Joint Power Control, Scheduling and Routing for Multihop Energy Harvesting Sensor Networks

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ABSTRACT

We study wireless multihop energy harvesting sensor networks employed for random field estimation. The sensors sense the random field and generate data that is to be sent to a fusion node for estimation. Each sensor has an energy harvesting source and can operate in two modes: Wake and Sleep. We consider the problem of obtaining jointly optimal power control, routing and scheduling policies that ensure a fair utilization of network resources. This problem has a high computational complexity. Therefore, we develop a computationally efficient suboptimal approach to obtain good solutions to this problem. We study the optimal solution and performance of the suboptimal approach through some numerical examples.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design

General Terms

Algorithms

Keywords

Energy harvesting, Power Control, Energy efficient routing, Joint routing-scheduling

1. INTRODUCTION

Sensor networks consist of a large number of small, inexpensive sensor nodes. These nodes have small batteries with limited power and also have limited computational power and storage space. When the battery of a node is exhausted, it is not replaced and the node dies. When a sufficient number of nodes die, the network may not be able to perform its designated task. Various studies have been conducted to increase the life time of a node by reducing the energy intensive tasks ([21], [24], [29], [31]). A general survey on sensor networks is [2] which provides more references on these issues.

The life time of the battery itself can be increased by energy harvesting techniques ([14], [20]). Common energy harvesting devices are solar cells, wind turbines and piezo-electric cells, which extract energy from the environment. Among these, solar energy harvesting seems to have emerged as a technology of choice ([20], [22]). Unlike for a battery operated sensor node, now there is potentially an *infinite* amount of energy available to the node. However, the source of energy and the energy harvesting device may be such that the energy cannot be generated at all times (e.g., a solar cell). Furthermore, the rate of generation of energy can be limited. Thus, one may need to modify the energy consumption profile of a sensor node so that the node can perform satisfactorily for a long time, i.e., can operate in *energy neutral operation* ([14]).

In the following, we survey the literature on sensor networks with energy harvesting nodes. Early papers on energy harvesting in sensor networks are [15] and [23]. [14] provides various deterministic theoretical models for energy generation and energy consumption profiles and provides conditions for energy neutral operation. In [11], the authors study optimal sleep-wake cycles such that event detection probability is maximized. In [19], finite state Markov models of solar energy harvesting are formulated, certain sleep-wake strategies are proposed and policy parameters optimized using Game Theory. A recent survey is [20] which also summarizes the results in [19].

In [13], [26] and [27], stochastic queuing models of data and energy generation and storage processes are considered. Stable throughput optimal and mean delay optimal energy management policies are obtained which also provide energy neutral operations. It was found that having energy storage allows a larger stability region as well as a lower mean delay. Efficient Multiple Access (MAC) protocols for such sensor nodes have also been developed in [26]. In [13], we obtained optimal and easily implementable suboptimal sleep-wake policies.

In this paper, we study wireless multihop energy harvesting sensor networks employed for random field estimation. The sensors sense a random field and generate data that is to be sent to a fusion node for estimation. Each sensor has an energy harvesting source and can operate in two modes: Wake and Sleep. The sleep mode is a power saving mode in which the sensor only harvests energy and performs no other functions so that the energy consumption is negligible. In the wake mode, a sensor node can sense and process data and communicate with other nodes.

The problem of scheduling and routing in adhoc multihop wireless networks has been extensively studied in recent years (see [10], [18] for general surveys and tutorials). In [17], the authors obtain a static multipath routing algorithm for networks with energy replenishment which is optimal with respect to a set of pre-computed paths. But, they do not consider power control in their formulation and they obtain the precomputed paths using a heuristic. To the best of our knowledge, optimal sleep-wake cycles for multihop energy harvesting sensor networks with power control has not been studied before. The general problem of optimal joint routing and scheduling with power control in wireless multihop networks is NP-complete ([5]). In [6], the authors considered this problem with the objective of minimizing the total average transmission power with a simplifying linear approximation for the rate on a wireless link. The problem was considered for a sensor network setting in [7] with an objective of minimizing the energy consumption. But, they assume a simplified interference model by only considering Time Division Multiple Access schemes. In [12], non-linear column generation is used to obtain an approach that converges to the global optimum solution. However, the column generation subproblem is also typically NP-Complete. In [5], the authors formulate the problem as an optimization problem involving timesharing across different transmission modes, establish a dimensionality bound for the optimal solution and obtain a computationally tractable approach to obtain good solutions to the problem. In this paper, we develop a similar approach for energy harvesting sensor networks. Energy harvesting sensor nodes introduce several new aspects to the problem. In addition to the energy consumed in transmission, a significant amount of energy is required for functions like reception, sensing etc. and to even stay in the wake mode. Thus, if the rate at which energy is harvested is less, a sensor might have to switch to sleep mode. Sensing cannot be done in sleep mode and hence the random field estimation suffers. We account for all these factors and formulate the problem and develop a tractable approach to obtain a good solution that ensures a fair distribution of the network resources to each sensor.

This paper is organized as follows. Section 2 describes the model and the assumptions. In Section 3, we consider a simpler model of a sensor node without a sleep mode and formulate a problem for fair allocation of network resources to satisfy the traffic requirements for a data gathering application. In Section 4, we discuss the use of the dimensionality bound to obtain a tractable approach to solve the problem. In Section 5, we discuss the general problem formulation considering sensor nodes with energy saving modes. In Section 6, we present some examples to understand the optimal solution and to study the performance of the tractable approach. Section 7 concludes the paper.

2. THE MODEL

We consider a sensor network with energy harvesting nodes, sensing a random field. The sensor nodes generate packets to be transmitted to a fusion node. The system is slotted with each slot being of length T seconds. In any slot, a sensor node is in one of two modes: Wake or Sleep. In the sleep mode, a node can only generate energy via an energy harvesting source. In the wake mode, it can sense, process, receive and/or transmit data. We assume that the energy consumed by a sensor node in the sleep mode is negligible. In the wake mode, a sensor cannot transmit and receive in the same slot (i.e., it has a half duplex channel). For transmission, a sensor node chooses its transmit power from a finite set of transmit powers. (CC2420 ([30]) and ADF7020 ([3]) are commercially available low power transceiver chips commonly used in sensor nodes that have a programmable output power). For simplicity in notation, in the rest of the paper, we assume that all the nodes choose their transmit powers from the same set consisting of K elements. In most of these low power transceivers, during transmission, only a small fraction of the total power consumed appears as transmit power. We will denote the extra power consumed in the transceiver as e_t. The power consumption during reception is approximately constant and is denoted by e_r. Let e_s denote the power consumed by the sensor for sensing data.

