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Maximizing the Lifetime of Query-Based Wireless Sensor Networks

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We consider the problem of maximizing the lifetime of a query-based wireless sensor network in which all of the sensor nodes are both producers and consumers of network resources. Of particular concern is the problem of selecting a common transmission range for all of the sensor nodes, the resource replication level (or time-to-live counter) and the active/sleep schedule of nodes while satisfying connectivity and quality-of-service constraints. To this end, we first formulate a general, mixed integer programming model that selects the optimal operating parameters in each period of a finite planning horizon. Subsequently, we examine in detail specific connectivity and quality-of-service constraints that can be considered within this framework. Due to the complexity of the model, we formulate an alternative linearized version that can be solved more efficiently. Additionally, we devise a simple algorithm to solve a special case of the problem when alive nodes are always active. Computational results indicate that the maximum attainable lifetime can be significantly improved by adjusting the key operating parameters as sensor nodes fail over time due to energy depletion.

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1. INTRODUCTION

A wireless sensor network (WSN) is a collection of small, autonomous, low-cost sensing devices (sensor nodes) linked via a wireless communication medium. Each node in a WSN is capable of sensing, computation and communication, albeit in a limited way. Many WSNs use one or more base stations (or sink nodes) to gather data from the other nodes (the sources) in the network. By contrast, in query-based WSNs, all of the nodes can be both sources and sinks, and the communication between nodes is either event- or query-driven. That is, communication between nodes is triggered either by the witnessing of a significant event (e.g. a sudden increase in temperature), or the generation of a query (e.g. a request for a temperature reading at a distant region of the network). The emergence of WSNs is prevalent in such diverse applications as military, environmental, health care, industrial safety, infrastructure security and residential use (see [Schurgers and Srivastava 2001; Welsh 2004; Flammini et al. 2010; Mainwaring et al. 2002; Milenkovic et al. 2006; Gungor and Hancke 2009; Mishra et al. 2006; Herring and Kaplan 2000] for representative samples of applications). Significant breakthroughs in sensing technologies have enabled the design and manufacture of smaller and smaller sensor nodes with wireless communication capabilities. Because WSNs are able to sense and disseminate information about objects, their environments and their interactions without human intervention, they have generated enormous interest from researchers and practitioners alike [Akyildiz et al. 2002]. Although each WSN application is unique, the networks themselves have in common small sensor nodes with limited transmitting and sensing ranges, limited energy reserves, limited local memory, and limited computational capabilities.

Because WSNs are often deployed to detect and transmit critical information, the network's lifetime is an important measure of performance. However, the very definition of WSN lifetime has emerged as an important issue in the sensor networking community. Dietrich and Dressler [Dietrich and Dressler 2009] surveyed several definitions of WSN lifetime including the number of nodes that are still functional, network coverage, network connectivity, and quality-of-service (QoS) considerations (e.g. event detection rates). The appropriate lifetime definition is usually governed by the network configuration and the means by which data are retrieved and disseminated. Some recent work has focused on delay-tolerant WSNs that use a single mobile sensor node (or mobile sink) to visit a fixed set of locations and gather the accumulated data of surrounding nodes. In this context, the network lifetime is viewed as the number of tours the mobile sink can complete, subject to energy consumption and flow conservation constraints, as well as a requirement that each node drains its accumulated arrival data when the sink visits. The decision variables are the dwell times of the sink at each location and the transmission rate used by the sensors at that location. Decomposition algorithms have been employed to solve these difficult mixed-integer programs (cf. [Papadimitriou and Georgiadis 2005; Yun and Xia 2010; Behdani et al. 2013; Yun et al. 2013; Behdani et al. 2012]).

By contrast, in delay-intolerant networks, the sensed information is time sensitive – that is, deadlines are imposed on significant witnessed events and on query packets transmitted throughout the network. To ensure the timely delivery of critical data, it may be necessary to adjust network parameters over time (e.g. increasing the transmission range of nodes) at the expense of increased energy consumption. However, there is a delicate tradeoff between meeting the performance requirements of the network and prolonging its useful lifetime by expeditious use of its energy reserves. In this context, network lifetime may refer to the number of consecutive time periods in which the network is connected, or satisfies certain QoS constraints. In any case, network lifetime metrics are strongly correlated with the functionality of the sensor nodes which are failure-prone due to energy depletion, degradation due to environmental effects, or adversarial attacks. (Our focus here is on failures due to energy depletion.) The main purpose of this paper is to provide a general optimization framework for maximizing the lifetime of a query-based WSN with energy-constrained sensor nodes that detect and transmit time-critical data, subject to quality-of-service and connectivity constraints. In this general context, the network lifetime is viewed as the first time at which the network fails to satisfy either the quality-of-service or the connectivity constraint.

Network energy conservation can be achieved in several ways including the design of optimal (or near-optimal) routing protocols, the use of node sleep schedules, adjustable transmission ranges, and the optimization of important network operating parameters (e.g. the hop counter for generated packets). Routing techniques have been extensively reviewed by Al-Karaki and Kamal [Al-Karaki and Kamal 2004] in a cogent survey. However, our work here is focused instead on the latter three strategies for maximizing network lifetime, which are discussed in what follows.

First, it is well known that remarkable energy conservation can be achieved by turning-off the communication capability (radio) of a node during idle time-slots (see [Akyildiz et al. 2002; Sinha and Chandrakasan 2001; Ye et al. 2004]). When a node is in *active* mode, it performs all of its sensing, computation and communication functions; however, when it is in *sleep* mode, it continues sensing the environment but does not communicate with other nodes in order to conserve energy. This energy conservation comes at the expense of throughput capacity and increased response time. Niyato and Hossain [Niyato et al. 2007] developed a queueing model to investigate the performance of different sleep and wake-up strategies. Chiasserini et al. [Chiasserini et al. 2007] developed a fluid model to analyze WSNs with a random sleep scheme, where at a time instant there is a certain probability that an arbitrary node is active. Liu et al. [Liu et al. 2010] developed a queueing-based framework to study the interaction between random sleep schemes and packet delivery delay, and network throughput as a measure of network performance. Ha et al. [Ha et al. 2006] developed an integer linear programming model based on a network flow model to schedule the active/sleep modes that satisfy a network coverage constraint. Sarkar and Cruz

[Sarkar and Cruz 2004] proposed a dynamic programming formulation to numerically solve the problem of selecting optimal sleep times and durations, subject to an average delay constraint. Turkogullari et al. [Turkogullari et al. 2010] developed a mixed integer linear programming model to maximize network lifetime by simultaneously setting sleep schedules, sensor locations and data routing, and they proposed heuristic algorithms. They concluded that, by simultaneously considering sleep schedules, node placement and routing protocols in a single model, the network lifetime can be substantially improved. Cerulli et al. [Cerulli et al. 2012] developed an exact column generation algorithm to maximize network lifetime by determining subsets of sensors that cover an entire set of targets in a sensor field and assigning the activation times of the covering sets. Their model considers adjustable sensing ranges for the nodes.

The maximum one-hop transmission distance of a node is called its *transmission range*. Chen et al. [Chen et al. 2002] and Deng et al. [Deng et al. 2004] determined the optimal transmission range of all nodes that minimizes the total network energy expenditure and demonstrated the impact of transmission range on WSN lifetime using a general energy consumption model. They showed that a larger transmission range decreases response time at the expense of higher energy consumption. Gao et al. [Gao et al. 2006] showed on a simple linear network (i.e. a WSN in which sensor nodes are arranged in a serial configuration) that energy expenditure can be reduced significantly if the transmission range is updated when the node density changes due to the nodes' active/sleep schedules. Ata [Ata 2005] considered the problem of dynamically choosing the transmission rate in a general wireless communications network to minimize the long-run energy consumption per unit time, subject to a QoS constraint. In that work, the transmission queue was modeled as a finite-buffer, $M/M/1$ queueing system. Aneja et al. [Aneja et al. 2010] presented three model formulations to assign transmission power (a proxy for transmission range) to each node such that there is a directed path between each pair of sensor nodes. A branch-and-cut algorithm was developed to solve the problem, and its performance was evaluated empirically using a network with up to 150 nodes.

