A Distributed Algorithm for Joint Sensing and Routing in Wireless Networks with Non-Steerable Directional Antennas

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[1] ***Abstract*— In many energy-rechargeable wireless sensor networks, sensor nodes must both sense data from the environment, and cooperatively forward sensed data to data sinks. Both data sensing and data forwarding (including data transmission and reception) consume energy at sensor nodes. We present a distributed algorithm for optimal joint allocation of energy between sensing and communication at each node to maximize overall system utility (i.e., the aggregate amount of information received at the data sinks). We consider this problem in the context of wireless sensor networks with directional, non-steerable antennas. We first formulate a joint data-sensing and data-routing optimization problem with both per-node energy-expenditure constraints, and traditional flow routing/conservation constraints. We then simplify this problem by converting it to an equivalent routing problem, and present a distributed gradient-based algorithm that iteratively adjusts the per-node amount of energy allocated between sensing and communication to reach the system-wide optimum. We prove that our algorithm converges to the maximum system utility. We quantitatively demonstrate the energy balance achieved by this algorithm in a network of small, energy-constrained X-band radars, connected via point-to-point 802.11 links with non-steerable directional antennas.**

I. Introduction

Wireless sensor networks have been proposed for myriad applications, ranging from environmental monitoring, to surveillance/security, to industrial control [1]. Sensing and communication are two tasks that must be performed by any such wireless sensor network. The sensing task can be performed either passively (via in-situ observation) or actively (via remote-sensing technologies such as radar, lidar, or sonar), with these latter sensing modalities typically requiring more sensor node resources. Communication can be performed over a variety of wireless radios, ranging from commodity 802.11 (with either longer-distance directional antennas or shorter-distance omni-directional antennas) to specialized mote-based radios. A characteristic of these networks, however, is that they are often energy-constrained, and thus must achieve a balance of how energy is expended among sensing, communication, and computation. This balance needs to be achieved not just locally at an individual node, but *systematically,* since sensor network nodes must interact and collaborate with each other to perform the sensor network's task.

[1]This work was performed while Chun Zhang was a student at the University of Massachusetts, Dept. Computer Science.

In this paper, we present a distributed algorithm for optimal joint allocation of energy (a resource) between *sensing* and *communication* tasks within a sensor network. To make the problem concrete, we consider a sensing network of collaborating low-powered X-band magnetron radars for meteorological sensing, connected via an 802.11 mesh network with (non-steerable) directional antennas [2]; the energy constraint is imposed by the amount of solar energy that can be harvested and stored from the environment [3]. From a sensing standpoint, we are interested in how much data should be ingested at each individual node, taking into account the amount of energy needed to acquire this data. From the communication standpoint, we are interested in how to route data to a sink, taking into account the energy needed for frame transmission and reception over 802.11 links; note that routing is coupled with link capacity assignment, since, for example, little energy would be needed to provide capacity on a seldomly-used link. The sensing/routing problems are tightly coupled, since it is useless to expend energy acquiring data if there is insufficient energy to route that data to its destination. The overall objective of the distributed resource allocation algorithm is to maximize the overall sensor network system utility, the aggregate rate at which sensed information is delivered to sinks. A distributed solution is especially important for wireless sensor networks, given the unpredictable nature of environmental changes, the need to respond to local changes (e.g., in the amount of energy need to realize a given link capacity as a result of environmental changes), and the lack of centralized control.

In this paper, we formulate the sensor network system utility optimization problem as a joint sensing rate control, data routing and energy allocation problem. We first map the combined sensing/routing problem into a unified routing problem [4], using so-called dummy nodes to accommodate the (initially unknown) sensed-data input rates. To solve the resulting two-layer (routing, energy allocation) problem, instead of separating the joint optimization problem into subproblems coordinated by a master dual problem as [5] [6] [7], we use a penalty function approach [8], in which the virtual costs are directly derived from per-node energy consumption. Our distributed algorithm extends Gallager's distributed routing optimization algorithm for wired networks [9]. In traditional

1-4244-0593-9/06/$20.00 ©2006 IEEE

wired network formulations of the resource allocation problem [9] [10] [11], the resource are link-level capacities, with a link's cost increasing as the link-level resource is consumed. In contrast, we consider energy as a node-level resource, with a node energy penalty cost that increases as energy is consumed on a node's incoming links (data sending) and outgoing links (data receiving). By generalizing [9]'s cost function from link-level to node-level, our energy penalty cost function reflects the node-level energy consumption. Our approach to routing also shares similarities with Xue *et al.*'s distributed routing algorithm for wireless networks with given, fixed traffic demands [12]. We prove that our generalized distributed algorithm will converge to the optimal system-wide energy allocation between data sensing and data routing. Using our algorithm, we quantitatively demonstrate the energy balance in a network of small, energy-constrained X-band radars, connected via point-to-point 802.11 links with directional antennas using simulation. Our results demonstrate that different nodes in the energy-constrained network should indeed strike a different balance among sensing and communication, e.g., with nodes nearer data sinks expending more energy in communication than nodes near the edge of the sensor network.

Previous work [5] [13] [6] [14] [15] [7] [12] on maximizing network system utility in wireless communication networks do not consider traffic demand generation (i.e., the sensing activity needed to gather and ingest data) as a resource-consuming processes. Assuming that the network system utility is the sum of all data flow utilities, each of which is a concave and increasing function of the flow rate, these works formulate and solve the problem as a convex optimization problem. However, in wireless sensor networks, where the energy used for sensing is not negligible, we demonstrate that energy allocation between both sensing and communication must be considered.

This paper is organized as follows. Section II reviews related work. In section III, we introduce our system model, and formalize the joint data sensing, data routing, and energy allocation problem to maximize the network system utility. In section IV, we map the data sensing, data routing, and energy allocation optimization problem into a data routing, and energy allocation problem. In section V, we present a distributed formulation for this optimization problem. In section VI, we propose a distributed algorithm to solve this problem by generalizing Gallager's result [9]. In section VII, we illustrate the balance achieved between sensing and communication by considering a scenario in which sensor network nodes must balance their energy expenditures among sensing with low-power X-band radars, and communication over point-to-point 802.11 wireless links. We conclude this paper with a discussion of possible extensions, a summary of this work and some directions for future research.

