J Sign Process Syst (2009) 57:385–400
DOI 10.1007/s11265-008-0324-1

Lifetime Maximization Based on Coverage and Connectivity in Wireless Sensor Networks

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Received: 26 October 2007 / Revised: 22 July 2008 / Accepted: 19 November 2008 / Published online: 25 December 2008

Abstract We consider information retrieval in a wireless sensor network deployed to monitor a spatially correlated random field. We address optimal sensor scheduling and information routing under the performance measure of network lifetime. Both single-hop and multi-hop transmissions from sensors to an access point are considered. For both cases, we formulate the problems as integer programming based on the theories of coverage and connectivity in sensor networks. We derive upper bounds for the network lifetime that provide performance benchmarks for suboptimal solutions. Suboptimal sensor scheduling and data routing algorithms are proposed to approach the lifetime upper bounds with reduced complexity. In the proposed algorithms, we consider the impact of both the network geometry and the energy consumption in communications and relaying on the network lifetime. Simulation examples are used to demonstrate the performance of the proposed algorithms as compared to the lifetime upper bounds.

Keywords Network lifetime · Sensor scheduling · Routing · Coverage · Connectivity

This work was supported by the Army Research Laboratory CTA on Communication and Networks under Grant DAAD19-01-2-0011 and by the National Science Foundation under Grant ECS-0622200. Part of this work was presented in the Conference on Information Sciences and Systems, 2007 and the SPIE Conference on Advanced Signal Processing Algorithms, Architectures, and Implementations, 2007.

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1 Introduction

In this paper we address the problem of lifetime maximization in a wireless sensor network deployed for the reconstruction of a spatially correlated random signal field [1]. Since it is often undesirable or infeasible to replace or recharge sensors, the network lifetime is a critical issue when designing wireless sensor networks [2, 3]. The goal of this paper is to design an optimal information retrieval scheme such that the signal field can be reconstructed from the collected sensor measurements within a given QoS requirement while the network lifetime is maximized. We consider the problem under two transmission structures: single-hop and multi-hop transmissions from sensors to the access point. In the former, the design issue is sensor scheduling: which subset of sensors should send their measurements to the access point in each data collection. The key idea is to minimize the number of sensors scheduled for transmission in each data collection by exploiting the spatial correlation of the signal field and the redundancy in sensor deployment. In the latter, we design sensor scheduling and information routing jointly to maximize the network lifetime.

In the case of single-hop transmission, we formulate the problem of optimal sensor scheduling for lifetime maximization as the problem of searching the maximum number of subsets of sensors that cover the monitored area. This is essentially a constrained coverage problem due to the total energy constraint at each sensor. It can be formulated as an integer optimization problem. To solve this problem, we observe that there are two elements that have significant impact on the network lifetime. One is the consumed energy by each sensor for data transmission. The other is the network topology. For example, sensors located in areas that are sparsely covered should be treated differently even if they have the same energy conditions as other sensors.

Base on these observations, we propose a greedy-search based suboptimal method, in which we consider both the network geometry and the energy consumed by sensors in each data collection to prolong the network lifetime. We also derive a network lifetime upper bound that can be computed with low complexity. This upper bound is shown to be tight and provides a performance benchmark for suboptimal algorithms.

In the case of multi-hop transmissions, in addition to the sensor scheduling, we also need to design the information routing. The joint design of sensor scheduling and information routing is related to the problem of coverage and connectivity in sensor networks. We observe that to maximize the network lifetime, scheduling and routing cannot be treated as two separate problems. For example, certain sensor nodes have crucial roles to cover some area; hence, to prolong the network lifetime, we should schedule these nodes for sensing only and avoid using them as relays in information routing. Therefore, the relation between scheduling and routing should be studied carefully, and they should be designed jointly to maximize the network lifetime.

We formulate the joint design as an integer programming. In the problem formulation, instead of directly designing the data transmission route for each scheduled sensor, we seek the optimal assignments of flow to each link and data generation rate to each sensor to maximize the network lifetime under the conditions of flow conservation, energy limitation, and full area coverage. A suboptimal algorithm for node scheduling and data routing is proposed and its performance compared with an upper bound that we have obtained. The proposed joint design of scheduling and routing is shown to achieve significant improvement over the separate design approach.

We observe that in our work we assume sensors are densely deployed in the wireless sensor network. Another method is to deploy "just-enough" sensors, each equipped with multiple/extended batteries. However, the wireless sensor network with the later deployment will lose the robustness. This is because the sensor node will be out of work not only because of the power but also other reasons, e.g., physical damage. If only a very small number of sensors cannot work, the whole sensor network will lose function. Another disadvantage for the "just-enough" sensor deployment is that it will increase the wireless transmission distance and hence, cost more energy.

1.1 Related Work

The problem of sensor scheduling to maximize the lifetime of a wireless sensor network has been studied in [3–5] where distributed scheduling protocols are proposed that exploit both channel state and residual energy information. In [6] an upper bound of network lifetime to achieve α portion of the area coverage is derived. In [7] the authors devise a fully decentralized and localized density control algorithm, the goal of which is to maintain coverage using a minimal number of sensor nodes. The methods in [8–10] focus on maximizing the number of disjoint cover sets. A method for energy-efficient target coverage is proposed in [11] that allows sensors to participate in multiple cover sets. All of the above work focuses on the coverage problem.

Some research work on energy efficient routing in wireless sensor networks can be found in [12–14]. The approaches in these papers are to find the path to the destination that minimizes the total consumed energy. In [15], the optimal flow assignment on each link to maximize the network lifetime is studied. The problem of sensor scheduling is not considered in the above work.

Coverage based on multi-hop transmission has been investigated in [7] and [16–20]. In [7] and [16], the authors investigate the relationship between coverage and connectivity and prove that the condition that the communication range is at least twice of the sensing range is both necessary and sufficient to ensure that the coverage implies connectivity. In [17] and [18] the authors address the optimization problem of selecting a minimum set of sensors that ensures both coverage and connectivity. They combine coverage and connectivity in a single algorithm. However, network lifetime is not the design objective. In [19] the authors consider the problem of connected target coverage to maximize the network lifetime. They create a tree to represent the data transmissions from sensors to the sink, and develop a heuristic algorithm to maximize the number of such cover trees. In this paper we address the problem of area coverage. We formulate the routing problem into energy constrained optimal flow assignment which is more general than creating cover trees. In [20] the authors also address the problem of maximizing network lifetime while providing coverage and connectivity in wireless sensor networks. Different from the problem formulation in this paper, the authors divide the sensor nodes into mutually exclusive connected cover sets, and they try to maximize the number of such sets. They separate the original problem into two sub-optimal problems and solve them individually.

2 Lifetime Maximization: Single-Hop Transmissions

We first address the lifetime maximization problem under the situation that the data from each sensor are sent to the access point through single-hop transmissions. Our basic idea is that, considering the node redundancy and the spacial correlation of the signal field, to prolong the network lifetime, during each data collection, we only select a subset of sensor nodes to transmit their measurements. This set of sensors is chosen to guarantee a certain QoS requirement. Therefore, our goal is to optimally schedule the sensor nodes for each data collection such that the signal field is reconstructed within a given QoS and the network lifetime is maximized. In this section, we first formulate the lifetime maximization as a coverage-related problem; we then apply the approach based on the theory of coverage to solve it. The proposed method is a centralized algorithm carried out at the access point.

2.1 Problem Formulation

Let $\mathcal{D}$ denote the area being monitored and $S(\mathcal{D})$ the random signal field. A network of sensor nodes with fixed initial energy is deployed to monitor this area. Our task is to reconstruct the signal field for a given QoS requirement using sensor measurements collected by an access point. We consider the following scenario: based on the spatial correlation of the underlying signal field, the specified QoS, and the reconstruction method, if the access point receives a measurement from a sensor located at point (x, y), it can reconstruct every point in a r-radius disk centered at (x, y) for a given QoS requirement. This scenario can be applied to a number of sensor network applications. Under this scenario, we define the network lifetime as the time duration from the instant of the sensor network deployment to the instant that the signal field $S(\mathcal{D})$ cannot be reconstructed with a given QoS requirement from the current live sensors.

Based on the above assumption, we note that our QoS specific information retrieval can be formulated as a coverage problem. That is, we assume each sensor has a coverage area of a disk with radius r; then, if we can find a set of sensors such that the union of the coverage areas of these sensors covers the whole region being monitored, the field $S(\mathcal{D})$ can be reconstructed within a given QoS requirement. Hence, the network lifetime can be redefined as the time interval from the instant of the network deployment to the instant when we cannot find a set of live sensors that covers the whole area. Therefore, maximizing the network lifetime is equivalent to searching for the maximum number of cover sets with the energy constraint. Each cover set corresponds to the set of sensors scheduled to collect the data during each data collection. Here, the cover set means a set of live sensors that covers the monitored area, and we denote r the coverage range that is related to a specific QoS requirement.