If sensor node n is sensing in slot k (which denotes time interval $[(k-1)T, kT]$ seconds), X_k^n bits are generated in the slot. We assume that $\{X_k^n; k \geq 1\}$ is a stationary, ergodic random process. Then, sensor n when it is sensing is effectively generating data at a rate $d_n = E[X_k^n]/T$. Further, in wake mode, we assume that a sensor consumes energy at a constant rate of e_w. This accounts for the energy consumed by the processor, the energy lost due to leakage etc.. In every slot, a sensor node is harvesting energy. Sensor node n is able to replenish energy by Y_k^n in slot k. We assume that $\{Y_k^n; k \geq 1\}$ is a stationary, ergodic random process. Then energy is harvested at a rate $P_n^{av} = E[Y_k^n]/T$ by sensor node n. We assume that each node has infinite data and energy buffers. This is a good approximation if the buffers are large enough. In any case, it is always a good assumption to start with so that one can focus on some essential aspects of the problem.

We consider a network consisting of N stationary (e.g., not mobile) energy harvesting sensor nodes and a fusion node. Let $\mathcal{N}$ denote the set of all sensor nodes in the network. Due to the broadcast nature of wireless links, each node can potentially transmit to every other node although the link quality will depend upon the distances between the nodes and possible shadowing and other physical obstacles in the way. Let $\mathcal{O}(n)$ denote the set of outgoing links and $\mathcal{I}(n)$ the set of incoming links of a node n. There are $L = N^2$ links in the network (note that the fusion node doesn't have any outgoing links) and we denote the set of all links in the network by $\mathcal{L}$. We assume that a node can communicate with at most one other node at any time.

We obtain jointly optimal power control, routing and scheduling policies for sensor networks with energy harvesting sensor nodes. We have seen in [13], [26], [27] that for energy neutral operation in steady state, it is necessary and sufficient for the nth node to use average power $< P_n^{av}$. In the following, we will address the optimality problem for two scenarios: Given the traffic requirements d_n of each sensor node n, obtain policies which satisfy these requirements. If it is not possible, then satisfy their requirements in a "fair" (to be explained below) way. Next, we exploit the energy saving sleep-wake modes to obtain policies that can satisfy the traffic requirements better. We will find that complexity of these problems is high and hence we develop a computationally efficient suboptimal approach to obtain good solutions to this problem.

We define a mode of the network as a possible combination of active links along with their transmit powers such that any node is communicating with only one other node over a half duplex channel. Thus, there can only be upto $N_A = \lfloor (N+1)/2 \rfloor$ active links. Since each sensor node chooses its transmit power from a finite set, the number of modes is finite. Let $\mathcal{M}$ denote the set of all modes. Corresponding to any transmission mode m, we have a link transmit power vector $\mathbf{P}^m = (P_1^m, ..., P_L^m)$ where the lth element, P_l^m, is the transmit power of link l in mode m. Clearly, only upto N_A elements of this vector can be non-zero.

Let the channel gain from the transmitting sensor node of link k to the receiver node of link l be h_{kl}. This includes the effect of fading, shadowing and attenuation due to distance. We assume slow fading which is realistic for a sensor network with stationary nodes. Hence, in the following, h_{kl} will be assumed constant $\forall\ k, l \in \mathcal{L}$. For any link transmit power vector $\mathbf{P}$, the SINR (Signal to Interference + Noise Ratio) at the receiver of link l is

$$\gamma_l\left(\mathbf{P}\right) = \frac{h_{ll} P_l}{\sum_{k \neq l} h_{kl} P_k + \sigma_l^2}$$

where σ_l^2 is the noise power at the receiver of link l. (Many low power transceivers, e.g., ADF7020 ([3]), ATA542X ([4]) can transmit at multiple rates using Adaptive Modulation and/or Coding). The data rate, $R_l(\mathbf{P})$, over link l can be taken as a non-decreasing concave function of $\gamma_l\left(\mathbf{P}\right)$. In this paper, we use the Shannon formula

$$R_l(\mathbf{P}) = W log_2(1 + \gamma_l\left(\mathbf{P}\right)),$$

where W is the bandwidth of the wireless channel.

In the following, we consider scheduling of transmission modes for the network which satisfies the average power constraints as well as the transmission requirements of different nodes in a fair way.

3. PROBLEM FORMULATION

We consider each sensor node as a source of a flow with fusion node as the destination. Thus, we have N source-destination flows in the network. Denote the source of a flow f by $s(f)$ and the set of all flows by $\mathcal{F}$. Also, let N_F denote the fusion node. Let r_f denote the rate at which flow f is transmitted to the fusion node. To obtain the routing, we use a multi-commodity flow model ([1]) where each flow f corresponds to a commodity in the network. Let x_l^f denote the traffic assigned to link l by the routing scheme for flow f. The flow assignment given by the routing scheme must satisfy the flow conservation constraints at each node n:

$$\sum_{l \in \mathcal{O}(n)} x_l^f - \sum_{l \in \mathcal{I}(n)} x_l^f = 0, \forall\ n \in \mathcal{N} \backslash \left\{s(f)\right\}, \ \forall\ f \in \mathcal{F},$$
$$\sum_{l \in \mathcal{O}(s(f))} x_l^f = \sum_{l \in \mathcal{I}(N_F)} x_l^f = r_f, \forall\ f \in \mathcal{F};$$
$$\sum_{l \in \mathcal{I}(s(f))} x_l^f = \sum_{l \in \mathcal{O}(N_F)} x_l^f = 0, \ \forall\ f \in \mathcal{F}.$$

These equations express the facts that if a node is not the fusion node or a source node for a flow, then the total input flow rate to it must equal the total output flow rate. If a node is a source node for a flow, then the difference between the output flow rate and the input flow rate equals the rate at which it generates the traffic corresponding to the flow.