The *resource replication level* is the number of times a resource is reproduced in the network. For example, if a node in the network senses a spike in the ambient temperature locally, it may forward that information, by way of a transmitted packet, to at most ℓ other nodes in the network. The resource (i.e. the temperature reading) is therefore replicated in the network ℓ times. The integer ℓ is sometimes referred to as the *time-to-live counter* or hop counter. Studies related to this parameter are relatively sparse. Bellavista et al. [Bellavista et al. 2005] developed a simulation model (REDMAN) to explore resource replication levels and related network settings. Krishnamachari and Ahn [Krishnamachari and Ahn 2006] derived cost expressions as a function of the resource replication level for unstructured networks in which the source node is unknown. They used expanding ring queries to search for the information and formulated a nonlinear programming (NLP) model to determine the optimal number of resource replicates, subject to a network storage capacity constraint. Ahn and Krishnamachari [Ahn and Krishnamachari 2007] extended the results of [Krishnamachari and Ahn 2006] to structured networks in $d-$dimensional space, and in [Ahn and Krishnamachari 2006a], studied structured and unstructured two-dimensional grid and random topology networks. Ahn and Krishnamachari [Ahn and Krishnamachari 2006b] presented a model to obtain the optimal resource replication level that minimizes the total expected cost of replication and searching, subject to a storage capacity constraint. An algorithm for dissemination and retrieval of information that ensures an even geographical distribution of informed nodes was proposed for unstructured wireless ad-hoc networks by Miranda et al. [Miranda et al. 2007]. Chen et al. [Chen et al. 2011] developed an algorithm based on hop-by-hop data delivery for information retrieval. Their aim was to determine the optimal source and path level redundancy considering application-specific reliability and timeliness requirements. The source level redundancy refers to the use of multiple sensors to return the requested sensor reading. The path level redundancy is the use of multiple paths to relay the reading to the query node. Mann et al. [Mann et al. 2008] used the limiting distribution of a three-dimensional Markov process to formulate an energy cost function in which the total packet arrival rate to a node's transmission queue is a proxy for energy expenditure. Subsequently, they optimized the resource replication level subject to a constraint on the allowable proportion of query failures. The model includes time-limited event agents and queries but assumes an infinite transmission range and is restricted to exponentially distributed event and query lifetimes. Degirmenci et al. [Degirmenci et al. 2013] extended the results in [Mann et al. 2008] to include general event and query packet lifetimes while taking into account the effect of a limited transmission range on the proportion of query failures.

Although some models have focused on adjusting the transmission range and sensor node sleep schedules to maximize network lifetime, no existing studies consider the simultaneous selection of sensor transmission range, time-to-live counter, and node active/sleep schedules, while accounting for the energy expended by sensor nodes over time. Furthermore, with the exception of [Mann et al. 2008; Degirmenci et al. 2013], none of the existing models accounts explicitly for the limited lifetimes of event or query packets. The primary objective of this research is to provide a general optimization framework to maximize the lifetime of a query-based WSN with energy-constrained sensor nodes that detect and transmit time-critical data, subject to quality-of-service and connectivity constraints. The network lifetime is defined as the number of consecutive time periods in which the network satisfies general quality-of-service and connectivity constraints, and it is maximized by optimally selecting the transmission range, time-to-live counter and node active/sleep schedules for each period in a finite planning horizon. The optimal parameter values within each period are selected *a priori* by solving a nonlinear mixed integer programming model. Additionally, we consider specific QoS and connectivity constraints, the latter of which stems from an improved connectivity approximation that explicitly accounts for the boundary effects of the network's deployment region. Finally, we examine a special case of the optimization model that ignores active/sleep decisions and show that the solution to this problem is obtained by solving a sequence of single-period models.

The remainder of the paper is organized as follows. Section 2 describes the WSN model and presents the general mixed integer programming model before presenting specific QoS and connectivity constraints. By considering the boundary effects of the deployment region, we also provide an improved approximation for the network connectivity probability. Section 3.1 then presents a linearized version of the model that is amenable to solution by a commercial solver (such as CPLEX [CPLEX 2011]). Section 3.2 examines a special case of the main model in which alive nodes are always active. For this case, we present a simple algorithm for solving a sequence of single-period problems to obtain the optimal solution. Section 4 presents computational experiments that illustrate the advantages of optimizing the network parameter values. Finally, in Section 5, we summarize the main results of our work and discuss a few avenues for future research.

2. PROBLEM FORMULATION

In this section, we first describe the dynamics of a query-based WSN model before introducing a general optimization framework that can be used to optimize the performance of the WSN in a variety of settings. Specifically, the mathematical programming model selects the optimal transmission range, time-to-live counter and active/sleep schedules for each time period of a finite planning horizon to maximize the overall network lifetime. Subsequently, we derive an improved (approximate) connectivity constraint for the WSN that explicitly accounts for the border effects of the deployment region, and we discuss representative energy expenditure and QoS constraints that can be used within the optimization framework.

2.1. WSN Model Description

Consider a WSN with N sensor nodes deployed on a two-dimensional square sensor field $\mathcal{R}$ whose area is L. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote the set of nodes, and assume the nodes are randomly (spatially uniformly) distributed in $\mathcal{R}$. Every node in the network is assumed to use the same transmission range r. Nodes i and j communicate if and only if they are within transmission range. We assume the nodes in the network are stationary and homogeneous (i.e. they have identical physical attributes, energy storage in the form of an on-board battery, and identical sensing and computing capabilities).

For many WSN applications, a mobile sensor node is used to gather relevant data and to disseminate those data as needed (cf. [Yun et al. 2013]). By contrast, in a hybrid push-pull WSN, all of the sensor nodes are both producers (sources) and consumers (sinks) of resources. In this context, a *resource* refers to specific data that are witnessed, stored and disseminated by the network's nodes. In addition to data gathering, nodes are also required to execute specific applications in support of the network's objectives. When a node requires access to a resource that is not available locally, it must query the network to locate the necessary information and/or services. When a node witnesses a relevant phenomenon, it broadcasts this information to a subset of the network by means of an *event agent* – a packet that describes the resource available, the location of the resource, and the duration of time the resource is available or valid. We term this duration the *event lifetime*.

In this paper, we assume that event agents are transmitted from node-to-node via a random walk until either the data expires (i.e. it reaches its deadline), or it exhausts its time-to-live counter – a positive integer (ℓ) representing the maximum number of times the resource may be replicated in the network. It is worth noting that a variety of routing protocols can be assumed (cf. [Mann et al. 2007]), but our model assumes that nodes transmit to a randomly selected node from the set of nodes within its transmission range. While this assumption may appear restrictive at first glance, a random walk protocol is often very appropriate for large-scale networks because, as noted by Rodero-Merino et al. [Rodero-Merino et al. 2010], it is simple to implement, requires only local information to make routing decisions, and consumes minimal network energy and bandwidth. Moreover, it can easily adapt to changes in network topology due to node failures and/or sleep schedules. Each sensor node is equipped with an on-board *event table*. Whenever an event agent is received, or an event is witnessed by the node, the contents of the event agent are added to the event table, and the node is labeled as *informed* as long as the event agent has not expired.

Nodes can also generate *queries* to request data from the network. A query contains at least three pieces of information: the identifier and/or location of the node originating the request, the resource sought, and the maximum amount of time the query is permitted to traverse the network in search of an informed node. Only informed nodes are capable of answering the queries of uninformed nodes. Similar to event agents, queries are forwarded from node-to-node via a random walk. If a query is received by an informed node, the query is terminated and the informed node generates a response that is returned to the query origin node via shortest-path routing. The response packet contains the information stored in the informed node's event table and, if available, the desired data. If a query cannot locate an informed node before its designated *query lifetime* expires, the query is said to have failed. The total proportion of generated queries that are not answered on time, i.e. the *limiting proportion of query failures*, is a critical performance measure for a query-based WSN (see [Mann et al. 2008]).

In addition to event agents and queries, the sensor nodes themselves have limited lifetimes. If a node fails due to battery drain, we say the node is *failed*. Otherwise, the node is said to be *alive*. An alive node is either in *sleep* mode or *active* mode. When in sleep mode, a node turns off its sensing and communication capabilities to conserve energy (see [Anastasi et al. 2009]). It is very common in dense networks to place a subset of network nodes in sleep mode for energy conservation to prolong the lifetime of the network. However, the performance of the network can suffer when only some of the nodes are available for sensing and forwarding event agents or query packets.