II. Related Work

The joint rate control, routing and resource allocation problem in wireless networks has been studied by several groups from different angles. Dual decomposition is typically used to separate the joint optimization problem into subproblems, coordinated by a master dual problem, in different ways. In [5], by introducing a price on each *link*, the authors decompose the joint optimization problem into a network flow subproblem, which solves the rate control and routing problems given link prices, and a resource allocation subproblem, which maximizes the network-wide gain. However, no distributed algorithm is developed to solve the two subproblems. In [6], Lin et al., instead, introduced a price on each *node* for forwarding traffic to each destination. The problem is decomposed into a rate control subproblem, and a joint routing and scheduling subproblem. While the rate control subproblem can be solved locally by each node, the routing and scheduling subproblem is solved by a centralized algorithm. The impact of an approximate scheduling algorithm was investigated in [13]. In [7], a similar approach is taken to study the joint optimization problem with a node-exclusive interference model in which two links sharing a common node cannot transmit or receive simultaneously. Here again, the scheduling problem, essentially a matching problem, is solved in a centralized fashion. A distributed approximate algorithm was presented in the paper. Our approach differs from this earlier work in the following ways: a) we explicitly take into account energy consumption in sensing; b) we consider energy consumption in both data transmission and data reception in wireless networks with non-steerable directional antennas. We develop a fully distributed algorithm to solve the joint sensing rate control, data routing and energy allocation problem; c) instead of adopting the dual decomposition approach, we introduce the notion of a virtual price, derived from an energy consumption penalty function, to directly regulate both sensing and routing. Compared to the dual approach, our approach responds more quickly to environmental changes and avoids energy consumption overflow. Our virtual price approach is similar to the shadow price approach developed in [10] [11] for network rate control. While we use the virtual price to regulate energy allocation on each node, the shadow price in [10] [11] is used to regulate rate allocation on each link. In their setting, each user employs one or multiple fixed routes and determines how much to send to maximize network-wide utility under capacity constraints on all links. In our setting, each node can employ any set of possible routes to reach the sink with the goal of maximizing network-wide sensing utility under energy constraints on all nodes. The joint scheduling and congestion control problem has also been studied for multi-hop wireless networks in [14] and cellular networks in [15]. They assume user routes are fixed and propose a fair resource allocation consisting of a distributed scheduling algorithm and an asynchronous congestion control algorithm for a node-exclusive interference model.

III. System Model and Problem Formulation

For ease of reading, we list all notations in Table I. We model the wireless sensor network by a directed graph $G = (V, L)$ where V is the set of nodes, and L the set

TABLE I
NOTATIONS

G	graph	V	$n+1$ node set
L	link set	0	sink
$L_I(i)$	links terminate at i	$L_O(i)$	links emanate from i
$L(i)$	$L_I(i) \cup L_O(i)$		
$\mathcal{P}_i$	power budget at i	p_i	power usage at i
P_i^S	sensor-on power at i	p_i^S	sensing power usage
P_{ik}^O	link-on power at i	p_{ik}^O	sending power usage
P_{ik}^I	link-on power at k	p_{ik}^I	receiving power usage
τ_i	sensor-on time fraction	τ_{ik}	link-on time fraction
S_i	sensor-on rate at i	s_i	average sensing rate
$\rho_{ik}F_{ik}$	link-on goodput	f_{ik}	average link goodput
Z	overall power penalty	z_i	power penalty function
D	overall link penalty	d_{ik}	link penalty function
U	utility function	Y	cost function
A	transformed objective		
R_i	traffic initiated $i \to 0$	t_i	all traffic $i \to 0$
ϕ_{ik}	routing fraction $i \to k$	η	step size to adjust ϕ
T	length of period	$\mathcal{E}$	energy budget every T

of directed lossy links. Each directed link is implemented by a pair of dedicated radios and non-steerable directional antennas at two end nodes. We assume the data transmission over different links are interference-free. First, we assume that the data transmission over links without common nodes are interference-free due to the fact that directional antenna narrows its beamwidth of the main lobe to the desired direction only. Second, we assume that the data transmission over links with common nodes are interference-free. The interference arising from sidelobes/backlobes can be resolved/mitigated for low-degree network, by placing links with common nodes on non-overlapping/partial-overlapping channels (802.11a offers 12 non-overlapping channels, while 802.11b offers 3) with directional antennas separated by 1 meter [16] [17]. Now we focus on the case where the network has only one data sink. See [18] for generalization to multiple sink case. Let 0 denote the single sink node in V, and $1, 2, \ldots, n$ denote non-sink nodes. Let $(i,k) \in L$ represent a directional link from node i to node k. For node i, we let $L_I(i)$ denote the set of links that terminate at node i, and $L_O(i)$ denote the set of links that emanate from i. We denote $L(i) = L_I(i) \cup L_O(i)$ as the set of links adjacent to node i.

Each non-sink sensor node consists of three major components: a sensor, a rechargeable battery, and non-steerable directional antennas. We can think of each node operating in a periodic manner. Within each time period (length T), *(i)* the sensor collects data from its environment, and *(ii)* locally-sensed data and the data the node receives from its upstream neighbors are sent out to its downstream neighbors through directional antennas. To save energy, a sensor/link is assumed to be turned off when no data is being sensed/transmitted. Sensing and data transmission are powered by a solar-rechargeable battery that is continuously charged by a solar panel. In a real environment, a solar panel collects energy at a variable rate. We denote $\mathcal{P}_i$ as the average rate of energy collection over a long time duration, which in turn determines the power supply budget of $\mathcal{P}_i$ for sensing and data communication. (Note: depending on its capacity, the battery can support an instantaneous power consumption rate higher than $\mathcal{P}_i$. The power budget is thus in an average sense and conservatively ensures that the total energy consumption within each period is bounded by the energy generation.) For every period, the energy budget is $\mathcal{E}_i = \mathcal{P}_i T$.

When the sensor of node i is turned on, the data is sensed at fixed rate S_i (referred to as the sensor-on data rate), with fixed power P_i^S consumed at node i (referred to as the sensor-on power). We have,

$$P_i^S = \alpha_i^S S_i \tag{1}$$

where α_i^S is a node-dependent constant.

The sensor at node i is turned on/off to control the amount of sensed data. Let $0 \le \tau_i \le 1$ be the fraction of time that the sensor of node i is on during each period. The average sensing rate at node i, s_i, is

$$s_i = \tau_i S_i \le S_i \tag{2}$$

Within each period, for node i, let p_i^s be the average power allocated for sensing. Combined with equation (1), we have

$$p_i^S = \tau_i P_i^S = \alpha_i^S s_i \tag{3}$$

Each directed link (i,k) is implemented by a pair of non-steerable antennas. When link (i,k) is on, the data is transmitted at fixed raw data rate F_{ik} (referred to as the link-on data rate), with fixed power P_{ik}^O consumed at sender i (referred to as the link-on sender power), and P_{ik}^I consumed at receiver k (referred to as the link-on receiver power). We have,

$$\begin{aligned} P_{ik}^O &= \alpha_{ik}^O F_{ik} & (4)\\ P_{ik}^I &= \alpha_{ik}^I F_{ik} & (5)\end{aligned}$$

where α_{ik}^O and α_{ik}^I are link-dependent constants. Due to noise and multipath characteristics of wireless links, packets may get lost during transmission. We use ρ_{ik} to denote the link (i,k) goodput probability, the link-on goodput of link (i,k) is $\rho_{ik}F_{ik}$.

