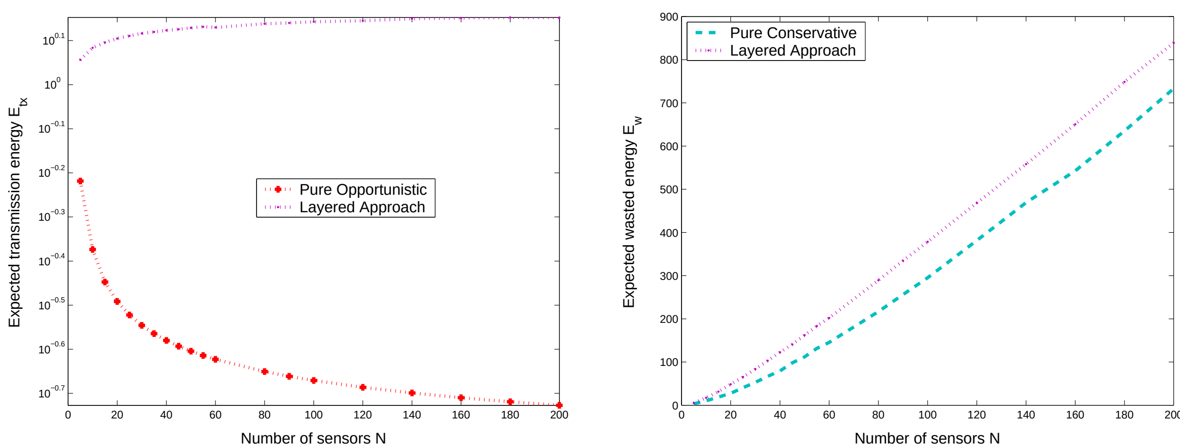
[3]Consider M i.i.d. trials, *i.e.*, the network is deployed M times sequentially with identical settings. Let $L^{(m)}$ be the network lifetime in the m-th trial and $E_{tx}(m,k)$ the energy consumption in the k-th data collection of the m-th trial, where $1 \leq k \leq L^{(m)}$. Consider a data collection chosen with equal probability from the total $\sum_{m=1}^{M} L^{(m)}$ data collections. The expected energy consumption $\mathbb{E}[E_{tx}]$ in this randomly chosen data collection is defined as

$$\mathbb{E}[E_{tx}] \triangleq \lim_{M\to\infty} \frac{\sum_{m=1}^{M}\sum_{k=1}^{L^{(m)}} E_{tx}(m,k)}{\sum_{m=1}^{M} L^{(m)}}, \tag{4}$$

i.e., $\mathbb{E}[E_{tx}]$ can be viewed as the time average (over an infinite horizon) of the total energy consumption in one data collection. The existence of the limit is shown in [7].

B. The Impact of Exploiting CSI

Equation (1) shows that the transmission energy consumption decreases with the channel gain of the chosen sensor. Hence, to reduce the expected energy consumption $\mathbb{E}[E_{tx}]$ in a data collection, MAC protocols should exploit CSI by favoring sensors with better channel realizations for transmission. In Fig. 2(a), we study the expected energy consumption $\mathbb{E}[E_{tx}]$ of the pure opportunistic protocol that chooses active sensors with the best channel realizations in each transmission slots. Compared to a layered approach to MAC design that ignores the diversities at the PHY layer and chooses active sensors randomly in each data collection, the pure opportunistic protocol offers significant reduction in $\mathbb{E}[E_{tx}]$ by exploiting the channel diversity among sensors. As the number N of sensors increases, the expected transmission energy of the pure opportunistic protocol decreases while that of the layered approach increases.



(a) The impact of using CSI. (b) The impact of using REI.

Fig. 2. The individual impact of using CSI and REI on network lifetime in i.i.d. Rayleigh fading channel. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (mean of the channel gain) for all i, $\mathcal{E}_c = 0.1$ (transmitter circuitry energy consumption).

C. The Impact of Exploiting REI

From (2), we find that to minimize the expected wasted energy $\mathbb{E}[E_w]$, MAC protocols should balance the energy consumption among sensors. At the end of the last data collection, sensors that are still alive should have minimal energy left. This requires the use of REI in scheduling. One intuitive way of exploiting REI is to schedule active sensors with the most residual energies in each data collection. In Fig. 2(b), we compare the expected wasted energy of this pure conservative protocol with that of the layered approach. Capturing the diversity among sensor residual energies, the pure conservative protocol reduces the expected wasted energy in the network. The performance gain of the pure conservative protocol over the layered approach increases with the number of sensors.

IV. EXPLOITING BOTH CSI AND REI FOR LIFETIME MAXIMIZATION

In Section III, we have shown in (3) that the expected network lifetime $\mathbb{E}[L]$ is a decreasing function of the expected wasted energy $\mathbb{E}[E_w]$ and the expected energy consumption $\mathbb{E}[E_{tx}]$ in a randomly chosen data collection. This observation has led to the identification of two key PHY layer parameters (the channel state and the residual energy) that should be exploited in MAC design for network lifetime maximization. Specifically, to reduce $\mathbb{E}[E_{tx}]$, sensors with better channel realizations should be scheduled for transmission. To reduce $\mathbb{E}[E_w]$, sensors with more residual energies should be favored in order to balance the energy consumption among sensors.

Realizing that channel realizations are independent of the residual energies (the sensor with better channel may have less residual energy), we address in this section the second issue: how to exploit both CSI and REI in MAC design for lifetime maximization. The design focus is the optimal tradeoff between CSI and REI. To maximize the network lifetime, MAC protocols should strike a balance between reducing $\mathbb{E}[E_{tx}]$ and reducing $\mathbb{E}[E_w]$ by taking into account both channel states and residual energies of individual sensors.

A. Problem Formulation

To formulate the problem of exploiting both CSI and REI in MAC design, we introduce the concept of energy-efficiency index. At the beginning of a transmission slot, the energy-efficiency index γ_i of sensor i with channel gains C_i and residual energy E_i is defined as

$$\gamma_i = g(C_i, E_i), \tag{5}$$

where g is a real-valued function. The *active* sensors with the largest L energy-efficiency indices are then scheduled for transmission, where L $(1 \leq L \leq N_0)$ is the number of additional measurements required to complete the current data collection. The problem of exploiting CSI and REI in MAC design is thus reduced to the design of the function g. For example, for the pure opportunistic protocol that enables active sensors with the best channels, we have $\gamma_i = C_i$. Similarly, $\gamma_i = E_i$ leads to the pure conservative protocol that schedules active sensors with the most residual energies.

We point out that it is possible to have a time-varying definition of energy-efficiency index, *i.e.*, $\gamma_i = g_k(C_i, E_i)$ where k denotes the k-th data collection. In this paper, however, we focus on time-invariant function g for its ease of implementation. We show in Section IV.C that protocols defined by a time-invariant energy-efficient index can still be dynamic with respect to the age of the network.

B. A Greedy Approach to Lifetime Maximization

We consider first a greedy approach to lifetime maximization. Referred to as the max-min protocol, it uses an energy-efficiency index defined as

$$\gamma_i = E_i - \frac{1}{C_i}. \tag{6}$$

From (1), we see that the energy-efficiency index given in (6) is essentially (differs by a constant $\mathcal{E}_c$) the residual energy of sensor i after it transmits in the current transmission slot.

The energy-efficiency index defined in (6) ensures that the scheduled active sensors must have the largest energy-efficiency indices among the set of eligible sensors. Below, we give an analytical characterization of the greedy and the static nature of the max-min protocol.

Property 1: **The Greedy Nature of the Max-Min Protocol**
Given the network energy profile $\mathbf{E} = \mathbf{e}$*, the number* $L = l$ *of additional measurements required to complete the current data collection, and the set* $A = \mathcal{A}$ *of eligible sensors at the beginning of a transmission slot, the max-min protocol*

P1.1 *maximizes the minimum residual energy in the network at the end of this transmission slot.*

P1.2 *minimizes the probability that the network dies at the end of this transmission slot.*

Proof: See Appendix A. □□□

Note that P1.1 holds for any realization of the channel state $\mathbf{C}$ while P1.2 is based on the probability space given by $\mathbf{C}$. P1.2 shows that the max-min protocol, exploiting both CSI and REI, is a greedy approach to lifetime maximization. In other words, if the max-min protocol cannot keep the network alive at the end of a transmission slot, then no protocol can.

