An Integrated Approach to Energy-Aware Medium Access for Wireless Sensor Networks

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***Abstract*—This paper 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 individual and collective impacts of incorporating these parameters in MAC design on network lifetime are studied. We show that a lifetime-maximizing protocol should dynamically trade off the channel state information (CSI) with 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 local information of both channel state and residual energy. Analytical and simulation results are provided to demonstrate the dynamic property and the asymptotic optimality of DPLM: its relative performance loss as compared to the performance limit defined by the optimal centralized protocol using global CSI and REI diminishes as the initial energy of each sensor increases.**

***Index Terms*—Cross-layer design, distributed protocol, energy efficiency, medium access control (MAC), network lifetime, opportunistic transmission, wireless sensor network.**

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 the data collection process by broadcasting beacon signals to activate sensors. Activated sensors then transmit, according to a medium access control (MAC) protocol, their measurements to the AP through a common wireless channel (see Fig. 1).

In the conventional layered approach, MAC protocols are designed with minimal input from the physical layer. The physical layer is treated as a black box in which nodes are indistinguishable. Starting to gain recognition in the communications and the signal processing communities 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 physical-layer model that captures diversities among nodes. We show that protocols exploiting dependencies between the MAC and the physical 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 for a single-hop WSN where sensors communicate directly with the AP through a common fading channel. We aim to address the following three issues: 1) what physical-layer parameters should be exploited in MAC design for network lifetime maximization; 2) how to use these parameters; and 3) how to implement, in a distributed fashion, MAC protocols that integrate physical-layer parameters. The main focus of this paper is the first two issues. Our goal is to reveal the inherent interaction between the physical and the MAC layers. By exploiting the individual and the collective impacts of physical-layer parameters on the performance of MAC protocols, we aim to develop a general principle for the design of lifetime-maximizing protocols. To make distributed implementation possible, we focus on MAC protocols that exploit local instead of global information of physical-layer parameters when we address the first two issues. As a starting point to address the third issue, we provide a possible solution to distributed implementation. There are, however, several open problems in this regard that require further investigation as discussed in Section V.

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 physical-layer parameters that affect network lifetime: the channel state and the residual energy of individual sensors. We study the individual

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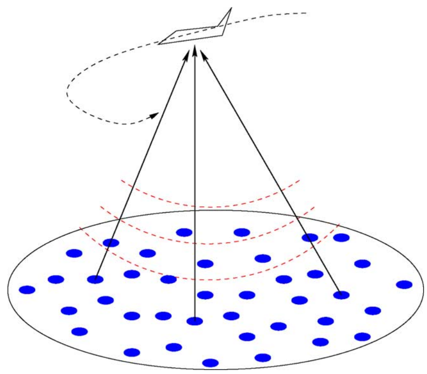


Fig. 1. Sensor network with mobile access point.

impact of exploiting these two parameters in MAC design on network lifetime.

In Section IV, we address the second issue. By studying the collective impact of the channel state information (CSI) and the residual energy information (REI) on network lifetime, we show that lifetime-maximizing protocols should dynamically trade off CSI with 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 local information of both channel state and residual energy. 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 and across sensors. That is, the relative performance loss of DPLM as compared to the performance limit of any MAC protocols (including centralized protocols using global information of channel state and residual energy) diminishes as the initial energy of each sensor increases.

The third issued is addressed in Section V. Based on the idea of opportunistic carrier sensing, first proposed in [8], we study distributed implementations of MAC protocols that exploit physical-layer parameters. Specifically, we address how to schedule sensors with the desired property using only local information of the physical-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 [11] that this opportunistic transmission 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-efficient design [12]–[14]. In the context of sensor networks, numerous energy-efficient MAC protocols have been developed under the unconstrained formulation (see [15]–[18] and references therein). Often, the design objective is to reduce collisions or prolong sensor sleeping time to achieve energy efficiency.

On the other hand, the constrained formulation of energy-efficient design aims at maximizing 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 [19]–[24].

What is lacking in existing work is the joint exploitation of CSI and REI in network design and the study of the optimal tradeoff between these two. As revealed by the general law of network lifetime given in [7], both parameters are crucial to network lifetime and ignoring either one leads to performance loss. This work appears to be the first that addresses the joint exploitation of CSI and REI. The general design principle stating that the optimal tradeoff between CSI and REI should adapt to the network age is particularly informative given that it applies to many aspects of network design (for example, MAC and routing) under the performance measure of network lifetime.

Other related work includes the analysis of upper bounds on network lifetime [25]–[28] and sensor placement for lifetime maximization [29]–[31]. In [32], [33], and references therein, the design of lifetime-maximizing routing protocols in multihop networks where sensors collaboratively relay all their measurements to the AP has been investigated.

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 $\mathbb{E}[X]$.

II. Problem Statement

A. Network and Radio Model

We consider a WSN with N sensors (see Fig. 1). In each data collection initiated by the AP, 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 transmit is determined by the underlying application and the QoS requirement of the network. Due to node redundancy and spatial correlation among sensor measurements, we generally have $N_0 \ll N$. This network model has applications in field estimation [34]–[36]. 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 sensors in the network, where the number N_0 of required samples is determined by the desired estimation performance (e.g., mean-square error).

Each sensor's measurement is encoded in a fixed-size packet. Due to bandwidth limitation, we assume that in each data collection, the chosen sensors transmit their packets sequentially in successive transmission slots.[1] The channels between the AP and the sensors follow a block fading model with block length equal to a transmission slot. That is, the channel realizations remain unchanged over each transmission slot. Let $\mathbf{C} \triangleq (C_1, \ldots, C_N)$, where C_i is the channel gain of sensor i 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 $E_{\rm tx}^{(i)}$ required for sensor i to successfully transmit its packet to the AP in a transmission slot can be modeled by

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

where $\mathcal{E}_{\rm c}$ 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 $E_{\rm tx}^{(i)}$.

B. Network Lifetime Definition

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

At the beginning of a transmission slot, a sensor can be in one of the following four states: dead, ineligible, inactive, and active. With the aid of Fig. 2, we define these states as follows.

- A sensor is considered *dead* if its residual energy drops below the transmitter circuitry consumption, i.e., $E_i \leq \mathcal{E}_{\rm c}$. In other words, it does not have enough energy for transmission under any channel condition.
- A live sensor is considered *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., $\mathcal{E}_{\rm c} \leq E_i < E_{\rm tx}^{(i)}$.
- An eligible sensor is considered *active* if it has sufficient residual energy for the current transmission, i.e., $E_i \geq E_{\rm tx}^{(i)} = \mathcal{E}_{\rm c} + (1/C_i)$.

In each transmission slot, an active sensor is chosen for transmission. If there is no active sensor in the network, this transmission slot is considered *invalid*, and the AP initiates a new one by broadcasting a beacon signal.[2] Each data collection consists of N_0 *valid* transmission slots. We define network lifetime L as the number of data collections until the number of dead sensors in the network reaches a certain threshold N_T $(1 \leq N_T \leq N)$.[3] For the example application of parameter estimation given in Section II-A, a natural network lifetime definition would be given by $N_T = N - N_0 + 1$, i.e., the remaining $N_0 - 1$ sensors can no longer achieve the targeted estimation performance.

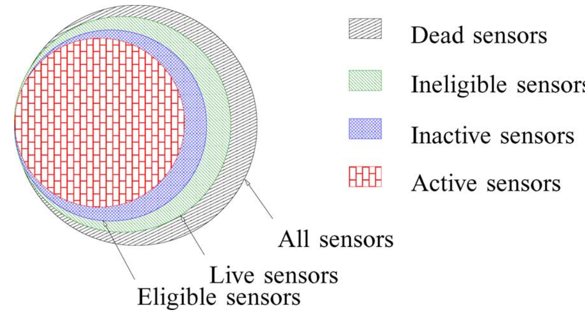


Fig. 2. Illustration of sensor states.

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 residual energy of sensor i at the end of the Lth data collection.

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

III. Two Key Physical-Layer Parameters: CSI and REI

In this section, we address the first issue: What physical-layer parameters should be exploited in MAC design for network lifetime maximization? Using the law of lifetime developed in [7], we identify two key physical-layer parameters that affect network lifetime: the channel state and the residual energy. We then study the individual impact of CSI and REI on network lifetime.

