Energy-Efficient Scheduling for Wireless Sensor Networks

Yingwei Yao, *Member, IEEE,* and Georgios B. Giannakis, *Fellow, IEEE*

***Abstract*—We consider the problem of minimizing the energy needed for data fusion in a sensor network by varying the transmission times assigned to different sensor nodes. The optimal scheduling protocol is derived, based on which we develop a low-complexity inverse-log scheduling (ILS) algorithm that achieves near-optimal energy efficiency. To eliminate the communication overhead required by centralized scheduling protocols, we further derive a distributed inverse-log protocol that is applicable to networks with a large number of nodes. Focusing on large-scale networks with high total data rates, we analyze the energy consumption of the ILS. Our analysis reveals how its energy gain over traditional time-division multiple access depends on the channel and the data-length variations among different nodes.**

***Index Terms*—Energy efficiency, fading channels, packet scheduling, power-delay tradeoff, wireless networks.**

I. Introduction

A WIRELESS sensor network typically consists of a large number of sensor nodes distributed over a certain region. Each node monitors its surrounding area, gathers application-specific information, and transmits the collected data to a "master" node (a.k.a. fusion center or gateway). The fusion center processes the data and takes appropriate actions if needed; e.g., it may notify a human operator, or, if the nodes are equipped with actuators, the fusion center may direct these nodes to respond to the events autonomously. Compared with using a single powerful sensor to monitor a large area, a sensor network with a large number of nodes of limited ability is more robust, and may provide a more accurate picture of the monitored area. With advances in microscopic microelectrical mechanical systems (MEMS), networks of hundreds or even thousands of miniature sensor nodes may become a reality in the near future [10].

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A sensor node may need to operate for long periods of time relying on a tiny battery. It is, therefore, important to optimize the energy efficiency of all sensor operations, which include sensing, computation, and communication. This calls for designing communication protocols that are energy-efficient in the sense of requiring low-complexity processing and low transmission power. Lowering the computational complexity of communication protocols is important, because it reduces both hardware cost and energy consumption.

It is known that the energy required to transmit a certain amount of information is exponential to the inverse of the transmission time [2]. This delay-energy tradeoff principle has been applied to the design of energy-efficient packet-scheduling protocols for single-user communication links [8], [11], [14], which perform smoothing or filtering on the packet arrival-time intervals, resulting in an output packet traffic that is less bursty than the input traffic, and leading to significant energy savings. In [9], a discretized version of the "lazy scheduling protocol" of [14] is applied to a network, where the channel gains between different users are assumed to be identical. A more realistic setting is used in [6], where channels experienced by different users may be different, and an iterative algorithm called "MoveRight," derived for a multiuser network, is shown to converge to the optimal schedule.

In this paper, we consider energy-efficient data fusion in wireless sensor networks. The delay-energy efficiency tradeoff in a sensor network has been studied recently in [17], where several energy-efficient protocols have been proposed based on a data aggregation tree. Our study, on the other hand, focuses on a single-hop sensor data collection, although the scheduling protocol we develop can also be used in multihop networks with multilevel hierarchy to support communication between nodes and cluster heads, and between cluster heads and higher level gateways. Supposing time-division multiple access (TDMA), our objective is to design an energy-efficient TDMA protocol for the fusion center to collect data from all sensor nodes before a certain deadline. This problem may arise in several different application scenarios. For example, a fusion center might want to receive periodic updates from all sensors (or all cluster heads in a cluster-type network); thus, within one update period, every node must transmit to the fusion center the information it collects during the previous period. Another example is a sensor network with mobile agents [13], [15], where a mobile fusion center (UAV) makes a pass over the monitored area from time to time, and thus, all sensors must finish transmission before the mobile agent leaves the area.

Viewing the sensor-fusion problem as a special case of the packet-scheduling problem studied in [6], one can readily apply the MoveRight algorithm. The MoveRight algorithm, however, is complicated, and requires knowledge of all users' channels as well as their queue lengths. We will develop optimal and suboptimal *centralized* scheduling protocols having much lower computational complexity. To avoid the communication bandwidth and power overhead required by centralized protocols, we also design a *distributed* scheduling protocol, in which each sensor needs only to know its own channel and queue length. We demonstrate that this distributed protocol performs very close to optimal scheduling, especially in large-scale networks.

The rest of this paper is organized as follows. In Section II, we formulate the problem and derive the optimal scheduling protocol. Two suboptimal protocols based on inverse-log scheduling (ILS) are developed in Section III. A distributed scheduling protocol is presented in Section IV, and is shown to achieve substantial energy gains over the traditional TDMA. In Section V, we conduct asymptotic analysis on the energy consumption of the inverse-log algorithm. Finally, we present our conclusions in Section VI.

II. Problem Formulation and Optimal Scheduling

Suppose a fusion center needs to collect information from N sensors within the time interval [0, T]. We assume that the nth sensor has a data sequence of B_n bits to transmit, the channel between it and the fusion center is flat fading over [0, T] with coefficient h_n, and the noise is additive white Gaussian. Our objective is to design an optimal scheduling protocol that consumes the least amount of energy.

Suppose, without loss of generality, that the communication channel bandwidth is $W = 1$, and a time interval of T_n is assigned to sensor n. If $WT_n \gg 1$,[1] then the minimum transmission power P_n needed to transmit B_n bits within this interval is approximately determined by the channel capacity [4]

$$T_n \log_2\left(1 + \frac{P_n|h_n|^2}{N_0}\right) = B_n \tag{1}$$

where N_0 is the noise power spectral density. The energy consumption (normalized by the noise power) of the nth node is, therefore

$$E_n := \frac{P_n T_n}{N_0} = \frac{T_n}{|h_n|^2}\left(2^{\frac{B_n}{T_n}} - 1\right). \tag{2}$$

Our objective is to find a set of time allocations $\{T_n\}_{n=1}^N$ for all N sensors, such that the total energy consumption over $T = \sum_{n=1}^N T_n$ is minimized.

Written formally, we need to solve the following constrained optimization problem:

$$\text{minimize} \quad \sum_{n=1}^N E_n = \sum_{n=1}^N \frac{T_n}{|h_n|^2}\left(2^{\frac{B_n}{T_n}} - 1\right) \tag{3}$$

$$\text{subject to} \quad \sum_{n=1}^N T_n = T \tag{4}$$

$$T_n > 0, \quad n = 1, \ldots, N. \tag{5}$$

[1]Actually, a looser condition of $WT/N \gg 1$ suffices for our purpose. If a particular terminal n is assigned T_n such that WT_n is not much greater than one, then $T_n \ll T/N$. Increasing T_n to render the information rate sufficiently lower than the capacity (and thus, realizable) will not have major impact on the time available to other nodes.