Property 2: **The Static Property of the Max-Min Protocol**
The max-min protocol is static with respect to the total energy $\sum_{i=1}^{N} E_i$ *in the network. Specifically, given the network energy profile* $\mathbf{E} = \mathbf{e}$*, the number* $L = l$ *of additional measurements required to complete the current data collection, and the set* $A = \mathcal{A}$ *of eligible sensors at the beginning of a transmission slot, we have,* $\forall \epsilon > 0$,

$$\begin{aligned}&\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\ &\quad = \Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e} + \epsilon, A = \mathcal{A}, L = l\},\end{aligned} \tag{7a}$$

$$\begin{aligned}&\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\ &\quad = \Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e} + \epsilon, A = \mathcal{A}, L = l\},\end{aligned} \tag{7b}$$

where $\mathbf{I} = (I_1, \ldots, I_l)$ *are the sensors that have the largest* l *energy-efficiency indices defined in* (6) *among those eligible sensors in* $\mathcal{A}$*,* $\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\}$ *and* $\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\}$ *denote, respectively, the conditional probabilities that the chosen sensors* $\mathbf{I}^*$ *have the best channel realizations and the most residual energies among those eligible sensors.*

Proof: See Appendix B. □□□

Property 2 shows that with the max-min protocol, the probabilities of scheduling the sensor with the best channel realizations and the most residual energies are invariant to a uniform change (ϵ) in the residual energy profile $\mathbf{E}$. Since a uniform decrease in $\mathbf{E}$ leads to a decrease in the total energy in the network which can be viewed as a measure of the network age (the smaller the total energy, the older the network), Property 2 reveals that the max-min protocol is static with respect to the network age. The weight of CSI over REI (and vice versa) remains the same over the span of the network lifetime. We show in the following section that a lifetime-maximizing protocol should dynamically trade off CSI and REI according to the age of the network. The lack of adaptation to the network age limits the performance of the max-min protocol. By contrasting the max-min protocol with the dynamic protocol proposed in Section IV-C and comparing their performance in Section V, we demonstrate the importance of and the significant gain resulted from the adaptability of a MAC protocol to the network age.

C. A Dynamic Protocol for Lifetime Maximization (DPLM)

1) A General Design Principle: To obtain the optimal trade off between CSI and REI, we resort to the law of lifetime given in (3). Consider first the expected energy consumption

$\mathbb{E}[E_{tx}]$ in a randomly chosen data collection. It is shown in [7] that $\mathbb{E}[E_{tx}]$ can be obtained[4] by averaging the expected energy consumption $\mathbb{E}[E_{tx}(k)]$ consumed in the k-th data collection over the randomly chosen data collection index K:

$$\mathbb{E}[E_{tx}] = \mathbb{E}_K\{\mathbb{E}[E_{tx}(K)]\}, \tag{9}$$

where $\mathbb{E}_K\{\cdot\}$ denotes the expectation over K. Note that the probability mass function $\Pr\{K = k\}$ decreases with the data collection index k [7]. This observation leads to the conclusion that the energy consumed at the early stage of the network lifetime carries more weight. Thus, reducing the energy consumption $\mathbb{E}[E_{tx}(k)]$ in the k-th data collection is crucial when k is small (*i.e.*, when the network is young). On the other hand, the wasted energy E_w only depends on the sensor residual energies when the network dies (see (2)). Hence, maintaining small dispersiveness of sensor residual energies is only crucial when the network is approaching the end of its lifetime.

The above discussion suggests that a lifetime-maximizing protocol should be adaptive with respect to the network age. Specifically, MAC protocols should be more opportunistic by favoring sensors with the better channels (focusing on reducing $\mathbb{E}[E_{tx}]$) when the network is young and more conservative by favoring sensors with more residual energies (focusing on reducing $\mathbb{E}[E_w]$) when the network is old. We see here an intuitive connection between extending network lifetime and the retirement-planning strategy. When we are young, we can afford to be more aggressive, putting retirement savings to relatively more risky investments. As we age, we become more conservative.

[4]For completeness, we provide a brief proof of (9). The definition of $\mathbb{E}[E_{tx}]$ given in (4) can be written as

$$\begin{aligned}\mathbb{E}[E_{tx}] &= \lim_{M\to\infty} \frac{\sum_{k=1}^{\max L}\sum_{m=1}^{M} E_{tx}(m,k)1_{[k\le L^{(m)}]}}{\sum_{m=1}^{M} L^{(m)}} \\ &= \sum_{k=1}^{\max L} \underbrace{\lim_{M\to\infty} \frac{\sum_{m=1}^{M} E_{tx}(m,k)1_{[k\le L^{(m)}]}}{\sum_{m=1}^{M} 1_{[k\le L^{(m)}]}}}_{=\mathbb{E}[E_{tx}(k)]} \underbrace{\lim_{M\to\infty} \frac{\sum_{m=1}^{M} 1_{[k\le L^{(m)}]}}{\sum_{m=1}^{M} L^{(m)}}}_{=\Pr\{K=k\}},\end{aligned} \tag{8}$$

where $\max L = \frac{N\mathcal{E}_0}{\mathcal{E}_c}$ is the upper bound on network lifetime, which is finite.

2) The Protocol: Following the general design principle, we propose a dynamic MAC protocol that adaptively trades off CSI with REI according to the age of the network. Referred to as DPLM, the proposed protocol selects active sensors whose current channel realizations demand the least portions of their residual energies for the transmission. The energy-efficiency index of DPLM is defined as

$$\gamma_i = \frac{E_i}{E_{tx}^{(i)}} = \frac{E_i}{\mathcal{E}_c + \frac{1}{C_i}}. \tag{10}$$

Note that the energy-efficiency index defined above in (10) ensures that the scheduled active sensors must have the largest energy-efficiency indices among the set of eligible sensors.

Before investigating the properties of DPLM in a general setting, let us first consider a simple example to gain some intuitions on the dynamic nature of DPLM. Consider a network with two sensors and one of them needs to be chosen in each data collection. Suppose that the network energy profile at the beginning of a data collection give by $\mathbf{E} = (e_1, e_2)$. Without loss of generality, we assume that $e_1 > e_2$. The absolute dispersiveness between sensor residual energies is given by $\Delta = e_1 - e_2$. It can be readily shown from (10) that sensor 2, the one with less energy, is selected if and only if it has larger energy-efficiency index, *i.e.*,

$$\gamma_2 > \gamma_1 \quad \Rightarrow \quad \frac{C_2 - C_1}{C_1 C_2 \mathcal{E}_c + C_2} > \frac{\Delta}{e_1}. \tag{11}$$

Hence, for a given difference Δ in the residual energies, the relative improvement in channel condition required for selecting the sensor with less residual energy decreases with e_1, which is a measure of the network age since the total network energy is given by $2e_1 - \Delta$. Consider the following two extreme cases. When e_1 approaches infinity, we have $\lim_{e_1 \to \infty} \frac{\Delta}{e_1} = 0$ and the condition (11) reduces to $C_2 > C_1$. That is, when there is plenty of energy in the network (the network is young), DPLM acts like the pure opportunistic protocol by selecting the sensor with the best channel. On the other hand, when e_1 approaches zero (the network is old), we have $\lim_{e_1 \to 0} \frac{\Delta}{e_1} = \infty$ and the condition (11) holds with probability 0; DPLM puts more weight on REI by selecting the sensor with the most residual energy (specifically, sensor 1). Property 3 gives an analytical characterization of the dynamic nature of DPLM.

Property 3: **The Dynamic Nature of DPLM**
DPLM dynamically trades off CSI with REI according to the network age measured by the total energy $\sum_{i=1}^{N} E_i$ *in the network. Specifically, given the network energy profile* $\mathbf{E} = \mathbf{e}$*, the number* $L = l$ *of additional measurements required to complete the current data collection, and the set* $A = \mathcal{A}$ *of eligible sensors at the beginning of a transmission slot, we have,* $\forall \epsilon > 0$,

$$\begin{aligned} &\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\ &\qquad \leq \Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e} + \epsilon, A = \mathcal{A}, L = l\}, \end{aligned} \tag{12a}$$

$$\begin{aligned} &\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\ &\qquad \geq \Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e} + \epsilon, A = \mathcal{A}, L = l\}, \end{aligned} \tag{12b}$$

where $\mathbf{I} = (I_1, \ldots, I_l)$ *are the sensors that have the largest* l *energy-efficiency indices defined in* (10) *among those eligible sensors in* $\mathcal{A}$*,* $\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\}$ *and* $\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\}$ *denote, respectively, the conditional probabilities that the chosen sensors* $\mathbf{I}^*$ *have the best channel realizations and the most residual energies among those eligible sensors.*

Proof: See Appendix C. □□□

Property 3 shows that the probability of choosing sensors with the best channels increases while the probability of choosing sensors with the most residual energies decreases with the total residual energy in the network. In other words, when the network is young, DPLM is more likely to choose the sensors with the best channels to reduce the transmission energy. When the network grows old, DPLM becomes more conservative in order to reduce the wasted energy when the network dies.

3) The Asymptotic Optimality of DPLM: When channel fading is i.i.d. across transmission slots, the optimal MAC protocol under the unconstrained formulation is the pure opportunistic protocol which enables the active sensors with the best channel realizations to transmit [8], [10]. One would expect that the optimal MAC protocol under the constrained formulation approaches the pure opportunistic protocol when the constraint on the initial energy becomes less restrictive, *i.e.*, $\mathcal{E}_0 \to \infty$. In Property 4, we prove this statement and characterize the maximum rate at which the network lifetime increases with the initial energy $\mathcal{E}_0$. We then show in Property 5 that DPLM is asymptotically optimal. Specifically, in the asymptotic regime, DPLM approaches the pure opportunistic protocol and its relative performance loss as compared to the optimal lifetime diminishes.

Property 4: **The Asymptotic Behavior of the Optimal MAC Protocol**
Assume that the channel gains are bounded below and i.i.d. across transmission slots.

