Constrained Resource Optimization in Large-Scale Wireless Sensor Networks with Mobile Sinks

Weifa Liang
Research School of Computer Science, Australian National University, Canberra, ACT 0200, Australia
Email: wliang@cs.anu.edu.au

***Abstract*—In this position paper we address key challenges in the deployment of wireless sensor networks (WSNs) with mobile sinks for large-scale, continuous monitoring. We propose a heterogeneous and hierarchical WSN architecture for such purpose. we also introduce several novel, constrained optimization problems related to this new paradigm of data gathering, which serve as the potential research topics in this area.**

I. Introduction

Driven by the steady miniaturization of computer chipsets and by the continuing proliferation of wireless devices and communication technology, Wireless Sensor Networks (WSNs) have emerged as a major, interdisciplinary area of research and industrial application [1]. WSNs have been seen more as a solution to large-scale tracking and monitoring applications, because their low-data rate, low-energy consumption and short-range communication presents the great opportunity to instrument and monitor the physical world at unprecedented scale and resolution. Deploying a large number of tiny sensors that can sample, process and deliver information to external systems such as fixed or mobile sinks and even Internet applications opens many novel application domains. These include industrial control and monitoring, home automation and consumer electronics, security and military sensing, asset tracking and supply chain management, intelligent agriculture and health monitoring, environmental and habitat monitoring, and so on. However, the deployment of WSNs for large-scale, continuous monitoring still necessitates solutions to a number of theoretical and technological challenges that stem primarily from the constraints imposed on the tiny sensor components: limited power, limited communication bandwidth, limited processing capacity, and small storage capacity. The central challenge among these is the provision of quality-guaranteed monitoring while minimizing critical WSN resource consumption. Thus, most resource optimization problems in WSNs can be formulated as *constrained optimization problems* with one or multiple constraints, and much of the research on these optimization problems has focused on developing *exact* and *heuristic* solutions [2], [11], [18], [22], [23], [30], [31], [33]. Exact procedures are limited to solving smaller instances and are not applicable to large-scale networks, due to exponential running time. Although heuristic techniques can yield solutions for some WSN optimization problems, they do not guarantee how far of the solutions obtained from the optimal. To utilize the critical WSN resources precisely, the development of *approximation algorithms* with quality-guaranteed solutions in WSNs is desperately needed, and the search for such algorithms is a key research issue.

In this position paper we address key challenges in the deployment of WSNs with mobile sinks for large-scale, continuous monitoring. We will propose a heterogeneous and hierarchical WSN architecture for such purpose. We will also pose several resource-constrained optimization problems, using this new paradigm of data gathering. To the best of our knowledge, these novel optimization problems have not yet been explored. The development of approximation algorithms with guaranteed performance for them is quite challenging, and they are the potential research topics in this area in the near future.

The rest of this paper is organized as follows. Section II introduces our motivations and related works. Section III proposes a heterogeneous and hierarchical WSN architecture for large-scale continuous monitoring. Section IV addresses several open constrained optimization problems related to the adoption of this new paradigm of data gathering. The conclusion will be given in Section V.

II. Related work

Although several approximation algorithms for different optimization problems in *stationary* WSNs have been proposed in the past few years [14]–[16], [25], [35], [36], developing approximate solutions to optimization problems in dynamic WSNs with mobile sinks poses great challenges, and is largely unexplored except very few results available [21], [29]. The theoretical difficulties lie in the network dynamics and the constraints on mobile sinks: On one hand, the physical network topology dynamically changes with mobile sinks moving to different locations and the data routing patterns change as well. On the other hand, each mobile sink is usually restricted not only by its maximum travel distance but also by its travel region, as the mobile sink is mechanically driven by petrol or electricity and should avoid traveling towards obstacle locations or subregions in the monitoring area.

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As a result, the development of any efficient algorithm for such dynamic networks must take into account both the network dynamics and the constraints on mobile sinks.

To develop novel solutions for quality-guaranteed monitoring in dynamic WSNs with mobile sinks, the key challenges associated with this investigation lie in (i) how to collect enormous amount of sensing data generated by the sensors efficiently and effectively while minimizing critical network resource consumptions (e.g. energy consumption, the number of sensors used, etc); and (ii) how to ensure the quality of the collected data by mobile sinks while meeting specified stringent constraints on the mobile sinks. In the following we will address these issues.

Traditionally, a WSN consists of a fixed sink (a base station) and hundreds of thousands of sensors. The data generated by the sensors is transmitted to the fixed sink through multi-hop relays for further processing [3], [17], [24]. 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 the sensors will shorten the network operational time, and can affect data delivery reliability and other network performance.