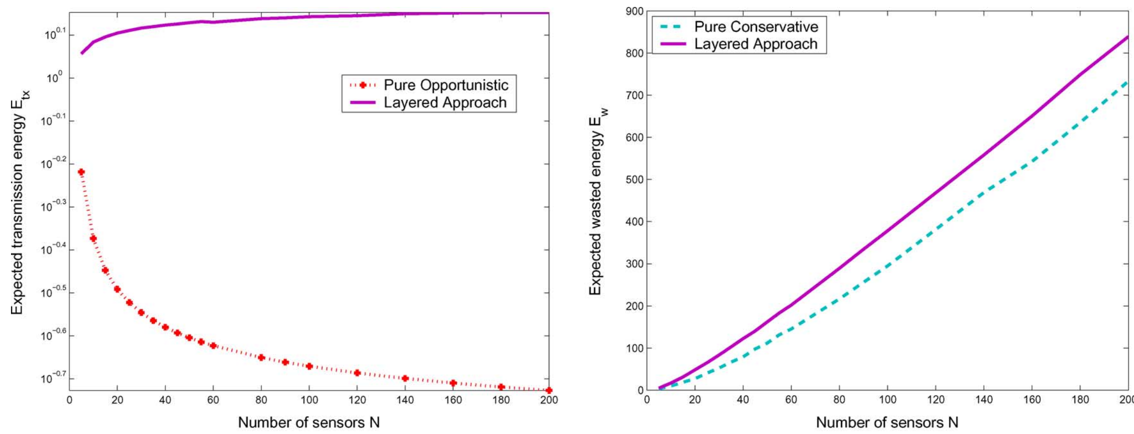
A. General Formula for Network Lifetime

In [7], we have obtained a general formula for 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

[1]Without bandwidth limitation, the chosen N_0 sensors can transmit simultaneously using standard multiple access techniques such as frequency-division multiple access (FDMA) and code-division multiple access (CDMA). In this case, the proposed protocols can still be implemented in a distributed fashion and the analytical results presented in this paper still hold. See details in [37].

[2]We assume that an active sensor must transmit its packet to the AP if it is chosen. Thus, invalid transmission slots only occur in the tail portion of network lifetime when sensors only have enough energy for exceptionally good channel realizations.

[3]Invalid transmission slots cause delay in data collections. For delay-sensitive applications, the network should also be considered dead if the number of invalid transmission slots reaches a certain threshold, which is determined by the delay constraint. The protocols and results presented in this paper still hold for this modified lifetime definition.



(a) (b)

Fig. 3. 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). (a) Impact of using CSI. (b) Impact of using REI.

energy consumption model. Applying this lifetime formula to the current network setting, we obtain the expected network lifetime as

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

where $\mathbb{E}[E_w]$ is the expected wasted energy over the whole network [see (2)] and $\mathbb{E}[E_{\rm tx}]$ is the expected total energy consumption in a randomly chosen data collection.[4] Note that $\mathbb{E}[E_{\rm tx}]$ includes the energy consumption in all N_0 valid transmission slots of the randomly chosen data collection.

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

B. Impact of Using CSI

From (1), we see that the energy consumed in a transmission slot decreases with the channel gain of the chosen sensor. Hence, to reduce the expected energy consumption $\mathbb{E}[E_{\rm tx}]$ in a data collection, MAC protocols should exploit CSI by favoring sensors with better channel realizations for transmission. In Fig. 3(a), we study the expected energy consumption $\mathbb{E}[E_{\rm tx}]$ of the pure opportunistic protocol that schedules the active sensor with the best channel realization in each transmission slot. Compared to a layered approach to MAC design that ignores the diversities at the physical layer and chooses an active sensor randomly in each transmission slot, the pure opportunistic protocol offers significant reduction in $\mathbb{E}[E_{\rm tx}]$ by exploiting the channel diversity among sensors. Due to increased channel diversity, the expected transmission energy of the pure opportunistic protocol decreases with the number N of sensors in the network. However, the expected transmission energy of the layered approach increases with N. The reason behind this observation is that the expected energy consumption $\mathbb{E}[E_{\rm tx}]$ does not take into account those invalid transmission slots when channel realizations are poor. When N is small, the network quickly approaches the end of its lifetime when sensors only have enough energy for exceptionally good channel realizations, resulting in less transmission energy consumption.

C. Impact of Using 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 network lifetime, live sensors should have minimal energy left. This requires the use of REI to balance the energy consumption across the network. One intuitive way of exploiting REI is to schedule the active sensor with the most residual energy in each transmission slot. We have shown in [38] and [39] that in the absence of CSI, this pure conservative protocol is optimal in network lifetime when the threshold N_T in the lifetime definition is $N_T = 1$ and the channel fading is i.i.d. across transmission slots. In Fig. 3(b), we compare the expected wasted energy $\mathbb{E}[E_w]$ 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 $\mathbb{E}[E_{\rm tx}]$ in a randomly chosen data collection. This observation has led to the identification of two key physical-layer parameters that should be exploited in MAC design for network lifetime maximization.

[4]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 mth trial and $E_{\rm tx}(m,k)$ the energy consumption in the kth data collection of the mth trial, where $1 \le k \le L^{(m)}$. Consider a data collection chosen with equal probability from the total $\sum_{m=1}^{M} L^{(m)}$ data collections. The expected energy consumption $\mathbb{E}[E_{\rm tx}]$ in this randomly chosen data collection is defined as

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

i.e., $\mathbb{E}[E_{\rm tx}]$ 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].

Specifically, to reduce $\mathbb{E}[E_{\rm tx}]$, 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. To make distributed implementation possible, we focus on MAC protocols exploiting local rather than global information of channel state and residual energy. The design focus is the optimal tradeoff between CSI and REI. By studying the collective impact of exploiting CSI and REI in MAC design on network lifetime, we develop a general principle for the design of lifetime-maximizing protocols, including but not limited to MAC protocols. Following this general principle, we propose DPLM and demonstrate analytically its dynamic nature and asymptotic optimality.

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

$$\gamma_i = g(C_i, E_i) \tag{4}$$

where g is a real-valued function. The *active* sensor with the largest energy-efficiency index is then scheduled for transmission. 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 the active sensor with the best channel, we have $\gamma_i = C_i$. Similarly, $\gamma_i = E_i$ leads to the pure conservative protocol that schedules the active sensor with the most residual energy.

We point out that it is possible to have a time-varying definition of energy-efficiency index, i.e., $\gamma_i = g_{k,n}(C_i, E_i)$ where (k, n) denotes the nth transmission slot of the kth 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. 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

$$\gamma_i = E_i - \frac{1}{C_i}. \tag{5}$$

From (1), we see that the energy-efficiency index given in (5) is essentially (differs by a constant $\mathcal{E}_{\rm c}$) the residual energy of sensor i after it transmits in the current transmission slot. Note that if the eligible sensor (i.e., a sensor whose packet has not been retrieved by the AP in the current data collection) with the largest energy-efficiency index defined in (5) is inactive, i.e., $E_i - (1/C_i) < \mathcal{E}_{\rm c}$ for every eligible sensor i, then there is no active sensor in the network and the current transmission slot will be invalid. In other words, the scheduled active sensor must have the largest energy-efficiency index 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: Greedy Nature of the Max–Min Protocol: Given the network energy profile and the set of eligible sensors[5] 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 for any channel state;

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

Proof 1: 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: 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 $\mathbf{E} = \mathbf{e}$ and the set $\mathcal{A}$ of eligible sensors at the beginning of a transmission slot, we have, $\forall \epsilon > 0$,

$$\Pr\left\{C_{I^*} = \max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\right\} = \Pr\left\{C_{I^*} = \max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E} = \mathbf{e}+\epsilon, \mathcal{A}\right\} \tag{6a}$$

$$\Pr\left\{e_{I^*} = \max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\right\} = \Pr\left\{e_{I^*} = \max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E} = \mathbf{e}+\epsilon, \mathcal{A}\right\} \tag{6b}$$

where $I^* = \arg\max_{i\in\mathcal{A}}\{E_i - (1/C_i)\}$ is the eligible sensor that has the largest energy-efficiency index defined in (5), $\Pr\{C_{I^*} = \max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\}$ and $\Pr\{e_{I^*} = \max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\}$ denote, respectively, the conditional probabilities that sensor I^* has the best channel realization and the most residual energy among those eligible sensors.

Proof: See Appendix B. ■

Following the proof of Property 2, we can further show that with the max–min protocol, the probabilities of selecting the sensor with the kth best channel realization and the kth most residual energy 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 network energy $\sum_{i=1}^{N} E_i$, which can be viewed as a measure of network age (the smaller the total energy, the older the network), Property 2 reveals that the max–min protocol is static with respect to network age. The weight of CSI over REI (and vice versa) remains the same over the span of network lifetime. We show in the following section that a lifetime-maximizing protocol should dynamically trade off CSI with REI according to the age of the network. The lack of adaptation to network age limits the performance of the max–min

[5]Note that the set of eligible sensors does not depend on the current channel state while the set of active sensors does.

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 resulting from the adaptability of a MAC protocol to network age.

C. Dynamic Protocol for Lifetime Maximization

1) General Design Principle: To obtain the optimal tradeoff between CSI and REI, we again resort to the law of lifetime given in (3). Consider first the expected energy consumption $\mathbb{E}[E_{\rm tx}]$ in a randomly chosen data collection. It is shown in [7] that $\mathbb{E}[E_{\rm tx}]$ can be obtained[6] by averaging the expected energy consumption $\mathbb{E}[E_{\rm tx}(k)]$ consumed in the kth data collection over the randomly chosen data collection index K, as follows:

$$\mathbb{E}[E_{\rm tx}] = \mathbb{E}_K\left\{\mathbb{E}\left[E_{\rm tx}(K)\right]\right\} \tag{7}$$

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 network lifetime carries more weight. Thus, reducing the energy consumption $\mathbb{E}[E_{\rm tx}(k)]$ in the kth 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 network age. Specifically, lifetime-maximizing protocols should be more opportunistic by favoring sensors with the better channels (focusing on reducing $\mathbb{E}[E_{\rm tx}]$) 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 a 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. Since the law of lifetime given in (3) holds independently of network protocols, this general principle can be used to guide the design of all lifetime-maximizing protocols, including but not limited to MAC protocols.

