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A Survey of Optimization Algorithms for Wireless Sensor Network Lifetime Maximization

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Abstract

Wireless sensor networks (WSN) consist of a set of sensors and collection sinks that gather and analyze environmental conditions. Spurred by the growing need for data collection and transmission, WSN research topics have gained interest in recent years. WSNs are often deployed in hostile or inaccessible locations in which sensor replacement or repair is impractical. This survey explores various research approaches and extensions to the problem, which include online routing, clustering approaches, and lifetime maximization on specially structured networks. We additionally consider the impact of having mobile and/or multiple sinks and delay-tolerant routing. Finally, we expand our analysis to examine multicriteria optimization problems, and outline future research challenges in the field.

Keywords: Optimization, Wireless Sensor Network, Lifetime Maximization, Survey

1. Introduction

Wireless sensor network (WSN) research has recently gained substantial attention in the engineering, computer science, and mathematics literature because of the challenges involved in deploying effective networks in energy- and bandwidth-constrained settings. WSNs incorporate battery-powered sensors that expend energy to collect, analyze, and transmit information. Where and how these sensors are placed may depend on environmental characteristics, the accessibility of the environment, forces that relocate the sensors, and factors that potentially impede the operation of those sensors.

We consider a general WSN having a set of target nodes, sensor nodes, and a single sink node (Figure 1). Targets are physical locations within the environment where the conditions of interest originate. Information found at these targets must be monitored and retrieved by a sensor. Upon retrieval, sensors are tasked with sending this data to the sink for collection and processing. The WSN sink then aggregates and processes environmental information retrieved by sensors. Sensors can transmit data directly to the sink, as depicted in Figure 1a. Alternatively, sensors can transmit data to the sink via multi-hop communication, where sensors relay data through neighboring sensors en route to the sink, as shown in Figure 1b [81, 83]. Note that in

WSNs employing multi-hop communication, a significant amount of data flows through a relatively small set of sensors located near the sink, which may consume their battery prematurely. This behavior is called the *energy-hole problem* [57, 58], and is typical of WSNs employing multi-hop communication.

Figure 1: Wireless sensor network routing

Whereas the energy required for a sensor to receive data may only be a function of the amount received, energy required to transmit data to an object (such as another sensor or sink) predominantly depends on both the amount of data transmitted and the distance between the sensor and that object. Each sensor possesses finite battery power to handle these expenditures. Because WSNs can be used to, e.g., observe adversarial movement, monitor weapons testing, and detect seismic activity [28, 68, 108], sensors often dwell in hostile or inaccessible areas where battery replacement is impractical or prohibitively costly. When the battery is fully consumed, a sensor is no longer able to monitor targets, thus rendering the network inoperative. As a result, many studies address maximizing WSN lifetime, defined as the first time at which a sensor’s battery is exhausted [10, 13, 19, 20, 48, 33].

Most WSN studies omit the targets in our problem setting and assume that the sensors are assigned *a priori* to targets. We will adopt that assumption in this survey unless otherwise specified.

Multi-hop communication is often employed to prolong network lifetime by balancing energy consumption across all sensors. To illustrate this balancing mechanism and its benefits, the small example in Figure 2 depicts a network having two sensors, A and B, and a single sink, C. The goal is to transmit data from A to C as long as possible, with B serving solely as a relay node where data is not retrieved. In this example, each unit of data transmitted a distance of d consumes d units of energy at the transmitting sensor and one unit of energy at the receiving sensor. The distances from A to B, A to C, and B to C are 6, 9, and 5 units, respectively (Figure 2a). Suppose that batteries at sensors A and B possess 18 total units of energy each.

Using direct communication, sensor A would only be able to send two units of data directly to C, while B would not consume any battery power (Figure 2b). On the other hand, suppose data is sent from A to B, and then from B to C, as in Figure 2c. Each transmitted unit consumes six units of energy at A, while B consumes one unit to receive the data and five more to relay it to C. Thus, while only two units can be transmitted directly from A to C, three units of data can be transmitted on the A-B-C path. The latter route requires more total energy, but more importantly balances energy consumption to extend the network lifetime.

Due to their low cost and practical importance, sensor applications arise in many diverse areas. Three examples of these areas follow.

- The advent of *body area networks* (BANs) promises to allow physicians to monitor individual health on a real-time basis. A BAN is a type of WSN that consists of a networked group of sensors located in a non-invasive or invasive manner on the body, tracking items such as sleep habits, blood glucose, blood pressure, and EEG patterns [22, 51]. Of interest in this survey are sensors that can be implanted in the body, for whom battery conservation is more critical. Movassaghi et al. [71] discuss opportunities for implanted BANs to monitor diabetes, cardiovascular disease, and cancer detection and spread.
- The ability to monitor or provide surveillance in military applications clearly relies on WSN deployment and operations. Lee et al. [55] describe several defense scenarios. Some involve the deployment of sensors on equipment or personnel in the field in order to coordinate operations and avoid casualties due to friendly fire. Others place sensors behind enemy lines, forcing them to self-organize and conserve battery utilization. These sensors can be ground-, sea-, or air-based in practice.
- Environmental monitoring is a third primary application area for WSN deployment. Lundquist et al. [64] describe an application in which sensors are used to monitor meteorological and hydrologic processes in the Sierra Nevada mountain range. This landscape is difficult to traverse, and so it becomes advantageous to use sensors to monitor conditions in these areas. A similar project is discussed in the Swiss Alps, in which the researchers seek to detect conditions under which avalanches will occur [9], in addition to the same types of data sought in [64]. The inaccessibility of these environment and dangers associated with avalanches justify the need for WSN use and the conservation of sensor batteries.

Figure 2: WSN multi-hop communication example

Figure 3: WSN taxonomy

Some WSNs group sensors into clusters to decentralize and simplify network coordination. Rather than randomly deploying sensors, some WSNs assume a specific topology, such as a uniform two-dimensional grid to simplify routing decisions. Other application areas allow sensors to fuse data gathered from multiple targets before transmission to the sink. By doing so, the size of data transmission packets are reduced to lessen energy consumption. Additionally, sinks may be able to move about the sensing area to balance energy consumption. In such cases, sensors may locally buffer data to delay transmission until the moving

sink arrives at a more favorable location. Furthermore, WSN optimization problems also consider alternative metrics (e.g., coverage area, connectivity, and transmission delay) in addition to network lifetime. Our survey discusses these various optimization challenges and describes some of the proposed algorithms currently existing in the literature. Figures 3, 4, and 5 display a taxonomy of WSN lifetime maximization research to describe various attributes of and interrelationships between the problems we address.

Figure 4: Static WSN taxonomy

Figure 5: Mobile WSN taxonomy

Because of the recent attention to WSNs, other papers have reviewed a portion of the research literature in this field. Yick et al. [111] and Rawat et al. [85] provide a broad overview of fundamental WSN research, in which they highlight various application areas, in addition to standard operating systems, communication protocols, and network services. Other review articles focus on algorithms and mathematical modeling approaches for WSN optimization. Anastasi et al. [6] and Rault et al. [84] review papers that examine WSN design for various application areas. Another set of articles review WSN routing protocols. Akkay and Younis [3] focus on hierarchical and location-based approaches for routing, while Pantazis et al. [78] consider communication models, topology, and reliability when making routing decisions. Additionally, Yu et al. [113], Tunca et al. [101], and Sara and Sridharan [91] survey routing protocols and deployment techniques for mobile-sink WSNs. Whereas these works primarily focus on algorithms for energy consumption minimization, our paper concentrates on algorithms and mathematical models for maximizing WSN lifetime.

Rather than minimizing energy consumption, Younis et al. [112] and Li et al. [60] explore topology design and control techniques for maximizing coverage and connectivity. Other authors review clustering approaches for improving network scalability ([1, 2, 92]). These papers review algorithms that focus on various objectives independent of WSN lifetime. Alternatively, we also give a broader overview of topology-based approaches that focus on maximizing WSN lifetime.

The rest of the paper is organized as follows. In Section 2 we present notation and solution techniques for the fundamental WSN lifetime maximization problem. We discuss online routing, clustering techniques, and lifetime maximization on special structures in Section 3. Section 4 then highlights extensions to the fundamental problem that result from having multiple sinks, which may also be mobile instead of stationary. We review problems and algorithms that consider alternative optimization metrics to lifetime maximization in Section 5. Finally, we examine some of the ongoing and future challenges facing WSN optimization in Section 6. Summary tables appear in the beginning of each section that provide an overview of the research discussed in that section.

2. Mathematical Optimization Models for the Fundamental Lifetime Maximization Problem

This section begins by formally describing and stating the fundamental lifetime maximization problem in Section 2.1. Because of its prevalence in the WSN optimization literature, we also describe a column-generation scheme for the solution of this problem in Section 2.2. Table 1 summarizes the most pertinent papers discussed in Section 2.

Author (Model)	Problem specification	Technique
<i>General topology single-sink algorithms</i>		
Chang and Tassiulas [19] (FR and MREP)	Data-routing to balance energy consumption	LP formulation, two flow-augmenting algorithms that redirect flow from a longest path to a shorter path
Xue et al. [110]	Tree-based data-routing	$(1 - \epsilon)$ -approximation polynomial time algorithm to create a data-routing tree rooted at the sink
Madan and Lall [66]	Partially-distributed data-routing	Lagrangian relaxation of an LP, subgradient algorithm to solve separable subproblems

Table 1: Section 2 summary

2.1. Fundamental Problem Description and Formulation

The fundamental problem we consider determines a data-routing plan consisting of a set of data flows from all targets to the sink in a manner that maximizes network lifetime. This problem can be formulated as a linear program (LP) introduced by Chang and Tassiulas [19], who assume that each target is assigned *a priori* to a sensor. As such, data origination rates associated with the targets can instead be assigned directly to a sensor, allowing us to omit targets from our analysis. Consider a graph $\mathcal{G}$ having a set of nodes $\mathcal{N}$ composed of sensors $\mathcal{S}$ and a single sink. Let each sensor $i \in \mathcal{S}$ possess an initial battery power $P_i > 0$ and a total data origination rate of $b_i > 0$. The energy required by sensor i to send a unit of data to node j is $e_{ij} > 0$, $\forall i \in \mathcal{S}, j \in \mathcal{N}$. Chang and Tassiulas assume that the energy required to receive a unit of data is negligible, but for the sake of generality, we define c_{hi} as the amount of energy required by sensor i to retrieve one unit of data from sensor h . Let variable z represent the WSN lifetime and variables y_{ij} be the data transmitted from node $i \in \mathcal{S}$ to $j \in \mathcal{N}$. The following LP maximizes WSN lifetime [19].

$$\max z \tag{1a}$$

$$\text{s.t. } \sum_{j \in \mathcal{N}} y_{ij} - \sum_{h \in \mathcal{S}} y_{hi} - b_i z = 0 \quad \forall i \in \mathcal{S} \tag{1b}$$

$$\sum_{j \in \mathcal{N}} e_{ij} y_{ij} + \sum_{h \in \mathcal{S}} c_{hi} y_{hi} \leq P_i \quad \forall i \in \mathcal{S} \tag{1c}$$

$$y_{ij} \geq 0 \quad \forall i \in \mathcal{S}, j \in \mathcal{N} \tag{1d}$$

The objective function (1a) and constraints (1b) maximize WSN lifetime while ensuring flow balance. Constraints (1c) enforce energy-capacity constraints on sensor $i \in \mathcal{S}$ and constraints (1d) guarantee that no flows become negative.

