On the Deployment of Wireless Data Back-haul Networks

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Abstract

We study the deployment of data back-haul nodes for wireless networks with energy constraints. We address the following problem: given the required lifetime of a sensor network, the energy constraint of back-haul nodes, and the area to be covered, what is the minimum number of nodes needed to construct such a back-haul network and what is the corresponding deployment scheme? Finding an efficient deployment scheme involves location management, routing, and power management. We focus on linear networks and formulate a deployment optimization problem. We then propose and analyze a greedy deployment scheme that achieves close to optimal performance. We reveal the closed-form relationship among different design parameters, namely, the number of sensor nodes, the desired lifetime, and the coverage distance. We also study the effect of miscellaneous power consumptions and non-uniform data density, and consider extensions to planar networks.

I. Introduction

We study the deployment of data back-haul nodes for wireless networks with energy constraints. An application scenarios is in wireless sensor networks. For many sensor-network applications, the desired lifetime of the network is on the order of a few years. It may be infeasible or expensive to change batteries in sensor nodes once a wireless sensor network is deployed. Thus, it is critical and challenging to deploy sensor nodes effectively to form long-lived sensor networks under energy constraints.

Hierarchical structure has been considered as a necessity for large wireless systems. An example is shown in Figure 1. The bigger gray nodes represent more capable and expensive nodes in the higher hierarchy that are responsible for data processing and back hauling. The smaller dark nodes represent sensing nodes that collect information on interested events and report to nearby gray nodes for processing and communication. Consider a real-world example. Crossbow Technology Inc. supplies both smaller and less expensive mote series and more sophisticated and expensive Gateways series. We can consider the mote series as sensing nodes and the Gateways series as data back-hauling nodes in the Figure. In a remote area, both sensing nodes and data back-haul nodes can be energy constrained, which limit the lifetime of a sensor network. In this study, we focus on data back-haul nodes that consume more energy for communications and are mission-critical. Because these nodes are important and usually expensive, strategic deployment of these nodes is justified. In this paper, we study the deployment of these nodes to satisfy the desired lifetime requirement. The degrees of freedom for such a design are multi-fold. They involve topology management, power management, and routing.

We focus on a many-to-one sensor network. In a many-to-one network, data from all nodes is directed to a sink-node/fusion-center. Many-to-one communication is typical in sensor networks used for monitoring/surveillance purposes. Unlike a distributed peer-to-peer wireless networks, the traffic load is highly asymmetric in a many-to-one network, i.e., nodes closer to the sink node have heavier relay load, as illustrated in Figure 1. Thus, the traffic load and the corresponding power consumption are location-dependent. The lifetime of a network can be limited by nodes with heavy traffic load or power consumptions. This problem is adequately captured in this work.

We use data density to model the amount of data generated in a sensor network and assume that the data density is uniform unless otherwise stated. Given the energy constraint and data density, our objective is to answer the following question:

> What is the minimum number of data back-haul nodes we need to construct a sensor network and how these data back-haul nodes should be placed such that the network can satisfy the predetermined life-time and coverage requirement?

An alternative question is: *given the number of data back-haul nodes, and the desired life time of the sensor network, how large an area can this sensor network cover and how?* Yet another objective is: *given the number of nodes and the area to be covered, what is the maximum lifetime of the network and what is the deployment scheme to achieve it?*

In this paper, our primary focus is on *linear* sensor networks, in which the data back-haul nodes are deployed in a linear topology. Such a topology can be used in a narrow and long sensor network, as shown in Figure 1. This is justified by real world examples. For instance, the sensor network deployed on Great Duck Island is in a narrow-and-long shape (about 50 nodes long and 5 nodes wide) [17]. Other applications include sensor networks for border surveillance, highway traffic monitoring, safeguarding railway tracks, oil and natural gas pipeline protection, and structural monitoring and surveillance of bridges and long hallways. In addition, we have also provided heuristics for analyzing planar networks using the analysis of the basic linear topology.

We assume the deployment of data back-haul nodes is carefully planned and controlled instead of randomly performed. First, in most current sensor network deployments, sensor nodes are manually deployed instead of randomly thrown into the field of interest. Furthermore, because data back-haul nodes are mission-critical, expensive, and in a relatively small number, careful planning and deployment is justified. Our numerical results show that the lifetime of a randomly deployed network is an order of magnitude lower than that of a carefully deployed one.

The paper is organized as follows. We discuss related work in Section II. In Section III, we elaborate the problem and introduce a deployment optimization problem. In Section IV, we propose and analyze a greedy deployment scheme. We show that the performance of the greedy scheme is close to optimal. The closed-form analysis of the greedy scheme allows us to understand the relationship among the design parameters. We study the effects miscellaneous power consumptions and non-uniform data density, and consider extensions to planar networks in Section V. The paper is concluded in Section VI.

II. Related Work

In this section we briefly discuss the related work on the capacity and lifetime of wireless adhoc/sensor networks. Bhardwaj *et al* have provided upper bounds on the lifetime of sensor networks [1], [2] where sensor node locations are given. In [13], the authors propose a transmission range distribution optimization scheme to maximize the network lifetime given fixed node locations. In comparison, our work is to address the deployment issue of sensor networks. Energy conservation and lifetime extension is investigated in [3] using cell-based techniques [20]. In comparison, our work focuses on many-to-one networks, which is significantly different from random distributed peer-to-peer networks. In [12], the authors study the problem of placing the sink-node to maximize the life-time of the network in a two-tiered wireless sensor network. Furthermore, the placement and power management of additional relay nodes are also considered in [9]. The joint design problem is formulated as a mixed-integer nonlinear programming problem and heuristic algorithms are proposed. Our work is different in the sense that we assume only one fixed sink node. In addition, the relay nodes do not have their own traffic load in [9], which also differs from our scenario.

The most closely related work is by Ganesan *et al* [8], where our work differs in terms of the data collection model. The problem is not solved for the general model in [8], and the optimal scheme presented in [8] assumes that each node has the same amount of data regardless of its coverage distance. In comparison, we assume uniform data density across the network, and thus a node that covers a larger distance has more data. In our model, more complexity is involved because the data volume at each node is a function of its distance from its neighboring node. In other words, the total amount of data relayed to the fusion center is linearly proportional to the total number of nodes in [8], while it is proportional to the total distance that the network covers in our work. Thus, their results do not yield our results. We justify our assumption using the following example of a borderline surveillance network. Assume that events happen uniformly and randomly in the surveillance area. Then it is reasonable to assume that the total number of events reported to the fusion center is proportional to the length of the borderline instead of the number of nodes deployed. In other words, a node that covers a larger area/distance observes more events and thus generates more data. This phenomena is particularly evident when we consider the higher layers in a hierarchical network.