Link (i,k) is turned off when no data are to be transmitted over the link. Let $0 \le \tau_{ik} \le 1$ be the fraction of time that link (i,k) is on for every period. The average goodput over link (i,k), f_{ik}, is calculated as follows.

$$f_{ik} = \tau_{ik}\rho_{ik}F_{ik} \le \rho_{ik}F_{ik} \tag{6}$$

At non-sink nodes, flow conservation constraints require that the aggregate outgoing link goodput rates equal the sum of the incoming goodput rates (locally sensed data plus incoming transmissions):

$$\sum_{(i,k)\in L_O(i)} f_{ik} - \sum_{(l,i)\in L_I(i)} f_{li} \;=\; s_i, \quad i \neq 0 \tag{7}$$

Within each period, let p_{ik}^O and p_{ik}^I be the average power allocated for transmitting and receiving over link (i,k) respectively. Combined with equations (4)(5), We have,

$$\begin{aligned} p_{ik}^O &= \tau_{ik}P_{ik}^O = \alpha_{ik}^O f_{ik}/\rho_{ik} & (8)\\ p_{ik}^I &= \tau_{ik}P_{ik}^I = \alpha_{ik}^I f_{ik}/\rho_{ik}. & (9)\end{aligned}$$

Then the average overall power consumption at node i is

$$p_i = p_i^S + \sum_{(l,i)\in L_I(i)} p_{li}^I + \sum_{(i,k)\in L_O(i)} p_{ik}^O \quad (10)$$

Clearly, p_i must be less than or equal to the power budget $\mathcal{P}_i$. Therefore,

$$p_i \le \mathcal{P}_i, \quad i \in V \quad (11)$$

As shown in Figure 1, our goal is to design a joint sensing rate control, data routing, and energy allocation mechanism to maximize the system utility: the aggregate rate at which sensed *information* is delivered to the data sink. We distinguish here between data and information in the following sense. Let s_i be the rate at which sensed data from sensor node i is delivered to the sink 0. A utility function $U_i(s_i)$ quantifies the *value* of this data to the data-consuming applications. We assume that U_i is a concave and increasing function, reflecting the decreasing marginal returns of receiving more data. Our goal is to maximize utility, rather than the rate at which data is delivered.

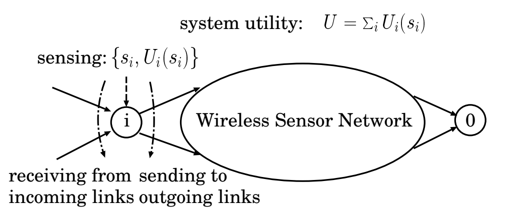


Fig. 1. Maximizing the utility of a wireless sensor network

The joint sensing rate control, data routing and energy allocation problem is then formulated as follows:

Given: $G = (V, L)$, power budget $\mathcal{P}$, sensor/link on-rate S, F and on-power P^S, P^I, P^O, goodput probability ρ
Maximize: network sensing utility $U = \sum_i U_i(s_i)$
Constraints:
1) Flow conservation. See (7).
2) Power constraint. See (11).
3) Sensor/link capacity constraint. See (2)(6).

Given that the utility function U is concave and increasing, the above problem can be solved as a convex optimization problem in a centralized manner. In this chapter, we are interested in a distributed solution. We first map the combined sensing/routing problem into a single unified routing problem, using so-called dummy nodes to accommodate the (initially unknown) sensed-data input rates. To solve the resulting two-consideration (routing, power allocation) problem, we use a penalty function approach, in which the virtual costs are directly derived from node-level energy utilization. Then we solve the routing/power-allocation problem by generalizing Gallager's distributed algorithm for wired networks [9]. Note that the optimal solution is not affected by the length of the period T. However, as $T \rightarrow 0$, the data rates and energy consumption rates are smoothed out to be constant. In practice, it is easier to for intermediate nodes to handle a constant flow than a bursty flow. In the following, we assume that T is small enough to achieve smoothed data flow rates.

IV. Simplification: from three-considerations to two-considerations

Now we simplify the three-consideration (sensing rate control, data routing, energy allocation) optimization problem defined in III by mapping it to a two-consideration (data routing, energy allocation) optimization problem with fixed traffic demands. We do so by introducing additional dummy nodes, and dummy links as shown in Figure 2.

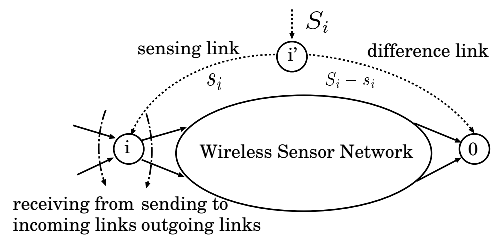


Fig. 2. Mapping from three-layer to two-layer problem

For each non-sink node $i \in V$, we introduce a dummy node $i' = i + n$. [2] We also add a dummy sensing link (i', i), and a dummy difference link $(i', 0)$. A fixed-rate traffic demand enters the dummy node i' at rate S_i, which is equal to the maximum achievable sensed data rate of node i. At node i', traffic arrives at rate S_i, and is forwarded to sink 0 at rate s_i over link (i', i) , and rate $S_i - s_i$ over link $(i', 0)$. The utility to maximize $U = \sum_i U_i(s_i)$ corresponds to utility of data routed over link (i', i). We can equivalently minimize the utility loss over link $(i', 0)$. i.e., $\min Y = \sum_i Y_i(S_i - s_i)$ where $Y_i(x) = U_i(S_i) - U_i(S_i - x)$. Since the utility function U_i is a concave and increasing function, the cost function Y_i is a convex and increasing function.

We assume that the dummy node i' always has infinite power. i.e.,

$$\mathcal{P}_{i'} = \infty \quad (12)$$

For link (i', i), let the link-on data rate be S_i, the link-on sender power be 0, the link-on receiver power be P_i^S, and the goodput probability be 100%. i.e.,

$$F_{i'i} = S_i, \quad P_{i'i}^O = 0, \quad P_{i'i}^I = P_i^S, \quad \rho_{i'i} = 100\% \quad (13)$$

For link $(i', 0)$, let the link-on data rate be S_i, the link-on sender power be 0, the link-on receiver power be 0, and the goodput probability be 100%. i.e.,

$$F_{i'0} = S_i, \quad P_{i'0}^O = 0, \quad P_{i'0}^I = 0, \quad \rho_{i'0} = 100\% \quad (14)$$

The sensing rate at node i, s_i, then corresponds to the goodput rate over link (i', i), $f_{i'i}$, where

$$f_{i'i} = \tau_{i'i} F_{i'i} \quad (15)$$

where $\tau_{i'i}$ is the fraction of time that dummy sensing link (i', i) is on.

