OPPORTUNISTIC POWER ALLOCATION SCHEMES FOR THE MAXIMIZATION OF NETWORK LIFETIME IN WIRELESS SENSOR NETWORKS

Javier Matamoros and Carles Antón-Haro

Centre Tecnològic de Telecomunicacions de Catalunya (CTTC)
Parc Mediterrani de la Tecnologia, Av. Canal Olimpic s/n, Barcelona, Spain 08860
e-mail: {javier.matamoros,carles.anton}@cttc.es

ABSTRACT

In this paper, we propose and analyze two Opportunistic Power Allocation (OPA) schemes suitable for decentralized parameter estimation in wireless sensor networks. In these schemes, only sensors for which some *locally* obtained quality measure exceeds a threshold computed and then broadcasted by the FC, can actually participate in the estimation process. Subsequently, the sensors adjust their transmit power in such a way that the prescribed estimation quality target can be met at the FC. In particular, we consider two different criteria to design the reporting threshold: (1) to minimize the transmit power, which merely requires partial Channel State Information (CSI); and, (2) to maximize network lifetime which additionally requires Residual Energy Information (REI). For each design, we first define the local decision rule and then we derive closed-form expressions of the global reporting threshold. Then, we assess the performance of the proposed OPA schemes by means of computer simulations, and we carry out a comparison with the optimal Water-Filling (WF) solution. Results are given in terms of transmit power and average network lifetime.

Index Terms**—** Sensor Networks, Opportunistic Power Allocation, Network Lifetime

1. INTRODUCTION

In recent years, research on Wireless Sensor Networks (WSN) has attracted considerable attention. In general, a WSN consists of one fusion center (FC) and a potentially large number of sensing devices capable of transmitting their measurements over a wireless link. In the case of gaussian observations, the amplify-and-forward (i.e. analog) retransmission of the measurements turns out to be asymptotically optimal [1]. In this context, the authors in [2] derived the optimal power allocation strategies for two different problems: (1) the minimization of distortion subject to a sum-power constraint, and (2) the minimization of transmit power subject to a maximum distortion target. In both cases, the optimal power allocation is given by a kind of water-filling (WF) solution. Clearly, the price to be paid for such optimality is the extensive signalling to exchange information between the FC and the sensor nodes which results into a high energy consumption, which is barely desirable in WSNs.

The so-called opportunistic scheduling schemes [3] provide a means to efficiently grant scarce resources, in particular, when the population of terminals (or sensors) is large. By granting access to the terminal(s) experiencing the most favorable channel conditions, one can either maximize the resulting sum-rate or, equivalently, minimize the energy consumption. However, in large networks the *signalling* load in the feedback channels from the terminals to the centralized scheduler may be prohibitively high. To circumvent that, one can resort to some thresholding strategy whereby only sensors with channel gains above a pre-defined threshold are allowed to send their reports either in analog [4] or digital [5] form. In all cases, opportunistic schemes capitalize on the multi-user diversity (MUD) resulting from the assumption of independent fading conditions over terminals.

Unfortunately, in a WSN the sensors have finite batteries and, thus, network lifetime is of major concern. Network lifetime is often defined as the time elapsed until one sensor runs out of energy [6]. In the context of WSN, the authors in [7] (and references therein) propose an opportunistic backoff method that exploits both CSI and REI for Lifetime maximization.

In this paper, we propose and analyze an Opportunistic Power Allocation (OPA) scheme suitable for decentralized parameter estimation in WSNs. Inspired by [4][5], we consider a threshold strategy by which only sensors experiencing certain local conditions (above a global threshold) participate in the estimation process. In order to keep signalling as low as possible, the proposed power allocation scheme merely requires (1) *statistical* CSI and REI at the FC (in [2] full CSI is required) in order to compute the global threshold; (2) one signalling bit per sensor (instead of analog feedback as in [4] or [2]) to notify the FC about the channel conditions experienced by each sensor and, (3) local CSI and REI at each sensor node in order to adjust the transmit power. We consider two different cases: (1) the minimization of the transmit power, which merely requires partial channel state information (CSI); and, (2) the maximization of network lifetime which additionally requires residual energy information (REI). For both cases, and, unlike [7], we derive the power allocation rule to minimize the transmit power under a prescribed estimation quality constraint and, then, we obtain closed-form expressions for the global threshold. In the second case, we substantially enhance the network lifetime while the transmit power remains reasonably low.