Consider the following single-sink WSN lifetime maximization example in Figure 6, where a WSN contains

sensors A, B, C, and D, and one sink, E. The edge labels denote the distance between each pair of objects. For this example, c - and e -values equal the distance between objects (e.g., a unit of flow from A to C consumes 10 units of energy at both A and C). We assume that sensors A and B are unable to transmit data directly to E. Sensors possess $P_i = 500$ units of energy, $\forall i = A, B, C, D$. Additionally, the amount of data originating at each sensor is $b_A = 8$, $b_B = 10$, $b_C = 0$, and $b_D = 0$ units/hour.

Figure 6: Single-sink WSN distances

We define the lifetime, L_i , of sensor i to be the number of hours that sensor i retrieves and transmits data given its battery power. Letting y_{ij} be the data flow per hour on arc (i, j) , the energy required per hour by sensor $i \in \mathcal{S}$ is T_i . The lifetime for sensor i becomes $L_i = P_i/T_i$. We then define the WSN lifetime to be the minimum lifetime among all sensors. Figure 7 presents an optimal set of data flows per hour that maximizes WSN lifetime.

Figure 7: Optimal data flows per hour

Given these flows, the lifetime of sensor A is $500/80 \approx 6.3$ hours, sensor B is $500/100 = 5$ hours and sensors C and D are $L_C = L_D = 500/217.3 \approx 2.3$ hours. Therefore, the maximum WSN lifetime is 2.3 hours.

2.2. Column Generation Approach

For a fixed value of z , the formulation given by (1) contains traditional network flow constraints (1b), which are then complicated by the presence of energy-capacity constraints (1c). The latter set of constraints are accordingly referred to as *complicating constraints* in the literature. In general, complicating constraints are those that, when removed, reveal a constraint structure that is more amenable to solution via mathematical optimization or specialized algorithms, thus reducing solution time and possibly decentralizing decision-making [24]. Two notable decomposition methods that exploit this special structure are column generation (CG) [26] and subgradient optimization of a Lagrangian relaxation (LR) problem [29].

We focus on describing a CG approach for solving (1); see also [4, 13, 15, 16, 17, 34, 88, 89, 102]. For an example of LR applied to (1), see Madan and Lall [66]. Let $\mathcal{K}$ be the set of all possible data-routing patterns, where a pattern is given by an acyclic set of flows on $\mathcal{G}$ that satisfies (1b) and (1d) with z fixed to 1. Define constants y_{ij}^k as the amount of flow from sensor $i \in \mathcal{S}$ to $j \in \mathcal{N}$ in pattern $k \in \mathcal{K}$. The following LP contains variables λ_k that represent the amount of time we send flow on pattern $k \in \mathcal{K}$, and is equivalent to model (1).

$$\max \sum_{k \in \mathcal{K}} \lambda_k \tag{2a}$$

$$\text{s.t. } \sum_{k \in \mathcal{K}} \left(\sum_{j \in \mathcal{N}} e_{ij} y_{ij}^k + \sum_{h \in \mathcal{S}} c_{hi} y_{hi}^k \right) \lambda_k \leq P_i \quad \forall i \in \mathcal{S} \quad (\alpha_i) \tag{2b}$$

$$\lambda_k \geq 0 \quad \forall k \in \mathcal{K} \tag{2c}$$

The objective function (2a) maximizes WSN lifetime while constraints (2b) enforce energy-capacity constraints on each sensor and constraints (2c) enforce flow nonnegativity.

By enumerating all possible patterns, model (2) is equivalent to (1) [26]. Since a majority of patterns in $\mathcal{K}$ will be non-basic at an optimal solution to (2), we formulate a restricted master problem (RMP) that maximizes network lifetime considering only a subset of all patterns $\mathcal{K}^* \subset \mathcal{K}$. Suppose that we optimize this RMP and identify primal and dual optimal solutions. (The RMP must have a feasible solution since the trivial solution $\lambda_k = 0, \forall k \in \mathcal{K}^*$ is feasible. The fact that all e -values are positive guarantees that the RMP is bounded. These facts guarantee the existence of an optimal solution to the RMP.) Let α_i be the optimal dual values for the energy-capacity constraints (1b) in the RMP. We formulate an LP subproblem to find a new data-routing pattern having a positive reduced cost. Letting the continuous variable w_{ij} be the flow

from sensor $i \in \mathcal{S}$ to $j \in \mathcal{N}$, we formulate the following subproblem:

$$\min \sum_{i \in \mathcal{S}} \alpha_i \left(\sum_{h \in \mathcal{S}} c_{hi} w_{hi} + \sum_{j \in \mathcal{N}} e_{ij} w_{ij} \right) - 1 \quad (3a)$$

$$\text{s.t.} \quad \sum_{j \in \mathcal{N}} w_{ij} - \sum_{h \in \mathcal{S}} w_{hi} - b_i = 0 \quad \forall i \in \mathcal{S} \quad (3b)$$

$$w_{ij} \geq 0 \quad \forall i \in \mathcal{S}, j \in \mathcal{N}, \quad (3c)$$

where the objective function (3a) is the negative of the reduced cost of a data-routing pattern. This negation is performed to show that the subproblem (also called the *pricing problem*) reduces to a min-cost-flow problem with nonnegative costs.

The CG algorithm proceeds as follows. The RMP is solved with some set of initial feasible patterns in $\mathcal{K}^*$. We obtain the dual values α_i to formulate the objective function of (3). If the optimal objective function value to (3) is negative, then the identified pattern has a positive reduced cost. We add that pattern to $\mathcal{K}^*$ and re-solve the RMP. This process repeats until no positive reduced-cost patterns are found, which implies that the current solution to the RMP is also optimal to (1).

For large networks, solving (1) directly or by a decomposition method may require significant computational effort. Thus, Chang and Tassiulas [19] present two flow-augmenting heuristics: the flow redirection (FR) and minimum residual energy path (MREP) algorithms. Starting with an initial feasible data-routing plan, both algorithms seek to balance flow among all target-to-sink paths. The balancing strategy establishes a mechanism for evaluating path length, and the algorithms redirect a portion of flow from a longest path to a shorter path. The FR algorithm defines path length as the minimum lifetime of sensors on the path, whereas the MREP defines it as the minimum inverse residual energy of sensors along the path. The FR algorithm produces solutions whose objectives are on average 95% of optimality, while the MREP algorithm produces a ratio of 96%.

Xue et al. [110] create an approximation algorithm to the maximum lifetime problem as opposed to solving (1). Their algorithm constructs a routing solution based on path augmentation, where arc lengths are a function of the data currently transmitted on them. Based on those lengths, the authors iteratively employ the Garg-Könemann algorithm [32] to find a shortest path from all sensors to the sink, push a limited amount of flow on the shortest among these paths, and then recalculate the arc lengths. The authors demonstrate that their polynomial-time algorithm provides a $(1 - \epsilon)$ -approximation, for any given parameter $\epsilon > 0$.

The elegant LP (1) and associated algorithms mentioned in this section are effective for many classes of

WSN optimization problems, but even minor adjustments to the assumptions on how these networks function necessitate completely different algorithms for these problems. Moreover, many other considerations exist beyond data-routing and energy utilization in these networks. The following sections explore these models and algorithms in more detail.

3. Extensions to the Fundamental Lifetime Maximization Problem

In Section 3 we examine several extensions to the fundamental lifetime maximization problem presented in Section 2. First, Section 3.1 details online algorithms, which determine data transmission paths without knowledge of future data-routing requests. In Section 3.2, we examine the case when sensors are partitioned into multiple clusters to improve scalability. In Section 3.3, we consider the case in which sensors are uniformly deployed to form a grid-like topology. Then, in Section 3.4, we review protocols and algorithms used to form virtual tree backbones among sensors in the network. Table 2 summarizes key papers found in Sections 3.1 and 3.2 and Table 3 summarizes those found in Sections 3.3 and 3.4.

3.1. Online Algorithms

Solution techniques to the problem presented in Section 2 are said to be *offline* since all data-routing requests are known before the routes are planned. Alternatively, *online* data-routing algorithms consider the case in which data-routing requests arrive nonsimultaneously. These algorithms must therefore determine data transmission paths without knowledge of future requests. As such, the optimal maximum lifetime assuming offline routing is an upper bound on the maximum lifetime assuming online routing.

Aslam et al. [7] propose an online heuristic that tends to avoid data transmission through low-energy sensors while choosing relatively low total-energy paths. Define the residual energy fraction of edge (i, j) as $u_{ij} = (P_i - e_{ij})/P_i$. The heuristic evaluates the quality of a path by the smallest residual energy fraction edge that lies on the path. The goal is to find the highest quality path possible, subject to the restriction that the total energy consumed by the path cannot exceed some maximum threshold value, τ . Their algorithm first employs Dijkstra's algorithm to find a minimum energy path and computes the minimum residual energy fraction u_{min} among all edges on the path. The algorithm then removes all edges whose residual energy fraction is no more than u_{min} from the graph, and finds a new minimum energy path. When the energy consumed by a minimum energy path exceeds τ , or when no path exists, the data-routing request is transmitted on the minimum energy path from the most recent iteration. This approach requires centralized coordination, which may be difficult to implement for large networks. Thus, the authors also propose a

Author (Model)	Problem specification	Technique
<i>Online algorithms</i>		
Aslam et al. [7]	Zone-based data-routing	Avoid high total-energy paths, maximize the smallest residual-energy fractional edge in a path
Toh et al. [100]	Data-routing	Avoid low-remaining-energy sensors, minimize total energy consumed on a path
Park and Sahni [80] (OML)	Distributed data-routing	Successive minimum weight path routing, where weight is a function of residual energy
Mohanoor et al. [70]	Data-routing	Minimum weight routing as a function of residual energy, tiebreaking by energy consumption
Wahid et al. [105]	Distributed data-routing on dynamic underwater networks	Myopic routing based on distance to sink and residual energy
<i>Clustering algorithms</i>		
Heinzelman et al. [39] (LEACH)	Distributed clusterhead selection	Localized clusterhead selection based on residual energy levels of neighboring sensors
Heinzelman et al. [38] (LEACH-C)	Clusterhead selection	Simulated annealing approach to cluster construction and clusterhead selection
Kumar et al. [53] (EEHC)	Clusterhead selection	Restrict sensors that cover targets, avoid selecting low-energy sensors as clusterheads
Muruganathan et al. [74]	Clusterhead selection and data-routing	Clusters chosen based on residual energy, minimum spanning tree for routing and data scheduling
Javaid et al. [43]	Dynamic clusterhead selection	Periodic clusterhead selection based on dynamic residual energy levels
Ducrocq et al. [27]	Distributed clusterhead selection	Clusterhead selection based on node degree, density, and residual energy, tree construction for routing
Leu et al. [56] (REAC-IN)	Distributed zone-based clusterhead selection	Based on average residual energy and distance between sensors within each zone
Nikolidakis et al. [76]	Clusterhead selection and scheduling	LP to minimize clusterhead energy consumption, scheduling protocol to avoid data collisions
Latiff et al. [54] (PSO-C)	Clusterhead selection and data-routing	PSO algorithm based on residual energy levels, scheduling protocol to avoid data collisions
Singh and Lobiyal [98]	Clusterhead selection with data retransmission	PSO algorithm based on intra-cluster distances
Kuila and Jana [52]	Cluster formation and data-routing	PSO algorithm to solve optimization models that balance energy usage among intra-cluster sensors

Table 2: Section 3.1 and 3.2 summary

hierarchical zone-based approach to implement their algorithm within smaller sensor zones. The authors conclude that their initial approach achieves over 90% of the optimal offline data-routing objective for many instances.

