TIME-VARYING OPPORTUNISTIC PROTOCOL FOR MAXIMIZING SENSOR NETWORKS LIFETIME

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ABSTRACT

We consider transmission scheduling by medium access control (MAC) protocols for energy limited wireless sensor networks (WSN) in order to maximize the network lifetime. Time-varying Opportunistic Protocol (TOP) for maximizing the network lifetime is proposed. By executing TOP each sensor exploits local channel state information (CSI) and local residual energy information (REI). TOP implements opportunistic strategy in terms of favoring sensors with better channels when the network is young, while less opportunistic and more conservative strategy in terms of prioritizing sensors with higher residual energy when the network is old. TOP significantly simplifies the implementation of carrier sensing as compared to other distributed MAC protocols. Simulation results show that TOP achieves significant performance gains over other distributed MAC protocols.

Index Terms— Wireless sensor networks, network lifetime, opportunistic Medium Access Control.

1. INTRODUCTION

Lifetime maximization is a major issue in non-rechargeable battery-powered wireless sensor networks (WSN). We consider sensor networks with mobile access (SENMA) [1]. In SENMA each sensor measures a certain phenomenon and upon request transmits its measurement directly to an access point (AP) through a fading channel. The question is which set of sensors should transmit during each data collection in order to maximize the overall network lifetime. It has been shown in [2] that exploiting channel state information (CSI) and residual energy information (REI) is essential for maximizing the network lifetime. In this paper we consider distributed protocols which exploit local CSI and REI, without sharing CSI and REI between sensors. CSI acquisition consumes energy (due to receiver operation) which affects the network lifetime. In cases where the energy consumed by CSI acquisition is significantly high we should relinquish CSI acquisition. However, in most networks this is not the case and CSI acquisition significantly increases the network lifetime. The transmission scheduling problem can be formulated as stochastic control problem in centralized fashion, as shown in [3], [4]. An optimal centralized transmission scheduling exploiting global CSI and REI is formulated as stochastic shortest path in [5]. However, the overhead and computational complexity of optimal centralized transmission is extremely high. Distributed MAC protocols have been extensively analyzed in [6], and significantly reduce overhead and computational complexity. Therefore, they are generally preferred over centralized protocols. As shown in [6], the transmission scheduling is executed by selecting the sensor with the largest energy-efficiency index for transmission at each data collection (this can be done by opportunistic carrier sensing [7]). The energy-efficiency index is a function of the local CSI and REI and it is generally time-invariant[1]. The design principle for the energy-efficiency index is to prioritize sensors with better channels when the network is young, while prioritizing sensors with higher residual energy when the network is old. A common problem for protocols which determine their energy-efficiency index based on REI is that the varying residual energy during the network lifetime reduces the carrier sensing performance. In this paper we propose the Time-varying Opportunistic Protocol (TOP). By implementing TOP, the energy-efficiency index is time-varying and it is determined by exploiting CSI and REI. However, TOP overcomes the problem of degraded carrier sensing performance.

2. NETWORK MODEL AND LIFETIME DEFINITION

2.1. Network Model

Consider a WSN with N sensors, each sensor n is powered by a battery with initial energy, e_{in}. Every sensor has fixed equal-sized packet measurement to be transmitted through a flat fading channel to the AP. We assume 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 the path loss, and thus the channel gain mean, is approximately equal for all the sensors. During each data collection, the AP broadcasts a beacon signal and each sensor estimates its channel state. We define e_{ce} as the energy consumed by each sensor during channel estimation. We assume that local REI is available to each sensor. We define the residual energy of each sensor by $e_{res,n}$. During each data collection only a single sensor (which can represent 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 straightforward). 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) $\frac{N_0}{2}$, and $x_n(t)$ is the transmitted signal using fixed power P_{out} equal for all the sensors. We define the data packet length by $I[bits]$, and the transmission data packet time of sensor n by T_n. The total transmission energy $e_{tr,n}$ consumed by sensor n transmission during specific data collection is given by:

$$e_{tr,n} = P_{tr} \cdot T_n = P_{tr} \cdot \frac{I}{W \cdot \log(1 + |h_n|^2 \cdot \frac{P_{out}}{\Gamma W N_0})} \ . \quad (1)$$

This research was partially supported by the NWO-STW Vici Project (DTC 5893, 10459).