Maximum lifetime routing in sensor and ad hoc networks have been studied extensively in the literature, see e.g., [5], [21], [15], [18], [10]. Most of proposed schemes assume given node locations (potentially mobile in ad hoc networks), which is different from the deployment requirement. On the other hand, for a given deployment, the proposed schemes can be used so that the lifetime of the deployment can be numerically evaluated, and thus beneficial to obtain good 2D deployments.

Our preliminary work is presented in [6], [11]. We extend the previous work by including studies on miscellaneous power consumptions and non-uniform data density, as well as heuristics on planar networks in this paper.

III. Problem Description

It is well-known that in a many-to-one communication network, the sink node is usually the capacity bottleneck. It is also noticed that the sink node can be the energy bottleneck. We elaborate the problem in the context of a linear network. Assume that the sink node is at the end of the network. Data back-haul nodes closer to the sink node will have much higher relay load. When evenly spaced, nodes close to the sink consume more power and die quickly, which causes the wireless sensor network to be disconnected. In this case, nodes closer to the sink node limit the lifetime of a sensor network. There are different approaches to alleviate the problem, including allocating more energy to nodes closer to the sink node, placing more nodes, and placing nodes closer in heavy load areas. Another possibility is to perform load balancing, i.e., a node with lower traffic load can send data over longer hops to release the burden of other nodes. We consider all these possibilities in the paper. Our objective is to deploy data back-haul nodes in an optimal way such that the network can cover as large an area as possible given the number of nodes available and the desired lifetime of the network.

A. System Model

In this paper, we assume a perfect medium access control as in [13], [8]. Due to low energy supplies and low duty-cycles of wireless sensor networks, many research efforts have suggested (localized) TDM-type of access schemes, which is in accord with our assumption.

We use the following communication model in the paper. Let d be the distance between the sender and the receiver, and P be the transmission power. Then the data rate R is proportional to the received signal strength; i.e., $R = P/\beta d^\gamma$, where γ is the distance loss factor, $2 \leq \gamma \leq 5$, and β is a constant, which can be considered as the signal strength requirement. This model is widely used in the literature, e.g., [7], [4]. We are interested in the case where d is relatively large (e.g., at least on the order of tens of meters).

We assume that background noise is at a constant level, and therefore the received signal strength infers signal to noise ratio (SNR). Thus, the energy consumption to convey one unit of data over distance d is

$$P \times \frac{1}{R} = \beta d^{\gamma}. \tag{1}$$

Note that we only consider the transmission power here. Other power consumptions, such as receiving power and miscellaneous power at the transmitter, are considered in Section V-A.

In practice, due to shadowing and fading phenomena in the transmission environment, the received signal strength is often random. However, without precise information about the territory and considering the *long-term average*, it is reasonable to assume a direct relationship between distance and per bit energy consumption [16]. Thus, we use Eq. (1) as a the model to understand the deployment issue in wireless sensor networks.

The ideal bit-energy model in Eq. (1) can also be extended to a more practical power-goodput model. Basically, we explore the fact that goodput increases as SINR increases. First, with the advances in DSP and sensor developments, newer versions of sensors, especially more expensive and sophisticated ones, have the capability to adjust data rates based on channel conditions. In addition, for a given modulation/coding rate, where SINR is higher, the BER (bit error rate) is lower, and thus the probability of failure is smaller, which implies higher goodput and thus lower energy consumption. All results in this paper can be directly applied to systems with power-goodput model where per-bit energy consumption is a polynomial function of distance. Such a model can take into account less-than-ideal hardware realization and capture a less aggressive correlation between energy and distance.

We should note that the communication model does not impose a constraint on the transmission range. Instead, it is possible for two far-away nodes to communicate with each other at the cost of high transmission power. Thus, the model is general. On the other hand, imposing an additional range constraint will not change the problem significantly because communications over a long link is penalized in teams of power consumption. Furthermore, the proposed greedy algorithm does not rely on the assumption of unlimited communication range, yet yields close-to-optimal performance. Thus, the impact of allowing large communication range is negligible.

We assume that each unit coverage distance generates c unit of data per unit time. An example where this assumption holds is a surveillance sensor network where incidents happen uniformly along the surveillance line (e.g., a border line).

B. Problem Formulations

Let E be the initial energy of each node and T be the desired lifetime of the sensor network. We are interested in the case of a relatively large T. Let d_i be the distance between the ith the $(i+1)$th nodes, $i = 1, \cdots, n-1$, and d_0 be the area covered by node 1, as shown in Figure 2. We assume that the node i will collect all the data between nodes $(i-1)$ and i, which is $d_{i-1}c$ per time unit. Therefore, d_{i-1} is the coverage distance of node i. Node n is the sink node. We have $d_i \leq D$ for all i, where D is the predefined maximum distance between two nodes. In the case of a hierarchical network, D limits the distance between a sensor node to its neighboring data back-haul node (i.e., the cluster head) in the higher hierarchy.

We first introduce Problem IDEAL. In this problem, we assume that energy can be allocated arbitrarily among nodes. In other words, we only have a total energy constraint. Given $(n-1)$ nodes, the total initial energy is $(n-1)E$. (Note that node n is the sink node.) This is an idealized case, and its result serves as a *benchmark* of the system. When energy can be allocated arbitrarily among nodes, the network dies only when there is absolutely no energy left in any nodes. Thus, the definition of the lifetime of such a network is very general. We will show later that the performance of the proposed scheme under more realistic assumption is close to that in the benchmark case, and thus the effect of arbitrary power allocation is limited.

When energy can be allocated arbitrarily among nodes, routing in a linear network is greatly simplified. A necessary condition for optimality is that node i should relay all data to node $i+1$, its nearest neighbor toward the destination because $(a+b)^\gamma > a^\gamma + b^\gamma$, where $a, b > 0$ and $\gamma > 1$. In other words, it consumes more energy to transmit data over longer hops than over multiple shorter hops. This holds when energy can be arbitrarily allocated among nodes.