Whereas Aslam et al. [7] place an upper bound on a path’s energy consumption, Toh et al. [100] present an algorithm that minimizes the energy consumption of each data transmission path, in which data may only be transmitted through sensors having remaining energy levels above some threshold. Their approach trims the network of low-energy sensors and implements a shortest-path algorithm to determine each path, where edge weights are defined as the energy required to transmit data between two nodes. If no path exists in the trimmed network, then their algorithm chooses a path in the original network that maximizes the minimum remaining energy level among all sensors on the path.

Park and Sahni [80] also present an online maximum lifetime (OML) heuristic, in which they define the residual energy of edge (i, j) to be $P_i - e_{ij}$. Their algorithm first trims the network of all edges requiring more energy than available for transmission, determines a minimum energy path in the resulting network, computes the minimum residual energy (*minRE*) of all edges on this path, and finally removes all edges whose residual energy is less than *minRE*. The authors then assign a weight to each remaining edge as a function of e_{ij} and E_i . This weighting function assigns a relatively high weight to each edge whose use will reduce a sensor’s energy level below some minimum threshold. The authors then choose a minimum-weight path on which the data-routing request is transmitted. The authors also present a distributed version of the OML algorithm that divides sensors into clusters, with each cluster having a designated clusterhead (see Section 3.2 for more research on WSN clustering). The OML algorithm results in higher average lifetime values than those found in [7] and [100].

Mohanoor et al. [70] extend the previous works to develop a two-phase online algorithm that maximizes lifetime if multiple shortest paths exist in the trimmed network for each incoming data-routing request. In the first phase, a variant of Dijkstra’s algorithm computes a path that maximizes the minimum residual energy, B , among all sensors on the path, where residual energy is again defined as in [80]. If multiple shortest paths are found during phase one, the second phase removes edges whose residual energy is less than B and selects (from among the shortest paths in the first phase) a path that minimizes total energy consumption. The authors show that their algorithm prolongs WSN lifetime compared to algorithms in [7] and [80].

Online routing algorithms are especially useful in applications where network information dynamically

changes due to environmental influences. One such application arises in underwater WSNs, where sensors may be periodically relocated due to ocean currents. Wahid et al. [105] formulate an online routing protocol to maximize the number of successful data transmissions for underwater WSNs. Rather than individually routing each incoming request, their protocol determines a data-routing plan for a set of requests at each sensor over some time period. To determine this plan, their protocol first computes edge lengths and quality by transmitting minuscule messages between neighboring sensors. Each sensor then transmits data on a high-quality edge to a node closer to the sink having sufficient residual energy. This process iterates at each node until the data transmission arrives at the sink. Since currents constantly change sensor positions, their protocol intermittently updates edge length, edge quality, and residual sensor energy levels, and determines a new data-routing plan for the next set of incoming requests. Their approach outperforms distance-based routing protocols for underwater WSNs in terms of network lifetime, energy consumption, and transmission delay.

3.2. Clustering Techniques

Sensors can be partitioned into multiple clusters to employ techniques that reduce the size of the network and simplify data-routing decisions. These techniques divide sensors into clusters, each having a designated clusterhead that computes local routing decisions among sensors within its own cluster (Figure 8). Creating sensor clusters also minimizes the burden of communication since only the clusterhead communicates with the sink. Some studies assume that clusters are given (e.g., [54]), while others examine the generation of the clusters (e.g., [52, 98]). Other research strategies use sensor clustering to decentralize network protocols [43, 63, 76, 98].

Figure 8: WSN clustering method

In addition to data-routing decisions, clustering algorithms often need to determine which node will serve as the clusterhead. Heinzelman et al. [39] present the low-energy adaptive clustering hierarchy (LEACH) protocol, which uses localized coordination and control for cluster formation and operation. In this protocol sensors elect themselves to serve as the clusterhead based on residual energy levels among neighboring sensors. Sensors then transmit data directly to the most favorable clusterhead to form clusters. The clusterhead creates a schedule of data-flow paths from each sensor in its cluster to avoid data collisions, which may occur when a clusterhead simultaneously receives data from multiple sensors, thus resulting in inaccurate data transmissions. To balance energy consumption, clusterhead locations are rotated according to some probability when the current clusterhead's residual energy reaches a minimum threshold. Maximum lifetime values found using LEACH were significantly larger than those computed by algorithms that primarily focus on minimizing energy consumption.

Sensors employing the LEACH protocol rely on localized information to elect themselves as clusterheads independent of energy levels at non-neighboring sensors, which can lead to uneven distribution of clusterheads within the WSN. To ameliorate this problem, Heinzelman et al. [38] formulate the centralized LEACH (LEACH-C) protocol in which each sensor broadcasts its information across the network. Considering only sensors having above-average energy levels, LEACH-C implements a simulated annealing algorithm to find a near-optimal set of k clusters and clusterheads. The energy efficient heterogeneous clustered scheme (EEHC) by Kumar et al. [53] provides a related approach for the case in which some predetermined set of sensors is only allowed to monitor targets, while sensors having high initial energy levels can relay, process, and transmit data to the sink.

Muruganathan et al. [74] also implement a centralized clustering protocol to balance energy consumption in which only sensors having above-average residual energy levels serve as the clusterhead. At each iteration of the algorithm, some central node determines a set of clusterheads and partitions sensors into clusters to balance the load of each clusterhead. (One cluster of sensors will have the sink represent the clusterhead.) For inter- and intra-cluster routing decisions, their protocol creates a minimum spanning tree rooted at the clusterhead to minimize energy consumption and ensure full connectivity. They additionally provide a scheduling scheme to minimize the number of data collisions. Their approach ensures that each clusterhead serves approximately the same number of sensors to avoid early exhaustion and ensure an even distribution of clusterheads throughout the network. As a result, their approach reduces overall energy consumption and prolongs network lifetime when compared to LEACH and LEACH-C.

The previous approaches are designed for static sensing environments. For the dynamic case, the choice

of clusterhead should change depending on evolving sensing needs. Accordingly, Javaid et al. [43] examine a dynamic approach to the clusterhead selection problem. After a sensor serves as the clusterhead for some predetermined period of time, their approach updates residual energy levels and chooses a sensor having the maximum residual energy level to serve as the clusterhead. This technique enables dynamic adaptation to the environment, allowing data flows to balance energy consumption across the network. Simulations show that this approach results in longer lifetime values than static clustering protocols.

For WSNs incapable of centralized sensor coordination, Ducrocq et al. [27] propose an energy-aware clustering protocol to create non-overlapping clusters in a distributed fashion. This protocol considers node degree and density in addition to residual sensor energy levels when selecting a clusterhead. Each link is initially assigned a weight as a function of the residual energy of the nodes incident to the link, where a large weight corresponds to an edge connecting high-energy sensors. In the first step, their protocol trims the WSN graph by removing an edge having the smallest weight in every triangle of the graph. Once the graph is reduced, some predetermined number of clusterheads are selected based on residual energy levels, and clusters are formed through a tree construction algorithm. For a semi-distributed implementation, each sensor broadcasts its residual energy, node degree, and density level to neighboring sensors. Their algorithm provides longer network lifetime values than LEACH for WSNs having relatively few clusterheads, while LEACH performs better in WSNs having a large number of clusterheads.

Unbalanced cluster formations can also lead to isolated sensors, defined as any sensor that is located excessively far from the nearest clusterhead, and thus requires substantial energy expenditures to transmit data to a neighboring sensor. To minimize energy consumed at such a node, Leu et al. [56] propose the regional energy aware clustering with isolated nodes (REAC-IN) protocol to select clusterheads based on the residual energy of each sensor, the average residual energy of sensors within a cluster, and the distance between each sensor and proposed clusterhead. Their protocol identifies isolated nodes and decides whether data at such nodes should be transmitted to the nearest clusterhead or directly to the sink, depending on the average residual energy among neighboring sensors and the distance between those sensors and the sink.

Rather than taking a heuristic approach, Nikolidakis et al. [76] propose a centralized LP model for the cluster formation and clusterhead selection problems to minimize the energy consumption at each clusterhead. A solution to this problem provides the frequency and duration of time each sensor serves as a clusterhead. After solving the LP, they implement a scheduling protocol to avoid data collisions. Furthermore, the authors solve their LP again to determine a new set of clusterhead locations if there is some change in node position or energy consumption. Results show that their approach not only minimizes energy consumption

but maximizes network lifetime compared to LEACH [39] and the algorithms presented by Muruganathan et al. [74].

Another portion of the literature employs particle swarm optimization (PSO) for clustering decisions related to WSN lifetime maximization. A PSO algorithm consists of a swarm or pool of candidate solutions called particles that explore some solution space in search of a global optimal solution [46]. Each particle possesses a fitness function to evaluate the quality of the associated solution. Particles also use velocity and direction vectors to iteratively move through the search space until either an acceptable solution is found or a fixed number of iterations is reached.

Latiff et al. [54] implement a centralized energy-aware clustering PSO algorithm (PSO-C) for the cluster-head selection and data-routing problems. During the setup phase of PSO-C, each sensor notifies the sink of its position and residual energy level to compute the average residual energy among all sensors. Clusterheads may only be selected from among sensors having above-average residual energy levels. To finish the setup phase, the PSO-C selects the k best sensors to serve as clusterheads, based on a particle fitness function that rewards minimum intra-cluster distances and balanced energy consumption. The authors then employ a scheduling protocol to coordinate data transmissions with the goal of avoiding data collisions. This two-phase algorithm iterates until an acceptable solution is found. Their algorithm evenly distributes clusterheads throughout the network to provide higher network lifetime values than those given by LEACH [39] and LEACH-C [38] algorithms.

Singh and Lobiyal [98] also take a PSO approach for generating energy-aware clusters. Their approach seeks to minimize the average distance between a sensor and its clusterhead, using a particle fitness function that combines average transmission distance, residual energy levels, node degree, retransmission levels, and the number of times a sensor serves as the clusterhead. Rather than preventing data collisions, their approach simply retransmits initially unsuccessful transmissions. They seek to minimize data retransmissions by avoiding sensors prone to data collisions. The authors show that their algorithm achieves better energy savings and WSN lifetime values than those produced by PSO-C [54].