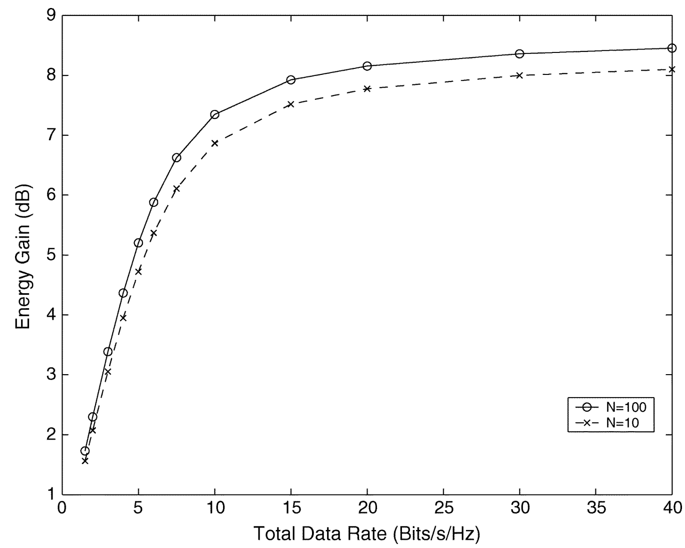

Fig. 1. Energy gain of optimal scheduling.

Remark 1: The energy-consumption function (2) is obtained assuming that optimal channel coding is adopted. Other energy-consumption functions may be more appropriate in some applications. For example, in an uncoded system, the transmission power may be determined by the target bit-error rate (BER) and the modulation format [3]. While the algorithms presented in this paper are designed for the energy-consumption function (2), the design methodology we develop can also be applied to other kinds of energy-consumption functions.

The optimization problem described by (3)–(5) can be solved using Lagrange's multiplier method, and it is straightforward to find that the optimal set of $\{T_n\}_{n=1}^N$ should satisfy

$$\frac{1}{|h_n|^2}\left(2^{\frac{B_n}{T_n}} - 1 - \frac{B_n}{T_n}2^{\frac{B_n}{T_n}}\ln 2\right) = \lambda, \quad n = 1, \ldots, N \tag{6}$$

where λ is determined by the constraint $\sum_{n=1}^N T_n = T$. In Fig. 1, we plot (in decibels) the energy gain relative to TDMA of the optimal scheduling protocol for networks of 100 and 10 sensors, respectively. In this simulation, we assume that $B_1 = \cdots = B_N$. We observe that compared with the traditional TDMA protocol, the optimal scheduling can reduce the total energy consumption of a sensor network by more than 8 dB at high data rates. The energy gain of the optimal scheduling depends mainly on the total data rate, instead of the number of sensors in the network. On the other hand, the energy saved by optimal scheduling is insignificant when the total data rate is less than 1 b/s/Hz, but increases quickly as the demand on the total data rate increases.

It is not surprising that the energy gain of the optimal scheduling is insignificant when the data rate is low. From (2), we can see that if B_n/T_n is small, then $E_n \approx (B_n/|h_n|^2)\ln 2$ is not sensitive to the change of T_n. This observation motivates the focus of this paper on sensor networks with relatively high data rates.

III. Inverse-Log Scheduling Protocols

Given λ, finding the set of transmission intervals $\{T_n\}_{n=1}^N$ requires N one-dimensional searches (one per sensor) to solve (6) numerically for each n. In this section, we develop suboptimal scheduling protocols in which T_n is determined in closed-form for any given λ, thus reducing the computational complexity drastically, especially for sensor networks with a large number of nodes.

A. ILS for High Data Rates

Let us consider the following *ILS* policy:

$$2^{\frac{B_n}{T_n}} = \lambda |h_n|^2, \quad n = 1, \dots N. \tag{7}$$

which leads to a closed form for each sensor's transmission interval

$$T_n' = \frac{B_n}{\log_2(\lambda |h_n|^2)} \tag{8}$$

where λ is determined by the constraint $\sum_n T_n' = T$ and can be obtained by numerical search.

To check whether (7) leads to a good approximation of the optimal policy at high data rates, consider two nodes n_1 and n_2 with corresponding optimal transmission intervals T_{n_1} and T_{n_2}. Assume without loss of generality that $B_{n_2}/T_{n_2} \geq B_{n_1}/T_{n_1}$. Supposing that B_n/T_n is much greater than 1 for all sensors, we can write (6) approximately as $(1/|h_n|^2)2^{B_n/T_n}(B_n/T_n)\ln 2 = \lambda$. Considering the latter for $n = n_1$ and $n = n_2$ to eliminate λ, we arrive at

$$\begin{aligned} \kappa_{n_1,n_2} &:= \frac{\left(\frac{B_{n_2}}{T_{n_2}}\right)}{\left(\frac{B_{n_1}}{T_{n_1}}\right)} \\ &\approx 1 + \frac{T_{n_1}}{B_{n_1}} \log_2 \frac{|h_{n_2}|^2}{|h_{n_1}|^2} - \frac{T_{n_1}}{B_{n_1}} \log_2 \kappa_{n_1,n_2}. \end{aligned} \tag{9}$$

From the assumption that $B_{n_2}/T_{n_2} \geq B_{n_1}/T_{n_1}$, we have

$$1 \leq \kappa_{n_1,n_2} \leq 1 + \frac{T_{n_1}}{B_{n_1}} \log_2 \frac{|h_{n_2}|^2}{|h_{n_1}|^2}. \tag{10}$$

Hence, $|h_{n_2}| \geq |h_{n_1}|$. Since $B_{n_1}/T_{n_1} \gg 1$, we find that $\kappa_{n_1,n_2} \approx 1$, unless $|h_{n_2}|^2 \gg |h_{n_1}|^2$. But when $|h_{n_2}|^2 \gg |h_{n_1}|^2$, we can use $\ln x \leq x - 1$ to bound $\log_2 \kappa_{n_1,n_2}$ in (9), which, in turn, bounds κ_{n_1,n_2} as follows:

$$1 + \frac{\frac{T_{n_1}}{B_{n_1}} \log_2 \frac{|h_{n_2}|^2}{|h_{n_1}|^2}}{1 + \frac{T_{n_1}}{B_{n_1}} \log_2 e} \leq \kappa_{n_1,n_2} \leq 1 + \frac{T_{n_1}}{B_{n_1}} \log_2 \frac{|h_{n_2}|^2}{|h_{n_1}|^2}. \tag{11}$$

Equation (11) leads to

$$\kappa_{n_1,n_2} \approx 1 + \left(\frac{T_{n_1}}{B_{n_1}}\right) \log_2 \left(\frac{|h_{n_2}|^2}{|h_{n_1}|^2}\right) \tag{12}$$

for $|h_{n_2}|^2 \gg |h_{n_1}|^2$. The last equation approximates also cases for which $|h_{n_2}|^2 \gg |h_{n_1}|^2$ does not hold, since $B_{n_1}/T_{n_1} \gg 1$ implies that $\kappa_{n_1,n_2} \approx 1$.

On the other hand, let us look at the transmission intervals T_{n_1}' and T_{n_2}' assigned by the ILS. Upon defining $\kappa_{n_1,n_2}' := (B_{n_2}/T_{n_2}')/(B_{n_1}/T_{n_1}')$, it follows readily from (8) that after eliminating λ, we have

$$\kappa_{n_1,n_2}' = 1 + \frac{T_{n_1}'}{B_{n_1}} \log_2 \frac{|h_{n_2}|^2}{|h_{n_1}|^2}. \tag{13}$$

From the similarity of κ_{n_1,n_2} and κ_{n_1,n_2}', we infer that when the transmission rate is high, the approximation $T_{n_1} \approx T_{n_1}'$ is indeed accurate; hence, $T_n \approx T_n', \forall n$, and therefore, the closed-form scheduler in (8) approximates closely the optimal one in (6).

