Transmit Rate Control for Energy-efficient Estimation in Wireless Sensor Networks

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Abstract—We study the impact of physical layer (PHY) transmit rate control on energy efficient estimation in wireless sensor networks. A sensor network collects measurements and transmits them to a Fusion Center (FC) with controllable PHY transmission rates. The FC performs estimation of an unknown parameter process based on sensor measurements, and it needs to adhere to an estimation error constraint. The objective is to maximize network lifetime. High transmission rates consume more energy per transmitted bit, however they convey larger amount of data per unit time and thus can aid in satisfying the estimation error constraint. We identify basic structural properties of the optimal solution, and we propose an iterative algorithm for reaching a solution based on light-weight feedback from the FC.

I. INTRODUCTION

Recent advances in hardware and signal processing modules of miniature sensor devices have enabled dynamic adaptation of physical layer parameters such as modulation level or channel coding rate in response to varying link conditions. Higher transmission rates, realized through higher modulation levels and/or coding rates are used in favorable link conditions so as to convey more bits to the destination. On the other hand, lower transmission rates are used when link conditions deteriorate so as to make transmission robust to link errors.

In this paper we study the impact of physical layer transmit rate control on lifetime of a wireless sensor network that estimates an unknown quantity under a given estimation error constraint. Although higher transmission rates require a larger amount of energy per bit for given link conditions, they may turn out to be beneficial in terms of estimation quality and could be employed if needed. For instance, it is beneficial to opportunistically exploit good channel conditions by transmitting a large amount of data to the fusion center so as to achieve better performance in terms of estimation error. At the same time, energy efficient communication is achieved, since moderate energy is needed to achieve a certain signal quality level that guarantees reception at the FC.

A seminal work on lifetime maximization in wireless sensor networks is [1], where routing of data with certain generation rates was addressed. Network lifetime was defined as the time until the first sensor battery empties. Although transmit rate control has been around in cellular wireless systems for quite some time (see [2] and references therein), its employment in wireless sensor networks started later [3] due to the need of advanced signal processing modules to support adaptation techniques in sensor devices. The work [4] studies the impact of spatial correlation on sensor sampling rate and routing to maximize lifetime subject to an estimation error constraint. The recent work [5] studies sensor network sum utility maximization for rechargeable batteries, where the utility is a concave function of sampling rate of each sensor. In [6] the authors study the effect of link rate adaptation on end-to-end information transfer delay.

To the best of our knowledge, this is the first work that brings together PHY layer transmit rate control and the application layer aspect of estimation quality. Our contribution is as follows: (i) We model the effect of PHY rate control on energy consumption by taking into account the energy consumed for transmitting a message through the power amplifier and the energy to keep the hardware circuitry on, (ii) we relate PHY layer rate adaptation to the estimation error performance and formulate the problem of sensor lifetime maximization subject to an estimation error constraint, (iii) we solve the problem precisely for two sensors and show that it is an instance of a max-min optimization problem, (iv) we provide a lightweight decentralized algorithm for reaching a solution.

II. SYSTEM MODEL

We consider a set \( N \) of \( m \) sensors that transmit to a fusion center (FC) in single-hop. Each sensor uses a dedicated channel, and channels of different sensors are orthogonal to each other. Each sensor has initial energy reserve \( A_i \).