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[1] The 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.

Where $P_{tr} = P_c + P_{out}$ is the total transmission power consumption of each sensor and P_c is the power consumption of the transmitter circuitry and it is equal for all the sensors. The term $W \log(1 + |h_n|^2 \cdot \frac{P_{out}}{\Gamma W N_0})$ is the data transmission rate, where Γ and W are the Shannon gap to capacity(which is a function of noise margin, BER and coding gain) and the channel bandwidth, respectively.

We define the wasted energy as the total unused energy in the network when it dies (the network functionality definition is given in Sec. 2.2). Therefore, the total wasted energy of the network is given by:

$$E_w = \sum_{n=1}^{N} e_{w,n} \ , \tag{2}$$

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

2.2. Network Lifetime Definition

We define sensor as nonfunctional when its residual energy drops below the threshold energy, e_{th}, required for transmission with predetermined probability. We define the network as nonfunctional when the number of nonfunctional sensors reaches N_0, where $1 \leq N_0 \leq N$. The network lifetime is defined as the number of data collections until the network is defined as nonfunctional. Since we wish to prolong the network lifetime before the first sensor dies, we consider the network lifetime when $N_0 = 1$. Based on lifetime analysis in [2], the expected network lifetime is given by:

$$\mathbf{E}\{L\} = \frac{N \cdot e_{in} - \mathbf{E}\{E_w\}}{N \cdot e_{ce} + \mathbf{E}\{e_{tr}\}} \ , \tag{3}$$

where $\mathbf{E}\{e_{tr}\}$ is the expected transmission energy consumed in a randomly chosen data collection and $\mathbf{E}\{E_w\}$ is the expected wasted energy. As explained in [2], we infer from (3) that we should reduce the transmission energy (by exploiting CSI for selecting sensor with a better channel) when the data collection index ℓ is small (i.e. the network is young), since the probability that the network lives ℓ data collections decreases with ℓ. On the other hand we should reduce the wasted energy (by exploiting REI for selecting sensor with large residual energy) when ℓ is increased.

3. DISTRIBUTED TRANSMISSION PROTOCOLS

3.1. Implementation via Opportunistic Carrier Sensing

By executing opportunistic carrier sensing [7], each sensor in the network calculates an 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 where the propagation delay can not be ignored, $f(\gamma)$ has to be designed judiciously. The design of $f(\gamma)$ is based on finding values range which bounds most of the energy-efficiency index values and provides separation in backoff time only for sensors with energy-efficiency index value in this range. Sensors with energy-efficiency index value above this range transmit immediately, while sensors with energy-efficiency index value below this range do not listen the channel and wait for the next data collection. 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:

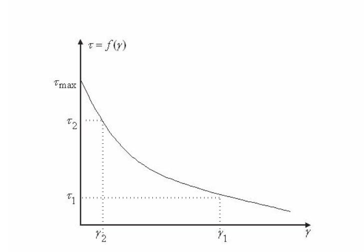

Fig. 1. An example of decreasing function $f(\gamma)$ for opportunistic carrier sensing.

$$\widehat{n}(\ell) = \arg \max_{1 \leq n \leq N} \gamma_n(\ell) \quad s.t. \ \ e_{res,n}(\ell) \geq e_{tr,n}(\ell) + e_{th} \ , \tag{4}$$

where $\widehat{n}(\ell)$ denotes the index of the chosen sensor in the ℓ'th data collection, and $\gamma_n(\ell)$ is chosen according to some scheme. n and ℓ denote the sensor index and the data collection index, respectively. Therefore, 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 (4) as local survivability condition. Our goal is to find a strategy for obtaining $\gamma_n(\ell)$ in problem (4) in terms of maximizing the network lifetime according to (3).

