Maximum Lifetime Routing to Mobile Sink in Wireless Sensor Networks

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Abstract—We address the problem of maximizing the lifetime in a wireless sensor network with energy-constrained sensor nodes and mobile data collection points (sinks). Information generated by the monitoring sensors needs to be routed efficiently to the location where the sink is currently located across multiple hops with different transmission energy requirements. We exploit the capability of the sink to be located in different places during network operation and give a novel linear programming formulation that maximizes network lifetime. We show that the maximum lifetime can only be achieved by solving optimally two joint problems: a scheduling problem that determines the sojourn times of the sink at different locations, and a routing problem in order to deliver the sensed data to the sink in an energy-efficient way. Our model provides the optimal solution to both of these problems and gives the best achievable network lifetime. We evaluate numerically the performance of our model by comparing it with the case of static sink and with previously proposed models that focus mainly on the sink movement patterns and sojourn times, leaving the routing problem outside the linear programming formulation. Our approach always achieves higher network lifetime, as expected, leading to a lifetime up to more than twice that obtained with models previously proposed as the network size increases. It also results in a fair balancing of the energy depletion among the sensor nodes.

I. INTRODUCTION

Wireless sensor networks have attracted significant attention because of the large number of new applications in home automation, environmental monitoring, military operations, health services, and other commercial environments. A sensor network is composed of a large number of small low-cost sensors, which are typically densely and randomly deployed in the area where a phenomenon is being monitored. One or more data collection points (sinks), either static or mobile, have the responsibility of collecting the information from sensors for further processing. The unique characteristics of sensing devices pose many new issues that have to be addressed when designing a sensor network [1], [2], [3], like the efficient management of finite amount of energy provided by battery-operated sensors.

We focus on the problem of maximizing the lifetime of a wireless sensor network where the sensors communicate with the sink across multiple hops with different transmission energy requirements. That is, there is flexibility of power adjustment and the energy consumption rate per unit information transmission is not the same for all neighbors of a sensor, but depends on the choice of the next hop node. The network lifetime is defined as the time until a sensor drains out of energy for the first time, a definition commonly used in the literature. Although the problem of maximum lifetime routing has been studied extensively (see Section II for related work), most of previous approaches assume static sinks and focus on the problem of selecting energy-efficient routing paths to prolong network lifetime.

However, some recent papers have started to explore the idea of exploiting the mobility of the sink for the purpose of collecting the information from the sensors in a more efficient manner.

In our setup, the sensors are realistically randomly deployed in the field (their placement does not rely on any specific pattern, e.g., grid network, etc.). The sink is mobile and can move to different places during network operation (the sensors’ locations and the possible sink locations are not necessarily the same). The problem that arises is, for how long the sink must stay at each place and how the sensors must deliver their data to the sink during its sojourn time at a given location, in order to maximize network lifetime. We show that maximum lifetime can only be achieved by solving optimally these two joint problems: the scheduling problem that determines the sink sojourn times, and the routing problem to find the appropriate energy-efficient paths. We show in Section III-B that these two optimization problems can be written as a linear programming model, capable of expressing network lifetime in terms of sink sojourn times. Our model provides the optimal solution to both problems and gives the best achievable network lifetime.

Numerical results for various network sizes are presented in Section IV. We evaluate through simulations the performance of our model by comparing it with the case of static sink and with previously proposed models that focus mainly on the sink movement patterns and sojourn times, leaving the routing problem outside the linear programming formulation. Our approach always achieves higher network lifetime, as expected, leading to a lifetime up to more than twice that obtained with other models as the network size increases. It also results in a fair balancing of the energy depletion among sensors. Our formulation reveals the necessity to develop on-line heuristic algorithms that take into account at the same time the scheduling and the routing problem, in order to be used in an adaptive and distributed environment where the sink sojourn times are not determined a priori. These issues are discussed in Section V.