2. SIGNAL MODEL

Consider a WSN composed of one Fusion Center (FC) and a large population of N_0 energy-constrained sensors aimed at estimating a scalar, slowly-varying and spatially-homogeneous parameter θ. The observation at sensor i can be expressed as

$$x_i = \theta + n_i, \tag{1}$$

where n_k denotes AWGN noise of variance σ_n^2 (i.e. $n_i \sim \mathcal{CN}\left(0, \sigma_n^2\right)$). Motivated by the results in [1], in each sensor the observation is scaled by a factor $\sqrt{p_i}$ and then it is transmitted to the FC (i.e. amplify-and-forward). In the sequel, we assume non-frequency selective rayleigh block-fading channel conditions and, further, pairwise synchronization between each sensor node and the FC. Hence, the received signal at the FC can be written as:

$$y_i = \sqrt{p_i}\sqrt{c_i}\,(\theta + n_i) + w_i = \sqrt{p_i c_i}\theta + \sqrt{p_i c_i} n_i + w_i, \quad (2)$$

where w_i stands for i.i.d. AWGN (i.e. $w \sim \mathcal{CN}\left(0, \sigma_w^2\right)$) and c_i denotes the channel power gain which is modelled as an exponentially-distributed random variable with mean μ_c. Furthermore, such channel gains are assumed to be i.i.d across sensors. In each time-slot, $N \leq N_0$ sensors transmit their observations to the FC over a set of orthogonal channels (e.g. FDMA) and, thus, the $N \times 1$ received signal vector $\mathbf{y}$ reads

$$\mathbf{y} = \mathbf{h}\theta + \mathbf{z}, \quad (3)$$

with $\mathbf{h} = \left[\sqrt{p_1 c_1}, \ldots, \sqrt{p_N c_N}\right]^T$ and $\mathbf{z}$ standing for AWGN with $\mathsf{diag}\left[\mathbf{C}\right] = \left[p_1 c_1 \sigma_n^2 + \sigma_w^2, \ldots, p_N c_N \sigma_n^2 + \sigma_w^2\right]^T$ being $\mathbf{C}$ its (diagonal) covariance matrix. In an attempt to make our estimator simple and universal (i.e. independent of particular noise distributions), we will be using BLUE [2] at the FC. In the sequel, we will take the variance as a distortion measure D. It is straightforward to show that the variance of this estimator (which is known to be efficient for the linear signal model described above) is given by

$$D = \mathsf{Var}(\hat{\theta}) = \left(\sum_{i=1}^{N} \frac{p_i c_i}{p_i c_i \sigma_n^2 + \sigma_w^2}\right)^{-1}. \quad (4)$$

where it becomes apparent that the actual distortion depends on the power allocation strategy. In WSN the power consumption is of paramount importance and, typically, the power allocation rule is aimed at minimizing the total amount of transmit power while a prescribed distortion D_t is met. This optimal solution was derived in [2] which turns out to be a waterfilling-like solution.

3. PROTOCOL DESCRIPTION

Clearly, the price to be paid for the optimality of the solution derived in [2] is the need to inform the sensor nodes about the optimal transmit power computed in a centralized way in the FC. This unavoidably entails an extensive signalling between the FC and the sensor nodes which results into a high energy consumption, which is barely desirable in WSN. In an attempt to reduce the amount of feedback, we propose the following communication protocol for the Opportunistic Power Allocation (OPA) scheme:

1. **In each time Slot**, compute and broadcast the threshold $\gamma_{\mathsf{th}}[s]$ on the basis of *statistical* CSI (and, possibly, REI) available at the FC.
2. **Identification of the active sensor set**: Each sensor node notifies the FC whether it will participate in the estimation process or not (i.e. 1 bit message). Only sensors above the threshold will participate. As we will see later, this process merely requires *local* information at each sensor node. The number of active sensors, $N = N(t)$, is then broadcasted by the FC.
3. **Power Allocation and Transmission**: The N active sensor nodes accordingly adjust the transmit power and send their observations to the FC[1].
4. **Go to Step[2] 1**

[1]The task of scheduling active sensors on orthogonal channels is delegated to the MAC layer and, therefore, is out of the scope of this paper.