A. Sensor Measurement Model

Time is divided in intervals of duration \((T_s + T_a)\) each, which we call epochs. Within each epoch, sensors submit measurements to the FC about a slowly time-varying, unknown, spatially homogeneous phenomenon process. The process under observation is a sequence \( \{\theta_i\}_{t=1,2,...} \), where \( \theta_i \) is the unknown value of the process at epoch \( t \), assumed to remain fixed for an epoch duration. Each epoch consists of a measurement/ control interval of duration \( T_a \) and a transmission interval of duration \( T_s \). In the former, the FC broadcasts control information to sensors. The FC transmit power is large enough so that it reaches all sensors. In the same interval, each sensor \( i \) collects measurements at time instants \( \tau \), \( x_i(\tau) = \theta + n_i(\tau) \), where \( x_i(\tau) \) is the measurement at time \( \tau \) and \( \theta = \theta_i \). The noise process \( n_i(t) \) captures uncertainty of sensor \( i \) observation due to different perception of the phenomenon process and residual measurement errors. For
each $i$, $n_i(t)$ is Gaussian, zero mean, wide-sense stationary and uncorrelated in time. The variance of $n_i(t)$, $\sigma_i^2 = \mathbb{E}[n_i^2(t)]$, is fixed for all $t$ and captures the magnitude of measurement inaccuracy. The noise processes of any two sensors $i$ and $j$ are spatially and temporally uncorrelated.

During the transmission interval, sensors transmit measurements to the FC. We assume no quantization or compression at bit level. The epoch length is large enough so that measurements of sensors reach the FC. At the end of the epoch, the FC makes the estimation. Coordination of transmissions of sensors to gather the data collision-free to the FC is realized through transmission to orthogonal channels (frequencies) for each sensor.

### B. Transmission Model

Each sensor $i$ can adapt its PHY layer transmission rate $b_i$ (in bits/symbol) at each epoch. In this work, we treat transmission rate as a continuous variable and we do not restrict its value in order to gain insight into properties of the solution. Note that in reality, transmission rate is chosen from a finite set $B = \{b^{(1)}, \ldots, b^{(K)}\}$ of $K$ different modulation levels, where $b^{(t)}$ denotes number of bits/symbol for the $t$th modulation level, and $b^{(1)} < \ldots < b^{(K)}$.

Define $s > 0$ to be the (fixed) symbol rate (in symbols/sec), common for all sensors. Let $b_t$ be the number of bits of each measurement packet. The PHY transmission rate (in bits/sec) for sensor $i$ is $b_t i s$ and the time needed to transmit one packet is $L/(b_t s)$ sec. We consider the following types of energy:

- The energy to feed the power amplifier for transmitting a measurement packet to the FC under certain bit error rate (BER) specification $\epsilon$. This is referred to as transmit energy (per packet) and denoted by $e_{t,i}$ for sensor $i \in N$.

- The energy required for the transmission circuitry to be on during transmission of one packet. This energy is called on-energy and is denoted by $e_o$.

Fix attention to sensor $i$. Let $P_i$ be the transmit power to transmit one packet to the FC under the constraint $BER \leq \epsilon$. Clearly, $P_i$ depends on the propagation environment between sensor $i$ and the FC receiver, which includes path loss, shadowing and fading at the specific channel. Let $G_i$ be the link gain capturing the factors above, assumed to remain unchanged during each epoch. The SNR at the FC receiver is $SNR_i = G_i P_i / dw$, where $w$ is the average Gaussian noise power at the FC receiver. For an M-QAM modulation level with $M = 2^b$, the minimum SNR that guarantees $BER \leq \epsilon$ is $\gamma(b) = d(\epsilon) \cdot (2^b - 1)$, where $d(\cdot) : (0, 1/2) \mapsto [0, \infty)$ is a non-increasing function of the BER requirement $\epsilon > 0$ that depends on physical layer realization, with $d(\epsilon) \rightarrow 0$ as $\epsilon \rightarrow 1/2$ and $d(\epsilon) \rightarrow \infty$ as $\epsilon \rightarrow 0$. If $\epsilon < 1/5$, a widely used assumption is $d(\epsilon) = -\ln(5\epsilon)/1.5$ [2].

Combining the SNR expression above with $SNR_i \geq \gamma(b_i)$ shows that $P_i \geq w / \gamma(b_i)$ must hold in order to satisfy the BER requirement. Obviously, a necessary condition for achieving a maximum network lifetime is that $P_i = w / \gamma(b_i)$ for each $i \in N$, which is assumed to be true in all that follows. Therefore, the transmit energy of sensor $i$ for one packet is

$$e_{t,i} = P_i \times L / b_t i s = \tilde{P}_i L / b_t i s (2^b - 1)$$

where $\tilde{P}_i = P_i / d(\epsilon)$, measured in Watts, is a factor that depends on link gain from sensor $i$ to the FC, the receiver noise power and the BER specification. We assume that each sensor knows $P_i$ through feedback from the FC during the control interval of each epoch. Due to time variation of link conditions, this will change from epoch to epoch.