The objective of Problem IDEAL is to find a deployment scheme to cover the maximum distance given the number of data back-haul nodes and the lifetime requirement. The problem is formulated as

$$\underset{\vec{d}}{maxmize} \quad \sum_{i=0}^{n-1} d_i \tag{2}$$

$$\text{subject to} \quad \beta \sum_{i=0}^{n-2} cd_i \sum_{k=i+1}^{n-1} d_k^{\gamma} \leq \frac{(n-1)E}{T} \tag{3}$$

$$0 \leq d_i \leq D, \quad i = 0, \cdots, n-1. \tag{4}$$

In Eq. (2), cd_i is the amount of data collected by node $(i+1)$ in one time unit and it is relayed to node $(i+2)$, ..., and node $(n-1)$, to node n. Furthermore, $(n-1)E$ is the total initial energy and T is the required life time, and thus $(n-1)E/T$ is the maximum amount of energy consumed per time unit by all nodes. Therefore, Eq. (3) is the energy constraint. Eq. (4) is the maximum distance constraint. We note that it can take several hops for a packet (bit) to be forwarded to the sink, and thus the energy consumption could happen at different time periods. The problem formulation assumes steady state. This is reasonable in a long-lived sensor network, where the time period to forward a packet, on the order of seconds, is much smaller than the life-time of the network, on the order of months or longer. Problem IDEAL serves as a *benchmark* because of its arbitrary energy allocation assumption and the corresponding definition of lifetime. A similar problem can be formulated to introduce individual energy constraints on each node. We refer interested readers to [11] for details.

We note that Problem IDEAL is not a convex optimization problem because the domain is not a convex set. However, because the number of variables is relatively small, we use the *fconmin* function in matlab to obtain the solution numerically. Next, we present a heuristic deployment scheme that achieves close-to-optimal performance and enables analysis.

IV. Greedy Deployment Scheme

Problem IDEAL serves as a *benchmark* because of its arbitrary energy allocation assumption and the corresponding definition of lifetime. However, such a heterogeneous energy allocation may be inconvenient and impractical in production and deployment. In this section, we present a greedy deployment scheme where each node has an individual (usually homogeneous) energy constraint. The intuition of the greedy scheme is as follows: a node relays data for all nodes that are further away from the sink. It tries to push its data as far away as possible given the lifetime and energy constraints, which determines the distance to its nearest neighbor toward the sink. To elaborate, the total traffic load of node i is $c\left(\sum_{j=0}^{i-1} d_i\right)$. Let x_i be the pushing distance; i.e., the maximum distance that node i can push this amount of data given the energy and lifetime constraints. We have $\beta(c\sum_{j=0}^{i-1} d_j)x_i^\gamma = \frac{E}{T}$. The algorithm is greedy in the sense a node tries to push its data as far away as possible under the constraints. Furthermore, node i does not directly send data to node j, where $j \geq i+2$, because it consumes more energy. Because of the maximum distance constraint, we have $d_i = \min\{D, x_i\}$, where d_i is the distance between nodes i and $i+1$. Therefore, the greedy algorithm can be stated as:

$$\begin{cases} d_0 = D \\ d_i = \min\left(D, \left(\frac{E}{\beta Tc\sum_{j=0}^{i-1} d_j}\right)^{\frac{1}{\gamma}}\right), \quad i = 1, \cdots, n-1. \end{cases} \tag{5}$$

In the greedy algorithm, d_i can be calculated iteratively. We note that d_i is monotonically decreasing — a node with heavier relay load is compensated through a smaller transmission distance. The greedy algorithm can be easily adopted to more general cases. For example, if each node has heterogeneous initial power constraints, E_i, we can replace E by E_i in Eq. (5). If data density is non-uniform, we can replace $c\sum_{j=0}^{i-1} d_j$ by the aggregated load from distance 0 to $\sum_{j=0}^{i-1} d_j$.

A. Numerical Comparison

We compare the performance of the greedy scheme with that of Problem IDEAL. Figure 3 compares the numerical solution of Problem IDEAL and the performance of the greedy one. Problem IDEAL serves as a benchmark because of its arbitrary energy allocation assumption and the corresponding general definition of life time. Define a constant $C = E/(c\beta T)$. When $D \geq C^{(1/(\gamma+1))}$, we have $x_i \leq D$ for all i. This is the case where the required lifetime is long and/or the initial energy in each data back-haul node is low, which is of our primary interest. In the numerical result, $C = 1$, $D = 1$, and $n = 50$. We set $\gamma = 4$ for all numerical results in this paper unless otherwise specified. In Figure 3, the x-axis is the index of nodes and the y-axis is d_i, which is the distance between two consecutive nodes. In the legend, D_n is the total coverage distance given n nodes. We notice that the difference in performance of the greedy algorithm with the optimal one is very small. Figure 4 compares the energy allocation of the two schemes. In the greedy scheme, all nodes consume the same amount of energy by definition in Eq. (5). In the optimal solution of Problem IDEAL, we notice that the leftmost nodes have slightly higher energy allocations, which infers to the slightly larger d_i in Figure 3.

Figure 5 compares the coverage length of the greedy algorithm with the optimal solution of the Problem IDEAL where $D = 1$ and $C = 0.01,\ 1,\ 10$, respectively. (Note that smaller values of C are of more interests since they correspond to long network lifetime.) It includes both cases where $D \geq C^{(1/(\gamma+1))}$ and $D < C^{(1/(\gamma+1))}$. The x-axis is the number of nodes and y-axis is the total distance covered. For each fixed C, we can see that the performance of the greedy algorithm is almost indistinguishable from that of the optimal scheme with arbitrary energy allocations. Figure 6 shows the results for $\gamma = 2$.

In summary, the advantage of allowing arbitrary energy allocation is negligible; the greedy algorithm where each node has the same initial energy performs very well. Its coverage distance is almost equal to that of the optimal deployment. Thus, it justifies the greedy deployment of homogeneous data back-haul nodes.