[2]If no REI is used, then the threshold $\gamma_{\mathsf{th}}[s]$ is fixed and has to be computed and broadcasted only once

Many different criteria can be adopted in order to design the optimal reporting threshold $\gamma_{\mathsf{th}}[s]$ [8]. In the next section, we will outline the derivation of a threshold which minimizes the transmit power on the basis of statistical CSI only (the interested reader is referred to [8] for details). Next we will extend those derivations and find a threshold which maximizes the network lifetime by using statistical CSI and REI.

4. REVIEW: MINIMIZATION OF TRANSMIT POWER

In this section we attempt to find a reporting threshold γ_{th} such that it minimizes the total transmit *power* (subject to a given distortion constraint). Mathematically, the optimization problem can be expressed as follows:

$$\begin{aligned} &\min_{\gamma_{\mathsf{th}}} \left\{ \mathbb{E}_{\{c_i\}_{i=1}^{N}, N; \gamma_{\mathsf{th}}} \left[\sum_{i=1}^{N} p_i \right] \right\} \\ &\text{subject to} \quad D = D_T, \end{aligned} \quad (5)$$

where D and D_T stand for the actual and target distortion, respectively. From (4), the overall distortion D can be readily expressed in terms of the individual contributions D_i from every active sensor node, namely

$$D = \left(\sum_{i=1}^{N} \frac{1}{D_i}\right)^{-1}. \quad (6)$$

Since sensor nodes only have local CSI, we cannot but impose their individual contributions to the overall distortion to be identical. To make sure that the constraint in (5) is met, we let $D_i = N D_T$ and force each sensor to adjust its transmit power accordingly. From (4), we have

$$p_i = \frac{\frac{1}{N D_T}\sigma_w^2}{c_i\left(1 - \frac{1}{N D_T}\sigma_n^2\right)}. \quad (7)$$

The optimization problem can now be re-written as

$$\min_{\gamma_{\mathsf{th}}} \left\{ \mathbb{E}_{\{c_i\}_{i=1}^{N}, N; \gamma_{\mathsf{th}}} \left[\sum_{i=1}^{N} \frac{\frac{1}{N D_T}\sigma_w^2}{c_i\left(1 - \frac{1}{N D_T}\sigma_n^2\right)} \right] \right\} \quad (8)$$

Unfortunately, the expression above is barely tractable. Instead, we will compute a lower bound for the score function in (8). To do so, we need the pdf function of the set of random variables $\{c_i\}_{i=1}^{N} | N; \gamma_{\mathsf{th}}$ (or $\{c_i\}_{i=1}^{N}; \gamma_{\mathsf{th}}$ in short); and the pmf of $N; \gamma_{\mathsf{th}}$. Since $\{c_i\}_{i=1}^{N}; \gamma_{\mathsf{th}}$ are i.i.d., it suffices to find the pdf of the individual truncated random variable $c_i; \gamma_{\mathsf{th}}$. One can easily prove that[3]:

$$f_{c_i;\gamma_{\mathsf{th}}}(x) = \frac{f_{c_i}(x)}{1 - F_{c_i}(\gamma_{\mathsf{th}})} = \frac{e^{\frac{\gamma_{\mathsf{th}}}{\mu_c}}}{\mu_c} e^{-\frac{x}{\mu_c}} \quad x \in [\gamma_{\mathsf{th}}, \infty) \quad (9)$$

where $F_{c_i}(\cdot)$ denotes the CDF function of the r.v. c_i. Besides, for each of those truncated r.v. we have that $\mathbb{E}_{c_i;\gamma_{\mathsf{th}}}[x] = \int_{\gamma_{\mathsf{th}}}^{\infty} x f_{c_i;\gamma_{\mathsf{th}}}(x) = \mu_c + \gamma_{\mathsf{th}}$. Concerning $N; \gamma_{\mathsf{th}}$, it clearly follows a binomial distribution:

$$\mathsf{Pr}\{N = n; \gamma_{\mathsf{th}}\} = \binom{N_0}{n} p^n (1-p)^{N_0 - n}. \quad (10)$$

with $p = 1 - F_{c_i}(\gamma_{\mathsf{th}}) = e^{-\frac{\gamma_{\mathsf{th}}}{\mu_c}}$. Bearing all the above in mind, we found in [8] that (8) can be lower bounded by

$$\min_{\gamma_{\mathsf{th}}} \left\{ \frac{\frac{1}{D_T}\sigma_w^2}{(\mu_c + \gamma_{\mathsf{th}})\left(1 - \frac{1}{D_T N_0 e^{-\gamma_{\mathsf{th}}/\mu_c}}\sigma_n^2\right)} \right\}. \quad (11)$$