[2] In this chapter, we use i' to denote non-sink node i's corresponding dummy node. i.e., $i' = i + n$

We now formally map the original three-consideration optimization problem into a joint data routing and resource allocation problem with fixed traffic demands. Let $\mathcal{V} = \{0, 1, ..., n, n+1, ..., 2n\}$ denote the expanded node set, and $\mathcal{L} = L \cup \{(i', i), (i', 0) | i \in V - \{0\}\}$ the expanded link set. We use $R = \{R_1, \ldots, R_{2n}\}$ to denote the traffic demand, where R_i is the average data rate originated from node i destined to sink 0. We have,

$$R_i = 0, \quad i \in \{0, 1, ..., n\} \tag{16}$$

$$R_{i'} = S_i, \quad i' \in \{n+1, ..., 2n\} \tag{17}$$

Given fixed traffic demand R, the flow conservation constraint is expressed:

$$\sum_{(i,k) \in L_O(i)} f_{ik} - \sum_{(l,i) \in L_I(i)} f_{li} = R_i, \quad i \neq 0 \tag{18}$$

We use p_i to denote the overall power consumption of node i . Since there is no sensing operation at node i (recall that data sensing at node i is mapped to data communication over sensing link (i', i)), we have

$$p_i = \sum_{(l,i) \in L_I(i)} p^I_{li} + \sum_{(i,k) \in L_O(i)} p^O_{ik} \tag{19}$$

It is straightforward to see that the joint sensing rate control, data routing, and energy allocation problem defined in III is equivalent to the joint data routing and energy allocation problem defined as follows:

> **Given:** network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, power budget $\mathcal{P}$, link on-rate F and on-power P^I, P^O, goodput probability ρ, fixed demand R
> **Minimize:** Cost $Y = \sum_{(i',0) \in \mathcal{L}} Y_i(f_{i'0})$.
> **Constraints:**
> 1) Flow conservation. See (18).
> 2) Power constraint. See (11).
> 3) Link capacity constraint. See (6).

In this paper, we introduce convex and increasing penalty functions to replace the power constraints, and link capacity constraints. We use power penalty functions $z_i(p_i)$ at each node $i \in \{1, \ldots, n\}$ to replace power constraints; and link capacity penalty functions $d_{ik}(f_{ik})$ at each link $(i, k) \in L$ to replace link capacity constraints. We have,

$$\lim_{p_i \to P_i} z_i(p_i) \to \infty, \quad \{1, \ldots, n\} \tag{20}$$

$$\lim_{f_{ik} \to \rho_{ik} F_{ik}} d_{ik}(f_{ik}) \to \infty, \quad (i, k) \in L \tag{21}$$

Let $D + Z = \sum_{(i,k) \in L} d_{ik}(f_{ik}) + \sum_{i \in \{1,...,n\}} z_i(p_i)$ be the network overall penalty cost. Then the problem becomes:

> **Given:** network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, power budget $\mathcal{P}$, link on-rate F and on-power P^I, P^O, fixed demand R
> **Minimize:** Cost $A = Y + \epsilon(D + Z)$.
> **Constraints:** Flow conservation. See (18).

In order to design a distributed algorithm, we further decompose cost A into node-level local costs. The node i cost, A_i, is defined as follows.

$$\begin{aligned} A_i &= \epsilon z_i(p_i) + \sum_{(i,k) \in L_O(i)} \epsilon d_{ik}(f_{ik}), \quad i \in \{1, \ldots, n\} \\ A_i &= Y_{iw}(f_{iw}), \quad i \in \{n+1, \ldots, 2n\} \end{aligned} \tag{22}$$

Therefore,

$$A = \sum_i A_i \tag{23}$$

The use of penalty functions can result in an allocation that is not strictly identical to the optimal solution to the original problem before the penalty function was introduced. However, when $\epsilon \to 0$, this standard approach results in a solution that is arbitrarily close to the optimal solution of the initial problem formulation [8]. A penalty function may also prevent a node energy (or a link capacity) from being completely allocated. In practice, such remaining energy (or capacity) could be used to better accommodate the changing demand, or be used for faster recovery in the case of node or link failures.

V. Distributed Problem Formulation for Joint Routing and Energy Allocation

In the previous section, the joint routing and energy allocation problem formulation used flow rates f as the optimization control variables. However, these flow rates f are network wide information: not completely known at each node. In order to solve this problem using a distributed algorithm, we reformulate the problem using local routing fractions as control variables.

Let t_i be the total expected traffic rate at node $i \in \mathcal{V}$. Thus t_i includes both R_i and traffic from other nodes that is routed through i. Let ϕ_{ik} be the fraction of t_i that is routed over link (i, k). Since t_i is the sum of the data rate entering the network at i and the traffic routed to i from other nodes,

$$t_i = R_i + \sum_l t_l \phi_{li} \tag{24}$$

$$f_{ik} = t_i \phi_{ik} \tag{25}$$

Equation (24) implicitly expresses the conservation of flow at each node: the traffic rate into a node destined for sink 0 is equal to the traffic rate out of the node destined for sink 0. Next, we define ϕ in the same ways as in [9] to ensure that equation (24) has a unique solution of t given R and ϕ.

Definition : A routing variable set ϕ for network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$ with sink node 0 is a set of nonnegative numbers ϕ_{ik}, $i, k \in \mathcal{V}$, satisfying the following conditions.

1) $\phi_{ik} = 0$ if $i = 0$, or $(i, k) \notin \mathcal{L}$,
2) $\sum_k \phi_{ik} = 1$ if $i \neq 0$,
3) $\forall i \neq 0$, there is a routing path from i to 0, which means there is a sequence of nodes, $i, k, l, \ldots, m$ such that $\phi_{ik} > 0$, $\phi_{kl} > 0$, $\ldots$, $\phi_{m0} > 0$.

Theorem 5.1: Let a network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$ have input set R and routing variable set ϕ. Then the set of equations (24) has a unique solution for t. Each component t_i is nonnegative and continuously differentiable as a function of R and ϕ. (Proved in [9])

The joint data routing and energy allocation problem is reformulated using routing variable Φ as control variables:

Given: network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$, power budget $\mathcal{P}$, link on-rate F and on-power P^I, P^O, fixed demand R
Minimize: Cost $A = \sum_i A_i$.
Constraints: Flow set f is implemented by routing variable set ϕ.

Next, we propose a distributed algorithm to solve the above problem. This algorithm requires each node to make its own local energy allocation decision and construct its own routing tables based on periodic update information from its neighbors.