II. RELATED WORK

The maximum lifetime routing problem in wireless sensor networks has received significant attention. In [4] the information from sensors needs to be routed in an energy-efficient way to a set of static designated gateway nodes. The routing problem is formulated as a linear program and a shortest cost path algorithm is proposed. Other energy-aware routing algorithms in networks with lifetime requirements are proposed in [5], [6], [7]. In [5] the maximum lifetime data gathering and aggregation problem in sensor networks is considered. A routing mechanism to prolong lifetime is proposed in [6], where each node adjusts its transmission power to send data to its neighbors. The energy conserving routing problem is formulated in

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[7] as a nonlinear program. The problem of efficiently positioning data collection points is addressed in [8], [9].

Some of the recent works that exploit the mobility of the sinks using a different approach than ours are [10], [11], [12], [13], [14], [15]. In [10] power saving is achieved using predictable observer mobility in a single hop communication network. A scalable energy-efficient asynchronous dissemination protocol is presented in [11] to minimize energy consumption. The authors in [12] present an integer linear programming model to determine the locations of multiple sinks and a flow-based routing protocol is used. In [13], [14] a learning-based approach is proposed to efficiently route data to a mobile sink. Instead of using multi-hop routing to the sink, a clustered network is considered in [15] where each sensor sends the information to its cluster head and a mobile collector visits every cluster head according to a schedule to collect the data.

The work closest to ours is [16]. A linear programming formulation is given for the problem of determining the sink sojourn times that induce maximum lifetime. However, only a special case of networks is considered, where the homogeneous sensors are arranged in a bi-dimensional square grid composed of same-size cells. The initial energy and the data generation rate are the same for all sensors. There is no power control since the transmission range is the same for all sensors (equal to the size of a cell of the grid), and the sensor locations and possible sink locations are the same. Differently from our approach, their model determines only the sink sojourn times, leaving the routing problem outside the linear programming formulation. The shortest path algorithm used to route packets to the sink during its sojourn time at a location, although energy-aware, does not take into account the remaining energy of sensors, thus resulting in an overall network lifetime which is not optimal.

III. DEFINITIONS AND PROBLEM FORMULATION

A. Wireless Sensor Network Model

The wireless sensor network consists of a set $N$ of sensor nodes and a sink node $s$ collecting the information. After having been randomly deployed in the field, the sensors remain stationary at their initial locations and continuously monitor the physical environment where they have been placed. Hence, there is a constant information generation rate $Q_i > 0$ at every sensor $i \in N$ (not necessarily the same for every sensor). On the contrary, the sink is mobile and can be found in different random places during network operation, not necessarily co-located with the sensors. Let $L$ be the set of possible sink locations and $t_l \geq 0$ the time for which it stays at location $l \in L$. For the analysis in the next sections, we assume that the traveling time of the mobile sink from one location to another is small and thus can be neglected as in [16].

Sensors communicate with the sink during its sojourn time at a given location by delivering the sensed data across multiple hops. That is, for a given location $l \in L$, the sink is not necessarily within the transmission range of every sensor. Let $S_l^i \subseteq N \cup \{s\}$ be the set of nodes (either sensors or the sink) that are in the transmission range of sensor $i \in N$ for a given location $l \in L$ of the sink. If $j \in S_l^i$, then $j$ is called a neighboring node of $i$ for location $l$. Note that the only element that may be different among two sets $S_l^{i1}, S_l^{i2}, l_1, l_2 \in L$, is the sink $s$, since the rest of the network (consisting of all sensors) remains static.

Consider for example the sensor network in Fig. 1. Sensors $B$ and $C$ are in the transmission range of $A$, regardless where the sink node is located. When $s$ is placed at location 1, sensor $A$ can also communicate with $s$. Therefore, the set of neighboring nodes of sensor $A$ for location 1 is $S_A^1 = \{B, C, s\}$. However, when $s$ moves to locations 2, 3, 4, it is not in the transmission range of sensor $A$. Hence, $S_A^2 = S_A^3 = S_A^4 = \{B, C\}$.

Similarly for another sensor node, say node $C$, we have that $S_C^1 = S_C^2 = S_C^3 = \{A, B, D\}$, while $S_C^4 = \{A, B, D, s\}$.