B. Performance Analysis

Because the greedy scheme achieves close to optimal performance, its closed-form analysis can provide insight into the design of wireless data back-haul networks, which is one of the reasons to introduce the greedy algorithm. In this section, we obtain a closed-form approximation for the greedy algorithm. Let $D_i = \sum_{k=0}^{i-1} d_k$, i.e., D_i is the total length covered by nodes 0 to $(i-1)$, which can be calculated iteratively using Eq. (5). We claim a closed-form approximation of D_i as follows:

$$D_i \approx C^{\frac{1}{\gamma+1}} \left(\frac{\gamma+1}{\gamma} i \right)^{\frac{\gamma}{\gamma+1}}, \quad i = 1, \cdots, n, \tag{6}$$

To justify our claim, we only need to show that the above equation satisfies Eq. (5) iteratively. Assume Eq. (6) hold for $k = 0, 1, \cdots, i-1$. By Eq. (5), we have

$$d_k = \left(\frac{E}{c\beta T \sum_{j=0}^{i-1} d_j} \right)^{\frac{1}{\gamma}} = \left(\frac{C}{D_k} \right)^{\frac{1}{\gamma}} \approx C^{\frac{1}{\gamma+1}} \left(\frac{\gamma}{(\gamma+1)k} \right)^{\frac{1}{\gamma+1}}, \quad k = 1, \cdots, i-1. \tag{7}$$

In the above equation, the first equality holds by definition (Eq. (5)) and the second by Eq. (6). Then, we have

$$D_i \;=\; \sum_{k=1}^{i-1} d_k + d_0 \approx \int_1^i C^{\frac{1}{\gamma+1}} \left(\frac{\gamma}{(\gamma+1)x}\right)^{\frac{1}{\gamma+1}} dx + d_0 \approx C^{\frac{1}{\gamma+1}} \left(\frac{\gamma+1}{\gamma} i\right)^{\frac{\gamma}{\gamma+1}} \tag{8}$$

Thus, Eq. (6) is an approximation of the total distance covered by i nodes in the greedy algorithm. In Eq. (8), approximations occur when we replace a summation with an integral, and when the impact of d_0 (i.e., the boundary effect) is ignored. The approximation is very close, especially for relatively large n (e.g., $n \geq 5$). We compare the numerical result to a network up to 10000 nodes, for $0.01 \leq C \leq 10$, and observe that the maximum discrepancy between the approximation and the actual value is smaller than 0.2% for all n, where $5 \leq n \leq 10000$. When n is reasonably large, the approximation of summation by integral is relatively small.

This closed-form approximation in Eq. (6) reveals the relationship among the design parameters, n, the number of data back-haul nodes needed, T, the life time of the data back-haul network, L, the total distance that the network can covered ($L = D_n$ when there are n data back-haul nodes). We have

$$L^{\gamma+1} = \frac{E}{Tc\beta} \left(\frac{\gamma+1}{\gamma} n\right)^{\gamma}. \tag{9}$$

Having any two design parameters fixed, we can obtain the third. For example, given T, $n \propto L^{\frac{\gamma+1}{\gamma}}$, which indicates a super-linear increase in the number of node required with respect to the coverage distance. Given L, $n \propto T^{\frac{1}{\gamma}}$ is sub-linear. In addition, the marginal effect of adding one more node is sub-linear. Suppose that $\gamma = 4$ and all other parameters are fixed. To double the lifetime of a sensor network, we only need 19% more data back-haul nodes. To double the length of the sensor network, we need 138% more nodes.

Finally, we compare the greedy scheme with the uniform deployment scheme. In the uniform deployment scheme, nodes are evenly placed along the line. Assume the routing decision is to relay data to the nearest node toward the sink node. Because node $n-1$ is the closest to the sink node and has the most heavy relay load, it exhausts its energy first. Thus, its lifetime limits the lifetime of the network. Our analysis show that given n, E and T, the greedy scheme can cover $((\gamma+1)/\gamma)^{\gamma/(\gamma+1)}$ larger in distance than that of the uniform deployment [11]. For example, the coverage distance of our greedy scheme is 24% and 19% longer than the uniform one when $\gamma = 3$ and $\gamma = 4$, respectively. Alternatively, the lifetime of the greedy deployment is $(1+1/\gamma)^\gamma$ times of that of the uniform deployment, which is 237% and 244% when $\gamma = 3$ and $\gamma = 4$, respectively.

V. DISCUSSIONS

A. Miscellaneous Power Consumptions

In a wireless device, power consumption is multi-facet. It consumes energy to keep the circuit awake, to receive and process signals, etc. Such power consumption is usually not negligible in practice. For instance, the power consumption for reception is usually of the same order as that for transmission. In this section, we consider such miscellaneous power consumptions and their impact on deployment.

To conserve energy in a wireless device, the device should be put into sleep mode when no transmission/reception occurs. We assume that the energy consumption in the sleep mode is negligible. We assume perfect synchronization, and thus the transmitter and the receiver are awake only when transmission occurs. We also assume that data back-haul nodes do not perform sensing or the power consumption of infrequent sensing/event-driven sensing is negligible.

Let P_a be the amount of additional power consumed by the transmitter in order to keep the circuit "awake", P_t be the transmission power, i.e., the power emitted by the antenna, and P_{max} be the maximum transmission power allowed by the power amplifier, where $0 \leq P_t \leq P_{max}$. Thus, $P_t + P_a$ is the total power consumed by the transmitter. Let P_r be the total power consumed by the receiver, including the power consumed by a circuit, to receive signals, and to perform signal processing. Given the transmission power P_t and the SNR requirement β, if the distance between the transmitter and the receiver is d, then the achievable data transmission rate R is $R = P_t/(\beta d^\gamma)$. The total energy consumption by the transmitter to send one bit over distance d is

$$E_t = \frac{1}{R}(P_t + P_a) = \frac{\beta d^\gamma}{P_t}(P_t + P_a) \geq \beta d^\gamma \frac{P_{max} + P_a}{P_{max}} \triangleq E_t^*, \tag{10}$$

where the inequality holds when $P_t \leq P_{max}$, and E_t^* is the minimum amount of energy consumed to transmit a bit. The energy consumption by the receiver for the bit is

$$E_r = \frac{1}{R}(P_r) = \frac{\beta d^\gamma}{P_t}(P_r) \geq \beta d^\gamma \frac{P_r}{P_{max}}, \triangleq E_r^*. \tag{11}$$

Again, the last inequality holds when $P_t \leq P_{max}$, and E_r^* is the minimum amount of energy consumed to receive one bit. Thus, it saves energy to transmit with the maximum power at the *highest data rate* instead of lower power at lower data rate because this mode takes the smallest amount of time and thus reduces the miscellaneous power consumption at both the transmitter and the receiver. This accords to current research findings [19]. We assume from now on that *transmitting at the maximum power* is the transmission mode used. The challenge remains to determine the deployment and routing strategy.