The optimization framework of Section 2.2 considers a discrete, finite planning horizon $\mathcal{T} = \{1, 2, \ldots, T\}$, where each element of $\mathcal{T}$ is a decision epoch, and the time between two epochs is referred to as a period (e.g. one week). At the beginning of period τ, each alive node can either switch to sleep mode with probability $(1 - p_\tau)$, or stay active with probability p_τ. We assume that p_τ is the same for all nodes. Our primary objective is to devise a model to determine the optimal transmission range (r_τ), event time-to-live counter (ℓ_τ), and probability that a node is in active mode (p_τ) for each $\tau \in \mathcal{T}$. The following notation will be used in the model:

— $\mathcal{A}$: The set of possible policy decisions given by

$$\mathcal{A} \;=\; \{(r, \ell, p) : r \in (0, \overline{r}],\, \ell \in \mathcal{N} \setminus \{N\},\, p \in (0, 1]\}\,,$$

where $\overline{r} = \sqrt{2L}$ is the maximum distance between two nodes in the square deployment region $\mathcal{R}$;

— $a_\tau \in \mathcal{A}$: The decision to make at the start of period τ. The triplet $a_\tau = (r_\tau, \ell_\tau, p_\tau)$ includes decisions about the transmission range (r_τ), event time-to-live counter (ℓ_τ), and the proportion of active nodes (p_τ);

— s_τ: The integer number of alive nodes at the start of period τ, $\;1 \le s_\tau \le N$;

— n_τ: The expected number of active nodes at the start of period τ. Conservatively, set

$$n_\tau = \lfloor s_\tau p_\tau \rfloor;$$

— U_τ: The random battery energy consumed by any active node during period τ. We assume that the energy consumed by the nodes is an independent and identically distributed (i.i.d.) sequence of non-negative, non-defective random variables;

— $c(s_\tau, a_\tau)$: The expected battery energy consumed by an active node during period τ. That is, $c(s_\tau, a_\tau) = \mathbb{E}(U_\tau)$;

— b_τ: The expected available battery energy at a node at the start of period τ. To simplify matters, we will use the expected available energy as a point estimate of the true available energy at a single node. A node in sleep mode consumes no energy with probability $1 - p_\tau$; however, with probability p_τ, it is in active mode and consumes energy. Therefore, the expected available energy during period $\tau + 1$ is obtained recursively by

$$b_{\tau+1} = b_\tau - p_\tau\, c(s_\tau, a_\tau);$$

— $f(s_\tau, a_\tau, b_\tau)$: The probability that a node alive at the start of period τ fails during this period. We assume that any active node fails at the end of period τ if the energy required during the period exceeds the *mean* energy available at the start of the period. Specifically,

$$f(s_\tau, a_\tau, b_\tau) = \mathbb{P}(U_\tau > b_\tau), \quad \tau \in \mathcal{T} \setminus \{T\}.$$

We use this probability to compute the conservative estimate

$$s_{\tau+1} = \lfloor s_\tau - f_\tau(s_\tau, a_\tau, b_\tau) n_\tau \rfloor,$$

since only active nodes can fail due to battery drain;

— $\Delta(n_\tau, a_\tau)$: A generic function describing the steady state proportion of query failures in a query-based WSN with n_τ active nodes operating under policy a_τ. This function represents the QoS measure;

— $\Psi(n_\tau, a_\tau)$: A generic function describing the connectivity probability of a WSN with n_τ active nodes operating under policy a_τ;

— x_τ: The status of the network at the start of period τ.

$$x_\tau = \begin{cases} 1, & \text{if the network is } \textit{functional}, \\ 0, & \text{otherwise.} \end{cases}$$

By *functional*, we mean that the network is connected and satisfies the QoS requirement at the start of period τ.

Subsection 2.2 presents the general optimization framework, followed by three subsections describing specific instances of the functions c, Ψ and Δ, respectively. However, it is important to note that this framework is not limited to these specific functions and can be tailored to specific applications as needed.

2.2. General Problem Formulation

To set the stage for the main model, let ρ be the minimum allowable probability that the network is connected, let φ be the maximum allowable proportion of query failures (in steady state), and let $\bar{b}$ denote the initial energy available at a node. In general, ρ should be close to 1 and φ should be close to 0. Problem $(\mathbf{P}_1)$ maximizes the network lifetime by choosing the optimal transmission range (r_τ), time-to-live counter (ℓ_τ) and proportion of active nodes (p_τ) for each period $\tau \in \mathcal{T}$.

$$\text{Problem } (\mathbf{P}_1) \qquad \max \sum_{\tau=1}^{T} x_\tau \tag{1a}$$

$$\text{s.t.} \quad \Delta(n_\tau, a_\tau) \leq \varphi + M(1 - x_\tau), \quad \tau \in \mathcal{T} \tag{1b}$$

$$\Psi(n_\tau, a_\tau) \geq \rho - M(1 - x_\tau), \quad \tau \in \mathcal{T} \tag{1c}$$

$$n_\tau \leq s_\tau p_\tau, \quad \tau \in \mathcal{T} \tag{1d}$$

$$s_{\tau+1} \leq s_\tau - f(s_\tau, a_\tau, b_\tau) n_\tau, \quad \tau \in \mathcal{T} \setminus \{T\} \tag{1e}$$

$$b_{\tau+1} = b_\tau - p_\tau c(s_\tau, a_\tau), \quad \tau \in \mathcal{T} \setminus \{T\} \tag{1f}$$

$$x_\tau \geq x_{\tau+1}, \quad \tau \in \mathcal{T} \setminus \{T\} \tag{1g}$$

$$a_\tau = (r_\tau, \ell_\tau, p_\tau) \in \mathcal{A}, \quad \tau \in \mathcal{T} \tag{1h}$$

$$x_\tau \in \{0, 1\}, \, b_\tau \in [0, \bar{b}], \quad \tau \in \mathcal{T} \tag{1i}$$

$$s_\tau \in \{0, 1, \ldots, N\}, \; n_\tau \in \{0, 1, \ldots, N\}, \, \tau \in \mathcal{T}. \tag{1j}$$

The objective function (1a) represents the number of *consecutive* time periods the network satisfies the QoS and connectivity requirements. In constraints (1b) and (1c), M is a large, positive constant that forces x_τ to assume the value 1 if and only if the QoS and connectivity constraints are simultaneously satisfied in the τth period. Also included are constraints (1d) and (1e) to set the number of active and alive nodes, respectively. Constraint (1f) ensures that the expected available energy in each time period is computed considering the energy consumed in the prior time period. Constraint (1g) ensures that the network can be functional in period $\tau + 1$ only if it was functional in period τ. Finally, the admissible ranges of variables are given in (1h) through (1j).

Problem ($\mathbf{P}_1$) is a broadly applicable optimization model for maximizing the lifetime of the network and can be solved for arbitrary connectivity (Ψ), energy expenditure (c), and quality-of-service (Δ) functions, as long as these functions can be obtained analytically or numerically. The next three subsections consider specific functions for inclusion in the model. In particular, the next subsection presents an approximate network connectivity probability that explicitly accounts for the boundary effects of the deployment region.

2.3. Approximate Connectivity Constraint

Network connectivity is obviously an important consideration for static WSNs whose nodes are subject to failure and sleep schedules. In this subsection, we provide an improved approximate expression for the probability that the network is connected. Viewing the WSN as an undirected graph, the network is said to be *connected* if for each pair of nodes $i, j \in \mathcal{N}$, there exists at least one path between i and j. As noted by Bettstetter [Bettstetter 2002], the connectivity of a WSN is closely related to the number of *isolated* nodes in the network. A node $i \in \mathcal{N}$ is said to be isolated if there are no other nodes within its transmission range (i.e. if its node degree is 0); the WSN contains no isolated nodes if the minimum node degree of the network is positive. The probability that there are no isolated nodes in a random graph can be used to bound the connectivity probability from above, and we use this fact to establish an approximate connectivity constraint.