Kuila and Jana [52] present LP and nonlinear programming (NLP) models for the WSN data-routing and cluster formation problems, respectively. The routing approach is an LP that jointly minimizes the maximum data transmission distance and the maximum number of transmission hops. The objective function for the NLP balances energy consumption by maximizing the ratio of the minimum clusterhead lifetime to the average distance between sensors and their clusterhead. Due to the difficulty of solving these two models,

the authors propose PSO-based algorithms for their solution. For routing decisions, the particle fitness function is based on the objective function of their LP model. In the clustering problem, the fitness function is based on energy balance and conservation among sensors in each cluster. The authors show that the proposed algorithms result in better network lifetime and total transmitted data than existing algorithms.

3.3. Grid-based Topology

In some WSN application areas, sensors are deployed in a grid-like topology (Figure 9) in which sensors are uniformly deployed [90]. Such topologies balance sensor distribution and simplify data-routing decisions. Kacimi et al. [44] formalize the WSN lifetime maximization problem for two-dimensional grid-based network topologies to derive an optimal load-balanced data-routing plan. They formulate an NLP model to minimize the maximum energy consumption among all sensors, and solve this NLP via a heuristic scheme. Using this heuristic, a sensor distributes data among multiple shortest paths according to the residual energy levels at each forwarding sensor.

Figure 9: Square grid topology

In addition to routing decisions, Li et al. [61] consider two cases of sensor deployment to further reduce energy consumption in grid-based WSNs. Assuming the sink is located at the center of the sensing area, the authors consider partitioning this area into hexagonal cells (Figure 10). In the uniform sensor deployment problem, a single sensor may be placed at the center of each cell, and in the non-uniform version, a variable number of sensors may be placed in cells nearest the sink. Due to restrictions on transmission range, sensors are only allowed to transmit data to sensors in neighboring cells. Given this grid-based topology, the authors seek to determine an optimal uniform distance between all neighboring sensors that ensures full coverage and balances energy consumption. The authors formulate an NLP model for each case of sensor deployment and employ a greedy protocol for all data transmission decisions, in which data is transmitted to the sensor closest to the sink. The authors employ a generalized reduced gradient method [30] to solve the

NLP for uniform sensor deployment and a genetic algorithm (GA) for the non-uniform sensor deployment case.

Author (Model)	Problem specification	Technique
<i>Grid-based topology algorithms</i>		
Kacimi et al. [44]	Grid-based data-routing	Heuristic solution to NLP that distributes data among multiple low-energy paths
Li et al. [59]	Grid-based sensor deployment and data-routing	Solve NLP to determine hexagon-based sensor density, provide a greedy protocol for routing
Zhang et al. [117]	Grid-based sensor deployment and clusterhead selection	Near-minimum CDS-based algorithm for clusterhead selection
<i>Virtual backbone techniques</i>		
He et al. [37]	Virtual backbone formation and non-backbone allocation	NLP used to determine a load-balanced backbone, IP used to assign non-backbone sensors to backbone
Zhao et al. [118]	Virtual backbone formation and scheduling	Avoid selecting low-energy sensors for the backbone, graph-based algorithm for backbone scheduling
Rizvi et al. [86]	Distributed virtual backbone formation	Depth-first search to minimize energy consumed when forming backbone
Luo et al. [65]	Tree-based data fusion and routing	Minimum-cost perfect matching algorithm to construct fusion and routing tree

Table 3: Section 3.3 and 3.4 summary

Figure 10: Hexagon grid topology

Zhang et al. [117] propose two grid-based topology control algorithms to minimize the number of active sensors required to maximize WSN lifetime. The algorithm initially identifies the midpoint of the sensing area and divides it into equally-sized square cells that may or may not contain sensors. Additionally, the authors designate a sensor (if one exists) within each cell to serve as the clusterhead and adds edges between

all pairs of clusterheads located in adjacent cells. Their algorithm then builds a near-minimum connected dominating set (CDS) for this new clusterhead graph, where a CDS is a subset of clusterheads such that a path exists between every pair of clusterheads in the CDS, and all clusterheads not in the CDS are adjacent to a clusterhead in the CDS. Furthermore, the authors propose an algorithm to determine the minimum number of columns or rows in the grid needed to cover all network sensors and form a CDS.

3.4. Virtual Backbone Techniques

Another line of research considers forming a virtual backbone within a WSN (Figure 11) to ensure full coverage and connectivity regardless of sensor deployment. A virtual backbone is composed of a subset of sensors tasked with forwarding data retrieved by neighboring sensors. The backbone nodes, along with the sink, establish a CDS in the network. A routing tree structure is typically formed over these nodes, rooted at the sink. Routing is performed by transmitting data from each non-backbone sensor to the most favorable backbone sensor, which transmits that data through the backbone tree to the sink.

Figure 11: WSN backbone

He et al. [37] investigate a three-phase approach to establish a backbone that balances energy consumption among all sensors. The first phase considers the min-max degree maximal independent set (MDMIS) problem, which seeks to find a maximal independent set that minimizes the maximum degree of any sensor in the set. The authors formulate an integer NLP for the MDMIS problem and use an approximation algorithm that solves the linear programming relaxation and rounds any fractional values. (See Figure 12b for an example solution to the MDMIS problem.) The solution to this problem yields a subset of the backbone nodes. The second phase solves the load-balanced virtual backbone (LBVB) problem to identify a backbone that balances

the number of neighboring non-backbone sensors of each backbone sensor. The authors present a heuristic scheme to select a minimum set of additional nodes that, when connected to the nodes in the MDMIS solution, provide a solution to the LBVB problem. Using the LBVB solution, the third phase solves the min-max valid-degree non-backbone node allocation (MVBA) problem to assign each non-backbone sensor to a backbone sensor in a way that balances the transmission load of all backbone sensors (Figure 12c). The authors formulate the MVBA problem as an integer program (IP) and present an approximation algorithm based on a random rounding heuristic. The authors show that their three-phase approach can prolong WSN lifetime by up to 69% compared to other CDS-based virtual backbone algorithms [118].

Figure 12: Load-balanced virtual backbone

Rather than forming a single WSN backbone, Zhao et al. [118] examine the formation of multiple backbones in dense WSNs. Their protocol alternates the sequence in which these backbones are used in order to balance energy consumption. The authors formulate the maximum lifetime backbone scheduling (MLBS) problem to determine the schedule in which each backbone is used to retrieve and transmit data. They propose two approximation algorithms for the MLBS problem, which are based on a schedule transition graph (STG) and virtual scheduling graph (VSG). The STG-based algorithm constructs and schedules a polynomial set of n virtual backbones $bb_1, \dots, bb_n$. Their algorithm maps this set of backbones to a transition graph (Figure 13), where the series of transition levels $T_1, \dots, T_i$ corresponds to the backbone schedule sequence, in which

each backbone transmits data for some predetermined period of time. The authors define the energy level of the network after transmitting data on backbone bb_j at transition level T_k to be a tuple of the residual energy values of all sensors. The STG-based algorithm is as follows. After the network transmits data on some backbone at T_k , the authors determine the set of n energy levels associated with the case when each backbone $bb_1, \dots, bb_n$ is implemented at T_{k+1} . From among this set, they select the backbone resulting in an energy level with the maximal minimum residual energy value to be utilized at T_{k+1} . After the network transmits data on this backbone, their algorithm iterates until a sensor exhausts its energy to determine a backbone schedule.

Figure 13: Schedule transition graph

For the VSG-based algorithm, each sensor i in the original WSN is transformed into a clique of E_i virtual nodes, where E_i is a positive integer that corresponds to the remaining energy at sensor i . The virtual nodes are indexed from $0, \dots, E_i - 1$. An edge connects the u th virtual node for sensor i with the v th virtual node for sensor j if and only if (a) an edge connects sensors i and j in the original WSN, and (b) $\max\{u, v\} \leq \min\{E_i, E_j\} - 1$. Figure 14 illustrates this transformation. In particular, note that $E_A = 3$ and $E_B = 2$, and so there exist edges between virtual node u associated with sensor A and both virtual nodes associated with sensor B, for $u = 0$ and 1 . However, virtual node 2 associated with sensor A is not connected to virtual nodes associated with sensors B or C because E_B and E_C are both less than 3 .

By forming the virtual graph in this way, sensors having high energy tend to be a part of the backbone. The authors then obtain a minimum CDS in the virtual graph that does not contain multiple virtual nodes of the same sensor. Finally, the authors remove all duplicate virtual nodes to reveal a backbone in the original graph. They also present a distributed algorithm for the MLBS problem, in which each backbone sensor finds a replacement node among neighboring sensors to form a new backbone.

Figure 14: Virtual scheduling graph, in which $E_A = 3$, $E_B = 2$, $E_C = 1$, and $E_D = 1$

Rizvi et al. [86] seek to find a set of sensors that form a CDS corresponding to a virtual backbone to reduce the size of the network and simplify routing decisions. The authors define active sensors as those sensors able to relay data through the network, and non-active sensors as those that only retrieve data. The authors present a tree-based distributed algorithm that starts by forming a virtual graph containing all sensors using a depth-first search from some initial sensor. Each leaf node of this graph is designated as non-active sensor with the other sensors being active. The authors conclude that their algorithm consumes less energy when forming a virtual backbone compared to other CDS-based algorithms.

Network trees are useful in WSNs with data fusion capabilities. Data fusion is the process of locally aggregating information retrieved from multiple sensors before being transmitted to another node [21, 65]. Luo et al. [65] implement a routing algorithm to determine an energy efficient data-routing plan in WSNs implementing data fusion. The authors first propose an IP to solve this problem, in which integer variables determine if data is fused at a sensor. Due to the difficulty of solving this model, they present an approximation algorithm that first employs a shortest-path algorithm to find a minimum-cost path between every pair of non-sink nodes (u, v) , where edge costs are a function of the energy required for transmission from u to v and the energy required for fusion at v . Their algorithm then finds a minimum-cost perfect matching between all non-sink nodes to construct a data routing and fusion tree that minimizes the total energy consumed. Their algorithm achieves a tree with a $\frac{5}{4}\log(n+1)$ approximation to the optimal objective, where n is the number of sensors in the network.

4. Extensions Based on Sink Characteristics

We now describe various extensions to the lifetime maximization problem based on sink properties. In Section 4.1 we explore lifetime maximization algorithms for WSNs having multiple sinks. We then present

in Section 4.2 extensions to model (1) that consider the presence of a mobile sink. Finally, we examine the lifetime maximization problem for WSNs having multiple mobile sinks in Section 4.3. Table 4 summarizes key papers in Sections 4.1 and 4.2 and Table 5 summarizes those in Section 4.3.