[6]For completeness, we provide a brief proof of (7). Details can be found in [7]. By definition, we can write $\mathbb{E}[E_{\rm tx}]$ as

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

where $L_{\max}=(N\mathcal{E}_0/\mathcal{E}_{\rm c})$ is the upper bound on network lifetime and $1_{[x]}=1$ if x is true and 0 otherwise.

2) 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 the active sensor whose current channel realization demands the least portion of its residual energy for the transmission. The energy-efficiency index of DPLM is defined as

$$\gamma_i = \frac{E_i}{E_{\rm tx}^{(i)}} = \frac{E_i}{\mathcal{E}_{\rm c}+\frac{1}{C_i}}. \tag{8}$$

That is, the active sensor that is able to transmit the most number of times under the current channel condition is scheduled for transmission. Note that if the eligible sensor with the largest energy-efficiency index defined in (8) is inactive, i.e., $(E_i/(\mathcal{E}_{\rm c}+(1/C_i)))<1$ for every eligible sensor i, then no sensor in the network is active, resulting in an invalid transmission slot.

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 is given 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 (8) that sensor 2, the one with less energy, is selected when

$$\gamma_2>\gamma_1 \quad\Rightarrow\quad \frac{C_2-C_1}{C_1C_2\mathcal{E}_{\rm c}+C_2}>\frac{\Delta}{e_1}. \tag{9}$$

Hence, for a given difference Δ in the residual energies, the relative improvement in channel condition required for selecting the sensor that has less residual energy decreases with e_1, which can be considered as a measure of 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 $\lim_{e_1\to\infty}(\Delta/e_1)=0$, and the condition (9) 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 $\lim_{e_1\to 0}(\Delta/e_1)=\infty$, and condition (9) holds with probability 0. DPLM puts more weight on REI by selecting the sensor with the most residual energy (specifically, sensor 1). This dynamic nature of DPLM is analytically characterized in Property 3.

Property 3: 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 $\mathbf{E}=\mathbf{e}$ and the set $\mathcal{A}$ of eligible sensors at the beginning of a transmission slot, we have, $\forall\epsilon>0$,

$$\begin{aligned}&\Pr\left\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\ &\quad\le\Pr\left\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e}+\epsilon,\mathcal{A}\right\}\end{aligned} \tag{10a}$$

$$\begin{aligned}&\Pr\left\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\ &\quad\ge\Pr\left\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e}+\epsilon,\mathcal{A}\right\}\end{aligned} \tag{10b}$$

where $I^* = \arg\max_{i\in\mathcal{A}}\{E_i/(\mathcal{E}_c + (1/C_i))\}$ denotes the eligible sensor that has the largest energy-efficiency index defined in (8), $\Pr\{C_{I^*} = \max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\}$ and $\Pr\{e_{I^*} = \max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E} = \mathbf{e}, \mathcal{A}\}$ denote, respectively, the conditional probabilities that sensor I^* has the best channel realization and the most residual energy among those eligible sensors.

Proof: See Appendix C. ■

Property 3 shows that the probability of choosing the sensor with the best channel increases while the probability of choosing the sensor with the most residual energy decreases with the total energy in the network. In other words, when the network is young, DPLM is more likely to choose the sensor with the best channel 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) Asymptotic Optimality of DPLM: When channel fading is i.i.d. across transmission slots and across sensors, the optimal MAC protocol under the unconstrained formulation is the pure opportunistic scheme that enables the active sensor with the best channel realization in each transmission slot [10], [11]. One would expect that the optimal MAC protocol under the constrained formulation approaches the pure opportunistic scheme 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: Asymptotic Behavior of the Optimal MAC Protocol: Assume that the channel gains are bounded below[7] and i.i.d. across transmission slots and across sensors.

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

$$\mathcal{E}_{\min} = N_0\mathcal{E}_c + \sum_{n=1}^{N_0}\mathbb{E}\left[\frac{1}{\max\{C_i\}_{i=1}^{N-n+1}}\right] \tag{11}$$

where $\max\{C_i\}_{i=1}^{N-n+1}$ is the first order statistic of $N-n+1$ i.i.d. channel gains $\{C_i\}_{i=1}^{N-n+1}$. 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 $\mathbb{E}[E_{\rm tx}^{\rm opt}]$ of the optimal MAC protocol in a randomly chosen data collection is given by

$$\lim_{\mathcal{E}_0\to\infty}\mathbb{E}\left[E_{\rm tx}^{\rm opt}\right] = \mathcal{E}_{\min}. \tag{12}$$

P4.2) The asymptotic rate at which the optimal lifetime $\mathbb{E}[L^{\rm opt}]$ increases with respect to the sensor initial energy $\mathcal{E}_0$ is given by

$$\lim_{\mathcal{E}_0\to\infty}\frac{\mathbb{E}[L^{\rm opt}]}{\mathcal{E}_0} = \frac{N}{\mathcal{E}_{\min}}. \tag{13}$$

Proof: See Appendix E for details. ■

[7]A similar assumption is that the transmission power of sensors is bounded above by $\mathcal{E}_u$. In this case, Properties 4 and 5 hold with $\mathcal{E}_{\min} \triangleq N_0\mathcal{E}_c + \sum_{n=1}^{N_0}\mathbb{E}[1/\max\{C_i\}_{i=1}^{N-n+1}|\mathcal{E}_c+(1/\max\{C_i\}_{i=1}^{N-n+1}) \leq \mathcal{E}_u]$.

The optimal lifetime $\mathbb{E}[L^{\rm opt}]$ defines the performance limit of all MAC protocols (including centralized protocols). As shown in [39], to achieve the performance limit for a finite initial energy $\mathcal{E}_0$, we need global rather than local CSI and REI in each transmission slot, resulting in large implementation overhead. As shown in Property 5 and Section V, DPLM provides a distributed solution to approaching the performance limit in the asymptotic regime. Numerical examples in [39] also demonstrate the nearly optimal performance of DPLM for small values of initial energy $\mathcal{E}_0$.

Property 5: Asymptotic Optimality of DPLM: Assume that the channel gains are bounded below and i.i.d. across transmission slots and across sensors. In the asymptotic regime ($\mathcal{E}_0 \to \infty$),

P5.1) DPLM approaches the pure opportunistic protocol. Specifically, the expected total energy consumption $\mathbb{E}[E_{\rm tx}^{\rm DPLM}]$ of DPLM in a randomly chosen data collection approaches $\mathcal{E}_{\min}$ as given in (11), as follows:

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

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

$$\lim_{\mathcal{E}_0\to\infty}\frac{\mathbb{E}[L^{\rm opt}] - \mathbb{E}[L^{\rm DPLM}]}{\mathbb{E}[L^{\rm opt}]} = 0 \tag{15}$$

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

Proof: The proof of Property 5 is built upon Lemmas 1–4 developed in Appendix D. See Appendix F for details. ■

We point out that other designs of energy efficiency index γ may also achieve asymptotic optimality. As shown in Fig. 10, however, DPLM approaches the optimal performance for small initial energy $\mathcal{E}_0$.

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 [8]. 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. 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 beacon signal, each eligible sensor estimates its channel gains C_i (using the beacon signal) and calculates the predefined energy-efficiency index γ_i based on its own channel

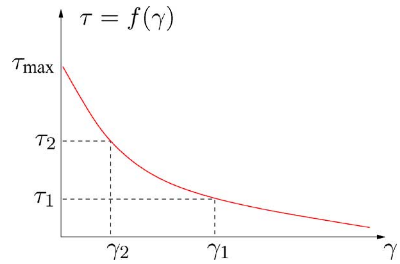


Fig. 4. Opportunistic carrier sensing.

gain $C_i = c_i$ and/or residual energy $E_i = e_i$. Then, every active sensor maps its energy-efficiency index γ_i to a backoff time τ_i (see Fig. 4) according to a predetermined common 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. An active sensor will transmit with its chosen backoff delay τ_i if and only if no one transmits before its backoff time expires. If $f(\gamma)$ is chosen to be a strictly decreasing function of the energy-efficiency index γ as shown in Fig. 4, 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 the opportunistic carrier sensing scheme 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. In practice, collisions occur, resulting in invalid transmission slots where no information is collected by the AP and multiple sensors have wasted transmission energy.

To reduce the occurrence of collision, the backoff function $f(\gamma)$ needs to be designed judiciously. It should map energy-efficiency indexes to well-separated backoff times but at the same time keep the maximum backoff time $\tau_{\max}$ small so that the energy consumed in carrier sensing will not dominate (see Fig. 4). A detailed discussion in this regard can be found in [11]. Furthermore, a backoff function $f(\gamma)$ that has graceful performance degradation with respect to propagation delay has been constructed in [11] for the pure opportunistic scheme with energy-efficiency index $\gamma_i = C_i$. The key idea proposed in [11] is to find a confidence range of the largest energy-efficiency index $\max\{C_i\}$ and provide separation in backoff time only for sensors whose energy efficiency indexes are in this range; sensors with energy efficiency indexes below this range do not need to participate in carrier sensing to conserve energy.