To mitigate this uneven energy consumption among sensors, the concept of mobile sinks has been exploited by many researchers, and such studies usually assume that a mobile sink (or multiple mobile sinks) can either traverse anywhere across the entire network or, alternatively, be constrained to stop only at some pre-defined strategic locations in the monitoring area for data collection [8], [20], [33], [40]. Recent studies have shown that the use of mobile sinks can significantly improve various network performance including network lifetime, connectivity, data delivery reliability, throughput, etc [2], [11], [20], [22], [29], [33], [34], [37].

Extensive studies on optimizing critical network resources with mobile sinks, such as maximizing the network lifetime and/or minimizing the number of mobile sinks used, have been extensively conducted in the past few years [2], [11], [18], [20]–[23], [29], [33], [36], [40]. Although the benefits brought by deploying mobile sinks have been well recognized, their deployment still poses great challenges in terms of the management of critical WSN resources, due to the network dynamics and the constraints on mobile sinks. Most existing studies focused on either the travel distance constraint on mobile sinks [23], [36] or the network lifetime [2], [11], [20], [22], [23], [33], [40], by providing exact and heuristic solutions. Although several approximation algorithms have already been developed [21], [29], [36], [40], they are all based on simplified assumptions. To be explicit, these works suffer the following four major drawbacks.

The first drawback is over simplified assumptions. Most studies assumed that mobile sinks can traverse anywhere or stop at some specified locations. In reality, these assumptions however is questionable.

- How do we know "which locations" should be the strategic locations beforehand?
- Is that possible that a mobile sink takes no time traveling from one location to another location?
- Can a mobile sink travel forever without being recharged or refueled?

In fact, in many realistic applications scenarios, a mobile sink cannot travel everywhere without restriction, it may only be allowed to travel in some restricted subregions and must avoid traveling towards obstacles such as rivers, water ponds, big rocks, buildings, bushes in the monitoring area. In addition, not only its travel distance but also its travel speed must be bounded, as each mobile sink is mechanically powered by either petrol or electricity with finite fuel resources. In some circumstances, a mobile sink (e.g. a moving vehicle) is not allowed to "stop" on a high-speed highway or a busy traffic street for data collection.

The second drawback is that almost all existing studies on network resource optimization have focused on either the mobile sinks [23], [32] or the network lifetime [2], [20], [40]. Very few works that have accounted for both of these issues at the same time have been based on quite unrealistic assumptions. For example, the result in [36] was obtained under the assumption that the forwarding load of each relay node is identical and irrespective of the number of descendants the relay node has. As another example, the approximation result in [40] is assumed that each sensor can transmit its data to the sink through multihop relays when the sink is within a given distance of the sensor, and it took neither the travel distance nor the travel speed of the mobile sink into consideration.

The third drawback is that most existing studies assumed it takes a mobile sink no time to collect data from gateway nodes, where a gateway node can be either a common sensor or a powerful sensor node that can communicate with the mobile sink directly [23], [32], [36]. Recent studies however showed that this time is significant and cannot be neglected [31], [41].

Finally, the fourth drawback is that these studies are based on a "flat" architecture consisting of homogeneous sensors and mobile sinks. Although this flat architecture may work very well for small to medium-size sensor networks, it may not be appropriate for large-scale, continuous monitoring purpose, because (i) it has a poor scalability. With the increase of network size, the routing paths from remote sensors to the mobile sink(s) become longer and longer, whereas the communications in wireless networks are unreliable. Consequentially, there will be more and more broken links and will incur much longer delays on sensing data delivery to the mobile sinks; and (ii) it is also impossible to keep all mobile sinks in working status, they need be refueled or recharged over time. During the absences of mobile sinks, the component sensors will not be able to hold all the generated sensing data. Some important data will be lost due to the buffer overflow of sensors or become obsolete. Consequently, the quality of monitoring of the network cannot be guaranteed and will be compromised.

III. A NEW WSN ARCHITECTURE

To enable a WSN for large-scale, continuous monitoring through overcoming the drawbacks discussed above while meeting realistic constraints on mobile sinks, in the following a new heterogeneous and hierarchical WSN architecture is proposed for such a purpose.