To frame this discussion, we adopt the following definitions and notation, similar to those used in [Bettstetter 2002]. The WSN is a random graph $\mathcal{G}$ whose N stationary nodes are uniformly distributed in a two-dimensional square region $\mathcal{R}$ with area L. That is, the locations of the nodes can be viewed as points in $\mathcal{R}$ generated by a two-dimensional, spatial Poisson process with constant intensity (node density) N/L. Assuming that each sensor node uses the same transmission range r, and that $L \gg \pi r^2$, one can ignore the border effects of $\mathcal{R}$ to obtain the exact probability that no node is isolated. Let E_0 be the event that no node is isolated when the border effects can be ignored, and let $\widetilde{\Lambda}$ be the true probability that no node is isolated in the network. Clearly, $\widetilde{\Lambda} \leq \mathbb{P}(E_0)$ since the degrees of nodes near the borders of $\mathcal{R}$ are smaller than those whose transmission areas are contained inside of $\mathcal{R}$. Let C be the event that the network is connected. Using basic results for spatially homogeneous Poisson point processes in two dimensions (cf. Diggle [Diggle 2003]), Proposition 2.1 provides an upper bound for the probability that the network is connected, $\mathbb{P}(C)$.

PROPOSITION 2.1. *Suppose $\mathcal{G}$ is an ad hoc WSN with N stationary sensor nodes distributed uniformly in a region of area L. Assuming each node uses the same transmission range r ($r > 0$), an upper bound for the connectivity probability of the network is*

$$\mathbb{P}(C) \leq \widetilde{\Lambda} \leq \mathbb{P}(E_0) = \left[1 - \exp(-N\pi r^2/L)\right]^N . \tag{2}$$

By Theorem 1 of [Bettstetter 2002], the minimum transmission range needed to ensure no isolated nodes with probability ρ is

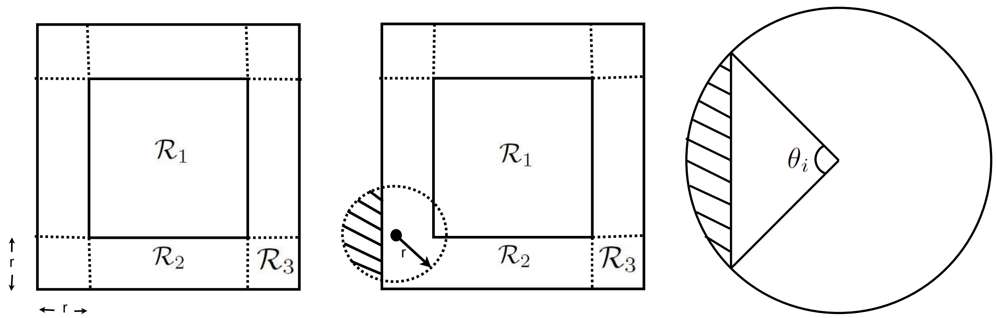
$$r \geq \sqrt{\frac{-\ln(1-\rho^{1/N})}{\pi N/L}}, \tag{3}$$

or equivalently, one may choose r such that

$$\rho \leq \left[1 - \exp(-N\pi r^2/L)\right]^N .$$

To simplify notation, let $\widehat{\Lambda}_1 := \left[1 - \exp(-N\pi r^2/L)\right]^N$ serve as an approximation for $\widetilde{\Lambda}$. It is important to note that the upper bound of (2) and, consequently, the lower bound of (3), ignore the border effects of the deployment region. By accounting for these effects, our aim is to derive an improved approximation for $\widetilde{\Lambda}$ (call it $\widehat{\Lambda}_2$), thereby providing a tighter upper bound for $\mathbb{P}(C)$. Although (2) provides only an upper bound for $\mathbb{P}(C)$, Bettstetter [Bettstetter 2004] has shown that when $\widetilde{\Lambda}$ is close to 1, the bound is in fact rather tight.

Let $d_i(r)$ be the degree of node $i \in \mathcal{N}$ when all the nodes use transmission range r. Our approximation is formed by partitioning $\mathcal{R}$ into three subareas, $\mathcal{R}_1$, $\mathcal{R}_2$ and $\mathcal{R}_3$, as depicted in Figure 1a.



(a) Partitioning the region $\mathcal{R}$. (b) The effect of $\mathcal{R}$'s borders. (c) Transmission area of a node.

Fig. 1. Graphical depiction of the partitioning of $\mathcal{R}$ and the border effects.

Nodes in $\mathcal{R}_1$ are located at least r units away from any of the borders. Nodes in $\mathcal{R}_2$ are located closer than r units to one of the borders but at least r units away from the others. Nodes in $\mathcal{R}_3$ are located closer than r units to two of the borders. To simplify matters slightly, we will use the degree of nodes in $\mathcal{R}_2$ to approximate the degree of nodes in $\mathcal{R}_3$. The expected degrees of nodes in $\mathcal{R}_1$ and $\mathcal{R}_2$ are provided in Lemma 2.2.

LEMMA 2.2. *Consider a WSN with $N \geq 1$ nodes. Let $\mathcal{N}_1$ and $\mathcal{N}_2$ be the set of nodes located in regions $\mathcal{R}_1$ and $\mathcal{R}_2$, respectively. Then,*

$$\mathbb{E}[d_i(r)] \approx \begin{cases} \dfrac{N\pi r^2}{L}, & i \in \mathcal{N}_1, \\ \dfrac{(3\pi^2+4)r^2}{4\pi} \cdot \dfrac{N}{L}, & i \in \mathcal{N}_2. \end{cases}$$

PROOF. Nodes in $\mathcal{R}_1$ are located at least r units away from any of the borders; therefore, their transmission area is πr^2, and the expected node degree is just the node density multiplied by the area, or $(N/L)\pi r^2$. Nodes in $\mathcal{R}_2$ are located closer than r units to the border, so they have a smaller effective transmission area, leading to a smaller degree. Figures 1b and 1c illustrate the transmission area of a node located in $\mathcal{R}_2$. In these two figures, no nodes are located in the shaded regions. Let $A_0(i)$ be the area of intersection between the transmission area of node i and the network's deployment region. Moreover, let θ_i be a random variable denoting the central angle of the circle surrounding the transmission area of node i so that θ_i sweeps the arc that remains of the network's deployment region as seen in Figure 1c. Then, for $i \in \mathcal{N}_2$

$$A_0(i) = \pi r^2 - \left(\pi r^2 \frac{\theta_i}{2\pi} - \frac{r^2 \sin\theta_i}{2}\right),$$

and the expectation of $A_0(i)$ is

$$\begin{aligned}\mathbb{E}[A_0(i)] &= \pi r^2 - \frac{r^2}{2}\int_0^{\pi} (u - \sin u)\,\frac{1}{\pi}\,\mathrm{d}u \\ &= \frac{(3\pi^2+4)r^2}{4\pi}.\end{aligned} \tag{4}$$

Therefore, the expected degree of a node in $\mathcal{R}_2$ is $(N/L)[(3\pi^2+4)r^2]/4\pi$. $\square$

The expression in (4) will also be used to approximate $\mathbb{E}[A_0(i)]$ for each $i \in \mathcal{N}_3$, where $\mathcal{N}_3$ is the set of nodes located in region $\mathcal{R}_3$. It is worth noting that we followed an approach here similar to the one used in [Xing et al. 2009]; however, in [Xing et al. 2009], the authors used a lower bound for the expected transmission area of nodes located in $\mathcal{R}_2$, whereas equation (4) is exact. Therefore, a tighter bound on $\mathbb{P}(E_0)$ can be obtained. The following result from [Bettstetter 2004] gives an exact expression for $\mathbb{P}(E_0)$ as a function of the expected degree of a node located in the deployment region. We make use of this result, along with Lemma 2.2, to derive our approximation.

LEMMA 2.3 (EQUATION (23) OF [BETTSTETTER 2004]). *Consider a node at a given location $\boldsymbol{x} \in \mathcal{R}$ that is randomly placed according to a p.d.f. $h(\boldsymbol{x})$. Let $g(r, \boldsymbol{x})$ be the expected degree of a node located at x using transmission range r. Given a WSN with $N \geq 120$ and $\pi r^2/L \leq 0.08$, the probability that there is no isolated node in the network is*

$$\mathbb{P}(E_0) = \exp\left(-N\int_{\mathcal{R}} e^{-g(r,\boldsymbol{x})} h(\boldsymbol{x})\mathrm{d}\boldsymbol{x}\right).$$

Next, we provide an approximation for the probability that there is no isolated node in the network.