VI. Distributed Algorithm for Joint Routing and Energy Allocation

Now we solve the joint routing and energy allocation optimization problem by generalizing Gallager's distributed algorithm [9]. We note that while Gallagers algorithm needs only consider the rate of flows at *individual link* (due to its assumption of a wired network, and the goal of minimizing delay), in wireless networks, we must further consider both incoming and outgoing links at *each node*, since node energy is expended in both sending and receiving packets. We solve this problem in an iterated two-step process. We first solve this optimization problem in the case of a fixed set of routes (thus fixed data flow). With a fixed set of routes, the energy allocation problem is then decoupled so that each node independently allocates energy to satisfy the data flow. In addition, each node also locally calculates the marginal cost with respect to link data rates. These marginal cost then drive the global routing optimization similar in spirit to [9].

A. Power Allocation for Fixed Data Flow f

With fixed route set ϕ (thus fixed f), each node i requires power $p^O_{ik}(f_{ik})$ on outgoing link (i,k) for data transmission, and power $p^I_{li}(f_{li})$ on incoming link (l,i) for data reception. From equations (6)(8)(9), power allocation p_i is determined by flow rates f (or data routing ϕ). Combined with equation (22), the objective function A to minimize can be viewed solely as a function of flow rates f (or routing variables ϕ). Next, we use $A^f(f) = \sum_i A^f_i(f)$ (or $A^\phi(\phi) = A^\phi_i(\phi)$) denote $A = \sum_i A_i$ as a function of f (or ϕ).

While optimizing energy to satisfy a fixed data flow f, each node i also locally calculates the marginal cost with respect to the link data rates $\partial A^f_i(f)/\partial f_{kl}$, $(k,l) \in L(i)$. An increase of data flow f_{kl} requires a concomitant increase of energy consumption at both sender node k and receiver node l, which results in the increase of cost at both sender node k and receiver node l. Therefore, the marginal global cost with respect to the link data rate of link (k,l), $\partial A^f(f)/\partial f_{kl}$, is calculated as the sum of the marginal node cost over two end nodes k and l.

$$\frac{\partial A^f(f)}{\partial f_{kl}} = \frac{\partial A^f_k(f)}{\partial f_{kl}} + \frac{\partial A^f_l(f)}{\partial f_{kl}} \qquad (26)$$

Note that these marginal global costs $\partial A^f(f)/\partial f_{kl}$ can be derived through local communication between nodes k and l.

Next, we focus on distributed routing optimization. i.e., an algorithm for each node to locally adjust routing variables to converge to the optimal set of routes by generalizing Gallager's result [9]. We first generalize [9]'s necessary and sufficient condition for optimal set of routes.

B. Necessary and Sufficient Conditions for Optimal Cost

Now we generalize [9]'s necessary and sufficient conditions to minimize A^ϕ over all feasible sets of routes. Similar to [9], we compute the partial derivatives of A^ϕ with respect to the inputs R and the routing variables ϕ as follows.

$$\frac{\partial A^\phi(\phi)}{\partial R_i} = \sum_k \phi_{ik} \left[\frac{\partial A^f(f)}{\partial f_{ik}} + \frac{\partial A^\phi(\phi)}{\partial R_k} \right] \qquad (27)$$

$$\frac{\partial A^\phi(\phi)}{\partial \phi_{ik}} = t_i \left[\frac{\partial A^f(f)}{\partial f_{ik}} + \frac{\partial A^\phi(\phi)}{\partial R_k} \right] \qquad (28)$$

The existence and uniqueness of $\partial A^\phi(\phi)/\partial R_i$ and $\partial A^\phi(\phi)/\partial \phi_{ik}$ is given by the following theorem.

Theorem 6.1: Let a network $\mathcal{G} = (\mathcal{V}, \mathcal{L})$ have input traffic set R and routing variable set ϕ, and let each marginal link cost $\frac{\partial A^f(f)}{\partial f_{ik}}$ be continuous in $f_{ik}, (i,k) \in \mathcal{L}$. Then the set of equations (27) has a unique set of solutions for $\frac{\partial A^\phi(\phi)}{\partial R_i}$. Furthermore, (28) is valid and both $\frac{\partial A^\phi(\phi)}{\partial R_i}$ and $\frac{\partial A^\phi(\phi)}{\partial \phi_{ik}}$ for $(i,k) \in \mathcal{L}$ are continuous in R and ϕ.

Proof: See technical report [18]. ∎

Using Lagrange multipliers for the constraint $\sum_k \phi_{ik} = 1$, and taking into account the constraint $\phi_{ik} \geq 0$, the necessary conditions with respect to ϕ are, $(i,k) \in \mathcal{L}$,

$$\frac{\partial A^\phi(\phi)}{\partial \phi_{ik}} \begin{cases} = \lambda_i & \phi_{ik} > 0 \\ \geq \lambda_i & \phi_{ik} = 0. \end{cases} \qquad (29)$$

However, as shown by [9], (29) is not a sufficient condition to minimize A^ϕ even for the routing optimization problem in wired networks. Next, we proceed to show the sufficient condition for the optimization problem.

Theorem 6.2: Let $\mathcal{F}$ be a convex and compact set of flow sets, which is enclosed by $|\mathcal{L}|$ planes (each of which corresponds to $f_{ik} = 0$, $(i,k) \in \mathcal{L}$), and a boundary envelope $\mathcal{F}_\infty$. Assume that A^f is convex and continuously differentiable for $f \in \mathcal{F} - \mathcal{F}_\infty$, Let Ψ be the set of ϕ for which the resulting set of flow rates f are in the above convex and bounded set $\mathcal{F} - \mathcal{F}_\infty$. Then (30) is sufficient to minimize A^ϕ over Ψ, for all $(i,k) \in \mathcal{L}$

$$\frac{\partial A^f(f)}{\partial f_{ik}} + \frac{\partial A^\phi(\phi)}{\partial R_k} \geq \frac{\partial A^\phi(\phi)}{\partial R_i} \qquad (30)$$

Proof: See technical report [18]. ∎

C. A Distributed Algorithm for Routing Optimization

Based on the above sufficient condition, we now develop a gradient-based algorithm by generalizing [9]. Each node i must incrementally decrease those routing variables ϕ_{ik} for which the marginal cost $\partial A^f(f)/\partial f_{ik}+\partial A^\phi(\phi)/\partial R_k$ is large, and increase those for which it is small. The algorithm divides into two parts: a protocol between nodes to calculate the marginal costs, and an algorithm for calculating the routing updates and modifying the routing variables.

Given goodput rates f_{kl} for each incoming and outgoing link $(k,l) \in L(i)$, each node i locally allocates power to satisfy the traffic, and calculates $\partial A_i^f(f)/\partial f_{kl}, (k,l) \in L(i)$. Then, for each pair of neighbor node i, j with common link (i,j), node j sends $\partial A_j^f(f)/\partial f_{ij}$ to node i. Upon receiving it from node j, node i computes $\partial A^f(f)/\partial f_{ij}$ using (26).