We assume N sensors $\{s_1, \ldots, s_N\}$ are randomly deployed to cover the area $\mathcal{D}$, and the i-th sensor has an initial energy $E_0^{(i)}$ and an r-radius disk coverage area. We denote $\{C_j, j = 1, \ldots, K\}$ a sequence of cover sets, i.e., the sensors s_i's in set C_j satisfy

$$\bigcup_{s_i \in C_j} A(s_i) \supset \mathcal{D} \quad \text{for} \quad j = 1, \ldots, K, \tag{1}$$

where $A(s_i)$ represents the coverage area of s_i. In the j-th data collection, measurements from the sensor nodes in C_j are collected. Then, the problem of maximizing the network lifetime for a given QoS can be described as follows. Here we assume that a sensor is dead only because it is out of energy.

Given an area $\mathcal{D}$ and a set of sensors $\{s_1, \ldots, s_N\}$, find a sequence of cover sets $\{C_1, \ldots, C_K\}$ such that

1. K is maximized,
2. for sensor s_i, $(i = 1, \ldots, N)$ appearing in the cover sets $\{C_1, \ldots, C_K\}$, the total consumed energy is no larger than the initial energy $E_0^{(i)}$.

We define a boolean variable b_{ij} for $i = 1, \ldots, N$ and $j = 1, \ldots, K$, such that

$$b_{ij} = \begin{cases} 1, & s_i \in C_j \\ 0, & s_i \notin C_j \end{cases}. \tag{2}$$

In each data collection, sensor s_i consumes energy $E_c^{(i)}$ if it is scheduled for transmission. Clearly, $E_c^{(i)}$ depends on the distance from sensor s_i to the access point. Then, the above optimization problem can be formulated as:

$$\begin{aligned} &\text{Maximize} \quad K \\ &\text{subject to} \bigcup_{\{i \mid b_{ij}=1\}} A(s_i) \supset \mathcal{D}, \quad \text{for} \quad j = 1, \ldots, K, \\ &\qquad \sum_{j=1}^{K} b_{ij} E_c^{(i)} \le E_0^{(i)}, \quad \text{for} \quad i = 1, \ldots, N, \end{aligned}$$

where $b_{ij} \in \{0, 1\}$.

The first condition represents that each set C_j is a cover set, and the second condition represents the energy constraint of each sensor. In the following we propose a sub-optimal method using greedy techniques to solve this problem.

2.2 Network Lifetime Upper Bound

We first derive an upper bound for the network lifetime to achieve full area coverage for the case that the lifetime for each sensor is different. It is an extension of the result in [6]. This upper bound provides a measure for the performance of suboptimal methods. It also represents some critical elements we should consider when designing the scheduling.

To derive the upper bound, we first define a concept of a *subregion* as follows [10].

Definition A subregion is a set of points such that two points belong to the same subregion if and only if they are in the coverage area of the same set of sensors.

An example of the subregion is shown in Fig. 1, in which a rectangular area is divided by three sensors into six subregions.

According to the definition of the subregion, we can divide the whole monitored area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$ such that

$$\bigcup_{l=1}^{L} \mathcal{F}_l = \mathcal{D} \quad \text{and} \quad \mathcal{F}_i \cap \mathcal{F}_j = \emptyset \quad \text{for} \quad i \neq j. \tag{3}$$

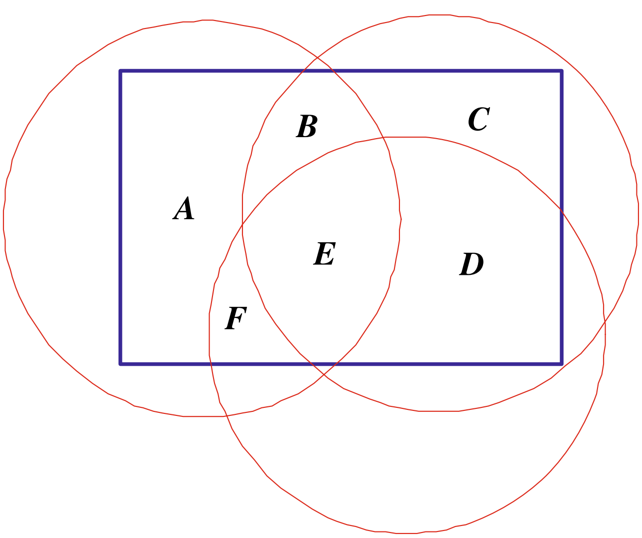

Figure 1 A rectangular area is divided by three sensors into six subregions.

Based on the relationship between subregions and sensor nodes, we associate each subregion with a subset F_l of all sensors that cover the subregion, i.e., $F_l = \{s_{n_1}, \ldots, s_{n_l}\}$ where

$$\mathcal{F}_l \subset A(s_i) \quad \text{for} \quad i = n_1, \ldots, n_l. \tag{4}$$

We observe that for subregion $\mathcal{F}_l$, $l = 1, \ldots, L$, during each data collection, at lease one sensor $s_{n_i} \in F_l$ is selected to transmit its measurement. We also have that for sensor s_{n_i}, its lifetime is define as

$$\left\lfloor \frac{E_0^{(n_i)}}{E_c^{(n_i)}} \right\rfloor, \tag{5}$$

which is the number of data collection that can be provided by this sensor. Therefore, to reconstruct subregion F_l, at most M_l times of data collection can be contributed by all the sensors covering that subregion, where

$$M_l = \sum_{s_{n_i} \in F_l} \left\lfloor \frac{E_0^{(n_i)}}{E_c^{(n_i)}} \right\rfloor. \tag{6}$$

Since we want to cover all the subregions, the network lifetime is upper bounded by

$$\min_{F_l} \sum_{s_{n_i} \in F_l} \left\lfloor \frac{E_0^{(n_i)}}{E_c^{(n_i)}} \right\rfloor. \tag{7}$$

We note that if the lifetime of each sensor is the same, the above lifetime upper bound is the same as the result in [6].

From the above equation of the lifetime upper bound, we observe that the subregions that are most sparsely covered by the sensors play an important role to prolong the network lifetime. Hence, when designing the scheduling method, we try to identify the sparsely covered subregions in the area and cover them first. By doing this, we choose the most potential sensor nodes to cover the critical subregions. We also try to prevent the redundant coverage of the sparsely covered subregions in one cover set.

2.3 A Greedy Approach for Lifetime Maximization

According to the above discussion, in this section, we propose a greedy approach to solve the problem of maximizing the number of cover sets. This algorithm is carried out at the access point before each data collection. Here we assume that the access point has the information of the location and the residual energy level of all the sensors. The basic procedure of the proposed method is the following: we identify a critical subregion that is the subregion of most sparsely covered, and then select a sensor to cover it first. Among all the sensors that cover the critical subregion, we choose a sensor into the cover set according to certain criterion that is based on the sensor's residual energy, consumed energy, and the redundance coverage. Applying this method, we take into account both the network geometry information and residual energy level of sensors to design our scheduling scheme. The greedy approach is presented as follows.

Step 1: Subregion creation

- Based on the position of live sensors and their coverage range r, the whole area is divided into a series of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$.
- Each subregion is associated with a subset of the sensors covering that subregion. And sensor s_i is associated with a subset S_i of subregions covered by s_i, i.e., $S_i = \{\mathcal{F}_{n_1}, \ldots, \mathcal{F}_{n_i}\}$ such that

$$\bigcup_{n=n_1}^{n_i} \mathcal{F}_n = A(s_i). \tag{8}$$

Step 2: Cover set searching

The following two substeps are repeated until all the subregions are covered. The output is a cover set C_j for the j-th data collection.

1. *Critical subregions* We select the critical subregion as

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} \left\lfloor \frac{E_r^{(i)}}{E_c^{(i)}} \right\rfloor \tag{9}$$

   where $E_r^{(i)}$ is the residual energy of sensor s_i before the current data collection.
2. *Sensor node selection*
   - In order to decrease the redundant coverage of the sparsely covered subregions, we define a redundance index v_i of sensor s_i as

$$v_i = \text{the number of } \mathcal{F}_c | \mathcal{F}_c \in S_i, \quad \text{for} \quad i = 1, \ldots, N. \tag{10}$$

     That is, v_i is the number of the selected critical subregions covered by s_i.
   - For the sensors covering the current critical subregion, we first choose the sensors satisfying $v_i = v_{\min}$, where $v_{\min} = \min\{v_1, \ldots, v_N\}$.
   - Among the selected sensors, we calculate a value of a utility function $f(\cdot)$ based on the sensor's residual energy and the consumed energy. The sensor with the greatest value is chosen into the current cover set.
   - The subregions covered by the selected sensors are removed from the set of uncovered subregions.

