Network Lifetime Maximization in Sensor Networks with Multiple Mobile Sinks

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***Abstract*—In this paper we deal with the network lifetime maximization problem under multiple mobile sink environments, namely, the h-hop-constrained multiple mobile sink problem, which is defined as follows. Given a stationary sensor network with K mobile sinks that traverse and sojourn in a given space of locations in the monitoring area, assume that the total travel distance of each sink is bounded by a given value L and the maximum number of hops from each sensor to a sink is bounded by an integer $h \geq 1$, the problem is to find an optimal trajectory for each mobile sink and determine the sojourn time at each sojourn location in the trajectory such that the network lifetime is maximized. We first formulate this problem as a joint optimization problem consisting of finding an optimal trajectory and determining the sojourn time at each chosen location. We then show that the problem is NP-hard. We instead devise a novel three-stage heuristic, which consists of calculating the sojourn time profile at each potential sojourn location, finding a high-quality trajectory for each mobile sink, and determining the actual sojourn time at each sojourn location. We finally conduct extensive experiments by simulations to evaluate the performance of the proposed algorithm in terms of network lifetime. We also investigate the impact of constraint parameters on the network lifetime. The experimental results demonstrate that the performance of the proposed heuristic is highly comparable to the optimal one, and the ratios of network lifetime of the proposed algorithm to the optimal network lifetime are ranged from 56% to 93%.**

I. Introduction

The availability of a large variety of sensor devices allows wireless sensor networks to be exploited in different application fields. Applications which rely on 24×7 (continuous) monitoring are required for environmental monitoring, precision agriculture, health-care, security surveillance, and national defense [1]. Wireless sensor network has emerged as a major, inter-disciplinary research area. It is usually expected to operate for an extended period of time but the fundamental constraint on it is the limited energy supplies on sensors. Traditionally, a wireless sensor network consists of a fixed sink (or a base station) and hundreds of thousands of tiny sensors powered by batteries. The sensing data generated by sensors is transmitted to the sink through multihop relays for further processing. Since the sensors near to the sink have to relay data for others, they usually bear disproportionate amounts of traffic and thus deplete their energy much faster than others. Such an unbalanced energy consumption among sensors will shorten the network operational time, data delivery reliability, and other network performance. To mitigate this uneven energy consumption among sensors, the concept of mobile sinks has been explored, and recent studies have shown that mobile sinks can significantly improve various network performance including network lifetime, connectivity, data delivery reliability, throughput, etc [16], [20], [25], [28].

A. Related work

Most of existing studies on network lifetime maximization focused on the single mobile sink [26], [16], [17], [20], [3], [19], [22], [29], [11], [23], [30], [12], [28], [15]. Very few studies considered multiple mobile sinks. Jea *et al.* [14] employed multiple mobile sinks (referred to as data mules) to traverse the sensing field along parallel straight lines and gather data from one-hop sensors. Although this scheme works well for large scale, uniformly or randomly distributed sensor networks, in practice the data mules cannot always move in straight lines, since obstacles or boundaries may block them on their paths. Chatzigiannakis *et al.* [6] dealt with the network lifetime maximization problem by partitioning the monitoring region into equal-sized subregions and assigning each subregion one mobile sink for data collection. Ma and Yang [18] addressed minimizing the number of mobile sinks needed under the assumption that the total travel distance of each sink is bounded. They focused on the sojourn region partitioning of mobile sinks without considering the energy consumption of sensors. Tang *et al.* [24] dealt with the network lifetime prolongation through the use of multiple sinks, their objective is to find a feasible tour for each mobile sink such that the longest tour is minimized, subject to the assumption that there is an available road map and the sinks can only move along the paths in the map. They devised several approximation algorithms. However, they did not consider the sojourn time at each sojourn location. In summary, most of existing approaches on multiple mobile sinks in the literature are to partition the monitoring region into a number of equal-sized subregions and to assign each subregion a mobile sink. As a result, the case of multiple mobile sinks can be reduced to the case of a single mobile sink [14], [6], [18]. These approaches, however, suffer the following drawbacks. (i) If the monitoring region is irregular, the work load assigned to each mobile sink

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will be imbalanced if the partition-based paradigm is adopted. (ii) None of these methods ensure that the data generated by each sensor at *each time instance* will be collected by one of the mobile sinks. (ii) None of them takes into account of both the network lifetime (of sensors) and the distance constraint of mobile sinks jointly. By contrast, in this paper we will take the mobile sink coordination into consideration to ensure that all sensing data will be collected at each time instance. We also incorporate the end-to-end distance constraint into the problem formulation. To incorporate the distance constraint makes the problem more realistic but poses more challenges.

Specifically, we will deal with a joint optimization problem consisting of finding optimal trajectories for the K mobile sinks and the sojourn time at each sojourn locations, with an objective to maximize the network lifetime, subject to the following two constraints: (1) the total travel distance of each mobile sink is bounded by a given value, as the mobile sinks are mechanically driven by petrol or electricity. (2) At each sojourn time instance, all sensing data generated by sensors must be collected by one of the K mobile sinks, and the maximum number of hops from each sensor to its nearest sink is bounded by an integer $h \geq 1$, where parameter h reflects the tolerable delay on data delivery.

B. Contributions

Our major contributions in this paper are as follows. We first formulated a novel joint optimization problem in a wireless sensor network with multiple mobile sinks, namely, the h-hop-constrained multiple mobile sink problem with aim to maximize the network lifetime, subject to the constraints on the distance of mobile sinks and the maximum number of hops from each sensor to a sink. We then showed the NP-hardness of the problem and devised a novel three-stage heuristic. We finally conducted extensive experiments by simulation to evaluate the performance of the proposed algorithm. The experimental results demonstrate that the performance of the proposed heuristic is highly comparable to the optimal one, and the performance ratios of the proposed algorithm are ranged from 56% to 93%.