A. The architecture

This architecture consists of a large number of low-cost sensor nodes for sensing and a few powerful, large-storage gateway (sensor) nodes (sometimes referred to as aggregate nodes or base stations [?], [19], [28]). The main roles of each gateway node are to store the sensing data generated by its nearby sensors temporarily, perform data aggregation if needed, and transmit the stored data to mobile sinks or to other gateway nodes. Note that here "a few" gateway nodes is relative to "the large number" of low-cost sensors in the network. To incorporate the constraints on the travel distance and the travel region constraint of mobile sinks into problem formulation, we will assume that there is a road map in the monitoring area and mobile sinks are only allowed to travel on the roads in the road map. We assume that the gateway nodes can be recharged by mobile sinks directly or through the infrared ray within their transmission ranges, or reusable energy sources like solar energy panels. For the convenience of access of gateway nodes by mobile sinks, we further assume that the gateway nodes are deployed along road shoulders. Thus, mobile sinks can travel along predefined or to-be-determined trajectories to collect data from the gateway nodes, rather than from low-cost sensor nodes, when the mobile sinks pass by their transmission ranges. The collected data by mobile sinks will finally be uploaded to mainframe computers for further processing.

The above proposed heterogeneous and hierarchical WSN architecture can also be treated as a three-tier WSN architecture: The top tier consists of mobile sinks to collect data from gateway nodes directly. The bottom tier consists of lots of sensors sensing and transmitting their data to the gateway nodes in the middle tier, and the middle tier consists of gateway nodes storing sensing data temporarily. Two extreme cases of this hierarchical paradigm of data gathering have been exploited in the past. One is that all sensors serve as "gateway nodes" uploading their data to mobile sinks when the mobile sinks are within their transmission ranges, i.e. they can communicate with the mobile sinks directly. By doing so is most energy-efficient by eliminating the energy consumption of nodes on multi-hop relays. However, this approach may result in much longer delays on data delivery. Another is that there is only one gateway node (a static sink or a base station) in the entire network and all sensors have to relay their data to the gateway node. This will lead to much less delays on data delivery but will result in much severe energy imbalance among the sensor nodes. It can be seen that the proposed heterogeneous and hierarchical WSN architecture is expected to achieve a desirable trade-off between the energy consumption of sensors and the data delivery latency. It thus is more appropriate for large-scale, continuous monitoring.

B. Application backgrounds

The proposed heterogeneous and hierarchical WSN architecture falls into many realistic application scenarios. In particular, a large-scale smart city network could be realized through the deployment of such a network consisting of different types of sensors (e.g. scalar sensors and multimedia video sensors), gateway nodes, and mobile sinks. The deployed sensors are used to monitor various attributes of a city such as the structural health of key infrastructures (e.g. landmark buildings and bridges), security surveillance of public places, road traffic, electricity and water-meter readings, and so on. There are also a number of gateway nodes installed along both sides of streets, which are used to store the sensing data generated by nearby sensors temporarily. The gateway nodes can communicate with each other by transmitting the received data to the mainframe server(s) for further processing through long range transmission, at the cost of the consumption of significant amount of energy. Alternatively, mobile sinks can be employed to collect data from the gateway nodes through short range transmission, and the cost by doing so is also quite cheap, because public transports like buses equipped with transceivers can serve as the mobile sinks to collect data stored at the gateway nodes on their routes.

C. Challenges

By deploying the proposed heterogeneous and hierarchical WSN architecture for large-scale, continuous monitoring, we have the following important issues to be addressed.

Given the maximum travel distance of each mobile sink per tour, if the mobile sink travels at a constant speed, then the duration the mobile sink takes per tour, which is its maximum travel distance divided by its speed, is fixed, where this duration is also the longest delay a sensing (reading) value from its generation to its collection by a mobile sink. We refer to this duration as the tolerant latency on data delivery, reflecting the "freshness" or "obsoleteness" of the collected data. Meanwhile, the amount of data collected by each mobile sink from a gateway node is determined by both its duration within the transmission range of the gateway node and the transmission rate of the gateway node. This implies the faster a mobile sink travels, the less data it can collect per tour. Now, if the volume of data stored at a gateway node is larger than the amount of data a mobile sink can collect per tour, then it is unavoidable that some of the stored data will not be collected in the current or future tour and will ultimately be discarded. Consequently, the monitoring quality of the network will be seriously compromised, since not all sensing data has been collected.

To maximize the quality of monitoring in the proposed WSN architecture while meeting the given tolerant data latency and the constraints on the travel distance and the travel region of mobile sinks, the following challenging questions need to be answered.

1) If not all sensing data generated by sensors can be collected by mobile sinks per tour, then which sensors should have their data collected in order to maximize the quality of monitoring?
2) What is the optimal routing strategy to route the sensing data of the chosen sensors to the gateway nodes such that the network cost is minimized? And how should the chosen sensors be partitioned?
3) If not all gateway nodes can be visited by a single mobile sink per tour, then multiple mobile sinks should be deployed. What is the minimum number of them needed?
4) Given the number of mobile sinks K, what is the optimal trajectory for each of the K mobile sinks so that the quality of data collected by them is maximized?