Author (Model)	Problem specification	Technique
<i>Multi-sink models</i>		
Xue et al. [110]	Tree-based data-routing	$(1 - \epsilon)$ -approximation polynomial time algorithm to create a set of trees, each rooted at a sink
Castaño et al. [17]	Data-routing and scheduling	CG scheme to maximize lifetime, greedy randomized algorithm to solve subproblem
Kim et al. [50]	Constrained sensor and sink deployment and data-routing	MIP to determine sink locations and data-flows
Türkoğullari et al. [102]	Sensor and sink deployment and data-routing	Require a sufficiently large number of sinks be within a minimum distance to sink, CG scheme for routing
<i>Non-delay tolerant single mobile-sink models</i>		
Papadimitriou and Georgiadis [79] (MSM)	Sink traversal and data-routing	LP for sink movement and dwelling times and routing
Wang et al. [107]	Sink traversal on a uniform two-dimensional grid	LP for sink traversal, shortest-path algorithm for routing
Huang et al. [41]	Reactive sink relocation on a hexagonal grid	Sink moves to nearby area with higher average residual energy, shortest-path algorithm for routing
Gatzianas and Georgiadis [33]	Distributed sink traversal and routing	Subgradient algorithm for Lagrangian relaxation of LP, minimum-cost flow algorithm for routing
Liang and Luo [62]	Distance-constrained sink tour and hop-constrained routing	Heuristic that determines sink trajectory first, then dwelling times at each location
<i>Delay-tolerant single mobile-sink models</i>		
Yun and Xia [114] (DT-MSM)	Sink traversal and routing varying delay restrictions	LP to determine sink traversal and dwelling times
Yun et al. [115]	Distributed sink traversal and routing	Lagrangian relaxation of an LP, fractional knapsack algorithm for subproblem at each sensor
Behdani et al. [13]	Partially-distributed sink traversal and routing	CG scheme with separable shortest-path subproblems at each sensor
Keskin et al. [48]	Sink traversal and routing with non-negligible sink travel time	Heuristic for an MIP with an upper bound on the number of transmission hops
Behdani et al. [12]	Sink traversal and routing with non-negligible sink travel time	Branch-and-cut approach to solving an MIP with subtour elimination constraints

Table 4: Section 4.1 and 4.2 summary, where sink travel times are negligible unless otherwise specified

4.1. Multiple-Sink WSNs

Introducing multiple sinks can extend WSN lifetime by improving energy consumption balance across the network [95]. Model (1) can be extended to address the multi-sink WSN lifetime maximization problem, assuming either that collected data can be transmitted to any sink, or that each data-routing request has a specific sink to which it is transmitted. In this survey, we employ the former assumption.

We extend the prior single-sink WSN example to demonstrate how the presence of a second sink prolongs network lifetime. Figure 15 presents a two-sink example similar to the WSN example in Figure 6.

Figure 15: Two-sink WSN example

A new sink E_1 is added to the network while sink E_2 remains at the same location as E in the single-sink example. The energy required to send a unit of data from sensors C and D to E_1 is $e_{CE_1} = 10$ and $e_{DE_1} = 20$ units. All other information regarding battery power, data origination amounts, and energy expenditures are the same as those used in the single-sink WSN example. Figure 16 presents an optimal set of data flows per hour for the two-sink WSN.

Figure 16: Optimal data flows per hour

Instead of relaying data through sensor D , sensor C now transmits all data from sensor A directly to the new sink E_1 . Sensor D now relays a portion of data from B through C to E_1 . The updated total energy

usages per hour at sensors C and D are $T_C = T_D = 186$, while $T_A = 80$ and $T_B = 100$. The maximum WSN lifetime becomes $L_C = L_D = 500/186 \approx 2.7$ hours. An additional sink thus extends network lifetime from 2.3 to 2.7 hours.

Xue et al. [110] extend their single-sink algorithm to determine optimal data flows in a WSN having multiple sinks. The algorithm first finds a shortest path from each sensor to a sink and determines the amount of flow on this path, based on data origination rates. The authors iteratively combine these paths to create a set of trees, each rooted at a sink. The running time of this algorithm thus remains the same as with the single-sink case, and the multi-sink adaptation of their algorithm achieves a $(1 - \epsilon)$ -approximation in polynomial time.

Castañó et al. [17] propose a hybrid CG scheme to determine a schedule of data flows that maximizes lifetime for multi-sink WSNs. In this problem, there exist a set of targets that are covered by a subset of sensors. Each column in the CG formulation corresponds to a subset of sensors that collectively cover the entire set of targets. As such, the column can be viewed as an in-flow tree rooted at a supersink node (to which all sinks can send flow), and each target location corresponds to a leaf node. To solve the CG subproblem, the authors propose a greedy randomized algorithm that uses a variation of depth-first search. If this algorithm fails to generate an attractive set of data flows, the authors solve an IP to generate such a set, or show that no positive reduced-cost column exists. The authors conclude that mixing their heuristic algorithm with the IP reduces computational time compared to a standard CG-based approach, and computes an optimal solution within the given time limit for most instances.

Whereas the previous works assume sink locations are established *a priori*, Kim et al. [50] address how to optimally position multiple sinks from among the set of discrete sensor locations, in addition to finding an optimal set of data flows. The authors formulate mathematical models to address these two problems. They first consider an LP to compute optimal data flows from all sensors to a sink, in which sink locations are predetermined. The authors then formulate a mixed-integer program (MIP) to find an optimal set of sink locations and data flows, where an upper bound exists on the number of sinks. Similarly, Türkoğullari et al. [102] formulate an MIP model to combine sensor and sink deployment and data-flow decisions. They provide a heuristic technique that first deploys sinks so that a sufficiently large number of sensors are within a minimum distance to a sink. Using these sink locations, the authors reformulate and solve the LP relaxation of the MIP using a CG scheme, where each column corresponds to a set of deployed sensors and data flows. Finally, they obtain a feasible solution to the MIP using an optimal set of columns from the relaxation.

4.2. Mobile-Sink WSNs

As an alternative to deploying multiple stationary sinks, sink mobilization extends network lifetime by balancing energy consumption among a larger set of sensors. In such cases the sink is permitted to move among a set of stationary locations at a predetermined speed. Mobile sinks are also useful in dynamic sensing environments that change over time as new targets emerge in the network [49].

4.2.1. Mobile-sink models with no transmission delay

Papadimitriou and Georgiadis [79] introduce the following LP to address the *mobile-sink lifetime maximization problem* (MSM) in which $\mathcal{L}$ is the set of possible sink locations, and where the time required for the sink to move from one location to another is assumed to be negligible. The variables and parameters for this problem are the same as in model (1), except that the dwelling times per sink location and data flows are now indexed by the sink location $\ell \in \mathcal{L}$.

$$\max \sum_{\ell \in \mathcal{L}} z_{\ell} \quad (4a)$$

$$\text{s.t.} \quad \sum_{j \in \mathcal{N}} y_{ij}^{\ell} - \sum_{h \in \mathcal{S}} y_{hi}^{\ell} - b_i z_{\ell} = 0 \quad \forall i \in \mathcal{S}, \ell \in \mathcal{L} \quad (4b)$$

$$\sum_{\ell \in \mathcal{L}} \left[\sum_{j \in \mathcal{N}} e_{ij} y_{ij}^{\ell} + \sum_{h \in \mathcal{S}} c_{hi} y_{hi}^{\ell} \right] \leq P_i \quad \forall i \in \mathcal{S} \quad (4c)$$

$$y_{ij}^{\ell} \geq 0 \quad \forall i \in \mathcal{S}, j \in \mathcal{N}, \ell \in \mathcal{L} \quad (4d)$$

The objective function (4a) maximizes WSN lifetime defined as the sum of the sink dwelling times at all possible locations, and all other constraints are analogous to those in (1). An optimal solution to (4) provides the set of sink dwelling times and data flows to those sink locations.

While (4) determines both sink dwelling times and data flows, Wang et al. [107] formulate an LP solely to determine sink movements and dwelling times in which sinks must be located at a corner point of a cell within a two-dimensional grid. Instead of determining data flow between nodes as in (4), they implement a shortest-path algorithm for data originating at each sensor. The authors observe that the network lifetime of mobile-sink WSNs increases by almost five times compared to a WSN having a single static sink.

Rather than assuming that the sink moves along a set predetermined locations, Huang et al. [41] propose a reactive sink relocation method for hexagonal-grid WSNs. When the average residual energy within each cell reaches a minimum threshold, the sink moves to a neighboring cell having the highest average residual energy.

Once the sink relocates to a new position, their method employs a shortest-path algorithm to determine data flows, in which edge weights are based on residual energy levels and data transmission size. Results show that relocating sinks according to a hexagonal grid-like topology can double the network lifetime in most cases compared to a static-sink WSN.

Whereas [79] implements a centralized solution technique by solving model (4), Gatzianas and Georgiadis [33] assume decentralized coordination by using dual decomposition. The authors introduce locally-stored Lagrangian multipliers for energy-capacity and peak transmission constraints to formulate the Lagrangian dual problem. Taking advantage of the dual’s special structure, they split this problem into a set of smaller subproblems and use a minimum-cost flow algorithm to solve the subproblem at each sensor to obtain a set of data flows. The authors show that their algorithm runs in polynomial time and results in maximum lifetime values within 3% of solutions using centralized approaches [79].

In some cases, sink movement forces sensors to use excessively many hops to transmit data to a sink. To mitigate this problem, Liang and Luo [62] jointly determine the sink trajectory and dwelling times with upper bounds limiting the distance traveled by each sink and the number of allowable hops for data transmission. They prove this problem to be NP-hard and consequently present a heuristic to identify a near-optimal solution. The algorithm first calculates the maximum potential dwelling time at each sink location. Next, the algorithm searches for a high-quality sink trajectory and determines the actual dwelling times at each location based on this trajectory.

4.2.2. Delay-tolerant models

Algorithms in the previous subsection assume that the time required for the sink to move from one location to another is negligible, and that sensors cannot delay transmission of their flows to a sink. In some cases, though, sensors may also be able to locally store data to delay transmission until the sink arrives at a more favorable location. We discuss these delay-tolerant models in this subsection, along with situations in which the travel time between sinks is non-negligible.

When data transmission can be delayed indefinitely, single mobile-sink and multiple stationary-sink WSNs yield identical optimal solutions, regardless of the sink’s travel time. Similarly, this equivalence also holds when the sink can move infinitely fast and data can be delayed for any positive period of time (assuming negligible data transmission speeds). In more general cases, such as when data transmission cannot be delayed indefinitely, multiple stationary-sink WSNs yield lifetimes that are no less than those given by single

mobile-sink WSNs.

For sinks having a fixed finite travel speed, maximum WSN lifetime is a nondecreasing function of maximum tolerable delay D , and reaches the maximum lifetime for its multiple stationary-sink WSN counterpart when D becomes sufficiently large. When the travel time between two sink locations is greater than D , the sink cannot move between these locations. The reason for this restriction is that while the sink traverses from one location to the other, data is being collected and stored for delivery to the latter sink location. If the distance between these locations is too large, then the sink cannot arrive to the destination location within the delay limit. Thus, when D is less than the travel time between any two sink locations, the sink must remain stationary, and the problem reduces to choosing the best solution among several single-sink problems, one for each possible sink location.

Yun and Xia [114] consider single mobile-sink WSNs with a finite positive maximum tolerable delay but negligible sink travel time. The authors extend (4) to propose a pair of LP models for the *delay-tolerant mobile sink lifetime maximization* (DT-MSM) problem, each with a unique variation of delay restriction. In the first variation, the sub-flow-based model, sensors are only allowed to store data gathered locally. For the second variation, the queue-based model, sensors may store data gathered by any sensor. The sub-flow-based formulation is similar to a standard multicommodity flow problem, which is solvable by fast, specialized algorithms [8, 47]. The queue-based model is more difficult to solve, but its increased flexibility leads to longer lifetimes than the sub-flow-based model.

