A Time-Varying Opportunistic Approach to Lifetime Maximization of Wireless Sensor Networks

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***Abstract*—In this paper, we examine the advantages of transmission scheduling by medium access control (MAC) protocols for energy-limited wireless sensor networks (WSN) as a means of maximizing network lifetime. We consider transmission scheduling for sensor networks with a mobile access point, where each sensor transmits its measurement directly to an access point through a fading channel. WSN lifetime maximization depends almost exclusively on the channel-state information (CSI) and the residual-energy information (REI) of each sensor in the network. We discuss distributed protocols which exploit local CSI and REI. We present a novel protocol for distributed transmission scheduling, dubbed the time-varying opportunistic protocol (TOP), for maximizing the network lifetime. TOP prioritizes sensors with better channels when the network is young, by exploiting local CSI to reduce transmission energy. However, TOP prefers sensors with higher residual energy when the network is old by exploiting local REI to reduce the wasted energy. We show that the relative performance loss of TOP compared to the optimal centralized protocol in terms of network lifetime decreases as the initial energy stored in the sensors increases. Furthermore, TOP significantly simplifies the implementation of carrier sensing compared to other distributed MAC protocols. We also explore the case of large-scale wireless sensor networks, where the activated sensors are picked randomly and modify the implementation of TOP for such networks. Simulation results show that TOP outperforms other distributed MAC protocols that have been proposed recently.**

***Index Terms*—Network lifetime, opportunistic medium access control, wireless sensor networks.**

I. Introduction

LIFETIME maximization in non-rechargeable battery-powered wireless sensor networks (WSN) has been extensively studied in recent years. Energy consumption is a major limitation in such networks and there is a growing body of literature on this subject. A good survey of available technology appears in [2] and [3]. Here, we deal with SEnsor Networks with a Mobile Access point (SENMA) [4]. In SENMA, each sensor (or sensors cluster head) measures a certain phenomenon and upon request transmits its measurement directly to an access point (AP) through a fading channel. In some networks the transmission energy required for successful one-hop transmission to the AP through the direct channel is very high. Therefore, appropriate transmission scheduling is crucial. It has been shown in [5] that exploiting channel-state information (CSI) and residual-energy information (REI) are essential to network-lifetime maximization. CSI acquisition consumes energy (due to receiver operation while receiving short beacon signal from AP) which affects the network lifetime. In cases where the energy consumed by CSI acquisition is very high CSI acquisition must be relinquished. However, in most networks this is not the case and CSI acquisition significantly increases network lifetime. Due to the presence of small-scale fading, sensors may experience deep fading channels [6], [7]. CSI allows sensors with better channel gains to transmit to reduce transmission energy. In most low-power wireless sensors such as Mica or Telos receive power operation consumes roughly 12–38 mW [8]. Receiving short beacon signal from access point is a small cost to pay to reduce transmission energy over a fading channel. Upper bounds on network lifetimes were presented in [9]–[11]. Energy-constraint routing for lifetime maximization was analyzed in [12] and [13]; however, this issue is not discussed in this paper.

We focus on energy-aware transmission scheduling for maximizing the lifetime of sensor networks. The goal is to decide, based on CSI and REI, which set of sensors should transmit during each data collection event in order to maximize the overall network lifetime. The transmission scheduling problem was formulated as a centralized stochastic control problem in [14]–[16]. Optimal centralized transmission scheduling exploiting global CSI and REI was formulated as the stochastic shortest path in [17]. However, the overhead and computational complexity of optimal centralized transmission is extremely high. Distributed MAC protocols which use local CSI and REI have been extensively analyzed in [18] and [19], and significantly reduce overhead and computational complexity. Therefore, they are generally preferred over centralized protocols. According to the distributed MAC protocol strategy, each sensor calculates an energy-efficiency index during each data collection event. The transmission scheduling in these protocols is executed by selecting the sensor with the largest energy-efficiency index for transmission at each data collection event (this can be done by opportunistic carrier sensing [20]). The energy-efficiency index is a function of local CSI and REI and is generally time-invariant.[1] The design principle for the energy-efficiency index was developed in [5]. The principle is to prioritize sensors with better channels when the network is

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[1]CSI and REI values are random variables and indeed time-varying. However, the formula for calculating the energy-efficiency index does not change during the network lifetime.

young, while prioritizing sensors with higher residual energy when the network is old. A common problem in protocols that set their energy-efficiency index based on REI is that varying residual energy during network lifetime reduces carrier-sensing performance.

In this paper, we present a distributed MAC protocol, dubbed time-varying opportunistic protocol (TOP). By implementing TOP, the energy-efficiency index is time-varying and is determined by exploiting CSI and REI. However, TOP also overcomes the performance-decreasing problem that occurs during carrier sensing. We show that if channel fading is independent and identically distributed (i.i.d.) across data collections and across sensors, the relative performance loss by executing TOP compared to the optimal centralized protocol decreases as the initial energy stored in the sensors increases. We also examine large-scale wireless sensor networks, where activated sensors are picked randomly. Then, we suggest a dynamic method to determine the average number of activated sensors in order to maximize the lifetime efficiency per sensor. Finally, we modify the TOP algorithm for such networks.

The rest of this paper is organized as follows. In Section II, we present the network model and the definition of network lifetime. In Section III, we review some existing distributed protocols which have been proposed recently. In Section IV, we introduce the time-varying opportunistic protocol (TOP). In Section V, we consider the network lifetime of large-scale networks containing a very large number of sensors. Then, we modify TOP algorithm over such networks. In Section VI, we provide simulation results.

II. Network Model and Lifetime Definition

A. Network Model

Consider a WSN that contains N sensors, each sensor n is powered by a battery with initial energy $e_{\rm in}$. Every sensor has a fixed equal-sized packet measurement transmitted through a flat fading channel to the AP. We assume a block-fading channel which remains constant during each data packet transmission. Thus, the channel gain for each sensor $n, |h_n|^2$, is constant within each slot and varies independently between slots. Due to the presence of small-scale fading the channel gain is a random variable. The distance from the sensors to the AP is typically much larger than the distance between sensors. Therefore, we assume that the path loss, and thus the channel gain mean, is approximately equal for all sensors. During each data collection event, the AP broadcasts a beacon signal and each sensor estimates its channel state. We define $e_{\rm ce}$ as the energy consumed by each sensor during channel estimation. We assume that each sensor knows its REI. We define $e_{{\rm res},n}(\ell)$ as the residual energy of sensor n at the beginning of the ℓth data collection event. During each data collection event only a single sensor (or sensors cluster head) is allowed to transmit its measurement to the AP (the extension to a larger number of sensors which are allowed to transmit is explained in Section III-A). The network's lifetime is affected by the transmission energy and the wasted energy:

1) Transmission Energy: By assuming that sensor n transmits its data to the AP during a block length of T_n seconds, the received signal $y(t)$ is given by

$$y(t) = h_n \cdot x_n(t) + v(t), \quad 0 \le t \le T_n$$

where h_n is the channel fading experienced by sensor n, $v(t)$ is the additive white Gaussian noise with power spectrum density (PSD) N_0, and $x_n(t)$ is the transmitted signal using fixed power $P_{\rm out}$ equal for all the sensors. Let P_c be the power consumption of the transmitter circuitry equal for all sensors. We define the data packet length by I[bits], and the data-packet-transmission time of sensor n by T_n. Therefore, the total energy $e_{{\rm tr},n}(\ell)$ required for transmission during the ℓth data collection event is given by

$$e_{{\rm tr},n}(\ell) = P_{\rm tr} \cdot T_n(\ell) = P_{\rm tr} \cdot \frac{I}{W \cdot \log\left(1+|h_n(\ell)|^2 \cdot \frac{P_{\rm out}}{\Gamma W N_0}\right)} \tag{1}$$

where $P_{\rm tr} = P_c + P_{\rm out}$ is the total transmission power consumption of each sensor. The term in the denominator is the data transmission rate, where Γ and W are the Shannon gap to capacity and the channel bandwidth, respectively. We also assume in this paper that the required transmission energy is bounded by $e_{\rm tr,min} \le e_{{\rm tr},n}(\ell) \le e_{\rm tr,max}$, where $e_{\rm tr,min}$ and $e_{\rm tr,max}$ denote the minimal and maximal transmission energy during each data collection event, respectively.[2] The transmission energy $e^c_{{\rm tr},n}(\ell)$ consumed during the ℓth data collection event of each sensor n is given by

$$e^c_{{\rm tr},n}(\ell) \triangleq \begin{cases} e_{{\rm tr},n}(\ell), & \text{if sensor } n \text{ transmits during the } \ell\text{th data collection} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The transmission energy $e_{\rm tr}(\ell)$ consumed by all the sensors in the network during the ℓth data collection event is

$$e_{\rm tr}(\ell) = e_{{\rm tr},\hat{n}}(\ell) \tag{3}$$

where sensor $\hat{n}$ is the chosen sensor for transmission at the ℓth data collection event.

2) Wasted Energy: We define the wasted energy as the total unused energy in the network when it dies. Therefore, the total wasted energy of the network is given by

$$E_w = \sum_{n=1}^{N} e_{w,n} \tag{4}$$

where $e_{w,n}$ is the residual energy across sensor n when the network dies.

B. Network-Lifetime Definition

We define a single sensor as nonfunctional when its residual energy drops below the threshold energy, $e_{\rm th}$, required for transmission with predetermined probability. We define a failed data collection event as a data collection event where no sensor has

[2]This assumption is fulfilled in any realistic transmission scheme, since the fading channel is typically bounded, or due to time-window limitation for transmission.

sufficient energy for current transmission. The network is defined as nonfunctional when the number of nonfunctional sensors reaches N_0, where $1 \leq N_0 \leq N$, or when the total number of failed data collection events reaches a finite constant number K_0. The network lifetime is defined as the number of data collection events until the network is defined as nonfunctional.

