Joint Rate Control and Routing for Energy-constrained Wireless Sensor Networks

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Abstract—In the following paper, we study the tradeoff between network utility and network lifetime for energy-constrained wireless sensor networks (WSNs). By introducing a parameter $r$, we combine these two objectives into a single weighted objective, and consider rate control and routing in this tradeoff framework simultaneously. First, using the dual decomposition method, we decompose the tradeoff model into two subproblems: congestion control/routing problem and network lifetime problem, both of which interact through the dual variables for energy dissipation constraints. Based on decomposition results, we derive a partially distributed algorithm where the network lifetime is a global information. Second, we propose a fully distributed algorithm by approximating the network lifetime maximization problem by the network utility maximization (NUM) framework. Our algorithms are more competent for practical implementation than those of literatures, since we have considered more practical factors in our network model.

I. INTRODUCTION

Wireless sensor networks have been extensively applied in many scenarios, such as wildlife monitoring and forest fire alarming. The distinguishing feature of WSNs lies in the resource-constrained sensors. Each sensor node has a limited energy supply and generates information that needs to be communicated to a sink node with one hop or multiple hops. Replacing batteries on up to thousands of nodes in harsh terrain, especially in an unapproachable or hostile environment, is infeasible. Thus energy is a scarce resource in WSNs. It is imperative to design energy-aware protocols in order to prolong the operational lifetime of WSNs [1].

Since the seminal papers [2]-[3] were published, the network utility maximization (NUM) framework has been widely used to design congestion protocols. After that, multipath routing problem of wireline networks [4]-[5] and wireless networks [6] was incorporated into this framework. Recently, energy-aware routing protocols for wireless sensor networks have been designed to maximize the network lifetime [6]-[9]. In this line of works, network lifetime is defined as the period from the time instant when the network starts functioning to the time instant when the first node runs out of energy [8]. The objective is to maximize the network lifetime while guaranteeing the required traffic rate. However, since sensor nodes are assumed to have fixed source rates, it is likely that the network cannot sustain these rates for the given system resource constraints. Hence, a rigorous framework was first proposed to study the network utility-lifetime tradeoff problem in [10]. However, the subgradient based approach did not allow a fully distributed solution. At the same year, Nama et al. improved upon their earlier results by proposing a fully distributed implementation [11]. For congestion control and routing coupled subproblem, Nama et al. appended the objective with a concave regulation term involving the flow variables and introduce some lifetime variables. As a result, the coupled subproblem was vertically decomposed into a congestion control problem and a routing problem. However, this transformation is only the approximation of the original problem. In addition, extra introduced lifetime variables bring too much communication overhead.

In this paper, we study the same tradeoff problem. We jointly consider rate control and routing under the tradeoff framework. First, by dual decomposition method, we develop a partially distributed algorithm based on the decomposition result. Second, we propose a fully distributed algorithm that approximates the optimal solution of the partially distributed algorithm very well. Different from [10] and [11], we use the variable substitution method to transform the original problem into a single variable constrained optimization problem. Thus our algorithms are derived based on an equivalent transformation. Additionally, we do not need to introduce extra lifetime variables.

Our work is similar to [12]. However, there are mainly four differences. First, we remove the assumption that the network is under-loaded. Second, we consider the sensing energy that usually takes a non-negligible energy consumption in energy dissipation model. Third, our partially distributed algorithm is derived based on the dual decomposition method. Last, we describe the system model in the node-centric formulation method [13] in contrast to the link-centric formulation method [12]. The former two differences enable our algorithms to be suited to wider application scenarios. The latter two differences sharply reduce the implementation complexity of our algorithms.

The rest of the paper is organized as follows. In Section II and Section III, we set up the network model. In Section IV and Section V, both partially and fully distributed algorithms are developed for the network model. Section VI presents numerical results and Section VII concludes this paper.
II. NETWORK OBJECTIVE

We consider a WSN that consists of a set $V$ of sensor nodes which are indexed from 1 to $N$ and a single sink that collects data from these nodes. There are two main metrics on the performance of WSNs, the network lifetime and the accuracy of information received at the sink node. In the following, we will define these two metrics in a rigorous mathematical formulation.