[3]To recall, c_i is an exponentially-distributed r.v. of mean μ_c

It is straightforward to show that (11) is convex in γ_{th} and, hence, by setting its derivative to zero, we have

$$\gamma_{\mathsf{th}}^{*}=\left[\mu_c \mathsf{LambertW}\left(\frac{D_T N_0 e^2}{\sigma_n^2}\right)-2\mu_c\right]^{+}, \tag{12}$$

where $\mathsf{LambertW}\,(W)$ is defined as the inverse function of $f(W)=We^{W}$ and $[x]^{+}$ denotes $\max\{x,0\}$. Clearly, the tighter the inequalities the closer γ_{th}^{*} will be to its actual value.

5. MAXIMIZATION OF NETWORK LIFETIME

Selecting those sensors which expirience the most favorable channel conditions results into a reduction in transmit power. However, this design is not beneficial from the network lifetime point of view. In the spirit of [7], we propose a selection method that incorporates REI information, as well. In other words, the sensor i participates in the estimation process if and only if $\varepsilon_i[s]c_i>\gamma_{\mathsf{th}}[s]$, with $\varepsilon_i[s]$, standing for the residual energy in slot s. With this selection strategy, only sensors with favorable channel conditions *and* sufficient residual energy are scheduled with probability

$$\mathsf{Pr}\left(\varepsilon_i[s]c_i>\gamma_{\mathsf{th}}[s]\right)=e^{-\frac{\gamma_{\mathsf{th}}[s]}{\mu_c\varepsilon_i[s]}}. \tag{13}$$

By doing so, we introduce individual thresholds for each sensor and, thus, individual activation probabilities. Note also that the energy vector[4] $\boldsymbol{\varepsilon}[s]=[\varepsilon_1[s],\ldots,\varepsilon_{N_o}[s]]$ is a non-stationary stochastic process the individual entries of which are locally updated as follows,

$$\varepsilon_i[s+1]=\varepsilon_i[s]-p_i[s]T_s \quad \text{with } \varepsilon_i[0]=\varepsilon_o, \tag{14}$$

where $p_i[s]$ denotes the transmit power in slot s, T_s is the duration of the time slot and ε_o stands for the initial energy. Bearing all the above in mind, the optimization problem can be re-written as

$$\min_{\gamma_{\mathsf{th}}[s]}\left\{\mathbb{E}_{\{c_i\}_{i=1}^{N},N;\gamma_{\mathsf{th}}[s]|\boldsymbol{\varepsilon}[s]}\left[\sum_{i=1}^{N}\frac{\frac{1}{ND_T}\sigma_w^2}{c_i\left(1-\frac{1}{ND_T}\sigma_n^2\right)}\right]\right\}. \tag{15}$$

Clearly, the optimum threshold $\gamma_{\mathsf{th}}^{*}[s]$ is the one which minimizes the total transmit power under this REI-based selection rule. This strategy is known to enhance the network lifetime [7] while, as we will see later on, keeping the transmit power reasonably low. Again, the above problem is barely tractable and, instead, we derive a lower bound.

First, though, we need to introduce three inequalities that will be useful for the derivation of the bound. Without loss of generality, let $\boldsymbol{\varepsilon}[s]$ be an *ordered* vector, namely $\varepsilon_1[s]>\varepsilon_2[s]>\ldots>\varepsilon_{N_o}[s]$. By resorting to Jensen's inequality, the average number of active sensors can be lower-bounded as follows:

$$\mathbb{E}_{N;\gamma_{\mathsf{th}[s]}|\boldsymbol{\varepsilon}[s]}\left[N\right]=\sum_{i=1}^{N_0}e^{-\frac{\gamma_{\mathsf{th}}[s]}{\varepsilon_i[s]\mu_c}}\geq N_0 e^{-\frac{\gamma_{\mathsf{th}}[s]}{\mu_c N_0}\sum_{i=1}^{N_0}\frac{1}{\varepsilon_i[s]}} \tag{16}$$