The reminder of this paper is organized as follows. Section II introduces the system model, terminologies, and the problem definition. Section III-A shows the NP-hardness of the problem and a routine for finding a load-balanced forest, which will be used later. Section IV proposes a novel heuristic for the problem. To evaluate the performance of the proposed algorithm, Section V conducts extensive experiments by simulations, and conclusions will be given in Section VI.

II. Preliminaries

A. System model

We consider a wireless sensor network consisting of n stationary *sensor nodes*. The location of each sensor is fixed and known *a priori*. Each sensor equipped with an omni-directional antenna has a fixed transmission range and identical data generation rate r_a. There are K mobile sinks located at a depot site initially, they will traverse and sojourn at some pre-defined strategic locations in a given space of sink locations for data collection and return to the depot site for refilling petrol or recharging the electricity. Let $\mathcal{L}$ be the set of these potential sink locations. We assume that each mobile sink has unlimited energy supply in comparison with the initial energy capacity of sensors, thus it does not have any energy constraint by transmitting and receiving data from sensors. However, it usually is powered by petrol or electricity to support its mechanical movement, its total travel distance L per tour is bounded by a value. Unless otherwise specified, for simplicity, in this paper we only take into account the transmission and reception energy consumptions of each sensor, and assume its other energy consumptions on sensing and computation are negligible, as the radio frequency (RF) transmission is the dominant energy consumption in wireless communications. In general, a wireless sensor network can be represented by an undirected graph $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$, where $\mathcal{N}$ is the set of n stationary sensor nodes, $\mathcal{L}$ is the set of potential sink locations of the K mobile sinks, and $\mathcal{E}$ is the set of links with $\mathcal{E} \subseteq (\mathcal{N} \cup \mathcal{L}) \times (\mathcal{N} \cup \mathcal{L})$. There is a link in $\mathcal{E}$ between two sensors (or a sensor and a sink) if they are within the transmission range of each other. The network lifetime is defined as the time of the first sensor node's failure due to the expiration of its energy [4].

B. h-feasible configurations

A *configuration* ϕ of K mobile sinks is to place the K mobile sinks to K locations in space $\mathcal{L}$ of potential sink locations. A *h-feasible configuration* ϕ is such a configuration that each sensor in the network can relay its message to one of the K mobile sinks no more than h-hops ($h \geq 1$). Otherwise, the configuration is *infeasible*. In other words, within a h-feasible configuration, each sensor can relay its data to one of the K mobile sinks within h hops, where parameter h quantifies the extent of multi-hop routing and the tolerable data delivery reliability. To determine whether a given configuration ϕ is a h-feasible configuration, we have the following lemma.

Lemma 1: Given a configuration ϕ for $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ and an integer h ($h \geq 1$), it takes $O(m+n)$ time to determine whether it is a h-feasible configuration, where $n = |\mathcal{N}|$, $n_m = |\mathcal{L}|$, and $m = |\mathcal{E}|$, assuming that $n_m \leq n$.

Proof: A *virtual node* is created and it replaces the K mobile sinks at configuration ϕ, any neighbor (sensor) of a sink in the network then becomes a neighbor of the virtual node, a Breadth-First-Search (BFS) tree T in the modified network topology rooted at the virtual node is then constructed layer by layer, started from the root. It finally checks whether T contains all the sensors when expanded to a layer numbered no greater than h. If yes, ϕ is a h-feasible configuration; otherwise, ϕ is infeasible. It can be seen that the running time of determining the h-feasibility of a configuration is dominant by the BFS tree construction, which takes $O(m + n + n_m) = O(m + n)$ time. ■

C. Problem definition

Given a sensor network $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ and K mobile sinks that start from their depot site v_0, where site v_0 may be outside of the monitored region. The *h-hop-constrained multiple mobile sink problem* for data gathering in G is defined as follows. Given K mobile sinks starting from a depot site, they traverse the monitoring region through a number of h-feasible configurations and eventually return to the site again. Within each configuration, each mobile sink sojourns at one potential location in $\mathcal{L}$ for the same amount of time, and all sensors can relay their data to K mobile sinks within h hops. The problem is to find K optimal trajectories for the K mobile sinks and to identify the sojourn time at each chosen configuration such that the network lifetime is maximized, subject to the total travel distance of each mobile sink being bounded by L.

In other words, let $\Omega = \{\phi_1, \phi_2, \ldots, \phi_k\}$ be the set of all potential h-feasible configurations. The h-hop-constrained multiple mobile sink problem is to find a sequence of h-feasible configurations in Ω, determine the sojourn time t_{i_j} at each configuration ϕ_{i_j} in the sequence, and find the K close trajectories built upon the configuration sequence such that the network lifetime $\sum_{j=1}^{k'} t_{i_j}$ is maximized, subject to the length of the longest trajectory being bounded by L, where $1 \leq j \leq k'$ and $1 \leq i_j, k' \leq k$. Note that in the problem definition, although each mobile sink is allowed to participate in multiple h-feasible configurations, each configuration is only allowed to appear once in the configuration sequence from which the K trajectories will be derived.

The challenges for this joint optimization problem lies in three components: (i) time-dependent network topology, the network topology dynamically changes with mobile sink motion. (ii) The choice of h-feasible configurations and the sojourn time at each of the chosen configurations. (iii) The longest trajectory length constraint on K mobile sinks.

III. NP-hardness and Load-balanced forest

In this section we first show that the NP hardness of the problem. We then introduce a routine for finding a load-balanced forest for each h-feasible configuration.