Every sensor $i \in N$ has an initial amount of battery energy $E_i^0 > 0$. The sink has no energy constraint. The energy consumed at sensor $i$ to transmit a data unit to its neighboring node $j$ is denoted by $e_{ij}^t > 0$ and the energy consumed for reception by the receiver $j$ is denoted by $e_{ji}^R > 0$. Note that we allow for the possibility of power control, i.e., the energy expenditure for an information unit transmitted by sensor $i$ depends on the next hop node and is not necessarily the same for every neighbor $j$.

The above description of the wireless sensor network indicates that in order to transfer the information from the sensors to the sink, two complementary algorithms are necessary:

- a scheduling algorithm that determines for every location $l \in L$ the duration $t_l$ for which the sink stays at that place,
- a routing algorithm to find energy-efficient paths from each sensor to sink for all locations $l \in L$ for which $t_l > 0$.

Since the sink can be found in different places, the decision of the routing algorithm depends on its location. Let $q_{ij}^l$ be the rate at which information is transmitted from sensor $i$ to its neighboring node $j$ to be assigned by the routing algorithm during time $t_l$. The overall objective is to maximize the duration of network operation before a sensor drains out of battery energy for the first time. In our model, the network lifetime is equal to the sum of the sink sojourn times at all possible locations (see Section III-B). The sojourn times are constrained by the fact that the total energy consumed by each sensor for all sink’s locations cannot exceed the sensor’s initial amount of energy.

B. Linear Programming Formulation

In the following we show that our optimization problem can be written as a Linear Programming (LP) problem [17]. Given the sink sojourn times $t_l$ and the information transfer rates $q_{ij}^l$, $i \in N$, $j \in S_l^i$, $l \in L$, the energy consumed per time unit at sensor node $i$ when the sink is placed at location $l$ is given by

$$\sum_{j \in S_l^i} e_{ij}^t q_{ij}^l + \sum_{j \in S_l^i} e_{ji}^R q_{ji}^l,$$

(1)
while the energy consumption for time duration $t_l$ is given by
\[
\left( \sum_{j \in S_l^i} e_{ij}^T q_{ij}^l + \sum_{j \in S_l^i} e_{ij}^R q_{ji}^l \right) t_l. \tag{2}
\]
The total energy consumed at sensor $i$ during network operation is the sum of the quantities in (2) over all locations $l \in L$,
\[
\sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^T q_{ij}^l t_l + \sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^R q_{ji}^l t_l. \tag{3}
\]
The network lifetime defined as the length of time until the first battery drain-out among all sensors, can also be expressed as the sum of the sink sojourn times at all possible locations, $\sum_{l \in L} t_l$.

Our goal is to find the sink sojourn times $t_l$ and the rates $q_{ij}^l$ that maximize network lifetime under the flow conservation condition and under the constraint that the total energy consumed by each sensor node when the sink stays at different locations cannot exceed the sensor’s initial amount of energy. From the above definitions, the problem of maximizing the overall network lifetime can be written as follows:

Maximize $\sum_{l \in L} t_l$ subject to
\[
t_l \geq 0, \quad l \in L, \tag{4}
\]
\[
q_{ij}^l \geq 0, \quad i \in N, \quad j \in S_l^i, \quad l \in L, \tag{5}
\]
\[
\sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^T q_{ij}^l t_l + \sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^R q_{ji}^l t_l \leq E_i, \quad i \in N \tag{6}
\]
\[
\sum_{j \in S_l^i} q_{ij}^l + Q_i = \sum_{j \in S_l^i} q_{ji}^l, \quad i \in N, \quad l \in L. \tag{7}
\]

Note that flow conservation condition (8) applies to each location $l \in L$ separately. That is, for every sink location, the total incoming information transfer rate plus the information generation rate at a sensor equals the total outgoing information transfer rate from the sensor. By defining $\tilde{q}_{ij}^l = q_{ij}^l t_l$ as the amount of information transmitted from sensor $i$ to its neighboring node $j$ during time $t_l$, the optimization problem becomes:

Maximize $\sum_{l \in L} t_l$ subject to
\[
t_l \geq 0, \quad l \in L, \tag{9}
\]
\[
\tilde{q}_{ij}^l \geq 0, \quad i \in N, \quad j \in S_l^i, \quad l \in L, \tag{10}
\]
\[
\sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^T \tilde{q}_{ij}^l + \sum_{l \in L} \sum_{j \in S_l^i} e_{ij}^R \tilde{q}_{ji}^l \leq E_i, \quad i \in N, \tag{11}
\]
\[
\sum_{j \in S_l^i} \tilde{q}_{ij}^l + Q_i t_l = \sum_{j \in S_l^i} \tilde{q}_{ji}^l, \quad i \in N, \quad l \in L. \tag{12}
\]

Linear programming formulation of the problem

The objective function (9) maximizes network lifetime, that is, the sum of the sojourn times of the sink at all possible locations. Constraints (10) and (11) assure the non-negativity of the quantities $t_l$ and $\tilde{q}_{ij}^l$, respectively. The left part of the inequality in (12) represents the total amount of energy consumed at sensor $i$ for transmitting and receiving data over all sojourn times of the sink at visited locations. Hence, the energy constraint in (12) simply states that the energy consumed at each sensor $i$ should not exceed its initial energy $E_i$. Finally, flow conservation condition (13) derives by multiplying (8) with $t_l$.

The LP model above determines for every location $l \in L$ the duration $t_l$ for which the sink stays at that place and the information transfer rates $q_{ij}^l$, $i \in N, \quad j \in S_l^i$, so that the network lifetime is maximized. Therefore, it provides an optimal solution to both problems described earlier, the scheduling and the routing problem. If the optimal value for a $t_l$ is 0, the sink does not visit location $l$. Every location $l \in L$ for which the optimal $t_l$ is positive, is visited by the sink for a time duration equal to $t_l$. The sink visiting order is not important since the traveling time of the sink between two locations is considered negligible and the information generation rate is independent of time.

Note 1: A more general version of our LP model is to consider that while the sink is at location $l \in L$, the information transfer rates $q_{ij}^l, i \in N, \quad j \in S_l^i$, are allowed to change. It may seem plausible that by modifying the rate $q_{ij}^l$ during time $t_l$, the amounts of sensors’ remaining energy can be utilized more efficiently and, therefore, the duration of network operation can be prolonged. However, it is proved that this generalization of the problem does not result in an improvement for the lifetime of the network (the proof is omitted due to page limitation).

IV. NUMERICAL RESULTS

A. Description of the Compared Models

1) LP Model with Shortest Path Routing (SPR): This is a generalization of [16], so that it can be applied to general networks (the approach in [16] is restricted only to square grid networks with homogeneous sensors and no power control). The LP model determines only the sink sojourn times at every location $l \in L$ and, therefore, it provides a solution only to the scheduling problem. The routing problem is solved using a shortest path algorithm, where the cost of a path depends on the number of hops and the transmission energy requirement of each hop (in [16] there is no power control and the algorithm reduces to a minimum-number-of-hops routing algorithm). The shortest path algorithm used to route the packets to the sink does not take into account the remaining energy of the sensors, thus resulting in an overall network lifetime which is not optimal.

2) LP Model with Multiple Shortest Path Routing (MSPR): When there are multiple shortest paths, the authors in [16] select two of them and alternate the route between these two paths. Motivated by this variation, we modify the previous model so that the routing algorithm uses all the existing shortest paths from a sensor to the sink. The LP model which determines the sink sojourn times remains the same.

3) LP Model for the Static Sink case (Static Sink): When the sink remains static, we have to determine the lifetime achieved at every location $l \in L$ separately and select the one that gives the maximum value. Given the location that maximizes lifetime, the sink stays there until a sensor node runs out of battery energy for the first time and does not move to another place. For each location $l \in L$ separately we use the linear programming formulation given in Section III-B, replacing $L$ by $L = \{l\}$. Therefore, the Static Sink model maximizes lifetime for every location, but it is not optimal for the overall objective which is the sum of the sink sojourn times at all possible locations.