Step 3: Residual energy update

- For all the sensors in the current cover set, we update their residual energy $E_r^{(i)}$ by deducting the consumed energy $E_c^{(i)}$ at the current data collection from the previous residual energy.
- If the residual energy of a sensor is less than the required energy for a data collection, this sensor is considered dead and removed from the set of live sensors.
- If any sensors are removed from the set of live sensors, the subregions and their associated relationship with sensors are updated.

Discussion In the above approach, in *Sensor node selection* step, we only consider the sensors with the minimum redundance index v_i. This will decrease the redundant coverage of the sparsely covered subregions. Specifically, among all the sensors covering the current critical subregion, if some of them do not cover any previous selected critical subregions, $v_{\min}$ is zero, and we choose a sensor from these nodes into the cover set; if all the sensors cover the previous critical subregions, then we select the sensor that cover the least number of the previous critical subregions into the cover set.

We create the utility function $f(\cdot)$ using the residual energy and the consumed energy. The possible choices for the $f(\cdot)$ can be

$$f(s_i) = E_r^{(i)} / E_c^{(i)}, \tag{11}$$

$$f(s_i) = E_r^{(i)} - E_c^{(i)}, \tag{12}$$

$$f(s_i) = E_r^{(i)}. \tag{13}$$

In the next section, we compare the performance of these utility functions via simulations.

2.4 Simulation Examples

In this section we evaluate the performance of the proposed greedy approach to maximize the network lifetime in the single-hop transmission case. In these examples sensor nodes are randomly deployed in a 20×20 area; each sensor has a disk coverage area with range r; and the initial energy for each sensor is the same. We consider both cases that the consume energy in each data collection by each sensor is the same and different.

In the first case, the lifetime of each sensor is the same. We compare the performance of the proposed method with the lifetime upper bound and three other lifetime maximization methods: (i) we choose the utility function to be the number of the uncovered subregions covered by the sensor; (ii) most constrained least constraining (MCLC) method [10], which maximize the number of disjoint cover sets; (iii) we randomly choose the sensor to cover the critical subregion. In the proposed method, we use the residual energy as the utility function. The energy consumed for the wireless transmission is proportional to the square of the distance. We deploy $N = 100$ sensor nodes into the area and the coverage range $r = 5$. We vary the initial energy E_0, and the result is shown in Fig. 2.

We observe that the performance of the proposed method approaches the lifetime upper bound, which demonstrates the near optimal performance of the proposed method. Its performance is better than MCLC and the method when we use the number of the uncovered subregions as the utility function. And the method with the randomly selected cover set has the worst performance. We know that the method of selecting the sensor node that covers the largest number of uncovered subregions into the cover set provides us the cover set with smaller number of sensors. Hence, we draw the conclusion that for maximizing the network lifetime, it is not always optimal to minimize the number of sensors in each cover set. This observation agrees with the result in [8].

In the second case, the lifetime for each sensor is different. We compare the performance of the proposed method with the lifetime upper bound and two other methods: (i) MCLC method; (ii) we choose the sensor from the sensor nodes that cover the critical subregion into the cover set randomly. In the proposed method, we use the utility function $f(s_i) = E_r^{(i)}/E_c^{(i)}$. We also fix the number of sensors and the coverage range and vary the initial energy. The result is shown in Fig. 3.

From the result, we also find that the proposed method has the near optimal performance and is much better than the other two methods. Especially, we observe that comparing with the MCLC algorithm, the performance of the proposed method has more substantial improvement than in the case that the lifetime of each sensor is the same. The reason is that, in MCLC method, the sensors are divided into mutually exclusive cover sets, and these cover sets are activated successfully. In the case that the lifetime of each sensor is different, the functional time of each cover set is determined by the sensor with the minimum lifetime in that set. Therefore, the total network lifetime is much smaller than the optimal value.

In the next example, we also consider the case that the lifetime of each sensor is different. We compare the performance of the proposed method when we apply three utility functions, as shown in Eqs. 11–13. The results are shown in Figs. 4 and 5. We first use the network lifetime as a measure to compare these three functions, and we find that the performance of all these three functions is very close to the lifetime upper bound, and the difference among themselves is very small. When we enlarge the figure, we can still find that the performance when we use utility function $E_r^{(i)}/E_c^{(i)}$ is better than $E_r^{(i)} - E_c^{(i)}$, which is better than

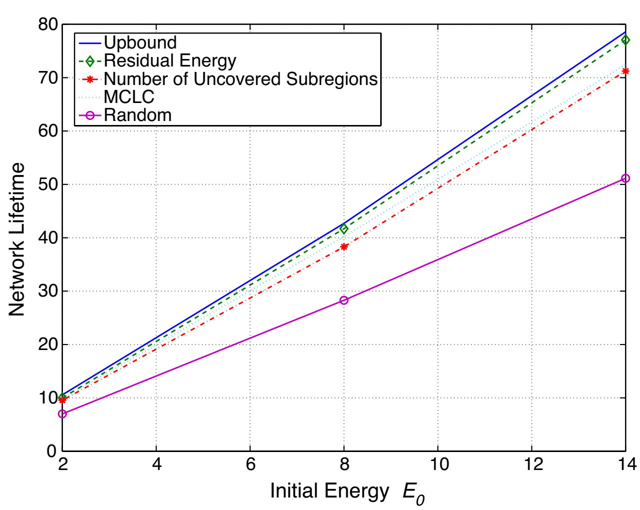

Figure 2 Lifetime vs. initial energy for the case that the consumed energy by each sensor is the same.

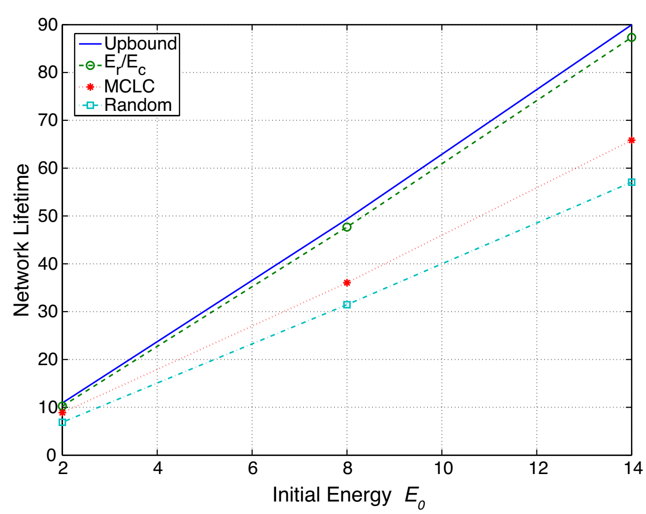

Figure 3 Lifetime vs. initial energy for the case that the consumed energy by each sensor is different.

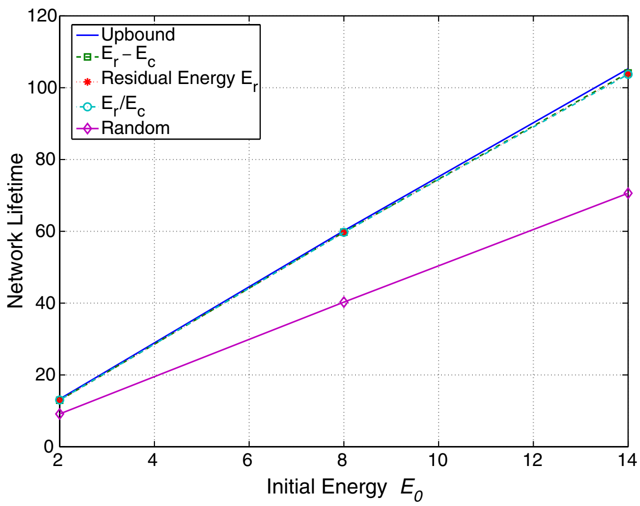

Figure 4 Lifetime vs. initial energy for the case the consumed energy by each is different.

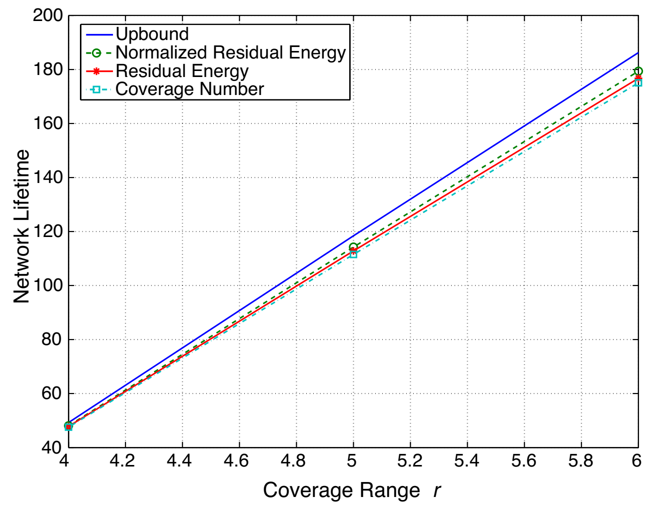

Figure 6 Lifetime vs. coverage range for the case the consumed energy by each is different.