Let us now consider how node i can calculate $\partial A^\phi(\phi)/\partial R_i$. Define node m to be downstream from node i (with respect to sink node 0) if there is a routing path from i to 0 passing through m (i.e., a path with positive routing variables on each link). Similarly, we define i as upstream from m if m is downstream from i. A routing variable set ϕ is loop free if there is no i, m $(i \neq m)$ such that i is both upstream and downstream for m. The protocol used for an update, now, is as follows: each node i waits until it has received the value $\partial A^\phi(\phi)/\partial R_k$ from each of its downstream neighbors $k \neq 0$. The node i then calculates $\partial A^\phi(\phi)/\partial R_i$ from (27) (using the convention that $\partial A^\phi(\phi)/\partial R_0 = 0$) and broadcasts this to all of its neighbors. It is easy to see that this procedure is free of deadlocks if and only if ϕ is loop-free.

To avoid deadlocks, similar to Gallager's work [9], our algorithm requires a small amount of additional information to maintain loop-free property: each node i maintains a set B_i of blocked node k for which $\phi_{ik} = 0$ and the algorithm is not permitted to increase ϕ_{ik} from 0. Due to space limit, see technical report [18] for the definition of B, and how we use B to maintain loop-free property.

The algorithm Γ, on each iteration, maps the current routing variable ϕ into a new set $\phi^1 = \Gamma(\phi)$. The mapping is defined as follows. For $k \in B_i$,

$$\phi^1_{ik} = 0, \quad \Delta_{ik} = 0. \tag{31}$$

For $k \notin B_i$, define

$$a_{ik} = \frac{\partial A^f(f)}{\partial f_{ik}} + \frac{\partial A^\phi(\phi)}{\partial R_k} - \min_{m \notin B_i}\left[\frac{\partial A^f(f)}{\partial f_{im}} + \frac{\partial A^\phi(\phi)}{\partial R_m}\right] \tag{32}$$

$$\Delta_{ik} = \min[\phi_{ik}, \eta a_{ik}/t_i] \tag{33}$$

where η is a scale parameter of Γ to be discussed later. Let $k_{min}(i,j)$ be a value of m that achieves the minimization in (33). Then

$$\phi^1_{ik} = \begin{cases} \phi_{ik} - \Delta_{ik} & k \neq k_{min}(i,j) \\ \phi_{ik} + \sum_{k \neq k_{min}(i,j)} \Delta_{ik} & k = k_{min}(i,j). \end{cases} \tag{34}$$

The algorithm reduces the fraction of traffic (and thus energy) sent on non-optimal links and increases the fraction on the best link. The amount of reduction, given by Δ_{ik}, is proportional to a_{ik}, with the restriction that ϕ^1_{ik} cannot be negative. In turn a_{ik} is the difference between the marginal cost to sink 0 using link (i,k) and using the best link. Note that as the sufficient condition (30) is approached, the changes become smaller, as desired. The amount of reduction is also inversely proportional to t_i. The reason for this is that the change in link traffic is related to $\Delta_{ik} t_i$. Thus when t_i is small, Δ_{ik} can be changed by a large amount without greatly affecting the marginal cost. Finally the changes depend on the scale factor η. For η very small, convergence of the algorithm is guaranteed, as shown in Theorem 6.3, but rather slow. As η increases, the speed of convergence increases but the danger of no convergence increases.

Theorem 6.3: Let $\mathcal{F}$ be a convex and compact set of flow sets, which is enclosed by $|\mathcal{L}|$ planes (each of which corresponds to $f_{ij} = 0$, $(i,j) \in \mathcal{L}$), and a boundary envelope $\mathcal{F}_\infty$. Assume that A^f is a convex and increasing function for $f \in \mathcal{F} - \mathcal{F}_\infty$ and that $\forall f_\infty \in F_\infty$, $\lim_{f \to f_\infty^-} A^f = \infty$. For every positive number A^0, if ϕ^0 satisfies $A^\phi(\phi^0) \leq A^0$, then with scale factor $\eta = [M|\mathcal{V}|^7]^{-1}$,

$$\lim_{m \to \infty} \Gamma(\phi^m) = \min_\phi(A^\phi(\phi)) \tag{35}$$

where

$$M = \max_{(l_1,m_1),(l_2,m_2) \in \mathcal{L}} \max_{f: A^f(f) \leq A^0} \frac{\partial^2 A^f(f)}{\partial f_{l_1 m_1} \partial f_{l_2 m_2}} \tag{36}$$

Proof: See technical report [18]. ■

Compared to Gallager's results [9], we require smaller value of η to guarantee convergence because we consider a more general problem definition than [9]. The proof uses a exceedingly small value of η to guarantee convergence under all conditions. In the next section, we use simulation to identify practical values for η.

We have proposed a distributed algorithm for routing optimization. Note that in each iteration, the power allocation achieves optimality through local independent local power allocation. Combining the collective routing optimization, and independent local power allocation at all nodes, we have achieved the optimal cost over all feasible resource allocation and routing combinations.

D. Mapping solution back to three-consideration optimization problem

The optimal solution of the two-consideration (data routing, energy allocation) optimization problem can be easily mapped back to the optimal solution of the three-consideration (data sensing, data routing, and energy allocation) optimization problem as follows.

First, the optimal average sensing rate s_i, $\forall i \in V$ is equal to $f_{i'i}$. Therefore,

$$s_i = f_{i'i}, \quad p_i^S = \alpha_i^S f_{i'i}, \quad \tau_i = s_i/S_i \tag{37}$$

Second, for each link (i,k), the optimal average goodput rate f_{ik} is directly derived from optimization result. Therefore,

$$\tau_{ik} = \frac{f_{ik}}{\rho_{ik} F_{ik}} \tag{38}$$

Finally, the routing fraction ϕ_{ik} is directly derived from two-consideration optimization results. We have mapped the two-consideration solution back to three-consideration solution.

VII. Numerical Results

In this section we examine the optimal solution of the joint sensing and routing problem. We first focus on energy-rich networks, then energy-constrained networks.

A. Energy-rich wireless sensor networks

As a special case of wireless sensor networks, an energy-rich network is not energy constrained: it either has a direct power supply, or an infinite energy harvest source. For the energy-rich network, we show that if all nodes use the same utility function, the optimal sensing rates are max-min fair.

Theorem 7.1: Consider an energy-rich sensor network $G = (V, L)$ with a single sink 0, in which all nodes use the same utility function. i.e., $U_i = U_j\ \forall i, j \in V$. If the utility function is strictly concave, the optimal sensing rates s^* (of the problem defined in section III) are max-min fair.