A. NP-hardness

Theorem 1: The decision version of the h-hop-constrained multiple sink problem in a wireless sensor network $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ is NP-complete.

Proof: We show the NP-hardness of this problem through a reduction from the well known NP-complete problem - the set sum problem.

Consider a special case of the problem of concern, where the space of all h-feasible configurations $\Omega = \{\phi_0, \phi_1, \phi_2, \ldots, \phi_k\}$ is given, and the sojourn time at each $\phi \in \Omega - \{\phi_0\}$ is identical, ϕ_0 is the depot site, and $K = 2$ trajectories will include all configurations in Ω.

Given k positive integers $a_1, a_2, \ldots, a_k$, *the set sum problem* is to partition these k integers into two disjoint subsets such that the sum of elements in each subset is equal, which has been shown to be NP-complete [10]. We perform a reduction from this instance of the set sum problem to the above special case of the problem as follows.

We construct a directed, weighted graph containing only the potential sink locations by ignoring the sensor nodes as follows. The graph consists of a starting node (the depot) v_0, a destination node v_0' that actually is v_0 as well, and two nodes v_i and $\overline{v}_i$ for each a_i, $1 \leq i \leq k$. There are two directed edges from v_i to v_{i+1} and from v_i to $\overline{v}_{i+1}$ with weight a_i, $1 \leq i \leq k$. Similarly, there two directed edges from $\overline{v}_i$ to $\overline{v}_{i+1}$ and from $\overline{v}_i$ to v_{i+1} with weight zero, $1 \leq i \leq k$. In addition, there are two directed edges from v_0 to v_1 and from v_0 to $\overline{v}_1$ with weight zero. There are two directed edges from v_k to v_0' and from $\overline{v}_k$ to v_0' with weight zero. Assume that the length of the longest one among the two trajectories is bounded by $L = \sum_{i=1}^{n} a_i/2$.

We reduce the set sum problem to the h-hop-constrained multiple mobile sink problem in the constructed graph, where $K = 2$ and the sojourn time at each h-feasible configuration $\phi_i = \{v_i, \overline{v}_i\}$ is identical, $1 \leq i \leq k$. Note that ϕ_0 consists of v_0 only. The problem in this graph then is to find two node-disjoint paths from v_0 to v_0' such that the length of the longest path is no greater than L. Clearly, let $v_0, b_1, b_2, \ldots, b_k, v_0'$ be one of the two paths, then, another path will be $v_0, c_1, c_2, \ldots, c_k, v_0'$, where c_i is assigned in the following: if $b_i = v_i$, then $c_i = \overline{v}_i$; otherwise, $c_i = v_i$, $1 \leq i \leq k$. It can be seen that a solution to this special h-hop-constrained multiple mobile sink problem will result in a solution to the set sum problem. While the set sum problem is NP-complete [10], the decision version of the problem is NP-complete. ■

B. Load-Balanced Forest

Given a configuration ϕ, we will find a load-balanced forest, consisting of load-balanced trees rooted at mobile sinks such that the maximum energy consumption among the sensors is minimized. To maximize the sojourn time at ϕ, it is required that the load (the energy consumption) among the children of each tree root is well balanced, because these children consume much more energy than others by relaying data for others.

Given a h-feasible configuration ϕ, the energy consumption of each sensor per time instance at ϕ is as follows.

A routing tree rooted at each mobile sink at ϕ will be used for data gathering, the sensors in the network thus are partitioned into K clusters with each cluster headed by a mobile sink. Let T_s be the tree rooted at mobile sink $s \in \phi$ and assuming that sensor $v_j \in \mathcal{N}$ in T_s. Denote by $d_\phi(v_j)$ the number of proper descendants of v_j in T_s at ϕ. Recall that the data generation rate of each sensor is r_a, then, the energy consumption of sensor v_j at ϕ per time instance is

$$ec_\phi(v_j) = r_a \cdot [(d_\phi(v_j) + 1)e_t + d_\phi(v_j)e_r], \quad (1)$$

where e_t and e_r are the amounts of energy consumptions by transmitting and receiving a unit-length data, assuming that there is no data aggregation at each relay node, following the same assumption in [26], [3], [19], [28].

As sensors in the network are partitioned into K clusters headed by the K mobile sinks, a load-balanced tree for each cluster is built such that the maximum load among the children of tree roots is minimized. *The load-balanced forest problem* for ϕ is then reduced to an optimal, load-balanced tree problem that is to find a tree such that the load among the children of the tree root is well balanced. The reduction proceeds as follows.

A *virtual node* is created, which replaces the K mobile sinks, any neighbor (sensor) of a mobile sink in the original network now becomes a neighbor of the virtual node, an optimal, load-balanced tree in the resulting network rooted at the virtual node is then founded. However, finding an optimal, load-balanced tree in a network has been shown to be NP-complete and a heuristic was proposed in [27].

The load-balanced tree rooted at the virtual node is constructed layer by layer. Starting from the root, during the expansion from lay l to layer $l+1$, the maximum flow technique is applied to balance the descendant load of each child of the root. We refer to this algorithm as algorithm `Balanced_Load_Tree`.

Lemma 2: [27] Given a wireless sensor network $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ and a h-feasible configuration ϕ, there is a heuristic algorithm `Balanced_Load_Tree` for finding a load-balanced tree rooted at the virtual node, which takes $O(mn \log n)$ time, where $n = |\mathcal{N}|$, $n_m = |\mathcal{L}|$, and $m = |\mathcal{E}|$, assuming that $n_m \leq n$.