$E_r^{(i)}$. This observation agrees with our previous results in [4]. When we increase the number of deployed sensor nodes and the coverage range, the difference among them is more obvious.

We also use another measure, the network lifetime divided by the total consumed energy by all sensors, to compare the performance of these three utility functions. That is, we use the network lifetime achieved by a unit energy as a measure. The utility function $E_r^{(i)}/E_c^{(i)}$ has the best performance, and the performance of $E_r^{(i)} - E_c^{(i)}$ is better than only using the residual energy. This observation represents that the method of using $E_r^{(i)}/E_c^{(i)}$ as a utility function is more energy efficient.

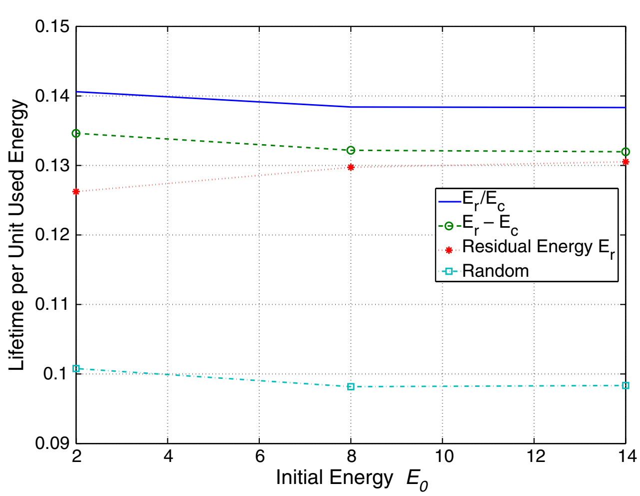

Figure 5 Lifetime per unit energy vs. initial energy for the case the consumed energy by each is different.

In the last example, we study the performance of the following three strategies to choose the critical subregion:

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} \left\lfloor \frac{E_r^{(i)}}{E_c^{(i)}} \right\rfloor, \quad (14)$$

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} E_r^{(i)}, \quad (15)$$

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} 1. \quad (16)$$

The strategy in Eq. 14 is what we use in the proposed method. The result is shown in Fig. 6. The performance of the strategy in Eq. 14 is better than the others. This can be explained as this strategy uses the sensor residual energy, consumed energy, and the network geometry information, while the other two strategies use only parts of these elements.

3 Lifetime Maximization: Multi-Hop Transmissions

In this section, we address the problem of lifetime maximization under the case that the data from each sensor are sent to the access point through multi-hop transmissions. Different from the case of the single-hop transmission in Section 2, in addition to schedule the sensors for data measuring to cover the whole area, we also need to design the transmission route such that the measured data can be sent to the sink through multi-hop transmissions. Since each sensor is energy constrained, our task is to optimally design the schemes for scheduling and routing to maximize the network lifetime. Here, we define the network lifetime as the number of data collections that can be processed from the instant the sensor network is deployed to the instant that either we cannot find a set of sensors that cover the monitored area or the measured data in the cover set cannot be transmitted to the access point. We first formulate the problem as an integer programming; we then derive a lifetime upper bound and propose a suboptimal method to solve the problem. The proposed approach is a centralized algorithm that is carried out at the access point.

3.1 Problem Formulation

We assume a set of sensors $S = \{s_1, \ldots, s_N\}$ are randomly deployed in a connected area $\mathcal{D}$. Each sensor has a coverage (sensing) range R_s and a maximum communication range R_c. The sink (access point) is denoted by s_D. Such a sensor network and the sink can be modeled as an undirected graph $G = (V, X)$, where $V = S \cup \{s_D\}$ and X is the set of edges. There exists a edge $(i, j) \in X$ between nodes s_i and s_j if and only if the distance between s_i and s_j is within the maximum communication range R_c.

In order to formulate the lifetime maximization problem, we associate each data collection process with a weighted undirected graph $G_k = (V_k, X_k)$, $k = 1, \ldots, K$, where K is the total number of data collections that can be supported by the whole sensor network. In the vertex set V_k, we associate node s_i, $i = 1, \ldots, N$, with a data generation function $g_k^{(i)}$ that is defined as: during the k-th data collection, if sensor s_i is selected for data measuring, $g_k^{(i)} = 1$ (we assume all the sensors generate the same length of measurement packages); otherwise, $g_k^{(i)} = 0$. In the edge set X_k, we associate edge (i, j) with a flow $q_k^{(i,j)}$, which can be positive number, negative number, or zero, defined as follows.

- If $q_k^{(i,j)} = 0$, there is no flow through the edge (i, j).
- If $q_k^{(i,j)} > 0$, there exists flow from node s_i to s_j. The amount of flow is $|q_k^{(i,j)}|$.
- If $q_k^{(i,j)} < 0$, there exists flow from node s_j to s_i. The amount of flow is $|q_k^{(i,j)}|$.

The similar definition exists for $q_k^{(j,i)}$ that satisfies $q_k^{(i,j)} = -q_k^{(j,i)}$. Here, we consider the scenario that the transmission package cannot be split. Hence, $q_k^{(i,j)}$ is an integer.

The problem is to maximize the network lifetime, which is equivalent to maximizing the number of possible data collections while guaranteeing certain conditions. These conditions are coverage constraint, flow conservation, and energy constraint, which are formulated as follows based on the above graph model.

Coverage Constraint We denote by C_k the set of sensors that are selected to measuring the signal field in the k-th data collection, i.e.,

$$C_k = \{s_i | s_i \in V_k \text{ and } g_k^{(i)} = 1\}. \tag{17}$$

Then, to satisfy the coverage condition, we require the set C_k to be a cover set, which is defined in Eq. 1.

To simplify the formulation, following the same procedures as in Section 2.1, we first divide the whole monitored area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$; we then associate each subregion with a subset F_l including all sensors covering the subregion, $F_l = \{s_{n_1}, \ldots, s_{n_l}\}$; after that, we can define a boolean variable $b_k^{(i)}$ for $i = 1, \ldots, N$ and $k = 1, \ldots, K$, such that

$$b_k^{(i)} = \begin{cases} 1, & s_i \in C_k \\ 0, & s_i \notin C_k \end{cases}. \tag{18}$$

Hence, the coverage condition can be written as

$$\sum_{i: s_i \in F_l} b_k^{(i)} \geq 1, \forall l, \quad \text{for} \quad k = 1, \ldots, K, \tag{19}$$

which means in each cover set, there exists at least one sensor that covers each subregion.

Flow Conservation The flow conservation condition represents that for node $s_i \in V_k - \{s_D\}$, the sum of the incoming flows and the data generated by this node equals the outgoing flows from this node. The flow conservation guarantees that all the data measured by the selected sensors can be sent to the access point through multi-hop transmissions.

According to the definitions of $q_k^{(i,j)}$ and $g_k^{(i)}$, the flow conservation is formulated as

$$\sum_{j: s_j \in S^{(i)}} q_k^{(i,j)} = g_k^{(i)} \quad \forall i \in V_k - \{s_D\}, \quad \text{for} \quad k = 1, \ldots, K, \tag{20}$$

where $S^{(i)}$ denotes the set of neighbors of s_i, i.e., $S^{(i)} = \{s_j \mid (i, j) \in X_k\}$.

To further understand the flow conservation (20), we divide $S^{(i)}$ into two sets: $S_{\text{out},k}^{(i)}$ and $S_{\text{in},k}^{(i)}$, where $S_{\text{out},k}^{(i)}$ represents the set of the neighbors that the flows leaving s_i go into, i.e., $S^{(i)}_{\text{out},k} = \{s_j | q^{(i,j)}_k > 0\}$; and $S^{(i)}_{\text{in},k}$ represents the set of the neighbors from which the flows go into s_i, i.e., $S^{(i)}_{\text{in},k} = \{s_j | q^{(i,j)}_k < 0\}$. Then, the Eq. 20 can be rewritten as

$$- \sum_{j:s_j \in S^{(i)}_{\text{in},k}} q^{(i,j)}_k + g^{(i)}_k = \sum_{j:s_j \in S^{(i)}_{\text{out},k}} q^{(i,j)}_k, \tag{21}$$

in which the first term represents the incoming flows to s_i, the second term is the data generated by s_i, and the term on the right hand side is the outgoing flows from s_i.