The above equations can be compactly written as $\boldsymbol{A}\mathbf{x}^f = \mathbf{y}^f, \ \forall\ f \in \mathcal{F}$ where $\boldsymbol{A}$ is the node-link incidence matrix, $\mathbf{x}^f$ is length L column vector with its lth element being x_l^f and $\mathbf{y}^f$ is an $N+1$ column vector with $\left[\mathbf{y}^f\right]_{s(f)} = r_f$, $\left[\mathbf{y}^f\right]_{N_F} = -r_f$ and all other elements zero.

We initially consider a simplified model where the sensor nodes are always awake and perform sensing in all the slots. The data generated at each sensor node has to be sent to the fusion node through the network. But, the network may not be able to carry all the data originating at each sensor node. In such a case, we require a flow control mechanism at the sensor nodes so that each sensor node gets a *fair* share of the network resources. In order to ensure fairness, we maximize the minimum of the satisfied fractions of demand of the sensor nodes in the network. This notion of fairness has been previously used ([28], [16]). The ratio of net flow from a node to the fusion node to the node's demanded rate is the satisfied fraction of demand for that node. Thus, we have the following formulation for the optimization problem:

OPT-1: maximize λ subject to

$$\frac{r_f}{d_{s(f)}} \geq \lambda, \ \forall f \in \mathcal{F}; \tag{1}$$

$$\boldsymbol{A}\mathbf{x}^f = \mathbf{y}^f, \ \forall f \in \mathcal{F}; \tag{2}$$

$$\sum_{f \in \mathcal{F}} x_l^f \leq \sum_{m \in \mathcal{M}} \alpha_m R_l(\mathbf{P}^m) - \delta, \ \forall l \in \mathcal{L}; \tag{3}$$

$$\sum_{m \in \mathcal{M}} \alpha_m \left(\sum_{l \in \mathcal{O}(n)} (P_l^m + e_t I(P_l^m > 0)) + e_r \sum_{l \in \mathcal{I}(n)} I(P_l^m > 0) \right) + e_s + e_w \leq P_n^{av} - \epsilon, \ \forall n \in \mathcal{N}; \tag{4}$$

$$\sum_{m \in \mathcal{M}} \alpha_m \leq 1 \tag{5}$$

$$x_l^f \geq 0, \ \forall l \in \mathcal{L}, \ \forall\ f \in \mathcal{F}; r_f \geq 0, \ \forall f \in \mathcal{F}; \alpha_m \geq 0, \ \forall m \in \mathcal{M}, \tag{6}$$

where ϵ and δ are arbitrarily small positive constants and $I\left(\right)$ is the indicator function. This is a linear programming problem where we maximize the minimum, λ, of the satisfied fractions of demand $r_f/d_{s(f)}$ of the sensor nodes. The variable α_m is the fraction of time the network operates in mode m. The inequalities in (3) state that the traffic through any link should be less than its capacity. This is a necessary condition for stability of the data queue corresponding to link l. Under some weak conditions, it is also sufficient. The inequalities (4) state that the average power consumed for transmission, reception and sensing at each node n should be slightly less than P_n^{av}. This ensures energy neutral operation at each sensor node ([26], [27]). We do not consider any power constraints on the fusion node whose main activity is reception (we assume that it has enough power to receive data in every slot).

By solving **OPT-1**, we obtain:
1) Optimal λ which we denote by λ^*. If $\lambda^* \geq 1$, then the network can carry all the traffic originating from the nodes to the fusion node. But, if $\lambda^* < 1$, there are sensor nodes that are generating more data than what can be sent by the network to the fusion node under the condition of all nodes being awake all the time. These nodes will drop the excess data. In this case, using the energy saving mode will be useful which can possibly increase λ^*. This will be considered in Section 5.
2) Optimal (mode scheduling) fractions of time $\{\alpha^*_m, m \in \mathcal{M}\}$ that the network operates in the various valid modes.
3) Optimal x^{*f}_l and the fair share of traffic r^*_f carried by the network for flow f. At each node n, we have a queue corresponding to each outgoing link l and the fraction $x^{*f}_l / \sum_{i \in \mathcal{O}(n)} x^{*f}_i$ of each flow f arriving at node n gets buffered in this queue. Data in these queues can be served on a first come first serve basis.

The optimization could be done at the fusion node for which it needs $\{P^{av}_n; n \in \mathcal{N}\}$, $\{d^{av}_n; n \in \mathcal{N}\}$ and $\{h_{kl} \ \forall \ k, l \in \mathcal{L}\}$. Since the links experience only slow fading, the optimization doesn't have to be performed frequently. Depending on the coherence time of the network, after some F slots the algorithm can be run again. Let these F slots denote a frame. Every frame could begin with a synchronization phase where every node synchronizes its clock with respect to the fusion node. This could be done using a scheme like Timing-sync Protocol for Sensor Networks (TPSN) ([9]). As part of the protocol, it also provides a hierarchical structure which we can use during the initial phase of a frame. To determine $\{h_{kl} \ \forall \ k, l \in \mathcal{L}\}$, each node can be alloted a slot during the initial phase in which it transmits a packet at its highest transmit power. If the value of the transmit power is also sent in the packets, the receiving nodes can evaluate the corresponding channel gains by taking the ratio of the receive power to the transmit power. Nodes that are not able to decode the packet could take the channel gain as zero. Then, each node can transmit a packet to the fusion node containing its energy harvesting rate, data generation rate and channel gains through the hierarchical structure that is obtained during the synchronization phase in TPSN. After computing the optimal solution, the fusion node can use the same hierarchical structure to pass the part of the optimal solution relevant to each node. Then, the initial phase will end and during the rest of the frame, nodes will use the routing, scheduling and power control in the optimal solution. Thus, our approach is centralized in nature. But, centralized algorithms have been proposed earlier ([5], [6], [7]) and are considered practical although decentralized ones are preferred. For very large networks, solving **OPT-1** becomes computationally intensive and the number of control messages required in each frame also is very high. For such cases, an approach similar to that mentioned in [6] could be used where the network is partitioned into clusters and **OPT-1** could be solved at cluster level.