Similar to Gatzianas and Georgiadis' [33] approach to the MSM problem, Yun et al. [115] implement a distributed algorithm for the DT-MSM problem, in which they examine the dual decomposition of the LP in [114] with Lagrangian multipliers on the flow-balance constraints. The authors split this problem into smaller problems at each sensor using information local to the sensor and its neighbors. They employ a fractional knapsack algorithm to separately solve each subproblem for the sub-flow-based and queue-based models. Based on analyzing a Lyapunov drift, the authors prove that this algorithm converges to an optimal solution.

Behdani et al. [13] also take an exact solution approach to the queue-based DT-MSM problem in [114] and develop a partially-distributed CG algorithm. To identify an attractive set of data flows, the authors exploit the uncapacitated nature of WSN arcs and form separable shortest-path problems with non-negative costs at each sensor. While more efficient, this approach is only partially distributed, because the CG scheme requires the communication and solution of a master problem.

Whereas the previous approaches assume the sink travel time between locations to be negligible, Keskin et al. [48] propose two MIP models to determine a sink tour that maximizes the lifetime of a WSN having a non-negligible sink travel time. The authors allow the sink to complete multiple identical tours and place an upper bound on the duration of the sink tour to enforce a maximum tolerable delay. For the first model, gathered data is transmitted to the sink with no restrictions on the number of transmission hops, while the second model places an upper bound of the number of hops. To determine data flows in both cases, the authors implement a shortest-path algorithm based on residual energy levels. Rather than solving the MIP, the authors propose a set of heuristics to find a good feasible sink tour.

Alternatively, Behdani et al. [12] determine a sink traversal tour and a set of data flows to maximize the lifetime of a WSN with a finite maximum tolerable delay and non-negligible sink travel time. For this problem, the authors allow sensors to transmit data to some location ℓ even when the sink is not currently dwelling at, or traveling to, ℓ . The sink must thus arrive at ℓ no more than D time units after a sensor begins transmission to ℓ . The goal is to find a sink tour over a subset of $\mathcal{L}$, and determine data flows to each location visited by the sink.

Because their model is important to the discussion in this section, we cover it in detail below. The authors first define $t_{\ell m}$ to be the time it takes the sink to travel from $\ell \in \mathcal{L}$ to $m \in \mathcal{L}$. Thus, the sink can only travel on arcs that satisfy $t_{\ell m} \leq D$, resulting in a directed sink graph $\mathcal{G}' = (\mathcal{L}, \mathcal{A})$ with an arc set $\mathcal{A} = \{(\ell, m) : t_{\ell m} \leq D\}$. For convenience, define node sets $K_\ell^+ = \{m \in \mathcal{L} : (\ell, m) \in \mathcal{A}\}$ and $K_\ell^- = \{m \in \mathcal{L} : (m, \ell) \in \mathcal{A}\}$.

Let $\bar{P}_i = P_i/C$ be the energy capacity of each sensor i during a sink tour, where C corresponds to the number of tours the sink must complete. Variable r_ℓ represents the period of time during which sensors transmit data to location ℓ . Let v_ℓ and $u_{\ell m}$ be binary variables that equal 1 if location ℓ is visited by the sink and if the sink travels along arc $(\ell, m) \in \mathcal{A}$, respectively. Therefore, the sink's dwelling time at ℓ must be at least $t_{m\ell}$ if $u_{m\ell} = 1$. Let the binary variable s_ℓ equal 1 if the sink tour originates at ℓ . Also, define $q_{\ell m} = s_\ell \times$ [the amount of time that sensors transmit data to m before the sink begins movement toward m from its preceding sink location]. Thus, if $s_\ell = 1$, then data is transmitted to m for $q_{\ell m} + \sum_{k \in K_m^-} t_{km} u_{km}$ time units before the sink arrives at m . Letting M be a large constant value, the DT-MSM problem with a finite tolerable delay and non-negligible travel time can be formulated by the following NLP model [12].

$$\max \sum_{\ell \in \mathcal{L}} r_\ell \tag{5a}$$

$$\text{s.t. } r_\ell \leq M v_\ell \quad \forall \ell \in \mathcal{L} \tag{5b}$$

$$\sum_{\ell \in \mathcal{L}} \left(\sum_{j \in \mathcal{N}} e_{ij}^\ell + \sum_{j \in \mathcal{S}} c_{ji} y_{ji}^\ell \right) \leq \bar{P}_i \quad \forall i \in \mathcal{S} \quad (5c)$$

$$\sum_{j \in \mathcal{N}} y_{ij}^\ell - \sum_{j \in \mathcal{S}} y_{ji}^\ell - b_i r_\ell = 0 \quad \forall i \in \mathcal{N}, \ell \in \mathcal{L} \quad (5d)$$

$$\sum_{m \in \mathcal{K}_\ell^+} u_{\ell m} = v_\ell \quad \forall \ell \in \mathcal{L} \quad (5e)$$

$$\sum_{m \in \mathcal{K}_\ell^-} u_{m\ell} = \sum_{m \in \mathcal{K}_\ell^+} u_{\ell m} \quad \forall \ell \in \mathcal{L} \quad (5f)$$

$$\sum_{\ell \in \mathcal{T}} \sum_{m \in \mathcal{T}} u_{\ell m} \geq v_k + v_r - 1 \quad \forall \mathcal{T} \subset \mathcal{L} : 2 \leq |\mathcal{T}| \leq |\mathcal{L}| - 2, k \in \mathcal{T}, r \in \mathcal{T} \quad (5g)$$

$$\sum_{\ell \in \mathcal{L}} s_\ell = 1 \quad (5h)$$

$$s_\ell \leq v_\ell \quad \forall \ell \in \mathcal{L} \quad (5i)$$

$$q_{\ell m} + \sum_{k \in \mathcal{K}_m^-} t_{km} u_{km} \leq D \quad \forall \ell \in \mathcal{L}, m \in \mathcal{L} \quad (5j)$$

$$q_{\ell m} \geq \sum_{k \in \mathcal{K}_m^-} \left(q_{\ell k} + \sum_{h \in \mathcal{K}_k^-} (t_{hk} - r_k) u_{hk} \right) u_{km} - D(1 - s_\ell) \quad \forall \ell \in \mathcal{L}, m \in \mathcal{L} \quad (5k)$$

$$D(1 - s_\ell) + r_\ell \geq q_{\ell\ell} + \sum_{m \in \mathcal{K}_\ell^-} t_{m\ell} u_{m\ell} \quad \forall \ell \in \mathcal{L} \quad (5l)$$

$$v_\ell \in \{0, 1\} \quad \forall \ell \in \mathcal{L} \quad (5m)$$

$$u_{\ell m} \in \{0, 1\} \quad \forall \ell \in \mathcal{L}, m \in \mathcal{K}_\ell^+ \quad (5n)$$

$$q_{\ell m} \geq 0 \quad \forall \ell, m \in \mathcal{L} \quad (5o)$$

$$r_\ell \geq 0 \quad \forall \ell \in \mathcal{L} \quad (5p)$$

The objective function (5a) maximizes the total time data is transmitted to any sink location $\ell \in \mathcal{L}$ while constraints (5b) ensure that data can only be transmitted to location ℓ if visited by the sink. Constraints (5c) and (5d) enforce energy-capacity and flow-balance constraints, respectively. Constraints (5e)–(5g) ensure that the sink's traversal corresponds to a single tour that visits all nodes ℓ such that $v_\ell = 1$. Note that the exponential set of constraints (5g) in particular serve as subtour elimination constraints. Constraints (5h) and (5i) guarantee that one node is selected as the origin, from among those nodes ℓ for which $v_\ell = 1$. Constraints (5j) and (5k) ensure that data transmitted to location $m \in \mathcal{L}$ is not delayed longer than D time units if $v_m = 1$, while (5l) enforces a similar maximum tolerable delay restriction at the origin location. Finally, constraints (5m) and (5n) enforce binary constraints on variables v and u , while constraints (5o) and (5p) enforce non-negativity of variables q and r . To solve this problem, the authors add a set of auxiliary variables to linearize model (5), and add the subtour elimination constraints (5g) as needed in a

branch-and-cut fashion.

To illustrate the relationship between maximum lifetime and maximum tolerable delay, we consider a single mobile-sink delay-tolerant WSN lifetime maximization example. For this example the sink can move among locations 1, 2, and 3 traveling at a fixed speed of 1 km per hour. The arc labels in Figure 17a depict the distances between sink locations, and the table in Figure 17b displays the distances between sensors and sink locations. The energy to send one unit of data from a sensor to a sink location is equal to the distance between the two nodes. Each sensor possesses a battery power of 500 units, and the data generation rate for each sensor is 1 data unit per hour.

(a) Distance between sink locations

Sensor	Sink location		
	1	2	3
4	13	6	7
5	10	4	14
6	4	12	3

(b) Distance between sensors and sink locations

Figure 17: Distances (in km) for the single mobile-sink WSN example

Figure 18 shows how maximum WSN lifetime grows as a function of maximum tolerable delay. In general, WSN lifetime is nondecreasing in terms of delay, but this function might be nonconcave and even discontinuous, as is the case even in this simple example. When data cannot be delayed by three or more hours, the sink must remain stationary. Therefore, the sink remains at location 2 in Figure 17a for a maximum lifetime of 41.7 hours, which is longer than the maximum lifetime achieved if the sensor were stationary at locations 1 or 3. We thus vary the maximum tolerable delay parameter and solve (5) to determine the maximum WSN lifetime. Next, suppose that data can be delayed by three hours. The sink can then travel between locations 2 and 3 without violating the delay constraint. The maximum lifetime increases by 46% to 60.9 hours. As the maximum tolerable delay increases from three to six hours, the maximum lifetime linearly increases as sensor 6 is able to transmit more data to the more favorable sink location 3, thus prolonging network lifetime.

Figure 18: Maximum WSN lifetime as a function of maximum tolerable delay

The WSN lifetime also has a discontinuous jump when data can be delayed by 6 hours because the sink can then move between location 1 and location 3. As the maximum tolerable delay increases beyond 6 hours, each sensor is able to transmit more data to its nearest sink location to balance energy consumption to prolong network lifetime. When the maximum tolerable delay surpasses roughly 30.7 hours, the single mobile-sink WSN reaches the maximum lifetime for its multiple stationary-sink WSN counterpart and yields equivalent flows to the case when a sink is placed at each possible location.

4.3. Multiple Mobile-Sink WSNs

Just as independently adding and mobilizing sinks prolongs WSN lifetime, introducing multiple mobile sinks further balances energy consumption and prolongs WSN lifetime. Gandham et al. [31] present a sink-relocation and data-routing approach for multiple mobile-sink WSNs. The authors first assume that a limited number of sinks dwell at some set of locations for a predetermined period of time until they are relocated to a new set of locations. Assuming that the sink relocation time is negligible, they formulate an IP model to determine this new set of locations from among a set of predefined discrete locations, along with data flows from the sensors to one of the sink locations, in a manner that minimizes the maximum energy consumption among all sensors. They heuristically solve the IPs by rounding fractional LP relaxation values, repeating the process until a sensor exhausts its energy.