4) Optimal LP Formulation (LP-opt): This is the LP model proposed in Section III-B which provides the optimal solution.
B. Performance Evaluation Through Simulations

We compare numerically for various network sizes the performance of the above four models. The simulations that follow model the physical environment in a wireless sensor network, where the sensors are randomly deployed on a terrain with various obstacles that may prohibit direct communication of certain sensors. The sink can be located in certain places inside the terrain (not necessarily co-located with the sensors) and, for a given location, the sink is not within the transmission range of every sensor. That is, multi-hop routing may be needed in order to transfer the information from a sensor to the sink.

The figures that follow represent the averages of the results obtained from 100 randomly generated network instances for each network size considered. We generate random networks with a specified number of sensors (20, 40, ..., 100) as follows. We fix a square grid of 100 × 100 points. A number of these points is randomly selected with uniform probability to represent the sensors. Note that the placement of the sensors does not form a grid network, but models a random deployment of the sensors on the terrain. The energy consumed at sensor \( i \) to transmit a data unit to its neighboring sensor \( j \) depends on the distance \( d_{ij} \) and is given by \( e_{ij}^T = 2d_{ij}^2 \). For simplicity in performing the experiments, we assume that the energy consumed by receiver \( j \) can be neglected. Note that this assumption is not restrictive (in any case, the reception cost is included in our LP formulation) and does not affect intensely the relative performance of the compared models. For every instance there is a constraint on the maximum transmission energy expenditure among sensors, \( e_{\text{max}}^T \), which is defined as the smallest value that guarantees connectivity among sensors. Hence, a sensor \( j \) is a neighbor of \( i \) if \( e_{ij}^T \leq e_{\text{max}}^T \). This constraint results in sparsely connected networks where multi-hop routing is necessary. Regarding the sink placement, it can be placed at the four corners and at the center of the grid, that is, at coordinates (0,0), (0,100), (100,0), (100,100), (50,50). We also set \( Q_i = 1 \), \( E_i = 10^6 \), for every sensor \( i \in N \). The LP models are solved for a given set of parameters using LINGO [18].

The main performance metric of interest is the duration of network operation until a sensor “dies” for the first time. Fig. 2 shows the average lifetime obtained by each model over the 100 instances created for each network size. The symbols \( \downarrow \) on top of each bar represent the corresponding standard deviations. We observe that our LP-opt model performs significantly better than the other models. The lifetime achieved by LP-opt is 28.8% higher than SPR and 14% higher than Static Sink for \(|N| = 20\), while these percentages rise to 114.4% and 24.5%, respectively, for \(|N| = 100\). We see that the lifetime improvement ratio increases with the network size. As the network size increases, the density of sensors increases as well. Hence, there are more alternative paths used by LP-opt to route the information from every sensor to the sink. This results in a more balanced energy depletion among sensors and, therefore, the lifetime achieved by LP-opt is considerably higher. An interesting observation is that SPR and MSPR perform almost the same. This is due to the fact that the sensors are randomly deployed inside the network and the transmission energy requirements depend on the distance between the communicating nodes. Hence, the costs of multiple paths that may exist from a sensor to the sink are typically different and, most of the times, there exists only one shortest path to route the data. Another interesting observation is that Static Sink performs better than SPR and MSPR. This is because Static Sink uses the optimal linear programming formulation of Section III-B and maximizes lifetime for every location separately. Although the overall network lifetime achieved is shorter than LP-opt, since the sensors close to the sink always relay the packets of all other sensors, it is still higher than SPR and MSPR which leave the routing problem outside the linear programming formulation (using a shortest path algorithm which is not optimal).