The problem **OPT-1** is a linear programming problem (L.P.) that can be solved to obtain the optimal λ. But, the set $\mathcal{M}$, which contains all valid combinations of active links and various power levels on these links, is a very large set (it contains $\sum_{i=0}^{N_A} (K-1)^i \, C(N,i) P(N+1-i, i)$ elements where $C(a,b) = \frac{a!}{b!(a-b)!}$ and $P(a,b) = \frac{a!}{(a-b)!}$). For every element $m \in \mathcal{M}$, we have a time fraction variable α_m in the optimization problem. As a result, **OPT-1** becomes computationally demanding as we increase the number of nodes. In the next section, we obtain a tractable approach to solve **OPT-1** by using the method given in [5] and find a good suboptimal solution.

4. AN EFFICIENT ALGORITHM

Let $\mathbf{q}^m$ be a vector of length N whose nth element is the power consumed by node n for transmission and reception in mode m. Then,

$$[\mathbf{q}^m]_n = \sum_{l \in \mathcal{O}(n)} (P^m_l + e_t I(P^m_l > 0)) + e_r \sum_{l \in \mathcal{I}(n)} I(P^m_l > 0).$$

Let $\mathbf{c}$ and $\mathbf{P}_{av}$ be vectors defined by $\mathbf{c} = \sum_{m \in \mathcal{M}} \alpha^*_m R(\mathbf{P}^m)$, $\mathbf{P}_{av} = \sum_{m \in \mathcal{M}} \alpha^*_m \mathbf{q}^m$ where $R(\mathbf{P}^m)$ is a vector of length L with its lth element being $R_l(\mathbf{P}^m)$. Then, $(\mathbf{c}, \mathbf{P}_{av})$ lies in the convex hull of the set $\{(R(\mathbf{P}^m), \mathbf{q}^m) : m \in \mathcal{M}\} \subset \mathbb{R}^{L+N}$. By Caratheodory's Theorem ([8]), $(\mathbf{c}, \mathbf{P}_{av})$ can be expressed as a convex combination of at most $L + N + 1$ elements of the set. Therefore, if we could find the $\mathcal{M}^* \subset \mathcal{M}$ with $|\mathcal{M}^*| = L+N+1$ which would yield the optimal solution, we could have solved **OPT-1** by considering the modes in $\mathcal{M}^*$ only which reduces the required computations drastically. So, we start with a randomly chosen subset $\mathcal{M}'$ containing $L + N + 1$ valid modes and solve **OPT1** (after replacing $\mathcal{M}$ with $\mathcal{M}'$). Let $\{\mu^*_l : l \in \mathcal{L}\}$, $\{\lambda^*_n : n \in \mathcal{N}\}$ and β^* denote the optimal dual variables corresponding to the constraints (3), (4) and (5) respectively. Let α^* denote the optimal time fractions. As in [5], we use these variables to identify a new mode to enter $\mathcal{M}'$ by solving the column generation subproblem:

OPTMODE:

$$\text{maximize}_{m \in \mathcal{M} \setminus \mathcal{M}'} \sum_{l \in \mathcal{L}} \mu^*_l R_l(\mathbf{P}^m) - \sum_{n \in \mathcal{N}} \lambda^*_n \, [\mathbf{q}^m]_n - \beta^*$$

$$\text{subject to} \sum_{l \in \mathcal{L}} \mu^*_l R_l(\mathbf{P}^m) - \sum_{n \in \mathcal{N}} \lambda^*_n \, [\mathbf{q}^m]_n - \beta^* > 0.$$

Since $\mathcal{M} \setminus \mathcal{M}'$ is a large set, the above optimization problem is computationally demanding. Thus, we use the following greedy heuristic algorithm to obtain a new mode:

1) Initially, let $\mathcal{T} = \mathcal{L}$, $\mathbf{P} = 0$, $\theta(\mathbf{p}) = \sum_{l \in \mathcal{L}} \mu^*_l R_l(\mathbf{p}) - \sum_{n \in \mathcal{N}} \lambda^*_n \, [\mathbf{q}^m]_n - \beta^*$ and $\theta^* = \theta(\mathbf{P})$.
2) For each link $l \in \mathcal{T}$, obtain $\mathbf{p}_l$ by raising power level on link l in $\mathbf{P}$ to the next level and let $l^* = argmax_{\{l \in \mathcal{T}\}} \theta(\mathbf{p}_l)$.
3) If $\theta(\mathbf{p}_{l^*}) < \theta^*$, goto step 4; else $\mathbf{P} = \mathbf{p}_{l^*}$, $\theta^* = \theta(\mathbf{P})$ and $\mathcal{T} = \mathcal{T} \setminus \mathcal{L}(l^*)$ where $\mathcal{L}(l^*)$ is the set of all links excluding l^* for which the transmitting or receiving node is the same as the transmitting or receiving node of l^*. Also $\mathcal{T} = \mathcal{T} \setminus \{l^*\}$ if link l^* has been alloted its maximum power. Now, if $\mathcal{T} = \phi$, goto step 4; else, goto step 2.
4) Obtain new mode vector m_n from the link transmit power vector $\mathbf{P}$.

After running the above algorithm, if $\mathbf{P} = 0$ (i.e., the algorithm didn't give any new mode), then we terminate the procedure and the solution of the optimization problem with the latest $\mathcal{M}'$ as the solution. If $\mathbf{P} \neq 0$, we remove a mode $m \in \mathcal{M}'$ with $\alpha_m^* = 0$ and replace it with the new mode m_n. Then we solve the problem with the new set $\mathcal{M}'$ and repeat the above procedure. Note that if the new mode $m_n \in \mathcal{M}'$, then we remove a mode $m \in \mathcal{M}'$ with $\alpha_m^* = 0$ (if no such m exists, stop the procedure) and replace it with a new randomly chosen mode. Note that the above algorithm can only have upto $N_A(K-1)$ link power increments and thus requires much less computation than **OPTMODE**. But, the algorithm greedily tries to find a mode that would maximize the objective of the column generation subproblem which is not concave. Hence, the procedure might give a local optimum as the solution. But, we have observed (and illustrated in Section 6) that this approach provides solutions that are close to the optimal value. We will call this algorithm **ALGO-M**.