The on-power required to transmit one packet is constant, call it $P_o$, and it depends on the circuit hardware implementation, semiconductor material, and other related factors. The on-energy to transmit a packet is $e_o = LP_o / (b_s)$. Therefore, the amount of required energy per packet for a sensor $i$ with transmission rate $b$ bits per symbol is equal to

$$e_i = e_{t,i} + e_o = \frac{L}{s b} \left( \tilde{P}_i (2^b - 1) + P_o \right).$$

### C. ML Estimation

Within each epoch, the FC obtains the sensor measurements and computes an estimate $\hat{\theta}_i$ of $\theta_i$ in the Maximum Likelihood (ML) sense. ML is a valid estimation in the absence of prior knowledge about $\theta_i$. First, assume that each sensor sends one measurement to the FC, so that an ensemble of $m$ measurements $\{x_i\}_{i=1}^m$ is available. Since measurements of sensors are uncorrelated, the joint p.d.f. of measurement vector $x = (x_1, \ldots, x_m)^T$ is $p(x) = \prod_{i=1}^m p(x_i)$ where p.d.f. $p(x_i)$ is the Gaussian one, with mean $\theta_i$ and variance $\sigma_i^2$. The ML estimate of $\theta$ is

$$\hat{\theta}_{ML} = \left( \sum_{i=1}^m \frac{1}{\sigma_i^2} \right)^{-1} \times \left( \sum_{i=1}^m x_i \sigma_i^{-2} \right).$$

The criterion for estimation quality is mean squared error (MSE), defined as $\mathbb{E}[(\theta - \hat{\theta}_{ML})^2]$, where expectation is with respect to randomness of observations. To make estimation quality independent of $\theta$, we consider unbiased estimators, i.e., $\mathbb{E}(\hat{\theta}_{ML}) = \theta$. Then, MSE equals $\text{var}(\hat{\theta}_{ML})$ and we require that $\text{var}(\hat{\theta}_{ML}) \leq \epsilon$ for some $\epsilon > 0$ representing the estimation quality requirement. We assume a minimum variance unbiased (MVU) estimator, in which case the ML estimate is unbiased, and we have $\text{var}(\hat{\theta}_{ML}) = \left( \sum_{i=1}^m \frac{1}{\sigma_i^2} \right)^{-1}$.

Assume now that at a given epoch, each sensor $i$, $i = 1, \ldots, m$ takes $N_i$ measurements, denoted by vector $x^{(i)} = (x^{(i)}_1, \ldots, x^{(i)}_{N_i})$ and submits them to the FC. Let $n_i, i = 1, \ldots, m$ be indices with $1 \leq n_i \leq N_i$. Measurements of each sensor are uncorrelated among themselves. Since sensors are also spatially uncorrelated, all sensor measurements are uncorrelated, and under Gaussian assumption, they are also independent. The ML estimate of $\theta$ is

$$\hat{\theta}_{ML} = \left( \sum_{i=1}^m \frac{N_i}{\sigma_i^2} x^{(i)}_{n_i} \right) \times \left( \sum_{i=1}^m \frac{1}{\sigma_i^2} \right)^{-1}$$

and the variance of estimation error is $\text{var}(\hat{\theta}_{ML}) = \left( \sum_{i=1}^m \frac{N_i}{\sigma_i^2} \right)^{-1} \leq \epsilon$, due to an estimation quality requirement.
III. PHY TRANSMISSION RATE ADAPTATION IN WIRELESS SENSOR NETWORKS

A. Problem Statement and Formulation

A high PHY transmission rate means more consumed energy per packet for transmission to FC, as observed by (2). On the other hand, with high transmission rate, data is conveyed faster to the FC, which means that more measurement packets are sent to the FC in an epoch, and performance in terms of estimation error is improved. Nevertheless, different sensors have different link gain to the FC due to different physical locations and fading. Thus, they need different energy per packet. They may also have different energy budget and measurement accuracies. For example, among sensors with the same energy budget and measurement accuracies, it is better to use larger transmission rate (more measurements) from the sensor that has larger link gain, since in that case, consumed energy per packet is smaller.