Fig. 3 presents the average sink sojourn times at the specified locations. The models compared are SPR, MSPR, and LP-opt, since the lifetime achieved by Static Sink corresponds only to one location (the sink stays in that location for the whole network operation and does not move to another place). It is worth noticing that the sink stays most of the time at location (50,50) (center of network) and considerably less at the four corners. This observation is explained as follows. Averaging the results obtained from 100 randomly generated instances for each network size, is almost the same as if we created a network with nearly uniform deployment of sensors. However, the sink node placements are not uniform with respect to the sensors’ deployment (there are more sensors around the center of the network than near the four corners of the area). Therefore, the sink stays considerably more time at location (50,50), since there are a lot of sensors close to it which can be used to relay the packets of all other sensors and prolong the overall network lifetime.

The fact that our approach results in a fair balancing of energy depletion among sensors can be justified by the results in Table 1. The models compared are SPR, Static Sink, and LP-opt, since MSPR performs almost the same as SPR. Let \( E_i^r \) be the residual energy of sensor \( i \in N \) at the end of network operation. For every instance, we compute the percentages of sensors \( i \) whose residual energy satisfies the relations: \( E_i^r = 0 \), \( E_i^r < 0.25E_i \), \( E_i^r < 0.5E_i \) (\( E_i \) is the initial energy of \( i \)). We then average the corresponding percentages over the 100 instances for each network size. By expressing the residual energy of every sensor as a fraction of its initial amount of energy, these percentages provide an indication about the distribution of sensors’ residual energies. For example, when there is a high percentage of sensors with zero residual energy, it means that their initial amounts of energy have been utilized efficiently and the energy is more evenly consumed among sensors. Hence, higher percentages of sensors with little residual energy, usually imply a higher network lifetime. We observe that LP-opt achieves much higher percentages of sensors with little (or even zero) residual energy. We also see that Static Sink performs better than SPR, since the corresponding percentages are higher in all cases. SPR provides the worst performance, since there are many sensors at the end with high amounts of residual energy that have not been utilized to increase network lifetime. An interesting observation is that, as the network size increases, the percentages for LP-opt increase, while the corresponding percentages for SPR decrease. For example, the percentages of LP-opt for \( E_i^r = 0 \) are 47% for \(|N| = 20\) and 70% for \(|N| = 100\). The corresponding percentages of SPR are 15% and 4%. This behavior can be explained by the fact that
the optimal performance of LP-opt can be more easily observed in larger networks, while the non-optimal performance of SPR also becomes more obvious as the network size increases.

**Note 2:** We performed similar experiments for another set of possible sink locations, namely at the centers of the four quarters of the grid, (25, 25), (25, 75), (75, 25), (75, 75). The corresponding results are not presented here due to page limitation.

### V. Conclusions - Issues for Further Study

In this paper we addressed the problem of maximizing the lifetime in a wireless sensor network where the information generated by the monitoring sensors needs to be routed efficiently to a mobile sink. Our proposed LP model determines the optimal sink sojourn times at different locations, and the optimal rates at which the sensed data must be transmitted from one sensor to another in order to be routed to the sink. However, implementing this model implies that the information obtained by solving the LP problem must be flooded to the network, so that every sensor is aware of the sink sojourn times and of the rate at which it has to transmit data to its neighboring nodes.

An interesting issue for future research is to develop an online heuristic algorithm which can be used in an adaptive environment, where the sensors do not know the schedule of the sink in advance and the information generation process is arbitrary. Such an approach could use one of the energy-aware routing algorithms of Section II for a given sink location. After an update interval, the sink can decide whether to stay at its current location or move to another place. The remaining lifetimes of sensors can be used by the routing algorithm to determine new paths to the sink, so that the bottleneck nodes are avoided and a more balanced energy depletion is achieved. Another interesting issue is the implementation of our model in a distributed environment where the sink sojourn times and the information transfer rates are not determined by a central node (possibly the sink). Distributed maximum lifetime routing algorithms exist [19]. Such algorithms could be used in an approach where the sink determines on-line the time to spend in every location and the sensors route the data to the sink distributively.

### References


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**TABLE I**

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**Fig. 2.** Average lifetime (over all instances - various network sizes).

**Fig. 3.** Average sink sojourn times (over all instances - various network sizes).