A. Network Lifetime

In a WSN, each sensor node is usually battery driven, non-rechargeable and irreplaceable. Thus, sensor nodes have much tighter energy constraints than the sink node. Here, we focus on the energy dissipated in the sensor nodes in this paper. Let $T_v$ denote the lifetime of node $v$, $v = 1, 2, \cdots, N$, i.e., the time at which it runs out of energy.

**Definition 1**[9]. We consider a general definition of network lifetime given by a concave function of the node lifetimes. In particular, we define

$$T_{\text{net}} = f(T_1, \cdots, T_N)$$

where $f: \mathbb{R}^N \rightarrow \mathbb{R}$ is a concave function in the vector of node lifetimes.

In this paper, we just concentrate on the special case of

$$T_{\text{net}} = \min_{v \in V} (T_v) \tag{1}$$

The lifetime maximization problem maximizes the time at which the first node dies, i.e., it minimizes the maximum ratio of average power consumption to initial energy among all nodes. Thus, definition (1) balances the data flow in the network such that no node incurs a very high power consumption.

B. Network Utility

Here we use the utility function to describe the level of satisfaction attained by a source node. Different shapes of utility functions lead to different types of fairness. For example, the following family of utility functions, parameterized by $\alpha \geq 0$, is proposed in [14]:

$$U^\alpha(x) = \begin{cases} (1 - \alpha)^{-1}x^{1-\alpha} & \text{if } \alpha \neq 1 \\ \log x & \text{otherwise} \end{cases} \tag{2}$$

When $\alpha = 1$, the utility function guarantees to achieve proportional fairness; when $\alpha = 2$, then harmonic mean fairness; when $\alpha \rightarrow \infty$, then max-min fairness.

Based on the chosen utility function, we will adopt the NUM framework to study the rate allocation for WSNs. The objective function of the NUM can be formulated as

$$\sum_{v \in V} \omega_v U_v(s_v) \tag{3}$$

where $s_v$ is the rate allocation for source $v$ and $\omega_v$ is the weight associated with $U_v(s_v)$. In this way, we can achieve weighted fairness on source rates of sensor nodes.

C. Tradeoff between Network Lifetime and Network Utility

There is an intrinsic tradeoff between network lifetime and network utility. By introducing a system parameter $r \in [0, +\infty)$, we can combine these two objectives together as a single weighted objective. The weighted objective function can be obtained as follows

$$\sum_{v \in V} r\omega_v U_v(s_v) + T_{\text{net}} \tag{4}$$

Obviously, (4) degenerates to (1) for $r = 0$ and (3) for $r \rightarrow +\infty$.

III. CONSTRAINTS FORMULATION

We represent the WSN as a directed graph $G(V, L)$, where $L$ denotes the set of logical links. Let $L_{\text{out}}(v)$ denote the set of outgoing links from node $v$, $L_{\text{in}}(v)$ the set of incoming links to node $v$.

A. Flow conservation constraint

On each link $l$, let $f_l$ denote the average amount of flow destined to the sink. For the sink, we define a source-sink vector $s \in \mathbb{R}^N$, whose $v$th entry is $s_v$. Therefore, we obtain the first constraint (flow conservation law)

$$\sum_{l \in L_{\text{out}}(v)} f_l = \sum_{l \in L_{\text{in}}(v)} f_l = s_v, \ v \in V \tag{5}$$

For simplicity, we define a node-link incidence matrix $A \in \mathbb{R}^{N \times |L|}$, whose entry $A_{vl}$ is associated with node $v$ and link $l$ via

$$A_{vl} = \begin{cases} 1, & \text{if } v \text{ is the transmitter of link } l \\ -1, & \text{if } v \text{ is the receiver of link } l \\ 0, & \text{otherwise} \end{cases}$$

The equation (5) can be compactly rewritten as

$$Af = s \tag{6}$$

where $f = [f_1, \cdots, f_{|L|}]^T$, $|L|$ denotes the cardinality of link set $L$.