Following [5] and [18], since we would like to prolong the network lifetime before the first sensor dies or the first failed data collection event occurs, we consider the network as nonfunctional when $N_0 = 1$ or $K_0 = 1$. Based on lifetime analysis in [5] and [18], the expected network lifetime is given by

$$\mathbf{E}\{L\} = \frac{N \cdot e_{\rm in} - \mathbf{E}\{E_w\}}{N \cdot e_{\rm ce} + \mathbf{E}\{e_{\rm tr}\}} \tag{5}$$

where $\mathbf{E}\{e_{\rm tr}\}$ is the expected transmission energy consumed in a randomly chosen data collection event and $\mathbf{E}\{E_w\}$ is the expected wasted energy. As explained in [5], (5) implies that we should reduce the transmission energy (by exploiting CSI for selecting a sensor with a better channel) when the data collection event index ℓ is small (i.e., the network is young), since the probability that the network lives ℓ data collection events decreases with ℓ. On the other hand, we need to reduce the wasted energy (by exploiting REI for selecting sensor with large residual energy) when ℓ is increased.

III. Distributed Transmission Scheduling Protocols

Our goal is to decide during each data collection event which sensor should transmit in a distributed fashion by exploiting local CSI and REI in order to maximize the network lifetime. First, in this section we review the implementation of distributed MAC protocols via opportunistic carrier sensing [20]. Then, we analyze some recent distributed protocols.

A. Opportunistic Carrier Sensing

By executing opportunistic carrier sensing [20], each sensor in the network calculates an energy-efficiency index γ_n, which can be a function of local CSI and REI, and maps its γ_n to a backoff time τ_n based on predetermined common function $f(\gamma)$. Each sensor listens to the channel and if no other sensor transmits before its backoff time expires, the sensor is allowed to transmit. When the propagation delay is negligible, the function $f(\gamma)$ can be any decreasing function in order to enable the sensor with the largest index γ_n to transmit, as illustrated in Fig. 1. However, in a realistic case when the propagation delay cannot be ignored, $f(\gamma)$ must be designed judiciously. The design of $f(\gamma)$ is based on finding a range of values which bounds most of the energy-efficiency index values and provides a separation in backoff time only for sensors with an energy-efficiency index value in this range. Sensors with an energy-efficiency index value above this range transmit immediately, whereas sensors with an energy-efficiency index value below this range do not transmit at the current data collection event. Hence, the transmission scheduling can be readily implemented in a distributed fashion via opportunistic carrier sensing. By implementing opportunistic carrier sensing we define the transmission scheduling problem in this paper explicitly by

$$\hat{n}(\ell) = \arg\max_{1 \leq n \leq N} \gamma_n(\ell) \quad \text{s.t.} \quad e_{{\rm res},n}(\ell) \geq e_{{\rm tr},n}(\ell) + e_{\rm th} \tag{6}$$

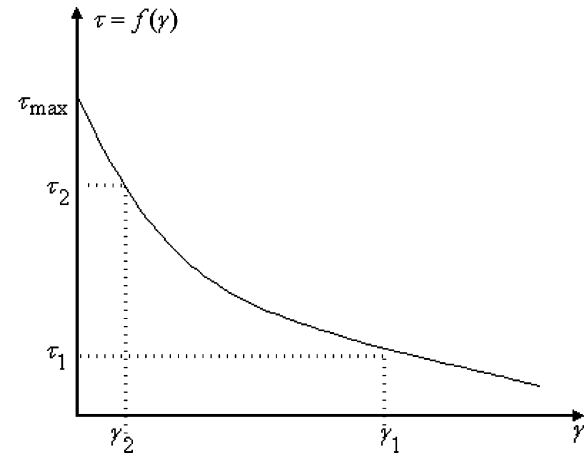


Fig. 1. Example of decreasing function $f(\gamma)$ for opportunistic carrier sensing.

where $\hat{n}(\ell)$ denotes the index of the chosen sensor, and $\gamma_n(\ell)$ is chosen according to some scheme. n and ℓ denote the sensor index and the data collection event index, respectively. Therefore, the sensor which has the largest index $\gamma_n(\ell)$ transmits only if after the transmission it is still functional, and consequently the network lifetime is prolonged. We denote the constraint in (6) as the local survivability condition. Our goal is to find a strategy for obtaining $\gamma_n(\ell)$ in problem (6) in terms of maximizing the network lifetime according to (5).

We point out that the transmission scheduling can be readily extended to the case where $K > 1$ sensors (or sensors cluster head) are allowed to transmit in each data collection event. This can be done by implementing opportunistic carrier sensing techniques for more than a single-sensor transmission as described in [20].

B. Distributed MAC Protocols

In order to extend the sensor network lifetime, several solutions have been proposed. We review some existing protocols and their advantages and limitations:

1) Pure Opportunistic Protocol: The pure opportunistic protocol was discussed in [17]–[20], and serves us in the remainder of this paper. A pure opportunistic strategy involves choosing the sensor with the best channel to minimize the average transmission energy. Explicitly, the energy-efficiency index in (6) of sensor n, during the ℓth data collection event is given by

$$\gamma_n(\ell) = |h_n(\ell)|^2 \quad \forall n \in N.$$

2) Max-Min Protocol: In this protocol [19], the energy-efficiency index is given by

$$\gamma_n(\ell) = e_{{\rm res},n}(\ell) - e_{{\rm tr},n}(\ell) \quad \forall n \in N.$$

Max-Min protocol trades off between CSI and REI and maximizes the minimum residual energy in the network [19].

3) Dynamic Protocol for Lifetime Maximization (DPLM): In this protocol [19], the energy-efficiency index is given by

$$\gamma_n(\ell) = \frac{e_{{\rm res},n}(\ell)}{e_{{\rm tr},n}(\ell)} \quad \forall n \in N.$$

This scheme selects the sensor which is able to transmit the highest number of times under the current channel condition during each data collection event. It was shown that DPLM is asymptotically optimal (when $e_{\rm in} \rightarrow \infty$) [19] in terms of maximizing the expected network lifetime. Specifically, the relative performance loss of the expected network lifetime achieved by DPLM compared to the optimal protocol diminishes with the initial energy.

As discussed at the beginning of this section, the proposed distributed MAC protocols are implemented via opportunistic carrier sensing. By executing the pure opportunistic protocol the range of the energy-efficiency index values does not change during network lifetime. Therefore, only one predetermined backoff function $f(\gamma)$ is needed during the network's lifetime. A backoff function $f(\gamma)$ was constructed in [20] for the pure opportunistic protocol which has very good performance with respect to propagation delay. However, since the pure opportunistic protocol does not exploit REI, the wasted energy across the sensors when the network dies is extremely high (since sensor can be chosen for transmission although its residual energy is low). Therefore, the performance of the pure opportunistic protocol in terms of network lifetime is extremely poor. On the other hand, DPLM and Max-Min protocols exploit REI to reduce the wasted energy. However, the implementation of such protocols via opportunistic carrier sensing is more complicated. The range of energy-efficiency index values is time-varying due to the decreasing residual energy during each data collection event. Therefore, in order to minimize the occurrence of collisions, the backoff function should vary during the network lifetime (theoretically, different backoff functions are required for each data collection event, which is impractical). The backoff function must vary during the network lifetime such that it prioritizes a group of sensors in terms of transmission order as intended while minimizing the occurrence of collisions. Another challenge is constructing a backoff function for each realization during the network lifetime (depending on channel distribution and residual energy distribution).

IV. Time-Varying Opportunistic Protocol

In this section we develop the TOP. In designing TOP we need to fulfill three requirements.

1) Define an opportunistic strategy in terms of favoring sensors with better channels when the network is young, while a less opportunistic and more conservative strategy in terms of prioritizing sensors with higher residual energy is used when the network is old.
2) Provide a simple implementation via opportunistic carrier sensing.
3) Approach the pure opportunistic protocol as $e_{\rm ce} \rightarrow 0$.

The first and second requirements were discussed in Sections II and III. The third requirement is analyzed in this section. First we consider the case where $e_{\rm ce} = 0$ (i.e., no energy is consumed during channel estimation). We show that selecting the sensor with the best channel for transmission is generally preferred over other distributed protocols in this special case. Then, we consider the realistic case where $e_{\rm ce} > 0$. By estimating the predicted energy loss due to CSI acquisition, we design the transmission scheduling decision. We show that selecting the sensor with the best channel for transmission is generally preferred over other distributed protocols, as long as the sensor has sufficient energy for current transmission plus the estimated predicted energy loss.

A. *Special Case:* $e_{\rm ce} = 0$

Consider the case where $e_{\rm ce} = 0$. We can rewrite (5) as

$$\mathbf{E}\{L\} = \frac{N \cdot e_{\rm in} - \mathbf{E}\{E_w\}}{\mathbf{E}\{e_{\rm tr}\}}.$$

Theorem 1: Assume $e_{\rm ce} = 0$. Let $\mathbf{E}\{e_{\rm tr}^{(P_1)}\}$ and $\mathbf{E}\{e_{\rm tr}^{(P_2)}\}$ be the achieved expected transmission energies by two different protocols, denoted by P_1 and P_2. If there exists $\epsilon > 0$ such that

$$\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\} < \mathbf{E}\left\{e_{\rm tr}^{(P_2)}\right\} - \epsilon, \quad \forall e_{\rm in} \tag{7}$$

then there exists a finite constant e_0 such that

$$\mathbf{E}\left\{L^{(P_1)}\right\} > \mathbf{E}\left\{L^{(P_2)}\right\}, \quad \forall e_{\rm in} > e_0 \tag{8}$$

where $\mathbf{E}\{L^{(P_1)}\}$ and $\mathbf{E}\{L^{(P_2)}\}$ are the achieved expected lifetimes when implementing P_1 and P_2, respectively.

Proof: The proof is given in Appendix A. ■

From Theorem 1, we infer that minimizing the expected transmission energy in the case where $e_{\rm ce} = 0$, generally maximizes the network lifetime, since the wasted energy is upper bounded by a constant independent of the initial energy (for details, the reader is referred to the Proof of Theorem 1). Therefore, the pure opportunistic protocol is generally preferred over other distributed protocols in the case where $e_{\rm ce} = 0$.