Compared with (6), (8) presents a much simpler way of determining T_n for a given λ. The drawback of the scheduler in (8) is that a sensor node experiencing a very bad channel state may be assigned an unreasonably large fraction of the total available transmission time, leading to a large total energy consumption. To gain more insight on this issue, we derive next an upper bound on the probability that the interval T_n assigned to sensor n is larger than a certain fraction of the total transmission time T.

Proposition 1: Suppose that in a large sensor network, B_n and h_n are independent random variables and $E[|h_n|^2] = 1$, then the probability that any sensor n is assigned a transmission time T_n such that $T_n > K_\alpha B_n T/B$ is upper bounded by $\Pr\{|h_n|^2 \leq 2^{((1/K_\alpha)-1)B/T}\}$, where $B := \sum_{n=1}^{N} B_n$.

Proof: Substituting (8) into (4), we find

$$\begin{aligned} T &= \sum_{n=1}^{N} \frac{B_n}{\log_2(\lambda |h_n|^2)} = B \sum_{n=1}^{N} \frac{B_n}{B} \frac{1}{\log_2(\lambda |h_n|^2)} \\ &\geq \frac{B^2}{\sum_{n=1}^{N} B_n \log_2(\lambda |h_n|^2)} \end{aligned} \tag{14}$$

where the lower bound follows from Jensen's inequality. Because B_n and h_n are independent and $E[|h|_n^2] = 1$, arguing through the law of large numbers, we have

$$\begin{aligned} T &\geq \frac{B}{\log_2 \lambda + \sum_{n=1}^{N} \frac{B_n}{B} \log_2(|h_n|^2)} \\ &\geq \frac{B}{\log_2 \lambda + \log_2\left(\sum_{n=1}^{N} \frac{B_n}{B} |h_n|^2\right)} \\ &= \frac{B}{\log_2 \lambda} \text{ for } N \gg 1. \end{aligned} \tag{15}$$

Having established that $\log_2 \lambda \geq B/T$ for N sufficiently large, the wanted probability $P^{(n)} := \Pr\{T_n \geq K_\alpha T B_n/B\}$ is

$$\begin{aligned} P^{(n)} &= \Pr\left\{\frac{B_n}{\log_2(\lambda |h_n|^2)} \geq \frac{B_n}{B} K_\alpha T\right\} \\ &= \Pr\left\{\log_2 |h_n|^2 \leq \frac{1}{K_\alpha} \frac{B}{T} - \log_2 \lambda\right\} \\ &\leq \Pr\left\{|h_n|^2 \leq 2^{\left(\frac{1}{K_\alpha} - 1\right)\frac{B}{T}}\right\}. \end{aligned} \tag{16}$$

■

To appreciate the implication of *Proposition 1* to pragmatic wireless channels, suppose the probability density function (pdf) of the channel gain $|h_n|^2$ satisfies $p(|h_n|^2 = \beta) = \alpha\beta^t + o(\beta^{t+\epsilon})$, where $\epsilon > 0$, and

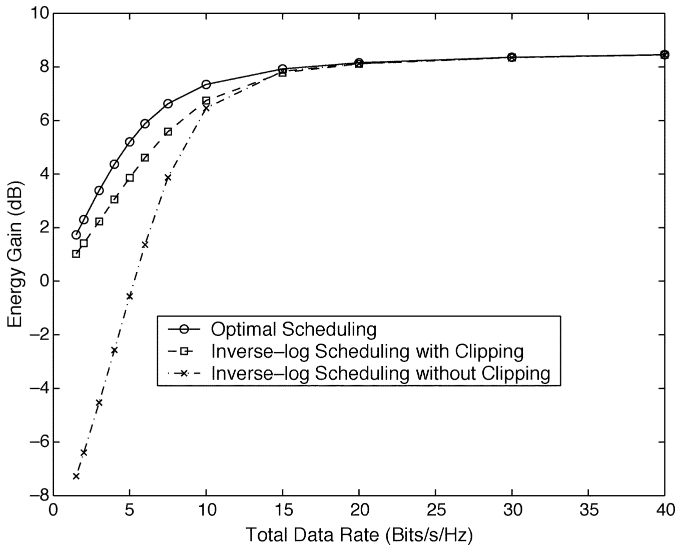

Fig. 2. Energy gain of ILS protocols.

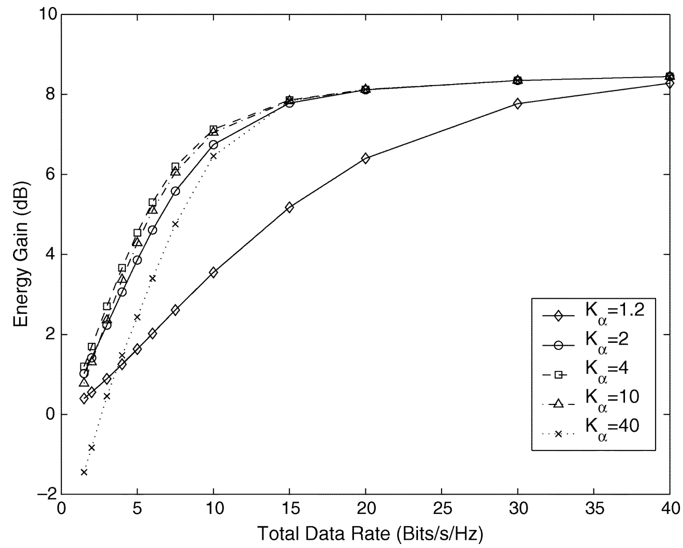

Fig. 3. Impact of the clipping threshold on average energy gain of the ILS protocols.

$f(x) \sim o(x) \Rightarrow \lim_{x\to 0} f(x)/x = 0$.[2] Using the results of [16], it follows readily that

$$P^{(n)} \leq \frac{\alpha}{t+1} 2^{(t+1)\left(\frac{1}{K_\alpha}-1\right)\frac{B}{T}} + o\left(2^{(t+\epsilon+1)\left(\frac{1}{K_\alpha}-1\right)\frac{B}{T}}\right). \quad (17)$$

From (17), we observe that for $K_\alpha > 1$, $P^{(n)}$ goes to zero as B/T goes to infinity. So, energy inefficiency caused by overcompensating a weak user is not an issue for large B/T.

B. ILS With Clipping for Low Data Rates

For small B/T, however, we observe that the scheduling protocol of (8) may assign an inordinate amount of transmission time to a user with a very bad channel, leading to an increase in the total energy consumption. To remedy this shortcoming, we propose the following *ILS protocol with clipping*:

$$T_n = \begin{cases} T'_n, & 0 < T'_n \leq \frac{B_n}{B} K_\alpha T \\ \frac{B_n}{B} K_\alpha T, & \text{otherwise} \end{cases} \quad (18)$$

where $T'_n := B_n / \log_2(\lambda |h_n|^2)$ and $K_\alpha > 1$.