All these questions can be cast in a unified framework, namely, the constrained optimization problem, with an optimization objective under stringent constraints on the travel distance and the travel region of each mobile sink and on sensor nodes. To the best of our knowledge, none of the above problems has been explored, the existence of approximate solutions for each of them therefore is still open. In the following we address the challenges and the strategies on solving these problems.

IV. Potential research problems

To adopt the new paradigm of data gathering efficiently and effectively, in this section we introduce several potential research problems related to the deployment of the proposed heterogeneous and hierarchical WSN with mobile sinks for large-scale, continuous monitoring.

A. Capacity-constrained data quality maximization problem

Since the duration τ that each mobile sink takes per tour is determined by its maximum travel distance and its speed, if the mobile sink travels at a constant speed, then the duration τ is fixed. Recall that the amount of data collected by a mobile sink from a gateway node is determined by the data transmission rate of the gateway node and by the duration of the mobile sink within the transmission range of the gateway node, the total amount of data collected by a mobile sink per tour will be determined. If the data collected by all mobile sinks per tour is less than the amount of data stored at all gateway nodes, some stored data (at gateway nodes) will never be collected and be ultimately discarded.

Since the sensors in WSNs usually are densely and randomly deployed, the data generated by the sensors are spatio-temporally correlated. Instead of transmitting all sensing data to gateway nodes, we can identify a subset of sensors whose sensing data is not highly correlated with each other, and we only transmit the data of the identified sensors to the gateway nodes. Thus, all data stored at the gateway nodes can be collected by mobile sinks per tour. We refer to these identified sensors as the chosen sensors, and we use their data to estimate the data of the entire network approximately. Thus, the problem is to identify a subset of sensors whose data can be used to provide an approximate representation of the sensing data of the entire network so that the quality of monitoring is maximized.

To measure the quality of monitoring (or the data quality of the collected data) by mobile sinks per tour at a constant speed v with the data tolerant latency τ, we use *the mean of the squared prediction error* $\mathrm{MSE}(v,\tau)$ to measure the data quality,

$$\mathrm{MSE}(v,\tau) = \frac{\sum_{i=1}^{n}\sum_{t=1}^{\tau}(\hat{x}_{i,t} - x_{i,t})^2}{n\tau}, \tag{1}$$

where $\hat{x}_{i,t}$ is an approximation of the actual sensing value $x_{i,t}$ of sensor i at time t, and n is the number of sensors, assuming that a sensing value is generated at constant rate, $1 \leq i \leq n$ and $1 \leq t \leq \tau$. Maximizing the quality of collected data is equivalent to minimizing $\mathrm{MSE}(v,\tau)$.

The capacity $c(g)$ of a gateway node g is defined as the number of chosen sensors sending their data to gateway node g during τ time units (the duration of each mobile sink per tour) such that all the data stored at g will be collected by the sink during next tour. Note that $c(g)$ is determined by the data transmission rate of g, the generation rate of sensing data, the duration of the sink passing by the transmission vicinity of g, and the duration τ of the sink per tour. Thus, the number of chosen sensors is the sum of the capacities of all gateway nodes in the network. We thus have the following constrained optimization problem.

The *capacity-constrained data quality maximization problem* is to identify a subset of sensors from the entire set of sensors such that the quality of monitoring is maximized, under the capacity constraint of each gateway node.

The key to this problem is to analyze the data correlation among the sensing data generated by all sensors for a certain period first. It then selects a subset of sensors such that $\mathrm{MSE}(v,\tau)$ in Eq. (1) is minimized, based on the correlation result of sensing data. Several techniques for sensor selection can be investigated, which include techniques based on linear regression [13], Gaussian distribution [6], and machine learning [9], and some preliminary results for it can be seen in [38], [39].

A generalization of this problem is to maximize the quality of monitoring under the assumption that either different mobile sinks have different travel speeds, or each mobile sink has multiple traveling speeds, while the duration of all mobile sinks per tour τ is given. In the study of the capacity-constrained data quality maximization problem, it is also worthwhile to investigate at which time instance the data correlation analysis and sensor selection procedures are to be re-run to reflect changes of sensing data over time.

B. Capacitated minimum forest problem

Given the capacity $c(g)$ of each gateway node g, and the number of sensors to be identified is $\sum_{g \in W} c(g)$ where W is the set of gateway nodes. Once these sensor nodes has been chosen, we now aim to find an optimal routing protocol to route their sensing data to the gateway nodes such that the cost of network resource consumption is minimized, where the cost measure of network resource can be the number of relay nodes required, the amount of energy consumed, or the other network resources. To simplify the problem discussion, in the following we adopt the cost measure as the number of relay nodes needed.