B. *Realistic Case:* $e_{\rm ce} > 0$

Consider the case where $e_{\rm ce} > 0$. According to (6), a sensor whose residual energy is bounded by $e_{\rm th} \leq e_{{\rm res},n}(\ell) < e_{\rm th} + e_{{\rm tr},n}(l)$, does not transmit during the current data collection event. However, since $e_{\rm ce} > 0$, its residual energy is decreased during the next channel estimation and the sensor may die. In this case, selecting the sensor with the best channel in order to minimize the transmission energy in each data collection event significantly increases the wasted energy, since REI has not been used to reduce it. However, the following theorem shows that the network lifetime can be extended by selecting the sensor with the best channel for transmission under certain conditions.

Theorem 2: Assume $e_{\rm ce} > 0$. Let $\mathbf{E}\{L^{(P_1)}\}$ and $\mathbf{E}\{e_{\rm tr}^{(P_1)}\}$, respectively, be the achieved expected lifetime and transmission energy by implementing protocol P_1. Define[3]

$$e_{\rm in}^{*} \triangleq e_{\rm in} - \mathbf{E}\left\{L^{(P_1)}\right\} \cdot e_{\rm ce}. \tag{9}$$

Assume there exists another sensor network, where the initial energy of each sensor is $e_{\rm in}^{*}$, and no energy is consumed during channel estimation $(e_{\rm ce} = 0)$. Let $\mathbf{E}\{L^{(*)}\}$ and $\mathbf{E}\{e_{\rm tr}^{(*)}\}$ be the achieved expected lifetime and transmission energy by implementing the pure opportunistic protocol over this network, respectively. If there exists $\epsilon > 0$ such that

$$\mathbf{E}\left\{e_{\rm tr}^{(*)}\right\} < \mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\} - \epsilon, \quad \forall e_{\rm in} \tag{10}$$

then there exists a finite constant e_0 such that

$$\mathbf{E}\left\{L^{(*)}\right\} > \mathbf{E}\left\{L^{(P_1)}\right\} \quad \forall e_{\rm in} > e_0. \tag{11}$$

Proof: The proof is given in Appendix B. ■

[3]Note that: $e_{\rm in}^{*} \geq e_{\rm in} - e_{\rm in}/(1 + e_{\rm tr,min}/N e_{\rm ce}) > 0$.

From Theorem 2 we infer that the network lifetime can be significantly extended by estimating the predicted energy loss due to CSI acquisition. In Section IV-C, we present the TOP algorithm based on this observation.

C. TOP Algorithm

Now we present the time-varying opportunistic protocol. By estimating the predicted energy loss due to CSI acquisition, we design the TOP strategy. We infer from Theorem 2 that we should select the sensor with the best channel only if the residual energy is higher than its required transmission energy in the current data collection event plus the predicted energy loss due to CSI acquisitions. At the beginning of the ℓth data collection event we assume that the AP has sent the ℓth beacon toward the network and that each sensor has estimated its channel gain $h_n(\ell)$ and calculated the required transmission energy $e_{\mathrm{tr},n}(\ell)$ according to (1).

Step 1) *Predicted Energy Loss Estimation*: The predicted energy loss consumed by CSI acquisition is estimated by each sensor n and is given by

$$\hat{E}_n^{\mathrm{Loss}}(\ell) = \hat{L}_n(\ell) \cdot e_{\mathrm{ce}} \tag{12}$$

where $\hat{L}_n(\ell)$ is the estimated network lifetime at the ℓth data collection event. The network-lifetime estimation process is discussed in Section IV-D.

Step 2) *Residual Energy Correction*: The sensor with the best channel gain is selected for transmission as long as the sensor has sufficient energy for current transmission plus the remaining estimated energy loss. As a result, each sensor updates its corrected residual energy, $e^*_{\mathrm{res},n}(\ell)$ by[4]

$$e^*_{\mathrm{res},n}(\ell) = \min\left\{ e_{\mathrm{res},n}(\ell), e_{\mathrm{in}} - \sum_{k=1}^{\ell-1} e^c_{\mathrm{tr},n}(k) - \hat{E}_n^{\mathrm{Loss}}(\ell) \right\} \tag{13}$$

The term $e^*_{\mathrm{res},n}(\ell)$ denotes the corrected residual energy of sensor n at the beginning of the ℓth data collection event.

Step 3) *Transmission Scheduling*: Each sensor transmits according to the following scheme:

$$\hat{n}(\ell) = \arg\max_{1\le n\le N} \gamma_n(\ell) \quad \text{s.t.} \quad e^*_{\mathrm{res},n}(\ell) \ge e_{\mathrm{tr},n}(\ell) + e_{\mathrm{th}} \tag{14}$$

where the transmission scheduling is implemented in a distributed fashion by opportunistic carrier sensing (as explained in Section III-A) and $\gamma_n(\ell)$ is given by

$$\gamma_n(\ell) = |h_n(\ell)|^2 \quad \forall n \in N. \tag{15}$$

We denote the constraint in (14) as the **long term local survivability condition**. Note that if the network lifetime is overestimated, there may be data collection events where no sensor has sufficient energy for transmission plus the remaining estimated energy loss, although they have sufficient energy for transmission. In that case the sensors should transmit without considering the long term local survivability condition. This can be done by the carrier-sensing operation. If no sensor transmits to the AP after the maximal backoff time expires, the transmission scheduling will take place without incorporating the long term local survivability condition. Another option is to receive information from the AP after a data collection request which has gone unanswered. However, simulation results show very good performance without exploiting the remaining energy due to estimation error.

D. Network-Lifetime Estimation

In this section, we explain how to estimate the network lifetime $\hat{L}_n(\ell)$ in (12). According to (5), the network lifetime is estimated by

$$\hat{L}_n(\ell) = \frac{N \cdot e_{\mathrm{in}} - \hat{\mathbf{E}}\{E_w\}_n(\ell)}{N \cdot e_{\mathrm{ce}} + \hat{\mathbf{E}}\{e_{\mathrm{tr}}\}_n(\ell)}$$

where the index ℓ indicates the update at the ℓth data collection event. Note that TOP requires each sensor to know the number of sensors in the network to estimate the network lifetime. However, in most networks this information is essential for other considerations. For instance, the design of the carrier-sensing function $f(\gamma)$ depends on the number of sensors. Furthermore, in other distributed protocols that need to vary $f(\gamma)$ during the network lifetime, the number of sensors information is essential to fit the appropriate function to each realization of the network during the network lifetime. Estimating the number of sensors is often done by the AP [21], [22]. Therefore, the AP can transmit this information back to the sensors.

In numerous cases the expected transmission energy is known *a priori* by off line measurements. However, if this is not the case, each sensor can estimate the expected transmission energy by averaging the transmission energy over its previous transmissions. Practically, the estimated transmission energy can be much more accurate. During the carrier-sensing operation, all the sensors know the backoff time $\tau_{\hat{n}}$ of the chosen sensor $\hat{n}$. Recall that the predetermined function $f(\gamma)$ maps the energy-efficiency index γ_n to a backoff time τ_n. Since $f(\gamma)$ is common to all the sensors, the energy-efficiency index of the chosen sensor can be found by calculating[5] $f^{-1}(\tau)$. Since the energy-efficiency index in the TOP scheme equals the channel gain, each sensor can calculate the transmission energy by (1). Another scheme to estimate the expected transmission energy can be done by the AP, by averaging over previous data collection events and transmitting its estimation to the sensors.

The wasted energy in the network can be estimated by

$$\hat{\mathbf{E}}\{E_w\}_n(\ell) = N\left(e_{\mathrm{th}} + \frac{\hat{\mathbf{E}}\{e_{\mathrm{tr}}\}_n(\ell)}{2}\right) \tag{16}$$

[4]Note that $e_{\mathrm{res},n}(\ell) = e_{\mathrm{in}} - \sum_{k=1}^{\ell-1} e^c_{\mathrm{tr},n}(k) - \ell \cdot e_{\mathrm{ce}}$. Therefore, as long as $\ell < \hat{L}_n(\ell)$, the corrected residual energy is given by $e^*_{\mathrm{res},n}(\ell) = e_{\mathrm{res},n}(\ell) - \left(\hat{L}_n(\ell) - \ell\right) e_{\mathrm{ce}}$. The term $\left(\hat{L}_n(\ell) - \ell\right) e_{\mathrm{ce}}$ is the remaining estimated energy loss due to CSI acquisition.

[5]Practically, $f(\gamma)$ maps a range of energy-efficiency indexes to a single backoff time. Therefore, the energy-efficiency index of the chosen sensor can be estimated by the middle index of this range, for instance.

i.e., all the sensors have been exploited when the network is defined as nonfunctional (Thus, the estimated wasted energy in each sensor is less than $e_{\rm th}+\hat{\mathbf{E}}\{e_{\rm tr}\}_n(\ell)$). We will shortly introduce in the form of a theorem the claim that the wasted energy achieved by implementing TOP approaches zero as the initial energy increases, which will be proved in the Appendix. Therefore, inaccuracy in the wasted energy estimation is generally tolerable and hardly affects TOP performance.

E. Main Properties of TOP

1) TOP Strategy: As long as the network is young, the long term local survivability condition is not valid, and the chosen sensor is determined according to the best channel during each data collection event. However, as the network becomes older, the long term local survivability condition is valid for some sensors. In this case, the chosen sensor is determined according to the channel gain and sufficient residual energy. Consequently, the sensor that has better channel gain may not transmit, although it has sufficient energy for current transmission. This fulfills Requirement 1 listed at the beginning of this section (Section IV).