PROPOSITION 2.4. *Assuming that nodes are spatially uniformly distributed in $\mathcal{R}$, considering the boundary effects, the probability that there is no isolated node in the network, $\widetilde{\Lambda}$, is approximated by*

$$\begin{aligned}\widetilde{\Lambda} \approx \widehat{\Lambda}_2 = \exp\left[-Ne^{-\frac{N\pi r^2}{L}}\left(\frac{(\sqrt{L}-2r)^2}{L}\right)\right] \\ \times \exp\left[-Ne^{-\frac{N(3\pi^2+4)r^2}{4\pi L}}\left(1-\frac{(\sqrt{L}-2r)^2}{L}\right)\right].\end{aligned} \tag{5}$$

PROOF. Because we assume a uniform node distribution over a finite, square deployment region $\mathcal{R}$, the p.d.f. $h(\boldsymbol{x})$ is

$$h(\boldsymbol{x}) = \frac{1}{L}, \quad \text{for all } \boldsymbol{x} \in \mathcal{R}.$$

By Lemmas 2.2 and 2.3,

$$\begin{aligned}\widehat{\Lambda}_2 &= \exp\left[-N\left(\int_{\mathcal{R}_1} e^{-\frac{N\pi r^2}{L}}\frac{1}{L}\mathrm{d}\boldsymbol{x} + \int_{\mathcal{R}_2\cup\mathcal{R}_3} e^{-\frac{N(3\pi^2+4)r^2}{4\pi L}}\frac{1}{L}\mathrm{d}\boldsymbol{x}\right)\right] \\ &= \exp\left[-Ne^{-\frac{N\pi r^2}{L}}\left(\frac{(\sqrt{L}-2r)^2}{L}\right)\right] \times \exp\left[-Ne^{-\frac{N(3\pi^2+4)r^2}{4\pi L}}\left(1-\frac{(\sqrt{L}-2r)^2}{L}\right)\right].\end{aligned}$$

□

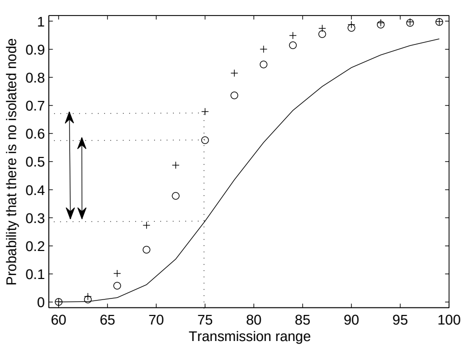
We compare the quality of the approximations $\widehat{\Lambda}_1$ and $\widehat{\Lambda}_2$ to simulated values of $\widehat{\Lambda}$ on a large number of randomly generated networks. We deployed, respectively, 1000 and 5000 nodes on a 1500 m × 1500 m region and determined if the network contains at least one isolated node (for a given transmission range r). The experiment was replicated K times and the proportion of networks with no isolated nodes estimated. Specifically, let $\mathcal{G}_i$ denote the ith generated network and let

$$\mathbf{1}(\mathcal{G}_i) = \begin{cases} 1, & \text{if network } i \text{ has no isolated nodes,} \\ 0, & \text{if network } i \text{ has at least one isolated node.} \end{cases}$$

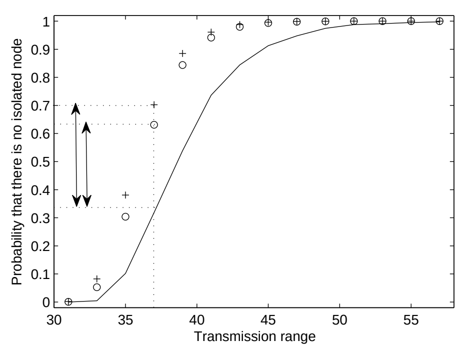
Assuming existence of the limit,

$$\frac{1}{K}\sum_{i=1}^{K}\mathbf{1}(\mathcal{G}_i) \to \widetilde{\Lambda} \quad \text{w.p. } 1$$

as $K \to \infty$ by the strong law of large numbers. Therefore, for K sufficiently large, we obtain a reasonable (relative frequency) estimate of $\widetilde{\Lambda}$. For both scenarios ($N = 1000$ and $N = 5000$), and for each selected transmission range, we randomly generated $K = 10^4$ networks. Figure 2 depicts the relative performance of the approximations.



(a) $N = 1000$ nodes.



(b) $N = 5000$ nodes.

Fig. 2. Comparison of $\widetilde{\Lambda}$ values: (-) Simulated values; (+) approximation $\widehat{\Lambda}_1$; (o) approximation $\widehat{\Lambda}_2$. Nodes deployed on a 1500 m×1500 m square region.

As expected, the approximations are close to the simulated values when $\widetilde{\Lambda}$ is close to 1. However, both Figures 2a and 2b indicate that the upper bound with border effects ($\widehat{\Lambda}_2$) is tighter than the one that ignores border effects ($\widehat{\Lambda}_1$) for the majority of transmission range values. Therefore, we prefer to use $\widehat{\Lambda}_2$ as a bound for the network connectivity probability as it exhibits better overall performance.

Finally, we let $\Psi(n_\tau, a_\tau)$ be the probability that the network is connected at time τ and note that Ψ is an explicit function of n_τ and r_τ. Based on the empirical tests presented in this subsection, we use the result of Proposition 2.4 to ensure the network remains connected with high probability in the optimization model. Specifically, for each $\tau \in \mathcal{T}$,

$$\Psi(n_\tau, a_\tau) \approx \widehat{\Lambda}_2 = \exp\left[-n_\tau e^{-\frac{n_\tau \pi r_\tau^2}{L}} \left(\frac{(\sqrt{L} - 2r_\tau)^2}{L}\right)\right] \times \exp\left[-n_\tau e^{-\frac{n_\tau (3\pi^2+4) r^2}{4\pi L}} \left(1 - \frac{(\sqrt{L} - 2r_\tau)^2}{L}\right)\right]. \quad (6)$$

We pause here to remark that the approximation (6) assumes that at the start of period τ, the node density n_τ / L is constant throughout $\mathcal{R}$. However, in general the node density is not constant, as some nodes fail over time due to battery depletion, while others enter sleep mode during certain periods of the planning horizon. Nevertheless, we use (6) as the approximate connectivity due to its tractability and the fact that it accounts for the border effects of the region. The approximation (6) explicitly accounts for the fact that nodes near the borders of the deployment region have smaller node degrees and are more likely to be isolated. As shown in Figure 1, $\widehat{\Lambda}_2$ is a tighter upper bound than the traditional upper bound that does not consider border effects (cf. [Bettstetter 2004]).

2.4. Expected Energy Expenditure

In this subsection, we present an illustrative energy expenditure model for a query-based WSN. To facilitate this discussion, some preliminary notation of this subsection is summarized in Table I.

Table I. Summary of notation for model parameters.

Parameter	Parameter description
μ	Transmitter's exponential transmission rate
λ	Poisson rate of locally-witnessed events
γ	Poisson rate of locally-generated queries
$1/\delta$ ($\delta > 0$)	Mean event lifetime
$1/\beta$ ($\beta > 0$)	Mean query lifetime

Additionally, let $\lambda_q(r_\tau, \ell_\tau, n_\tau)$ be the total arrival rate of event agents and queries to a node's transmission queue in period τ. While this rate depends explicitly on r, ℓ, and n, we will suppress this notation and simply write λ_q. The energy expended for transmitting event agents or forwarding queries serves as a proxy for the total energy expenditure at a node since transmitting is the primary energy-consuming activity. An approximation for λ_q was derived in [Degirmenci et al. 2013] and is given by

$$\lambda_q \approx \lambda \left[\frac{1-(1-\alpha)^{\ell}}{\alpha} \right] + \gamma\pi_0(r) \left[\frac{2-\pi_0(r)}{1-\pi_0(r)} \right]. \tag{7}$$

In equation (7), the value α $(0 < \alpha < 1)$ uniquely solves the fixed-point equation

$$\alpha = \mathbb{E}\left[e^{-[\mu-\lambda_q]Z_e} \right],$$

where Z_e denotes the equilibrium event lifetime and λ_q is a function of α as seen in (7). Assuming the event table is modeled as an $M/G/\infty$ queue, the steady-state probability that a node is uninformed is

$$\pi_0(r) = \exp\left[-\frac{\lambda}{\delta} \left(1 + \sum_{i=1}^{\ell} q(i,r)(1-\alpha)^i \right) \right],$$

where $q(i,r)$ is the probability that a query (or event agent) visits any one of the n active nodes for the first time at the ith visit. For detailed derivations of $\pi_0(r)$ and $q(i,r)$, the reader is referred to Degirmenci et al. [Degirmenci et al. 2013].