B. Energy Dissipation Constraint

Let $\varepsilon_s$ and $\varepsilon_r$ denote the energy consumed per bit in hardware in sensing and receiving data, respectively. We assume that all nodes have identical power dissipation characteristics in sensing and receiving. Let $\varepsilon_l^T$ denote the energy consumed per bit in transmitting on link $l$. Note that $\varepsilon_l^T$ also includes the radiated energy per bit for reliable communication of link $l$. $\varepsilon_l^T$ is given by

$$\varepsilon_l^T = \mu + \eta d_l^n \tag{7}$$

where $\mu$ is the energy cost of transmit electronics of node $v$, $\eta$ is a coefficient term corresponding to the energy cost of transmit amplifier, and $d_l$ is the distance between two terminal nodes of link $l$. $n$ is the path loss factor, $2 \leq n \leq 4$.

Then the total average power dissipated in the node $v$ is given by

$$P_{\text{avg}}^v = \sum_{l \in L_{\text{out}}(v)} \varepsilon_l^T f_l + \varepsilon_r \sum_{l \in L_{\text{in}}(v)} f_l + \varepsilon_s s_v \tag{8}$$
Let $E_v$ denote the initial energy of each sensor node $v$, then we obtain the second constraint (energy dissipation constraints)

$$\frac{E_v}{T_v} = P_v^{avg} \tag{9}$$

IV. Partially distributed algorithm

A. Dual decomposition

Next, we will combine the weighted function (4) and constraints ((6), (9)) as follows:

$$\max \sum_{v \in V} r_\omega U_v(s_v) + T_{net}$$

subject to $A_f = s$

$$P_v^{avg} \leq E_v q_v, \quad v \in V$$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{10}$$

where $c_l$ is the fixed capacity of link $l$. It is natural to add the bandwidth constraints that correspond to the last constraints in (10) into the NUM framework.

Obviously, constraint (9) is not convex, hence the problem (10) is not convex. Here, we use a technical skill to modify problem (10) into a convex function by introducing the variable $q$ satisfying $q = \frac{1}{T_{net}}$. Additionally, the objective function of problem (10) is not strictly concave in $q$, we change $q$ to $q^2$, since maximizing $-q$ is equivalent to maximizing $-q^2$. Then we get the following equivalent formulation to the problem (10):

$$\max \sum_{v \in V} r_\omega U_v(s_v) - q^2$$

subject to $A_f = s$

$$P_v^{avg} \leq E_v q_v, \quad v \in V$$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{11}$$

We introduce Lagrangian multiplier vector $\mu \in \mathbb{R}^N$. The lagrangian dual function associated with problem (10) is:

$$D(\mu) = \max_{s_v > 0} \sum_{v \in V} r_\omega U_v(s_v) - q^2 - \sum_{v \in V} \mu_v (P_v^{avg} - E_v q_v)$$

subject to $A_f = s$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{12}$$

Further, we can reformulate (12)

$$D(\mu) = \sum_{i=1}^{2} D_i(\mu)$$

where

$$D_1(\mu) = \max_{s_v > 0} \sum_{v \in V} (r_\omega U_v(s_v) - \mu_v P_v^{avg})$$

subject to $A_f = s$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{13}$$

$$D_2(\mu) = \max_{q \geq 0} \sum_{v \in V} \mu_v E_v q - q^2 \tag{14}$$

subject to $A_f = s$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{20}$$

As for subproblem (13), we cannot obtain the analytical solution. However, the objective function of (13) is a concave function since $U_v(s_v)$ is concave and $P_v^{avg}$ is linear function of $f$. Thus, problem (13) is convex optimization problem. It means that there is only a unique optimal objective value, i.e., a locally optimal solution is also a globally optimal solution.

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$$\min_{\mu \geq 0} D(\mu) \tag{15}$$

The master dual problem (15) coordinates these two separate subproblems by using the dual variable vector $\mu$.

