Optimal Communication-Computation Tradeoff for Wireless Multimedia Sensor Network Lifetime Maximization

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***Abstract*—We address the issue of network lifetime maximization for a special class of wireless sensor networks namely, wireless multi-media sensor networks. High data rates, in these networks at the sensor nodes, compared to the conventional sensor networks and the presence of high temporal correlation in the sampled data make them a suitable candidate for the in-network processing, primarily at the sensor node itself. Using these distinguishing features of wireless multi-media sensor networks to our advantage, we have proposed a framework achieving an optimal tradeoff between communication and computation power consumption leading to network lifetime maximization under the delay quality of service constraints. The distributed implementation of the algorithm realizing the proposed framework is achieved using duality theory. A max-min fairness index based measure of network lifetime maximization is studied as a function of end-to-end delay thresholds. Numerical results show how the total network power consumption is distributed between the communication and the computation power consumption components. The results also provide an insight about the maximum and minimum nodal power consumptions. Our results show that the superior performance in terms of max-min fairness index at higher end-to-end delay thresholds is mainly attributed to the relative lower computation cost compared to the communication cost.**

I. Introduction

The availability of low-cost hardware, for instance, CMOS cameras has resulted in fast growth of Wireless Multimedia Sensor Networks (WMSNs) with their applications in remote environment monitoring, video surveillance and image-based tracking to name a few. For such networks, in-network data compression is vital for reducing the communication cost over the data gathering tree. Some of the recent techniques perform maximum in-network compression [1], [2], which may be suitable for scalar sensing (e.g. temperature sensing, proximity detection etc.) where the computation cost of data compression is negligible compared to the cost of communication. However, for the case of WMSNs, the cost of compression for complex data sets is comparable to that of wireless communication. It is observed that blindly applying maximum compression may result in higher cost compared to transmitting even the raw data [3]. This requires alternative methods for an efficient trade-off between computation and communication costs [4].

For a class of WMSNs, where sensed data is highly time correlated, it is suitable to perform compression at the source node before its transmission to exploit the temporal correlation resulting in high resource savings. For a given data rate, how much compression should be performed before its transmission, leading to network lifetime maximization, is the question that we try to answer using resource optimization framework. At the node level our framework achieves an optimal tradeoff between communication and computation costs, while at the network level the communication overhead of highly loaded nodes is translated to the computational overhead of lightly loaded nodes.

The problem of network lifetime maximization has been studied widely in the context of protocol designs, cross-layer approaches, information theoretic analysis as well as application layer tradeoffs. In recent years energy-aware protocols have been studied extensively for wireless sensor networks [5], [6]. The problem of optimal routing using a network flow based approach to maximize the lifetime of a network defined as the time until the death of its first node is considered in [7]. Energy-efficient network routing protocols aimed at broadcasting in wireless sensor networks are discussed in detail in [8]. The cross-layer approaches addressing the problem of network life maximization while achieving different tradeoffs are discussed in [9], [10], [11]. Information theoretic lossy network data gathering, resulting in optimal transmission structure and the rate-distortion allocations while minimizing the total power consumption cost of the network is discussed in [12].

A node level energy-bandwidth tradeoff for image data communication is discussed in [13] by using an adaptive data codec based on wavelet image compression. The energy-bandwidth tradeoff in [13] effectively achieves a balance between nodal communication and computation power consumption. From a network perspective, only recently the problem of lifetime maximization has been discussed in the context of communication computation tradeoff [14], [15]. The authors in [14], using different data gathering tree structures, consider the data compression at the nodes one hop before the sink node. This strategy, might be good for exploiting the spatial correlation, will perform poorly for the data with high temporal correlation in a multi-hop network scenario, due to large communication costs. The work in [15] also aims to exploit the spatial correlation by modelling the sensed data as a stationary Gaussian field with zero mean. The rate of decay in the correlation between sensed data is modelled as a function of the distance between sensor locations. In contrast, our proposed framework differs from the work in [14] and [15] by exploiting the temporal correlation at the sensor node itself. This results in reduced communication cost due to lower data rates and leads to network lifetime maximization.