The advantage of the iterative approach discussed in this section is that the number of computations and the memory required for each iteration is considerably less. This is due to the significant reduction in the number of optimization variables in the linear program **OPT-1** by using $\mathcal{M}^*$ instead of $\mathcal{M}$ which only has $L+N+1$ elements. We will further study the performance of this approach by comparing the solutions obtained using it against the optimal solution and by considering the number of iterations required to get good solutions. This will be done later in Section 6 in a more general setting.

5. PROBLEM FORMULATION WITH SLEEP-WAKE

Now we formulate the optimization problem for a network with energy harvesting sensor nodes that have sleep and wake modes. Then **OPT-1** can be modified as

OPT-2: maximize λ subject to (1), (2), (3), (5), (6),

$$\sum_{m\in\mathcal{M}} \alpha_m \left[\mathbf{q}^m\right]_n + u_{sn}e_s + u_{wn}e_w \leq P_n^{av} - \epsilon,\ \forall\, n \in \mathcal{N}; \quad (7)$$

$$\frac{r_f}{d_{s(f)}} \leq u_{sn},\ \ \forall\, n \in \mathcal{N};\ u_{sn} \leq u_{wn},\ \ \forall\, n \in \mathcal{N}; \qquad (8)$$

$$\sum_{m\in\mathcal{M}} \alpha_m \left(\sum_{l\in\mathcal{O}(n)} I(P_l^m > 0) + \sum_{l\in\mathcal{I}(n)} I(P_l^m > 0) \right) \leq u_{wn},\ \ \forall\, n \in \mathcal{N}; \qquad (9)$$

$$u_{wn} \geq 0,\ \forall\, n \in \mathcal{N};\ u_{sn} \geq 0,\ \forall\, n \in \mathcal{N}. \qquad (10)$$

In the above formulation, we denote by u_{wn} and u_{sn}, the fractions of time sensor node n is in wake mode and the fraction of time it is performing sensing, respectively. Thus, the sensor node spends energy at the rate of e_w in u_{wn} fraction of time and at the rate of e_s in u_{sn} fraction of time. This is taken into account while writing inequalities (7). Since a sensor n is sensing and thus generating data only for u_{sn} fraction of time, $r_f/d_{s(f)}$ is upper bounded by u_{sn} and a sensor can perform sensing only when it is in the wake mode. Thus, we have the inequalities (8). Similarly, the fraction of time a sensor is transmitting or receiving is limited by the fraction of time it is in the wake mode which is stated in inequalities (9).

Using the optimal solution, routing and scheduling with power control can be done as discussed in Section 3. The scheduling of the sleep slots can be done as follows. Note that a node has to be awake when a mode is scheduled in which it has to transmit or receive. For the rest of the time, the sleep slots of the sensors can be scheduled in any manner as long as the sensors are awake for the fraction u_{wn} and they sense for u_{sn}/u_{wn} fraction of time they are awake.

OPT-2 is also an LP which becomes computationally demanding as we increase N and so we can use the method described in Section 4. Note that here we need to consider $L+2N+1$ modes to obtain the optimal solution (we need N additional modes for this problem because of additional constraints (9)).

The notion of fairness that has been used in formulating **OPT-1** and **OPT-2** is somewhat inflexible because even a single bottleneck node could severely affect the performance of the other nodes. A useful modification of this notion of fairness is used in the formulation of **OPT-1*** and **OPT-2*** as follows. Suppose the optimal solution obtained using **OPT-1** or **OPT-2** is λ^*. **OPT-1*** and **OPT-2*** use the same constraints as **OPT-1** and **OPT-2** except for a modification in (1) and the objective. The constraint (1) is modified to

$$\frac{r_f}{d_{s(f)}} \geq \kappa\lambda^*,\ \forall f \in \mathcal{F}; \qquad (11)$$

where $0 \leq \kappa \leq 1$. The objective is to maximize $\sum_{f\in\mathcal{F}} w_f r_f$ where $\{w_f; f \in \mathcal{F}\}$ are some positive weights. By changing κ, we could control the effect of the bottleneck nodes, i.e., we can relax the fairness constraint to maximize a global reward function. We will see in the next section that it can substantially increase the overall network throughput.

6. EXAMPLES

In this section, we will provide examples to gain some insights into the optimal solutions of the problem formulations discussed in the previous sections. We will also illustrate the performance of **ALGO-M** using examples.

In the following, each sensor node selects its transmit power from $\{0, 0.1, 1, 10\}\, mW$. Channel gain over a link is taken inversely proportional to the squared distance between its nodes. We take $e_t = 60mW$, $e_r = 60mW$, $e_s = 2mW$ and $e_w = 20mW$. The transmit powers, e_t and e_r correspond to some typical values in ADF7020 ([3]) and e_s is a typical value seen in sensors like SHT1x/SHT7x ([25]). We take $\sigma_l^2 = 10^{-7}W$ and $W = 5MHz$. These settings are applicable to all the examples in this section unless mentioned otherwise.

We first consider the solution of **OPT-2** for a simple network consisting of six sensor nodes and a fusion node. Each node is generating data at the rate of 25 $Kbps$ and harvesting energy at the rate of 50 mW. In Fig. 1, the net flows over each of the links in the network are shown. The net flow for a link l is obtained as $\sum_{f\in\mathcal{F}} x_l^f$. In the optimal solution for this example, $\lambda = 0.88$, $u_{wn} = u_{sn} = 0.88$ $\forall n \in \mathcal{N}$, fractions of time the nodes transmit and receive are [0.27 0.27 0.02 0.40 0.40 0.02] and [0.17 0.17 0 0.02 0.02 0]