2) Simple Opportunistic Carrier Sensing Implementation: As discussed in Section III-A, each sensor in the network maps its energy-efficiency index $\gamma_n(\ell)$ to a backoff time τ_n based on predetermined common function $f(\gamma)$, and then listens to the channel. By implementing TOP, $\gamma_n(\ell)$ is simply the channel gain if the long term local survivability condition is not valid (i.e., the sensor is allowed to transmit), and does not depend on the decreasing residual energy. Therefore, only one predetermined backoff function $f(\gamma)$ is needed during the network's lifetime (a backoff function $f(\gamma)$ for the case where the energy-efficiency indexes are the channel gain constructed in [20] which performs very well with respect to propagation delay). This satisfies the second requirement.

3) Approach the Pure Opportunistic Protocol: By implementing the TOP when $e_{\rm ce} = 0$, the corrected residual energy in (13), $e^*_{{\rm res},n}(\ell)$, is equal to the residual energy $e_{{\rm res},n}(\ell)$. Therefore, TOP approaches the pure opportunistic protocol as $e_{\rm ce} \to 0$. This satisfies the third requirement.

4) Asymptotic Optimality of TOP: Theorem 3 shows that the relative performance loss of TOP compared to the optimal protocol decreases as the initial energy across the sensors increases.

Theorem 3: Assume the channel gains are i.i.d across data collection events and across sensors. Then

$$\left|\frac{L^{\rm TOP}-L^{\rm opt}}{L^{\rm opt}}\right| \xrightarrow{P} 0 \quad \text{for} \quad e_{\rm in}\to\infty \tag{17}$$

where $L^{\rm opt}$ and $L^{\rm TOP}$ denote the network lifetime achieved by the optimal protocol and TOP, respectively.

Proof: The proof is given in Appendix D based on Lemmas 1–4 given in Appendix C. ■

V. Modifying TOP for Large-Scale Networks

In this section, we consider large-scale networks containing a very large number of sensors. In the case where $e_{\rm ce} = 0$ (i.e., there is no energy consumption during channel estimation), it is straightforward that we should exploit all the sensors in each data collection event in order to obtain a better channel gain and therefore to reduce the transmission energy. However, in the realistic case where $e_{\rm ce} > 0$, activating all the sensors in such networks in each data collection event is an extreme waste of resources and significantly shortens network lifetime. Recall from (5) that the expected lifetime is given by

$$\mathbf{E}\{L\} = \frac{N\cdot e_{\rm in} - \mathbf{E}\{E_w\}}{N\cdot e_{\rm ce} + \mathbf{E}\{e_{\rm tr}\}}.$$

Hence,

$$\mathbf{E}\{L\} \le \frac{e_{\rm in}}{e_{\rm ce}}.$$

We infer that the network lifetime is upper bounded by $(e_{\rm in}/e_{\rm ce})$, if all the sensors are activated during each data collection event. In this section we suggest a successful strategy to extend the network lifetime beyond this bound. We suggest a random approach where each sensor autonomously decides whether to invest energy in order to obtain CSI or whether to save energy by entering into a sleeping mode until the next data collection event. Then, we present TOP implementation when the operating sensors are picked randomly.

A. Random Approach

We consider a WSN containing N sensors. In order to maintain energy, we require that an average number n_e of sensors, where $1 \le n_e \le N$, will execute channel estimation in each data collection event. Therefore, each sensor decides to execute channel estimation with probability $p_e = n_e/N$ or to enter a sleeping mode until the next data collection event with probability $1-p_e$. We denote such strategy by (N, n_e). As explained in Section II-B, since we would like to prolong the network lifetime before the first sensor dies or the first failed data collection event occurs, we consider the network as nonfunctional when $N_0 = 1$ or $K_0 = 1$. We can show that the expected network lifetime is given by[6]

$$\mathbf{E}\{L\,|\,(N,n_e)\} = \frac{N\cdot e_{\rm in} - \mathbf{E}\left\{E_w\,|\,(N,n_e)\right\}}{n_e\cdot e_{\rm ce} + \mathbf{E}\{e_{\rm tr}\,|\,(N,n_e)\}} \tag{18}$$

where $\mathbf{E}\{L\,|\,(N,n_e)\}$ denotes the achieved expected network lifetime given that the (N,n_e) strategy is executed. The terms $\mathbf{E}\{E_w\,|\,(N,n_e)\}$ and $\mathbf{E}\{e_{\rm tr}\,|\,(N,n_e)\}$ are the achieved expected wasted energy and transmission energy given that the (N,n_e) strategy is executed, respectively. We infer from (18) that executing random estimation with probability $p_e = (n_e)/(N) \le 1$ replaces the linear increasing (with N) energy loss in (5) consumed by channel estimation, by a constant energy loss $n_e \cdot e_{\rm ce}$. By implementing the (N,n_e) strategy the expected lifetime is not upper bounded by $e_{\rm in}/e_{\rm ce}$. Note that large-scale networks must be in a sleeping mode for any lifetime maximization protocol. Therefore, knowing the number of sensors in the network is essential to determine the probability of executing channel estimation, p_e. Energy-aware protocols for estimating the number of sensors in the network have been proposed in [21] and [22].

B. Determining n_e

The expected transmission energy $\mathbf{E}\{e_{\rm tr}\}$ is indirectly proportional to the channel order statistics distribution. Therefore, increasing n_e decreases the transmission energy. However, the

[6]Since the number of activated sensors is a random variable distributed according to a binomial distribution and its expected value is n_e.

improvement rate in terms of minimizing the transmission energy is significantly decreased as n_e is increased. Furthermore, we need to decrease n_e to minimize the invested energy during channel estimation. Hence, maximizing the expected network lifetime requires a trade off. On one hand, we need to increase n_e in order to minimize the transmission energy. On the other hand, we need to decrease n_e in order to minimize the invested energy during channel estimation. In the case that *a priori* knowledge of the network is available, n_e can be determined according to offline experiments. However, there are advantages to a dynamic strategy to determine n_e when *a priori* knowledge is not available. Let $e_{\mathrm{tr}}^{\mathrm{bc}}$ denote the expected value of the achieved transmission energy by selecting the sensor with the best channel in the unconstrained problem (without energy constraints). We have shown in the Proof of Theorem 3 that for sufficiently high e_{in}, the achieved transmission energy by implementing TOP approaches $e_{\mathrm{tr}}^{\mathrm{bc}}$. Furthermore, since we are considering a large number of sensors, the number of activated sensors in each data collection event is approximately n_e. Hence, we define the desired expected lifetime as

$$\mathbf{E}^{(d)}\{L\,|\,(N,n_e)\} \triangleq N \cdot \frac{e_{\mathrm{in}} - C_{w,n_e}}{n_e \cdot e_{\mathrm{ce}} + e_{\mathrm{tr},n_e}^{\mathrm{bc}}}$$

where $e_{\mathrm{tr},n_e}^{\mathrm{bc}}$ denotes the transmission energy achieved by selecting the sensor with the best channel from a set of n_e i.i.d channel gains in the unconstrained problem. The term $C_{w,n_e} \triangleq e_{\mathrm{th}} + e_{\mathrm{tr},n_e}^{\mathrm{bc}}/2$, denotes the desired wasted energy of a single sensor. Therefore, if e_{in} and N are sufficiently large, a good scheme for determining n_e can be significantly simplified by

$$\arg \max_{1 \le n_e \le N} C_{s,n_e} \tag{19}$$

where $C_{s,n_e} = (e_{\mathrm{in}} - C_{w,n_e})/(n_e \cdot e_{\mathrm{ce}} + e_{\mathrm{tr},n_e}^{\mathrm{bc}})$ is the desired lifetime slope and is constant with N. The simplified maximization in (19) can be solved numerically and can be implemented dynamically by the AP, after estimating the channel distribution. After estimating the number of the sensors in the network, p_e can be updated. Simulation results show that this scheme achieves very good performance even for small numbers (less than 200) of sensors and for low initial energy (about 7 transmissions per sensor).

C. TOP Implementation via Random Approach

In this section we modify TOP algorithm for the Random Approach case, termed RA-TOP. We assume that n_e has been determined and all the sensors wake up with probability $p_e = (n_e/N)$. Note that similar to (28) we can rewrite (18) as

$$\mathbf{E}\{L\,|\,(N,n_e)\} = \frac{N \cdot (e_{\mathrm{in}} - \frac{n_e}{N} \cdot \mathbf{E}\{L\,|\,(N,n_e)\} \cdot e_{\mathrm{ce}}) - \mathbf{E}\{E_w\,|\,(N,n_e)\}}{\mathbf{E}\{e_{\mathrm{tr}}\,|\,(N,n_e)\}}. \tag{20}$$

Now, the predicted energy loss consumed by CSI acquisition is estimated according to (20), and is given by

$$\hat{E}_n^{\mathrm{Loss}}(\ell) = \frac{n_e}{N} \hat{L}_{n\,|\,(N,n_e)}(\ell) \cdot e_{\mathrm{ce}}$$

where $\hat{L}_{n\,|\,(N,n_e)}(\ell)$ is the estimated network lifetime given that (N, n_e) strategy is executed. The network lifetime is estimated according to (18). The transmission energy and the wasted energy estimation process was discussed in Section IV-D. The residual energy correction and the transmission scheduling steps is done by each awake sensor as described in Section IV-C.

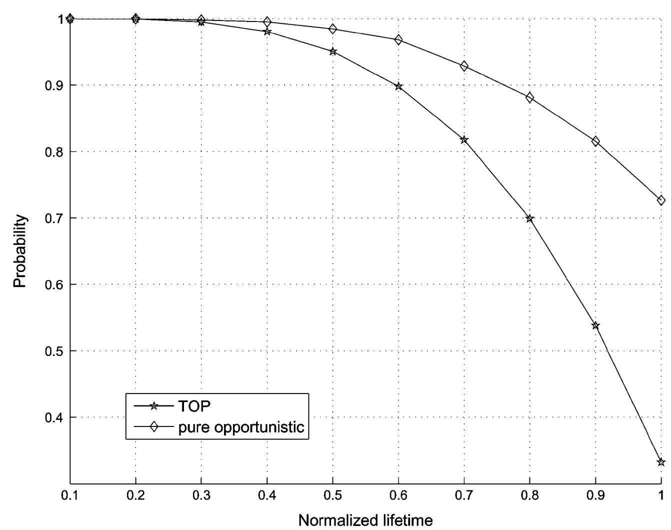
Simulation results have shown that implementing RA-TOP achieves a linearly increasing (with N) lifetime which was described in Section V-B. Furthermore, simulation results have shown that determining n_e by maximizing C_{s,n_e} in (19) approximately achieves the maximal lifetime efficiency per sensor.