Having the load-balanced tree rooted at the virtual node, we now partition the sensors into different clusters headed by the K mobile sinks, i.e., we will form K routing trees rooted at mobile sinks. To this end, a bipartite graph $G_S = (V_\phi, V_1, E')$ is constructed, where V_ϕ is the set of locations of the K mobile sinks at configuration ϕ, V_1 is the set of children of the virtual node in the tree. There is an edge $(u, v) \in E'$ if a mobile sink located at $u \in \phi$ is within the transmission range of sensor $v \in V_1$.

Let $M_S(\phi)$ be a maximum matching in G_S that takes $O(n|E'|) = O(mn)$ time because $|E'| \leq |\mathcal{E}|$, $|V_\phi| = K$, and $|V_1| \leq n$. Then, for each matched sensor (an endpoint of a matched edge), its another endpoint (a mobile sink) is the cluster head of the sensor. For each unmatched sensor $v' \in V_1$, if there are multiple edges in E' incident to it, one of the edges is chosen and its another endpoint is the cluster head of sensor v', the subtree rooted at v' in the load-balanced tree becomes part of the new tree. Thus, the sensors in the network are partitioned into K load-balanced trees and the depth of each tree is no more than h. We thus have the following theorem.

Theorem 2: Given a wireless sensor network $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ and a h-feasible configuration ϕ, the energy consumption $ec_\phi(v_i)$ of each sensor $v_i \in \mathcal{N}$ at ϕ per time instance can be computed in $O(mn \log n)$ time for all i with $1 \leq i \leq n$, where $n = |\mathcal{N}|$, $n_m = |\mathcal{L}|$, and $m = |\mathcal{E}|$, assuming $n_m \leq n$.

Proof: It takes $O(mn \log n)$ time to build a load-balanced tree rooted at the virtual node, by Lemma 2. It then takes $O(mn)$ time to construct a load-balanced forest by constructing a bipartite graph G_S and finding a maximum matching in G_S, based on the constructed load-balanced tree. Having the load-balanced forest, each sensor v_i is contained by a load-balanced tree in the forest. The number of proper descendants $d_\phi(v_i)$ of v_i can be computed, so can the energy consumption $ec_\phi(v_i)$ of v_i per time unit for all $v_i \in \mathcal{N}$ with $1 \leq i \leq n$. Thus, it takes $O(mn \log n)$ time. ■

IV. Heuristic Algorithm

In this section a three-stage heuristic for the problem is proposed. It first determines the sojourn time profile at each h-feasible configuration $\phi \in \Omega$. It then finds a feasible trajectory for each mobile sink, subject to its travel distance constraint L. It finally determines the exact sojourn time at each chosen h-feasible configuration. In the following we detail these stages one by one.

A. Sojourn time profile at each h-feasible configuration

Recall that Ω is the h-feasible configuration space ($|\Omega| \leq |\mathcal{L}|^K$) and let $k = |\Omega|$. Let t_i be the sojourn time profile at h-feasible configuration $\phi_i \in \Omega$. Assume that each h-feasible configuration will be visited by the K mobile sinks, then, t_i can be found through solving the following linear program, $1 \leq i \leq k$. To maximize the network lifetime is equal to

$$\textit{maximize } \sum_{i=1}^{k} t_i,$$

subject to

$$\sum_{i=1}^{k} ec_{\phi_i}(v_j) \cdot t_i \leq \text{IE}, \quad \text{for all } \ j \text{ with } 1 \leq j \leq n. \tag{2}$$

$$t_i \geq 0, \quad \text{for all } \ i \text{ with } 1 \leq i \leq k. \tag{3}$$

Inequality (2) ensures that the total amount of energy consumed by each sensor v_j is no more than its capacity IE.

B. Finding optimal trajectories for the K mobile sinks

Having the sojourn time profile t_ϕ at each ϕ, we then find trajectories and determine the sojourn time at each chosen h-feasible configuration. In other words, we aim to find a sequence of h-feasible configurations and the K trajectories for the K mobile sinks built upon the sequence such that the network lifetime is maximized.

The basic idea is to construct the sequence as well as the K trajectories greedily. Initially, the sequence only contains the depot location ϕ_0, i.e., each of the K close trajectories contains the depot location. Each time a h-feasible configuration that has not yet been included is added to the sequence if the *benefit* on network lifetime per unit length brought by the configuration is maximized, where the benefit by a h-feasible configuration will be defined later. The algorithm proceeds as follows.

Let $\phi_0, \phi_1, \ldots, \phi_{k'}$ be the sequence of h-feasible configurations constructed so far. Assume that a h-feasible configuration ϕ is not the sequence, we now decide whether it should be inserted into the position between ϕ_i and $\phi_{(i+1) \bmod k'}$ in the sequence. If yes, what is the benefit brought by ϕ? $0 \leq i \leq k' < k$. To achieve that, we start from the sequence segment $\langle \phi_0, \phi_1, \ldots, \phi_i \rangle$ of the sequence by including ϕ as an *immediate successor* of ϕ_i in the augmented sequence. To do so, a weighted, bipartite graph $G_B = (V_{\phi_i}, V_\phi, E_B, w_B)$ is constructed, where V_{ϕ_i} is the set of K sink locations at ϕ_i, corresponding to the K trajectory segments from ϕ_0 to ϕ_i, and V_ϕ is the set of sink locations at configuration ϕ. There is an edge $(u, v) \in E_B$ between any node $v \in V_{\phi_i}$ and any node $u \in V_\phi$ with weight $w(u, v) = l_{org}(CS_j) + d(v, u)$, where $l_{org}(CS_j) = \sum_{e \in CS_j} d(e)$ is the length of the current trajectory segment CS_j of mobile sink j from ϕ_0 to ϕ_i, $v \in \phi_i$ is the endpoint of CS_j, and $d(v, u)$ is the Euclidean distance between locations v and u, $1 \le j \le K$.