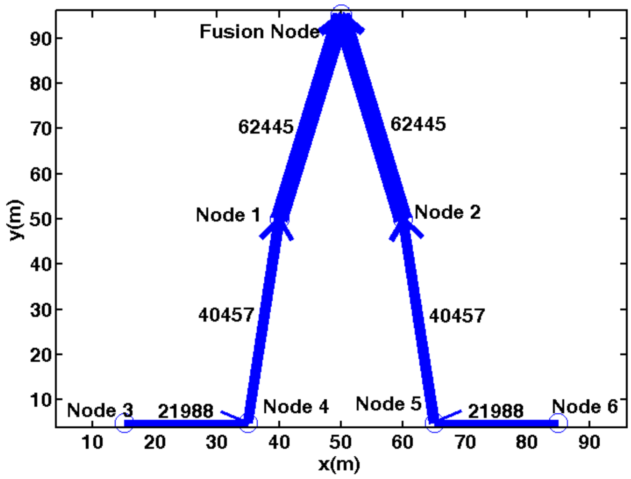

Figure 1: Optimal solution for $N = 6$

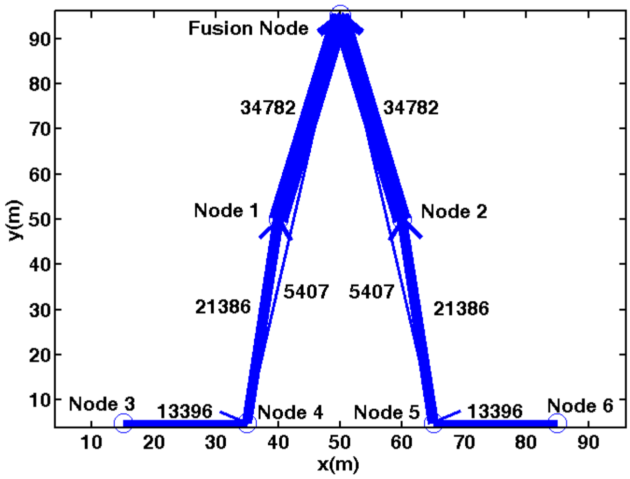

Figure 2: Optimal solution for $e_r = 300mW$

respectively. In Figs. 1, 2, 3 and 9, the thickness of a line representing a net flow is proportional to its rate (indicated against the arrow) and we have depicted only the significant net flows ignoring the ones with smaller rates.

Fig. 2 depicts the optimal net flows for the same network as in Fig. 1 using the same settings except for a higher power consumption during reception. We took $e_r = 300mW$. On increasing the power consumption required for reception, more energy is spent for the reception on routes with more hops. Thus, the increase in e_r results in an increase in the data flow over routes with lesser hops in the optimal solution. This has been pointed out in [7] and [6] also. In the optimal solution, $\lambda = 0.54$, $u_{wn} = u_{sn} = 0.54$ $\forall n \in \mathcal{N}$, fractions of time the nodes transmit and receive are [0.15 0.15 0.01 0.44 0.44 0.01] and [0.09 0.09 0 0.01 0.01 0] respectively. As expected, λ and the fractions of time nodes receive data have decreased. (Although e_r is usually not more than e_t, we took $e_r = 300mW$ to illustrate this point). Further, we have also observed that the number of simultaneous transmissions in the significant modes increase with an increase in σ_l^2. For example, the fraction of time there are more than one simultaneous transmissions is 0.67 when $\sigma_l^2 = 10^{-5}W$ whereas it is only 0.37 when $\sigma_l^2 = 10^{-7}W$. This increase in number of simultaneous transmissions has been discussed in [6] also.

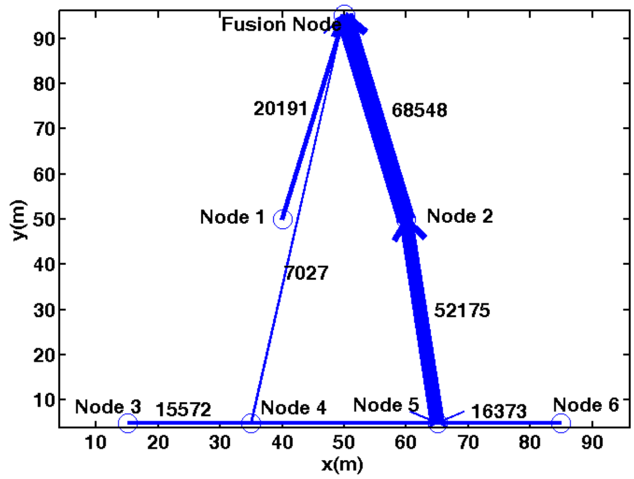

Figure 3: Optimal solution with Node 1 harvesting energy at a lower rate than others.

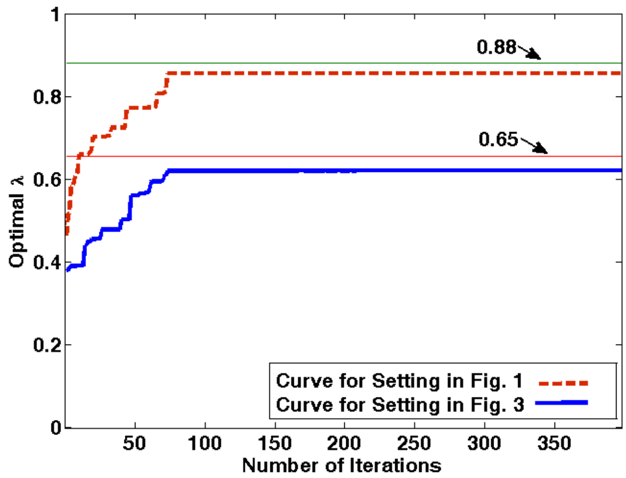

Figure 4: Performance of ALGO-M

Fig. 3 depicts the optimal net flows for the same network as in Fig. 1 using the same settings except for a different energy generation profile for Node 1. It harvests energy at a rate of 22 mW. We can see that, in the optimal solution, other nodes avoid Node 1 for routing their data.