Basagni et al. [11] present a set of heuristics for determining the movement of multiple sinks in addition to data-routing decisions. The authors formulate and decompose an LP model to the multiple MSM problem

Author (Model)	Problem specification	Technique
<i>Multiple mobile-sink models</i>		
Gandham et al. [31]	Periodic sink relocation and routing	Rounding heuristic to solve an IP that minimizes the maximum energy consumption among all sensors
Basagni et al. [11]	Sink relocation and routing	Decompose LP model to add violated dual constraints by solving a p -median problem
Basagni et al. [10]	Distributed sink relocation and routing	Allow sensors to communicate with neighboring sensors to improve network awareness
Marta and Cardei [67]	Distributed reactive sink movement on a hexagonal grid	Sink relocates to an area having greater energy when neighboring sensors reach a low-energy threshold
Saad and Touranchea [90]	Multiple mobile sink control within buildings	IP with a minimum sink dwelling time, shortest-path algorithm for routing

Table 5: Section 4.3 summary, where sink travel times are negligible and routing cannot be delayed

to add violated dual constraints using a p -median problem [69]. Additionally, Basagni et al. [10] formulate a distributed version of their heuristic that allows sensors to communicate with neighboring sensors to improve network awareness. Performance comparisons show that the distributed heuristic achieves near-optimal network lifetimes that provide significant improvements compared to random sink mobility and multiple static sink deployment.

Marta and Cardei [67] take a reactive approach for sink mobility to create a heuristic where sinks periodically move along the perimeter of a hexagonal grid to form a virtual backbone. Each sink monitors its neighboring sensors. When a predefined percentage of these sensors reaches a low energy threshold, the sink moves to avoid burdening those sensors with relaying a large amount of data to the sink. The sink thus searches for nearby areas along the perimeter whose local sensors have greater energy. Since sinks only utilize information within its neighborhood, this heuristic is implemented in a distributed manner. The authors also consider the case in which the sink moves along a non-predetermined path from one location to another.

Finally, as an application of these studies, Saad and Touranchea [90] examine the deployment of multiple mobile sinks in WSNs within buildings. The authors explore a clustering mechanism to decompose the WSN, using an IP to determine sink trajectories and dwelling times. Because frequently relocating sinks can be expensive, the authors require sinks to dwell at each location for a minimum time period. For local and global routing decisions, the authors implement a shortest-path algorithm that considers the distance between nodes and the residual energy capacities at each sensor. The authors compare three scenarios for

their application: stationary sinks, multiple sinks moving within different clusters, and multiple sinks moving throughout the entire network.

5. Alternative Optimization Metrics

Section 5.1 explores techniques for maximizing the lifetime of the remaining network after a sensor exhausts its energy. In Section 5.2 we examine algorithms for maximizing the coverage area and connectivity of a WSN. We explore approaches for minimizing data transmission delays in Section 5.3. Table 6 summarizes the papers discussed in this Sections 5.1 and 5.2, and Table 7 summarizes those discussed in Section 5.3.

Author (Model)	Problem specification	Technique
<i>Maximizing conditional sensor lifetime</i>		
Dagher et al. [23]	Conditional sensor lifetime	Iterative LP algorithm to identify a PO solution
Shah-Mansouri et al. [95]	Conditional commodity lifetime	Solve $ \mathcal{L} $ MIPs to determine PO solution
<i>Maximizing connectivity and coverage</i>		
Yun et al. [116]	Connectivity-constrained sensor deployment	Provides relation to general set-covering problem with polygon-based methodology to prove optimality
Wang and Wu [106]	Single-objective sensor deployment to avoid network fragmentation	Improves connectivity and coverage by deploying sensors at critical nodes and low-coverage areas
Pradhan and Panda [82]	Sensor deployment for coverage and connectivity	Particle swarm optimization algorithm
Sengupta et al. [93]	Sensor deployment/routing for coverage, lifetime, and energy use	GA to solve a series of weighted single-objective problems to find a PO solution
Sengupta et al. [94]	Same as [93], with varying connectivity requirements	Decompose IP into subproblems and use GA to simultaneously solve the subproblems
Özdemir et al. [77] (MOEA/D)	Cluster formation to balance energy consumption and coverage	Evolutionary algorithm that selects active sensors as clusterheads
Rossi et al. [88]	Max lifetime and min coverage breach under bandwidth limits	CG approach with a GA to solve the MIP subproblems
Rossi et al. [89]	Coverage/energy tradeoff when sensing ranges are adjustable	Formulations for two problems; CG approach with GAs to solve the MIP subproblems
Gentili and Raiconi [34]	Single-objective data-routing with minimum coverage constraints	Greedy approach to initialize CG scheme, additional subproblem constraints to avoid redundant columns

Table 6: Section 5.1 and 5.2 summary

5.1. Maximizing Conditional Sensor Lifetime

For this discussion, given a feasible solution to problem (1) represented by variables $\hat{\mathbf{y}}$ and $\hat{z}$, the lifetime of sensor $i \in \mathcal{S}$ is given by

$$\frac{P_i \hat{z}}{\left(\sum_{j \in \mathcal{N}} e_{ij} \hat{y}_{ij} + \sum_{h \in \mathcal{S}} c_{hi} \hat{y}_{hi} \right)}. \quad (6)$$

Suppose that for some feasible $\mathbf{y}$, we sort these sensor lifetimes in nondecreasing order, yielding lifetimes $L_1(\mathbf{y}), \dots, L_{|\mathcal{S}|}(\mathbf{y})$ (where we omit $\hat{z}$ from this notation for simplicity). Formulation (1) maximizes $L_1(\mathbf{y})$, with no regard to $L_j(\mathbf{y})$, for $j \geq 2$. Typically, though, multiple optimal solutions exist to (1). Defining $L_0(\mathbf{y}) = 0$ for any solution $\mathbf{y}$, the j th conditional lifetime is the maximum possible value of $L_j(\mathbf{y})$, over all solutions $\mathbf{y}$ feasible to the constraints in (1), such that $L_i(\mathbf{y})$ equals the i th conditional lifetime for all $i = 0, \dots, j-1$. By optimizing the $|\mathcal{S}|$ th conditional lifetime, we maximize $L_1(\mathbf{y})$, breaking ties by maximizing $L_2(\mathbf{y})$, and so on, with maximizing $L_{|\mathcal{S}|}(\mathbf{y})$ as the final criterion. We refer to this problem as the *conditional lifetime problem*.

Dagher et al. [23] present an algorithm for solving the conditional lifetime problem. The algorithm tracks “fixed” sensors, which are sensors whose lifetime values have been determined. Let E (initially empty) denote the set of all fixed sensors. Their algorithm iteratively solves a series of LPs, each of which contains the constraints in (1) plus constraints restricting the fixed sensors to take on their designated lifetime values. At each iteration, the algorithm enforces the condition that all lifetimes for sensors not in E must equal some common value ζ , and solves an LP to maximize ζ . Next, for every sensor j not in E , the algorithm solves individual LPs to maximize the lifetime of sensor j , subject to the constraints on the previous model, and constraints stating that every other sensor in E has a lifetime of at least ζ . If the maximum lifetime of each individual LP is ζ , for all $j \notin E$, then the current solution solves the conditional lifetime problem. If not, then the algorithm solves another LP for each sensor not in E to identify a sensor $\hat{j} \notin E$ whose lifetime cannot exceed ζ . Sensor $\hat{j}$ ’s lifetime is then fixed to ζ , and sensor $\hat{j}$ is placed in E .

Shah-Mansouri et al. [95] take a multi-commodity approach to maximize conditional lifetime, in which a commodity consists of all data originating at various targets destined for a common sink. A commodity’s lifetime is given by the minimum lifetime among all sensors transmitting that commodity. Using a similar conditional lifetime definition as [23], the authors propose an iterative algorithm that solves an MIP to maximize the first conditional commodity lifetime, in which binary variables specify whether a sensor transmits a specific commodity. Step $n \geq 2$ of the algorithm chooses a solution among those optimal in step $n-1$ that maximizes the next conditional commodity lifetime. The algorithm iteratively runs until the $|\mathcal{L}|$ th conditional commodity lifetime has been maximized, where $|\mathcal{L}|$ is the total number of sinks.

5.2. Maximizing Coverage and Connectivity

Sensor locations are not only vital in maximizing WSN lifetime, but are also critical in assuring that all targets are covered as desired. Optimizing lifetime and maximizing coverage are two different objectives, but can be considered in joint optimization studies as detailed in this section. Yun et al. [116] explore a proactive method to find the smallest set of deployed sensors that collectively monitors all target locations, under the condition that each sensor must be connected to k other nodes for some $k \leq 6$. They show how the sensor deployment problem relates to the general set-covering problem and use a polygon-based methodology to prove optimality.

Because the failure of a single sensor can potentially disconnect networks, Wang and Wu [106] seek to improve WSN connectivity by deploying additional sensors within an existing network. In particular, they place sensors at critical nodes whose removal would partition the network into two or more separate components.

Assuming that sensors correspond to a set of vertices located in Euclidean space (Figure 19a), the authors first create a planar subgraph of the WSN by removing a subset of crossing edges (Figure 19b). Next, for each sensor i , the algorithm finds its neighbors $\mathcal{C}_i$ in this planar graph. If there exist $|\mathcal{C}_i|$ 2-simplices involving i and a pair of nodes in $\mathcal{C}_i$, then i is deemed non-critical (see Figure 19c). (A 2-simplex is a two-dimensional polytope formed by the convex hull of three sensors, i.e., a triangle.) The algorithm then iteratively removes each of the remaining sensors to determine if it is critical. If so, a backup sensor is placed near the critical sensor (Figure 19d). Additionally, the authors implement a protocol to reduce the size of large 2-simplices in the subgraph that correspond to areas of low coverage in the WSN (Figure 20a). Their algorithm uses a localized method to identify these simplices and introduces a new sensor to reduce its size by eliminating at least one sensor its boundary (Figure 20b).

While the prior literature in this section focuses on deploying sensors to maximize connectivity, Pradhan and Panda [82] search for a Pareto-optimal (PO) solution that jointly considers coverage and lifetime. (A feasible solution x to a multi-objective problem is said to be PO if no other feasible solution exists that is better than x with respect to one objective and at least as good as x with respect to the other objectives [18].) The authors first define WSN coverage to be the percentage of target locations being monitored by at least one sensor. They then propose a multi-objective PSO algorithm in which each particle corresponds to a set of deployed sensors and data flows. After their algorithm initializes particle positions and fitness functions, each particle randomly moves through the solution space according to the fitness value of the

Figure 19: Locating critical sensors

Figure 20: Locating and reducing the size of a coverage hole

best current solution. During each iteration, their algorithm compares newly-generated solutions, stores any non-dominated solutions, and updates associated fitness functions. The authors show that their algorithm produces a diverse set of solutions along the Pareto frontier of the two objectives.