For sensor \( i \) that submits \( N_i \) measurement packets per epoch, the energy replenishment rate (in Joules per epoch) is \( z_i = c_i N_i \). The number of measurement packets, multiplied by the time needed to transmit a packet should not exceed \( T_s \). That is, \( N_i \times \frac{T}{T_s} \leq T_s \). Thus, packets should be transmitted with PHY rate \( b_i \geq \frac{(LN_i)}{(sT_s)} \). Since larger PHY transmission rates are more energy-consuming, the PHY rate employed should be exactly \( b_i = \frac{(LN_i)}{(sT_s)} \). Clearly, the number of measurement packets per epoch is proportional to the transmission rate, \( N_i = sT_s b_i/L \). Thus, the energy replenishment rate of sensor \( i \) in Joules per epoch is a function of its transmission rate \( b_i \),

\[
z_i(b_i) = T_s [\hat{P}_i(2^{b_i} - 1) + P_o] = E_i(2^{b_i} - 1) + E_o, \tag{5}
\]

where \( E_i = \hat{P}_i T_s \) and \( E_o = P_o T_s \) are the energy replenishment rates due to energy consumed in transmission and in keeping the circuitry on respectively.

The lifetime of sensor \( i \), namely the number of epochs until its battery empties is

\[
L_i(b_i) = \frac{A_i}{z_i(b_i)} = \frac{A_i}{E_i(2^{b_i} - 1) + E_o}. \tag{6}
\]

Network lifetime is defined as the number of epochs elapsed until the battery of the first sensor empties, \( L(b) = \min_{i=1,...,m} L_i(b_i) \) \[1\]. This is a function of the number of measurement packets, and with it of the transmission rate vector \( b = (b_1, \ldots, b_m) \) of sensors.

The problem of PHY transmission rate control with the objective to maximize lifetime subject to a maximum tolerable variance of estimation error, \( \text{var}(\hat{\theta}_{ML}) \leq \epsilon \) is formulated as:

\[
\begin{align*}
\operatorname*{sup}_{\omega(b)} \omega(b) & := \min_{i=1,...,m} \frac{A_i}{E_i(2^{b_i} - 1) + E_o} \\
\text{subject to:} & \sum_{i=1}^{m} \frac{b_i}{\sigma_i^2} \geq \frac{L}{s\epsilon T_s}. \tag{7}
\end{align*}
\]

Inequality (8), relating the variance of estimation error with PHY transmission rates arises from the estimation constraint and the fact that \( N_i = (sT_s/L)b_i \). Notice that since \( \omega(b) \) is strictly decreasing in each \( b_i \), we must have \( \sup_{\omega(b)} \omega(b) = \sup_{b \geq 0} \omega(b) \), where \( \Pi \{ \omega(b) : \sum_{i=1}^{m} \frac{b_i}{\sigma_i^2} \geq \frac{L}{s\epsilon T_s} \} \). Thus, as \( \omega(b) \) is a compact set and \( \omega(b) \) is continuous on \( \Pi \), the supremum in (7) is attained for some \( b \geq 0 \).

It is worth pointing out that the problem always has a solution, since we have neglected any constraints on transmit powers, and with it on transmission rates of the sensors. In contrast, if there were individual power constraints on each node \( \forall i \in N, P_i \leq \hat{P}_i \), then it may be verified that the problem had a solution if and only if

\[
\sum_{i=1}^{m} \frac{\log_2(1 + \frac{P_i \hat{P}_i}{\sigma_i^2})}{\sigma_i^2} \geq \frac{L}{s\epsilon T_s}. \tag{9}
\]

If the above inequality is not satisfied, then the estimation quality requirement cannot be met.