To solve the dual problem (15), we first consider the subproblems (13)-(14). For the given $\mu$, we get the analytical solution for subproblem (14):

$$q^*(\mu) = \frac{\sum_{v \in V} \mu_v E_v}{2} \tag{16}$$

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Since $Q(f)$ is differentiable with respect to $f$, the gradient $G(f)$ exists. The gradient component $G(f_i)$ is given as follow:

$$G(f_i) = \sum_{v \in V} (r_\omega \partial U_v(s_v) - \mu_v \partial P_v^{avg} - \mu_v \partial f_i). \tag{18}$$

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B. Subgradient-based solution

Since $Q(f)$ is not strictly concave in variable $f$, $D(\mu)$ may not be differentiable with respect to $\mu$. Hence, we have to adopt subgradient method to solve the dual problem (15).

**Definition 2**[15]. Given a convex function $f: \mathbb{R}^N \rightarrow \mathbb{R}$, a vector $d \in \mathbb{R}^N$ is a subgradient of $f$ at a point $u \in \mathbb{R}^N$ if $f(v) \geq f(u) + d^T (v - u), \forall v \in \mathbb{R}^N$.

Consider any two points $\mu$ and $\bar{\mu}$, by definition (12)

$$D(\bar{\mu}) = \max_{s_v > 0} \sum_{v \in V} r_\omega U_v(s_v) - q^2 - \sum_{v \in V} \bar{\mu}_v (P_v^{avg} - E_v q_v)$$

subject to $A_f = s$

$$0 \leq f_l \leq c_l, \quad l \in L \tag{20}$$

Obviously, the dual function $D(\mu)$ has been decomposed into the above two subproblems (13)-(14), which correspond to a decomposition of the optimization problem (10), into a congestion control/routing problem and a network lifetime maximization problem, respectively.
Hence,
\[ D(\bar{\mu}) \geq \max_{s_v > 0} \sum_{v \in V} r_{\omega_v} U_v(s_v(\mu)) - q^2(\mu) - \sum_{v \in V} \bar{\mu}_v (P_{avg} v(\mu) - E_v q(\mu)) = D(\mu) + (\bar{\mu} - \mu)^T g(\mu), \]
where \( g(\mu) = [E_v q(\mu) - P_{avg} v(\mu)]_{v \in V} \in \mathbb{R}^N \). According to Definition 2, \( g(\mu) \) is a subgradient of \( D(\mu) \) at point \( \mu \). The dual variables are adjusted in opposite direction of the subgradients as follows:
\[ \mu_v(t + 1) = [\mu_v(t) - \alpha(t)(E_v q(\mu(t)) - P_{avg} v(\mu(t)))]^+ \tag{21} \]
where \( \alpha(t) \) is the step size at \( t^{th} \) iteration.

C. Implementation

Now we present our cross-layer algorithm as follows:

Algorithm 1: At each iteration \( t \)
1) Routing problem: At each iteration \( k \)
   Step 1: Each sensor node \( v \) computes \( r_{\omega_v} U_v(s_v) \) and \( \mu_v(\varepsilon_v - \varepsilon_s) \).
   Step 2: Each sensor node sends back information computed in Step 1 to its upstream neighbors.
   Step 3: Compute the rate of all links.
      For each sensor \( v \in V \) do
      1. Compute \( G(f_l(k)) \) with (18).
      2. \( f_l(k + 1) = [f_l(k) + \lambda G(f_l(k))]_0^+ \).
   end for
Step 4: Go to Step 1 until \( \{f(k)\} \) converges.
2) Network lifetime problem: The sink node acts as a central controller that collects \( \mu_v \) from all the sensor nodes. The sink node performs network lifetime computation in a central manner
\[ q(t + 1) = \frac{\sum_{v \in V} \mu_v(t) E_v}{2} \tag{22} \]
Then the sink will broadcast new \( q(t + 1) \).
3) Dual variables: For each sensor node \( v \), it updates its dual variables \( \mu_v \) according to the local variables \( f_l \) and the broadcast message \( q \)
\[ \mu_v(t + 1) = [\mu_v(t) - \alpha(t)(E_v q(t) - P_{avg} v(q(t)))]^+ \tag{23} \]

