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Combining simulated annealing with Lagrangian relaxation and weighted Dantzig–Wolfe decomposition for integrated design decisions in wireless sensor networks

M. Emre Keskin [a], İ. Kuban Altınel [b], Necati Aras [b,*]

[a] Department of Industrial Engineering, Atatürk University, Erzurum, Turkey
[b] Department of Industrial Engineering, Boğaziçi University, İstanbul, Turkey

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ABSTRACT

A Wireless Sensor Network (WSN) is the outcome of the collaborative effort of multi-functional, low-power, low-cost, tiny electronic devices called sensors. Their ability to work autonomously provides a distributed environment capable to monitor even remote or inaccessible areas, which explains the wide application range of WSNs. There are four main issues in the design of a WSN: determining sensor locations (deployment), scheduling sensors, finding sink locations, and obtaining sensor-to-sink data routes. Sensors have very limited energy resources and their efficient management becomes critical for elongating network lifetime. As a result, most of the works on optimal WSN design are concerned with efficient energy usage. Unfortunately, only a few of them use an integrated approach and try to address these four issues simultaneously. In this work we also follow this line of research and develop first a monolithic mixed-integer linear programming model that maximizes network lifetime by optimally determining sensor and sink locations, sensor-to-sink data flows, active and stand-by periods of the sensors subject to data flow conservation, energy consumption and budget usage constraints. Then we propose a nested solution method consisting of two procedures: simulated annealing that performs search for the best sink locations in the outer level and Lagrangian relaxation based heuristic employed with weighted Dantzig–Wolfe decomposition for the multiplier update in the inner level, which determines sensor locations, activity schedules of the sensors and data flows routes. We demonstrate the efficiency and accuracy of the new approach on randomly generated instances by extensive numerical experiments.

1. Introduction

Wireless Sensor Networks (WSNs) are formed by the collaborative effort of a large number of small, low-power, low-cost, autonomous, multi-functional electronic devices called *sensors* which are deployed over a designated region called the *sensor field*. Each sensor can collect data from the area within its sensing range and transfer it to a central receiver called *sinks* either directly or indirectly. The indirect transfer of data from a sensor occurs by means of other sensors that transmit the data to neighboring sensors lying within their communication range. This mechanism is called hopping. The collaboration of multiple sensors provides a distributed monitoring environment in a wide variety of applications [33]. During its lifetime, a sensor can be in *active* or *stand-by* (i.e., inactive) mode. An active sensor can perform sensing, data receiving and transmitting activities that are energy consuming operations. A sensor in standby mode, on the other hand, consumes a negligible amount of energy.

There are four fundamental design issues when the goal is to set up a WSN. The first one is the determination of a sensor placement or deployment plan that provides the required sensing quality at discretized points in the sensor field. This is called the *Coverage Problem* (CP). If every point in the sensor field has the same importance in terms of the coverage requirements, then we talk about uniform coverage. However, if the points are not equally critical, namely some of them require a higher level of surveillance while some others do not, we deal with *differentiated coverage*. The second design issue is about scheduling the sensors, i.e., setting their active and standby periods and called the *Scheduling Problem* (SP). The best locations of the sinks are the subject of the third design issue addressed in the *Sink Location Problem* (SLP), where the aim is to find the fixed locations of the sinks in applications with static sinks and sink trajectories when mobile sinks are involved in the application. Finally, planning data transmission from sensors to sink(s), which is an energy consuming activity,

* Corresponding author. Tel.: +90 212 3597506.
E-mail address: arasn@boun.edu.tr (N. Aras).

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constitutes the fourth design issue. The *(Data) Routing Problem* (RP) aims at finding the most energy-efficient sensor-to-sink data routes. Note that in order to solve this problem both sensor locations and sink locations (or sink trajectories) as well as the schedules of the sensors should be known. We remark that sink locations (trajectories) and sensor-to-sink routes have a significant impact on the energy spent for data transmission, which is a primary factor in increasing the lifetime of the WSN. Another important point to emphasize is the multi-period or dynamic setting within which these problems must be formulated. This stems from the fact that the active and standby duration of the sensors needs to be determined and the sensor-to-sink data routes may change in time depending on the depletion of the battery energy of the sensors.