Energy Constraint Sensor s_i has an initial energy $E^{(i)}_0$. The energy constraint requires that during all the data collections, the total consumed energy by sensor s_i cannot be larger than its initial energy. Here, we consider each sensor consumes energy in sensing, receiving, and transmitting data.

- We denote e_s as the energy consumed by each sensor to measure a package of data. Then, in the k-th data collection, the energy consumed by s_i for data sensing is $e_s \cdot g^{(i)}_k$.
- We denote e_r as the energy consumed to receive a package. Then, in the k-th data collection, the energy consumed by s_i for data receiving is $e_r \cdot \left(-\sum_{j:s_j \in S^{(i)}_{\text{in},k}} q^{(i,j)}_k\right)$.
- We denote $e^{(i,j)}_t$ as the energy consumed to transmit a package from node s_i to s_j, which is related to the distance between s_i and s_j. Here, we use the energy transmission model

  $$e^{(i,j)}_t = \varepsilon_t + \alpha \cdot d^{\beta}_{ij} \tag{22}$$

  where ε_t represents the energy dissipation of the transmitter electronics, d_{ij} is the distance between s_i and s_j, and β is the path loss factor. Then, in the k-th data collection, the energy consumed by s_i for data transmission is $e^{(i,j)}_t \cdot \sum_{j:s_j \in S^{(i)}_{\text{out},k}} q^{(i,j)}_k$.

Then, in the k-th data collection, the total energy consumed by s_i, denoted by $E^{(i)}_{u,k}$, is

$$E^{(i)}_{u,k} = e_s \cdot g^{(i)}_k - e_r \cdot \sum_{j:j \in S^{(i)}_{\text{in},k}} q^{(i,j)}_k + e^{(i,j)}_r \cdot \sum_{j:j \in S^{(i)}_{\text{out},k}} q^{(i,j)}_k. \tag{23}$$

Then, the energy constraint condition is formulated as

$$\sum_{k=1}^{K} E^{(i)}_{u,k} \leq E^{(i)}_0, \quad \forall s_i \in V_k - \{s_D\}. \tag{24}$$

Hence, the energy constrained network lifetime maximization problem based on connected coverage can be presented as: Given an area $\mathcal{D}$, an access point s_D, and a set of networked sensors $\{s_1, \ldots, s_N\}$, which is modeled as an undirected graph $G(V, X)$, find a sequence of undirected weighted graphs $\{G_1(V_k, X_k), \ldots, G_K(V_k, X_k)\}$ such that K is maximized, and the coverage condition, flow conservation, and energy constraint are satisfied. Mathematically, this optimization problem can be formulated as

$$\text{Maximize} \quad K$$

Subject to

$$\sum_{i:s_i \in F_l} b^{(i)}_k \geq 1, \quad \forall\, l, \quad \text{for} \quad k = 1, \ldots, K;$$

$$\sum_{j:s_j \in S^{(i)}} q^{(i,j)}_k = g^{(i)}_k, \quad \forall s_i \in V_k - \{s_D\}, \quad \text{for} \quad k = 1, \ldots, K;$$

$$\sum_{k=1}^{K} E^{(i)}_{u,k} \leq E^{(i)}_0, \quad \forall\, s_i \in V_k - \{s_D\};$$

$$b^{(i)}_k \in \{0, 1\}, \quad g^{(i)}_k \in \{0, 1\}, \quad q^{(i,j)}_k \text{ is integer.}$$

This optimization problem is an integer programming. In the following, we first derive an lifetime upper bound to achieve full area coverage and connectivity under the condition that the communication range R_c is no less than twice the coverage range R_s. We then propose a suboptimal method for lifetime maximization.

3.2 Network Lifetime Upper Bound

In this section, we derive an algorithm to compute a lifetime upper bound for the above optimization problem. This upper bound provides a benchmark to the suboptimal methods for network lifetime maximization. To derive the upper bound, we consider the scenario that the sensor's maximum communication range is no less than twice of the sensor's coverage range, i.e., $R_c \geq 2R_s$. This condition is both necessary and sufficient to ensure that the coverage implies the connectivity [7]. Therefore, we redefine the network lifetime as the time span from the instant the network is deployed till the instant we cannot find a sensor set covering the whole area or the sensors in the cover set do not have enough energy to transmit the measured data to the sink. The algorithm is derived as follows.

We first divide the whole area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$. We associate subregion $\mathcal{F}_l$ with a subset F_l of all sensors covering $\mathcal{F}_l$, i.e., $F_l = \{s^{(l)}_1, \ldots, s^{(l)}_{N_l}\}$. The basic idea of the proposed algorithm is that: first, we calculate a lifetime upper bound for each subregion (the upper bound for each subregion is also an upper bound for the whole sensor network); then, we find the minimum value among all these upper bounds. This minimum value is the final lifetime upper bound for the whole sensor network. Here, we define the lifetime of a subregion as the number of data collections that can be supported by the energy of all the sensors covering the subregion.

To cover subregion $\mathcal{F}_l$, at least one sensor $s_i^{(l)} \in F_l$ should be selected to do measuring and transmission, and this sensor may also be used as a relay for the data transmission of other sensors. Hence, in order to derive the lifetime upper bound, we first find a path that costs minimum energy for the data transmission from $s_i^{(l)}$ to s_D. The basic procedure of the algorithm is as follows.

Step 1: For subregion $\mathcal{F}_l$, find a path for $s_i^{(l)} \in F_l$, consisting of only the sensors in F_l, that consumes minimum energy to transmit data from $s_i^{(l)}$ to s_D.

Step 2: Based on the above obtained minimum energy paths, calculate the lifetime upper bound of subregion $\mathcal{F}_l$.

Step 3: Among all the upper bounds for subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$, find the minimum value, which is the derived lifetime upper bound for the whole sensor network.

The step 1 and step 2 are discussed in details as follows.

Minimum Energy Path

For sensor $s_i^{(l)} \in F_l$, its measurement is transmitted to the sink s_D through a path P that is in the form

$$P = (s_i^{(l)}, \ldots, s_j^{(l)}, s_k, \ldots, s_D) \tag{25}$$

where, $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_k \notin F_l$. Then, our problem is, among all the possible paths $P = (s_i^{(l)} \ldots s_j^{(l)})$ that consist of only the sensors in F_l, we look for the minimum energy path $P_i^{(l)}$, associated to sensor $s_i^{(l)}$, that consumes the minimum transmission energy.

To derive an algorithm to find this minimum energy path $P_i^{(l)}$, we first define a set that includes the sensors nearest to the sensors in F_l. We denote this set as $S_C^{(l)}$. This set can be calculated as: for each $s_i^{(l)} \in F_l$, we find a sensor $s_{C,i}^{(l)}$ such that

$$s_{C,i}^{(l)} = \arg \min_{s \in S - F_l} \text{dist}\left(s, s_i^{(l)}\right). \tag{26}$$

Then, we obtain $S_C^{(l)} = \{s_{C,1}^{(l)}, \ldots, s_{C,N_l}^{(l)}\}$. Here, we assume all $s_{C,i}^{(l)}$'s are distinct. Otherwise, we only keep one $s_{C,i}^{(l)}$ in the set for all same $s_{C,i}^{(l)}$'s. Hence, to find $P_i^{(l)}$, we only consider the candidate paths $(s_i^{(l)}, \ldots, s_j^{(l)}, s_k)$, where $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_k \in S_C^{(l)} \cup \{s_D\}$. This result is based on the following proposition.

Proposition *For any paths $P_{i,m}^{(l)} = (s_i^{(l)}, \ldots, s_j^{(l)}, s_m)$ where $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_m \in S - F_l$, we can always find a path $P_{i,k}^{(l)} = (s_i^{(l)}, \ldots, s_h^{(l)}, s_k)$ where $\{s_i^{(l)}, \ldots, s_h^{(l)}\} \subset F_l$, and $s_k \in S_C^{(l)}$ such that the transmission energy of $P_{i,k}^{(l)}$ is smaller than or equal to that of $P_{i,m}^{(l)}$.*

Therefore, for each $s_i^{(l)} \in F_l$, we can find its associated minimum energy path $P_i^{(l)}$, which costs minimum energy of the sensors in F_l to send the measurements from $s_i^{(l)}$ to s_D through multi-hop transmissions. As an output, we have a list of such paths: $P_1^{(l)}, \ldots, P_{N_l}^{(l)}$.