For the pure conservative scheme, the max–min protocol, and DPLM, the energy-efficiency index depends on the sensor residual energy. The confidence range of the largest energy-efficiency index is thus time-varying. In this case, the backoff function $f(\gamma)$ may need to vary over time to achieve good performance. The design of $f(\gamma)$ in the presence of propagation delay and time synchronization errors is an interesting problem and will be investigated in the future.

VI. Simulation Examples

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

Suppose that N sensors are randomly deployed on a disk with radius R meters and the mobile AP is located H meters above the center of the disk. We normalize all the energy quantities by the energy required for a sensor to successfully transmit its packet to the AP if it is located at the center of the disk. Assume that the normalized transmitter circuitry consumption is $\mathcal{E}_c = 0.01$ and the normalized energy required for a sensor to estimate its channel realization is $\mathcal{E}_{es} = 0.001$. The channel gain C_i of sensor i follows an exponential distribution with normalized mean $\mathbb{E}[C_i] = (H/d_i)^\alpha \leq 1$, where $\alpha = 2$ is the path-loss exponent and d_i is the distance between sensor i and the AP. The channel gains are i.i.d. across transmission slots and independently distributed across sensors. In all the figures except Fig. 11, we assume that $H \gg R$ and $\mathbb{E}[C_i] = 1$ for all i (i.e., the channel gains are also i.i.d. across sensors).

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 also ignore the tail portion of the network lifetime when sensors only have enough energy for exceptionally good channel realizations. Specifically, a sensor with residual energy e_i is considered dead if it does not have enough energy for transmission in 99.995% of the time, i.e., $\Pr\{e_i < \mathcal{E}_c + (1/C_i)\} \geq 99.995\%$.

A. Lifetime versus 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. 5, the network lifetime $\mathbb{E}[L]$ increases with N, but the rate at which $\mathbb{E}[L]$ increases saturates. As expected, the layered approach that ignores diversities at the physical 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. 6, 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 (11). Due to multiuser diversity [10], the expected total energy consumption $\mathbb{E}[E_{tx}]$ in a randomly chosen data collection decreases with the number N of sensors. Not surprisingly, the pure opportunistic protocol, solely focusing on minimizing the transmission energy, performs the best

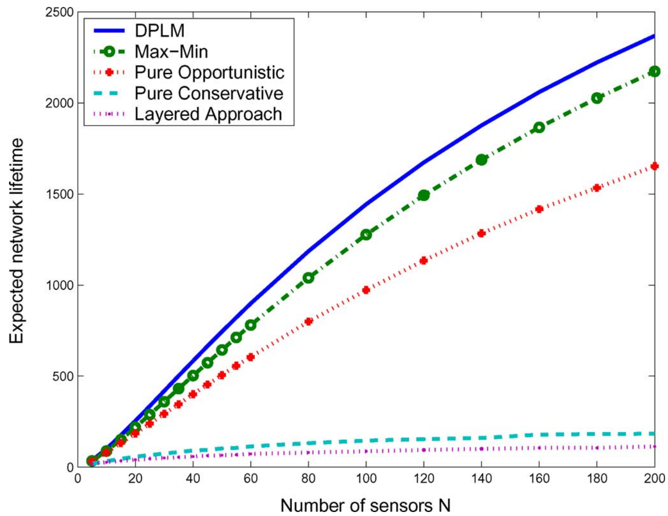


Fig. 5. Expected network lifetime $\mathbb{E}[L]$ versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

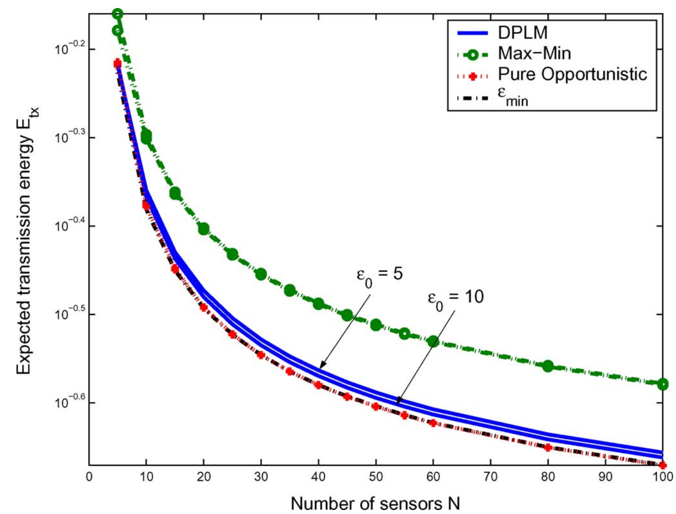


Fig. 6. Expected total energy consumption $\mathbb{E}[E_{\rm tx}]$ in a randomly chosen data collection versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$, 10 (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

in terms of $\mathbb{E}[E_{\rm tx}]$ 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 total energy consumption $\mathbb{E}[E_{\rm tx}^{\rm DPLM}]$ of DPLM in a data collection 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 $\mathbb{E}[E_{\rm tx}^{\rm DPLM}]$ close to $\mathcal{E}_{\min}$. We point out that the expected energy consumption $\mathbb{E}[E_{\rm tx}]$ 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 $\mathbb{E}[E_{\rm tx}]$ 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 $\mathbb{E}[E_{\rm tx}]$.

Fig. 7 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. 6 and 7, we see that DPLM achieves the best balance between reducing $\mathbb{E}[E_{\rm tx}]$ 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. Dynamic Nature of DPLM

Fig. 8 shows the expected dynamic range $\bar{\delta} = \mathbb{E}[\max\{E_i\}_{i=1}^N - \min\{E_i\}_{i=1}^N]$ of the network energy profile during

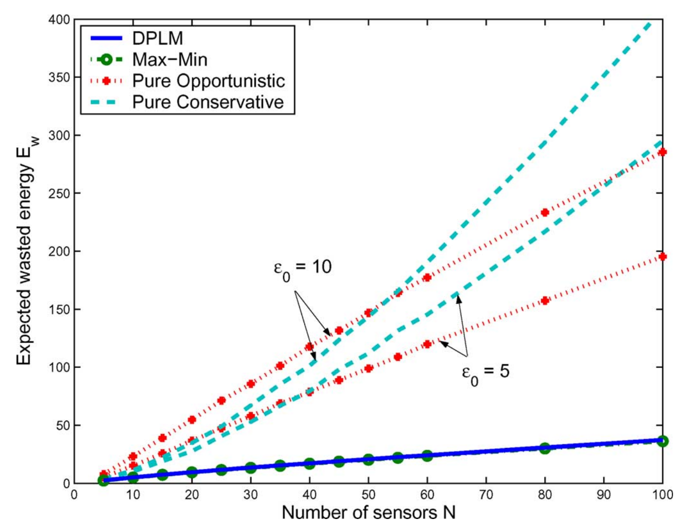


Fig. 7. Expected wasted energy $\mathbb{E}[E_w]$ versus the number N of sensors. $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$, 10 (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

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 wasted energy $\mathbb{E}[E_w]$ as shown in Fig. 7. The dynamic range of the max–min protocol remains constant during the whole network lifetime, confirming its static nature. Adaptive to 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 nearly minimum transmission energy $\mathcal{E}_{\min}$ without sacrificing performance in

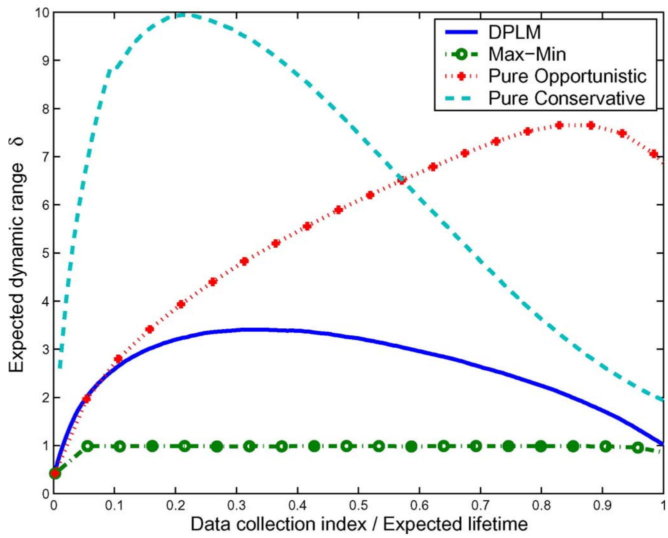


Fig. 8. Expected dynamic range $\overline{\delta} = \mathbb{E}[\max\{E_i\}_{i=1}^N - \min\{E_i\}_{i=1}^N]$ versus the network age. $N = 10$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 20$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