Let us consider the tradeoff between long and short hops. Without loss of generality (WLOG), we compare a long hop of distance l_d versus two short hops with distances s_1 and s_2, where $l_d = s_1 + s_2$. Assume all nodes transmit at P_{max} as discussed earlier. The total energy consumption to move 1 bit using the long hop of distance l_d is

$$E_{long} = \frac{1}{R}(P_{max} + P_a + P_r) = \beta l_d^\gamma \frac{P_{max} + P_a + P_r}{P_{max}}.$$

Using two short hops, the energy consumption per bit is

$$E_{short} = \beta(d_1)^\gamma \frac{P_{max} + P_a + P_r}{P_{max}} + \beta(d_2)^\gamma \frac{P_{max} + P_a + P_r}{P_{max}}.$$

For $\gamma > 1$, we have $(l_d)^\gamma = (s_1 + s_2)^\gamma \geq s_1^\gamma + s_2^\gamma$, and thus $E_{long} \geq E_{short}$. The intuition is that the total awake time for two short hops is shorter than that of a long hop when $\gamma > 1$ and the rate is proportional to the received SNR. Note that the important factor is that the (maximum) rate decays super-linearly with respect to distance, i.e., $\gamma > 1$. Thus, the time to transmit and receive one bit grows super-linearly over distance and so does the total power consumption. In a linear network, long hops can always be broken into two or more shorter hops iteratively, and thus short hops are preferred under the above stated assumption.

Compared to the case where we only take the transmission power into account, we notice that the energy consumption to transmit and receive one bit is scaled by a constant factor $(P_{max} + P_a + P_r)/P_{max}$.

We define

$$\rho = \frac{P_{max}}{P_{max} + P_a + P_r}$$

as the energy coefficient. In other words, ρ is the ratio of the energy that is used for signal transmission to the total energy consumption. A node consumes $1/\rho$ times of energy to handle one bit compared to the transmission-power only case. Because a node (except the sink node) receives and transmits the same amount of data, this is equivalent to scaling the original energy by a factor of ρ.

Note we make the assumption that a data back-haul node receives data from sensors in the lower hierarchy and does not perform sensing itself. Furthermore, we assume that a node consumes the same amount of energy to receive one unit of data from a neighboring data back-haul node and from sensors in the lower hierarchy. This assumption may not always be true because a sensor node in the lower hierarchy may have smaller transmission power and consumes longer time to transmit one bit to data back-haul nodes. However, for nodes with a large relay load, the difference is small. The larger the value of i, the better the approximation. The difference is more significant for nodes far away from the sink node.

In summary, the effect of miscellaneous power consumption can be well modeled by a scaling factor ρ. It may seem counterintuitive that smaller hops are desirable even when miscellaneous power consumptions are taken into account. The reason is that when nodes are closer, the reliable data rate is higher, the aggregated time for transmission/reception is shorter, the miscellaneous power consumption is lower, and thus the total energy consumption is lower.

B. Non-uniform Data Density

In sensor network applications, data density may vary over locations. For instance, different portions of a road may experience different volumes of traffic and intersections are in general busier. To model this phenomena, let $c(x)$ be the density at location x, where $x \geq 0$. The sink node is located at the rightmost location. The greedy algorithm can be extended to the case with non-uniform data densities along the coverage area as follows:

$$d_i = \min\left(D, x_i : \beta l(i) x_i^{\gamma} = \frac{E}{T}\right), \tag{12}$$

where $l(i)$ is the load for node i to forward; i.e., $l(i) = \int_0^{\sum_{j=0}^{i-1} d_j} c(x)dx.$ In words, in the greedy algorithm, node i tries to push its load $l(i)$ as far as possible within the constraint D, which reflects the same intuition as in Eq. (5).

Next, we show numerical results in the case of non-uniform data density. We consider a linear network of length 10000(m). The data density along the linear network is not uniform, as shown in Figures 7 and 8, respectively. In both figures, the x-axis represents location and y-axis shows the variation in data density. Figure 7 represents a linear network with location-varying data density, e.g., a border line with different volumes of traffic. Figure 8 represents a network with bursty data traffic, e.g., a highway with exits. We assume that the data density profile does not change over time and can be estimated when the sensor network is deployed. When the lifetime of the network is relatively long, short-term variation (e.g., rush-hour vs. mid-night) is smoothed. In addition, to evaluate the impact of estimation errors of data density on the network lifetime, a zero-mean Gaussian estimation error is added to the actual data density profile to create a noisy estimate, as shown by the lower plot in each figure. The standard deviation of the Gaussian-distributed error is 20% of the actual value of the load, which we consider as moderate estimation errors.

We compare the performance of the greedy scheme with perfect knowledge of the data density profile, the greedy scheme using noisy estimate, uniform deployment, and random deployment. We first use the greedy algorithm in Eq. (12) to calculate the number of data back-haul nodes needed to monitor the linear network, denoted as n. The greedy algorithm is then used based on the noisy estimated data density (the lower plot in each profile). In the uniform deployment, n nodes are evenly distributed along the linear network. In the random deployment, n nodes are randomly and uniformly distributed along the line. In all deployments, each node forwards data to its nearest neighbor toward the sink node, which is at the end of the linear network. The network is considered dead when the first node runs out of energy.

Figure 9 compares the greedy deployments with and without estimation errors on the data density. The x-axis is the node index, and y-axis represents the distance between two consecutive nodes. The two curves of the greedy deployment with and without estimation errors (noted as “greedy” and “w. error” in the legend) are almost indistinguishable. To achieve the desired lifetime, the greedy deployment requires 243 nodes with perfect density information. In the presence of estimation errors, 244 nodes are required and the deployment achieves 99$\%$ of the desired lifetime. The preliminary result shows that independent estimation errors have little impact on the performance of the greedy deployment. This is due to the fact that the aggregated load at each node is more important than the density at a location. Because estimation errors are independent, the *aggregated* estimation error at a particular location is small compared to the total aggregated load, due to the central limit theorem, for moderate or large values of i. Therefore, the impact of *independent* estimation errors is small. On the other hand, if estimation errors are correlated, say a large portion of the network is under-estimated, the impact will be larger. The impact of such correlated errors needs to be further investigated.