Lifetime Upper Bound of Subregions

Based on the minimum energy paths, we derive a lifetime upper bound for subregion $\mathcal{F}_l$, $l = 1, \ldots, L$. For the minimum energy paths $\{P_1^{(l)}, \ldots, P_{N_l}^{(l)}\}$ obtained above, we denote $E_i^{(l)}$ as the transmission energy of path $P_i^{(l)}, i = 1, \ldots, N_l$. Then, we find the path $P_m^{(l)}$ that has the minimum transmission energy, i.e., $m = \arg\min_i E_i^{(l)}$, which means $E_m^{(l)}$ is the minimum energy costed by the sensors in F_l to transmit the data from any sensor in F_l to the sink. Then, the lifetime upper bound of the subregion $\mathcal{F}_l$ is obtained as

$$\frac{\sum_{\{i:s_i \in F_l\}} E_0^{(i)}}{E_m^{(l)}}, \tag{27}$$

where $\sum_{\{i:s_i \in F_l\}} E_0^{(i)}$ is the total initial energy of the sensors covering subregion $\mathcal{F}_l$.

Therefore, the upper bound for the whole sensor network is

$$\min_{\mathcal{F}_l} \frac{\sum_{\{i:s_i \in F_l\}} E_0^{(i)}}{E_m^{(l)}}. \tag{28}$$

Computational Complexity For subregion $\mathcal{F}_l$, there are N_l sensors covering this subregion. For each $s_i^{(l)} \in F_l$, we first find a minimum energy path to sink s_D consisting of only the sensors in F_l. We can use Dijkstra's algorithm to find such a path, the computational complexity of which is $O(N_l^2)$ [22]. Since we need to find a minimum energy path for all $s_i^{(l)} \in F_l$, the computational complexity is $O(N_l^3)$. It can be verified that the number N_l is in the order of $(\pi R_c^2/|\mathcal{D}|) \cdot N$, where N is the number of deployed sensors, $|\mathcal{D}|$ is the size of the monitored area, and πR_c^2 is the size of the coverage area of each sensor. The number of subregions is in the order of N^2. Therefore, the total computational complexity is $O\{\left((\pi R_c^2/|\mathcal{D}|)\cdot N\right)^3 \cdot N^2\} = O\{(R_c^2/|\mathcal{D}|)^3 \cdot N^5\}$.

3.3 Joint Design of Scheduling and Routing

In this section, we derive a suboptimal method for joint design of scheduling and routing to maximize the network lifetime. This algorithm is carried out at the access point before each data collection. Here we assume that the access point has the information of the location and the residual energy level of all the sensors. We evaluate the performance of this suboptimal method by comparing the result with the above derived lifetime upper bound. This method is based on our observation that the network lifetime is determined by the subregions that have small lifetime. We call those subregions with small lifetime the sparsely covered subregions.

The basic idea of the proposed suboptimal method is similar with the lifetime maximization method for the single-hop transmission case. That is, we first identify the most sparsely covered subregion (critical subregion), and cover it first. Among all the sensors that cover the critical subregion, we find a sensor and the corresponding path from that sensor to the sink to cover the critical subregion according to certain criterion. This criterion is related to the energy and geometry information of the sensors. The main procedure of the method is described as follows.

1. We create a communication network among all the live sensors and the sink, and divide the whole monitored area into a set of disjoint subregions.
2. We identify a critical subregion according to certain criterion.
3. Among all the sensors covering the critical subregion, we choose a sensor for data measuring and determine its associated path to the sink according to certain criterion.
4. We remove all the subregions covered by the chosen sensor from the set of the uncovered subregions. We repeat the above two steps until there is no uncovered subregions.
5. We update the residual energy of the sensors selected for sensing and relaying. If the live sensors can still cover the whole area, we repeat the above steps to find another set of sensors for the next data collection; otherwise, the lifetime of the network is reached.

The flow chart of the method is shown in Fig. 7. In this method, we need to answer two key questions: (i) how do we identify a critical subregion? (ii) how do we select a covering sensor and a path from this sensor to the sink? These questions are addressed as follows.

Critical Subregion We define the critical subregion as the subregion with the minimum residual lifetime. The residual lifetime of a subregion is the maximum number of data collections to reconstruct the subregion that can be provided by the residual energy of sensors covering that subregion. Since it is difficult to compute the exact lifetime of a subregion, we use an upper bound to replace the lifetime. We use the residual lifetime upper bound for subregion $\mathcal{F}_l$ as

$$\sum_{i\in F_l} \frac{E_r^{(i)}}{E_c^{(i)}} \tag{29}$$

where, $E_c^{(i)} = e_t^{(i,i_n)}$ represents the energy consumed for transmission from node s_i to s_{i_n}, and s_{i_n} is the node that is nearest to s_i. Therefore, the critical subregion $\mathcal{F}_c$ is

$$\mathcal{F}_c = \arg\min_{F_l} \sum_{i\in F_l} \frac{E_r^{(i)}}{E_c^{(i)}}. \tag{30}$$

Covering Sensor and Transmission Path When we identify a critical subregion, the next step is: among all the sensors covering the critical subregion, we choose a sensor according to certain criterion to reconstruct the critical subregion; we also determine a path from the selected sensor to the sink for the data transmission. In the proposed method, we first define a cost for each link in the communication network; then, for each sensor covering the critical subregion, we find a minimum cost path from that sensor to the sink; the sensor whose path has the minimum cost is selected to cover the critical subregion, and the corresponding minimum cost path is selected for data transmission. Here, the cost of a path is defined as the sum of the cost of all the links in that path.

The definition of the cost of a link closely relates to the problem that which sensors we should choose as sensing and relaying in the current data collection such that we can prolong the network lifetime. We consider both the sensor's energy information and geometry information. We favor the sensors with larger amount of residual energy to be chosen into the data collection; we favor the path consumed smaller amount of energy for data transmission from the sensor to the sink. We observe that the sensors covering the critical

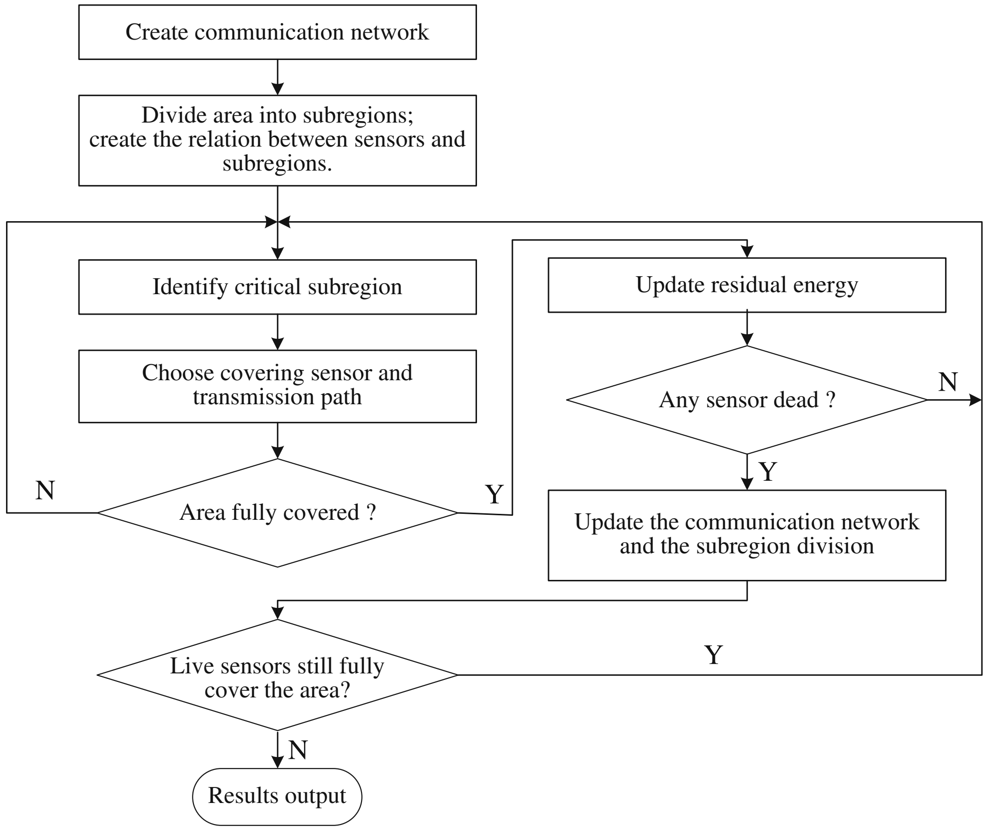

Figure 7 Flow chart of the suboptimal algorithm for lifetime maximization.

subregions have crucial roles to prolong the network lifetime. Hence, if a sensor is important to cover a critical subregion, we intend not to select that sensor as relays.

Based on the above discussion, for a link (i, j), we consider the following local sensor parameters to define the cost:

- $e_t^{(i,j)}$: unit transmission energy from node s_i to s_j.
- $E_r^{(i)}$, $E_r^{(j)}$: current residual energy of sensor s_i and s_j, respectively.
- $c_r^{(i)}$, $c_r^{(j)}$: critical values of sensor s_i and s_j, respectively.