Proof: See technical report [18]. ■

Due to the uniqueness of max-min fair sensing rates [19], Theorem 7.1 also suggests that the optimal sensing rates are independent of choice of utility function. Moreover, efficient algorithms [20] exist to find the max-min fair solution. However, as we have identified, Theorem 7.1 generally does not hold for energy-constrained networks (See technical report [18] for counter examples). Next, we further examine the optimal solution for energy-constrained networks using simulation.

B. Energy-constrained wireless sensor networks

We examine the optimal sensing rates using our numerical simulator based on parameters derived from an on-going weather-monitoring project [2] [21]. In the simulation scenario in Figure 3, we consider a wireless sensor network composed of 30 collaborating lower-powered X-band magnetron radars for meteorological sensing, connected via an 802.11b mesh network with non-steerable directional antennas. All sensed data are destined to sink 0. Each link is implemented by a pair of radios and directional antennas at the sender and the receiver. Note that between each pair of neighboring nodes, we only need one pair of directional antennas because of the loop free property of optimal routing solution: data can only be transmitted one direction at one time. To reduce the interference, we use four partial-overlapping channels $(1, 4, 8, 11)$ (marked as A, B, C, D in Figure 3): links on a straight line reuse the same channel every 4 hops; links sharing the same sensor node are assigned to different channels. To further reduce the interference, at each node, we physically separate the radios and antennas on different channels by 1 meter [16] [17].

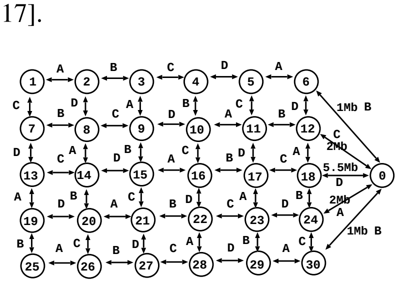


Fig. 3. Topology used for Simulation

When a sensing radar is on, its power consumption is $p_i^S = 34$W (based on a RayMarine 24 inch, 4kW radar), generating sensed data at rate $S_i = 1.5Mbps$. When a link is on, the power consumption at the sender is $P_i^O = 1.98W$, and $P_i^I = 1.39W$ at the receiver. The link-on data rate is determined by distance between two end nodes. Based on our preliminary measurement, the link-on goodput rate for links $(6, 0)$ and $(30, 0)$ are, $\rho_{6,0}F_{6,0} = \rho_{30,0}F_{30,0} = 1Mbps$; the link-on goodput rate for link $(18, 0)$ is, $\rho_{18,0}F_{18,0} = 5.5Mbps$. For all other links (i, k), $\rho_{ik}F_{ik} = 2Mbps$.

A solar-rechargeable battery is used for power. The energy charging process is affected by weather. During a sunny day, the energy collected per day is measured at $312Wh$, which translates to a power budget $\mathcal{P}_i = 13W$. During the cloudy day, the energy collected per day is measured at $168Wh$, which translates to $\mathcal{P}_i = 7W$. The battery capacity is $110Ah$, for $12V$ operation, it can store energy $1230Wh$, that relates to 94 hours if the power is consumed at $13W$. We prefer a smoothed energy usage: every 24 hours, we recompute the power budget $\mathcal{P}_i$ based on the overall energy in the battery: $\mathcal{P}_i$ is set to be the overall energy in the battery at that time divided by 48 hours. By doing so, the energy consumption rate is smoothed over a window size of 48 hours.

We adopt the utility function from [22], and use the negative standard error of the environment's reflectivity estimate σ_i as the node i utility function, which is roughly proportional to the value of $s_i^{-0.5}$.

$$U_i(s_i) = -\omega_i s_i^{-0.5} \tag{39}$$

in which ω_i is the weight of utility at node i, which reflects the importance of data sensed by node i.

Next, we first present numerical results of our distributed algorithm in the synthetic wireless network described above. We will illustrate how the choice of step-size scale factor η affects convergence speed. It will become clear that, in practice, it is possible to choose a η much larger than the value used in the proof of Theorem 6.3 to expedite the convergence. Second, through optimization over different power budgets, we demonstrate how the power budget affects the energy allocation decision between data sensing and data communication.

1) Scale factor η and convergence: In the previous section, with a small scale factor η, we have shown that optimization algorithm Γ will eventually converge to the optimum. The question of the speed of convergence deserves more study. Now, we numerically compare how the proposed algorithm converges to the optimum with different values of η.

We run our distributed algorithm assuming that all nodes have the same power budget $\mathcal{P} = 7W$, and have the same utility weight $\omega_i = 1$. At iteration 0, the sensing rate is $s_i = 0$ at all nodes. We choose three different scale factors $\eta = \{0.5, 5, 50\}$ to run the algorithm, that minimizes the overall function A. Note that all three choices of η are much larger than the value given in Theorem 6.3. As shown in Figure 4, the algorithm converges to the optimum for all three step sizes. The objective function A is reduced from ∞ to 24.1. We also see that the convergence depends to a great extent on the value of η: a larger value of η may lead to faster convergence. From Figure 6.3 we see that for $\eta = 0.5, 5, 50$, the algorithm takes roughly 30000, 3000 and 300 iterations to reduce A to within 10% of optimality. We also conducted simulations to evaluate how our algorithm adapts to link failures and changes of node utility weights. Using proper chosen η, our algorithm would re-converge to 10% of optimality in $100 - 200$ iterations. See technical report [18] for more details.

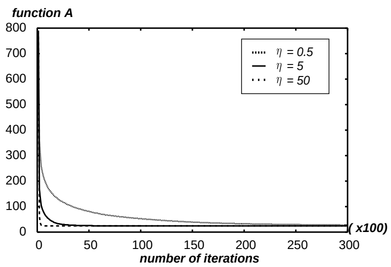


Fig. 4. Comparison of convergence speed for different values of η

2) Power budget affects optimization result: The energy collection rates of solar panels vary with weather condition, and thus affect power budget $\mathcal{P}$. We next demonstrate how power budgets affect the network-wide power allocation and the aggregate sensing utility. We assume all nodes have the same power budget $\mathcal{P}$. We run our distributed algorithm for seven different power budgets $\mathcal{P} = 7W \rightarrow 13W$. Figure 5 shows the aggregated sensing utility increases as energy budget $\mathcal{P}$ increases. We also plot in the same figure the average sensing power on all nodes as $\mathcal{P}$ increases. The more power available is, the more data will be collected by sensors. Observe that both the utility curve and sensing power curve eventually flatten out when $\mathcal{P}$ gets large. This is because when there is abundant power, all wireless links can operate at their maximum capacities, e.g. 11Mbps for $802.11b$ (goodput may vary). Consequently, the amount of data that can be sent to the sink is bounded from above. This upper bound is determined by the capacity of links on the min-cut of the network graph. Due to this capacity limitation, the aggregate sensing utility is also bounded, and there is no point for sensors to waste energy collecting more data that cannot be delivered to the sink.