Besides, for an ordered vector of energies and for some $N_o'\leq N_o$ the average number of active sensors can also be upper-bounded by:

$$\mathbb{E}_{N;\gamma_{\mathsf{th}[s]}|\boldsymbol{\varepsilon}[s]}\left[N\right]=\sum_{i=1}^{N_0}e^{-\frac{\gamma_{\mathsf{th}}[s]}{\varepsilon_i[s]\mu_c}}\leq N_0 e^{-\frac{\gamma_{\mathsf{th}}[s]}{\mu_c N_o'}\sum_{i=1}^{N_0'}\frac{1}{\varepsilon_i[s]}}. \tag{17}$$

[4]It is assumed that the energy consumption is dominated by the energy consumption during the wireless transmission

for $0\leq\gamma_{\mathsf{th}}[s]\leq\gamma^{'}$ (the rationale behind is omitted here for the sake of brevity). The interest in using $N_o'>1$ lies in the fact that the higher N_o', the tighter the resulting upper bound (for $N_o'=1$ the inequality is trivial for any $\gamma_{\mathsf{th}}[s]$). Still, for $N_o'>1$ the bound is only valid for part of the function domain and, hence, one should first identify $\gamma^{'}$ and then let N_o' take the highest value possible for which the inequality holds. We will go back to this later in this section.

By using (16) is straightforward to obtain the last inequality that we need:

$$\mathbb{E}_{c;\gamma_{\mathsf{th}}[s]|\boldsymbol{\varepsilon}[s]}\left[c\right]\leq\mu_c+\frac{\gamma_{\mathsf{th}}[s]}{H(\boldsymbol{\varepsilon}[s])_{1:N_o}}. \tag{18}$$

with $H(\boldsymbol{\varepsilon}[s])_{1:M}$ standing for the harmonic mean of the first M elements of the vector $\boldsymbol{\varepsilon}[s]$. Now, by repeatedly applying Jensen's inequality along with the three inequalities we have just derived (as displayed in the equations below) we can finally obtain the lower bound of the score function (15):

$$\mathbb{E}_{N;\gamma_{\mathsf{th}}[s]|\boldsymbol{\varepsilon}[s]}\left[\mathbb{E}_{\{c_i\}_{i=1}^{N};\gamma_{\mathsf{th}}[s]|\boldsymbol{\varepsilon}[s]}\left[\sum_{i=1}^{N}\frac{\frac{1}{ND_T}\sigma_w^2}{c_i\left(1-\frac{1}{ND_T}\sigma_n^2\right)}\right]\right]\overset{(18)}{\geq}$$

$$\mathbb{E}_{N;\gamma_{\mathsf{th}}[s]|\boldsymbol{\varepsilon}[s]}\left[\frac{\frac{1}{D_T}\sigma_w^2}{\left(\mu_c+\frac{\gamma_{\mathsf{th}}[s]}{H(\boldsymbol{\varepsilon}[s])_{1:N_o}}\right)\left(1-\frac{1}{ND_T}\sigma_n^2\right)}\right]\geq$$

$$\frac{\frac{1}{D_T}\sigma_w^2}{\left(\mu_c+\frac{\gamma_{\mathsf{th}}[s]}{H(\boldsymbol{\varepsilon}[s])_{1:N_o}}\right)\left(1-\frac{1}{\sum_{i=1}^{N_o}e^{-\frac{\gamma_{\mathsf{th}}[s]}{\mu_c\varepsilon[s]}}D_T}\sigma_n^2\right)}\overset{(17)}{\geq} \tag{19}$$

$$\frac{\frac{1}{D_T}\sigma_w^2}{\left(\mu_c+\frac{\gamma_{\mathsf{th}}[s]}{H(\boldsymbol{\varepsilon}[s])_{1:N_o}}\right)\left(1-\frac{1}{D_T N_0 e^{-\frac{\gamma_{\mathsf{th}}[s]}{\mu_c H(\boldsymbol{\varepsilon}[s])_{1:N_o'}}}}\sigma_n^2\right)}, \tag{20}$$