VI. Simulation Results

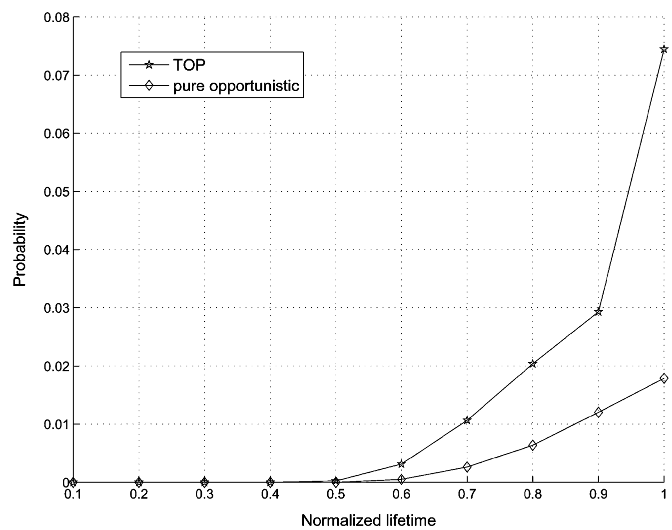
In this section, we compare the performance of the proposed TOP algorithm with the following recently proposed protocols: 1) the pure opportunistic protocol; 2) Max-Min protocol; 3) dynamic protocol for lifetime maximization (DPLM). We simulated a network with N sensors and the following parameters unless otherwise specified: the sensors transmit through a flat block-fading channel according to a Rayleigh fading distribution (therefore, the channel gain is exponentially distributed) i.i.d across data collection events and across sensors. We set the channel gain mean to 1, $\mathbf{E}\{|h_n|^2\} = 1$. Only a single sensor was selected for transmission during each data collection event. We normalized the channel bandwidth to $1 (W = 1)$, and the SNR was set to $\rho = 3$ dB. The normalized required power for transmission, times the data packet size, with respect to the normalized bandwidth is $P_{\mathrm{tr}} \cdot I = 5$. The normalized energy required for CSI acquisition by each sensor is $e_{\mathrm{ce}} = 0.001$. The normalized threshold energy which defines the sensor functionality is $e_{\mathrm{th}} = 0.3$. We assume perfect carrier sensing without collisions. The network is defined as non functional when $N_0 = 1$ or $K_0 = 1$, where N_0 and K_0 are defined in Section II-B.

First, we examine the time-varying opportunistic property of TOP. As explained in Section IV, TOP prioritizes sensors with better channels when the network is young, while prioritizing sensors with higher residual energy when the network is old. Due to the long term local survivability condition, the sensor with the best channel might not transmit, although it has sufficient energy for transmission (plus e_{th}). In contrast, in the pure opportunistic scheme, in each data collection event the sensor with the best channel transmits as long as its residual energy is sufficient for transmission (plus e_{th}). In Fig. 2, we show the probability to select the sensor with the best channel and the probability to select the sensor with the highest residual energy during the normalized lifetime by TOP and the pure opportunistic protocol for $N = 50$ and $e_{\mathrm{in}} = 10$. It can be seen that both TOP and pure opportunistic scheme select the sensor with the best channel with probability 1 when the network is young. However, due to the long term local survivability condition, the probability to select the sensor with the best channel by TOP decreases faster than the probability to select the sensor with the best channel by the pure opportunistic scheme. It can be seen that the probability to select the sensor with the highest residual energy by TOP increases faster than the probability to select the sensor with the highest residual energy by the pure opportunistic scheme.

Next, we investigated the expected network lifetime for sensor network model with different values of initial energy versus network size. We considered the case of a tight energy constraint where $e_{\mathrm{in}} = 5, 10$ and each sensor transmits about two to six times. As shown in Fig. 3(a), TOP achieves

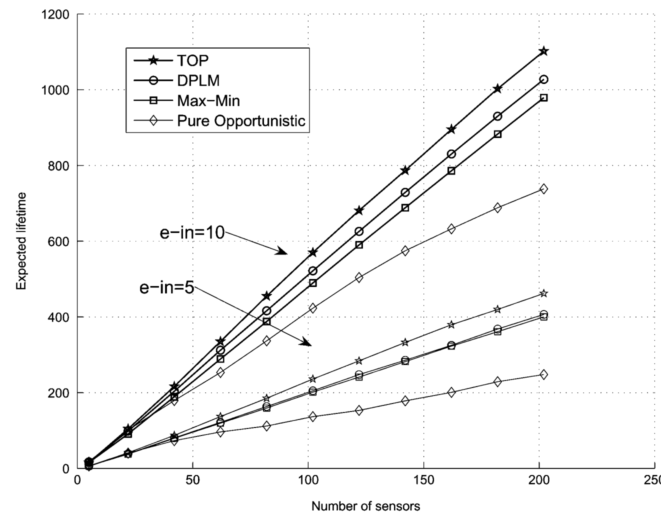


(a)

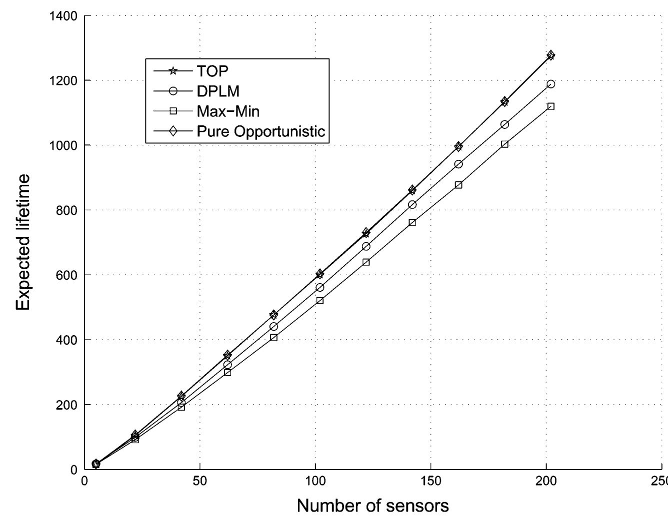


(b)

Fig. 2. Illustration of the time-varying opportunistic property. $N = 50$ and each sensor is initialized with $e_{\rm in} = 10$. (a) Probability to select the sensor with the best channel. (b) Probability to select the sensor with the highest residual energy.



(a)



(b)

Fig. 3. Expected lifetime versus the number of sensors. (a) Each sensor is initialized with $e_{\rm in} = 5, 10$. (b) Each sensor is initialized with $e_{\rm in} = 10$, and $e_{\rm ce} = 0$.

a significant performance gain over all other protocols. TOP achieves roughly an 8%–15% relative performance gain over DPLM (TOP also has simpler implementation and performs better via carrier sensing). TOP achieves about a 50% relative performance gain over the pure opportunistic protocol (and has a similar implementation and achieves similar performance via carrier sensing). DPLM outperforms Max–Min, and the pure opportunistic protocol performs the worst. In Fig. 4, we investigate the expected transmission and wasted energy behavior where $e_{\rm in} = 10$. As expected, the pure opportunistic protocol achieves the lowest transmission energy, where TOP, by selecting the sensor with the best channel most of the time, outperforms DPLM. Max-Min performs the worst in terms of transmission energy. In terms of wasted energy, the pure opportunistic performance is very poor, while TOP, by balancing the opportunistic strategy when the network is old, outperforms both the DPLM and MAx-Min protocols. We point out that we have also simulated the case of relaxed energy constraint where each sensor transmits more than 50 times. Simulation results show that TOP and DPLM performed about equally in this case and outperform other distributed protocols. These results confirm the asymptotic optimality property of both TOP and DPLM.

Next, we investigate the case where the CSI acquisition cost is negligible $(e_{\rm ce} = 0)$. According to Section IV-A, we expected the pure opportunistic protocol (which is identical to TOP in this special case) to outperform DPLM and Max-Min. Fig. 3(b) shows that the pure opportunistic and TOP indeed outperform DPLM and Max–Min. These results demonstrate the significance of TOP dependency on the CSI acquisition cost.