To minimize the length of the longest trajectory segment is equivalent to minimize the maximum weight among the matched edges in a perfect matching in G_B. Let M_B be a perfect matching in G_B such that the maximum weight among the matched edges is minimized. The following perfect matching procedure, referred to as procedure PM for short can be used for finding M_B.

Given a bipartite graph $G_{XY} = (X \cup Y, E_{XY}, w)$, where X and Y are sets of nodes with $|X| = |Y| = K$, respectively, there is an edge in E_{XY} between any $x \in X$ and any $y \in Y$ with weight $w(x, y) \ge 0$. Let $\mathcal{M}$ be the collection of all perfect matchings in G_{XY}, there is a perfect matching $M_B \in \mathcal{M}$ such that the maximum weight among the matching edges in M_B is minimized, i.e., $\min_{M_B \in \mathcal{M}}\{\max_{e \in M_B}\{w(e)\}\}$, where e is a matched edge. We have the following lemma.

Lemma 3: Given a weighted bipartite graph $G_{XY}(X \cup Y, E_{XY}, w)$, there is an algorithm for finding a perfect matching M_B in G_{XY} such that the maximum weight among the matched edges is minimized. The algorithm takes $O(K^{5/2} \log K)$ time, where $|X| = |Y| = K$.

Proof: Since G_{XY} contained $2K$ nodes and K^2 edges, sorting the edges in E_{XY} by their weights in increasing order takes $O(K^2 \log K)$ time. Let $e_1, e_2, \ldots, e_{K^2}$ be the sorted sequence of edges. A binary search is applied to the sequence to pick a minimum weighted edge, for example e_i, such that the subgraph $G_{XY}[e_i]$ of G_{XY} induced by the edges whose weights are no more than $w(e_i)$ contains a perfect matching. Such a perfect matching can be found within $O(\log K)$ iterations. Thus, it takes $O(K^{5/2} \log K)$ time in total, since it takes $O(K^{2.5})$ time to determine whether there is a perfect matching in $G_{XY}[e_i]$ and there are $\lceil \log K^2 \rceil$ such bipartite graphs to be examined. ■

What comes next is to concatenate the augmented sequence segment with another sequence augment $\langle \phi_{i+1}, \ldots, \phi_{k'}, \phi_0 \rangle$ of the current sequence to form an augmented sequence and K new trajectories for the K mobile sinks. To this end, we construct another weighted bipartite graph $G_C = (V_\phi, V_{\phi_{i+1}}, E_C, w_C)$, where V_ϕ and $V_{\phi_{i+1}}$ are the sets of sink locations of K mobile sinks in ϕ and ϕ_{i+1}, respectively. There is an edge between any pair of nodes $u \in V_\phi$ and $v \in V_{\phi_{i+1}}$ with weight $w_C(u, v) = w_B(i(u), u) + l_{org}(CS_j) + d(u, v)$, where $l_{org}(CS_j)$ is the length of trajectory segment of the current trajectory of mobile sink j starting from location v in the sequence segment $\langle \phi_{i+1}, \ldots, \phi_{k'}, \phi_0 \rangle$, $w_B(i(u), u)$ is the segment length of the trajectory segment of mobile sink l ending at node u in the augmented sequence $\langle \phi_0, \ldots, \phi_i, \phi \rangle$, and $i(u)$ is the endpoint of the trajectory segment of mobile sink $s_l \in \mathcal{L}$. We find a perfect matching M_C in graph G_C such that the maximum weight among the matched edges is minimized, using procedure PM again.

Denote by $EM(\phi, \phi_{i+1}) = \max_{e \in M_C}\{w_C(e)\}$ the length of the longest trajectory by this augmentation. Since both M_B and M_C are perfect matchings, each of the K mobile sinks has a corresponding matched edge in both of them. Thus, for each mobile sink s_j, let C'_j and C_j be the trajectory of s_j with and without including ϕ, respectively. Let $C_j = \langle v_{\phi_0}, \ldots, v_{\phi_i}, v_{\phi_{i+1}}, \ldots, v_{\phi_{k'}} \rangle$ and $C_l = \langle u_{\phi_0}, \ldots, u_{\phi_i}, u_{\phi_{i+1}}, \ldots, u_{\phi_{k'}} \rangle$ be the sequences of sojourn locations of trajectories j and l in their current trajectories. Then, $C'_j = \langle v_{\phi_0}, \ldots, v_{\phi_i}, v_\phi, u_{\phi_{i+1}}, \ldots, u_{\phi_{k'}} \rangle$ if $(v_{\phi_i}, v_\phi) \in M_B$ and $(v_\phi, u_{\phi_{i+1}}) \in M_C$. The increase on the maximum length among the K trajectories due to the insertion of ϕ is $\max\{l(C'_j) \mid 1 \le j \le K\} - \max\{l(C_j) \mid 1 \le j \le K\}$, where $l(C)$ is the sum of weighted edges in C.

Similarly, we can augment the original K trajectories in another way. That is, let $\langle \phi_{i+1}, \ldots, \phi_{k'}, \phi_0 \rangle$ be the sequence segment of the configuration sequence in the current K trajectories. We augment this sequence segment by including ϕ as its header. We then concatenate the sequence segment $\langle \phi_0, \phi_1, \ldots, \phi_i \rangle$ with the augmented sequence segment to form an augmented sequence and K augmented trajectories for the K mobile sinks. To this end, we construct a weighted bipartite graph $G_B = (V_{\phi_{i+1}}, V_\phi, E_B, w_B)$, followed by another bipartite graph $G_D = (V_\phi, V_{\phi_i}, E_D, w_D)$, where E_D is the set of all pairs of nodes $u \in V_\phi$ and $v \in V_{\phi_i}$ with weight $w_D(u, v)$, and the definition of w_D is similar to w_C in G_C, omitted. Let M_D be such a perfect matching in G_D that the maximum weight among the matched edges is minimized. Denote by $EM(\phi, \phi_i) = \max_{e \in M_D}\{w_D(e)\}$ the maximum weight among the matched edges.