In Fig. 2, we compare the energy gain over the traditional TDMA achieved by three different scheduling protocols: optimal scheduling (6); ILS (8); and ILS with clipping (18). We simulate a network of $N = 100$ sensors, each of which has the same amount of data to transmit to the fusion center. The channels between the sensors and the fusion center experience independent, identically distributed (i.i.d.) Rayleigh fading with unit variance. We observe that when the total data rate is very high, all three protocols exhibit similar performance, which is expected, because the inverse-log policies are obtained under the assumption of large B/T. When the data rate decreases, however, the relative energy efficiency of the inverse-log protocol prescribed by (8) deteriorates severely. In fact, it demands more energy than traditional TDMA when the total data rate is lower than 5 b/s/Hz. On the other hand, using the simple clipping operation described by (18) with $K_\alpha = 2$, we largely ameliorate this problem, achieving an energy efficiency very close to that of the optimal policy, even at relatively low values of B/T.

To determine the impact of the clipping threshold (K_α) on the performance of the inverse-log algorithm, we evaluate its average energy gain over traditional TDMA and the variation of energy consumption among different sensors using different clipping thresholds. In particular, we simulate a network of $N = 100$ sensors using $K_\alpha = 1.2, 2, 4, 10, 40$. Fig. 3 shows the average energy gains of the inverse-log protocol with these values of K_α. We observe that setting the threshold too low limits the ability of the scheduling algorithm to compensate for bad channels, leading to an increase in total energy consumption; while setting the threshold too high renders the clipping operation ineffective, leading to energy inefficiency at relatively low data rates. We also observe, however, that the average energy gain of the inverse-log algorithm is not very sensitive to the values of K_α, unless K_α either comes very close to one or becomes very large.

The ratio between the sample standard deviation of sensor nodes' energy consumption and the sample mean of sensor nodes' energy consumption is plotted in Fig. 4. We notice that the variation of energy consumption among different sensor nodes is generally negligible (except for $K_\alpha = 1.2$) at high data rates, indicating that at high data rates, the inverse-log protocol is nearly min-max optimal (minimizing the maximal energy consumption of a sensor). The variation of energy consumption among sensors becomes significant as the total data rate decreases. In this case, increasing the clipping threshold can lead to a more fairly distributed energy consumption among sensors.

IV. Distributed Inverse-Log Scheduling

All the scheduling protocols we described thus far are centralized protocols, since determining the Lagrange multiplier λ requires knowledge of the channel gains $|h_n|^2$ and the number

[2]The pdf of common wireless fading channels, including, e.g., Rayleigh, Rician, and Nakagami, satisfies this condition.

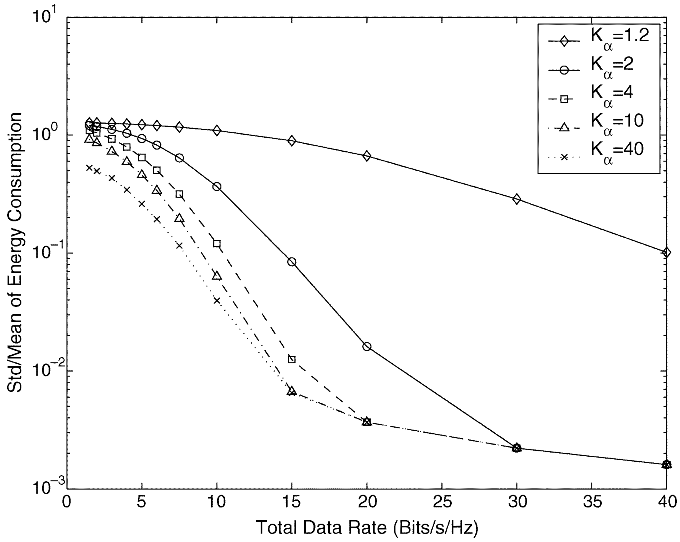

Fig. 4. Impact of the clipping threshold on the variation (among sensors) of the energy consumption of the ILS protocols.

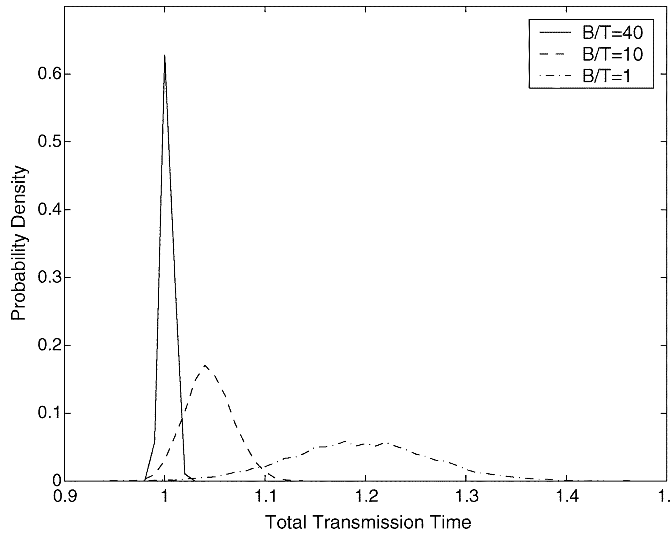

Fig. 5. Probability distribution of total transmission time obtained using the λ approximation in (22) ($N = 100$).

of bits B_n to be transmitted $\forall n \in [1, N]$. There are two possible ways in which these centralized protocols can be applied.

1) Each sensor n transmits a training sequence and the value of B_n to the fusion center; the fusion center estimates the channels between all N sensors and itself, and uses these estimates to compute the transmission times of all sensors; these transmission times are then fed back to the sensors.
2) The fusion center broadcasts a training sequence; each sensor estimates its own channel and exchanges this estimate and B_n with all other sensors; so that each sensor can then compute the transmission time it should use.

Apparently, both of these two schemes will incur a large overhead in terms of communication bandwidth and energy, especially in a sensor network with a large number of nodes. If, on the other hand, we can design a distributed scheduling protocol that requires only local channel and queue information per sensor, then this overhead can be greatly reduced.

Evidently, the overhead required by centralized protocols increases with the network size N. For this reason, when developing our distributed protocols, we will be primarily concerned with large sensor networks.

A. Batch Distributed Scheduling

For simplicity, we first consider the inverse-log protocol without clipping described by (8). Our objective is to find the value of λ such that the sum of the transmission times assigned to all sensors is equal to the target total transmission time

$$T = \sum_{n=1}^{N} T_n = \sum_{n=1}^{N} \frac{B_n}{\log_2(\lambda |h_n|^2)}. \tag{19}$$

Let us rewrite the denominator of the summand in (19) as $\log_2(\lambda|h_n|^2) = \log_2\lambda + \log_2|h_n|^2 = \log_2\lambda[1 + (\log_2|h_n|^2)/(\log_2\lambda)]$. If the data rate B/T is high, then $\log_2\lambda > B/T$ is also large. Since the probability of $\log_2|h_n|^2 \gg 1$ is very small, we have that $x := (\log_2|h_n|^2)/(\log_2\lambda)$ is small; which allows us to use the first-order approximation $(1+x)^{-1} \approx 1 - x$ to approximate the right-hand side of (19) as

$$\begin{aligned} T &\approx \sum_{n=1}^{N} \frac{B_n}{\log_2\lambda}\left(1 - \frac{\log_2|h_n|^2}{\log_2\lambda}\right) \\ &\approx \frac{\bar{B}}{\log_2\lambda} - \frac{\bar{B}\cdot E\left[\log_2|h_n|^2\right]}{(\log_2\lambda)^2} \end{aligned} \tag{20}$$

where the last approximation follows from the law of large numbers and the definition $\bar{B} := E[\sum_{n=1}^{N} B_n]$. From (20), we can obtain the following closed-form approximation:

$$\log_2\lambda \approx \frac{2\cdot E\left[\log_2|h_n|^2\right]}{1 - \sqrt{1 - \left(\frac{4T}{\bar{B}}\right) E\left[\log_2|h_n|^2\right]}}. \tag{21}$$

The transmission time T_n assigned to sensor n can then be obtained using (18) with B replaced by its expected value $\bar{B}$.