We also examine the case where $N/2$ sensors experience Ricean fading, where the channels have a dominant line-of-sight (LOS) component between the sensors and the AP with fading parameter $K = s^2/2\sigma^2 = 5$ (K is the ratio of the power in LOS component, s^2, to the power in non-LOS component, $2\sigma^2$), while $N/2$ sensors experience Rayleigh fading channel (i.e., there is no LOS between sensors and AP). We considered

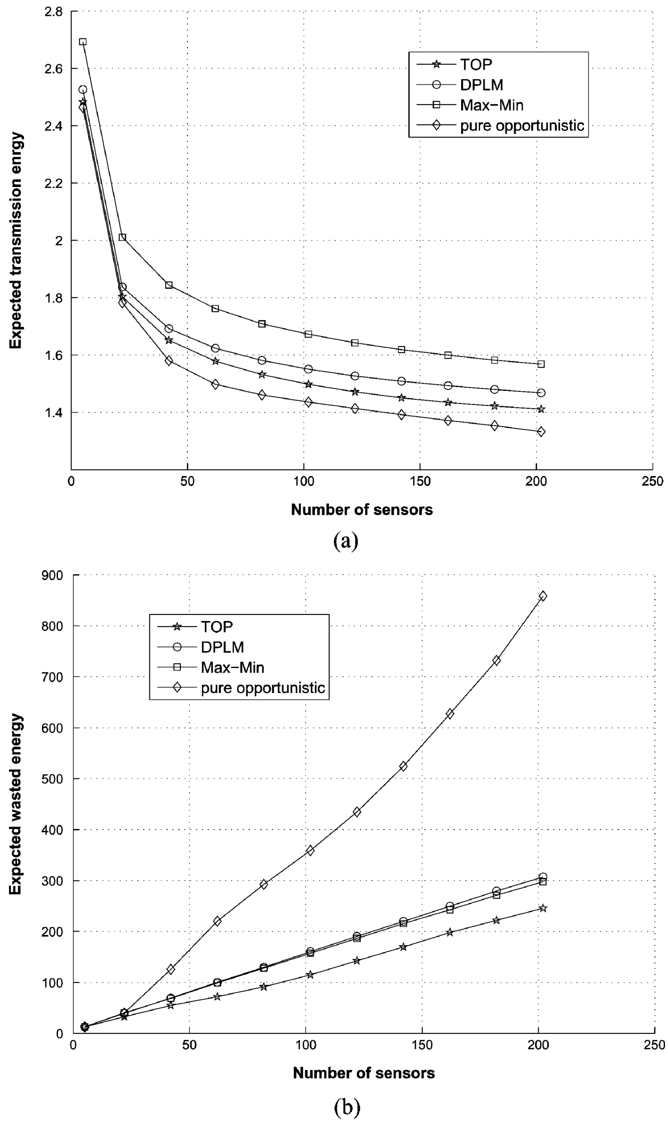


Fig. 4. Expected transmission and wasted energy versus the number of sensors. Each sensor is initialized with $e_{\rm in} = 10$. (a) Expected transmission energy. (b) Expected wasted energy.

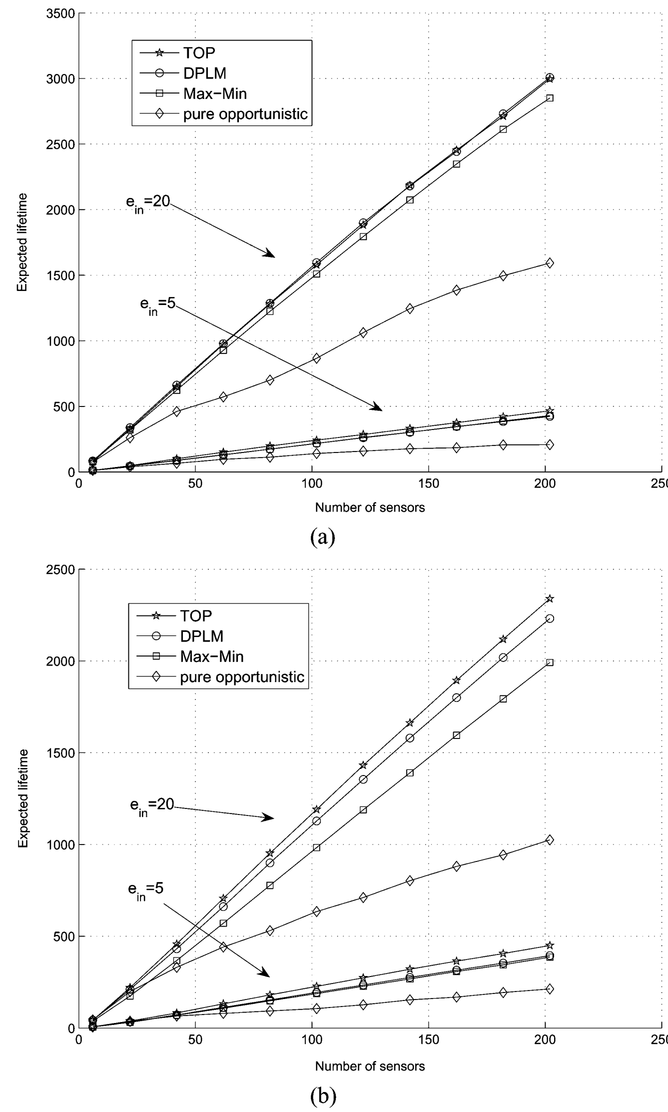


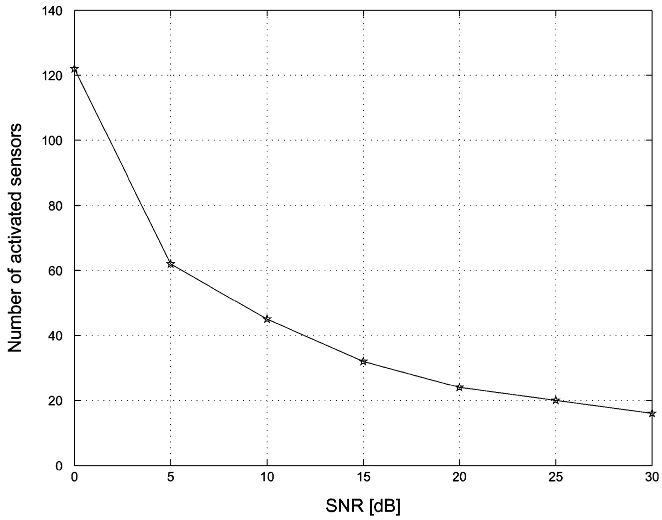
Fig. 5. Expected lifetime versus the number of sensors. Each sensor is initialized with $e_{\rm in} = 5, 20$. (a) $N/2$ sensors experience Ricean fading channel with dominant LOS component and $N/2$ sensors experience Rayleigh fading channel. (b) All sensors experience time-correlated Rayleigh fading channel. Each data collection event is correlated with the last 50 data collection events.

the case of a tight $(e_{\rm in} = 5)$ and relaxed $(e_{\rm in} = 20)$ energy constraint. As shown in Fig. 5(a), in the case of a tight energy constraint TOP achieves roughly a 10%–12% relative performance gain over DPLM. In the case of relaxed energy constraint TOP and DPLM performed about equally. The pure opportunistic protocol performs the worst in both cases. Next, we examine the case where all sensors experience a time-correlated Rayleigh fading channel modeled by an autoregressive (AR) stochastic process, as proposed in [23]. The order of the AR model was set to 50 (i.e., each data collection event is correlated with the last 50 data collection events). We assume maximum Doppler frequency 5 Hz, and every 30 ms a data collection event is performed. As shown in Fig. 5(b), in the case of a tight energy constraint $(e_{\rm in} = 5)$ TOP achieves roughly a 10%–15% relative performance gain over DPLM, while in the case of a relaxed energy constraint $(e_{\rm in} = 20)$ TOP achieves roughly a 5%–7% relative performance gain over DPLM. Again, the pure opportunistic protocol performs the worst in both cases.

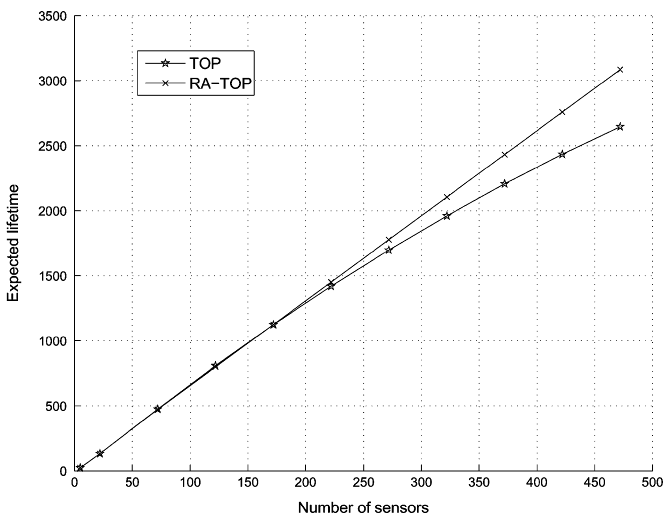
We investigated large-scale networks as discussed in Section V. We determined the number of activated sensors n_e as proposed in Section V-B. Fig. 6(a) depicts the optimal number of activated sensors which maximizes C_{s,n_e} versus the SNR. It can be seen that the number of activated sensors decreases with the SNR. Since increasing the SNR reduces the required transmission energy, n_e is decreased to keep the term $n_e \cdot e_{\rm ce}$ less dominant. In Fig. 6(b), we show the expected lifetime improvement by implementing TOP via the random approach, denoted by RA-TOP, as discussed in Section V-C. It can be seen that the network lifetime is approximately linear with N, as explained in Section V-B, even for small numbers (less than 200) of sensors and for low initial energy $(e_{\rm in} = 10)$.

VII. Conclusion

In this paper, we examined distributed MAC protocols for wireless sensor networks lifetime maximization. Based on the realization that the design principle for lifetime maximization should prioritize sensors with better channels when the network is young, while prioritizing sensors with higher residual energies when the network is old, we proposed the TOP algorithm.



(a)



(b)

Fig. 6. Optimal number of activated sensors and achieved expected lifetime for $e_{\rm in} = 10$. (a) Optimal number of activated sensors which maximizes C_{s,n_e} versus the SNR. (b) Expected lifetime versus the number of sensors for $\rho = 5$ dB.

Simulation results demonstrated that TOP achieves a significant performance gain over other protocols that have been proposed recently.

We also extended the analysis to large-scale networks containing a very large number of sensors. We developed a random approach for implementing TOP where only small portion of the sensors is activated in each data collection event. We suggested a dynamic method to determine the average number of activated sensors needed to maximize the lifetime efficiency per sensor.