We also solved **OPT-1** for the settings discussed in Figs. 1, 2 and 3 and in the respective optimal solutions, the values of λ were [0.82 0.44 0.48]. In the optimal solutions for **OPT-2**, the corresponding values of λ were [0.88 0.54 0.65]. Through these examples, we see the usefulness of having such sleep modes. The drastic reduction in performance in the **OPT-1** solution for the third case indicates that the

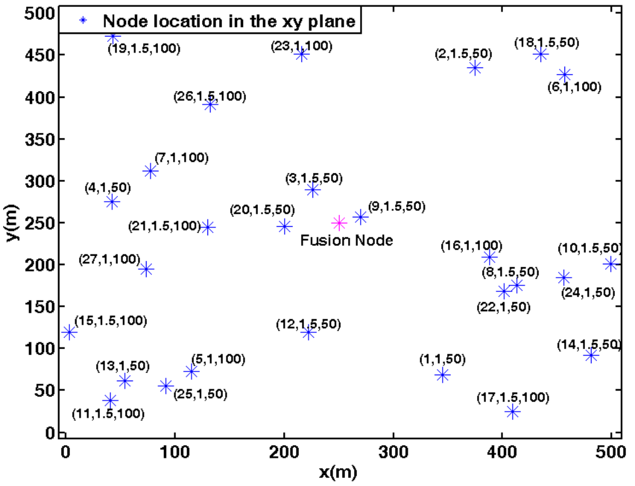

Figure 5: Location, Rate of Data Generation and Rate of Energy Harvesting of the Sensor Nodes in the Network

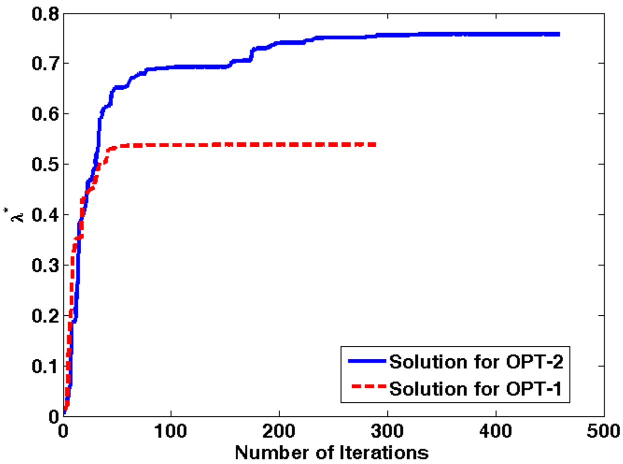

Figure 6: The solution obtained using ALGO-M for $N = 27$

sleep modes are more crucial for energy deprived nodes than for the other nodes.

Next, we study the performance of **ALGO-M** by comparing the solutions obtained using it against the optimal solution and by considering the number of iterations required to get good solutions. In Fig. 4, the fraction λ^* of traffic requirement satisfied for the settings in Fig. 1 and Fig. 3 obtained using **ALGO-M** are shown. The optimal solutions (for **OPT-2**) for the two settings, 0.88 and 0.65, are also shown. We can see that the solution obtained using **ALGO-M** quickly attains values near the optimal solution around the 100^{th} iteration. We have observed similar performance for **ALGO-M** for several other examples. This inspires confidence in **ALGO-M**. However, the optimal solution for **OPT-2** can be found only for small N and K. For example, for $K = 4$, we could find the optimal solution only for N upto 6. But **ALGO-M** could be used for much larger N and K as we next show.

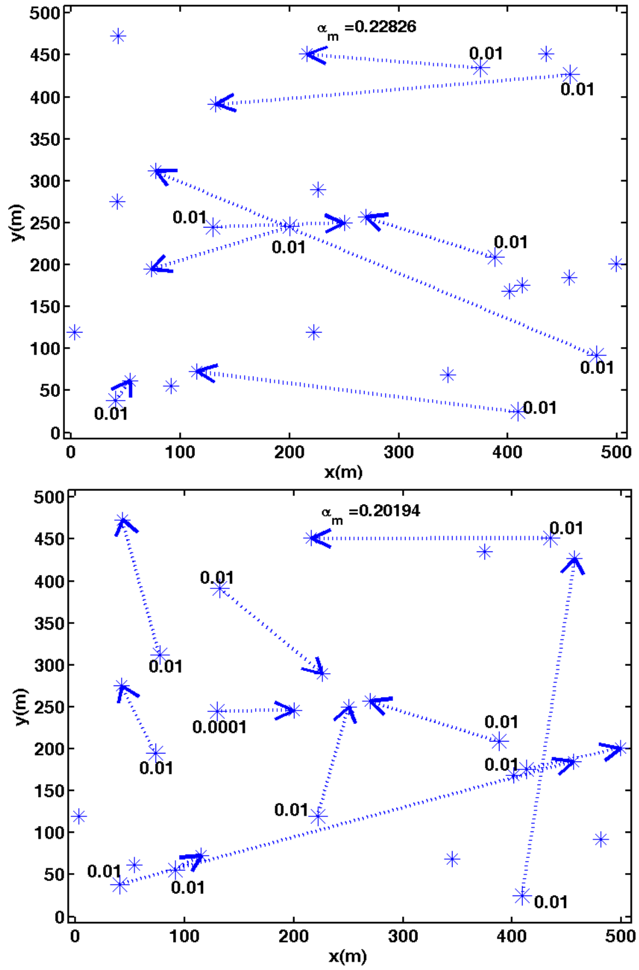

Figure 7: Two significant modes in the solution obtained using ALGO-M (the directed arrows indicate the active links); The numbers at the transmitting nodes are their transmit powers (in W**).**

Next, we consider a network with 27 energy harvesting sensor nodes (with sleep modes) placed over a region of dimensions 500m x 500m as shown in the Fig. 5. The elements of the 3-tuples in the figure are 1) Node Index n, 2) d_n $(Kbps)$ 3) P_n^{av} (mW). We solved **OPT-1** and **OPT-2** using **ALGO-M** and Fig. 6 depicts the λ^* at each iteration for the two formulations. For the curve corresponding to **OPT-2**, note that there is rapid increase in λ^* till around the 100 iterations after which the increase is less. After about 400 iterations, the increase is minimal and the optimal λ obtained using **ALGO-M** is 0.76. The pattern is similar for the curve corresponding to **OPT-1** also. We observed that many significant modes have several simultaneous transmissions and that the routing of data was often through multiple multihop paths. We have illustrated these two points in Fig. 7 and Fig. 8. Fig. 7 depicts two of the significant modes in the solution and Fig. 8 depicts the routing of the data generated at four sensors. We also ob-