The critical value of a sensor relates to the importance of that sensor to cover critical subregions. The smaller the critical value, the more important it is. The critical value of sensor s_i is defined as follows.

We denote $S_i = \{\mathcal{F}_{n_1}, \ldots, \mathcal{F}_{n_i}\}$ as a set of subregions covered by sensor s_i. For subregion $\mathcal{F}_{n_l} \in S_i$, we denote $L_r^{(n_l)}$ as its residual lifetime

$$L_r^{(n_l)} = \sum_{j \in F_{n_l}} \frac{E_r^{(j)}}{E_c^{(j)}} \tag{31}$$

where, the consumed energy $E_c^{(j)}$ of s_j is defined the same as in Eq. 29. Then, we define the critical value $c_r^{(i)}$ as

$$c_r^{(i)} = \min_{n_l \in \{n_1, \ldots, n_i\}} L_r^{(n_l)}. \tag{32}$$

If a sensor is important to cover certain critical subregions, we tend to prevent selecting it into the transmission path. Hence, we favor the sensors with larger critical values.

According to the above discussion, we define the link cost as

$$\text{cost}(i, j) = \left(e_t^{(i,j)}\right)^{x_1} \cdot \left(E_r^{(i)}\right)^{-x_2} \cdot \left(c_r^{(i)}\right)^{-x_3} + (e_r)^{y_1} \cdot \left(E_r^{(j)}\right)^{-y_2} \cdot \left(c_r^{(j)}\right)^{-y_3}. \tag{33}$$

Here, e_r is the unit receiving energy. The values x_k and y_k, $k = 1, 2, 3$, are integer constants. They represent the weights of each parameters.

Computational Complexity To find a cover set and the corresponding paths, we apply two steps: (i) identifying a critical subregion and (ii) finding the minimum cost path. When N sensors are deployed, the number of subregions is in the order of N^2; hence, to identify a critical subregion, the computational complexity is $O(N^2)$. To find the minimum cost path, we can use Dijkstra's algorithm, the computational complexity of which is $O(N^2)$ [22]. These two steps are repeated until all subregions are covered. The number of the iterations is approximately in the order of $|\mathcal{D}|/(\pi R_c^2)$. Therefore, the total computational complexity is $O\{(|\mathcal{D}|/R_c^2) \cdot N^2\}$.

3.4 Simulation Examples

In this section we use numerical examples to evaluate the performance of the proposed method for network lifetime optimization in the multi-hop transmission case. In these examples sensor nodes are deployed in a 20×20 area randomly following a uniform distribution. Each sensor has a disk coverage area with range R_s and a maximum communication range $R_c = 2R_s$. The initial energy for each sensor is the same. For the energy consumption due to the transmission, we use the model that $e_t^{(i,j)} = \alpha \cdot d_{ij}^{\beta}$ (see Eq. 22 for the notations). Here, we set $\alpha = 0.01$ and $\beta = 2$. In the cost function, the parameters x_k and y_k, $k = 1, 2, 3$, are all set to 1. Each value in the figures is obtained by averaging the results of 100 randomly generated network topologies.

In the first example, we study the performance of the proposed algorithm to derive the network lifetime upper bound. We compare the derived upper bound with another upper bound obtained by minimum transmission energy (MTE) algorithm. This method is also based on dividing the monitored area into a set of disjoint subregions. In MTE, the lifetime upper bound of subregion $\mathcal{F}_l$ is derived as

$$\sum_{i \in F_l} \frac{E_0^{(i)}}{E_c^{(i)}} \tag{34}$$

where $E_0^{(i)}$ is the initial energy of sensor s_i, and $E_c^{(i)}$ is the transmission energy from s_i to its nearest node. Hence, $E_0^{(i)}/E_c^{(i)}$ is an upper bound of the number of data collections that can be supported by sensor s_i (we omit the energy consumed for data measuring). Therefore, it is easy to verify that Eq. 34 is a lifetime upper bound of subregion $\mathcal{F}_l$. Then, the lifetime upper bound of the whole sensor network is

$$\min_{\mathcal{F}_l} \sum_{i \in F_l} \frac{E_0^{(i)}}{E_c^{(i)}}. \tag{35}$$

The result of the comparison of the upper bounds obtained by the proposed method and by MTE with respect to the number of sensors is shown in Fig. 8. Here we set the coverage to be 4 and the initial energy to be 15. From this result we observe that both upper bounds

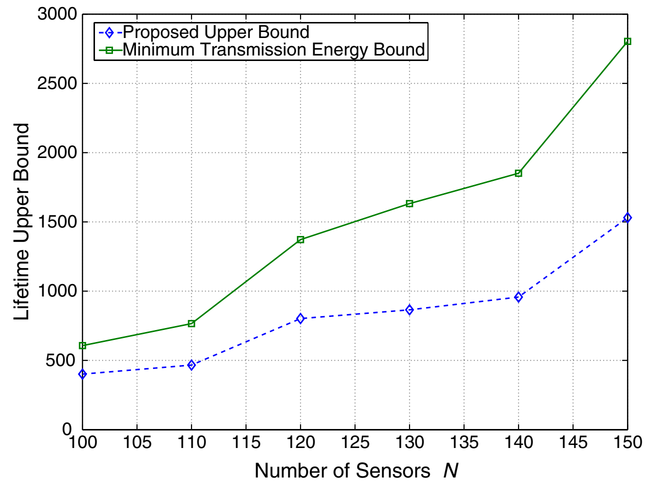

Figure 8 Lifetime upper bound vs. number of sensors

increase with the number of the deployed sensors, as we expected. And the upper bound obtained by the proposed method is much tighter than the upper bound obtained by MTE. This is because in MTE we consider only the minimum energy consumed by a single sensor; however, in the proposed method, we consider the minimum energy consumed by all the sensors covering the subregion for data transmission.

In the second set of examples, we study the performance of the proposed suboptimal method to maximize the network lifetime. We compare the result with the lifetime upper bound. We also compare the performance of the proposed approach with a separate design method. In the separate design method, we separate the design of the sensor scheduling and information routing to maximize the network lifetime. For the sensor scheduling, we use the method in Section 2.3 to select