P4.1 *Under the unconstrained formulation, the expected total energy consumption of the pure opportunistic protocol in a data collection is given by*

$$\mathcal{E}_{\min} \triangleq N_0\mathcal{E}_c + \sum_{n=1}^{N_0} \mathbb{E}\left[\frac{1}{C_{(n)}}\right] \tag{13}$$

where $C_{(n)}$ is the n-th largest element of channel gains $\{C_i\}_{i=1}^{N}$.
The optimal MAC protocol in terms of network lifetime approaches the pure opportunistic protocol as the initial energy goes to infinity. Specifically, the asymptotic expected total energy consumption $\mathbb{E}[E_{tx}^{opt}]$ of the optimal MAC protocol in a randomly chosen data collection is given by

$$\lim_{\mathcal{E}_0\to\infty} \mathbb{E}[E_{tx}^{opt}] = \mathcal{E}_{\min}. \tag{14}$$

P4.2 *The asymptotic lifetime increase rate achieved by the optimal MAC protocol is given by*

$$\lim_{\mathcal{E}_0\to\infty} \frac{\mathbb{E}[L^{opt}]}{\mathcal{E}_0} = \frac{N}{\mathcal{E}_{\min}}. \tag{15}$$

Proof: See Appendix E for details. □□

Property 5: **The Asymptotic Optimality of DPLM**

Assume that the channel gains are bounded below and i.i.d. across transmission slots. In the asymptotic regime ($\mathcal{E}_0 \rightarrow \infty$),

P5.1 DPLM approaches the pure opportunistic protocol. Specifically, the expected energy consumption $\mathbb{E}[E_{tx}^{\scriptscriptstyle DPLM}]$ of DPLM in a randomly chosen data collection approaches $\mathcal{E}_{\min}$, which is defined in (13)*:*

$$\lim_{\mathcal{E}_0 \rightarrow \infty} \mathbb{E}[E_{tx}^{\scriptscriptstyle DPLM}] = \mathcal{E}_{\min}. \tag{16}$$

P5.2 DPLM is asymptotically optimal. Specifically, the relative performance loss of DPLM as compared to the optimal lifetime $\mathbb{E}[L^{opt}]$ diminishes with the initial energy:

$$\lim_{\mathcal{E}_0 \rightarrow \infty} \frac{\mathbb{E}[L^{opt}] - \mathbb{E}[L^{\scriptscriptstyle DPLM}]}{\mathbb{E}[L^{opt}]} = 0, \tag{17}$$

where $\mathbb{E}[L^{\scriptscriptstyle DPLM}]$ denotes the lifetime achieved by DPLM.

Proof: The proof of Property 5 is built upon Lemmas 1 - 5 developed in Appendix D. See Appendix F for details. □□□

V. Distributed Implementation

In this section, we address the last issue: how to implement, in a distributed fashion, a MAC protocol that uses physical layer parameters, specifically, the channel state and the residual energy. We seek implementations that allow each sensor to determine whether to transmit based on its own energy-efficiency index.

Here, we provide a possible solution based on the opportunistic carrier sensing scheme first proposed in [25]. The basic idea is to incorporate the local information (*i.e.*, the energy-efficiency index) of each sensor into the backoff strategy of carrier sensing. This opportunistic carrier sensing scheme provides a distributed solution to the general problem of finding the global maximum or minimum. Let us consider the case where N_0 orthogonal codes are available and the chosen sensors transmit simultaneously using CDMA. We partition each transmission slot into two segments: carrier sensing and data transmission. During carrier sensing period, sensors with the largest L (the number of additional measurements required to complete the current data collection) energy-efficiency indices are chosen and the orthogonal codes are distributed among these chosen sensors. Specifically, at the beginning of each transmission slot, the AP broadcasts a beacon signal to activate and synchronize all eligible sensors in the network. Sensors that have already transmitted in previous transmission slots do not need to participate in the remaining slots of this data collection. Upon receiving the request, each eligible sensor estimates its channel gains C_i and calculates the predefined energy-efficiency index γ_i based on its own channel gain $C_i = c_i$ and/or residual energy $E_i = e_i$. Then, every active sensor maps its own γ_i to a backoff time τ_i based on a predetermined strictly decreasing function $f(\gamma)$ and listens to the channel. Note that inactive sensors will not participate and can turn off their transceivers until the next transmission slot. The active sensor i will transmit a short beacon signal with its chosen backoff delay τ_i if and only if less than L beacon signals have been transmitted before its backoff time expires. According to the order of these beacon signals, each active sensor that has transmitted a beacon signal can obtain one of the orthogonal codes. During data transmission period, the chosen L sensors transmit using the different orthogonal codes and the other sensors can turn off their electronics. If $f(\gamma)$ is chosen to be a strictly decreasing function of the energy-efficiency index γ as shown in Fig. 3, this opportunistic carrier sensing will ensure that the active sensor with the largest energy-efficiency index $\max_i\{\gamma_i\}$ seizes the channel under ideal conditions.

A collision-free implementation of opportunistic carrier sensing relies on the following ideal assumptions: (1) all sensors can hear each other; (2) the propagation delay among sensors is negligible; and (3) sensors are synchronized. The first two assumptions are inherent to any carrier sensing schemes to ensure collision-free while the third one is unique to the opportunistic carrier sensing scheme.

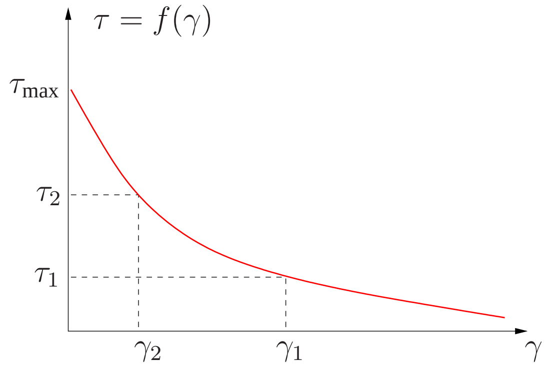


Fig. 3. Opportunistic carrier sensing.

VI. Simulation Examples

In this section, we compare the performance of several distributed MAC protocols via simulations. For each network setup, we perform $M = 2000$ Monte Carlo runs. The proposed DPLM and max-min protocols are compared with the following three schemes: (1) the layered approach which assumes that nodes are indistinguishable at the PHY layer; (2) the pure opportunistic protocol which uses solely CSI; (3) the pure conservative protocol which exploits only REI. We assume perfect carrier sensing unless otherwise specified.

In the following figures, we assume that $N_0 = 1$, *i.e.*, only one sensor is chosen in each data collection. Assume that the transmitter circuitry consumption is $\mathcal{E}_c = 0.01$ and the energy required for a sensor to estimate its channel realization is $\mathcal{E}_{es} = 0.001$. Channel fading is i.i.d. Rayleigh across transmission slots and across sensors with unit mean square. That is, the channel gain C_i follows an exponential distribution with mean $\mathbb{E}[C_i] = 1$.

The threshold on the number of dead sensors is $N_T = 1$, *i.e.*, the lifetime is defined as the number of data collections until any sensor in the network dies. We ignore the tail portion of the network lifetime when sensors only have enough energy for exceptionally good channel realizations. Specifically, a sensor is considered dead if it does not have enough energy for transmission in 99.995% of the time, *i.e.*, $\Pr\{e_i < \mathcal{E} + \frac{1}{C_i}\} \geq 99.995\%$.

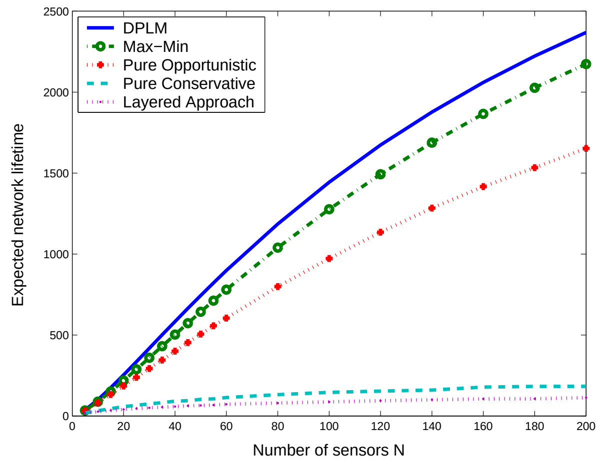


Fig. 4. The expected network lifetime $\mathbb{E}[L]$ versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

A. Lifetime vs. Network Size

We first study the expected network lifetime $\mathbb{E}[L]$ as a function of the number N of sensors. As shown in Fig. 4, the network lifetime $\mathbb{E}[L]$ increases with N, but the rate at which $\mathbb{E}[L]$ increases saturates. As expected, the layered approach which ignores diversities at the PHY layers performs the worst. MAC protocols exploiting CSI (such as the pure opportunistic scheme, the max-min scheme, and DPLM) outperform those without CSI (such as the layered approach and the pure conservative scheme). The max-min protocol outperforms the pure opportunistic protocol when the number of sensors is large. DPLM achieves the best performance, and its performance gain increases with the number of sensors.