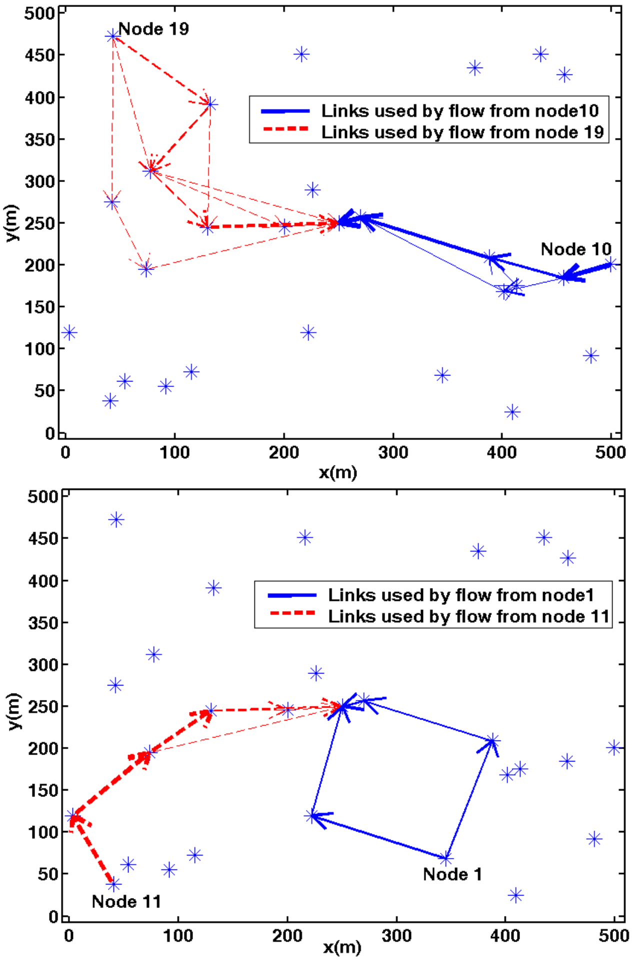

Figure 8: Routing of data in the solution obtained using ALGO-M

tained the optimal solution for **OPT-1** for this setting using **ALGO-M** and the optimal λ was 0.54 again illustrating the benefit of having sleep modes.

In Fig. 9, the net flows in the solution obtained using **ALGO-M** is shown for a setting with $N = 18$. The energy harvesting rate at Node 1 is 22 mW whereas that at Nodes 2, 3 and 4 is 100 mW. Note that Nodes 1, 2, 3 and 4 are nearest to the fusion node so that we can expect a significant amount of data to be routed through these nodes to the fusion node. But, such a routing will require a lot of power at such nodes for reception and transmission of data and hence, such nodes could end up becoming bottlenecks if their energy harvesting rates are less. In this solution also obtained using **ALGO-M**, we see the pattern that we had seen earlier in an optimal solution (See Figure 3). Although Node 1 is as close to the fusion node as Nodes 2, 3 and 4, the other nodes use the latter nodes more than the energy deprived Node 1 in routing their data. This indicates that the solutions obtained using **ALGO-M** are good even for large N and K.

Next, we discuss the optimal solutions obtained by solving **OPT-2*** where fairness can be sacrificed for an overall

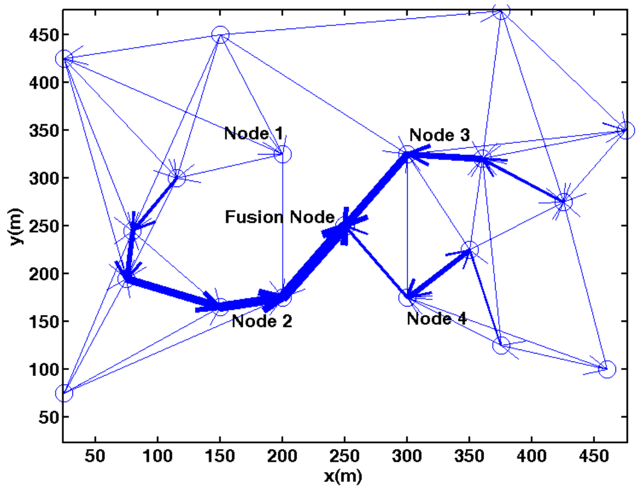

Figure 9: Net flows for $N = 18$ in the solution obtained using ALGO-M

increase in network throughput. We took $w_f = 1 \ \forall \ f \in \mathcal{F}$ so that the objective is maximization of total rate. For the setting in Fig. 1, the optimal total rates were 148 $Kbps$, 148 $Kbps$, 143 $Kbps$ and 132 $Kbps$ when κ took values 0, 0.5, 0.75 and 1.0 respectively. For the setting in Fig. 3, the optimal total rates were 111 $Kbps$, 109 $Kbps$, 105 $Kbps$ and 98 $Kbps$ when κ took values 0, 0.5, 0.75 and 1.0 respectively. We also solved **OPT-2*** using **ALGO-M** for the setting in Fig. 5 as follows. We found a solution to **OPT-2** via **ALGO-M** using 400 iterations. Then, we found a solution to **OPT-2*** via **ALGO-M** using 400 iterations. The optimal total rates were 36.14 $Kbps$, 34.05 $Kbps$ and 22.59 $Kbps$ when κ took values 0, 0.5 and 1.0 respectively. Thus, we see that by changing κ, we can relax the strict notion of fairness used in the **OPT-1** and **OPT-2** and improve a performance metric like total rate. We see that the total rate increases with decrease in κ. Also note that the increase is most significant for the network in Fig. 5 with $N = 27$. This could be due to the fact that the number of bottleneck nodes often are more in a larger network and thus, the scope for improvement in a metric like the total rate by the relaxation of the fairness constraint is also more.

7. CONCLUSIONS

We have studied wireless multihop energy harvesting sensor networks employed for random field estimation, and formulated and solved the problem of obtaining jointly optimal power control, routing and scheduling policies that ensure a fair utilization of network resources. We have also developed an efficient suboptimal approach to obtain good solutions to this problem. Finally, we studied the optimal solution and the performance of the new approach through some numerical examples. As the next step, we intend to obtain more decentralized and computationally efficient approaches to solve this problem.

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