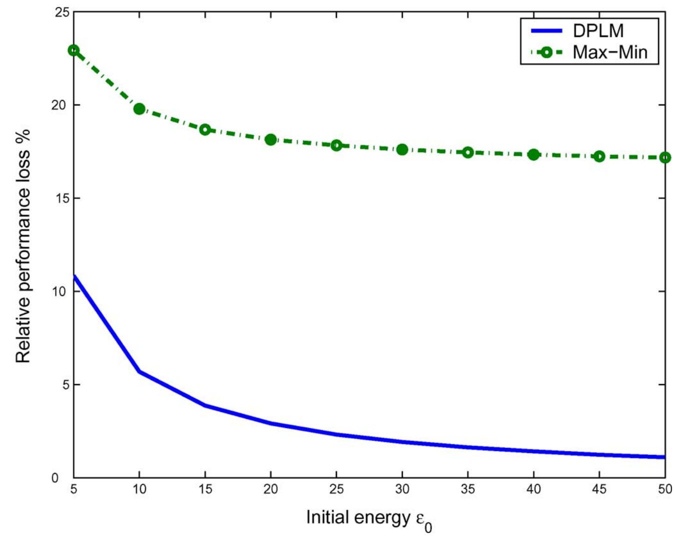


Fig. 10. Asymptotic optimality of DPLM in network lifetime. $N = 50$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

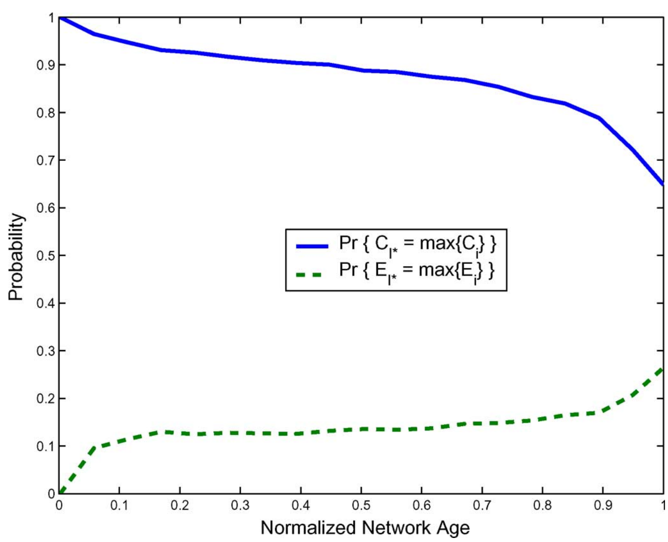


Fig. 9. Probability that DPLM chooses the sensor with the best channel and the probability that it chooses the sensor with the most residual energy. $N = 10$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 20$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

wasted energy $\mathbb{E}[E_w]$. Fig. 9 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. Asymptotic Optimality of DPLM

The asymptotic optimality of DPLM in terms of using CSI has been demonstrated in Fig. 6. In Fig. 10, we investigate the relative performance loss of the proposed DPLM and max–min protocols as compared to $N\mathcal{E}_0/\mathcal{E}_{\min}$, where $N/\mathcal{E}_{\min}$ 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, ten times during its lifetime, the relative performance loss is as low as 6%. The max–min protocol, however, is not asymptotically optimal.

D. Impact of Multisensor Selection

In Fig. 11, we investigate the impact of N_0, the number of sensors to be chosen in each data collection, on the performance of different MAC protocols. We assume that the height H of the mobile AP is comparable to the distance among sensors: $H = 2R$. Hence, the normalized mean $\mathbb{E}[C_i]$ of sensor i's channel gain is given by $\mathbb{E}[C_i] = (2R/d_i)^2$. From the upper figure, we can see that when multiple sensors are chosen in each data collection, DPLM still outperforms other MAC protocols. As expected, the lifetime of all MAC protocols decrease with N_0. In the lower figure, we examine the relative performance gains of the MAC protocols that exploit physical-layer parameters over the layered approach. As N_0 changes, we find that the relative performance gains achieved by different MAC schemes remain almost the same. The lifetime achieved by DPLM is almost 11 times longer than that of the layered approach.

E. Impact of Collisions

As mentioned in Section V, significant propagation delay or time synchronization errors may cause collisions among active sensors. In Fig. 12, we investigate the impact of collisions on the performance of different MAC protocols. We assume that when a collision occurs, it is between the sensors with the largest and the second largest energy-efficiency indices. For the layered approach, a collision also involves two sensors. We plot the expected network lifetime as a function of the collision probability in each transmission slot. We can see that, based on the carrier sensing implementation, the performance of all MAC protocols

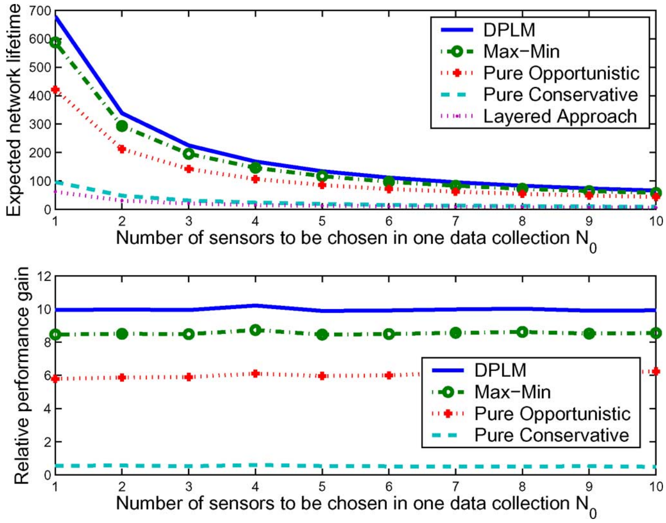


Fig. 11. Expected network lifetime versus the number N_0 of sensors to be chosen in each data collection. $N = 50$ (number of sensors in the network), $\mathcal{E}_0 = 5$ (initial energy of each sensor).

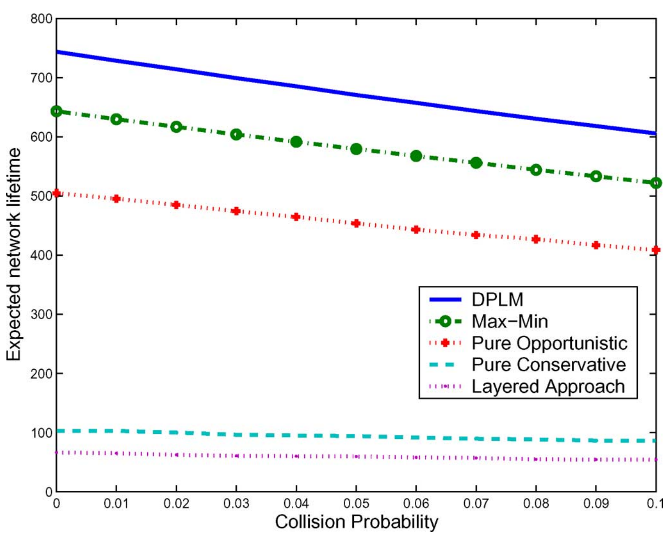


Fig. 12. Expected network lifetime versus the collision probability. $N = 50$ (number of sensors in the network), $N_0 = 1$ (number of sensors to be chosen in each data collection), $\mathcal{E}_0 = 5$ (initial energy of each sensor), $\mathbb{E}[C_i] = 1$ (normalized mean of channel gain) for all i.

decreases almost linearly with the collision probability. Protocols that can achieve longer network lifetime experience larger performance loss because more collisions occur during their network lifetime. In the presence of collisions, DPLM still outperforms other MAC schemes. However, collisions can cause considerable performance loss. For example, when the collision probability is 0.1, the relative performance loss of DPLM as compared to the collision-free case is about 18.6%. Hence, the backoff function $f(\gamma)$ used in opportunistic carrier sensing should be carefully designed to reduce the collision probability.

VII. Conclusion

In this paper, we studied the integrated design of MAC protocols for lifetime maximization in sensor networks. We identified two key physical-layer parameters—the channel state and the residual energy—that affect network lifetime. We further revealed that maximizing network lifetime requires adaptively trading off CSI with REI according to the age of the network. Specifically, lifetime-maximizing protocols should be more aggressive by prioritizing sensors with better channels (focusing on reducing energy consumption) when the network is young and more conservative by favoring sensors with more residual energies (focusing on balancing energy consumption) when the network is old. Following this general design principle, we proposed DPLM that selects the sensor whose channel realization demands the least portion of its residual energy for the current transmission. We demonstrated analytically that DPLM is adaptive to network age and asymptotically optimal in network lifetime. 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 resulting from the adaptability of a MAC protocol to network age.

Appendix A
Proof of Property 1

Given the network energy profile $\mathbf{E} = \mathbf{e}$ and the set $\mathcal{A}$ of eligible sensors at the beginning of transmission slot, for any channel realization $\mathbf{C} = \mathbf{c}$, the minimum residual energy $E'_{\min}$ at the end of this transmission slot is given by

$$E'_{\min} = \min\left\{\min\{e_i\}_{i=1}^N, e_{i^*} - \left(\mathcal{E}_c + \frac{1}{c_{i^*}}\right)\right\} \qquad (16)$$

where $i^* \in \{i \in \mathcal{A} : e_i - (\mathcal{E}_c + (1/c_i)) \geq 0\}$ is the index of the chosen active sensor. If there is no active sensor in the network, then $E'_{\min} = \min\{e_i\}_{i=1}^N$ for all MAC protocols. Otherwise, the max-min protocol that chooses sensor $i^* = \arg\max_{i\in\mathcal{A}}\{e_i - (1/c_i)\}$ maximizes the minimum residual energy $E'_{\min}$ given in (16). Hence, we obtain P1.1.