Similarly, Sengupta et al. [93] propose a sensor deployment and data-routing approach that (a) maximizes coverage, (b) maximizes network lifetime, and (c) minimizes energy consumption. The authors decompose this problem into a series of weighted single-objective optimization problems to find PO solutions. Sengupta et al. [94] extend the work in [93] to maximize network lifetime and coverage area, in which different portions of the network require varying levels of connectivity. They decompose a multi-objective IP into a series of smaller weighted subproblems that are simultaneously solved using a GA.

Özdemir et al. [77] use a weighted-sum approach to implement a decomposition-based multi-objective evolutionary algorithm (MOEA/D) to determine a set of sensor clusters and clusterheads that maximizes coverage and minimizes energy consumption. A solution using their MOEA/D algorithm contains a set of

clusterheads and a set of active sensors that relay data to a clusterhead. In each iteration of the algorithm, clusterheads are selected from among the set of active sensors from the previous solution. Results show that the MOEA/D improves upon solutions provided by standard GAs when solving the clusterhead selection problem with a coverage maximization objective.

Another portion of literature focuses on optimizing a single objective while ensuring that secondary objectives meet some desired level. Rossi et al. [88] present a CG-based solution technique for two alternative WSN network problems that also optimize network coverage. The first problem, minimizing coverage breach under bandwidth constraints (MCBB), determines a set of data flows that minimizes the number of uncovered targets given lifetime and bandwidth constraints. The second problem searches for a solution that maximizes network lifetime under coverage and bandwidth constraints (MNLB). The authors formulate an MIP for both problems, in which binary variables denote whether a sensor monitors some set of targets. The authors implement a CG algorithm to solve these models and present a GA to solve the MIP subproblem. If the GA reaches a local optimum, then the authors solve the MIP to find an attractive column or prove optimality of the current solution. The authors also consider a bi-objective problem to explore the trade-off between maximizing network lifetime and minimizing the number of uncovered targets. They solve a series of MCBB instances with varying levels of lifetime constraints to search for the Pareto frontier of the two objectives. Results show that mixing the GA and MIP to solve the MCBB and MNLB subproblems produces competitive results compared to strictly solving the MIP.

Rossi et al. [89] extend their work in [88] to maximize WSN coverage when sensors are capable of adjusting their coverage ranges to conserve energy. The authors present two MIP variations in which sensing ranges are continuously adjustable or are chosen from among a set of predetermined values. Similar to [88], they present a CG algorithm using a GA to solve the subproblem. In this case, results show that the GA decreases computational time over solving the subproblem exactly by branch-and-bound, without compromising solution quality.

Gentili and Raiconi [34] also give a CG-based algorithm to determine a schedule of data flows that maximizes lifetime when some $(1 - \alpha)$ percentage of targets may be left uncovered. They implement a greedy approach to initialize their CG scheme and implement some regularity conditions to speed up convergence. Additionally, they add a set of constraints to the subproblem to avoid redundant columns. Compared to the case when all targets must be covered, the authors show that the lifetime increases by 48.2% for $\alpha = 85\%$.

Author (Model)	Problem specification	Technique
<i>Minimizing Transmission Delay</i>		
Shah-Mansouri and Wong [96]	Distributed data-routing to max lifetime and min delay	Iterative LP algorithm, regularized method with dual decomposition to solve subproblems
Xu et al. [109]	Sink traversal with delay limits	Set-covering formulation, in-tree for routing flows
Ammari [5] (TED)	Data-routing to min and balance energy consumption and min delay	Decompose area around sensors to prioritize nearby sensors, weighted-sum model for routing
Shan et al. [97]	Distributed backbone construction to min data transmission length	Balances energy consumption among sensors some number of hops away from the sink

Table 7: Section 5.3 summary

5.3. Minimizing Transmission Delay

As described in Section 4.2.2, some WSNs permit delays in data transmission. While long delays may be permitted for some cases, other applications give higher priority to data transmitted to the sink in real-time. For such applications, researchers also consider minimizing total delay, defined as the time between when the data arrives at a sensor and when it arrives at a sink.

Shah-Mansouri and Wong [96] examine the problem of finding a data-routing plan that maximizes network lifetime; furthermore, if multiple optimal solutions to this problem exist, then the procedure optimizes a secondary objective. The secondary objectives they consider are the minimization of transmission delay and the minimization of total energy consumption. One approach simply solves an initial LP to maximize network lifetime. Then, one can solve an additional LP to minimize the secondary objective, in which all sensors' lifetimes are constrained to be no less than the maximum lifetime value. As an alternative, the authors propose a regularization method to combine these two LPs into a single optimization problem. They present a regularization function corresponding to each secondary objective that can be added to the objective function of the initial LP to formulate a regularized optimization model. The authors show that as long as the coefficient on this regularization function is no greater than some positive threshold, a solution to this regularized model corresponds to an optimal solution using the iterative LP approach. Using dual decomposition, they decompose this model into subproblems located at each sensor that can be solved in a distributed manner. The authors show that this regularized approach maximizes network lifetime and provides shorter transmission delays and lower energy consumption compared to the algorithms in [19] and [66].

Xu et al. [109] examine the trade-off between network lifetime and transmission delay for the DT-MSM problem (see Section 4.2.2). The authors develop a heuristic that determines a mobile sink trajectory and routing protocol with varying bounds on maximum delay. At each iteration of the algorithm, a new sink location is added to the trajectory as long as delay bounds are not violated. Sink locations are chosen with respect to the total number of sensors that neighbor the sink location, and the distance between each sensor and the sink location. The algorithm then builds an in-tree of data flows at each sink location so as to minimize total energy consumption. Additionally, the authors propose two heuristics to determine the sink trajectory based on a set-covering formulation.

Ammari [5] propose a multi-objective optimization approach to determine a set of data flows that minimizes energy consumption, balances energy consumption among the sensors, and minimizes transmission delay. To solve this problem, the authors propose a data-forwarding protocol, trade-off with energy delay (TED), to find an appropriate trade-off among these three objectives. This protocol first decomposes the area around each sensor in such a way that gives priority to closer sensors when relaying data transmissions. To determine data flows, they formulate a weighted-sum model to optimize over the three objectives.

In some applications, data transmission must be delayed at a node until all data from neighboring nodes is received. Additionally, data originating at sensors located at nodes in a routing tree may require a large number hops for transmission. In these cases data transmission may accumulate significant delays due to paths that have a large number of hops. Shan et al. [97] take a centralized approach to this problem. Their approach builds a backbone that maximizes network lifetime while minimizing the length of data-flow paths from each sensor to a sink. The algorithm heuristically constructs a routing tree that balances energy consumption among all sensors that are at least some number of hops away from the sink. They propose a distributed refinement algorithm that exchanges information between neighboring nodes to balance the energy consumption among the children of each node.

6. Future Challenges

This survey reveals many open areas for future research. One key assumption that may not be satisfied in practice regards the *a priori* knowledge of instance data. Demands originating at targets (or sensors) would appear to be far less certain. The online approaches in Section 3.1 consider uncertain or unknown data demand distributions, while most other studies in the literature assume known uniform demands. We recommend research targeted towards situations in the middle, where some imperfect knowledge of demands is available. In these cases, future research could employ stochastic programming [40, 72, 75] or

robust optimization [14, 73, 87] principles to determine data flows in order to achieve an expected maximum lifetime, or worst-case maximum lifetime, as appropriate.

The previous works assume that data transmissions are free of interference that inhibit successful transmission and lead to low-quality or unreliable data. For practical implementation, future research needs to consider the presence of stochastic interference levels. Multi-path or redundant data transmissions may be viable options to embed interference countermeasures into network protocols. Similarly, works in this survey assume that network coordination and operation are free of attacks. Since WSNs often transmit data on public channels, they are susceptible to attacks on transmission links [25]. Similarly, sensors are prone to physical attacks since they are commonly left unattended after deployment. Countermeasures for such attacks could be modeled as a network interdiction problem [36, 42, 99], in which a WSN operator maximizes lifetime after an adversary attacks some set of links. Additionally, this problem could be extended to a three-stage model in which the WSN operator fortifies the WSN (e.g., relocating sensors, alleviating bandwidth restrictions) before an adversary attacks.

While the approaches in this survey seek to balance energy consumption among all sensors, WSN lifetime is still constrained by finite sensor battery power. Some WSNs allow for energy harvesting [35, 45, 103, 104], in which sensors gather energy by means of various mechanisms (e.g., solar power, radio frequency energy transfer, microwave energy transfer) to recharge their battery. Future optimization approaches need to address how to utilize these energy sources to prolong network lifetime. Employing such techniques also opens up the discussion for multiple optimization problems, such as when and how to harvest energy to sustainably operate a WSN.

Data flows are predominantly assumed to be non-negative continuous values, but for some applications, positive data-flow values less than some minimum threshold may be undesirable. To characterize such cases, future optimization approaches may utilize semicontinuous variables that, if positive, must be no less than some lower bound. Another common assumption is that data is transmitted (virtually) instantaneously from sensors to other nodes in the network. If this transmission time is non-negligible, then for problems having tolerable delays, the transmission times from the data origin to its destination must be taken into account. For mobile-sink WSN models, the sink may need to dwell at each location for some minimum amount of time to ensure that all data transmissions are retrieved.

Clustering techniques presented in Section 3.2 help to decentralize network protocols and coordination. A majority of the presented work propose heuristic techniques for the clusterhead selection and cluster

formation problems. While Nikolidakis et al. [76] and Kuila and Jana [52] propose LP models for a special case of the clusterhead selection problem, future work could employ mathematical programming techniques for the general clusterhead selection and cluster formation problems. This work might examine exact decomposition-based solution techniques, such as column generation and Lagrangian relaxation.

Typically, sinks are assumed to exist at specified discrete locations, although some research also regards the placement of sensors and sinks from among a set of discrete candidate locations. The placement of sensors in a more general Euclidean space is a very challenging research problem that warrants investigation. Additionally, if multiple sensor deployment is infeasible or too costly, sensor mobilization may be a viable solution. Future research could consider the presence of a mobile sensor that moves along a set of predetermined discrete locations. Similar to mobile-sink models, a mobile-sensor lifetime maximization model might consider determining a sensor's trajectory and dwelling times at each location. Furthermore, in mobile-sink examples, the speed of the sink is exogenous, and does not utilize any resources within the system. An alternative model regards the case in which sinks have energy too, and this energy is consumed by receiving data and by moving from one location to another. Moreover, the rate at which this energy is consumed would be a function of the sink's speed. Such a model could examine the alternative of maximizing the sink lifetime.

Finally, we submit that many future WSN studies will be guided within context-specific applications. The algorithms presented in this survey are mostly targeted toward models that have broad applicability. When implementing these algorithms for specific applications, certain aspects of the network will need to be tailored for the situation at hand, revealing even richer classes of problems for study.

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Acknowledgments

The authors sincerely thank three anonymous referees for their helpful comments, which led to an expansion of our survey and an improved presentation of its results. This research was supported by the Air Force Office of Scientific Research under grant FA9550-12-1-0353, and the Office of Naval Research under grant N000141310036.