B. Solution for \( m = 2 \) sensors

For \( m = 2 \), the problem becomes:

\[
\begin{align*}
\max_{b_1, b_2} \min_{b_1, b_2} & \left\{ \frac{A_1}{E_i(2^{b_1} - 1) + E_o}, \frac{A_2}{E_i(2^{b_2} - 1) + E_o} \right\} \\
\text{subject to:} & \frac{b_1}{\sigma_1^2} + \frac{b_2}{\sigma_2^2} = \frac{L}{s\epsilon T_s} \tag{10}
\end{align*}
\]

and \( b_1, b_2 \geq 0 \). Define \( x_1 = 2^{b_1} \), so that \( b_1 = \log_2 x_1, i = 1, 2 \) and transform the problem to the following equivalent one:

\[
\begin{align*}
\min_{x_1, x_2} & \max_{x_1, x_2} \left\{ \frac{E_o + E_i (x_1 - 1)}{A_1}, \frac{E_o + E_i (x_2 - 1)}{A_2} \right\} \\
\text{subject to:} & x_1^{1/\sigma_1^2} x_2^{1/\sigma_2^2} = \frac{2L}{s\epsilon T_s}, \tag{12}
\end{align*}
\]
and $x_1, x_2 > 0$. From (13), variables $x_1$ and $x_2$ should satisfy:

$$x_2 = \frac{2L\sigma^2_i/sT_s}{x_1^2 + \sigma^2_i} = \beta x_2^*,$$

(14)

with $\alpha = \sigma^2_i/\sigma^2_t > 0$ and $\beta = 2L\sigma^2_i/sT_s > 0$. Thus, the solution to the problem is given as the solution of:

$$\min_{x_1} \left\{ \frac{E_o + E_1(x_1 - 1)}{A_1}, \frac{E_o + E_2(3x_1^2 - 1)}{A_2} \right\}$$

(15)

with $x_1 \geq 0$. The functions $f_1(x) = (E_o + E_1(x_1 - 1))/A_1$ and $f_2(x) = (E_o + E_2(3x_1^2 - 1))/A_2$ are positive and $f_1(x)$ is linear and strictly increasing with $x_1 > 0$. Function $f_2(x)$, $x > 0$, is convex and strictly decreasing for any $\alpha > 0$. It turns out at these functions have exactly one point of intersection, which is given by the solution to equation:

$$A_2 E_1 x^*_1 + \gamma x^* - \beta A_1 E_2 = 0$$

(16)

with $\gamma = A_2(E_o - E_1) - A_1(E_o - E_2)$. For instance, for equal initial energy reserves $A_1 = A_2$ and variances $\sigma^2_1 = \sigma^2_2$, so that $\alpha = 1$, the positive solution to the second-order polynomial equation $E_1 x^2_1 + (E_2 - E_1)x_1 - \beta E_2 = 0$ is

$$x^*_1 = \frac{-(E_2 - E_1) + \sqrt{(E_2 - E_1)^2 + 4\beta E_1 E_2}}{2E_1}.$$  

(17)

In Figure 1 we depict functions $f_1(\cdot)$ and $f_2(\cdot)$ and their intersecting min-max point $x^*_1$. Transmission rates of sensors are $b^*_i = \log_2 x^*_1$ and $b^*_o = \log_2 \beta - \alpha b^*_1$.