To show P1.2), we notice that when there are less than $N_T - 1$ dead sensors in the network, the network will be alive at the end of this transmission slot no matter which MAC protocol is employed. When there are exactly $N_T - 1$ dead sensors, the network dies if and only if there exists an active sensor and the scheduled sensor dies after its transmission. In this case, the probability that the network dies at the end of this transmission slot is given by

$$\Pr\left\{\max_{i\in\mathcal{A}}\left\{e_i - \frac{1}{C_i}\right\} \geq \mathcal{E}_c \text{ and } e_{I^*} - \left(\frac{1}{C_{I^*}} + \mathcal{E}_c\right) \leq \mathcal{E}_c\right\}. \qquad (17)$$

Note that the event $\{\max_{i\in\mathcal{A}}\{e_i - (1/C_i)\} \geq \mathcal{E}_c\}$ is independent of MAC protocols. From (17) and the energy-efficient index of the max–min protocol given in (5), 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 sensor $I^* = \arg\max_{i\in\mathcal{A}}\{E_i - (1/C_i)\}$ has the best channel $\max_{i\in\mathcal{A}}\{C_i\}$ among those eligible sensors in $\mathcal{A}$ is given by

$$\begin{aligned}\Pr&\left\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\sum_{j\in\mathcal{A}}\Pr\left\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\},I^*=j|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\sum_{j\in\mathcal{A}}\Pr\left\{C_j=\max_{i\in\mathcal{A}}\{C_i\},\gamma_j=\max_{i\in\mathcal{A}}\{\gamma_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\sum_{j\in\mathcal{A}}\Pr\left\{C_j\ge C_i,\frac{1}{C_i}-\frac{1}{C_j}\ge e_i-e_j,\right.\\&\qquad\qquad\left.\forall i\in\mathcal{A}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}.\end{aligned}\tag{18}$$

The probability that sensor I^* has the most residual energy $\max_{i\in\mathcal{A}}\{e_i\}$ can be derived as

$$\begin{aligned}\Pr&\left\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\Pr\{I^*=\min\mathcal{A}|\mathbf{E}=\mathbf{e},\mathcal{A}\}\\&=\Pr\{\gamma_{\min\mathcal{A}}\ge\gamma_i,\quad\forall i\in\mathcal{A}|\mathbf{E}=\mathbf{e},\mathcal{A}\}\\&=\Pr\left\{\frac{1}{C_i}-\frac{1}{C_{\min\mathcal{A}}}\ge e_i-e_{\min\mathcal{A}},\quad\forall i\in\mathcal{A}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}.\end{aligned}\tag{19}$$

From (18) and (19), we find that both $\Pr\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\}$ and $\Pr\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\}$ 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 energy profile $\mathbf{E}$. Since $(e_i+\epsilon)-(e_j+\epsilon)=e_i-e_j$, Property 2 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 $e_1\ge\ldots\ge e_N$ and obtain that

$$\begin{aligned}\Pr&\left\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\sum_{j\in\mathcal{A}}\Pr\left\{C_j\ge C_i,\frac{\frac{1}{C_i}+\mathcal{E}_c}{\frac{1}{C_j}+\mathcal{E}_c}\ge\frac{e_i}{e_j},\forall i\in\mathcal{A}|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&=\sum_{j\in\mathcal{A}}\Pr\left\{C_j\ge C_i,\forall i\in\mathcal{A},i>j,\frac{\frac{1}{C_i}+\mathcal{E}_c}{\frac{1}{C_j}+\mathcal{E}_c}\ge\frac{e_i}{e_j},\right.\\&\qquad\qquad\left.\forall i\in\mathcal{A},i<j|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\end{aligned}\tag{20}$$

$$\begin{aligned}\Pr&\left\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e},A=\mathcal{A}\right\}\\&=\Pr\left\{\frac{\frac{1}{C_{\min\mathcal{A}}}+\mathcal{E}_c}{\frac{1}{C_j}+\mathcal{E}_c}\le\frac{e_{\min\mathcal{A}}}{e_j},\forall j\in\mathcal{A}|\mathbf{E}=\mathbf{e}\right\}.\end{aligned}\tag{21}$$

From (20) and (21), we find that $\Pr\{C_{I^*}=\max_{i\in\mathcal{A}}\{C_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\}$ decreases and $\Pr\{e_{I^*}=\max_{i\in\mathcal{A}}\{e_i\}|\mathbf{E}=\mathbf{e},\mathcal{A}\}$ increases with e_i/e_j, $i<j$. Since $e_i/e_j\ge(e_i+\epsilon)/(e_j+\epsilon)$ for all $i<j$, Property 3 follows.

Appendix D
Proof of Lemmas 1–4

In this Appendix, 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 the network lifetime in the mth trial. Let $\mathbf{E}=(E_1,\ldots,E_N)$ denote the network energy profile at the beginning of a data collection chosen with equal probability from the total $\sum_{m=1}^{M}L^{(m)}$ complete data collections. For simplicity, we write $E_{\max}=\max\{E_i\}_{i=1}^N$ and $E_{\min}=\min\{E_i\}_{i=1}^N$. Note that the distribution of $\mathbf{E}$ depends on many factors including the initial energy $\mathcal{E}_0$. Let $\mathbf{C}(n)=(C_1(n),\ldots,C_N(n))$ be the channel state in the nth transmission slot (including both valid and invalid ones) of the randomly chosen data collection. We assume that channel gains are i.i.d. across transmission slots and across sensors, and bounded below. Let $\mathcal{E}_u$ be the maximum energy consumption in a transmission slot, which is determined by the worst channel realization. Hence, the total energy consumption $E_{\rm tx}$ in a data collection is bounded by $N\mathcal{E}_c<E_{\rm tx}\le N_0\mathcal{E}_u$, where $\mathcal{E}_c$ is the transmitter circuitry consumption.

Lemma 1: For any fixed $\epsilon>0$, there exists $\alpha>0$ independent of the initial energy $\mathcal{E}_0$ and the set $\mathcal{A}$ of eligible sensors, such that

$$\Pr\left\{C_{I^*}(n)\ne\max_{i\in\mathcal{A}}\{C_i(n)\}\,|\frac{E_{\max}-E_{\min}}{E_{\min}}<\alpha,\mathcal{A}\right\}<\epsilon,\qquad\forall\mathcal{E}_0,\forall\mathcal{A},\forall n\tag{22}$$

where $I^*=\arg\max_{i\in\mathcal{A}}\{E_i/(\mathcal{E}_c+(1/C_i))\}$ is the eligible sensor with the largest energy-efficiency index defined in (8) for DPLM.

Proof: For any eligible sensors $i,j\in\mathcal{A}$, the ratio between their residual energies are bounded by $e_i/e_j\le\max_{k\in\mathcal{A}}\{\mathbf{e}\}/\min_{k\in\mathcal{A}}\{\mathbf{e}\}\le e_{\max}/e_{\min}$, where $e_{\max}=\max\{e_i\}_{i=1}^N$ and $e_{\min}=\min\{e_i\}_{i=1}^N$. From (20), we obtain that for any transmission slot n of this randomly chosen data collection and any set $\mathcal{A}$ of eligible sensors

$$\begin{aligned}1\ge\Pr&\left\{C_{I^*}(n)=\max_{i\in\mathcal{A}}\{C_i(n)\}\,|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}\\&\ge\sum_{j\in\mathcal{A}}\Pr\left\{C_j(n)\ge C_i(n),\quad\forall i\in\mathcal{A},i>j,\right.\\&\qquad\frac{\frac{1}{C_i(n)}+\mathcal{E}_c}{\frac{1}{C_j(n)}+\mathcal{E}_c}\ge\frac{e_{\max}}{e_{\min}},\\&\qquad\left.\forall i\in\mathcal{A},i<j|\mathbf{E}=\mathbf{e},\mathcal{A}\right\}.\end{aligned}\tag{23}$$

Notice that as $e_{\max}/e_{\min}$ decreases to 1, the set $\{(((1/C_i(n))+\mathcal{E}_c)/((1/C_j(n))+\mathcal{E}_c))\ge e_{\max}/e_{\min},\forall i\in\mathcal{A},i<j\}$ monotonically increases to the set $\{C_j(n)\ge C_i(n),\forall i\in\mathcal{A},i<j\}$.