The resulting K trajectories $C'_1, \ldots, C'_K$ will include their corresponding locations at ϕ if $\min\{EM(\phi, \phi_i), EM(\phi, \phi_{i+1}\} \le L$. Otherwise, ϕ should not be included in the configuration sequence. In case, both $EM(\phi, \phi_i)$ and $EM(\phi, \phi_{i+1})$ meet the length constraint, the smaller one is chosen. As there are multiple such h-feasible configurations, only the one ϕ that brings the maximum benefit $g(\phi)$ will be chosen, where *the benefit* $g(\phi)$ on network lifetime brought by ϕ with respect to the current K trajectories is defined as follows.

$$g(\phi) = \frac{t_\phi}{\max_{1 \le j \le K}\{l(C'_j)\} - \max_{1 \le j \le K}\{l(C_j)\}}, \qquad (4)$$

where t_ϕ is the sojourn time profile of ϕ. As the range of i from 0 to k', we add a ϕ between ϕ_{i_0} and ϕ_{i_0+1} if this results in the maximum increase on the network lifetime per unit length, $0 \le i_0 \le k'$. This procedure continues until any further configuration additions will violate the end-to-end distance constraint. The detailed algorithm is described as follows.

Algorithm `Find_Trajectory`(G, L)

```
TC ← ⟨φ_0⟩; /*the initial sequence of configurations */
U ← Ω − TC; /* the set of configurations not in TC */
max_g ← 0; /* the maximum benefit brought */
continue ← 'true'; k' ← 1;
while (continue) and (U ≠ ∅) do
  for i ← 0 to k' do
    for each φ ∈ U do
      /* forward extension from φ_i to φ_{i+1} */
        construct G_B = (V_{φ_i}, V_φ, E_B, w_B);
        find the perfect matching M_B in G_B;
        construct G_C;
        find the perfect matching M_C of G_C;
        compute EM(φ, φ_{i+1});
      /*backward extension from φ_{i+1} to φ_i */
        construct G_B = (V_{φ_{i+1}}, V_φ, E_B, w_B);
        find the perfect matching M_B in G_B;
        construct G_D;
        find the perfect matching M_D in G_D;
        compute EM(φ, φ_i);
        if min{EM(φ, φ_{i+1}), EM(φ, φ_i)} ≤ L then
          compute g(φ);
          if g(φ) > max_g then
            max_g ← g(φ);
            i_0 ← i; /* the insertion position of φ */
            next_config ← φ;
  if (max_g ≠ 0) then /* the sequence is extended*/
    /* insert next_config between φ_{i_0} and φ_{i_0+1} in TC */
    TC ← ⟨φ_0, ..., φ_{i_0}, next_config, φ_{i_0+1}, ..., φ_{k'}⟩;
    update each of the K trajectories accordingly;
    U ← Ω − {φ | φ ∈ TC};
    k' ← k' + 1;
    max_g ← 0;
  else continue ← 'false'.
```

C. Calculating actual sojourn time

Assume that $\phi_0, \phi_1, \phi_2, \ldots, \phi_{k'}$ is the sequence of h-feasible configurations in the K trajectories. Clearly, a solution consisting of ϕ_i with sojourn time t_i for all i is a feasible solution to the problem, $1 \leq i \leq k'$. The rest is to find a better solution such that $\sum_{i=1}^{k'} t'_i \geq \sum_{i=1}^{k'} t_i$, where t'_i is the actual sojourn time at ϕ_i, all t'_i can be found by solving a linear program similar to the one in (IV-A), omitted. We refer to the above three-stage algorithm as algorithm `FTNL` and have the following theorems.

Theorem 3: Given a wireless sensor network $G(\mathcal{N} \cup \mathcal{L}, \mathcal{E})$ and K mobile sinks with the maximum length among the K trajectories being bounded by L, and the maximum number of hops from each sensor to its nearest sink being no more than $h \geq 1$, there is a heuristic algorithm `FTNL` for the h-hop-constrained multiple mobile sink problem, which takes $O(mnk \log n + n^2 k + k^3)$ time, where $n = |\mathcal{N}|$, $m = |\mathcal{E}|$, $|\mathcal{L}| \leq |\mathcal{N}|$, and $k = |\Omega|$.

Proof: We analyze the time complexity of algorithm`FTNL`. The calculation of sojourn time profiles takes $O(mn \log n)$ time by Lemma 2, and $O(n^2 k)$ time for solving a linear programming. The running time for finding the K trajectories is analyzed as follows. The constructions of G_B, G_C, and G_D take $O(K^2)$ time. It takes $O(K^{5/2})$ time to find a perfect matching in G_B, G_C or G_D respectively, and there are $O(\log K)$ G_Cs or G_Ds to be examined in order to find the one in which the maximum weight among the matched edges is minimized. Thus, finding K trajectories takes $O(K^{5/2} \log K)$ time for per inserting a configuration at a given position in the current sequence. Thus, it takes $O(k^3 K^{5/2} \log K)$ time in total. The proposed algorithm takes $O(mnk \log n + n^2 k + k^3)$ time. ■

We finally analyze the network lifetime delivered by algorithm `FTNL` as follows.