C. Distributed algorithm

We now provide an iterative decentralized algorithm for the problem in its general case. We convert the formulation above to an equivalent one by defining new variable

$$\omega = \min_{i=1,\ldots,m} \frac{A_i}{E_i(2^{b^*_i} - 1) + E_o}$$

(18)

The equivalent problem becomes

$$\max_{\omega>0, b^*_i>0} \omega$$

subject to:

$$\omega[E_i(2^{b^*_i} - 1) + E_o] \leq A_i, i = 1, \ldots, m,$$

(20)

and the estimation error constraint (8). We relax the problem constraints and form the Lagrangian,

$$L(\omega, b, \lambda, \mu) = -\omega + \sum_{i=1}^m \lambda_i [\omega[E_i(2^{b^*_i} - 1) + E_o] - A_i] + \mu \left( \frac{L}{sT_s} - \sum_{i=1}^m \frac{b^*_i}{\sigma^2_i} \right).$$

(21)

where $\lambda = (\lambda_1, \ldots, \lambda_m) \geq 0$ and $\mu \geq 0$ are the dual variables corresponding to (20) and the estimation error constraint respectively. For given $\lambda, \mu$, consider the primal problem:

$$\min_{\omega>0, b^*_i>0} L(\omega, b, \lambda, \mu).$$

(22)

A gradient descent step is executed by the FC to adjust $\omega^{(t)}$:

$$\omega^{(t)} = \omega^{(t-1)} - s_t \frac{\partial L(\cdot)}{\partial \omega}$$

(23)

where $s_t > 0$ is the step size at iteration $t$. The optimization with respect to $b^*_i$ is performed by each sensor by taking $\partial L(\cdot)/\partial b^*_i = 0$ to obtain at each epoch $t$:

$$b^*_i^{(t)} = \log_2 \left( \frac{\mu^{(t)}}{\sigma^2_i E_i^{(t)} + 2 \lambda_i^{(t)} \omega^{(t)}} \right).$$

(24)

The dual problem is:

$$\max_{\lambda, \mu} D(\lambda, \mu) = \max_{\lambda, \mu} \min_{b^*_i>0} L(\omega, b, \lambda, \mu),$$

(25)

where $D(\lambda, \mu)$ is the dual function. Note that due to the min-operator in (18), the dual function is not differentiable with respect to $\lambda, \mu$ since it is piecewise linear function. Hence, gradient update methods cannot be used for the dual problem, and we resort to sub-gradient ones [7, Sec. 6.3.1].

The dual function $D(\lambda, \mu)$ is concave in $\lambda, \mu$. For a concave function $f$, vector $d$ is a sub-gradient at point $x_0$ if $f(x) \leq f(x_0) + (x - x_0)^T d$. A sub-gradient for function $D(\lambda, \mu)$ with respect to $\lambda$ at $\lambda^{(t-1)}$ is the vector whose $i$-th component is

$$\omega^{(t-1)} [E_i^{(t)}(2^{b^{(t-1)}_i} - 1) + E_o] - A_i.$$  

(26)

Sensor $i$ knows instantaneous PHY transmission rate $b^{(t-1)}_i$ and variable $\omega^{(t-1)}$ and updates its Lagrange multiplier $\lambda_i^{(t)}$ with sub-gradient ascent:

$$\lambda_i^{(t)} = \lambda_i^{(t-1)} + s_t \left[ \omega^{(t-1)} [E_i^{(t)}(2^{b^{(t-1)}_i} - 1) + E_o] - A_i \right]^+, $$

(27)

where $x^+ = x$ if $x > 0$, and 0 otherwise. Similarly, a sub-gradient of $D(\lambda, \mu)$ with respect to $\mu$ at $\mu^{(t-1)}$ is found, and we get the FC sub-gradient update,

$$\mu^{(t)} = \mu^{(t-1)} + s_t \left( \frac{L}{sT_s} - \sum_{i=1}^m \frac{b^{(t-1)}_i}{\sigma^2_i} \right)^+. $$

(28)

Channel conditions $G_i^{(t)}$ and thus $E_i^{(t)}$ of sensor $i$ change at each epoch $t$. The steps of the primal-dual algorithm are:

- **STEP 0**: Initialization. At epoch $t = 0$, FC initializes $\mu^{(0)} \geq 0$ and $\omega^{(0)} > 0$ and broadcasts them to network. Each sensor $i$ initializes $\lambda_i^{(0)}$ and sends it to FC via low-rate feedback control channel. Go to Step 4.