Taking limit $(e_{\max}/e_{\min}) \to 1$ on both sides of (23), we obtain

$$\begin{aligned} 1 &\geq \lim_{\frac{e_{\max}}{e_{\min}} \to 1} \Pr\left\{ C_{I^*}(n) = \max_{i\in\mathcal{A}} \{C_i(n)\} \,|\mathbf{E}{=}\mathbf{e}, \mathcal{A} \right\} \\ &\geq \sum_{j\in\mathcal{A}} \Pr\left\{ C_j(n) \geq C_i(n), \quad \forall i \in \mathcal{A}, I \neq j | \mathbf{E} = \mathbf{e}, \mathcal{A} \right\} \\ &= \sum_{j\in\mathcal{A}} \Pr\left\{ C_j(n) = \max_{i\in\mathcal{A}} \{C_i(n)\} \,|\mathbf{E} = \mathbf{e}, \mathcal{A} \right\} = 1. \quad (24) \end{aligned}$$

Hence, $\lim_{(e_{\max}/e_{\min})\to 1} \Pr\{C_{I^*}(n) = \max_{i\in\mathcal{A}}\{C_i(n)\}|\mathbf{E} = \mathbf{e},\mathcal{A}\} = 1$. That is, for any $\epsilon > 0$, there exists $\alpha(\mathcal{A}) > 0$ such that $e_1/e_N < 1 + \alpha$ (i.e., $((e_1 - e_N)/e_N) < \alpha$) implies $\Pr\{C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}|\mathbf{E} = \mathbf{e},\mathcal{A}\} < \epsilon$. Since the number of all possible eligible sets $\mathcal{A}$ is finite and the channel gains are i.i.d. across transmission slots, we obtain Lemma 1 with $\alpha = \min_{\mathcal{A}} \alpha(\mathcal{A})$. ■

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

$$\Pr\{E_{\max} - E_{\min} > \beta\} < \epsilon, \quad \forall \mathcal{E}_0 \quad (25)$$

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

Proof: The probability that the event $\{E_{\max} - E_{\min} > \beta\}$ occurs in a randomly chosen data collection is given by (26), shown at the bottom of the page, where $\mathcal{E}_u$ and $\mathcal{E}_c$ are, respectively, the upper and the lower bounds of the energy consumption in a transmission slot. Note that (26) is obtained by the strong law of large numbers (SLLN). Let $I_{\min}$ and $I_{\max}$ denote, respectively, the indexes of the sensors with the least and the most residual energies when the event $\{E_{\max} - E_{\min} > \beta\}$ first occurs in a lifetime. Since every transmission consumes at most $\mathcal{E}_u$ energy and a sensor transmits at most once in a data collection, the difference between any two sensors' residual energies will increase by at most $\mathcal{E}_u$ from the beginning to the end of a data collection. Hence, if the event $\{E_{\max} - E_{\min} > \beta\}$ occurs in a lifetime, then there must have been at least $\lfloor \beta/\mathcal{E}_u \rfloor$ data collections in this lifetime when the following event, denoted by Q, occurs: sensor $I_{\min}$ has less residual energy but consumes more energy than sensor $I_{\max}$. Since channel gains are i.i.d. across sensors, the probability that event Q occurs can be uniformly bounded by a number that is strictly less than 1. Hence, we can show from (26) that

$$\Pr\{E_{\max} - E_{\min} > \beta\} \leq \frac{\mathcal{E}_u}{\mathcal{E}_c} q^{\lfloor \frac{\beta}{\mathcal{E}_u} \rfloor} \quad (27)$$

where $\Pr\{Q\} \leq q < 1$. The upper bound in (27) is independent of the initial energy $\mathcal{E}_0$. For fixed $\mathcal{E}_u$ and $\mathcal{E}_c$, the upper bound in (27) 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: If DPLM is employed, then for any finite fixed $\kappa > 0$, we have

$$\lim_{\mathcal{E}_0 \to \infty} \Pr\{E_{\min} \leq \kappa\} = 0 \quad (28)$$

where $\Pr\{E_{\min} \leq \kappa\}$ 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 $\Pr\{E_{\max} - E_{\min} > \beta\} < \epsilon/2$. Hence

$$\Pr\{E_{\max} > \kappa{+}\beta, E_{\min} \leq \kappa\} \leq \Pr\{E_{\max}{-}E_{\min} > \beta\} < \frac{\epsilon}{2}. \quad (29)$$

Similar to (26), 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 (30), shown at the bottom of the page. Since the total energy consumption in each data collection is bounded below by the transmitter energy consumption $N_0\mathcal{E}_c$, we can see that when $E_{\max} < \kappa + \beta$, there are at most $N(\kappa + \beta)/N_0\mathcal{E}_c$ data collections left in a network lifetime. Hence, we obtain from (30) that

$$\Pr\{E_{\max} < \kappa + \beta\} \leq \frac{N(\kappa+\beta)}{N_0\mathcal{E}_c} \frac{N_0\mathcal{E}_u}{N\mathcal{E}_0} = \left[\frac{(\kappa+\beta)\mathcal{E}_u}{\mathcal{E}_c}\right] \frac{1}{\mathcal{E}_0} \quad (31)$$

where $\mathcal{E}_u$ is the maximum energy consumption in a transmission slot and hence $N\mathcal{E}_0/N_0\mathcal{E}_u$ is the lower bound of network lifetime. Eq. (31) shows that there exists $\mathcal{E}_0^*$ such that $\Pr\{E_{\max} \leq \kappa + \beta\} < \epsilon/2$. We can thus obtain that

$$\begin{aligned} \Pr\{E_{\max} \leq \kappa + \beta, E_{\min} \leq \kappa\} &< \Pr\{E_{\max} \leq \kappa + \beta\} \\ &< \frac{\epsilon}{2}, \quad \forall \mathcal{E}_0 > \mathcal{E}_0^*. \quad (32) \end{aligned}$$

$$\begin{aligned} \Pr\{E_{\max} - E_{\min} > \beta\} &\triangleq \lim_{M\to\infty} \frac{\sum_{m=1}^{M} \#\text{ of data collections when } E_{\max} - E_{\min} > \beta \text{ occurs in the } m\text{th trial}}{\sum_{m=1}^{M} L^{(m)}} \\ &= \frac{\mathbb{E}[\#\text{ of data collections when } E_{\max} - E_{\min} > \beta \text{ occurs in a lifetime}]}{\mathbb{E}[L]} \\ &\leq \frac{\mathcal{E}_u}{\mathcal{E}_c} \Pr\{E_{\max} - E_{\min} > \beta \text{ ever occurs in a lifetime}\} \end{aligned} \quad (26)$$

$$\Pr\{E_{\max} < \kappa + \beta\} = \frac{\mathbb{E}[\#\text{ of data collections when } E_{\max} < \kappa + \beta \text{ in a network lifetime}]}{\mathbb{E}[L]}. \quad (30)$$

Combining (29) and (32), we obtain that, for any $\mathcal{E}_0 > \mathcal{E}_0^*$,

$$\begin{aligned}\Pr\{E_{\min} \le \kappa\} &= \Pr\{E_{\max} \ge \kappa + \beta, E_{\min} \le \kappa\} \\ &\quad + \Pr\{E_{\max} \le \kappa + \beta, E_{\min} \le \kappa\} \\ &< \epsilon,\end{aligned} \tag{33}$$

which completes the proof of Lemma 3. ■

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

$$\lim_{\mathcal{E}_0 \to \infty} \frac{\mathbb{E}\left[E_w^{\text{DPLM}}\right]}{\mathcal{E}_0} = 0. \tag{34}$$

Proof: Let $\mathbf{E}'$ be the network energy profile at the end of the last data collection. Without loss of generality, we assume that $E_1' \ge \ldots \ge E_N'$. From (2), the wasted energy E_w in the network can be bounded as

$$E_w = \sum_{n=1}^{N} E_n' \le N E_1' = N E_N' + N\left(E_1' - E_N'\right). \tag{35}$$

Since a sensor consumes at most $\mathcal{E}_u$ energy in a data collection, the least wasted energy E_N' must be less than $\mathcal{E}_u$: $E_N' < \mathcal{E}_u$ (otherwise, at least one more data collection can be carried out). Hence, $E_w \le N(\mathcal{E}_u + E_1' - E_N')$.

From (27), we obtain that

$$\begin{aligned}\Pr\left\{E_1' - E_N' > \beta\right\} &\le \Pr\{E_{\max} - E_{\min} > \beta \text{ ever occurs} \\ &\qquad \text{in a lifetime}\} \\ &< q^{\left\lfloor \frac{\beta}{\mathcal{E}_u} \right\rfloor}.\end{aligned} \tag{36}$$

Fix $\epsilon > 0$. Since $q < 1$, there exists β independent of $\mathcal{E}_0$ such that $\Pr\{E_1' - E_N' > \beta\} < \epsilon/2$. Let $\mathcal{E}_0^* = 2(\mathcal{E}_u + \beta)/\epsilon$. Noting that $E_w \le N[\mathcal{E}_u + \beta]$ when $E_1' - E_N' \le \beta$, we have, for any $\mathcal{E}_0 \ge \mathcal{E}_0^*$

$$\begin{aligned}\frac{\mathbb{E}\left[E_w^{\text{DPLM}}\right]}{\mathcal{E}_0} &\le \Pr\left\{E_1' - E_N' > \beta\right\} \frac{N\mathcal{E}_0}{\mathcal{E}_0} \\ &\quad + \Pr\left\{E_1' - E_N' \le \beta\right\} \frac{N[\mathcal{E}_u + \beta]}{\mathcal{E}_0} \\ &\le N\epsilon.\end{aligned} \tag{37}$$

Since ϵ is arbitrary, (34) follows. ■

Appendix E
Proof of Property 4

Under the unconstrained formulation, every sensor is assumed to have an infinite amount of energy. Hence, all eligible sensors are active and all transmission slot are valid. Since channel gains are i.i.d. across transmission slots and across sensors, the minimum expected energy consumption in the nth transmission slot of any data collection is given by $\mathcal{E}_c + \mathbb{E}[1/\max\{C_i\}_{i=1}^{N-n+1}]$, where $N - n + 1$ is the number of eligible sensors in the nth transmission slot. The minimum expected total energy consumption $\mathcal{E}_{\min}$ in any data collection is thus given by (11), which can be achieved by the pure opportunistic scheme.