To verify the accuracy of (21), we simulate two large sensor networks with 100 and 1000 sensors, respectively. The channels between the fusion center and the sensors are assumed to be i.i.d. Rayleigh distributed with variance one. The target total transmission time is $T = 1$. For such channels, it can be shown that $E[\log_2|h_n|^2] = -\gamma/\ln(2)$, where $\gamma \approx 0.577216$ is the Euler–Mascheroni constant [1, p. 3]. Hence, for a given $\bar{B}/T$, we find from (21)

$$\lambda = \exp\left(\frac{2\gamma}{\sqrt{1} + \frac{\frac{4\gamma T}{\bar{B}}}{\ln 2} - 1}\right). \tag{22}$$

Figs. 5 and 6 show the probability distribution of the total transmission time obtained using the ILS with clipping in (18), and with λ given by (22). We verify that the actual total transmission time is very close to the target value 1 when the total data rate is high. As the total data rate decreases, both the mean and the variance of the actual total transmission time increases. Increasing the number of sensor nodes reduces the variance, but not the bias, of the total transmission time for smaller $\bar{B}/T$.

The bias in total transmission time comes from two sources: 1) in (20), we use $1 - x$ to approximate $(1 + x)^{-1}$, and thus underestimate the actual transmission time; and 2) the clipping

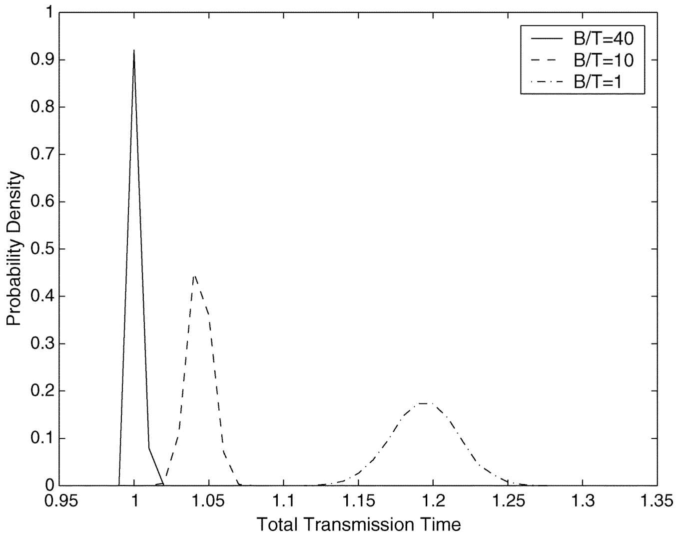

Fig. 6. Probability distribution of total transmission time obtained using the λ approximation in (22) ($N = 1000$).

operation is not considered when determining λ. To mitigate this problem, we can use a more accurate approximate of $(1+x)^{-1}$ and also take into account the clipping operation of (18). Keeping the first $M+1$ terms of the Taylor series expansion for $(1+x)^{-1}$ and denoting

$$\Pi := \left\{ n \,\middle|\, 0 < \frac{B_n}{\log_2(\lambda|h_n|^2)} \le \frac{B_n}{B} K_\alpha T \right\} \tag{23}$$

we can use the following equation to determine λ:

$$\begin{aligned} T &= \sum_{n\in\Pi} \frac{B_n}{\log_2(\lambda|h_n|^2)} + \sum_{n\notin\Pi} \frac{B_n}{B} K_\alpha T \\ &\approx \sum_{n\in\Pi} \frac{B_n}{\log_2 \lambda} \sum_{m=0}^{M} \left(-\frac{\log_2 |h_n|^2}{\log_2 \lambda} \right)^m + \sum_{n\notin\Pi} \frac{B_n}{\bar{B}} K_\alpha T \\ &\approx P(\lambda) \frac{\bar{B}}{\log_2 \lambda} \sum_{m=0}^{M} \left(-\frac{1}{\log_2 \lambda} \right)^m \theta^{(m)}(\lambda) \\ &\quad + [1 - P(\lambda)] K_\alpha T \end{aligned} \tag{24}$$

where

$$P(\lambda) := \Pr(n \in \Pi) = \int_{A(\lambda)}^{\infty} p_{|h|^2}(x) dx \tag{25}$$

$$\begin{aligned} \theta^{(m)}(\lambda) &:= E\left[\left(\log_2 |h_n|^2 \right)^m | n \in \Pi \right] \\ &= \frac{1}{P(\lambda)} \int_{A(\lambda)}^{\infty} p_{|h|^2}(x) \log_2 x dx \end{aligned} \tag{26}$$

$$A(\lambda) := \frac{1}{\lambda} 2^{\frac{B}{K_\alpha T}}. \tag{27}$$

Equation (24) generally does not have a closed-form solution, and numerical search is needed to find λ. Since numerical searches are computationally costly, they may not be affordable by microscopic sensor nodes with very limited computational power. Furthermore, the additional energy consumption required by this computation may offset the energy savings of the scheduling protocols. These considerations prompt us to explore distributed protocols using the simple closed-form approximate of λ, as given by (21).

B. Adaptive Distributed Scheduling

To ensure that the scheduling policy dictated by (18) and (21) meets the prescribed total transmission-time constraint, we develop here an *adaptive* distributed scheduling algorithm. The sensors in the network will be numbered from 1 to N, and sensor $n+1$ will start transmitting after sensor n's transmission ends. Each sensor will adjust its transmission time according to the total remaining transmission time and the number of sensors that have yet to transmit. More specifically, sensor n will execute the *distributed ILS* algorithm described by the following pseudocode.

Initialize:

$$\begin{aligned} N &= \text{total number of sensors} \\ T_r &= \text{remaining available transmission time} \\ \bar{B} &= E\left[\sum_{n=1}^{N} B_n \right] \\ \xi &= E\left[\log_2 \left(|h|^2 \right) \right] \\ K_\alpha &= 2. \end{aligned}$$

Case 1: $n < N - N_1$

$$\begin{aligned} T'_r &= \left(1 - \frac{1}{N-n+1} \right) T_r \\ \lambda_n &= 2^{\frac{2\xi}{1-\sqrt{1-\frac{4NT'_r\xi}{\bar{B}(N-n+1)}}}} \\ \eta_n &= \min\left\{ 1, \frac{NT_r}{(N-n+1)T} \right\} \\ T_n &= \min\left\{ \frac{\eta_n B_n}{\log_2(\lambda_n |h_n|^2)}, \frac{K_\alpha N B_n T'_r}{(N-n+1)\bar{B}} \right\} \\ \text{if } T_n &< 0,\ T_n = \frac{K_\alpha N B_n T'_r}{(N-n+1)\bar{B}}. \end{aligned}$$

Case 2: $N - N_1 \le n < N$

$$\begin{aligned} \lambda_n &= \lambda_{N-N_1-1} \\ K'_\alpha &= 1 + (N-n)/(2N_1) \\ T_n &= \min\left\{ \frac{B_N}{\log_2(\lambda|h_n|^2)}, \frac{K'_\alpha T'_r}{N-n+1}, \frac{K_\alpha B_n T}{\bar{B}} \right\} \\ \text{if } T_n &< 0,\ T_n = \min\left\{ \frac{K'_\alpha T'_r}{N-n+1}, \frac{K_\alpha B_n T}{\bar{B}} \right\}. \end{aligned}$$

Case 3: $n = N:\quad T_n = T_r$.