The argument in the first expression is clearly convex in c_i. As for (19), the argument is convex in N as long as $N\geq\lceil\sigma_n^2/D_T\rceil$ this meaning, in turn, that the distortion target D_T can be actually met (otherwise, from (7) the transmit power P_i would take negative values)[5]. The highest value of $\gamma_{\mathsf{th}}[s]$ for which (20) is still a convex function occurs when the second term in parenthesis in the denominator, which is a decreasing function in $\gamma_{\mathsf{th}}[s]$, tends to zero (for negative values, the bound is not a convex function anymore). Hence, we have:

$$\gamma^{'}=\mu_c H(\boldsymbol{\varepsilon}[s])_{1:N_o'}\ln\left(\frac{N_o D_t}{\sigma_n^2}\right) \tag{21}$$

and, from this value, the FC can compute the highest value of N_o' as commented before. Finally, by setting its derivative respect to $\gamma_{\mathsf{th}}[s]$ to zero, we obtain the threshold $\gamma_{\mathsf{th}}^{*}[s]$ which minimizes the bound, that is,

$$\gamma_{\mathsf{th}}^{*}[s]=\mu_c H(\boldsymbol{\varepsilon}[s])_{1:N_o'}\left[\mathsf{LambertW}\left(\frac{D_T N_0 e^{\frac{H(\boldsymbol{\varepsilon}[s])_{1:N_o'}+H(\boldsymbol{\varepsilon}[s])_{1:N_o}}{H(\boldsymbol{\varepsilon}[s])_{1:N_o'}}}}{\sigma_n^2}\right)-\frac{H(\boldsymbol{\varepsilon}[s])_{1:N_o}+H(\boldsymbol{\varepsilon}[s])_{1:N_o'}}{H(\boldsymbol{\varepsilon}[s])_{1:N_o'}}\right]^{+}. \tag{22}$$

[5]Under some regularity conditions and for large N_0, the probability of the event $\{N\geq\lceil\sigma_n^2/D_T\rceil\}$ can be made arbitrarily close to 1. Hence, the bound we are deriving is almost surely valid.

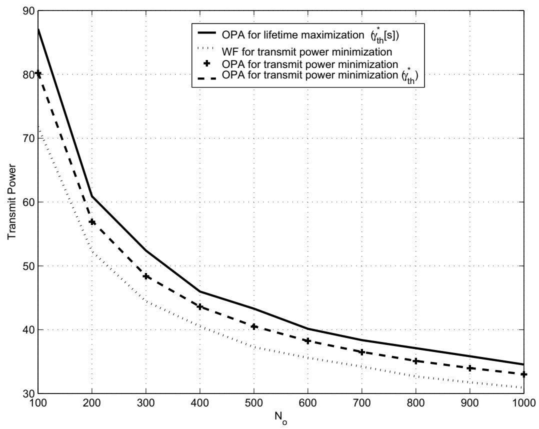

Fig. 1. Average power consumption vs. network size ($D_T = 0.001$,$\sigma_n^2 = 0.01$,$\sigma_w^2 = 0.1$). The performance of OPA (dotted curve) was evaluated with the approximate threshold γ^*_{th} in (12), whereas markers on that curve (+) show results with the true optimal threshold computed numerically.

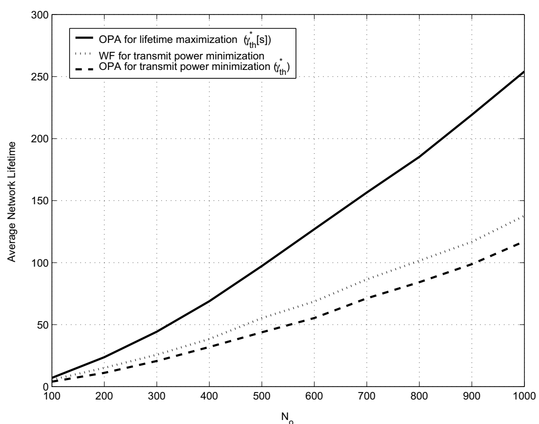

Fig. 2. Average lifetime vs. network size ($D_T = 0.001$,$\sigma_n^2 = 0.01$,$\sigma_w^2 = 0.1, \varepsilon_0 = 10$).

which can be shown to lie between $[0, \gamma^{'})$ (the analysis is omitted for space limitation). From the equation above one notes that the threshold $\gamma^*_{\text{th}}[s]$ depends on the residual energy vector $\boldsymbol{\varepsilon}[s]$ and thus, the FC needs REI for its computation. However, there is no need for sensors to send updates of their REI. Instead, $\boldsymbol{\varepsilon}[s]$ can be conveniently updated as detailed in (14), since both the individual sensors to send data and their channel gains c_i are already known at the FC.