The energy expended per transmission by a node can be computed as $E_t = (e_t + e_d r^{\eta})$, where e_t is the energy/bit consumed by the transmitter electronics, e_d accounts for energy dissipated in the transmission, r is the transmission range and η is the path-loss coefficient (see [Gao et al. 2006; Zhang et al. 2010]). Therefore, a model for the expected energy expenditure for transmissions is

$$c(s_\tau, a_\tau) = (e_t + e_d\, r_\tau^{\eta})\, \lambda_q. \tag{8}$$

It is important to note that, due to the dependence of λ_q on r_τ, ℓ_τ and n_τ, we were unable to formally prove the convexity or monotonicity of the function $c(s_\tau, a_\tau)$. However, after extensive numerical testing, it is conjectured that c is continuous and monotone increasing in r_τ.

2.5. Proportion of Query Failures

Here, we present an illustrative QoS function (Δ) that is appropriate for a query-based WSN, namely the limiting proportion of queries that fail to be answered on time. Degirmenci et al. [Degirmenci et al. 2013] developed an approximation for this proportion that has been shown to be very accurate and fairly insensitive to the event and query lifetime distributions. We now briefly review that approximation. The proportion of query failures is obtained by considering the limiting behavior of a single query that is generated at an uninformed node.

Let Q_k denote the status of the query just before it (potentially) joins the transmission queue of the kth node it visits on its sojourn. Specifically, following the $(k-1)$st visit, it is possible that the query will not join the next transmission queue because its lifetime may have ended, or it may have been answered at the $(k-1)$st visited node. At this time instant, the query can be in one of three mutually exclusive and exhaustive states in the set $S = \{0, 1, 2\}$. State 0 means that the query has not yet been answered; state 1 means the query was answered at the $(k-1)$st visited node; and state 2 corresponds to the case when the query fails (i.e. the query expires before visiting the kth node). It was shown in [Degirmenci et al. 2013] that $\{Q_k : k \geq 0\}$ can be modeled as a time-nonhomogeneous discrete-time Markov chain (DTMC) with a well-structured transition probability matrix and limiting distribution. The main result for the limiting proportion of query failures was obtained by conditioning on the query lifetime, denoted by the nonnegative random variable X.

PROPOSITION 2.5 (EQUATION (20) OF [DEGIRMENCI ET AL. 2013]). *Let X be the random query lifetime, and let H denote the cumulative distribution function of X. When the transmission range is r, an approximation for the limiting proportion of query failures, denoted by Δ_r, is*

$$\Delta_r \approx \int_0^\infty v_2(x)\mathrm{d}H(x), \tag{9}$$

where

$$v_2(x) := \lim_{k\to\infty} \mathbb{P}(Q_k = 2|X = x)$$

is the limiting probability that a query fails to be answered on time, given that its lifetime is x.

It was shown in [Degirmenci et al. 2013] that the proportion of query failures depends not only on the transmission range (r_τ), but also on the number of active nodes in the network (n_τ) and the event time-to-live counter (ℓ_τ).

3. SOLUTION APPROACHES

Solving $(\mathbf{P}_1)$ is nontrivial for at least the following reasons. First, constraints (1b) through (1f) are nonlinear in general. Second, the structure of the constraints, as well as the convexity of $c(s_\tau, a_\tau)$ in ℓ_τ, are difficult to prove; therefore, it is unclear if the feasible region is convex. Fortunately, $(\mathbf{P}_1)$ can be viewed as a nonlinear knapsack-like problem with additional constraints. One possible method for addressing this type of problem is to linearize the model (cf. [Hochbaum 1995]) and solve it using a commercial solver (e.g. CPLEX [CPLEX 2011]). In this section, we exploit this approach. We also show how to solve, in a more efficient manner, a special case of the model that assumes alive nodes never enter the sleep mode (i.e. $p_\tau = 1$ for all τ).

3.1. Linearized Model

In this subsection, we linearize problem $(\mathbf{P}_1)$ to set the transmission range (r_τ), time-to-live counter (ℓ_τ) and the proportion of nodes that are in active mode (p_τ), for each $\tau \in \mathcal{T} = \{1, 2, \ldots, T\}$. Piecewise linear approximations of the functions $c(s_\tau, a_\tau)$ and $f(s_\tau, a_\tau, b_\tau)$ (see (1e) and (1f)) are used to convert the nonlinear problem $(\mathbf{P}_1)$ into a linear 0–1 problem. In addition to the previous notation, we introduce the following:

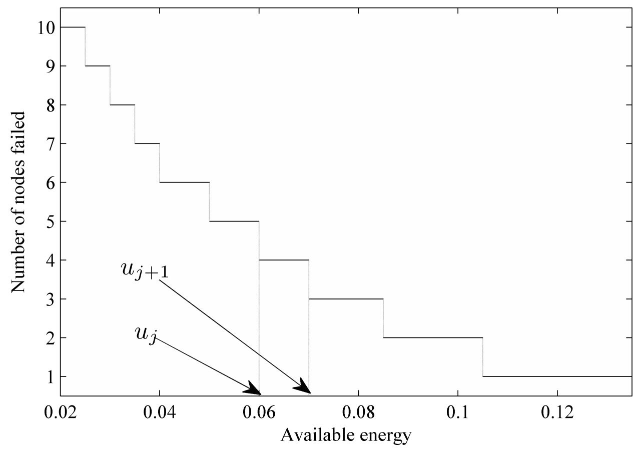


Fig. 3. Discretization of the interval $[0, \bar{b}]$.

— $\mathcal{A}(s) \subset \mathcal{A}$: Given s alive nodes, $\mathcal{A}(s)$ is a subset of policy decisions (r, ℓ, p) satisfying the following requirements:

(i) The proportion of query failures and connectivity requirements are met:

$$\Delta(n, (r, \ell, p)) \leq \varphi \text{ and } \Psi(n, (r, \ell, p)) \geq \rho;$$

(ii) The transmission range is set such that the energy expenditure is minimized for fixed ℓ and p. That is, there does not exist an $r' \neq r$ such that

$$\Delta(n, (r', \ell, p)) \leq \varphi,$$
$$\Psi(n, (r', \ell, p)) \geq \rho,$$
$$c(s, (r', \ell, p)) < c(s, (r, \ell, p)).$$

— c_{sa}: The expected energy expenditure with s alive nodes using $a = (r, \ell, p) \in \mathcal{A}(s)$;

— u_j, $j \in J = \{1, 2, \ldots, B\}$, where B is a finite positive integer so that $|J| < \infty$: A split-point in $[0, \bar{b}]$ to discretize the interval in which the expected available energy is defined. Note that $u_j < u_{j+1}$ and $u_{j+1} - u_j$ is assumed to be small enough to ensure that, for any given $a \in \mathcal{A}(s)$ and $s \in \mathcal{N}$, the number of failed nodes is constant for $b_\tau \in [u_j, u_{j+1})$. Moreover, $u_1 = 0$ and $u_{|J|} = \bar{b}$. Figure 3 depicts the relationship of u_j values to the node failures for a given $a \in \mathcal{A}(s)$ and $s \in \mathcal{N}$, which is denoted by m^τ_{sa} (see the definition of m^τ_{sa} that follows);

— k_{saj}: The number of nodes that fail when there are s alive nodes, the policy decision is a and $b_\tau \in [u_j, u_{j+1})$. Note that the expected number of failed nodes is used as a proxy for this variable, i.e. $k_{saj} = s \cdot p \cdot f(s, a, u_j)$ for $a \in \mathcal{A}(s)$;

— y_{sa}^{τ}: A binary variable to set the policy decisions, i.e. for $\tau \in \mathcal{T}$, $a \in \mathcal{A}(s)$ and $s \in \mathcal{N}$

$$y_{sa}^{\tau} = \begin{cases} 1, & \text{if } a_\tau = a \text{ and } s_\tau = s, \\ 0, & \text{otherwise;} \end{cases}$$

— z_j^{τ}: A binary variable to set the expected available energy, i.e. for $\tau \in \mathcal{T}$ and $j \in J$

$$z_j^{\tau} = \begin{cases} 1, & \text{if } u_j \leq b_\tau < u_{j+1}, \\ 0, & \text{otherwise;} \end{cases} \tag{10}$$

— m_{sa}^{τ}: An integer variable to set the number of nodes failed in the τth period, i.e.

$$m_{sa}^{\tau} = \begin{cases} k_{saj}, & \text{if } y_{sa}^{\tau} = 1 \text{ and } z_j^{\tau} = 1, \\ 0, & \text{otherwise.} \end{cases}$$

Using these parameters and variables, we next present a mixed integer linear model to determine the optimal transmission range, time-to-live counter and proportion of active modes (among those that are alive) for each time in $\mathcal{T}$. We label this formulation as problem $\mathbf{P}_2$.