In this adaptive algorithm, we let the last N_1 sensors transmit differently to ensure that the deadline is met without requiring the last few sensors to spend excessive energy. The remaining vast majority of sensors belong to **Case 1**. When sensor $n-1$ finishes transmitting, sensor n first computes λ_n according to the remaining time and the number of sensors, and then uses (18) to obtain the transmission time it should use. To ensure that enough time is left for the remaining sensors, we adopt a progressively decreasing (as n increases) target total transmission time, and scale the preclipping time assigned to sensor n by the

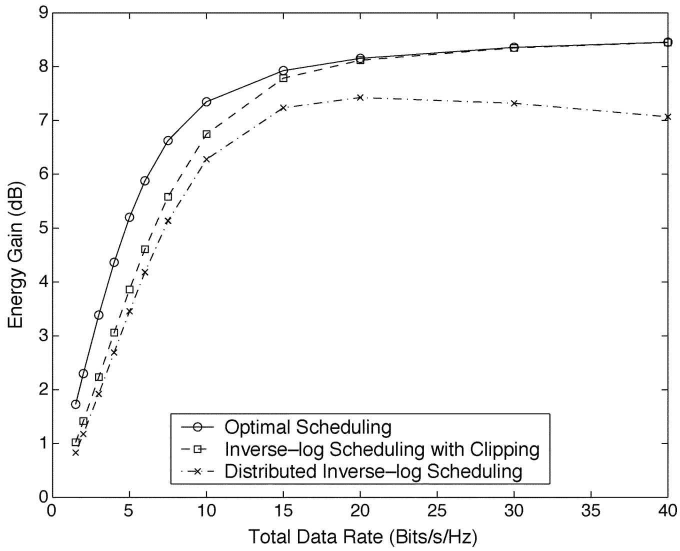

Fig. 7. Performance of the distributed scheduling algorithm $(N = 100)$.

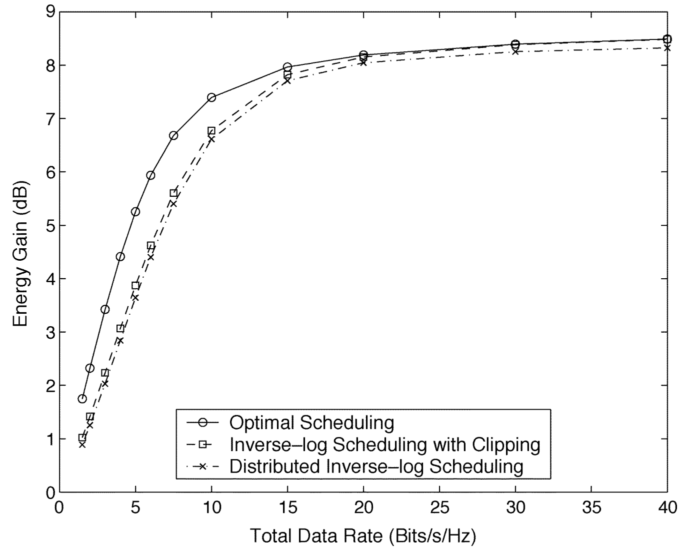

Fig. 8. Performance of the distributed scheduling algorithm $(N = 1000)$.

ratio of the percentage of time consumed over the percentage of sensors that have already finished transmission. The last N_1 sensors must be treated very carefully; otherwise, too little time might be left for the last few sensors (especially the last one), leading to a dramatic increase in energy consumption for them, especially if they happen to be in a bad channel state. To make certain that this does not happen, we use an additional clipping operation to further limit the amount of extra transmission time that can be assigned to these last N_1 sensors.

Remark 2: In this distributed algorithm, we assume that sensor n knows when sensor $n-1$ finishes transmission and starts transmitting immediately. This assumption is realistic, because we can number the sensors so that the sensor nodes close in numerical order are also close to each other geographically, and sensor n can reliably monitor the transmission of sensor $n-1$.

The energy efficiency of the distributed ILS algorithm is compared with that of the centralized optimal scheduling and suboptimal ILS algorithms in Figs. 7 and 8, where we simulate networks of 100 and 1000 sensors, respectively. We assume, as usual, that the channels between the sensors and the fusion center are i.i.d. Rayleigh fading, and all sensors have the same queue length. For both networks, we set $N_1 = 5$. When the network size is $N = 100$, we observe that there is a gap of 0–2 dB between the centralized and the distributed algorithms, but the distributed scheduling still achieves a substantial amount of energy gain over the traditional TDMA protocol. On the other hand, in a network of $N = 1000$ sensors, the performance gap between the centralized ILS and the distributed scheduling is almost negligible. This suggests that with the adaptive implementation, the performance-limiting factor in distributed scheduling is not the bias, but the variance of the actual total transmission time shown in Figs. 5 and 6.

In our simulations so far, we have assumed that all sensor nodes have the same amount of data to report. From the derivation of the distributed inverse-log algorithm, we can see, however, that it can also be applied when nodes have different queue lengths. In Fig. 9, we simulate a network with $N = 100$ sensors.

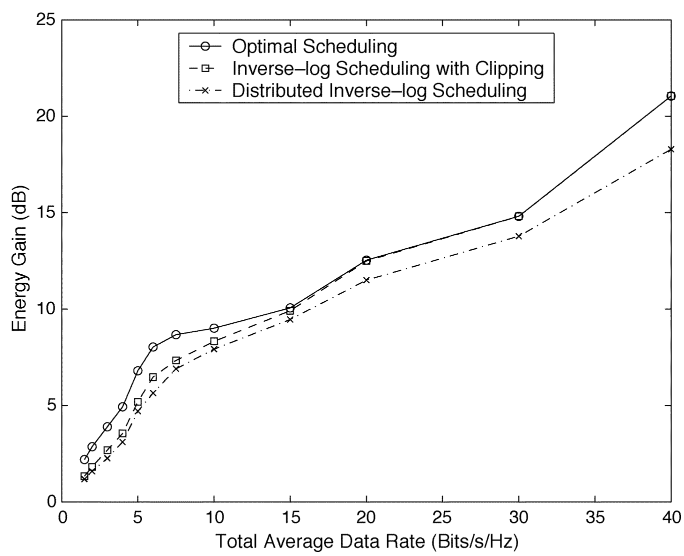

Fig. 9. Performance of the distributed scheduling algorithm with Poisson-distributed queue lengths $(N = 100)$.

The simulation setting is the same as the one we used to obtain Fig. 7, except that the amount of data in each sensor's buffer is now assumed to be Poisson distributed. We observe that the distributed inverse-log protocol still achieves close-to-optimal energy efficiency. Different from the case of equal queue length, the energy gain of the proposed scheduling algorithms over traditional TDMA does not reach a plateau at high data rates, but continues increasing with the total average data rate.