6. SIMULATIONS AND NUMERICAL RESULTS

In Fig. 1, we compare the average transmit power as a function of the network size for a given distortion target. First, we observe that the performance of OPA for transmit power minimization is close to that of the WF (i.e. optimal) power allocation scheme. Note, however, that such a marginal gain of WF entails a much larger amount of FC-sensor signalling and exchange of information. Besides, the increase in the transmit power associated with the use of OPA for network lifetime maximization can also be regarded as moderate, this is despite of the fact that the sensor(s) experiencing the best channel conditions might not be scheduled in some situations (e.g. when a sensor is running out of batteries). It is worth noting that, in the network lifetime maximization case, it is not possible (within a reasonable time frame) to numerically compute the true optimal thresholds and, as in the OPA for transmit power minimization case, to check the performance loss w.r.t. the approximate ones derived with the bound. Still, such curve would necessarily lie in between those of OPA for network lifetime maximization and OPA transmit power minimization which, as commented above, are very close to each other.

In Fig. 2, we depict the average network lifetime as a function of the network size (N_0) for a given distortion target. First, one can clearly observe that WF and OPA for transmit power minimization solutions offer comparable network lifetimes. More importantly, OPA for lifetime maximization almost doubles the ones obtained with the other two solutions. Hence, by making a sensible use of REI information in the scheduling process, we can notably increase the network lifetime with a slight penalty in terms of transmit power.

7. CONCLUSIONS

In this paper, we have proposed and analyzed two Opportunistic Power Allocation (OPA) schemes suitable for decentralized parameter estimation in wireless sensor networks. In OPA schemes, only sensors for which some *locally* obtained quality measure exceeds a threshold computed in a centralized way at the FC can actually participate in the estimation process. To that aim, sensors adjust their transmit power on the basis of *local* information (as opposed to WF solutions) along with some system parameters broadcasted by the FC. We have addressed two different criteria: (1) to minimize the transmit power, which merely requires partial channel state information; and, (2) to maximize network lifetime by effectively combining partial channel state information and residual energy information. For each criterion, we have derived closed-form expressions of the reporting thresholds. The OPA scheme for transmit power minimization exhibits a negligible performance loss w.r.t. a water-filling solution. Alternatively, the average network lifetime can be twofold increased by OPA schemes when the residual energy is explicitly taken into account, while the increase in the associated transmit power remains reasonably low.

8. REFERENCES

[1] M. Gastpar and M. Vetterli, "Source-channel communication in sensor networks," in *Lecture Notes in Computer Science*, April 2003, pp. 162–177.

[2] S. Cui, J. Xiao, A. Goldsmith, Z.-Q. Luo, and H. V. Poor, "Estimation diversity and energy efficiency in distributed sensing," *IEEE Trans. on Signal Proc.*, 2007 (To appear).

[3] R. Knopp and P. A. Humblet, "Information capacity and power control in single-cell multiuser communications," in *IEEE ICC*, June 1995, vol. 1, pp. 331–335.

[4] D. Gesbert and M.-S. Alouini, "How much feedback is multiuser diversity really worth?," in *IEEE ICC*, June 2004, pp. 234–238.

[5] S. Sanayei and A. Nosratinia, "Opportunistic downlink transmission with limited feedback," *IEEE Trans. on IT*, (To appear).

[6] Y. Chen and Q. Zao, "On the lifetime of wireless sensor networks," *IEEE Comm. Letters*, , no. 1, pp. 976–978, Nov. 2005.

[7] Qing Zhao and Lang Tong, "The interplay between signal processing and networking in sensor networks," *IEEE Signal Proc. Magazine*, vol. 2006, no. 4, pp. 84–93, 2006.

[8] J. Matamoros and C. Antón-Haro, "Opportunistic power allocation schemes for wireless sensor networks," in *Proc. IEEE ISSPIT*, December 2007 (To appear).