In Fig. 5, we investigate the expected total energy consumptions $\mathbb{E}[E_{tx}]$ of MAC protocols exploiting CSI in a randomly chosen data collection and compare them with the asymptotic lower bound $\mathcal{E}_{\min}$ given in (13). Due to multiuser diversity [10], $\mathbb{E}[E_{tx}]$ decreases with the number N of sensors. Not surprisingly, the pure opportunistic protocol, solely focusing on minimizing the transmission energy, performs the best in terms of $\mathbb{E}[E_{tx}]$ and achieves $\mathcal{E}_{min}$ even when the initial energy $\mathcal{E}_0$ is small. As the initial energy $\mathcal{E}_0$ increases, the expected

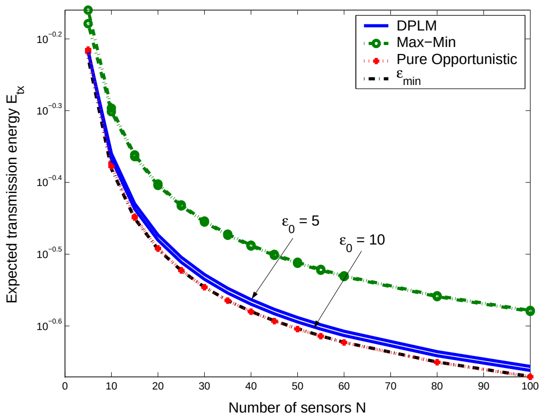


Fig. 5. The expected energy consumption $\mathbb{E}[E_{tx}]$ in a randomly chosen data collection versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5, 10$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

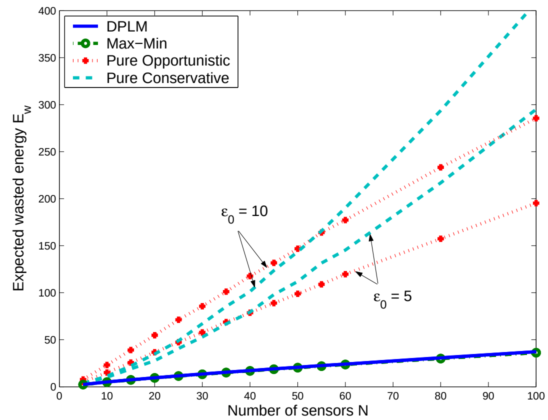


Fig. 6. The expected wasted energy $\mathbb{E}[E_w]$ versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5, 10$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

energy consumption $\mathbb{E}[E_{tx}^{\text{DPLM}}]$ of DPLM decreases and quickly approaches $\mathcal{E}_{\min}$, confirming P5.1. A small $\mathcal{E}_0$ that allows a sensor to transmit, on the average, only 10 times in its lifetime seems to be sufficient to bring $\mathbb{E}[E_{tx}^{\text{DPLM}}]$ close to $\mathcal{E}_{\min}$. We point out that the expected energy consumption $\mathbb{E}[E_{tx}]$ of the pure opportunistic protocol under the constrained formulation may be larger than $\mathcal{E}_{\min}$ especially when N is small. This is because when the sensor with the best channel is inactive, the pure opportunistic protocol will have to choose an active sensor with a worse channel realization. DPLM, by balancing the energy consumption among sensors and thus enlarging the set of active sensors, can even outperform the pure opportunistic scheme in $\mathbb{E}[E_{tx}]$ when N is small. Compared to the pure opportunistic approach and DPLM, the max-min protocol performs the worst in terms of the expected energy consumption $\mathbb{E}[E_{tx}]$.

Fig. 6 investigates the expected wasted energy $\mathbb{E}[E_w]$ of different MAC protocols. As the number N of sensors increases, $\mathbb{E}[E_w]$ of all protocols increases, which can be readily seen from (2). The max-min protocol and DPLM offer significant reduction in the expected wasted energy as compared with the pure opportunistic and the pure conservative protocols.

As the initial energy $\mathcal{E}_0$ increases, the expected wasted energies $\mathbb{E}[E_w]$ of the max-min protocol and DPLM remain almost the same while those of the pure opportunistic and the pure conservative protocols increase significantly. Combining Figs. 5 and 6, we see that DPLM achieves the best balance between reducing $\mathbb{E}[E_{tx}]$ and reducing $\mathbb{E}[E_w]$; it consumes nearly minimum energy consumption $\mathcal{E}_{\min}$ per data collection without sacrificing $\mathbb{E}[E_w]$. The reason behind this desired property is the dynamic nature of DPLM as illuminated below.

B. The Dynamic Nature of DPLM

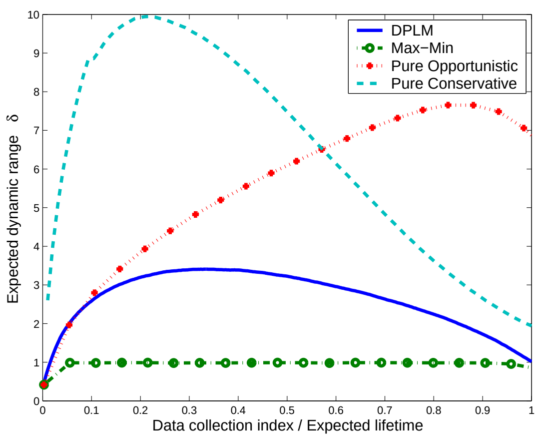


Fig. 7. The expected dynamic range $\bar{\delta} = \mathbb{E}[E_{(1)} - E_{(N)}]$ versus the network age. $N = 10$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 20$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

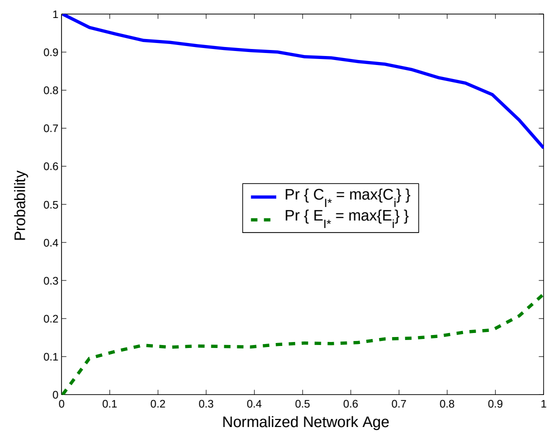


Fig. 8. The probability that DPLM chooses the sensor with the best channel and the probability that it chooses the sensor with the most residual energy. $N = 10$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 20$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

Fig. 7 shows the expected dynamic range $\bar{\delta} = \mathbb{E}[\max\{\mathbf{E}\} - \min\{\mathbf{E}\}]$ of the network energy profile during the network lifetime. Since different MAC protocols may achieve different network lifetime, we normalize the data collection index by the expected network lifetime of the protocol. The expected dynamic range of the pure opportunistic scheme grows large toward the end of the network lifetime, resulting in its poor performance in terms of the expected wasted energy $\mathbb{E}[E_w]$ as shown in Fig. 6. The dynamic range of the max-min protocol remains constant during the whole network lifetime, confirming its static nature. Adaptive to the network age, DPLM allows large variation in sensors' residual energies at the early stage of the lifetime (when reducing the transmission energy is more crucial) and brings down the dynamic range to as low as that of the max-min protocol toward the end of the lifetime (when balancing energy consumption among sensors becomes crucial). This explains how DPLM achieves the nearly minimum transmission energy $\mathcal{E}_{\min}$ without sacrificing the performance in the wasted energy $\mathbb{E}[E_w]$. Fig. 8 further demonstrates the dynamic nature of DPLM. As the age of the network increases, the probability that DPLM selects the sensor with the best channel realization decreases while the probability of choosing the sensor with the most residual energy increases.

C. The Asymptotic Optimality of DPLM

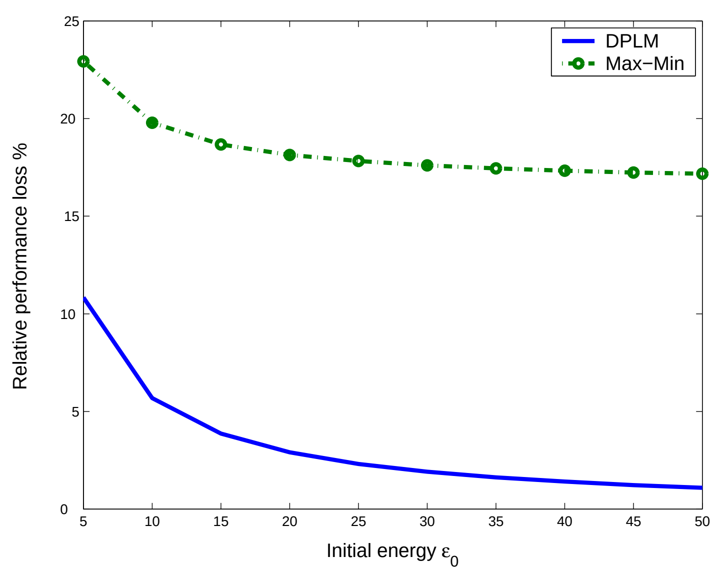


Fig. 9. The asymptotic optimality of DPLM in network lifetime. $N = 50$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

The asymptotic optimality of DPLM in terms of using CSI has been demonstrated in Fig. 5. In Fig. 9, we investigate the relative performance loss of the proposed DPLM and max-min protocols as compared to $\frac{N\mathcal{E}_0}{\mathcal{E}_{\min}}$, where $\frac{N}{\mathcal{E}_{\min}}$ is the asymptotic increase rate of the optimal lifetime with respect to $\mathcal{E}_0$. We can see that as the initial energy $\mathcal{E}_0$ increases, the relative performance loss of DPLM approaches 0, which confirms P5.2. Moreover, its convergence rate is fast. For example, when the initial energy is $\mathcal{E}_0 = 10$, *i.e.*, a sensor can transmit, on average, 10 times during its lifetime, the relative performance loss is as low as 6%. The max-min protocol, however, is not asymptotically optimal.