APPENDIX

A. Proof of Theorem 1

Proof: The achieved expected lifetime by implementing P_1 is given by

$$\mathbf{E}\left\{L^{(P_1)}\right\} = \frac{N\cdot e_{\rm in} - \mathbf{E}\left\{E_w^{(P_1)}\right\}}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}}. \tag{21}$$

According to (6), each sensor with residual energy bounded by $e_{\rm th} \leq e_{{\rm res},n}(\ell) < e_{\rm th} + e_{{\rm tr},n}(l)$, is not allowed to transmit during the current data collection event. Since $e_{\rm ce} = 0$, its residual energy is not decreased during the next channel estimation. Therefore, as long as at least one sensor has residual energy above $e_{\rm th} + e_{\rm tr,max}$, the network lives at least one more data collection event. Consequently, the wasted energy across the network can be upper bounded by

$$\mathbf{E}\left\{E_w^{(P_1)}\right\} \leq N\cdot e_{w,\max} < N(e_{\rm th} + e_{\rm tr,max}), \tag{22}$$

where $e_{w,\max} = \max_{1\leq n\leq N} e_{w,n}$ is the maximal wasted energy of a single sensor. Note that the upper bound in (22) is a constant independent of $e_{\rm in}$. Substituting (22) in (21) yields

$$\mathbf{E}\left\{L^{(P_1)}\right\} \geq \frac{N(e_{\rm in} - e_{\rm th} - e_{\rm tr,max})}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}}. \tag{23}$$

The achieved expected lifetime by implementing P_2 is

$$\mathbf{E}\left\{L^{(P_2)}\right\} = \frac{N\cdot e_{\rm in} - \mathbf{E}\left\{E_w^{(P_2)}\right\}}{\mathbf{E}\left\{e_{\rm tr}^{(P_2)}\right\}}. \tag{24}$$

By substituting (7) in (24), $\mathbf{E}\{L^{(P_2)}\}$ can be upper bounded by

$$\mathbf{E}\left\{L^{(P_2)}\right\} < \frac{N\cdot e_{\rm in}}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\} + \epsilon}. \tag{25}$$

Moreover, we can show that

$$\frac{N(e_{\rm in} - e_{\rm th} - e_{\rm tr,max})}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}} > \frac{N\cdot e_{\rm in}}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\} + \epsilon} \quad \forall e_{\rm in} > e_1 \tag{26}$$

where

$$e_1 \triangleq \frac{e_{\rm th} + e_{\rm tr,max}}{1 - \mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}\Big/\left(\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\} + \epsilon\right)}.$$

Since $e_{\rm tr,max} \geq \mathbf{E}\{e_{\rm tr}^{(P_1)}\}$, by combining (23), (25), and (26) we obtain (8), where

$$e_0 \triangleq \frac{e_{\rm th} + e_{\rm tr,max}}{1 - e_{\rm tr,max}/(e_{\rm tr,max} + \epsilon)}.$$

■

B. Proof of Theorem 2

Proof: The achieved expected lifetime by implementing P_1, is given by

$$\mathbf{E}\left\{L^{(}P_1)\right\} = \frac{N\cdot e_{\rm in} - \mathbf{E}\left\{E_w^{(P_1)}\right\}}{N\cdot e_{\rm ce} + \mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}}. \tag{27}$$

We can rewrite (27) as

$$\mathbf{E}\left\{L^{(P_1)}\right\} = \frac{N\cdot\left(e_{\rm in} - \mathbf{E}\left\{L^{(P_1)}\right\}\cdot e_{\rm ce}\right) - \mathbf{E}\left\{E_w^{(P_1)}\right\}}{\mathbf{E}\left\{e_{\rm tr}^{(P_1)}\right\}}. \tag{28}$$

Since all the entries on the right-hand side of (28) are positive, the numerator has to be positive since $\mathbf{E}\{L^{(P_1)}\} \geq 0$. This leads to $e_{\text{in}}^* \geq 0$ for any feasible $\mathbf{E}\{L^{(P_1)}\}$ which can be achieved by P_1.

We can rewrite (28) as

$$\mathbf{E}\left\{L^{(P_1)}\right\} = \frac{N \cdot e_{\text{in}}^* - \mathbf{E}\left\{E_w^{(P_1)}\right\}}{\mathbf{E}\left\{e_{\text{tr}}^{(P_1)}\right\}}. \tag{29}$$

The right-hand side of (29) is the problem of the second sensor network, where the initial energy of each sensor is e_{in}^*, and no energy is consumed during channel estimation ($e_{\text{ce}} = 0$). By assuming that there exists $\epsilon > 0$ such that (10) is fulfilled, we infer from Theorem 1 that

$$\mathbf{E}\left\{L^{(*)}\right\} > \mathbf{E}\left\{L^{(P_1)}\right\} \quad \forall e_{\text{in}}^* > \frac{e_{\text{th}} + e_{\text{tr,max}}}{1 - e_{\text{tr,max}}/(e_{\text{tr,max}} + \epsilon)}. \tag{30}$$

The term e_{in}^* is given in (9) and can be rewritten as

$$e_{\text{in}}^* = e_{\text{in}} - \frac{N \cdot e_{\text{in}} - \mathbf{E}\left\{E_w^{(P_1)}\right\}}{N \cdot e_{\text{ce}} + \mathbf{E}\left\{e_{\text{tr}}^{(P_1)}\right\}} \cdot e_{\text{ce}}. \tag{31}$$

Substituting (31) in (30) yields

$$\mathbf{E}\left\{L^{(*)}\right\} > \mathbf{E}\left\{L^{(P_1)}\right\} \quad \forall e_{\text{in}} > e_1 \tag{32}$$

where

$$e_1 \triangleq \left(\frac{e_{\text{th}} + e_{\text{tr,max}}}{1 - e_{\text{tr,max}}/(e_{\text{tr,max}} + \epsilon)} - \frac{\mathbf{E}\left\{E_w^{(P_1)}\right\} e_{\text{ce}}}{N \cdot e_{\text{ce}} + \mathbf{E}\left\{e_{\text{tr}}^{(P_1)}\right\}} \right) \frac{\mathbf{E}\left\{e_{\text{tr}}^{(P_1)}\right\} + N e_{\text{ce}}}{\mathbf{E}\left\{e_{\text{tr}}^{(P_1)}\right\}}.$$

Since $\mathbf{E}\{E_w^{(P_1)}\} \geq 0$ and $\mathbf{E}\{e_{\text{tr}}^{(P_1)}\} \geq e_{\text{tr,min}}$, we obtain (11), where

$$e_0 = \frac{e_{\text{th}} + e_{\text{tr,max}}}{1 - e_{\text{tr,max}}/(e_{\text{tr,max}} + \epsilon)} \cdot \frac{e_{\text{tr,min}} + N e_{\text{ce}}}{e_{\text{tr,min}}}.$$

■

C. Lemmas 1–4

We provide four lemmas used in the Proof of Theorem 3. We define L and ℓ as the achieved network lifetime and the data collection event index $(1 \leq \ell \leq L)$ by implementing TOP, respectively. The transmission energy of each sensor n is bounded by $e_{\text{tr,min}} \leq e_{\text{tr},n}(\ell) \leq e_{\text{tr,max}}$, and the channel gains are i.i.d across data collections and across sensors. We define $e_{\text{tr}}^{\text{bc}}$ as the achieved expected transmission energy by selecting the sensor with the best channel in the unconstrained problem (without energy constraints). For convenience we set $e_{\text{th}} = 0$.

As explained in Section IV-C, as long as at least one sensor has sufficient energy for current transmission plus the remaining estimated energy loss, the corrected residual energy in (13) is given by

$$e_{\text{res},n}^*(\ell) = \min\left\{ e_{\text{in}} - \sum_{k=1}^{\ell-1} e_{\text{tr},n}^c(k) - \ell \cdot e_{\text{ce}}, \right. \left. e_{\text{in}} - \sum_{k=1}^{\ell-1} e_{\text{tr},n}^c(k) - \hat{L}(\ell) \cdot e_{\text{ce}} \right\} \tag{33}$$

where $e_{\text{tr},n}^c(k)$ is given in (2), and $\hat{L}(\ell)$ is the estimated network lifetime[7] at the beginning of data collection event ℓ. Therefore, as long as $\hat{L}(\ell) > \ell$ and at least one sensor has sufficient energy for current transmission plus the remaining estimated energy loss, the corrected residual energy is restricted by the long term local survivability condition and is given by

$$e_{\text{res},n}^*(\ell) = e_{\text{in}} - \sum_{k=1}^{\ell-1} e_{\text{tr},n}^c(k) - \hat{L}(\ell) \cdot e_{\text{ce}}, \tag{34}$$

for all sensors.

However, as explained in Section IV-C, there may be data collections where no sensor has sufficient energy for transmission plus the remaining estimated energy loss, although they have sufficient energy for transmission. From that moment the sensors transmit without considering the long term local survivability condition. If this event occurs or $\hat{L}(\ell) < \ell$ occurs, the corrected residual energy is not restricted by the long term local survivability condition and is given by

$$e_{\text{res},n}^*(\ell) = e_{\text{res},n}(\ell) = e_{\text{in}} - \sum_{k=1}^{\ell-1} e_{\text{tr},n}^c(k) - \ell \cdot e_{\text{ce}}, \tag{35}$$

for all sensors.

Let

$$e_{\min}^*(\ell) \triangleq \min_{1 \leq n \leq N} e_{\text{res},n}^*(\ell)$$
$$e_{\max}^*(\ell) \triangleq \max_{1 \leq n \leq N} e_{\text{res},n}^*(\ell) \tag{36}$$

be the minimal and maximal corrected residual energy during the network lifetime at the beginning of the ℓth data collection event, respectively.

We define three major events, denoted by ℓ_1, ℓ_2 and ℓ_3 during the network lifetime. During the first $\ell_1 - 1$ data collection events the sensors are restricted by the long term local survivability condition (i.e., the corrected residual energy is given by (34)) and $e_{\min}^*(\ell) > e_{\text{tr,max}}$. We define ℓ_1 as the first data collection event when $e_{\min}^*(\ell) < e_{\text{tr,max}}$ occurs, or as the first data collection event when $\hat{L}(\ell) < \ell$ occurs. The event that occurs first determines ℓ_1. We assume that the lifetime estimation is updated until[8] $\ell = \ell_1$.