D. Convergence analysis

The flow control algorithm (19) is a gradient algorithm. Let \( F^* \) be the set of optimal solutions of problem (13). If constant step size \( \lambda \) is positive and sufficiently small, then (19) can converge to an optimal solution \( f^* \in F^* \). The algorithm (23) is a subgradient algorithm. If the stepsize \( \alpha(t) \) in (23) satisfies \( \alpha(t) \to 0 \) when \( t \to \infty \) and \( \sum_{t=0}^\infty \alpha(t) = \infty \), then \( \mu(t) \) will converge to optimal dual solutions \( \mu^* \) that solve the dual problem (15). Define \( w(t) = (f(t), q(t)) \), where \( f(t), q(t) \) are obtained by (19) and (22). Let \( W^* \) be the set of optimal solutions of problem (10). Besides, we define \( d(w(t), W^*) = \min_{w^* \in W^*} \|w(k) - w^*\| \), where \( \| \cdot \| \) denotes the Euclidian distance. Then, we have the following convergence result for Algorithm 1.

Proposition 1. If the stepsize \( \alpha(t) \) satisfies
\[ \alpha(t) \to 0(t \to \infty), \sum_{t=0}^\infty \alpha(t) = \infty \]
and there exists a positive and sufficiently small constant \( \lambda \), then
\[ \lim_{t \to \infty} d(w(t), W^*) = 0. \]

Comments 1: Though formula (19) and formula (23) are distributed, formula (22) requires the values of the Lagrange multipliers \( \mu_v \) to be communicated to the sink node at each iteration and the variable \( q \) needs to be broadcast to every sensor node. Therefore, Algorithm 1 is actually a partially distributed algorithm.

V. FULLY DISTRIBUTED ALGORITHM

A. Distributed approximation

Motivated by the fact that max-min rate allocation problem can be approximated in a distributed way with NUM framework as (2), we introduce an utility function \( W_v^\beta(q_v) \)
\[ W_v^\beta(q_v) = \frac{1}{\beta + 1} q_v^{\beta+1}. \tag{24} \]
where \( q_v = 1/E_v \). When \( \beta \to \infty \), max \( \min_{v \in V} T_v \) can be well approximated by \( -\sum_{v \in V} W_v^\beta(q_v) \) [14].

By choosing a sufficiently large \( \beta \), we study the following approximation version of problem (11)
\[ \max_{v \in V} \sum_{v \in V} (r_{\omega_v} U_v(s_v) - W_v^\beta(q_v)) \]
s.t. \( Af = s \)
\[ E_v q_v = P_{avg} v(q_v), v \in V \]
\[ 0 \leq f_l \leq c_l, l \in L \tag{25} \]
Similar to formula (17), both \( s_v \) and \( q_v \) are dummy variables, we define \( Q_1(f) = \sum_{v \in V} (r_{\omega_v} U_v(s_v) - W_v^\beta(q_v)) \). Since both \( U_v(s_v) \) and \( W_v^\beta(q_v) \) are twice differentiable, \( Q_1(f) \) is differentiable. Therefore, the gradient \( G(f) = \nabla Q_1(f) \) exists and its component is given by
\[ G(f_l) = \sum_{v \in V} (r_{\omega_v} \frac{\partial U_v(s_v)}{\partial f_l} - q_v^\beta \frac{\partial q_v}{\partial f_l}). \tag{26} \]
Next, we will carry out the fully distributed algorithm for (25).

B. Implementation

Algorithm 2: At each iteration \( t \)
1) Each sensor node \( v \) computes \( r_{\omega_v} U_v(s_v) \) and \( q_v^\beta \frac{\partial q_v}{\partial f_l} \).
2) Each sensor node sends back information computed in Step 1 to its upstream neighbors.
3) Compute the rate of all links.
   For each sensor \( v \in V \) do
      1. Compute \( G(f_l(t)) \) with (26).

2. \( f_i(t + 1) = [f_i(t) + \lambda G(f_i(t))]_{c_i} \).
end for
end for

**Proposition 2.** Let \( F^* \) be the set of optimal solutions of problem (25). If constant stepsize \( \lambda \) is positive and sufficiently small, then Algorithm 2 can converge to an optimal solution \( f^* \in F^* \).