- **IF $t > 0$ DO**

- **STEP 1**: The FC updates multiplier $\mu^{(t)}$ based on (28).

- **STEP 2**: Each sensor $i$ updates its multiplier $\lambda_i^{(t)}$ according to (27) and broadcasts it to the FC.

- **STEP 3**: The FC updates parameter $\omega^{(t)}$ based on (23):

$$\omega^{(t)} = \omega^{(t-1)} - s_t \left( -1 + \sum_{i=1}^m \lambda_i^{(t)} [E_o + E_i(2^{b^{(t-1)}_i} - 1)]^+ \right).$$

(29)

It broadcasts $\mu^{(t)}$ and $\omega^{(t)}$ to sensors. It also measures channel quality and broadcasts $E_i^{(t)}$ to sensors.
Fig. 2. Lifetime vs. range of channel means, $D$ for MaxLT and MinE approaches for channel variance 0.1.

Fig. 3. Lifetime vs. range of channel means, $D$ for MaxLT and MinE approaches for channel variance 0.5

- **END IF**
- **STEP 4:** Each sensor adapts its transmission rate $b^{(t)}_i$ based on equation (24).
- **STEP 5:** Sensor measurements during epoch $t$ reach the FC. The FC performs the estimation.
- **STEP 6** $t ← t + 1$. Go to 1. Continue until convergence.

If the sequence of steps $\{s_t\}$ satisfies $\lim_{t→+∞} s_t = 0$ and $\sum_t s_t = +∞$, $\sum_t s^2_t < +∞$, the algorithm converges at least to a local optimum of the original problem [7].

IV. NUMERICAL RESULTS

We consider a sensor network with $m = 10$ sensors, energy reserves $A = A_i = 0.1$ and measurement variance $\sigma^2 = \sigma^2_i = 1/v1i$. At each slot, link quality between sensor $i$ and the FC is log-normally distributed with mean $G_i$ and variance $\sigma^2_{G,i}$. The mean of all channel means is $G = \frac{1}{m} \sum_{i=1}^m G_i = 1$. Since performance strongly depends on different channel means, we define the range of channel means to be $D$. Thus, channel means of sensors are uniform in $[G - \frac{D}{2}, G + \frac{D}{2}]$.

We compare the maximum lifetime (MaxLT) strategy with that of minimizing total energy consumption (MinE) at each slot. We plot lifetime over the range of channel means $D$ for $\epsilon = 0.5$ and $\epsilon = 1$ and different channel variances (Fig. 2: $\sigma^2 G_1 = 0.1$, Fig. 3 $\sigma^2 G_1 = 0.5$). For small channel variance (Fig. 2), MaxLT outperforms MinE policy for all $D$. If all sensors have the same channel mean ($D = 0$) and channels vary slightly, the performance of both policies is nearly the same. In contrast, with increasing difference between channel means per sensor, MaxLT maximum lifetime outperforms the MinE policy. This is especially due to the fact that lifetime of the MinE policy decreases significantly with increasing $D$. Note that with increasing $D$, the lifetime of the MaxLT policy even marginally increases.

For strongly varying channel (Fig. 3, with $\sigma^2 G_2 = 0.5$), MinE outperforms MaxLT for channel means per sensor that differ only slightly; in this case, over long time period, sensor batteries empty nearly simultaneously and consume less energy compared to the MaxLT policy. Recall that the MaxLT policy equalsizes energy consumption per sensor at each epoch. We observe an intersection between policies, since with increasing $D$ MinE always suffers from a decreasing lifetime (assuming same $A$ and $\sigma^2$ for each sensor). Finally, $\epsilon$ has no effect on the principle behavior of MaxLT and MinE. For increasing $\epsilon$, we observe, as expected, an increasing lifetime.

V. CONCLUSION

We introduced PHY layer rate adaptation for maximizing sensor network lifetime subject to an estimation error constraint. Each sensor takes autonomous rate adaptation decisions based on instantaneous channel conditions, so that an average estimation error is maintained. In the future, we plan to extend our approach to a multi-hop network.

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