We define ℓ_2 as the first data collection event when the sensors are not restricted by the long term local survivability condition (i.e., the corrected residual energy is given by (35)). Two events can determine ℓ_2. The first event is that $\hat{L}(\ell) < \ell$ occurs first. The second is a data collection event when no sensor has sufficient energy for current transmission plus the remaining estimated energy loss, although they have sufficient energy for current transmission. The event that occurs first determines ℓ_2. Note that if the event $\hat{L}(\ell) < \ell$ determines ℓ_1, then $\ell_1 = \ell_2$.

During the data collection events from the ℓ_2^{th} data collection event until the $(\ell_3 - 1)^{\text{th}}$ data collection event, the corrected residual energy is given by (35) and $e_{\min}^*(\ell) > e_{\text{tr,max}}$ is fulfilled (If $e_{\min}^*(\ell) > e_{\text{tr,max}}$ is not fulfilled, $\ell_2 = \ell_3$). We define ℓ_3 as the data collection event when all the sensors are not restricted by the long term local survivability condition (i.e.,

[7]As discussed in Section IV-D, all the sensors exploit the same knowledge for the estimation. Therefore, $\hat{L}(\ell)$ is equal for all sensors.

[8]The theorem holds even if the estimation is updated until $\ell = L_p$ where L_p is a finite constant number, independent of the initial energy.

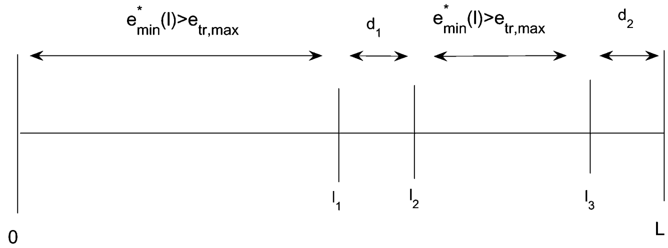


Fig. 7. A general illustration of major events during the network lifetime. Lemmas 1, 2 imply that $\lim_{e_{\rm in}\to\infty}\Pr\{(d_1+d_2)/(L)>\epsilon\}=0$.

the corrected residual energy is given by (35)) and the event $e^*_{\min}(\ell)<e_{\rm tr,max}$ first occurs.

Therefore, $e^*_{\min}(\ell)$ can be written as follows:

$$e^*_{\min}(\ell)=\begin{cases} e^*_{\min}(\ell)\geq e_{\rm tr,max}, & \forall 1\leq\ell\leq\ell_1-1\\ e^*_{\min}(\ell)< e_{\rm tr,max}, & \forall \ell_1\leq\ell\leq\ell_2-1\\ e^*_{\min}(\ell)\geq e_{\rm tr,max}, & \forall \ell_2\leq\ell\leq\ell_3-1\\ e^*_{\min}(\ell)< e_{\rm tr,max}, & \forall \ell_3\leq\ell\leq L.\end{cases} \tag{37}$$

A general illustration of these major events during the network lifetime is given in Fig. 7.

We define the dynamic range of the corrected residual energies at the beginning of the ℓth data collection event by

$$\mathrm{DR}^*(\ell)\triangleq e^*_{\max}(\ell)-e^*_{\min}(\ell). \tag{38}$$

Finally, we define $e^{\rm bc}_{\rm tr}$ as the expected value of the transmission energy achieved by selecting the sensor with the best channel in the unconstrained problem (without energy constraints).

Next, we present lemmas 1–4. For the sake of brevity and readability, we provide a rough sketch of the proofs.

Lemma 1: For any $\epsilon>0$, TOP has the following property:

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\frac{\ell_2-\ell_1}{L}>\epsilon\right\}=0 \tag{39}$$

where $\ell_2-\ell_1$ denotes the number of data collection events from the beginning of the $\ell_1^{\rm th}$ data collection event until the beginning of the $(\ell_2-1)^{\rm th}$ data collection event.

Proof: If the event $\hat{L}(\ell)<\ell$ occurs before the event $e^*_{\min}(\ell)<e_{\rm tr,max}$ occurs, then $\ell_2=\ell_1$ and the claim is trivial. We consider the case where ℓ_1 is determined by the data collection event that $e^*_{\min}(\ell)<e_{\rm tr,max}$ first occurs. Therefore, the total exploited energy from the beginning of the $\ell_1^{\rm th}$ data collection event until the beginning of the $\ell_2^{\rm th}$ data collection event, denoted by $E_{\ell_2-\ell_1}$, can be upper bounded by $E_{\ell_2-\ell_1}\leq Ne^*_{\max}(\ell_1)\leq N(e_{\rm tr,max}+\mathrm{DR}^*(\ell_1))$. According to (37), during the first ℓ_1-1 data collections all the sensors have sufficient energy for transmission (i.e., each sensor transmits with probability $1/N$ in each data collection event). Note that $\mathrm{DR}^*(\ell_1)=\sum_{\ell=1}^{\ell_1-1}e^c_{{\rm tr},1}(\ell)-\sum_{\ell=1}^{\ell_1-1}e^c_{{\rm tr},N}(\ell)$ (without any loss of generality, we assume that $e^*_{{\rm res},1}(\ell_1)=e^*_{\min}(\ell_1)$ and $e^*_{{\rm res},N}(\ell_1)=e^*_{\max}(\ell_1)$). Since the transmission energy is bounded by $e_{\rm tr,min}\leq e_{{\rm tr},n}(\ell)\leq e_{\rm tr,max}$, we can show that increasing $e_{\rm in}$ increases ℓ_1. Therefore, by using the weak law of large numbers (WLLN), we can show that $\mathrm{DR}^*(\ell_1)/\ell_1\xrightarrow{P}0$ as $e_{\rm in}\to\infty$. Hence, (39) follows when $e_{\rm in}\to\infty$. ■

Lemma 2: For any $\epsilon>0$, TOP has the following property:

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\frac{L-\ell_3+1}{L}>\epsilon\right\}=0 \tag{40}$$

where $L-\ell_3+1$ denotes the number of data collection events from the beginning of the $\ell_3^{\rm th}$ data collection event until the network is defined as nonfunctional.

Proof: By using the WLLN, and Lemma 1, the proof is similar to the Proof of Lemma 1. ■

Lemma 3: For any $\epsilon>0$, TOP has the following property:

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\left|\bar{e}_{\rm tr}-e^{\rm bc}_{\rm tr}\right|>\epsilon\right\}=0 \tag{41}$$

where $\bar{e}_{\rm tr}$ is the achieved average transmission energy by implementing TOP.

Proof: According to (37), all the sensors have sufficient energy for transmission (i.e., the chosen sensor is determined according to the best channel) for all $1\leq\ell\leq\ell_1-1$ and $\ell_2\leq\ell\leq\ell_3-1$. By using the WLLN, and Lemmas 1–2, (41) follows. ■

Lemma 4: For any $\epsilon>0$, TOP has the following property:

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\frac{E_w}{Ne_{\rm in}}>\epsilon\right\}=0 \tag{42}$$

where E_w is the achieved wasted energy by implementing TOP.

Proof: Since $E_w\leq Ne^*_{\max,n}(\ell_3)$, by using the WLLN and Lemmas 1–2, the rest of the proof is similar to the proof of Lemma 1. ■

D. Proof of Theorem 3

Proof: We define $L_{\min}\triangleq(e_{\rm in})/(Ne_{\rm ce}+e_{\rm tr,max})$ as the minimal lifetime achieved by any protocol. The minimal achieved lifetime $L_{\min}$ is obtained by investing $e_{\rm tr,max}$ energy for transmission during each data collection event by a single sensor until it dies. We investigate the term $|(L^{\rm TOP}-L^{\rm bc})/L_{\min}|$, where $L^{\rm TOP}$ is the network lifetime achieved by implementing TOP, and $L^{\rm bc}\triangleq(Ne_{\rm in})/(Ne_{\rm ce}+e^{\rm bc}_{\rm tr})$.

By using Lemmas 3–4, we can show that for any fixed $\epsilon>0$ we obtain

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\left|\frac{L^{\rm TOP}-L^{\rm bc}}{L^{\min}}\right|>\frac{\epsilon}{2}\right\}=0. \tag{43}$$

Next, we define a random variable $U^{\rm opt}$ as follows:

$$U^{\rm opt}\triangleq\frac{Ne_{\rm in}}{Ne_{\rm ce}+\bar{e}^{\rm opt}_{{\rm tr},U}}$$

where $\bar{e}^{\rm opt}_{{\rm tr},U}=(1/L^{\rm opt})\sum_{\ell=1}^{L^{\rm opt}}\min_{1\leq n\leq N}e_{{\rm tr},n}(\ell)$, where $L^{\rm opt}$ is the achieved lifetime by the optimal protocol (i.e., we reduce the achieved average transmission energy by implementing the optimal protocol, thus we upper bounded the achieved lifetime by the optimal protocol by $U^{\rm opt}$). Therefore, we obtain

$$L^{\rm TOP}\leq L^{\rm opt}\leq U^{\rm opt}.$$

Similar to (43), we can show that for any fixed $\epsilon>0$, we have

$$\lim_{e_{\rm in}\to\infty}\Pr\left\{\left|\frac{U^{\rm opt}-L^{\rm bc}}{L^{\min}}\right|>\frac{\epsilon}{2}\right\}=0. \tag{44}$$

Finally, we combine (43), (44). For any fixed $\epsilon > 0$, we obtain

$$\Pr\left\{\left|\frac{L^{\mathrm{TOP}} - L^{\mathrm{opt}}}{L^{\mathrm{opt}}}\right| > \epsilon\right\} \leq \Pr\left\{\left|\frac{L^{\mathrm{TOP}} - L^{\mathrm{bc}}}{L^{\min}}\right| > \frac{\epsilon}{2}\right\} + \Pr\left\{\left|\frac{U^{\mathrm{opt}} - L^{\mathrm{bc}}}{L^{\min}}\right| > \frac{\epsilon}{2}\right\}. \quad (45)$$

Therefore, we obtain (17) when $e_{\mathrm{in}} \to \infty$. ■

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