As a reference, we plot the curve of a greedy deployment where the data density is uniform with the same average density (average over the whole linear network), which is noted as "unif" in the legend. This deployment requires 256 nodes to achieve the desired lifetime. The difference between the uniform and non-uniform density cases is most significant when a low data density exists and thus the distance between two consecutive users are larger (e.g., nodes 20-50).

In the uniform deployment, n ($n = 243$) nodes are evenly spaced in the linear network. The lifetime of the uniform deployment is 34% of the desired lifetime. This is in accordance with the result presented in Section IV. In the random deployment, we run 100,000 independent realizations, where in each realization, n ($n = 243$) nodes are randomly and uniformly deployed. The average lifetime of the random deployment is less than 1% of the desired lifetime. This is due to the randomness in the deployment of nodes; i.e, there exists consecutive nodes with a large gap with a high probability. The larger the network, the worse the lifetime of the random network in comparison. This justifies strategic deployment of nodes and is in accord with theoretical results on the coverage and connectivity properties of randomly deployed networks (e.g., [14]). We also note that nodes closer to the sink are more likely to fail due to their heavier loads.

Bursty data density is also considered, as shown in Figure 8. Similar comparison is shown in Figure 10. In this case, the estimation error costs the greedy algorithm no additional node and 2% decrease in the desired lifetime. The uniform deployment achieves 47% percent of the desired lifetime and the random deployment achieves less than 1%.

While we consider the estimation error on data density above, another type of error occurs on deployment due to inaccurate geographic measurements or physical constraints. We expect the greedy deployment scheme to be robust against small independent deployment errors. Let d_i be the desired deployment and d'_i be the actual deployment with errors. The lifetime of the actual deployment is η times of the desired one, where

$$\eta = \min i \frac{d_i^\gamma \sum_{k=0}^{i} d_k}{(d'_i)^\gamma \sum_{k=0}^{i} d'_k}.$$

However, as n increases, the performance deteriorates because it is bounded by the worst-case scenario. We hope to study the issue further in the future.

C. Planar Networks

The deployment in planar networks presents great challenges, mainly due to the large search space of decision variables. For instance, even with the assumption of arbitrary power allocation, we cannot reduce the search space of routing possibilities much due to possible triangular routes. With x data back-haul nodes, we have $2x + x^2$ continuous variables to optimize. In addition, the coverage area of each data back-haul node needs to be determined so that the total transmission power is minimized while it is guaranteed that all sensors in the lower hierarchy can be connected to at least one back-haul node. In the following, we present two heuristics for the planar deployment.

Consider a square area where the sink is located at the right upper corner. A square-shaped deployment is shown in Figure 12. There are n^2 nodes and node (n, n) is the sink. The deployment is symmetric: d_i is the distance between nodes (i, j) and $(i+1, j)$, and the distance between (j, i) and $(j, i+1)$. Each node collects data of the left-lower rectangular. Assume only total energy constraint is considered. When $\gamma \geq 2$, to send data from (i, j) to $(i+1, j+1)$, it is more efficient to send to node $(i, j+1)$ and then to $(i+1, j+1)$ because

$$\left(\sqrt{d_i^2 + d_j^2}\right)^\gamma \geq (d_i^\gamma + d_j^\gamma).$$

In this case, routing is simple — a packet is routed either a right or upper neighbor until it reaches the sink. Formally, the problem is formulated as

$$\underset{\vec{d}}{maxmize} \quad \sum_{i=0}^{n-1} d_i \tag{13}$$

$$\text{subject to} \quad \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} cd_i d_j \beta \left(\sum_{k=i+1}^{n-1} d_k^{\gamma} + \sum_{k=j+1}^{n-1} d_k^{\gamma} \right) \leq \frac{(n^2-1)E}{T} \tag{14}$$

$$0 \leq d_i \leq D, \quad i = 0, \cdots, n-1. \tag{15}$$

Eq. (14) is the total energy constraint, where $cd_i d_j$ is the volume of data collected by node $(i+1, j+1)$ and $\beta(\sum_{k=i+1}^{n-1} d_k^{\gamma} + \sum_{k=j+1}^{n-1} d_k^{\gamma})$ is the energy to relay one bit to the sink from this node. Note that Eq. (13) is not a general 2D deployment problem because we limit the degree of freedom in allocating nodes.

An alternative is the strip deployment, shown in Figure 11. The whole area is divided into a number of strips, where the result in the linear network can be applied in each strip. In the figure, the greedy algorithm is used, shown as circles. At the right edge, a dense linear network is deployed vertically to pull data to the sink node, shown by the hexagon nodes. The strip deployment is similar to the proposed in [8], where linear approaches are extended to planar networks by dividing a planar network as strips or pieces of pies.

We compare the performance of the two schemes. For a fixed n, we solve Eq. (13) numerically to determine the maximum coverage given n^2 nodes. The perimeter of the area is denoted by L. We then run the greedy algorithm to determine how many nodes are needed to cover the same area. The number of horizontal rows in the strip deployment is determined by $m_r = \lceil L/D \rceil$ because the maximum width of a strip is D. The width of each strip is $w_r = L/m_r$. The load for the ith node in the strip is $cw_r \sum_{k=0}^{i-1} d_k$. Eq. (5) can then be used to determine the distance d_i. The vertical line at the right edge is determined with data density $cw_r L$ per strip.

In Figure 13, we show the perimeter of the coverage area as a function of n under different values of C. In Figure 14, we compare the number of nodes needed to cover the same area by the two schemes. In the figure, the x-axis represents the square deployment where n^2 is the number of nodes needed, the y-axis represents the strip deployment where n_{strip}^2 is the total number of nodes needed. The dashed line is the diagonal. The square deployment is better if the curve is above the diagonal line (e.g., $C = 10$), and the strip one is better if the curve is below the line (e.g., $C = 0.01$). We note that square deployment is preferred when C is large, and strip one preferred when C is small. Small C implies small energy budget per bit (e.g., long T or high c). In this case, it is more efficient to aggregate the data to a few heavy duty nodes with short transmission distances, as the dense vertical line in the strip mode. This implies that some kind of heavy-duty backbone may be desirable in optimal 2D deployments.