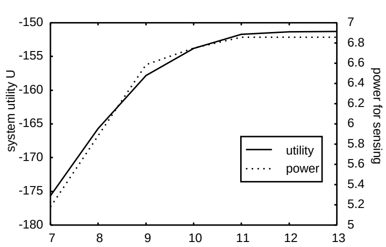


Fig. 5. Utility and sensing power increases as power budget increases

Figure 6 shows the average power used for communication at all nodes for different energy budgets. As expected, as $\mathcal{P}$ increases from $7W$ to $9W$, sensors collect more and more data to be sent to the sink. Consequently, the overall communication power, both for transmitting and for receiving, increases. Interestingly, when $\mathcal{P}$ increases from $9W$ to $13W$, the communication power decreases slightly. To understand this somewhat counter-intuitive behavior, we looked into not only the aggregate data rate flowing into the sink, but also the sources of those data. When $\mathcal{P}$ is low, the major performance bottleneck is sensing, all sensed data can be completely delivered to the sink. Therefore, the larger $\mathcal{P}$, the more data collected by sensors, and the higher the consequent communication power. However, as seen in Figure 5, when $\mathcal{P} \geq 9W$, wireless links near the data sinks operate almost close to their full capacities. The aggregate data rate to the sink approaches its upper limit. Due to this data rate limit, not all sensors will sense data at their full capacities. When $\mathcal{P}$ increases, sensors close to the sink have more power for sensing. Therefore in the optimal solution, while the aggregate data rate is fixed, more and more data are from sensors close to the sink, consequently, we see a slightly decrease in communication power consumption.

To further illustrate this, we compare the power allocations on a subset of nodes for $\mathcal{P} = 7, 9, 13W$ in Figure 7(a), 7(b) and 7(c). In Figure 7(a), when $\mathcal{P}$ is low, nodes far away from the sink, such as nodes $1, 7$ spend most of their power on sensing; nodes close to the sink, such as node $6, 12, 18$ are responsible for forwarding sensed data to the sink. On those nodes, the communication power is more than 40% of the overall power budget. Consequently, the sensing power is lower than that of node 1 or 7. In Figure 7(b), when $\mathcal{P}$ increases to $9W$, all nodes have more power for sensing; nodes close to data sink, $6, 12, 18$, spend a large portion of power (50% or more) to forward data to the sink at their close-to-full goodput capacities, $1, 2, 5.5Mbps$ respectively. In Figure 7(c), when $\mathcal{P} = 13W$, because wireless links connecting to the sink are already saturated, the overall link data rates delivered to the sink only slight increases compared to 7(b). However, due to the concavity of the utility functions, nodes close to sink, such as $6, 12, 18$ increase their sensing power further and generate more data, while nodes far way for the sink, such as node 1 and 7, have to reduce their sensing rates (and thus sensing power) accordingly. Now a larger portion of data are from sensors close to the sink, the power spent on data communication to the sink at $\mathcal{P} = 13W$ is lower than that at $\mathcal{P} = 9W$, as indicated in Figure 6. Actually, when $\mathcal{P} = 13W$, there is no longer a power constraint at each and every node, the optimal sensing rates given by our distributed algorithm are thus max-min fair as proved in Theorem 7.1.

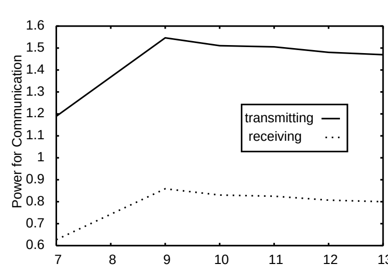
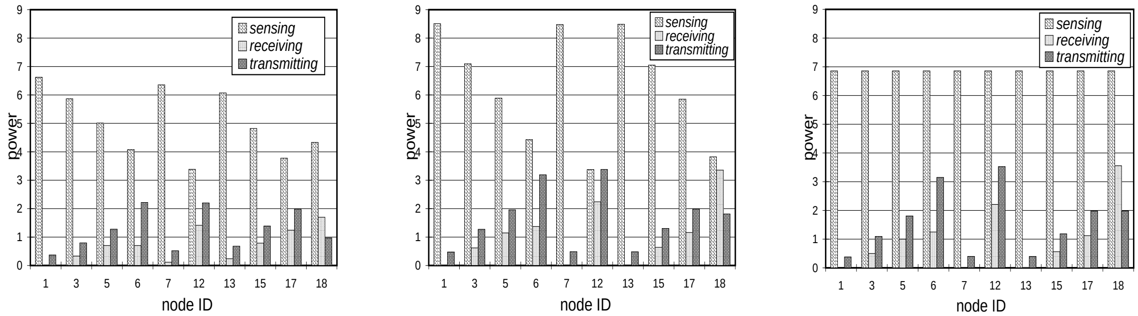


Fig. 6. Communication power changes as power budget increases



(a) Homogeneous when $\mathcal{P} = 7W$ (b) Homogeneous when $\mathcal{P} = 9W$ (c) Homogeneous when $\mathcal{P} = 13W$

Fig. 7. Individual node power consumption p_i for different power budgets and node utility weights

VIII. CONCLUSION

In this work, we proposed an optimal sensing and routing strategy for energy-constrained wireless sensor networks with non-steerable directional antennas. We first formulated a joint sensing rate control, data routing and energy allocation problem. We then converted the combined sensing/routing problem into a unified routing problem. A distributed algorithm was developed for all nodes to co-operatively drive the sensor network to its optimal operation point, where the network-wide sensing utility is maximized under node power constraints. Simulations for a network of small solar powered X-band radars illustrated the operation of our distributed algorithm. The tradeoff between sensing and communication was illustrated in different simulation settings on power collection rate.

Further research can be pursued in the following directions:

- Our simulation results are encouraging. We plan to implement our distributed algorithm in a network of X-band radars currently under development. We are especially interested in testing how our algorithm adapts to real environmental conditions, such as the strength of sunshine, the link goodput probabilities, and the location and movement of sensed objects.
- In this paper we have not considered a sensor node's consumption of power for computation. This factor will become more important as processing demands increase, e.g., if compression is performed before data transmission, less data the network will have to transmit to the sink. Then there is a trade-off on power allocation between processing and routing. We plan to incorporate this and other forms of computation into our framework.

ACKNOWLEDGMENT

We thank Brian Donovan of UMass Amherst for providing parameters used in an on-going weather-monitoring project. This work was supported in part by the National Science Foundation under grants EEC-0313747, ANI-0085848, and EIA-0080119. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect those of the National Science Foundation.

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