Problem ($\mathbf{P}_2$)

$$\max \sum_{\tau=1}^{T} x_\tau \tag{11a}$$

$$\text{s.t.} \sum_{\tau \in \mathcal{T}} \sum_{s \in \mathcal{N}} \sum_{a \in \mathcal{A}(s)} c_{sa}\, y_{sa}^{\tau} \leq \bar{b} \tag{11b}$$

$$\sum_{a \in \mathcal{A}(s)} y_{sa}^{\tau} = x_\tau,\ \tau \in \mathcal{T} \tag{11c}$$

$$x_{\tau+1} \leq x_\tau,\ \tau \in \mathcal{T} \setminus \{T\} \tag{11d}$$

$$m_{sa}^{\tau} \leq s y_{sa}^{\tau},\ \tau \in \mathcal{T},\ s \in \mathcal{N},\ a \in \mathcal{A}(s) \tag{11e}$$

$$m_{sa}^{\tau} \geq \sum_{j \in J} k_{saj} z_j^{\tau} - s\left(1 - y_{sa}^{\tau}\right),\ \tau \in \mathcal{T},\ s \in \mathcal{N},\ a \in \mathcal{A}(s) \tag{11f}$$

$$m_{sa}^{\tau} \leq \sum_{j \in J} k_{saj} z_j^{\tau},\ \ \tau \in \mathcal{T},\ s \in \mathcal{N},\ a \in \mathcal{A}(s) \tag{11g}$$

$$\sum_{a \in \mathcal{A}(s)} s y_{sa}^{1} = N \tag{11h}$$

$$\sum_{\substack{s \in \mathcal{N},\\ a \in \mathcal{A}(s)}} s\, y_{sa}^{\tau} \leq \sum_{\substack{s \in \mathcal{N},\\ a \in \mathcal{A}(s)}} (s y_{sa}^{\tau-1} - m_{sa}^{\tau-1}),\ \tau \in \mathcal{T} \setminus \{1\} \tag{11i}$$

$$b_1 = \bar{b}, \tag{11j}$$

$$b_\tau = b_{\tau-1} - \sum_{\substack{s \in \mathcal{N},\\ a \in \mathcal{A}(s)}} c_{sa} y_{sa}^{\tau-1},\ \tau \in \mathcal{T} \setminus \{1\} \tag{11k}$$

$$b_\tau \geq \sum_{j \in J} u_j z_j^{\tau},\ \tau \in \mathcal{T} \tag{11l}$$

$$\sum_{j \in J} z_j^\tau = 1, \ \tau \in \mathcal{T} \tag{11m}$$

$$x_\tau \in \{0, 1\}, \ b_\tau \in [0, \bar{b}], \ \tau \in \mathcal{T} \tag{11n}$$

$$y_{sa}^\tau \in \{0, 1\}, \ \tau \in \mathcal{T}, \ s \in \mathcal{N}, \ a \in \mathcal{A}(s) \tag{11o}$$

$$z_j^\tau \in \{0, 1\}, \ \tau \in \mathcal{T}, \ j \in J \tag{11p}$$

$$m_{sa}^\tau \in \{0, 1, \ldots, s\}, \ \tau \in \mathcal{T}, \ s \in \mathcal{N}, \ a \in \mathcal{A}(s) \tag{11q}$$

The objective function (11a) of ($\mathbf{P}_2$) is identical to (1a) in ($\mathbf{P}_1$). For the sake of completeness, we also include constraint (11b) to account for the limit on remaining useful battery life. With constraint (11c), x_τ is forced to be 1 if and only if there is a feasible policy in the τth period. Constraint (11d) (which mirrors constraint (1g) of ($\mathbf{P}_1$)) ensures the network satisfies the QoS and connectivity requirements in consecutive periods. Constraints (11e), (11f) and (11g) ensure that the number of node failures in the τth period is set. With constraints (11h) and (11i), node failures due to energy depletion are accounted for, and the number of alive nodes remaining in the network can be restricted. With constraints (11j) and (11k), the remaining available energy at a node in the τth period is determined. With constraints (11l) and (11m), z_j^τ is forced to be 1 to satisfy (10). The admissible ranges of variables are set in (11n) through (11q).

It is important to point out that the proposed linearization procedure is broadly applicable for more general query-based WSNs, as long as the optimization model parameters of ($\mathbf{P}_2$), namely $\mathcal{A}(s)$, c_{sa}, k_{saj} and u_j, can be obtained either analytically or numerically. The discussions and derivations of Sections 2.3 through 2.5 allow us to obtain these values for one possible class of WSNs in a straightforward manner; however, more general settings can be considered. Finally, before presenting numerical results for ($\mathbf{P}_2$), we first discuss a simplified version of ($\mathbf{P}_1$) in Section 3.2.

3.2. A Special Case

When all alive sensor nodes are active for all time periods, i.e. $p_\tau = 1$, for all $\tau \in \mathcal{T}$, we can solve a *single-period* model to determine the optimal transmission range and time-to-live counter for each period that maximizes the network's lifetime. In this section, we employ the following assumptions:

A1. $\Delta(n_\tau, a_\tau)$ is nonincreasing in n_τ for each $\tau \in \mathcal{T}$,
A2. $\Psi(n_\tau, a_\tau)$ is nondecreasing in n_τ for each $\tau \in \mathcal{T}$.

Assumption A1 can be justified by the so-called revisiting effect wherein queries or event agents might revisit already visited neighbors. This revisiting effect increases the proportion of time nodes are uninformed, the time to locate an informed node, and consequently, the proportion of failed queries (see [Degirmenci et al. 2013]). As the number of active nodes increases, the revisiting effect is less pronounced. Assumption A2 can be intuitively justified; however, for the specific connectivity function (6), we provide the following sufficient condition for A2 to hold.

PROPOSITION 3.1. *Assumption A2 holds when* $\sqrt{L} > 2r_\tau$ *and*

$$\frac{n_\tau\left(3\pi^2+4\right)r_\tau^2}{4L\pi} \geq 1. \tag{12}$$

PROOF. First note that when (12) holds,

$$1 \leq \frac{n_\tau\left(3\pi^2+4\right)r_\tau^2}{4L\pi} = \frac{n_\tau r_\tau^2}{L\pi} + \frac{3n_\tau\pi r_\tau^2}{4L} < \frac{n_\tau\pi r_\tau^2}{4L} + \frac{3n_\tau\pi r_\tau^2}{4L} = \frac{n_\tau\pi r_\tau^2}{L}.$$

Therefore, using (6),

$$\begin{aligned}\frac{\partial\Psi(n_\tau,a_\tau)}{\partial n_\tau} &= \exp\left[-e^{-\frac{n_\tau\left(4+3\pi^2\right)r_\tau^2}{4L\pi}}n_\tau\left(1-\frac{\left(\sqrt{L}-2r_\tau\right)^2}{L}\right)-\frac{e^{-\frac{n_\tau\pi r_\tau^2}{L}}n_\tau\left(\sqrt{L}-2r_\tau\right)^2}{L}\right]\\ &\quad\times\left(-e^{-\frac{n_\tau\left(4+3\pi^2\right)r_\tau^2}{4L\pi}}\left(1-\frac{\left(\sqrt{L}-2r_\tau\right)^2}{L}\right)\left(1-\frac{n_\tau\left(4+3\pi^2\right)r_\tau^2}{4L\pi}\right)\right.\\ &\quad\left.-e^{-\frac{n_\tau\pi r_\tau^2}{L}}\left(\frac{\left(\sqrt{L}-2r_\tau\right)^2}{L}\right)\left(1-\frac{n_\tau\pi r_\tau^2}{L}\right)\right)\geq 0.\end{aligned}$$

□

Note that the condition $\sqrt{L} > 2r_\tau$ is usually met in practice since the sensor transmission range is relatively small compared to the sensor field dimensions. We can interpret (12) as follows. If the expected node degree of the nodes in $\mathcal{R}_2$ is at least unity, then assumption A2 holds.