Under the constrained formulation, every sensor has a finite amount of energy. When the network approaches the end of its lifetime, sensors only have enough energy for exceptionally good channel realizations, resulting in invalid transmission slots. Hence, for those data collections in which invalid transmission slots may occur, the expected total energy consumption $\mathbb{E}[E_{\text{tx}}]$ under the constrained formulation can be less than that $\mathcal{E}_{\min}$ under the unconstrained formulation since poor channel realizations are not taken into account in $\mathbb{E}[E_{\text{tx}}]$. To show P4.1), we partition a network lifetime into two segments. In the first segment, we have $E_{\min} \ge \mathcal{E}_u$, where $\mathcal{E}_u$ is maximum energy consumption in a transmission slot, thus invalid transmission slots will not occur in these data collections. The expected total energy consumption $\mathbb{E}[E_{\text{tx}}|E_{\min} \ge \mathcal{E}_u]$ of any MAC protocol in this segment is then lower bounded by $\mathcal{E}_{\min}$, i.e., $\mathcal{E}_{\min} - \mathbb{E}[E_{\text{tx}}|E_{\min} \ge \mathcal{E}_u] \le 0$. In the second segment, we have $E_{\min} < \mathcal{E}_u$; invalid transmission slots may occur when channel realizations are poor. The expected total energy consumption $\mathbb{E}[E_{\text{tx}}|E_{\min} < \mathcal{E}_u]$ achieved by some MAC protocols in this segment can be less than $\mathcal{E}_{\min}$. Since the total energy consumption in a data collection is at most $N_0\mathcal{E}_u$, we obtain that, for any MAC protocol,

$$\begin{aligned}\mathcal{E}_{\min} - \mathbb{E}[E_{\text{tx}}] &= (\mathcal{E}_{\min} - \mathbb{E}[E_{\text{tx}}|E_{\min} \ge \mathcal{E}_u]) \\ &\quad \times \Pr\{E_{\min} \ge \mathcal{E}_u\} \\ &\quad + (\mathcal{E}_{\min} - \mathbb{E}[E_{\text{tx}}|E_{\min} < \mathcal{E}_u]) \\ &\quad \times \Pr\{E_{\min} < \mathcal{E}_u\} \\ &\le \mathcal{E}_{\min} \Pr\{E_{\min} < \mathcal{E}_u\} \\ &\le N_0\mathcal{E}_u \Pr\{E_{\min} < \mathcal{E}_u\}.\end{aligned} \tag{38}$$

Taking $\limsup_{\mathcal{E}_0 \to \infty}$ on both sides of (38) and applying Lemma 3, we obtain

$$\liminf_{\mathcal{E}_0 \to \infty} \mathbb{E}[E_{\text{tx}}] \ge \mathcal{E}_{\min}. \tag{39}$$

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

To show P4.2), we resort to the network formula given in (3). Applying P4.1) and noticing that the expected wasted energy $\mathbb{E}[E_w]$ is non-negative, we obtain an upper bound of the asymptotic rate $\mathbb{E}[L^{\text{opt}}]/\mathcal{E}_0$ at which the optimal expected network lifetime $\mathbb{E}[L^{\text{opt}}]$ increases with the sensor initial energy $\mathcal{E}_0$: $\limsup_{\mathcal{E}_0 \to \infty}(\mathbb{E}[L^{\text{opt}}]/\mathcal{E}_0) \le N/\mathcal{E}_{\min}$ The achievability of this upper bound is shown by P5.2).

Appendix F
Proof of Property 5

To show P5.1), we again consider the partition of a network lifetime as given in Appendix E. When $E_{\min} \ge \mathcal{E}_u$, all eligible sensors are active and all transmission slots are valid. In this case, the total energy consumption $E_{\text{tx}}^{\text{DPLM}}$ of DPLM in a data collection differs from that of the pure opportunistic scheme if and only if the chosen sensor does not have the best channel realization among eligible sensors $\mathcal{A}$ in any transmission slot

n of this data collection, i.e., $C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}$ for any $1 \leq n \leq N_0$ and $\mathcal{A}$. Since channel gains are i.i.d. across transmission slots and the total energy consumption in a data collection is at most $N_0\mathcal{E}_u$, we obtain that

$$\begin{aligned}&\left|\mathbb{E}\left[E_{\text{tx}}^{\text{DPLM}}\right] - \mathcal{E}_{min}\right| \\ &\leq N_0\mathcal{E}_u \max_{\substack{\mathcal{A}\subset\{1,\ldots,N\}\\ |\mathcal{A}|\geq N-N_0+1}} \Pr\left\{C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}\,|\mathcal{A}\right\} \\ &\quad + N_0\mathcal{E}_u \Pr\{E_{\min} < \mathcal{E}_u\}. \qquad (40)\end{aligned}$$

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

$$\Pr\{E_{\min} < \mathcal{E}_u\} < \epsilon, \quad \forall\mathcal{E}_0 > \mathcal{E}_0^{(1)}. \qquad (41)$$

On the other hand, for any n and $\mathcal{A}$, there exists $\alpha > 0$ independent of the initial energy $\mathcal{E}_0$ and the set $\mathcal{A}$ of eligible sensors such that (22) holds. Hence, for any n and $\mathcal{A}$, we have

$$\begin{aligned}&\Pr\left\{C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}\,|\mathcal{A}\right\} \\ &\leq \Pr\left\{C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}\,|\,\frac{E_{\max}-E_{\min}}{E_{\min}} < \alpha, \mathcal{A}\right\} \\ &\quad + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha\right\} \\ &\leq \epsilon + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha\right\} \\ &\leq \epsilon + \Pr\left\{\frac{E_{\max}-E_{\min}}{E_{\min}} \geq \alpha, E_{\min} > \kappa\right\} \\ &\quad + \Pr\{E_{\min} \leq \kappa\} \\ &\leq \epsilon + \Pr\{E_{\max} - E_{\min} > \alpha\kappa\} \\ &\quad + \Pr\{E_{\min} \leq \kappa\}, \quad \forall\kappa > 0. \qquad (42)\end{aligned}$$

According to Lemma 2, there exists $\kappa > 0$ such that $\Pr\{E_{\max} - E_{\min} > \alpha\kappa\} < \epsilon$. Applying this κ and Lemma 3 to (42), we obtain that

$$\begin{aligned}&\Pr\left\{C_{I^*}(n) \neq \max_{i\in\mathcal{A}}\{C_i(n)\}\,|\mathcal{A}\right\} \\ &\leq 2\epsilon + \Pr\{E_{\min} \leq \kappa\} \\ &\leq 3\epsilon, \quad \forall\mathcal{E}_0 > \mathcal{E}_0^{(2)}, \forall n, \forall\mathcal{A} \qquad (43)\end{aligned}$$

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

Applying (41) and (43) to (40) yields

$$\left|\mathbb{E}\left[E_{\text{tx}}^{\text{DPLM}}\right] - \mathcal{E}_{min}\right| \leq 4N_0\mathcal{E}_u\epsilon, \ \ \forall\mathcal{E}_0 > \max\left\{\mathcal{E}_0^{(1)}, \mathcal{E}_0^{(2)}\right\}. \qquad (44)$$

P5.1) follows from (44) since ϵ is arbitrary and $\mathcal{E}_u$ and N_0 are fixed.

To show P5.2), we apply the lifetime formula given in (3) and write the rate at which the expected lifetime $\mathbb{E}[L^{\text{DPLM}}]$ achieved by DPLM increases with the initial energy, as follows:

$$\frac{\mathbb{E}[L^{\text{DPLM}}]}{\mathcal{E}_0} = \left[1 - \frac{\mathbb{E}\left[E_w^{\text{DPLM}}\right]}{N\mathcal{E}_0}\right]\frac{N}{\mathbb{E}\left[E_{\text{tx}}^{\text{DPLM}}\right]}. \qquad (45)$$

Taking limit $\mathcal{E}_0 \to \infty$ and applying P5.1) and Lemma 4 to (45), we obtain

$$\lim_{\mathcal{E}_0\to\infty}\frac{\mathbb{E}[L^{\text{DPLM}}]}{\mathcal{E}_0} = \frac{N}{\mathcal{E}_{\min}}. \qquad (46)$$

P5.2) follows from (46) and P4.2).

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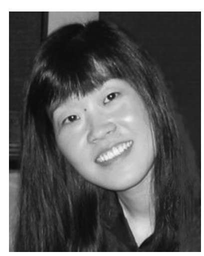

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