To speed up the convergence rates of Algorithm 1 and 2, we adopt a variation of gradient algorithm that was first used by [2]. At each iteration \( t \), the increment flow rate for \( f_i \) is updated by

\[
\Delta_i(t) = \lambda \frac{f_i(t)}{rU_v(s_v)} G(f_i(t))
\]

(27)

when flow rate \( f_i \) becomes zero, it will be zero forever. Thus, we assume that each flow has a small flow rate requirement \( \epsilon \). The flow rate \( f_i \) is updated as

\[
f_i(t + 1) = [f_i(t) + \Delta_i(t)]_{c_i}
\]

(28)

In numerical results section, we let \( \epsilon = 1 \).

**Comments 2:** Both Algorithm 1 and 2 in this paper do not require feedback from inside the network, while algorithms in [12] require the sum of the information along the path of the sensor node. In practical scenarios, feedback signals can result in inevitable time delay, moreover, they are vulnerable to the unreliable wireless channels. Thus, our algorithms are more robust than those of [12].

**VI. NUMERICAL RESULTS**

In this section, both the partially and the fully distributed algorithms are simulated over a network that is composed of ten sensor nodes and a sink node as shown in Figure 1. The locations of sensor nodes and the sink node are randomly generated over a 150m \( \times \) 150m square area.

Each node is assumed to have a maximum communication radius of 60m. Here, we use the energy dissipation parameters in [12], where \( \epsilon_v = 50nJ/bit \), \( \epsilon_r = 50nJ/bit \), \( \mu = 50nJ/bit \), \( \eta = 0.0015pJ/bit/m^4 \), path loss factor \( n = 4 \). We assume a fixed link capacity \( C_1 = 250kbps \), \( l \in L \), and each node is assumed to have equal initial energy of 5J. The weight \( w_v \) of each sensor node \( v \) is set to 1. Here we let \( U_v(s_v) = ln(s_v) \).

Figure 2 presents the convergence property of Algorithm 1. Here we set \( r = 1.0 \times 10^{-6} \), and we use the diminishing stepsize rule \( \alpha(t) = \alpha(0)/t \). Figure 2 shows that dual variables and source rates converge fast despite the oscillations at beginning. In this case, all sensor nodes, except sensor 1 and sensor 10, almost converge to the same optimal solution. In order to show the evolution clearly, we list five sensor nodes of them for simplicity. For Algorithm 2, Figure 3 shows the convergence result. Here we set \( r = 1.0 \times 10^{-35} \), \( \beta = 10 \), and \( \lambda = 0.05 \).

In Figure 4, there are two tradeoff curves between the network utility and network lifetime. One is the tradeoff curve as the factor \( r \) ranges from \( r = 1.0 \times 10^{-7} \) to \( r = 1.0 \times 10^{-5} \) for Algorithm 1, while the other is the tradeoff curve as the factor \( r \) ranges from \( r = 1.0 \times 10^{-50} \) to \( r = 1.0 \times 10^{-30} \) for Algorithm 2 with \( \beta = 10 \). We observe that when \( r \geq 1 \times 10^{-5} \) (Algorithm 1), the tradeoff between network utility and network lifetime is constant. That is due to the fact that some links have been saturated.

From Figure 4, we can also observe that the same \( r \) can result in different optimal objective values and solutions from these two algorithms. We use the method [12] to evaluate the impact of parameter \( \beta \) on Algorithm 2. Approximation ratio is defined as the ratio between the network lifetime of Algorithm 2 with respect to that of Algorithm 1. In Figure 5, when \( \beta \geq 6 \), \( \text{ratio} \geq 0.95 \), Algorithm 2 can approximate Algorithm 1 very well.

**VII. CONCLUSION AND FUTURE WORK**

We have studied the tradeoff between network utility and network lifetime for energy-constrained WSNs. Considering rate control and routing simultaneously, we have derived two algorithms: a partially distributed algorithm and a fully distributed algorithm. Compared with those literatures, our work has two features: 1. We consider more practical factors in our model; 2. The complexity of implementation has been sharply reduced due to the node-centric formulation method.

There are several extensions of our work. Our work can be easily extended to the case of multicommodity flows and multiple sinks. In wireless networks, the link capacity is not fixed any more when transmission scheduling and power...
In future, we will incorporate MAC/Physical layer issues into our network utility-lifetime tradeoff framework as well.

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