VII. CONCLUSION

In this paper, we studied the integrated design of MAC protocols for lifetime maximization in sensor networks. We identified two key PHY layer parameters — the channel state and the residual energy — that affect the network lifetime. Distributed protocols that exploit both CSI and REI were proposed for lifetime maximization. Referred to as DPLM, the proposed protocol selects the sensor whose channel realization demands the least portion of its residual energy for the current transmission. We demonstrated analytically that DPLM adaptively trades off CSI and REI according to the age of the network. It is more aggressive to reduce the total energy consumption by prioritizing the sensor with the best channel when the network is young and more conservative to balance the sensor residual energies by favoring the sensor with the most residual energy when the network is old. Its asymptotic optimality was established analytically. By contrasting the dynamic nature of DPLM with the static nature of the max-min protocol and comparing their performance, we demonstrate the importance of and the significant gain resulted from the adaptability of a MAC protocol to the network age.

APPENDIX A: PROOF OF PROPERTY 1

Let $\mathbf{C} = \mathbf{c}$ be any channel realization in this transmission slot. Then, the minimum residual energy $E'_{\min}$ at the end of this data collection is given by

$$E'_{\min} = \min\left\{\min\{\mathbf{e}\}, \min_{j\in\mathbf{i}}\left\{e_j - \left(\mathcal{E}_c + \frac{1}{c_j}\right)\right\}\right\}, \tag{18}$$

where $\mathbf{i} = (i_1, \ldots, i_l)$ are the indices of the chosen active sensors. Since the max-min protocol chooses sensors that have the largest $\left\{e_i - \frac{1}{c_i}\right\}$, it maximizes the minimum residual energy $E'_{\min}$ given in (18) for any channel realization. Hence, we obtain P1.1.

The probability that the network dies at the end of the given transmission slot is given by the probability that the $(N - N_T + 1)$-th largest residual energy after the transmissions of the chosen active sensors drops below $\mathcal{E}_c$. From the definition of the energy-efficient index of the max-min protocol, we can obtain P1.2.

Appendix B: Proof of Property 2

Without loss of generality, we assume that the given network energy profile $\mathbf{e}$ is ordered, *i.e.*, $e_1 \geq \ldots \geq e_N$. The probability that the chosen sensors $\mathbf{I} \triangleq (I_1, \ldots, I_l)$ have the best $L = l$ channel realizations among eligible sensors in the set $A = \mathcal{A}$ is given by

$$\begin{aligned}
&\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\
&= \sum_{\mathbf{i}\in\mathcal{I}} \Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I}, \mathbf{I} = \mathbf{i} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\
&= \sum_{\mathbf{i}\in\mathcal{I}} \Pr\{C_{i_k} \geq C_j, \gamma_{i_k} \geq \gamma_j, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k \in \mathbf{i} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\
&= \sum_{\mathbf{i}\in\mathcal{I}} \Pr\left\{C_{i_k} \geq C_j, \frac{1}{C_{i_k}} - \frac{1}{C_j} \geq e_{i_k} - e_j, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k \in \mathbf{i} \,\middle|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\right\},
\end{aligned} \tag{19}$$

where $\mathcal{I} = \{\mathbf{i} : \mathbf{i} \subset \{1, \ldots, N\}, |\mathbf{i}| = l\}$ is the sample space of the chosen sensors $\mathbf{I}$. The probability that the chosen sensors $\mathbf{I}$ have the most $L = l$ residual energies among the eligible set $A = \mathcal{A}$ of sensors can be derived as

$$\begin{aligned}
&\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\
&= \Pr\{\gamma_{i_k} \geq \gamma_j, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k = \text{the } k\text{-th smallest element in } \mathcal{A} \,|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\} \\
&= \Pr\left\{\frac{1}{C_j} - \frac{1}{C_{i_k}} \geq e_j - e_{i_k}, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k \,\middle|\, \mathbf{E} = \mathbf{e}, A = \mathcal{A}, L = l\right\}
\end{aligned} \tag{20}$$

We can see that both (19) and (20) only depend on the absolute dispersiveness $e_i - e_j$ of sensor residual energies; they are invariant to a uniform change (ϵ) in the network residual energy profile $\mathbf{E}$. Since $(e_i + \epsilon) - (e_j + \epsilon) = e_i - e_j$, (12) follows.

APPENDIX C: PROOF OF PROPERTY 3

The proof of Property 3 is similar to that of Property 2. Without loss of generality, we assume that $e_1 \geq \ldots \geq e_N$, and obtain that

$$\begin{aligned}
&\Pr\{C_{I_k} \geq C_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E}=\mathbf{e}, A=\mathcal{A}, L=l\} \\
&= \sum_{\mathbf{i}\in\mathcal{I}} \Pr\left\{ C_{i_k} \geq C_j, \frac{\frac{1}{C_j}+\mathcal{E}_c}{\frac{1}{C_{i_k}}+\mathcal{E}_c} \geq \frac{e_j}{e_{i_k}}, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k \in \mathbf{i} \,\middle|\, \mathbf{E}=\mathbf{e}, A=\mathcal{A}, L=l \right\}, \\
&= \sum_{\mathbf{i}\in\mathcal{I}} \Pr\left\{ C_{i_k} \geq C_j, \forall j > i_k, \frac{\frac{1}{C_j}+\mathcal{E}_c}{\frac{1}{C_{i_k}}+\mathcal{E}_c} \geq \frac{e_j}{e_{i_k}}, \forall j < i_k, j \in \mathcal{A}\backslash\mathbf{i}, i_k \in \mathbf{i} \,\middle|\, \mathbf{E}=\mathbf{e}, A=\mathcal{A}, L=l \right\}
\end{aligned} \tag{21}$$

and

$$\begin{aligned}
&\Pr\{e_{I_k} \geq e_j, \forall j \in \mathcal{A}\backslash\mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E}=\mathbf{e}, A=\mathcal{A}, L=l\} \\
&= \Pr\left\{ \frac{\frac{1}{C_j}+\mathcal{E}_c}{\frac{1}{C_{i_k}}+\mathcal{E}_c} \geq \frac{e_j}{e_{i_k}}, \forall j \in \mathcal{A}\backslash\mathbf{i}, \forall i_k = \text{the } k\text{-th smallest element in } \mathcal{A} \,\middle|\, \mathbf{E}=\mathbf{e}, A=\mathcal{A}, L=l \right\}.
\end{aligned} \tag{22}$$

We can see that (21) decreases and (22) increases with $\frac{e_i}{e_j}$, $i<j$. Since $\frac{e_i}{e_j} \geq \frac{e_i+\epsilon}{e_j+\epsilon}$ for all $i<j$, Property 3 follows.

APPENDIX D: PROOF OF LEMMAS 1 - 4

Here, we provide four lemmas used in the proofs of Properties 4 and 5. We consider M i.i.d. trials, *i.e.*, the network is deployed M times sequentially with identical settings. Let $L^{(m)}$ be network lifetime (*i.e.*, the number of data collections) in the m-th trial. Let $\mathbf{E}=(E_1,\ldots,E_N)$ and $\mathbf{C}=(C_1,\ldots,C_N)$ denote, respectively, the network energy profile and the channel state at the beginning of a data collection chosen with equal probability from the total $\sum_{m=1}^{M} L^{(m)}$ data collections. For simplicity, we write $E_{\max}=\max\{\mathbf{E}\}$ and $E_{\min}=\min\{\mathbf{E}\}$. We assume that channel gains are i.i.d. across transmission slots. The above notations and assumptions will be adopted throughout this Appendix. Note that the distribution of the network energy profile $\mathbf{E}$ at the beginning of the randomly chosen data collection depends on the initial energy $\mathcal{E}_0$ and the MAC protocol.