In Section II we outline the node and network models as well as the set of assumptions underlying these models. A framework for the network lifetime maximization problem formulation is discussed in Section III. The distributed algorithm using problem transformation and dual decomposition is provided in Section IV. Numerical results are provided in Section V and we conclude our findings in Section VI.

II. System Model

We model the network as a tree graph $G(N, L)$, where N represents the set of $|N|-1$ sensor nodes and a single sink node (also called the root node) and L is the set of direct wireless communication links present between any node pairs.

Processing for compression is performed for the locally sensed data at each of the sensor nodes (including the *leaf* as well as *inner* nodes). The classification of a node as a leaf node, an inner node or the root node is illustrated in Fig. 1, for an example sensor network. The compressed data transmission rate from sensor node n_i, to the sink node n_{sink}, is given by r_{n_i}. In defining our system model we have made the following assumptions:

- Computation and communication are assumed to occur simultaneously as supported by various platforms (e.g. CC2430[1] from Texas Instruments and MC13213 from Freescale).
- To achieve convergence of lifetime maximization algorithm a fixed transmission schedule is assumed.
- Computation delay is assumed to be negligible compared to the communication delay, which is true for many architectures in practical use today.
- At startup each of the nodes has the same amount of energy available.

We adopt the definition of the *network lifetime* as the time of the first node failure [7]. This is a reasonable measure in the sense that a single node failure can make the network become partitioned and some of the nodes in its subtree cannot reach the sink node. Since the energy cost, by definition, is instantaneous power consumption accumulated over time, the objective of network lifetime maximization can be achieved indirectly by minimizing the maximum of the nodal powers. In our framework we will adopt this approach to achieve the objective of the network lifetime maximization.

A. Network Model

For the uncompressed sensed data rate of R bps, we define $r_{n_i} \in \mathbf{r}$ as the data transmission rate from node n_i after

[1]Per bit energy consumption for transmission and reception used in the results are based on the corresponding CC2430 current consumptions at the operating voltage.

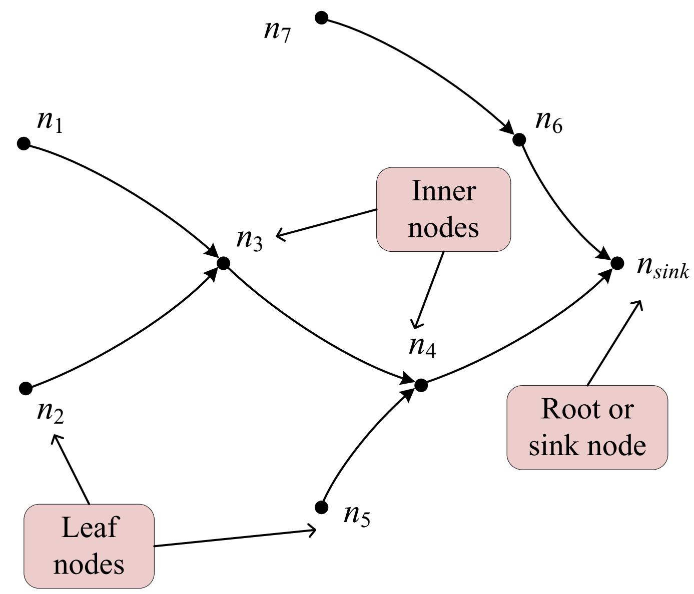

Fig. 1. An example WMSN consisting of seven sensor and single sink node with different node classifications marked.

compression. Application layer requires a maximum end-to-end delay threshold $D_{max}(n_i)$ to be met, for transporting data from source node n_i to n_{sink}. The set $I(n_i)$ comprises of all the sensor nodes in the subtree rooted at node n_i. We define $T(n_i)$ to be the set of transmitting nodes along the shortest path from source node n_i to the sink node including n_i itself. The resulting end-to-end delay constraint in a multi-hop setting is given by

$$\sum_{n_i \in T(n_k)} \frac{H}{r_{n_i} + \sum_{n_j \in I(n_i)} r_{n_j}} \leq D_{max}(n_k) \qquad \forall n_k. \qquad (1)$$

In (1), H is the packet length used for transmission and each term in the summation over $T(n_i)$ is effectively the link transmission delay along the shortest path.