V. Performance Analysis

In this section, we will analyze the energy consumption of ILS with clipping described by (18) in a large-scale sensor network. To model the channels between the sensors and the fusion center, we use the Nakagami-m fading for its flexibility. By changing the Nakagami parameter m, we can obtain different levels of channel variations. We will assume that $m > 1$; otherwise, the average energy consumption will be infinite.

Using (2) and recalling the definition (23), the total energy consumption under scheduling (18) is

$$\begin{aligned} E_{\text{tot}} &:= \sum_{n=1}^{N} \frac{T_n}{|h_n|^2}\left(2^{\frac{B_n}{T_n}}-1\right) \\ &= \sum_{n\in\Pi} \frac{B_n}{|h_n|^2 \log_2(\lambda|h_n|^2)}\left(\lambda|h_n|^2-1\right) \\ &\quad + \sum_{n\notin\Pi} \frac{B_n K_\alpha T}{B|h_n|^2}\left(2^{\frac{B}{K_\alpha T}}-1\right). \end{aligned} \tag{28}$$

Supposing that the total data rate B/T is large, λ can be approximated by (21). Since for $n \in \Pi$, $\lambda|h_n|^2 \geq 2^{B/K_\alpha T} \gg 1$, we have

$$\begin{aligned} E_{\text{tot}} &\approx \sum_{n\in\Pi} \frac{\lambda B_n}{\log_2(\lambda|h_n|^2)} + \sum_{n\notin\Pi} \frac{B_n K_\alpha T}{B|h_n|^2} 2^{\frac{B}{K_\alpha T}} \\ &\approx P(\lambda)\frac{\lambda \bar{B}}{\log_2 \lambda}\left(1 - \frac{E\left[\log_2 |h_n|^2 | n\in\Pi\right]}{\log_2\lambda}\right) \\ &\quad + [1-P(\lambda)](K_\alpha T)2^{\frac{B}{K_\alpha T}} E\left[\left.\frac{1}{|h_n|^2}\right| n\notin\Pi\right] \end{aligned} \tag{29}$$

where the last expression is obtained using the first-order approximation $(1+x)^{-1} \approx 1-x$ and the law of large numbers.

For Nakagami-m fading, the pdf of $|h_n|^2$ is [12]

$$p_{|h_n|^2}(x) = \frac{m^m x^{m-1}}{\Gamma(m)} \exp(-mx), \quad x \geq 0 \tag{30}$$

where $\Gamma(x) := \int_0^\infty t^{x-1} e^{-t} dt$ is the Gamma function. From (21), we have

$$\lambda \approx 2^{\frac{2\xi}{1-\sqrt{1-\frac{4\xi T}{B}}}} \tag{31}$$

where $\xi := E[\log_2 |h_n|^2]$ can be shown to be [7, p. 604]

$$\begin{aligned} \xi &= \int_0^\infty \frac{m^m}{\Gamma(m)} x^{m-1} e^{-mx} \log_2 x dx \\ &= \frac{1}{\ln 2}\left[\psi(m) - \ln m\right] \end{aligned} \tag{32}$$

and $\psi(x) := d\ln\Gamma(x)/dx$ is the Digamma function. Furthermore, using the definition of the set Π in (23), we have

$$P(\lambda) = \int_{A(\lambda)}^\infty p_{|h|^2}(x)dx = \frac{\Gamma(m, mA(\lambda))}{\Gamma(m)} \tag{33}$$

and

$$[1-P(\lambda)]\, E\left[\left.\frac{1}{|h_n|^2}\right| n\notin\Pi\right] = \frac{m\gamma(m-1, mA(\lambda))}{\Gamma(m)} \tag{34}$$

where (33) and (34) can be readily obtained using the definitions $\Gamma(\alpha, x) := \int_x^\infty e^{-t} t^{\alpha-1} dt$ and $\gamma(\alpha, x) := \int_0^x e^{-t} t^{\alpha-1} dt$ for the upper and lower incomplete Gamma functions, respectively.

Combining (29)–(34), we obtain

$$\begin{aligned} E_{\text{tot}} \approx \frac{T}{\Gamma(m)}\Big[&\Gamma(m, mA(\lambda))\lambda \\ &+ K_\alpha 2^{\frac{B}{K_\alpha T}} m\gamma(m-1, mA(\lambda))\Big] \end{aligned} \tag{35}$$

where we have used the approximation

$$\begin{aligned} E\left[\log_2 |h_n|^2 | n\in\Pi\right] &= \int_{A(\lambda)}^\infty \frac{m^m x^{m-1}}{\Gamma(m)} e^{-mx} \log_2 x dx \\ &\approx \int_0^\infty \frac{m^m x^{m-1}}{\Gamma(m)} e^{-mx} \log_2 x dx \\ &= \xi \end{aligned} \tag{36}$$

by noting that $A(\lambda) \leq 2^{B/T((1/K_\alpha)-1)}$ goes to zero as $\bar{B}/T$ grows large, and that $\lim_{x\to 0} x^{m-1}e^{-mx}\log_2 x = 0$ for $m > 1$. Having $A(\lambda) \ll 1$ also leads to the following approximation [7, p. 950]:

$$\gamma(m-1, mA(\lambda)) \approx \frac{(mA(\lambda))^{m-1}}{m-1} \tag{37}$$

and

$$\Gamma(m, mA(\lambda)) \approx \Gamma(m) - \frac{(mA(\lambda))^m}{m}. \tag{38}$$

Based on (37) and (38), we can further simplify (35) as follows:

$$\begin{aligned} E_{\text{tot}} &\approx \frac{T}{\Gamma(m)}\left\{\left[\Gamma(m) - \frac{(mA(\lambda))^m}{m}\right]\lambda \right. \\ &\qquad \left. + mK_\alpha 2^{\frac{\bar{B}}{K_\alpha T}} \frac{(mA(\lambda))^{m-1}}{m-1}\right\} \\ &= \lambda T + \frac{Tm^{m-1}}{\Gamma(m)}\left(\frac{mK_\alpha}{m-1} - 1\right)\frac{2^{\frac{m\bar{B}}{K_\alpha T}}}{\lambda^{m-1}}. \end{aligned} \tag{39}$$

For large $\bar{B}/T$, we have from (31) that

$$\lambda \approx 2^{\frac{2\xi}{1-\sqrt{1-\frac{4\xi T}{\bar{B}}}}} \approx 2^{\frac{\bar{B}}{T}-\xi}. \tag{40}$$

Substituting (40) into (39), we arrive at

$$\begin{aligned} E_{\text{tot}} &\approx \left[1 + \frac{m^{m-1}}{\Gamma(m)}\left(\frac{mK_\alpha}{m-1} - 1\right) 2^{\frac{m\bar{B}}{T}\left(\frac{1}{K_\alpha}-1\right)+m\xi}\right] \\ &\quad \times T 2^{\frac{\bar{B}}{T}-\xi} \\ &\approx mT 2^{\frac{\bar{B}}{T}} e^{-\psi(m)}. \end{aligned} \tag{41}$$

In Fig. 10, we show the ratio between the approximate E_{tot} given by (41), and the total energy consumption obtained by Monte Carlo simulation of a 100-node sensor network using the ILS with clipping for different values of the Nakagami parameter m. We observe that the approximation (41) is quite accurate when the total data rate is high, and that the accuracy of the approximation improves as m increases.