Since channel realizations are bounded below, the total energy consumption E_{tx} in any data collection is bounded by

$$N_0\mathcal{E}_c < E_{tx} \leq N_0\mathcal{E}_u, \tag{23}$$

where the upper bound $\mathcal{E}_u$ is determined by the worst channel realization and the lower bound $\mathcal{E}_c$ is the transmitter circuity consumption. Hence, the network lifetime in a trial is bounded by

$$\frac{N\mathcal{E}_0}{N_0\mathcal{E}_u} \leq L^{(m)} < \frac{N\mathcal{E}_0}{N_0\mathcal{E}_c}, \quad \forall m. \tag{24}$$

Lemma 1: Consider the first transmission slot of a randomly chosen data collection. For any fixed $\epsilon > 0$, there exists $\alpha > 0$ independent of the initial energy $\mathcal{E}_0$ such that

$$\Pr\left\{C_{I_k} \leq C_{(N_0+1)},\ \textit{for any}\ I_k \in \mathbf{I} \ \middle|\ \frac{E_{\max}-E_{\min}}{E_{\min}} < \alpha\right\} < \epsilon, \forall \mathcal{E}_0, \tag{25}$$

where $\mathbf{I} = (I_1, \ldots, I_{N_0})$ consists of the indices of sensors that have the largest N_0 energy-efficiency indices defined in (10) *for DPLM.*

Proof: Suppose the network energy profile at the beginning of a randomly chosen data collection is given $\mathbf{E} = \mathbf{e}$. Without loss of generality, we assume that $e_1 \geq \ldots \geq e_N$. Then, we have $\frac{e_i}{e_j} \leq \frac{e_1}{e_N}$ for any i, j. Note that in the first transmission slot of any data collection, the set of eligible sensors is given by $A = \{1, \ldots, N\}$ and the number of more measurements to collection is $N^* = N_0$. From (21), we obtain that

$$\begin{aligned} 1 &\geq \Pr\{C_{I_k} \geq C_{(N_0)}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}\} = \Pr\{C_{I_k} \geq C_j, \forall j \bar{\in} \mathbf{I}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}\} \\ &\geq \sum_{\mathbf{i} \in \mathcal{I}} \Pr\left\{ C_{i_k} \geq C_j, \forall j > i_k, \frac{\frac{1}{C_j} + \mathcal{E}_c}{\frac{1}{C_{i_k}} + \mathcal{E}_c} \geq \frac{e_1}{e_N}, \forall j < i_k, j \bar{\in} \mathbf{i}, i_k \in \mathbf{i} \ \middle|\ \mathbf{E} = \mathbf{e} \right\}, \end{aligned} \tag{26}$$

where the sample space of $\mathbf{I}$ is $\mathcal{I} = \{\mathbf{i} : \mathbf{i} \subset \{1, \ldots, N\}, |\mathbf{i}| = N_0\}$. Notice that as the ratio $\frac{e_1}{e_N}$ decreases to 1, the set $\left\{\frac{\frac{1}{C_j}+\mathcal{E}_c}{\frac{1}{C_{i_k}}+\mathcal{E}_c} \geq \frac{e_1}{e_N}, \forall j < i_k\right\}$ monotonically increases to the set $\{C_{i_k} \geq C_j, \forall j < i_k\}$. Taking limit $\frac{e_1}{e_N} \to 1$ on both sides of (26), we obtain

$$\begin{aligned} 1 &\geq \lim_{\frac{e_1}{e_N} \to 1} \Pr\{C_{I_k} \geq C_{(N_0)}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}\} \\ &\geq \sum_{\mathbf{i} \in \mathcal{I}} \Pr\{ C_{i_k} \geq C_j, \forall j \bar{\in} \mathbf{i}, \forall i_k \in \mathbf{i} \,|\, \mathbf{E} = \mathbf{e}\} \\ &= \sum_{\mathbf{i} \in \mathcal{I}} \Pr\{C_{i_k} \geq C_{(N_0)}, \forall i_k \in \mathbf{i}\} = 1. \end{aligned} \tag{27}$$

Hence, $\Pr\{C_{I_k} \geq C_{(N_0)}, \forall I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}\} \to 1$. That is, for any $\epsilon > 0$, there exists $\alpha > 0$ such that $\frac{e_1}{e_N} < 1 + \alpha$ (*i.e.*, $\frac{e_1 - e_N}{e_N} < \alpha$) implies $\Pr\{C_{I_k} \leq C_{(N_0+1)},$ for any $I_k \in \mathbf{I} \,|\, \mathbf{E} = \mathbf{e}\} < \epsilon$. Hence, we obtain Lemma 1. □

Lemma 2: If DPLM is employed, then for any fixed $\epsilon > 0$, there exists $\beta > 0$ independent of the initial energy $\mathcal{E}_0$ such that

$$\Pr\{E_{\max} - E_{\min} > \beta\} < \epsilon, \quad \forall \mathcal{E}_0, \tag{28}$$

where $\Pr\{E_{\max} - E_{\min} > \beta\}$ is the probability that the dynamic range $E_{\max} - E_{\min}$ of sensor residual energies $\mathbf{E}$ at the beginning of a randomly chosen data collection is greater than β.

Proof: The probability that $E_{\max} - E_{\min} > \beta$ occurs in a randomly chosen data collection is given by

$$\begin{aligned}\Pr\{E_{\max} - E_{\min} > \beta\} &\triangleq \lim_{M\to\infty} \frac{\sum_{m=1}^{M} \#\text{ of data collections when } E_{\max} - E_{\min} > \beta \text{ in the } m\text{-th trial}}{\sum_{m=1}^{M} L^{(m)}} \\ &= \frac{\mathbb{E}[\#\text{ of data collections when } E_{\max} - E_{\min} > \beta \text{ in a lifetime}]}{\mathbb{E}[\#\text{ of data collections in a lifetime}]} \\ &\leq \frac{\mathcal{E}_u}{\mathcal{E}_c} \Pr\{E_{\max} - E_{\min} > \beta \text{ ever occurs in a lifetime}\}.\end{aligned} \tag{29}$$

The second equation in (29) is obtained by the strong law of large numbers (SLLN). Let $\mathbf{E}' = (E'_1, \ldots, E'_N)$ be the network energy profile at the end of a data collection that starts with $\mathbf{E}$. Since the energy consumed in a data collection is upper bounded by $\mathcal{E}_u$ and a sensor transmits at most once in a data collection, the dynamic range $E_{\max} - E_{\min}$ of the network energy profile increases at most $\mathcal{E}_u$ from the beginning to the end of a data collection, *i.e.*, $E'_{\max} - E'_{\min} \leq E_{\max} - E_{\min} + \mathcal{E}_u$. Hence, if the dynamic range $E_{\max} - E_{\min}$ exceeds a fixed $\beta (> \mathcal{E}_u)$ in a lifetime, then there have been at least $\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor - 1$ data collections at the end of which the dynamic ranges increase ($E'_{\max} - E'_{\min} > E_{\max} - E_{\min}$) given that these data collections start with $E_{\max} - E_{\min} > \mathcal{E}_u$.

Next, we show that the probability $\Pr\{E'_{\max} - E'_{\min} > E_{\max} - E_{\min} \,|\, E_{\max} - E_{\min} > \mathcal{E}_u\}$ can be bounded by a number $q < 1$ independent of the energy profile and the initial energy. Let us consider the following event: Q denotes the event that the sensor with the most residual energy $E_{\max}$ has the N_0-largest channel realization in the first transmission slot. When event Q occurs and $E_{\max} - E_{\min} > \mathcal{E}_u$, the sensor with the most residual energy will be chosen by DPLM for transmission and it will consume the most transmission energy in this data collection. Hence, when event Q happens, the dynamic range of the energy profile will not increase at the end of this data collection (*i.e.*, $E'_{\max} - E'_{\min} \leq E_{\max} - E_{\min}$) given that this data collection starts with $E_{\max} - E_{\min} > \mathcal{E}_u$. Since channel gains are i.i.d. across transmission slots, we can show from

(29) that

$$\begin{aligned}
&\Pr\{E_{\max} - E_{\min} > \beta\} \\
&\quad\le \frac{\mathcal{E}_u}{\mathcal{E}_c}\left[\Pr\{E'_{\max} - E'_{\min} > E_{\max} - E_{\min} \,|\, E_{\max} - E_{\min} > \mathcal{E}_u\}\right]^{\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor - 1} \\
&\quad\le \frac{\mathcal{E}_u}{\mathcal{E}_c}[1 - \Pr\{Q\}]^{\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor - 1} \\
&\quad\le \frac{\mathcal{E}_u}{\mathcal{E}_c}[\underbrace{1 - \min_{i \in \{1,\ldots,N\}} \Pr\{C_i = C_{(N_0)}\}}_{\triangleq q}]^{\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor - 1}.
\end{aligned} \tag{30}$$

Since $\Pr\{C_i = C_{(N_0)}\} > 0$ for every $i \in \{1, \ldots, N\}$, there exists $q < 1$ independent of the energy profile and the initial energy. For fixed $\mathcal{E}_u$ and $\mathcal{E}_c$, the upper bound in (30) approaches 0 as $\beta \to \infty$. Hence, for any $\epsilon > 0$, there exists $\beta > 0$ independent of $\mathcal{E}_0$ such that $\Pr\{E_{\max} - E_{\min} > \beta\} < \epsilon$ holds for all $\mathcal{E}_0$. Lemma 2 follows. □□□

Lemma 3: Suppose that channel fading is i.i.d. across sensors. If DPLM is employed, then for any finite fixed $\kappa > 0$, we have

$$\lim_{\mathcal{E}_0 \to \infty} \Pr\{E_{\min} \le \kappa\} = 0, \tag{31}$$

where $\Pr\{E_{\min} \le \kappa\}$ is the probability that the least residual energy $E_{\min}$ at the beginning of a randomly chosen data collection drops below κ.