B. Node Power Consumption Model

To define the problem of network lifetime maximization we first require an estimate of the total power consumption at each of the sensor nodes. This estimate comprises of the communication and computation power consumption components. The communication power cost $(P_{comm}(n_i))$ for a given node n_i is proportional to the amount of data exchanged between any pair of nodes and is modelled as

$$P_{comm}(n_i) = E_b^{(tx)} r_{n_i} + \left(E_b^{(tx)} + E_b^{(rx)}\right) \sum_{n_j \in I(n_i)} r_{n_j}, \quad (2)$$

where $E_b^{(tx)}$ and $E_b^{(rx)}$ are the per bit transmission and reception energy costs, respectively. The computational power consumption $(P_{comp}(n_i))$ at node n_i [14], intuitively is proportional to the compression ratio as well as the uncompressed data rate (since each block of uncompressed data is required to be scanned once by the compression algorithm) and is modelled

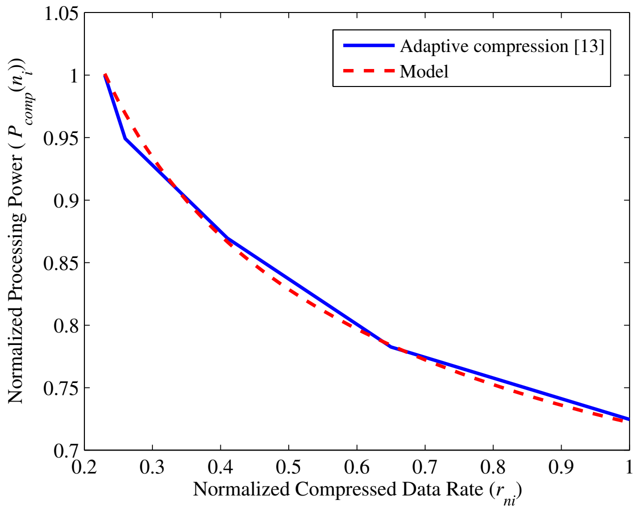

Fig. 2. A computational power consumption comparison of our nodal power consumption model with that of adaptive wavelet transform level compression of [13]. The matching parameters for the model are $\gamma = 0.5$ and $\alpha = 0.51$.

as:

$$P_{comp}(n_i) = R\left[\left(\frac{R}{r_{n_i}}\right)^{\alpha} - 1\right] E_b^{(comp)} + \gamma, \quad (3)$$

where $\alpha > 0$ is the compression algorithm dependent parameter, γ is the offset for boundary value compensation and $E_b^{(comp)}$ is the per bit processing energy cost. The parameters α and γ are obtained off-line for a given compression algorithm and the hardware platform chosen. For illustration the compression result in [[13], Fig. 8], employing variable wavelet transform level, is used to tune the α and γ parameters of our computational power consumption model. The model matches well with the wavelet based compression of [13] as shown in Fig. 2. Now combining the computation and communication power costs, the total power consumption at a node is given by:

$$P(n_i) = P_{comm}(n_i) + P_{comp}(n_i). \quad (4)$$

III. Network Lifetime Maximization Framework: Problem Formulation

In this section, we first formulate the network lifetime maximization problem, under the end-to-end delay QoS constraints in (1). Using the the node power consumption model discussed in previous section we define the network lifetime maximization problem as:

$$\begin{aligned}
\textbf{minimize} \quad & max\{P(n_i) \mid n_i \in \{N \setminus n_{sink}\}\} \\
\textbf{s.t.} \quad & \sum_{n_k \in T(n_i)} \frac{H}{r_{n_k} + \sum_{n_j \in I(n_k)} r_{n_j}} \\
& \qquad \le D_{max}(n_i) \qquad \forall n_i, \\
& r_{n_i} + \sum_{n_j \in I(n_i)} r_{n_j} \le c_{n_i} \qquad \forall n_i, \\
& R_{min}(n_i) < r_{n_i} \qquad \forall n_i, \quad (5)
\end{aligned}$$

where c_{n_i} is the maximum link transmission rate and $R_{min}(n_i)$ is the minimum transmission rate required by the application layer. The lifetime maximization problem in (5) is nonlinear and non-convex due to the structure of the objective function and the end-to-end delay constraints. However, using a set of slack variables and writing the problem in epigraph form we get the following equivalent maximal-node-power minimization problem:

$$\begin{aligned}
\textbf{minimize} \quad & \frac{1}{t} \\
\textbf{s.t.} \quad & P(n_i) \le \frac{1}{t} \\
& \sum_{n_k \in T(n_i)} d_{n_k} \le D_{max}(n_i) \qquad \forall n_i, \\
& \frac{H}{d_{n_k}} \le r_{n_k} + \sum_{n_j \in I(n_k)} r_{n_j} \qquad \forall n_k, \\
& r_{n_i} + \sum_{n_j \in I(n_i)} r_{n_j} \le c_{n_i} \qquad \forall n_i, \\
& R_{min}(n_i) < r_{n_i} \qquad \forall n_i. \quad (6)
\end{aligned}$$

In (6) the t and $d_{n_k} \in \mathbf{d}$ are slack variables introduced for problem transformation. The equivalent form of the network lifetime maximization problem in (6) is convex in variables t, r_{n_i} and d_{n_i}. Next we discuss the distributed algorithm and its realization to solve the problem in (6).

IV. Network Lifetime Maximization Framework: Distributed Algorithm

We use duality theory for problem decomposition leading to an efficient distributed realization. To achieve this we introduce dual variables $\lambda_{n_i} \in \mathbf{\Lambda}$ associated with power inequality constraints $P(n_i) \le \frac{1}{t}$ to form the partial Lagrangian [16] given by:

$$\begin{aligned}
\textbf{minimize} \quad & L(t, \mathbf{r}, \mathbf{d}, \mathbf{\Lambda}) = \frac{1}{t} + \sum_{n_i} \lambda_{n_i} \left(P(n_i) - \frac{1}{t}\right) \\
\textbf{s.t.} \quad & \sum_{n_k \in T(n_i)} d_{n_k} \le D_{max}(n_i) \qquad \forall n_i, \\
& \frac{H}{d_{n_k}} \le r_{n_k} + \sum_{n_j \in I(n_k)} r_{n_j} \qquad \forall n_k, \\
& r_{n_i} + \sum_{n_j \in I(n_i)} r_{n_j} \le c_{n_i} \qquad \forall n_i, \\
& R_{min}(n_i) < r_{n_i} \qquad \forall n_i. \quad (7)
\end{aligned}$$

The associated dual problem is given by

$$\begin{aligned}
\textbf{maximize} \quad & g(\mathbf{\Lambda}) \\
\textbf{s.t.} \quad & \lambda_{n_i} \ge 0, \qquad \forall n_i \quad (8)
\end{aligned}$$

where $g(\mathbf{\Lambda}) = L(t^*, \mathbf{r}^*, \mathbf{d}^*, \mathbf{\Lambda})$ and t^*, $\mathbf{r}^*$ and $\mathbf{d}^*$ are the optimal primal variables obtained by solving the problem in (7). By rearranging the terms the problem in (7) is decomposable into the following two subproblems:

- *Node power allocation subproblem*, defined in variables r_{n_i} and d_{n_i} for controlling the node power.
- *Maximal power minimization subproblem*, defined in variable t for minimizing the maximum of the nodal powers across the network.

The two subproblems, coupled through the dual variables, are discussed in the following.

A. Node Power Allocation Subproblem

By substituting the expression for P_{n_i} in the objective function, the node power allocation subproblem is given by

$$\begin{aligned}
\textbf{minimize} \quad & \sum_{n_i} \lambda_{n_i} \Bigg(E_b^{(tx)} r_{n_i} + \left(E_b^{(tx)} + E_b^{(rx)} \right) \\
& \sum_{n_j \in I(n_i)} r_{n_j} + R \left[\left(\frac{R}{r_{n_i}} \right)^{\alpha} - 1 \right] E_b^{(comp)} + \gamma \Bigg) \\
\textbf{s.t.} \quad & \sum_{n_k \in T(n_i)} d_{n_k} \le D_{max}(n_i) \qquad \forall n_i, \\
& \frac{H}{d_{n_k}} \le r_{n_k} + \sum_{n_j \in I(n_k)} r_{n_j} \qquad \forall n_k, \\
& r_{n_i} + \sum_{n_j \in I(n_i)} r_{n_j} \le c_{n_i} \qquad \forall n_i, \\
& R_{min}(n_i) < r_{n_i} \qquad \forall n_i. \qquad (9)
\end{aligned}$$

The problem in (9) is convex in r_{n_i} and d_{n_i} and can be solved using standard techniques from convex programming. For the distributed implementation the problem is further decomposable using the similar procedure that we adopted for the original problem in (6).