3.2. Overview of Distributed Protocols

We now review some existing distributed protocols:

3.2.1. Pure Opportunistic Protocol

The pure opportunistic protocol has been discussed in [5], [7], [6], and serves us in the continuation of this paper. The pure opportunistic strategy is to choose the sensor with the best channel in order to minimize the average transmission energy. Explicitly, the energy-efficiency index in (4) at the n'th sensor selection during the ℓ'th data collection is given by:

$$\gamma_n(\ell) = |h_n(\ell)|^2 \quad \forall n \in N \ . \tag{5}$$

where h represents the channel state, N represents the number of sensors in the network, and ℓ represents the data collection index. By implementing the pure opportunistic protocol via opportunistic carrier sensing, the energy-efficiency indices values range does not change during the network lifetime. Therefore, only one predetermined backoff function $f(\gamma)$ is needed during the network lifetime. A backoff function $f(\gamma)$ has been constructed in [7] 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 . Therefore, the performance of the pure opportunistic protocol in terms of network lifetime is extremely poor.

3.2.2. Dynamic Protocol for Lifetime Maximization (DPLM)

In this protocol, proposed in [6] , γ_n is defined by:

$$\gamma_n(\ell) = \frac{e_{res,n}(\ell)}{e_{tr,n}(\ell)} \quad \forall n \in N \ . \tag{6}$$

We infer from (6) that this scheme selects the sensor which is able to transmit the highest number of times under the current channel condition, during each data collection. It was shown in [6] that DPLM is asymptotically optimal (when $e_{in} \to \infty$). Specifically, the relative performance loss of DPLM as compared to the optimal protocol diminishes with the initial energy. However, the implementation of DPLM via opportunistic carrier sensing is more complicated. By implementing DPLM the energy-efficiency indices values range is time-varying due to decreasing residual energy during each data collection. Therefore, in order to minimize the occurrence of collisions, the backoff function should vary during the network lifetime (theoretically different backoff functions is required for each data collection, which is impractical). Another challenge is constructing backoff function for each realization during the network lifetime (depending on channel distribution and residual energy distribution).

4. TIME-VARYING OPPORTUNISTIC PROTOCOL (TOP)

In this section we introduce the Time-varying Opportunistic Protocol (TOP). By implementing TOP we require:

1. Opportunistic strategy in terms of favoring sensors with better channels when the network is young, while less opportunistic and more conservative strategy in terms of prioritizing sensors with higher residual energy when the network is old.
2. Simple implementation via opportunistic carrier sensing.
3. Approaching the pure opportunistic protocol as $e_{ce} \to 0$.

The first and the second requirements have been discussed in Sec. 2 and 3. The third requirement is analyzed in the complete paper of TOP [8]. In [8] we show that selecting the sensor with the best channel for transmission is generally preferred over other distributed protocols in the case where $e_{ce} \to 0$ (i.e. no energy is consumed during channel estimation). Then, we consider the realistic case where $e_{ce} \neq 0$. By estimating the future energy loss due to CSI acquisition, we design TOP strategy. We show that selecting the sensor with the best channel for transmission as long as the sensor has sufficient energy for current transmission plus the estimated future energy loss, is generally preferred over other distributed protocols.

4.1. The Protocol

We now present TOP algorithm. During the ℓ'th data collection we assume that the AP has sent the ℓ'th beacon toward the network and each sensor has estimated its channel gain $h_n(\ell)$ and calculated the required transmission energy $e_{tr,n}$ according to (1).

Step 1. Expected Transmission Energy Estimation: Each sensor which has sent data within previous data collections stores the average transmission energy over all the previous transmissions and updates the estimation each transmission. An alternative scheme is to estimate the expected transmission energy by exploiting knowledge from other sensors transmissions. This can be done by exploiting the delay τ during the carrier sensing. The transmission energy can be discover by $f^{-1}(\tau)$, where $f(\tau)$ is discussed in Sec. 3.1.