To relay the data from the chosen sensors to the gateway nodes, a routing forest, consisting of routing trees rooted at gateway nodes and spanning the chosen sensors, needs to be established. However, such a forest may not exist since the chosen sensors and the gateway nodes may not be within the transmission range of each other. Therefore, some not chosen sensors will be requisitioned as relay nodes, and the number of these requisitioned sensors will also need to be kept to a minimum in order to minimize the network cost. We thus have the following constrained optimization problem.

The *capacitated minimum forest* problem (CMF) is to find a routing forest consisting of routing trees rooted at gateway nodes and spanning chosen sensors such that the network cost (e.g. the number of relay sensors) is minimized, subject to the number of chosen sensors in each tree rooted at a gateway node being equal to the capacity of the gateway node.

It is not difficult to show that CMF is NP-hard through a reduction from a well-known NP-complete problem *the capacitated minimum spanning tree* problem (CMST) [27]. However, the state-of-the-art approximation technique for solving CMST and its generalized version, the *capacitated minimum Steiner tree* problem (CMStT) [12], cannot be applied to solve CMF, because CMF requires that different gateway nodes may have different capacities, and the number of sensors in the tree rooted at a gateway node must be equal to the capacity of the gateway node. New algorithms and techniques for CMF need to be developed. Particularly, the approximation algorithms with provably approximation ratio are desperately needed, despite the development of a recent heuristic algorithm for it [39].

C. Quality-guaranteed monitoring by mobile sinks

Recall that we use a road map to describe the restriction on the travel region of each mobile sink in Section III. If all roads in the road map can be visited by a single mobile sink per tour, then all sensing data stored at gateway nodes can be collected by the mobile sink, following the sensor selection and the construction of routing forests. However, for a large-scale WSN with a stringent constraint τ on tolerant data latency, it may not be sufficient to employ just a single mobile sink, instead, *multiple* mobile sinks should be deployed for data collection, and new challenges associated with this employment must be addressed. For example,

- How many mobile sinks are needed so that all data stored at gateway nodes can be collected by them per tour, while the constraints on the travel distance and the travel region of each mobile sink are still met?
- If the number of mobile sinks K is given and it is impossible for the mobile sinks to visit all roads without violating the specified constraints, then what is the optimal trajectory for each of the K mobile sinks such that the quality of the data collected by them is maximized?

We refer to the above two questions as the *distance-constrained mobile sink minimization* problem and the *distance-constrained data quality maximization* problem, respectively.

1) Distance-constrained mobile sink minimization problem: One potential strategy for solving this problem is to find a minimum spanning tree (MST) T in the road map with the length of each road as the cost metric first. It then partitions T into K subtrees such that the maximum cost subtree is no more than half the maximum travel distance of each mobile sink. The optimization objective is to minimize the number of mobile sinks K used. As tree T is a special topological structure, it is possible that the optimal value of K can be found, using dynamic programing. However, whether this problem is polynomially solvable needs further investigation.

2) Distance-constrained data quality maximization problem: One possible strategy for this problem is as follows. First, a Steiner tree (instead of an MST) in the road map is constructed such that the quality of the data collected by visiting each tree edge (the gateway nodes on the corresponding road of the tree edge) is maximized, subject to the weighted sum (the total length) of the tree edges being no more than *a half* of the sum of the travel distances of the K mobile sinks. The tree is then partitioned into K disjoint subtrees such that the maximum weighted sum of the edges in a subtree is minimized. The K-partitioning tree technique [26] can be investigated in the tree K-partitioning. Finally, each subtree is assigned a mobile sink for its data collection.

The key challenge in solving this problem is the construction of the Steiner tree and the analysis of the approximation ratio, since we do not know which road should or should not be included in the tree, i.e., the terminal set of the Steiner tree is not given in advance. Neither do we know the contribution of the data collected from each road to the optimization objective MSE(v, τ) in Eq. (1).

To deliver an approximate solution to this problem, it is worthwhile to study whether the problem can be reduced to *the prize collecting Steiner tree problem* [10] through a series of novel problem reductions. The approximation algorithms for the *k-MST problem* [7], the *Quota problem* and the *Budget problem* [10] will be investigated in a series of problem reductions.

V. CONCLUSION

In this position paper we addressed several key challenges in the deployment of WSNs with mobile sinks for large-scale, continuous monitoring. We detailed a new heterogeneous and hierarchical WSN architecture for such purpose. We also posed several novel, constrained optimization problems related to the adoption of this new paradigm of data gathering, which serve as the potential research topics in this area in the near future.

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