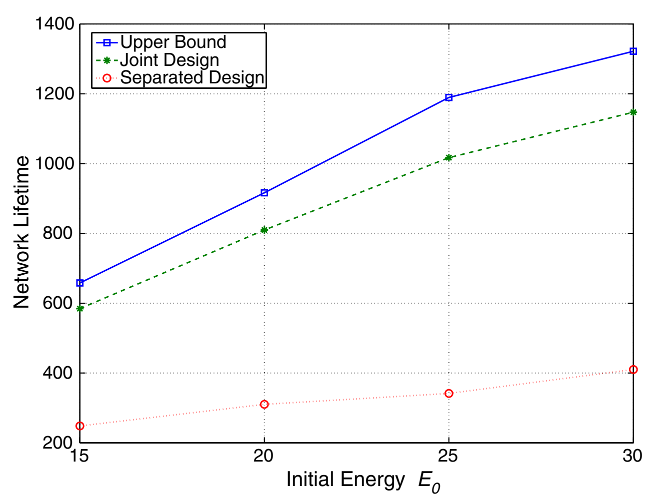

Figure 9 Network lifetime vs. initial energy

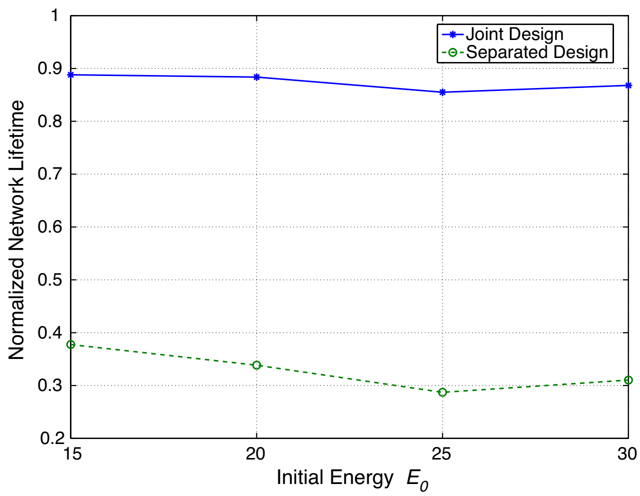

Figure 10 Normalized network lifetime vs. initial energy

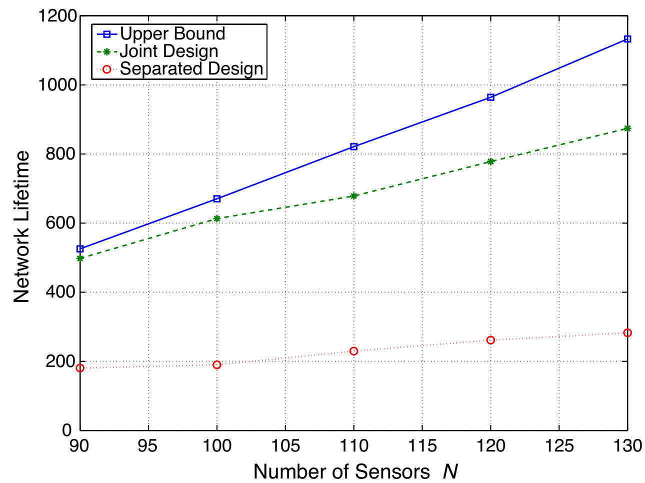

Figure 12 Network lifetime vs. number of sensors

the sensors into the cover set. For the routing, we use the minimum energy path [15] to send the measured data from the sensors to the sink. We first compare the obtained lifetime with the upper bound with respect to the initial energy of the sensor. The results are shown in Figs. 9 and 10. Here, we set the coverage range to be 4 and the number of sensors to be 100. We observe that the lifetime achieved by the proposed joint design method is close to the upper bound. When the initial energy increases, the performance decrease slightly. We also observe that the proposed joint design has substantial performance improvement comparing with the separate design method, which can achieve below 40% of the upper bound. The same observation can be found when we compare the performance with respect to the coverage range and the number of sensors. The comparison results are shown in Figs. 11 and 12. We also observe that some other parameters also have effects on the performance of the method. For example, when we increase the path loss factor, the performance becomes a little worse.

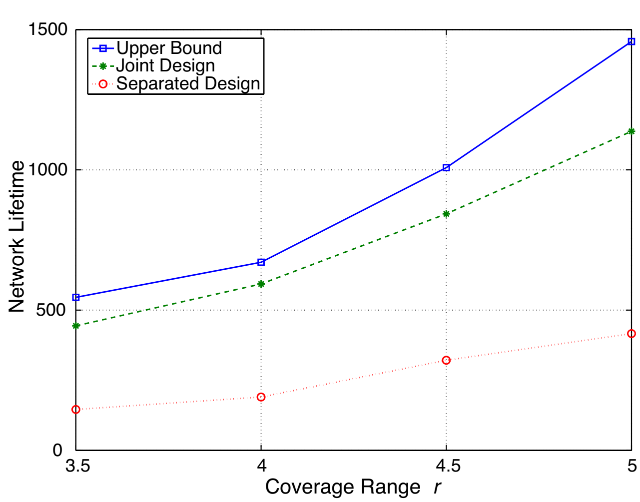

Figure 11 Network lifetime vs. coverage range

4 Conclusions

We studied the problem of network lifetime maximization for QoS specific information retrieval for the reconstruction of a spatially correlated signal field in a wireless sensor network. We considered two wireless transmission cases. In one case, we assumed there exist single-hop transmissions between sensors and the access point, and we designed the optimal sensor node scheduling scheme. In another case, the measurements are sent to the access point through multi-hop transmissions, and we jointly designed the sensor scheduling and information routing to maximize the network lifetime. To address both of these problems, we first formulated the problems as integer programming based on the theories of coverage and connectivity in sensor networks. We then derived upper bounds for the network lifetime that provide measures for the performance of suboptimal methods. After that, we proposed suboptimal methods for node scheduling and data routing to maximize the network lifetime. In the future work, we will consider the effect of the transmission channel fading on the network lifetime. Under that case, the transmission energy by each sensor is a random variable. We will study other random field models and the corresponding network lifetime maximization methods. The method we consider here is a centralized approach. We will also consider developing a distributed implementation.

References

1. Zhao, Q., & Tong, L. (2007). Energy-efficient information retrieval for correlated source reconstruction in sensor networks. *IEEE Transactions on Wireless Communications, 6*(1), 157–165, Jan.
2. Dietrich, I., & Dressler, F. (2006). On the lifetime of wireless sensor networks. University of Erlangen, Dept. of Computer Science, Technical Report, Dec.
3. Chen, Y., & Zhao, Q. (2005). On the lifetime of wireless sensor networks. *IEEE Communications Letters, 9*(11), 976–978, Nov.
4. Chen, Y., & Zhao, Q. (2007). An integrated approach to energy-aware medium access for wireless sensor networks. *IEEE Transactions on Signal Processing, 55*(7), 3429–3444, July.
5. Chen, Y., Zhao, Q., Krishnamurthy, V., & Djonin, D. (2007). Transmission scheduling for optimizing sensor network lifetime: A stochastic shortest path approach. *IEEE Transactions on Signal Processing, 55*(5), 2294–2309, May.
6. Zhang, H., & Hou, J. C. (2005). On the upper bound of α-lifetime for large sensor networks. *ACM Transactions on Sensor Networks, 1*(2), 272–300, Nov.
7. Zhang, H., & Hou, J. C. (2005). Maintaining sensing coverage and connectivity in large sensor networks. *Wireless Ad Hoc and Sensor Networks: An International Journal, 1*(1–2), 89–123, Jan.
8. Zhang, H., & Hou, J. C. (2005). Maxmizing α-lifetime for wireless sensor networks. *International Workshop on Measurement, Modeling, and Performance Analysis of Wireless Sensor Networks*, San Diego, CA, July.
9. Cardei, M., MacCallum, D., Cheng, X., Min, M., Jia, X., Li, D., et al. (2002). Wireless sensor networks with energy efficient organizaton. *Journal of Interconnection Networks, 3*(3–4), 213–229.
10. Slijepcevic, S., & Potkonjak, M. (2001). Power efficient organization of wireless sensor networks. *Proceedings of the IEEE International Conference on Communications, 2*, 472–476, June.
11. Cardei, M., Thai, M. T., Li, Y., & Wu, W. (2005). Energy-efficient target coverage in wireless sensor networks. *Proc. IEEE INFOCOM 2005, 3*, 1976–1984, March.
12. Al-Karaki, J. N., & Kamal, A. E. (2004). Routing techniques in wireless sensor networks: A survey. *IEEE Wireless Communications, 11*(6), 6–28, Dec.
13. Singh, S., Woo, M., & Raghavendra, C. S. (1998). Power-aware routing in mobile ad hoc networks. In *Proc. of IEEE/ACM int. conf. mobile computing and networking* (pp. 181–190), Oct.
14. Gomez, J., Campbell, A. T., Naghshineh, M., & Bisdikian, C. (1999). Power-aware routing in wireless packet networks. In *Proc. of IEEE int. workshop on mobile multimedia communications* (pp. 380–383), Nov.
15. Chang, J.-H., & Tassiulas, L. (2004). Maximum lifetime routing in wireless sensor networks. *IEEE/ACM Transactions on Networking, 12*(4), 609–619, Aug.
16. Wang, X., Xing, G., Zhang, Y., Lu, C., Pless, R., & Gill, C. (2003). Integrated coverage and connectivity configuration in wireless sensor networks. In *Proceedings of international conference on embedded networked sensor systems* (pp. 28–39).
17. Gupta, H., Zhou, Z., Das, S. R., & Gu, Q. (2006). Connected sensor cover: Self-organization of sensor networks for efficient query execution. *IEEE/ACM Transactions on Networking, 14*(1).
18. Zhou, Z., Das, S., & Gupta, H. (2004). Connected k-coverage problem in sensor networks. In *Proceedings of international conference on computer communications and networks* (pp. 373–378).
19. Zhao, Q., & Gurusamy, M. (2006). Maximizing network lifetime for connected target coverage in wireless sensor networks. In *IEEE International conference on wireless and mobile computing, networking and communications* (pp. 94–101).
20. Jaggi, N., & Abouzeid, A. A. (2006). Energy-efficient connected coverage in wireless sensor networks. In *Proceedings of 4th Asian international mobile computing conference*. Kolkata, India, Jan.
21. Garey, M. R., & Johnson, D. S. (1979). *Computers and intractability: A guide to the theory of NP-completeness*. San Francisco: W.H. Freeman.
22. Bertsekas, D., & Gallager, R. (1987). *Data networks*. Englewood Cliffs: Prentice-Hall.
23. Kalpakis, K., Dasgupta, K., & Namjoshi, P. (2002). *Maximum lifetime data gathering and aggregation in wireless sensor networks*. *Technical Report TR CS-02-12*, Computer Science and Electrical Engineering Department, University of Maryland Baltimore County, August.
24. Abrams, Z., Goel, A., & Plotkin, S. (2004). Set K-cover algorithms for energy efficient monitoring in wireless sensor networks. In *Proceeding of Information Processing in Sensor Networks*. Berkeley, CA, April.
25. Zeng, P., Zang, C., & Yu, H. (2006). Bounding the lifetime of target tracking sensor networks. *Proceedings of the IEEE International Conference on Communications, 8*, 3444–3449, June.

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