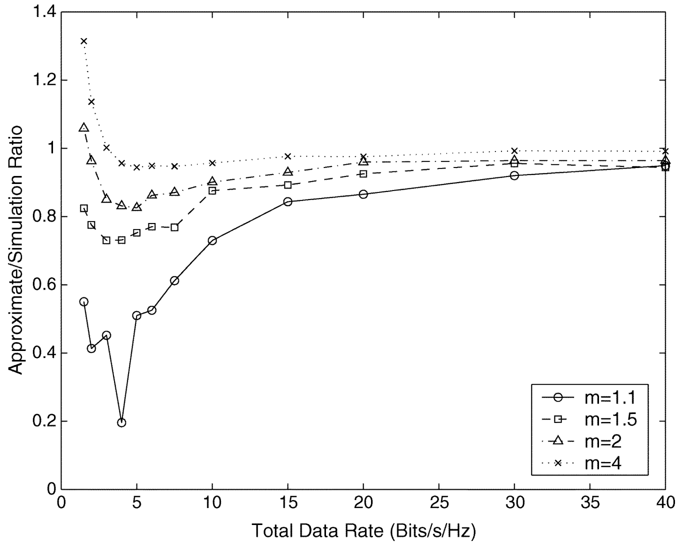

Fig. 10. Accuracy of the approximation in (41).

To determine the energy gain over traditional TDMA (with uniform time slots), we also compute the total energy consumption of the latter, assuming Nakagami-m fading

$$\begin{aligned} E_{\rm tot}^{(u)} &= \sum_{n=1}^{N} \frac{T}{N|h_n|^2}\left(2^{\frac{NB_n}{T}}-1\right) \\ &\approx TE\left[\frac{1}{|h|^2}\right]E\left[2^{\frac{NB_n}{T}}-1\right] \\ &= \frac{mT}{m-1}E\left[2^{\frac{NB_n}{T}}-1\right]. \end{aligned} \tag{42}$$

Equation (42) depends clearly on the distribution of B_n. For simplicity, let us assume that $NB_n/T \sim \mathcal{N}(\bar{B}/T, \sigma_B^2)$ and $\bar{B}/T \gg \sigma_B$. The total energy consumption when using traditional TDMA can then be written as

$$E_{\rm tot}^{(u)} \approx \frac{mT}{m-1} 2^{\frac{\bar{B}}{T}+\frac{\ln 2}{2}\sigma_B^2}. \tag{43}$$

Based on (41) and (42), we have thus established the following proposition.

Proposition 2: The asymptotic (for large $\bar{B}/T$ and N) energy gain of the ILS with clipping over traditional TDMA is

$$G := \frac{E_{\rm tot}^{(u)}}{E_{\rm tot}} = \frac{e^{\psi(m)}}{m-1} 2^{\frac{\ln 2}{2}\sigma_B^2}. \tag{44}$$

Notice that G consists of two factors. The first factor $e^{\psi(m)}/(m-1)$ depends only on the channel distribution and decreases as m increases; while the second factor $2^{(\ln 2/2)\sigma_B^2}$ depends only on the variance of B_n and increases as the variance increases. A couple of remarks are now in order.

Remark 3: In deriving (44), we have assumed Nakagami-m fading channels and Gaussian-distributed queue-length variation among different nodes. The insights provided by (44), however, are also applicable to more general scenarios. We expect that, in general, the energy gain G will increase if the channels experienced by different sensors and the amount of data in different sensors' buffers become more disparate.

Remark 4: Equation (44) also explains why the energy gain of the proposed scheduling protocols continues to increase with the total average data rate at high data rates in Fig. 9. In obtaining Fig. 9, we have assumed that B_n is Poisson distributed, which means that σ_B^2 increases linearly as $\bar{B}$ increases. Since the Poisson distribution can be approximated by a Gaussian when its mean is large, (44) predicts that at high data rates, the energy gain should grow linearly (in decibels) as the average data rate increases. We confirm from Fig. 9 that this prediction fits the simulation fairly well.

VI. Conclusions and Future Directions

Energy efficiency is critical to the longevity and performance of wireless sensor networks. In this paper, we have developed several centralized and decentralized energy-efficient scheduling protocols for sensor fusion. By assigning longer transmission times to sensors experiencing worse channel conditions, we are able to save more than 80% of the energy needed by the traditional TDMA protocol. The ILS we developed has very low computational complexity, and incurs negligible overhead in terms of hardware cost and energy consumption needed for executing the algorithm.

For sensor networks with a large number of nodes, we also designed a distributed version of the ILS algorithm. Under this distributed protocol, each sensor needs only to know its own channel gain with the fusion center and the amount of data in its buffer; hence, the communication overhead required by the centralized protocols is eliminated. Simulations demonstrated that the distributed ILS achieves near-optimal energy efficiency in large-scale networks.

To analyze the energy-consumption performance of the inverse-log algorithm, we further computed its asymptotic energy gain over the traditional TDMA protocol. We showed that the energy gain of the proposed algorithm increases as the channel variations among different sensor nodes increase. When the total data rate of a network is high, the energy gain does not depend on the total data rate, but increases as the variation among different nodes' queue lengths becomes larger.

The goal of this paper was to demonstrate the potential for energy savings with nonuniform TDMA scheduling and to gain insight on the source of these energy savings (channel and packet-length variations from user to user). A logical next step in this study would be to use a more realistic setting to investigate the impact of practical issues, including SNR gap, guard interval, and channel-estimation errors. Compared with uniform TDMA, our scheduling reduces the transmission time given to terminals with good channel conditions and/or small packet lengths, and increases the transmission time for terminals with poor channel conditions and/or large packet lengths. If there is a peak power constraint and a terminal experiences a very poor channel, both our scheduling algorithm and uniform TDMA may violate the peak power constraint. And such a terminal will experience outage under both schedulers, although our nonuniform TDMA will exhibit smaller probability of outage for a fixed peak-power constraint. Setting a peak-power constraint and evaluating the outage probability performance of different scheduling protocols constitutes an interesting future direction.

In this paper, we focused on the energy consumed by signal transmission. In applications where the fusion center is close to the sensor nodes, the energy consumption of the sensor nodes in the receiving mode and the idle mode may become comparable to the transmission energy consumption [5], [18]. For these scenarios, the techniques developed in this paper can be combined with other techniques, such as sleeping mode control, to reduce the total energy consumption.

We have assumed in this paper that the channels remain invariant over the data-fusion period and that the resultant fading is frequency-flat. The distributed scheduling protocols we developed, however, are applicable as long as the channel remains constant during the transmission time of one node. In certain applications, we may have to deal with fast fading and/or frequency-selective channels. The same methodology we used here can be applied to these more general scenarios, although distributed implementation will be more difficult. These issues and the more general problem of optimal resource allocation in wireless networks will be the subject of our future investigations.[3]

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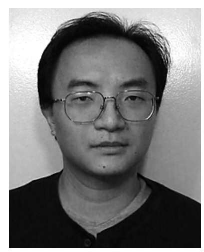

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