B. Maximal Power Minimization Subproblem

The subproblem of maximal power minimization involving the auxiliary variables t is given by

$$\textbf{minimize} \quad \frac{1}{t} - \sum_{n_i} \lambda_{n_i} \frac{1}{t}. \qquad (10)$$

The subproblem in (10) is convex in variable t. Differentiating the objective function in (10) with respect to t and setting it to 0 leads to

$$\begin{aligned}
-\frac{1}{t^2} \left(1 - \sum_{n_i} \lambda_{n_i} \right) &= 0, \\
&\approx \epsilon, \\
t &= \sqrt{\frac{\left(\sum_{n_i} \lambda_{n_i} - 1\right)}{\epsilon}}. \qquad (11)
\end{aligned}$$

In (11) we have made an approximation using $\epsilon \ll 1$. This approximation is valid since from the practical viewpoint, the power of a node cannot go arbitrary low and a minimum nodal power P_{min} is required to ensure the network connectivity. This is ensured by introducing the constraint $\frac{1}{t} \ge P_{min}$. Using this constraint along with the result in (11) we have the solution for t given by

$$t = \min \left\{ \frac{1}{P_{min}}, \sqrt{\frac{\left(\sum_{n_i} \lambda_{n_i} - 1\right)}{\epsilon}} \right\}. \qquad (12)$$

C. Dual Problem

The dual problem in (8) is solved by using the following projected sub-gradient [16] update

$$\lambda_l(k+1) = \left[\lambda_l(k) + \beta(k) \left(P(n_i) - \frac{1}{t} \right) \right]^+. \quad \forall n_i \qquad (13)$$

In (13) $[x]^+$ is defined as $max\{0, x\}$ and $\left(P(n_i) - \frac{1}{t}\right)$ is the sub-gradient. We use a variable step size rule to update the dual variables and the step size $\beta(k)$ at each iteration is updated using the $\beta(k) = 1/\sqrt{k}$.

In case of distributed implementation, the subproblems discussed above are solved at different nodes and only the coupling dual variables λ_{n_i} are required to be exchanged among different sensor nodes. An inner sensor node does not need to communicate explicitly for obtaining the rate variables from the nodes in its subtree. This is due to the fact that the inner node can extract these rate variables from the information it relays corresponding to each of the sensor nodes in its subtree. The inner node can also extract the delay information (to obtain d_{n_i}) from the rate variables.

V. Numerical Results

To study the effect of the proposed network lifetime maximization framework on the nodal power consumption and the convergence performance of the distributed algorithm we use the example network shown in Fig. 1. Since there can be a large number of possible combinations for different values of $R_{min}(n_i)$ and $D_{max}(n_i)$ we use $R_{min}(n_i) = R_{min}, \forall n_i$ and $D_{max}(n_i) = D_{max}, \forall n_i$ without any loss of generality. Different network parameters used in the performance evaluation are tabulated in Table I.

TABLE I
NETWORK PARAMETERS USED IN THE PERFORMANCE EVALUATION.

Network parameters	Values
Transmission energy cost/bit ($E_b^{(tx)}$)	.209 μJ/bit
Reception energy cost/bit ($E_b^{(rx)}$)	.252 μJ/bit
Minimum transmission rates (R_{min})	5 Kbps
Maximum delay threshold (D_{max})	$15 - 75$ msec
Packet length H	2 Kbits
Computational energy cost/bit ($E_b^{(comp)}$)	.0023 μJ/bit
Uncompressed data rate (R)	100 Kbps
Minimum transmit power (P_{min})	0.1 mW
Maximum link transmission rate (c_{n_i})	100 Kbps
Compression parameter (α)	.6
Offset parameter (γ)	.5
Approximation parameter (ϵ)	.001