Theorem 4: Given the sojourn time profile t_j at each h-feasible configuration $\phi_j \in \Omega$, assume that the solution by algorithm `FTNL` consisting of k' configurations $\phi_1, \ldots, \phi_{k'}$, let $E_i = \sum_{j=1}^{k'} t_j \cdot ec_{\phi_j}(v_i)$ be the total amount of energy consumed by sensor $v_i \in \mathcal{N}$ when the K mobile sinks sojourn at the k' h-feasible configurations along their trajectories with the given sojourn time t_j at ϕ_j, $1 \leq j \leq k'$. Let $\beta = \min_{1 \leq i \leq n}\{\frac{\mathrm{IE} - E_i}{E_i}\}$ be the minimum ratio of residual energy of each sensor to its consumed energy at the chosen configurations and $T_{total} = \sum_{j=1}^{n} t_j$, $0 \leq \beta < 1$. Denote by $\gamma = \frac{T_{total} - \sum_{j=1}^{k'} t_j}{\sum_{j=1}^{k'} t_j}$. Then, the approximation ratio of network lifetime by algorithm `FTNL` is no less than $(\frac{1+\beta}{1+\gamma})$, where IE is the initial energy capacity of each sensor.

Proof: Having the K mobile sinks sojourning at configuration ϕ_j with sojourn time t_j, $1 \leq j \leq k'$, the residual energy at sensor $v_i \in \mathcal{N}$ is $E_{res}(i) = \mathrm{IE} - \sum_{j=1}^{k'} t_j \cdot ec_{\phi_j}(v_i) = \mathrm{IE} - E_i$, the ratio of the residual energy of sensor v_i to its consumed energy so far is $\beta_i = \frac{E_{res}(i)}{E_i} = \frac{\mathrm{IE} - E_i}{E_i} = \frac{\mathrm{IE}}{E_i} - 1$. The rest is to show that there is enough energy at each sensor v_i to support the network operations when each configuration ϕ_j is assigned the amount of extra sojourn time βt_j as follows.

The amount of residual energy of each sensor v_i is $E'_{res}(i) = E_{res}(i) - \sum_{j=1}^{k'} \beta t_j \cdot ec_{\phi_j}(v_i) = (\mathrm{IE} - E_i) - \beta E_i = \mathrm{IE} - (1+\beta)E_i \geq \mathrm{IE} - (1+\beta_i)E_i = \mathrm{IE} - \frac{\mathrm{IE}}{E_i} \cdot E_i = 0$ since $\beta \leq \beta_i$, $1 \leq i \leq n$. Thus, the proposed solution that sojourns at a chosen configuration ϕ_j with $(1+\beta)t_j$ time is a feasible sojourn time scheduling, $1 \leq j \leq k'$. As the solution consisting of all t'_i is an optimal solution of a linear programming similar to the one in (IV-A), it is obvious that $\sum_{j=1}^{k'} t'_j \geq (1+\beta) \sum_{j=1}^{k'} t_j$. Let T_{opt} be the optimal network time and let $T_{upper} = \sum_{i=1}^{n} t_i$. Clearly, $T_{opt} \leq T_{upper}$. Let $T_{FTNL} = \sum_{j=1}^{k'} t'_i$ be the network lifetime by algorithm `FTNL`, then the performance ratio ζ of algorithm `FTNL` is

$$\zeta = \frac{T_{FTNL}}{T_{opt}} \geq \frac{T_{FTNL}}{T_{upper}} = \frac{\sum_{j=1}^{k'} t'_j}{\sum_{j=1}^{n} t_j} = \frac{1+\beta}{1 + \frac{\sum_{j'=k'+1}^{n} t'_{j'}}{\sum_{j=1}^{k'} t_j}} = \frac{1+\beta}{1+\gamma}. \quad (5)$$

The theorem then follows. ■

V. Performance Evaluation

In this section we evaluate the performance of the proposed algorithm FTNL. We also investigate the impact of constraint parameters on the network lifetime through experimental simulations. We consider a wireless sensor network consisting of sensors with network size from 100 to 400, which are randomly distributed in a circular area with radius $R = 100$ meters. The transmission range of each sensor is fixed to 25 meters and the initial energy capacity of sensor IE is $50 Jules$. We assume that the data generation rate is $r_a = 4 bits/s$. The coordinate $(0, 0)$ is the center coordinate of the circle, which is also the depot site of the K mobile sinks initially. There are $|\mathcal{L}| = 9$ potential sink sojourn locations which are uniformly distributed in the circle.

In all our experiments we adopt the actual energy consumption parameters of a real sensor - MICA2 mote [8], where the amounts of energy by transmitting and receiving 1-bit data are $e_t = 14.4 \times 10^{-6} J/bit$ and $e_r = 5.76 \times 10^{-6} J/bit$, respectively. The total travel distance of each mobile sink L is bounded by a given value ranged from $1/4$ to 1 of the circumference $C = 2\pi R$ meters of the circular area, i.e., L varies from $C/4 = 157$ meters to $1C = 628$ meters. The number of hops h varies from 6 to 12, while the number of mobile sinks K varies from 2 to 5. The value in each figure is the mean of the 10 results.