In general, deployment of large planar sensor network is of great challenge and requires further study. We hope that the strip and square deployments can shred lights on general 2D deployments. Other potential solutions include deploying multiple sink nodes, exploiting mobile sinks, and decreasing data dimension (e.g., the maximum temperature instead of temperature of all nodes).

VI. Conclusion

In this paper, we study the deployment issue for data back-hauling in wireless sensor networks. Determination of an optimal deployment scheme involves location management, routing, and power management. We formulate a general deployment optimization problem in a linear network and obtain numerical solutions. We then propose a greedy algorithm that performs close to optimal compared to the benchmark case. The closed-form analysis of the performance of the greedy algorithm revealed the relationship among the design parameters, i.e., the required lifetime, the number of data back-haul nodes, and the length of a linear network to be covered. We expect such relationship holds in the case of optimal deployments because the greedy scheme depicts close-to-optimal performance.

We study the effect of miscellaneous power consumptions, including circuit power consumption and receiving power consumption. We also study the cases of non-uniform data density and bursty data pattern. The greedy algorithm can be easily adapted to both cases with significant better performance compared to that of homogeneous and random deployment schemes. We present two heuristic extensions to planar networks. Future study include planar networks, and the impacts of realistic data aggregation models and deployment errors.

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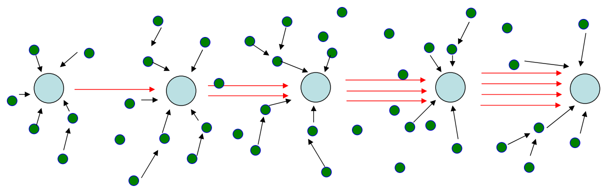

Fig. 1. A Hierarchical Linear Network

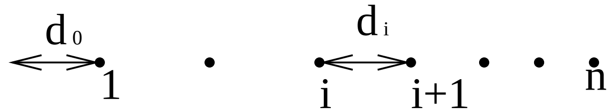

Fig. 2. A Linear Network

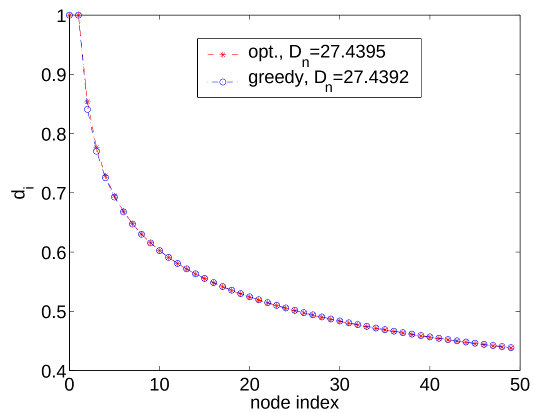

Fig. 3. Compare the locations of data back-haul nodes in the greedy scheme with the numerical solution of Problem IDEAL.

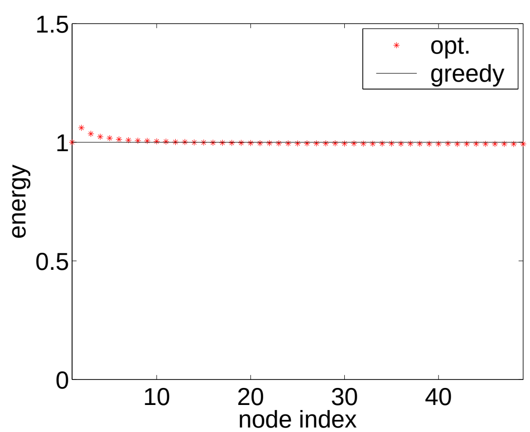

Fig. 4. Compare the power allocation among data back-haul nodes in the greedy scheme with the numerical solution of Problem IDEAL.

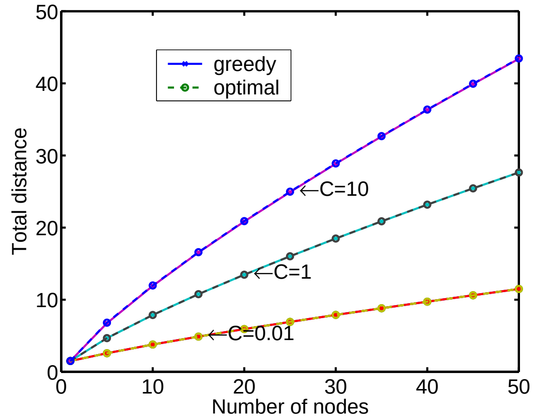

Fig. 5. Compare the coverage distance of the greedy scheme with the numerical solution of Problem IDEAL when $\gamma = 4$.

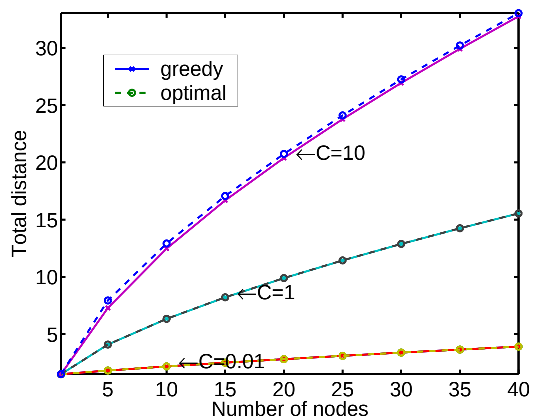

Fig. 6. Compare the coverage distance of the greedy scheme with the numerical solution of Problem IDEAL when $\gamma = 2$.

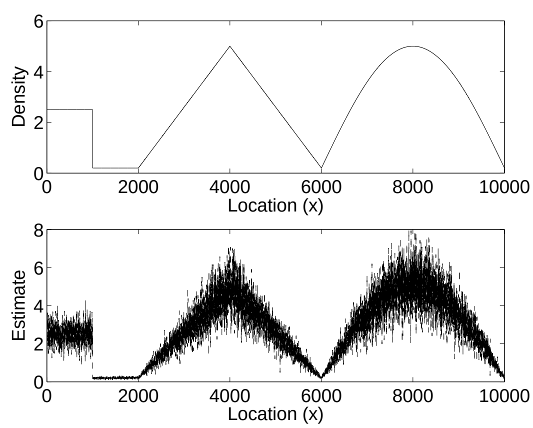

Fig. 7. Nonuniform data density profile.