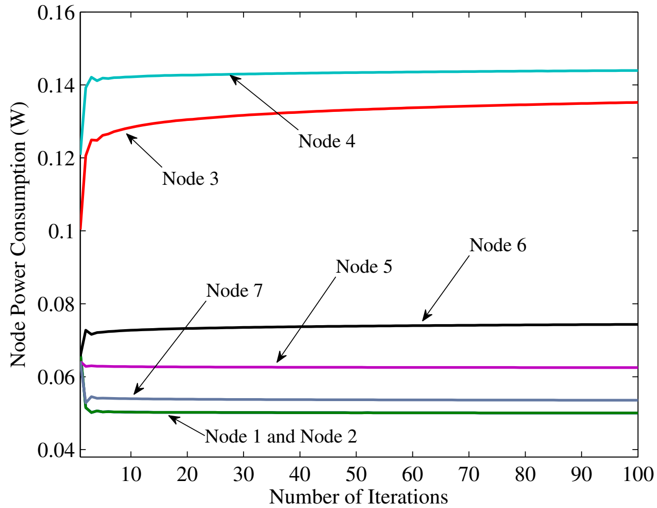

Fig. 3. The convergence performance of the distributed algorithm for nodal power consumption. The maximum delay threshold $D_{max} = 50$ msec is used in obtaining these results.

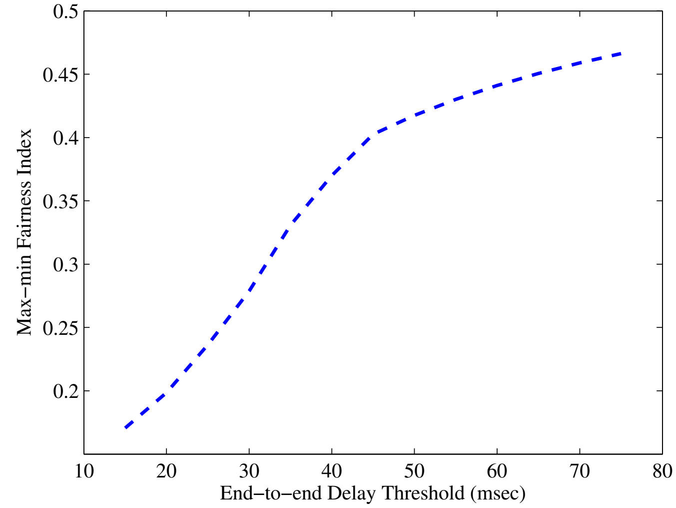

Fig. 4. Max-min fairness index as a function of maximum end-to-end delay threshold.

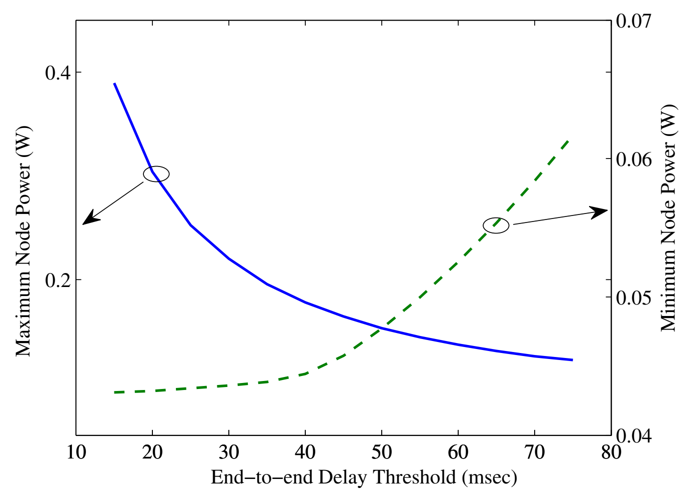

Fig. 5. Maximum and minimum nodal power consumptions as a function of maximum end-to-end delay threshold.

We first study the convergence performance of the proposed distributed algorithm for network lifetime maximization. The result in Fig. 3 shows the convergence of the node power consumption, for the example network, for a given end-to-end delay threshold.