All these design issues are translated into mathematical models by means of the following decision variables: location variables for sensor deployment and sink placement, time-dependent flow variables for data routing, and time-dependent scheduling variables for active and standby periods of sensors. Since these decisions are interrelated with each other, we have to consider them within a unified framework in order to obtain the most efficient WSN design. However, many of the existing studies concentrate on one type of decision only. For instance, Altınel et al. [2] try to find optimal sensor locations satisfying the given coverage requirements. Similarly, the papers by Wang et al. [31], Basagni et al. [4,5], and Keskin et al. [18] are the works that address the determination of the optimal sink locations for maximum network lifetime. The majority of the existing integration effort is spent for unifying the SLP and RP. For instance, the papers by Gandham et al. [10], Azad and Chockalingam [3], and Alsalih et al. [1] try to find energy-efficient sink locations and data routes. They all assume that the time is divided into rounds of equal-length periods and they handle each round independently. Luo and Hubaux [24] handle this deficiency by a mixed integer linear programming (MILP) model which determines sink locations in different periods simultaneously. These four papers aim to obtain good WSNs by means of optimization models concentrating on the energy usage rather than the network lifetime. On the contrary, Papadimitriou and Georgiadis [26] try to maximize the network lifetime by the optimal determination of sink locations and data routes. Gatzianas and Georgiadis [11] revisit the models of Papadimitriou and Georgiadis [26], and produce a distribution strategy for their model. Yun and Xia [34] extend the model of Papadimitriou and Georgiadis [26] and develop two new models that are appropriate for delay tolerant applications. Yun et al. [35] and Behdani et al. [6] propose decomposition algorithms for one of the models given by Yun and Xia [34] and implement it in a distributed setting where only the local sensor characteristics are considered. Finally, Güney et al. [13] and Luo and Hubaux [25] study a very similar problem to that of Papadimitriou and Georgiadis [26] but take multiple sinks into account.

There are relatively few studies that try to integrate at least three of the above-mentioned decisions. Güney et al. [14] revisit the setting of Güney et al. [13] by also determining optimal sensor deployment in addition to sink placement and data routing. This is the first attempt to simultaneously consider CP and SLP along with RP, where the authors propose a heuristic method consisting of two nested loops. Türkoğulları et al. [27–29] further extend the model of Güney et al. [14] by integrating the SP to also find out the best activity schedules of the sensor in order to maximize the lifetime of the WSN. The difference between these papers lies in the solution method employed. Türkoğulları et al. [27] develop a Lagrangian heuristic and a two-stage heuristic in which sensors are deployed and an activity schedule is found in the first stage, whereas sinks are located and sensor-to-sink data flow routes are determined in the second stage. The main idea of the disjoint sets heuristic devised in Türkoğulları et al. [29] is to find a disjoint connected sensor set in each period so that the points in the sensor field are covered at the required quality. A column generation based heuristic is proposed in Türkoğulları et al. [28] based on a reformulation of the original MILP. The linear programming relaxation of the reformulation is solved by column generation in the first phase of this heuristic, while the second phase consists of constructing a feasible solution for the original problem using the columns obtained in the first phase.

All three papers assume a sufficiently long planning horizon consisting of T periods of 12 h each and define a time index $t = 1, \ldots, T$ to be used in decision variables. This modeling technique is relatively inefficient since time is discretized by dividing into periods of equal length, which results in a very large number of binary decision variables. It is reported in Türkoğulları et al. [28] that although one of the state-of-the-art commercial MILP solvers CPLEX is given a larger amount of time than that required by the heuristic to solve instances with more than 100 points in the sensor field of rectangular grid structure, it cannot generate a feasible solution.

Keskin et al. [19] adopt a different modeling framework to incorporate time, and generate several MILP models with the objective of lifetime maximization. These models gradually integrate the WSN design decisions mentioned earlier and investigate empirically the effect of integration on the lifetime of the WSN by comparing the objective values of the MILP models. The novelty in these models is that rather than dividing the planning horizon into discrete time periods of equal length, time is taken continuously and the periods are determined by the events as will be further clarified in the next section. However, since the solutions are obtained only on the basis of the Gurobi solver, large-sized instances remain to be unsolved. Keskin et al. [20] develop two heuristics for the integrated model with mobile sinks rather than static sinks which is addressed in this paper.

In this study, we tackle the integrated problem with static sinks, where sensor deployment, activity scheduling of the sensors, sink placement, and data routing decisions are made concurrently. For the solution of this problem, we introduce a nested heuristic that consists of two phases. The first phase involves a search over the candidate sink locations using simulated annealing. In the second phase, we solve the reduced problem by a Lagrangian heuristic when the sink locations are fixed. The reduced problem can be decomposed into easy-to-solve subproblems and is amenable to develop an algorithm which eventually converges to the Lagrangian dual of the reduced problem using weighted Dantzig–Wolfe decomposition. A feasible solution is generated by making the use of the optimal solutions of the subproblems at each iteration.

The remainder of the paper is organized as follows. In the next section, we give the MILP model formulated for the integrated problem with static sinks. We provide the details of the heuristic approach in Section 3. Section 4 contains the numerical results given by the suggested heuristic on a large number of test instances. Finally, Section 5 concludes the paper by summarizing the contributions and points out possible future research directions.

2. Formulation of the MILP model

Before we give the MILP formulation of our model for the integrated design of a WSN, we describe the parameters and decision variables used in the model. We consider a sensor field consisting of a finite set of points to be monitored, and denote it by $\mathcal{K}$. Each point has a coverage requirement d_k, $k \in \mathcal{K}$. Namely, the number of sensors that can cover point k must be equal to or exceed d_k. Besides the number of sensors, there are also other measures to define coverage. For example, the coverage requirement may be based on the total sensing intensity at point k generated by all deployed sensors. There may exist different sensor types that can be deployed at potential sensor locations in the sensor field. We let $\mathcal{R}$ and $\mathcal{S}$ denote the set of sensor