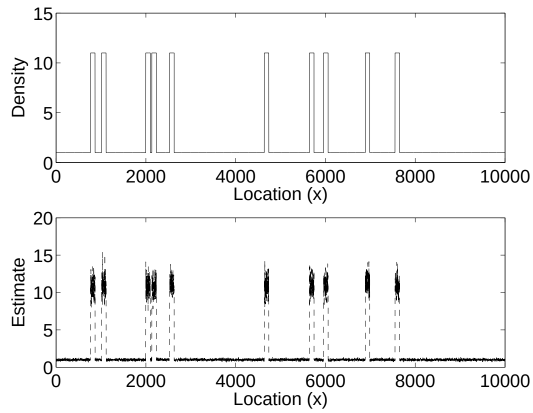

Fig. 8. Bursty data density profile.

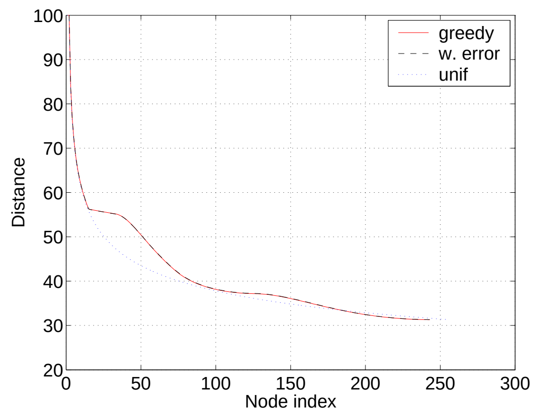

Fig. 9. Compare the deployment of the greedy algorithm with and without estimation errors.

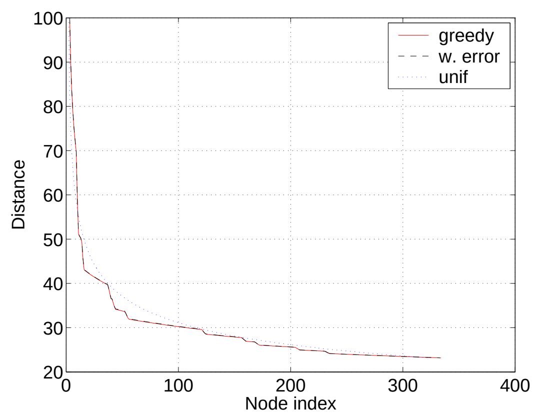

Fig. 10. Compare the deployment of the greedy algorithm with and without estimation errors.

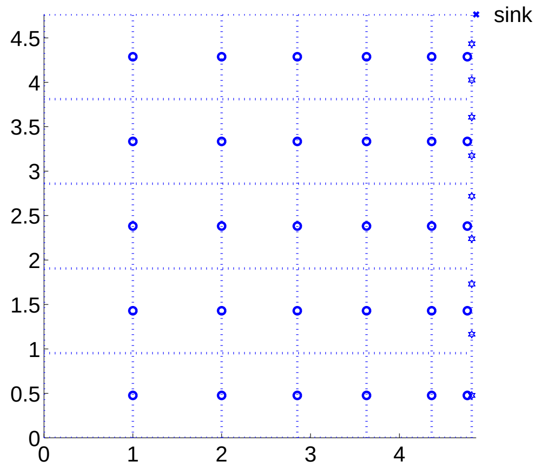

Fig. 11. Deployment of data back-haul nodes in the strip mode.

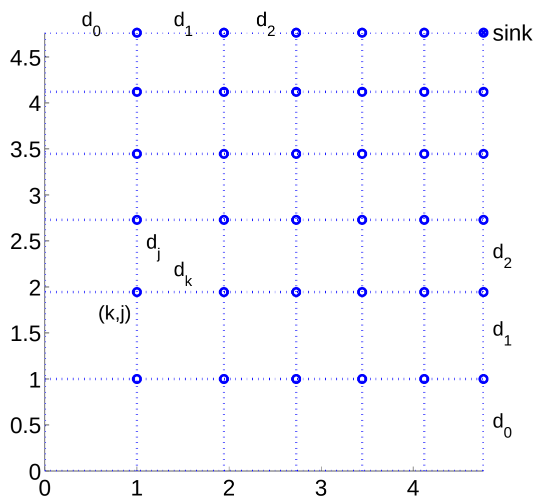

Fig. 12. Square-shape 2D deployment with total energy constraints.

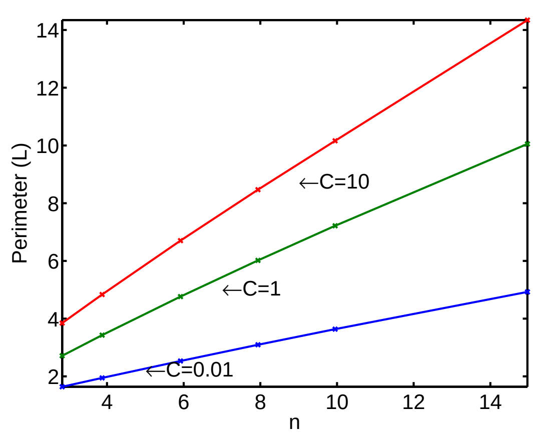

Fig. 13. Coverage area with given number of nodes in the square-shape deployment. The x-axis is n, where $n * n$ is the total number of nodes.

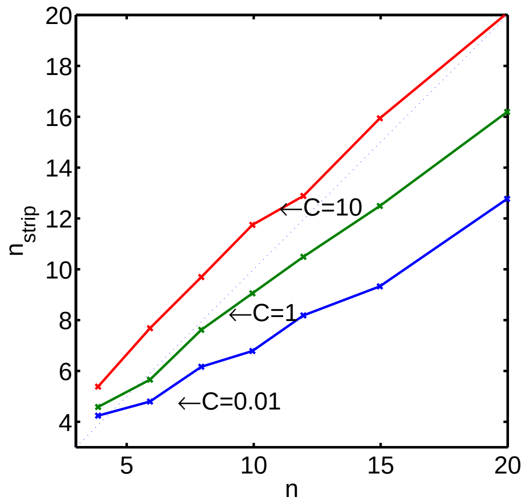

Fig. 14. Compare the number of nodes needed in the square-shape deployment and strip deployment. The x-axis is n_{strip}, where n_{strip}^2 is the total number of nodes.