Step 2. Desired Expected Wasted Energy Estimation: The desired expected wasted energy is estimated by:

$$\widehat{\mathbf{E}}\left\{E_w\right\}_n(\ell) = N\left(e_{th} + \frac{\widehat{\mathbf{E}}\{e_{tr}\}_n(\ell)}{2}\right), \tag{7}$$

where $\widehat{\mathbf{E}}\left\{e_{tr}\right\}_n(\ell)$ is the estimated expected transmission energy calculated in step 1. i.e. all the sensors have been exploited when the network is defined as nonfunctional.

Step 3. Expected Lifetime Estimation: The expected lifetime in (3) is estimated by:

$$\widehat{\mathbf{E}}\left\{L\right\}_n(\ell) = \frac{N\cdot e_{in} - \widehat{\mathbf{E}}\{E_w\}_n(\ell)}{N\cdot e_{ce} + \widehat{\mathbf{E}}\{e_{tr}\}_n(\ell)} \ . \tag{8}$$

Notice that TOP requires each sensor to know the number of sensors in the network, in order to estimate the network lifetime. In most networks this information is essential from other considerations (such as carrier sensing). Estimating the number of sensors is often done by the AP ([9], [10]). Therefore, the AP can transmit this information back to the sensors.

Step 4. Expected Future Energy Loss Estimation: The expected future energy loss consumed by future channel estimations for each sensor, $\mathbf{E}\left\{e_f\right\}_n(\ell)$, is given by:

$$\widehat{\mathbf{E}}\left\{e_f\right\}_n(\ell) = \begin{cases} \left(\widehat{\mathbf{E}}\left\{L\right\}_n(\ell) - \ell\right) e_{ce}, & \text{if } \widehat{\mathbf{E}}\left\{L\right\}_n(\ell) \geq \ell \\ 0\ , & \text{o.w} \end{cases}, \tag{9}$$

where $\widehat{\mathbf{E}}\left\{L\right\}_n(\ell) - \ell$ is the estimated remaining time until the network is defined as nonfunctional.

Step 5. Transmission Scheduling: The sensor with the best channel gain is selected for transmission as long as the sensor has sufficient energy for current transmission plus the estimated future energy loss. As a result each sensor updates its corrected residual energy, $e^*_{res,n}$ by:

$$e^*_{res,n}(\ell) = e_{res,n}(\ell) - \widehat{\mathbf{E}}\left\{e_f\right\}_n(\ell)\ , \tag{10}$$

where $e^*_{res,n}(\ell)$ is the corrected residual energy of sensor n. Hence, each sensor transmits in the following scheme:

$$\widehat{n}(\ell) = \arg\max_{1\leq n\leq N} \gamma_n(\ell) \quad s.t.\ \ e^*_{res,n}(\ell) \geq e_{tr,n}(\ell) + e_{th}\ , \tag{11}$$

where $\widehat{n}(\ell)$ denotes the index of the chosen sensor, and $\gamma_n(\ell)$ is chosen according to

$$\gamma_n(\ell) = |h_n(\ell)|^2 \quad \forall n \in N\ . \tag{12}$$

We denote the constraint in (11) as long term local survivability condition.

4.2. TOP Characteristics

4.2.1. 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. However, as the network becomes older, the long term local survivability condition is valid for some sensors. In that case, the chosen sensor is determined according to the channel gain and sufficient residual energy. Consequently, sensor which has better channel gain may not transmit, although it has sufficient energy for current transmission. This is the first requirement which we aimed to execute.

4.2.2. Opportunistic Carrier Sensing Implementation

By implementing TOP, γ_n is simply the channel gain if the long term local survivability condition is not valid and does not depend on the decreasing residual energy. Therefore, only one predetermined backoff function $f(\gamma)$ is needed during the network lifetime (a backoff function $f(\gamma)$ for the case where the energy-efficiency indices are the channel gain has been constructed in [7] which achieves very good performance with respect to propagation delay). This is the second requirement which we aimed to execute.

4.2.3. Special Case : $e_{ce} \to 0$

By implementing TOP when $e_{ce} \to 0$, the corrected residual energy in (10), $e^*_{res,n}$, is equal to the residual energy $e_{res,n}$. Therefore, TOP approaches the pure opportunistic protocol as $e_{ce} \to 0$. This is the third requirement.