A. Performance evaluation of the proposed heuristic

We first investigate the performance ratio of algorithm FTNL. We use an upper bound on the optimal network lifetime, the sum of sojourn time profiles $\sum_{i=1}^{k} t_i$, to estimate the performance ratio of algorithm FTNL, because it includes all potential sojourn locations and there is not any constraint on the lengths of K trajectories. It must be stressed that this estimate is very conservative, the real optimal network lifetime usually is much shorter than the estimate. Fig. 1 plots the ratio of network lifetime ζ of algorithm FTNL when $h = 8$, $K = 3$, and L varies from $1/4C$ to C with increment of $C/4$. It can

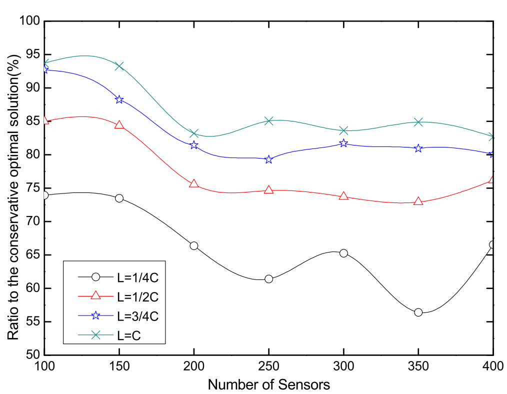


Fig. 1. The performance ratio ζ by algorithm FTNL.

be seen that the performance of algorithm FTNL is at least 56% to 93% of the optimal one, depending on the value of L.

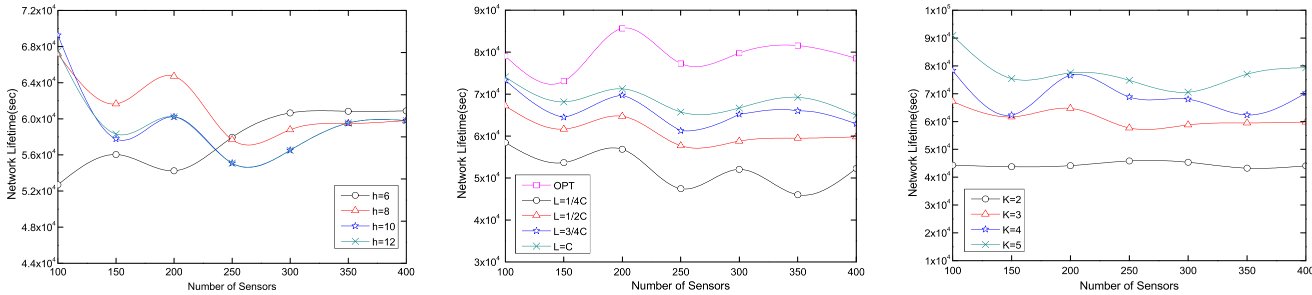
B. Impact of various parameters on the network lifetime

We then analyze the impact of constraint parameters h, L and K on the network lifetime by varying one of them while keeping others fixed at each time.

The impact of parameter h. We first vary h from 6 to 12 with increment of 2 when setting $L = 314m$ and $K = 3$. Fig. 2(a) plots the performance curves of algorithm FTNL by assigning $h = 6, 8, 10, 12$ when setting $L = 314m$ and $K = 3$. It can be seen that with the growth of h from 6 to 8, the network lifetime increases when $n \leq 250$, since a larger h implies more h-feasible configurations to be included in the K trajectories. However, for the case where $n \leq 250$, it is interesting to see that the network lifetime when $h = 10, 12$ is shorter than the one when $h = 8$. The reason behind is that in this case, the network is very sparse, there are only a few h-feasible configurations, and the average distance between sink locations in these configurations is relatively far away from each other, while the number of h-feasible configurations when $h = 10, 12$ is larger than that when $h = 8$. Since the end-to-end distance constraint $L = 314m$ is short, the proposed greedy algorithm always picks a configuration with the maximum benefit, this implies that it will pick a nearby h-feasible configuration at each time. Thus, the K trajectories when $h_1 = 10, 12$ may include several nearby h_1-feasible configurations that are not the h_2-feasible configurations when $h_2 = 8$. Consequently, the network lifetime when $h_1 = 10, 12$ is shorter than that of the one when $h_2 = 8$. With the network size $n \geq 350$ increases, the network density increases too, thus, the cardinality of the space of h-feasible configurations for different h does not change too much. This means that there will be no more h-feasible configurations included when h approaches the network diameter 10.

The impact of parameter L. We then vary the maximum travel distance L of each mobile sink. Fig. 2 (b) depicts the performance of algorithm FTNL by varying L from 157 meters to 628 meters with the increment of 157 while keeping $h = 8$ and $K = 3$, from which it can be seen that with the increase of L, the network lifetime increases too, because a longer L implies that each trajectory will contain more locations (or h-feasible configurations) to sojourn, the average load among bottleneck sensors will be better balanced, and a longer network lifetime will be delivered.

The impact of parameter K. We finally vary the number of mobile sinks K. Fig. 2(c) illustrates the performance of algorithm FTNL by varying K from 2 to 5 while keeping $h = 8$ and $L = 314m$. For a given network size n, the network lifetime increases with the growth of K, because adding more sinks into the system will result in a lighter load among the bottleneck sensors. However, with any further increase on the number of mobile sinks K, the network lifetime may not be necessarily increase as well. For example, when the value of K is large enough to make each sensor be within one-hop from one of the mobile sinks, any further increase on the number of mobile sinks will not lead to any improvement on the network lifetime.



(a) $L = 314$ and $K = 3$

(b) $h = 8$ and $K = 3$

(c) $L = 314$ and $h = 8$

Fig. 2. The impact of constraint parameters h, L and K on the network lifetime delivered by algorithm FTNL, where $|\mathcal{L}| = 9$

VI. Conclusion

In this paper we have studied a joint optimization problem for network lifetime maximization, by finding K optimal trajectories and sojourn time scheduling at each chosen sojourn location, provided that the constraints on mobile sinks and sensors are met. We first showed its NP-hardness. We then devised a novel heuristic for it. We finally conducted extensive experiments by simulations to evaluate the performance of the proposed heuristic and investigated the impact of constraint parameters on the network lifetime. The experimental results demonstrate that the solution delivered by the heuristic algorithm is highly comparable to the optimal solution, and the performance ratio of the proposed algorithm is ranged from 56% to 93%.

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