Ideally the definition of network lifetime maximization used in this paper will lead to an optimal solution of equal node power consumptions $P(n_i), \forall n_i$. The closeness of the proposed network lifetime maximization algorithm to the ultimate objective of equal nodal power consumption can be obtained by using a measure of fairness. For that we have chosen Max-min fairness index defined as

$$\text{Max-min Fairness Index} = \frac{P_{min}}{P_{max}}, \tag{14}$$

where $P_{min} = \min\{P_{n_1}, P_{n_2}, \cdots P_{n_i}\}$ corresponds to the node with minimum power consumption and $P_{max} = \max\{P_{n_1}, P_{n_2}, \cdots P_{n_i}\}$ corresponds to the one with maximum power consumption. Fig. 4 depicts the improvement in the fairness index as a function of increasing end-to-end delay threshold. The reason for this improvement is based on the fact that at larger D_{max} inner nodes can be offloaded by reducing the transmission rates of the incoming data from the nodes in their respective subtrees. This leads to the reduction in the power consumption of the highly loaded (in terms of the amount of data the node relays towards the sink) inner nodes and an increase in the P_{comp} of the nodes in the respective subtrees (mainly the leaf nodes). This is shown in Fig. 5 where P_{max} and P_{min} are plotted as a function of increasing end-to-end delay threshold. It can be observed from the result in Fig. 5 that the improvement in the fairness index is due to simultaneous decrease in P_{max} and the corresponding increase in P_{min}. This is due to the translation of the communication load (on the highly loaded inner nodes) to the computation load (on the lightly loaded leaf nodes).

From the network viewpoint, we study the effect of end-to-end delay on the total network power consumption as well as the respective computation and communication components. These results are shown in Fig. 6. We observe that for an increase in the end-to-end delay threshold, the total network power consumption reduces when D_{max} is relatively small, but for $D_{max} > 60$ msec there is no further decrease in total network power consumption. This is because for $D_{max} > 60$ msec any reduction in communication power consumption due to smaller rates resulting from larger D_{max} is completely counterbalanced by the respective increase in the computational power consumption.

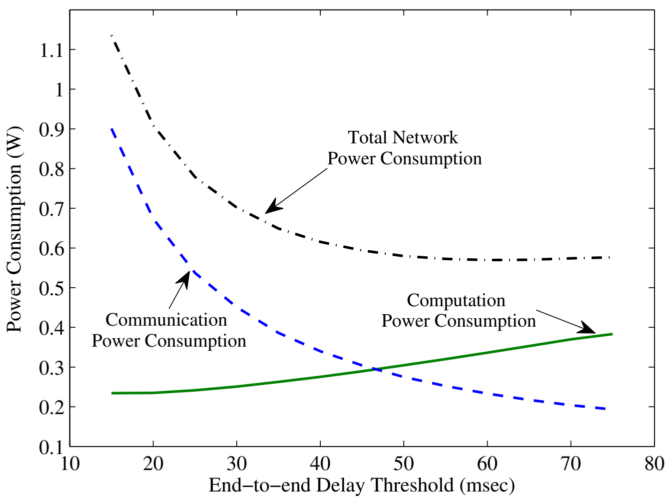

Fig. 6. Network communication and computation power consumption for different D_{max}. The accumulated communication and computation power representing the total network power consumption is also shown.

VI. Conclusions and Future Work

The issue of network lifetime maximization for wireless multi-media sensor networks is considered. The high data rates at the sensor nodes and the underlying temporal correlation in the sampled data provides an opportunity for the in-network processing. A framework to exploit these distinguishing features, while achieving an optimal tradeoff between communication and computation power consumption at the nodes is proposed. We have used dual decomposition for the distributed implementation of the algorithm. We study the network lifetime maximization as a function of end-to-end delay constraints using max-min fairness index. Our results show that an increase in the delay threshold leads to fast improvement in the fairness index for delay thresholds below 45 msec, which becomes moderate for the delay thresholds larger than 45 msec. The relative lower per bit computation cost compared to the per bit communication cost is the key factor in obtaining better performance at higher end-to-end delay thresholds. For the case when computational cost becomes comparable to the communication cost (e.g. in case of achieving high compression ratio) a further increase in the delay threshold may lead to degraded performance. In future we plan to exploit the spatial correlation, at an intermediate node with its subtree nodes observing a spatially overlapping region, which will further improve the network life time.

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