4.2.4. Asymptotic Optimality of TOP

Theorem 1 *Assume the transmission energy is bounded by* $e_{tr,min} \leq e_{tr,n}(\ell) \leq e_{tr,max}$*, and the channel gains are i.i.d across data collections and across sensors. Then, the relative performance loss of TOP as compared to the optimal protocol decreases as the initial energy across the sensors increases. Explicitly, we obtain:*

$$\lim_{e_{in}\to\infty} Pr\left(\frac{L^{opt}-L^{TOP}}{L^{opt}}=0\right)=1\ , \tag{13}$$

where L^{opt} *and* L^{TOP} *denote the network lifetime achieved by the optimal protocol and TOP, respectively.*
The proof is given in [8].

5. SIMULATION EXAMPLES

In this section we compare the performance of the proposed Time-varying Opportunistic Protocol (TOP) with the following protocols which have been proposed recently: 1) the pure opportunistic protocol; 2) Max-Min protocol ([6]); 3) Dynamic Protocol for Lifetime Maximization (DPLM). We simulated network with N sensors which transmit through a flat block fading channel according to Rayleigh fading distribution, i.i.d across data collections and across sensors. We set the channel gain mean to 1, $\mathbf{E}\left\{|h_n|^2\right\}=1$. We assume perfect carrier sensing without collisions. The initial energy of each sensor was set to $e_{in}=10$. We normalized the channel bandwidth to 1 ($W=1$), and the SNR was set to $\rho \triangleq \frac{P_{out}}{WN_0}=3dB$. The normalized required power for transmission, times the data packet size, with respect to the normalized bandwidth is $P_{tr}\cdot I=5$. The normalized energy required for a sensor for CSI acquisition is $e_{ce}=0.001$. We investigate the expected network lifetime versus the network size. As shown in Fig. 2, TOP achieves significant performance gain over all other protocols. TOP achieves about 9% relative performance gain over DPLM (TOP also has simpler implementation and achieves a better performance via carrier sensing). TOP achieves about 45% relative performance gain over the pure opportunistic protocol (and has similar implementation and achieves similar performance via carrier sensing). DPLM outperforms Max Min, and the pure opportunistic protocol performs the worst. In Fig. 3 we show the expected wasted energy versus the network size. As expected, the pure opportunistic performance is extremely poor, while TOP, by balancing the opportunistic strategy when the network is old, outperforms both DPLM and MAx-Min protocols.

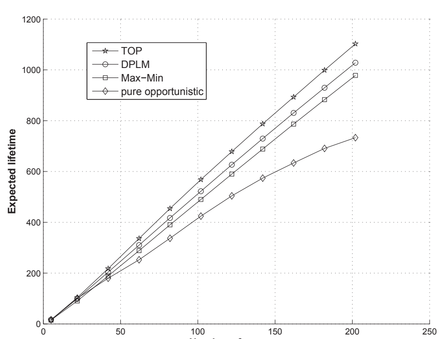

Fig. 2. Expected lifetime versus the number of sensors.

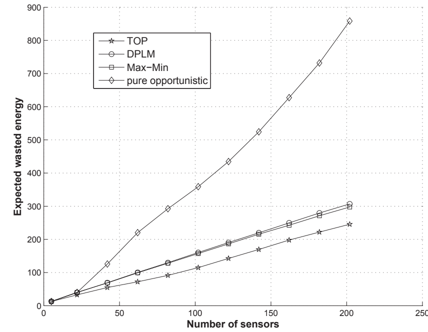

Fig. 3. Expected wasted energy versus the number of sensors.

6. CONCLUSIONS

In this paper we considered distributed MAC protocols for wireless sensor networks lifetime maximization. We proposed Time-varying Opportunistic Protocol (TOP). The design principle of TOP algorithm is to prioritize sensors with better channels when the network is young, while prioritize sensors with more residual energies when the network is old. TOP also simplifies the implementation of carrier sensing as compared to other distributed MAC protocols. Simulation results have shown that TOP achieves significant performance gain over other protocols that have been proposed recently.

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