Proof: Fix $\epsilon > 0$ and $\kappa > 0$. Applying Lemma 2, we can show that there exists $\beta > 0$ such that $\Pr\{E_{\max} - E_{\min} > \beta\} < \frac{\epsilon}{2}$. Hence,

$$\Pr\{E_{\max} > \kappa + \beta, E_{\min} \le \kappa\} \le \Pr\{E_{\max} - E_{\min} > \beta\} < \frac{\epsilon}{2}. \tag{32}$$

Similar to (29), we can show that the probability that the most residual energy $E_{\max}$ at the beginning of a randomly chosen data collection drops below $\kappa + \beta$ is given by

$$\Pr\{E_{\max} < \kappa + \beta\} = \frac{\mathbb{E}[\#\text{ of data collections when } E_{\max} < \kappa + \beta \text{ in a network lifetime}]}{\mathbb{E}[L]}. \tag{33}$$

From (23) and (24), we can see that when $E_{\max} < \kappa + \beta$, there are at most $\frac{N(\kappa+\beta)}{N_0 \mathcal{E}_c}$ data collections left in a network lifetime, and hence (33) can be bounded as

$$\Pr\{E_{\max} < \kappa + \beta\} \le \frac{N(\kappa + \beta)}{N_0 \mathcal{E}_c} \frac{N_0 \mathcal{E}_u}{N \mathcal{E}_0} = \left[\frac{(\kappa + \beta)\mathcal{E}_u}{\mathcal{E}_c}\right] \frac{1}{\mathcal{E}_0}. \tag{34}$$

Hence, there exists $\mathcal{E}_0^*$ such that $\Pr\{E_{\max} \le \kappa + \beta\} < \frac{\epsilon}{2}$ and we can obtain that

$$\Pr\{E_{\max} \le \kappa + \beta, E_{\min} \le \kappa\} < \Pr\{E_{\max} \le \kappa + \beta\} < \frac{\epsilon}{2}, \quad \forall \mathcal{E}_0 > \mathcal{E}_0^*. \tag{35}$$

Combining (32) and (35), we obtain that for any $\mathcal{E}_0 > \mathcal{E}_0^*$,

$$\Pr\{E_{\min} \leq \kappa\} = \Pr\{E_{\max} \geq \kappa + \beta, E_{\min} \leq \kappa\} + \Pr\{E_{\max} \leq \kappa + \beta, E_{\min} \leq \kappa\} < \epsilon, \tag{36}$$

which completes the proof of Lemma 3. □□□

Lemma 4: The ratio $\frac{\mathbb{E}[E_w^{DPLM}]}{\mathcal{E}_0}$ *between the expected wasted energy* $\mathbb{E}[E_w^{DPLM}]$ *of DPLM and the sensor initial energy* $\mathcal{E}_0$ *approaches zero as* $\mathcal{E}_0$ *approaches infinity, i.e.,*

$$\lim_{\mathcal{E}_0 \to \infty} \frac{\mathbb{E}[E_w^{DPLM}]}{\mathcal{E}_0} = 0. \tag{37}$$

Proof: Let $\mathbf{E}'$ be the network energy profile at the end of the last valid data collection. Without loss of generality, we assume that $E'_1 \geq \ldots \geq E'_N$. From (2), the wasted energy E_w in the network can be bounded as

$$E_w = \sum_{n=1}^{N} E'_n \leq NE'_1 = NE'_N + N(E'_1 - E'_N). \tag{38}$$

Since a sensor consumes at most $\mathcal{E}_u$ energy in a data collection, the least energy E'_N in the network must be less than $\mathcal{E}_u$: $E'_N < \mathcal{E}_u$ (otherwise, at least one more data collection can be carried out). Hence, $E_w \leq N(\mathcal{E}_u + E'_1 - E'_N)$.

From (30), we obtain that

$$\Pr\{E'_1 - E'_N > \beta\} \leq \Pr\{E'_1 - E'_N > \beta \text{ ever occurs in a lifetime}\} < q^{\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor - 1}. \tag{39}$$

Fix $\epsilon > 0$. Since $q < 1$, there exists β independent of $\mathcal{E}_0$ such that $\Pr\{E'_1 - E'_N > \beta\} < \frac{\epsilon}{2}$. Let $\mathcal{E}_0^* = \frac{2(\mathcal{E}_u + \beta)}{\epsilon}$. Noting that $E_w \leq N[\mathcal{E}_u + \beta]$ given $E'_1 - E'_N \leq \beta$, we have, for any $\mathcal{E}_0 \geq \mathcal{E}_0^*$,

$$\frac{\mathbb{E}[E_w^{\text{DPLM}}]}{\mathcal{E}_0} \leq \Pr\{E'_1 - E'_N > \beta\} \frac{N\mathcal{E}_0}{\mathcal{E}_0} + \Pr\{E'_1 - E'_N \leq \beta\} \frac{N[\mathcal{E}_u + \beta]}{\mathcal{E}_0} \leq N\epsilon. \tag{40}$$

Since ϵ is arbitrary, (37) follows. □□□

Appendix E: Proof of Property 4

Under the unconstrained formulation, since all sensors are active, every data collection only consists of one transmission slot (*i.e.*, the first one). Hence, the minimum expected energy consumed in a data collection is given by (13), which can be achieved by the pure opportunistic protocol.

Under the constrained formulation, we notice that when the network approaches the end of its lifetime, there may be less than N_0 active sensors in the first transmission slot. In this case, the inactive sensors in the first transmission slot will wait for better channel realizations to transmit and hence, the energy consumed in this data collection will be smaller than $N_0\mathcal{E}_c + \sum_{n=1}^{N_0}\frac{1}{C_{(n)}}$. Hence, we partition a network lifetime into two segments. In the first segment, we have $E_{\min} \geq \mathcal{E}_u$, where $\mathcal{E}_u$ is the upper bound on the sensor energy consumption in a transmission slot, thus all sensors are active in the first transmission slots of these data collections. The expected energy consumption $\mathbb{E}[E_{tx}|E_{\min} \geq \mathcal{E}_u]$ of any MAC protocol in this segment is then lower bounded by $\mathcal{E}_{min}$. In the second segment, we have $E_{\min} < \mathcal{E}_u$; there may be inactive sensors in the network when channel realizations are poor. The expected energy consumption $\mathbb{E}[E_{tx}|E_{\min} < \mathcal{E}_u]$ achieved by some MAC protocols in this segment can be less than $\mathcal{E}_{min}$. Since the energy consumption in any data collection is upper bounded by $N_0\mathcal{E}_u$, we obtain that, for any MAC protocol,

$$\begin{aligned}\mathcal{E}_{min} - \mathbb{E}[E_{tx}] =& (\mathcal{E}_{min} - \mathbb{E}[E_{tx}|E_{\min} \geq \mathcal{E}_u]) \Pr\{E_{\min} \geq \mathcal{E}_u\} \\ &+ (\mathcal{E}_{min} - \mathbb{E}[E_{tx}|E_{\min} < \mathcal{E}_u]) \Pr\{E_{\min} < \mathcal{E}_u\} \\ \leq& N_0\mathcal{E}_u \Pr\{E_{\min} < \mathcal{E}_u\}.\end{aligned} \tag{41}$$

Taking $\limsup_{\mathcal{E}_0\to\infty}$ on both sides of (41) and applying Lemma 4, we obtain

$$\liminf_{\mathcal{E}_0\to\infty} \mathbb{E}[E_{tx}] \geq \mathcal{E}_{min}. \tag{42}$$

Since $\mathcal{E}_{min}$ can be achieved asymptotically by DPLM (see P5.1), we obtain P4.1.

Applying (14) to the lifetime formula given in (3) and noticing that the expected wasted energy $\mathbb{E}[E_w]$ is non-negative, we obtain an upper bound on the asymptotic rate at which the optimal expected network lifetime $\mathbb{E}[L^{opt}]$ increases with $\mathcal{E}_0$ which is given in (15). The achieveability of this maximum lifetime increase rate is shown by P5.2.

APPENDIX F: PROOF OF PROPERTY 5

To show P5.1, we also consider the two-segment partition of the lifetime as explained in Appendix E. When $E_{\min} \geq \mathcal{E}_u$, the energy consumption E_{tx}^{DPLM} of DPLM in any data collection differs from that of the pure opportunistic approach if the channel realization of any chosen sensor is worse than the N_0-th best channel realizations. When $E_{\min} < \mathcal{E}_u$, the difference between E_{tx}^{DPLM} and that of the pure opportunistic approach is bounded above by $N_0\mathcal{E}_u$, where $\mathcal{E}_u$ is the maximum sensor energy consumption in a transmission slot. Hence, we obtain that

$$\begin{aligned}|\mathbb{E}[E_{tx}^{\text{DPLM}}] - \mathcal{E}_{min}| \leq & N_0\mathcal{E}_u \Pr\left\{C_{I_k} \leq C_{(N_0+1)},\ \text{for any } I_k \in \mathbf{I}\right\} \\ & + N_0\mathcal{E}_u \Pr\{E_{\min} < \mathcal{E}_u\}.\end{aligned} \tag{43}$$

Lemma 3 shows that for any $\epsilon > 0$, there exists $\mathcal{E}_0^{(1)}$ such that

$$\Pr\{E_{\min} < \mathcal{E}_u\} < \epsilon, \quad \forall \mathcal{E}_0 > \mathcal{E}_0^{(1)}. \tag{44}$$

On the other hand, there exists $\alpha > 0$ independent of the initial energy $\mathcal{E}_0$ such that (25) holds. Hence,

$$\begin{aligned}&\Pr\left\{C_{I_k} \leq C_{(N_0+1)},\ \text{for any } I_k \in \mathbf{I}\right\} \\ &\quad\leq \Pr\left\{C_{I_k} \leq C_{(N_0+1)},\ \text{for any } I_k \in \mathbf{I} \;\middle|\; \frac{E_{\max}-E_{\min}}{E_{\min}} < \alpha\right\} + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha\right\} \\ &\quad\leq \epsilon + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha\right\} \\ &\quad\leq \epsilon + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha, E_{\min} > \kappa\right\} + \Pr\{E_{\min} \leq \kappa\} \\ &\quad\leq \epsilon + \Pr\left\{E_{\max}-E_{\min} > \alpha\kappa\right\} + \Pr\{E_{\min} \leq \kappa\}, \quad \forall \kappa > 0.\end{aligned} \tag{45}$$

According to Lemma 2, there exists $\kappa > 0$ such that $\Pr\left\{E_{\max}-E_{\min} > \alpha\kappa\right\} < \epsilon$. Applying this κ and Lemma 3 to (45), we obtain

$$\Pr\left\{C_{I_k} \leq C_{(N_0+1)},\ \text{for any } I_k \in \mathbf{I}\right\} \leq 2\epsilon + \Pr\{E_{\min} \leq \kappa\} \leq 3\epsilon, \quad \forall \mathcal{E}_0 > \mathcal{E}_0^{(2)}, \tag{46}$$

where the existence of $\mathcal{E}_0^{(2)}$ is proven in Lemma 3.

Applying (44) and (46) to (43) yields

$$|\mathbb{E}[E_{tx}^{\text{DPLM}}] - \mathcal{E}_{min}| \leq 4N_0\mathcal{E}_u\epsilon, \quad \forall \mathcal{E}_0 > \max\{\mathcal{E}_0^{(1)}, \mathcal{E}_0^{(2)}\}. \tag{47}$$

P5.1 follows from (47) since ϵ is arbitrary and $\mathcal{E}_u$ and N_0 are fixed.

To show P5.2, we write the rate at which the expected lifetime $\mathbb{E}[L^{\text{DPLM}}]$ achieved by DPLM increases with the initial energy:

$$\frac{\mathbb{E}[L^{\text{DPLM}}]}{\mathcal{E}_0} = \left[1 - \frac{\mathbb{E}[E_w^{\text{DPLM}}]}{N\mathcal{E}_0}\right]\frac{N}{\mathbb{E}[E_{tx}^{\text{DPLM}}]}. \tag{48}$$

Taking limit $\mathcal{E}_0 \to \infty$ and applying P5.1 and Lemma 4 to (48), we obtain

$$\lim_{\mathcal{E}_0 \to \infty} \frac{\mathbb{E}[L^{\text{DPLM}}]}{\mathcal{E}_0} = \frac{N}{\mathcal{E}_{\min}}. \tag{49}$$

P5.2 follows from (49) and P4.2.

REFERENCES

[1] L. Tong, Q. Zhao, and S. Adireddy, "Sensor Networks with Mobile Agents," in *Proc. of IEEE Military Communications Conference (MILCOM)*, vol. 1, (Boston, MA), pp. 13 – 16, Oct. 2003.

[2] "NIMS: Networked Infomechanical Systems." http://www.cens.ucla.edu/portal/nims/.

[3] "The Princeton ZebraNet Project: Sensor Networks for Wildlife Tracking." www.ee.princeton.edu/ mrm/zebranet.html.

[4] A. Swami and L. Tong, "From the guest editors - Signal Processing for Networking: an integrated approach," *IEEE Signal Processing Magazine, Special issue on Signal Processing for Networking: An integrated approach*, vol. 21, pp. 18 – 19, September 2004.

[5] L. Tong, V. Naware, and P. Venkitasubramaniam, "Signal processing in random access," *IEEE Signal Processing Magazine, Special issue on Signal Processing for Networking: An integrated approach*, vol. 21, pp. 29–39, September 2004.

[6] L. Tong, "Signal processing for large-scale sensor networks: cross layer design for application specific networks." Plenary talk at ICASSP 2005. http://www.icassp2005.com/Tong.pdf.

[7] Y. Chen and Q. Zhao, "On the Lifetime of Wireless Sensor Networks," *IEEE Commununications Letters*, vol. 9, pp. 976–978, Nov. 2005.

[8] Q. Zhao and L. Tong, "Opportunistic Carrier Sensing for Energy Efficient Information Retrieval in Sensor Networks," *EURASIP Journal on Wireless Communications and Networking*, no. 2, pp. 231–241, 2005.

[9] J. Wieselthier, G. Nguyen, and A. Ephremides, "Energy-aware wireless networking with directional antennas: the case of session-based broadcasting and multicasting," *IEEE Trans. on Mobile Computing*, vol. 1, no. 3, pp. 176–191, 2002.

[10] R. Knopp and P. Humblet, "Information capacity and power control in single cell multi-user communications," in *Proc. Intl Conf. Comm.*, (Seattle, WA), pp. 331–335, June 1995.

[11] V. Tsibonis, L. Georgiadis, and L. Tassiulas, "Exploiting wireless channel state information for throughput maximization," *IEEE Transactions on Information Theory*, vol. 50, pp. 2566 – 2582, Nov. 2004.

[12] H. Wang and N. B. Mandayam, "A simple packet-transmission scheme for wireless data over fading channels," *IEEE Transactions on Communications*, vol. 52, pp. 1055 – 1059, July 2004.

[13] S. Adireddy and L. Tong, "Exploiting Decentralized Channel State Information for Random Access," *IEEE Trans. Info. Theory*, vol. 51, pp. 537 – 561, Feb 2005.

[14] J. Gomez, A. T. Campbell, M. Naghshineh, and C. Bisdikian, “Power-aware routing in wireless packet networks,” in *Proc. of IEEE International Workshop on Mobile Multimedia Communications (MoMuC’99)*, pp. 380–383, November 1999.

[15] O. Younis and S. Fahmy, “HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks,” *IEEE Trans. Mobile Computing*, vol. 3, pp. 366–379, 2004.

[16] N. AbouGhazaleh, P. Lanigan, S. Gobriel, D. Mosse, and R. Melhem, “Dynamic rate-selection for extending the lifetime of energy-constrained networks,” in *Proc. of the 23rd IEEE International Performance, Computing and Communications Conference*, pp. 553–558, April 2004.

[17] Q. Xie, C. Lea, M. Golin, and R. Fleischer, “Maximum Residual Energy Routing with Reverse Energy Cost,” in *Proc. IEEE Globecom*, vol. 1, pp. 564 – 569, Dec 2003.

[18] J. Chang and L. Tassiulas, “Maximum Lifetime Routing in Wireless Sensor Networks,” *IEEE/ACM Transactions on Networking*, vol. 12, pp. 609–619, August 2004.

[19] H. Wang and N. B. Mandayam, “Opportunistic file transfer over a fading channel under energy and delay constraints,” *IEEE Transactions on Communications*, vol. 53, pp. 632 – 644, April 2005.

[20] M. Bhardwaj, T. Garnett, and A. Chandrakasan, “Upper bounds on the lifetime of sensor networks,” in *Proceedings of the 2001 IEEE International Conference on Communications*, pp. 785–790, 2001.

[21] M. Bhardwaj and A. Chandrakasan, “Bounding the lifetime of sensor networks via optimal role assignments,” in *Proceedings of INFOCOM 2002*, (New York), pp. 1587–1596, June 2002.

[22] H. Zhang and J. Hou, “On deriving the upper bound of lifetime for large sensor networks,” in *Proc. of MobiHoc*, pp. 121 –132, May 2004.

[23] Z. Hu and B. Li, “On the fundamental capacity and lifetime limits of energy-constrained wireless sensor networks,” in *Proc. of Real-Time and Embedded Technology and Applications Symposium (RTAS)*, (Toronto, Canada), pp. 2 – 9, May 25-28 2004.

[24] Y. Chen and Q. Zhao, “An Integrated Approach to Energy-Aware Medium Access for Wireless Sensor Networks,” *Submitted to IEEE Transactions on Signal Processing*, Dec. 2005.

[25] Q. Zhao and L. Tong, “Quality-of-Service Specific Information Retrieval for Densely Deployed Sensor Network,” in *Proc. of IEEE Military Communications Conference (MILCOM)*, vol. 1, (Boston, MA), pp. 591 – 596, Oct. 2003.