Using these assumptions, the optimal solution of ($\mathbf{P}_1$) is obtained when the number of active nodes for each $\tau \in \mathcal{T}$ is maximized. This can be achieved by sequentially solving the following energy minimization problem (the *single-period* model) for each time $\tau \in \mathcal{T}$.

$$\text{Problem } (\mathbf{P}_3) \qquad \begin{aligned}\min\ & c\left(n_\tau,(r_\tau,\ell_\tau,1)\right)\\ \text{s.t.}\ & \Delta\left(n_\tau,(r_\tau,\ell_\tau,1)\right)\leq\varphi\\ & \Psi\left(n_\tau,(r_\tau,\ell_\tau,1)\right)\geq\rho\\ & (r_\tau,\ell_\tau,1)\in\mathcal{A}.\end{aligned}$$

Note that, after solving ($\mathbf{P}_3$) for each $\tau \in \mathcal{T}$, both the number of alive nodes and available energy must be updated as follows:

$$\begin{aligned} n_{\tau+1} &= \lfloor n_\tau - f_\tau(n_\tau,a_\tau,b_\tau)n_\tau\rfloor, && \tau\in\mathcal{T}\setminus\{T\}\\ b_{\tau+1} &= b_\tau - c(n_\tau,a_\tau), && \tau\in\mathcal{T}\setminus\{T\}.\end{aligned}$$

We next propose an algorithm to solve ($\mathbf{P}_3$). To this end, in addition to Assumptions A1 and A2, we also impose the following assumptions for each $\tau \in \mathcal{T}$:

A3. $c_\tau(n_\tau, a_\tau)$ is continuous and nondecreasing in r_τ;
A4. $\Delta(n_\tau, a_\tau)$ is nonincreasing in ℓ_τ;
A5. $\Delta(n_\tau, a_\tau)$ is nonincreasing in r_τ;
A6. $\Psi(n_\tau, a_\tau)$ is nondecreasing in r_τ.

Unfortunately, Assumptions A1 through A6 are difficult to prove analytically because the structures of $c_\tau(n_\tau, a_\tau)$, $\Delta(n_\tau, a_\tau)$ and $\Psi(n_\tau, a_\tau)$ are unknown. However, after extensive empirical testing using (5), (8) and (9) we failed to identify even a single case in which these assumptions are violated. Based on these assumptions, we propose the following algorithm to solve problem ($\mathbf{P}_3$):

Step 0: *Initialize*
$\tau := 1;\ \ b_\tau := \overline{b};\ \ r_0 := 0;$

Step 1: *Check for optimal solution*
$r_{\min} := \min\{r :\ r_{\tau-1} \leq r \leq \overline{r},\ \Psi(n_\tau, (r, 0, 1)) \geq \rho\};$
$\ell' \in \arg\min\{c(n_\tau, (r_{\min}, \ell, 1)) : \ell \in \{1, \ldots, n_\tau - 1\},\ \Delta(n_\tau, (r_{\min}, \ell, 1)) \leq \varphi\};$
If $\exists\, \ell'$, then
$\ell_\tau := \ell';\ \ r_\tau := r_{\min};$
$c^* := c(n_\tau, (r_\tau, \ell_\tau, 1));$
Go to *Step 3*.
Else
$\ell := n_\tau - 1;\ c^* := M;$
Go to *Step 2*.

Step 2: *Search for optimal solution*
$r' \in \arg\min\{c(n_\tau, (r, \ell, 1)) :\ r_{\min} \leq r \leq \overline{r},\ \Delta(n_\tau, (r, \ell, 1)) \leq \varphi\};$
If $\exists\, r'$, then
If $c(n_\tau, (r', \ell, 1)) < c^*$
$\ell^* := \ell;\ r^* := r';$
$c^* := c(n_\tau, (r', \ell, 1));$
$r_{\min} := r';\ \ \ell := \ell - 1;$
Go to *Step 2*.
Else
$\ell_\tau := \ell^*;\ r_\tau := r^*;$
Go to *Step 3*.

Step 3: *Check for feasibility*
If $c^* \leq b_\tau$, then
$x_\tau := 1;\ \ b_{\tau+1} := b_\tau - c^*;$
$\tau := \tau + 1;$
Go to *Step 1*.
Else
$x_\tau := 0,$

End.

In Step 1 of the algorithm, $r_{\min}$ is fixed considering the connectivity constraint, and if $c(n_\tau, (r_{\min}, \ell, 1))$ is convex in ℓ, then a simple bisection algorithm can be used to search for an ℓ that satisfies the QoS constraint. If there exists an ℓ' for given $r_{\min}$, then the solution is optimal due to Assumptions A3 and A6. On the other hand, if there does not exist an ℓ', we set $\ell = n_\tau - 1$ because, in this case, $\Delta(n_\tau, (r, \ell, 1))$ is minimized for any given r by Assumption A4. Therefore, if there exists a feasible solution to the problem, it can be obtained at $\ell = n_\tau - 1$. In Step 2, a simple bisection algorithm can be used to search for an r that satisfies both the QoS and connectivity constraints. In this step, ℓ is decremented by 1. By Assumptions A4 and A5, in order to maintain feasibility, we have $r_{\min} \leq r$. Note that ℓ is decremented until there is no feasible (ℓ, r) that simultaneously satisfies the QoS and connectivity constraints. The algorithm exploits the structural properties assumed in A3–A6; hence, the set of admissible values for r is reduced at each iteration of Step 2.

4. COMPUTATIONAL EXPERIMENTS

4.1. Description of Experiments

In this section, we explore the effect of the optimal choices of transmission range, time-to-live counter and active/sleep schedules on WSN lifetime. To see the significance of parameter settings for each period, we compare four cases on a network with N nodes ($N \in \{600, 700, 800, 900, 1000\}$) deployed randomly on a two-dimensional sensor field with node density 6.25×10^{-3} nodes/m^2 (cf. [Chen et al. 2011]). The four cases we consider are as follows:

(1) **Optimized/Optimized (OO)**: optimized transmission range, active/sleep decisions and time-to-live counter for each period of the planning horizon;
(2) **Fixed/Optimized (FO)**: fixed transmission range, optimized active/sleep decisions and time-to-live counter for each period of the planning horizon;
(3) **Optimized/Fixed (OF)**: optimized transmission range and time-to-live counter for each period of the planning horizon and sensor nodes are always active;
(4) **Fixed/Fixed (FF)**: fixed transmission range, sensor nodes are always active and optimized time-to-live counter.

For each of these four cases, the optimal time-to-live counter (ℓ) is selected for each time period. Although scenarios OO, FO and OF are termed optimal, it is important to note that the optimal decisions for each time period are made *a priori* – not dynamically. Nonetheless, these decisions do, in fact, account for the time-varying topology of the network due to sensor node battery depletion. In cases FO and FF, the transmission range is fixed at its minimum value that is chosen when the transmission range is optimized for each time period.

In the test instances, we assume each node initially has 10 Joules (J) of battery energy (cf. [Chen et al. 2011]). The node energy expenditures in the τth period are assumed to be i.i.d. truncated normal random variables (Tr-N) with mean $c(s_\tau, a_\tau)$ and standard deviation σ. Typical values for currently available radio transceivers are $e_t = 50 \times 10^{-9}$ J/bit, $e_d = 100 \times 10^{-12}$ J/bit/m^2 (cf. [Gao et al. 2006; Zhang et al. 2010]), and $\eta = 2$ (path-loss coefficient). The length of each period in the optimization model is one unit of time (e.g. one week). In order to analyze the effect of the variance of energy expenditure, we also compare the network lifetimes of four cases when $\sigma \in \{0.2, 0.4, \ldots, 2.0\}$. Larger dispersion of the energy expenditures values is likely to prevail due to a nonhomogeneous environment, or if some nodes serve as relays more frequently than others. For the test instances, the parameter values are summarized in Table II. In all test instances, the event and query lifetimes follow triangular and uniform distributions, respectively.

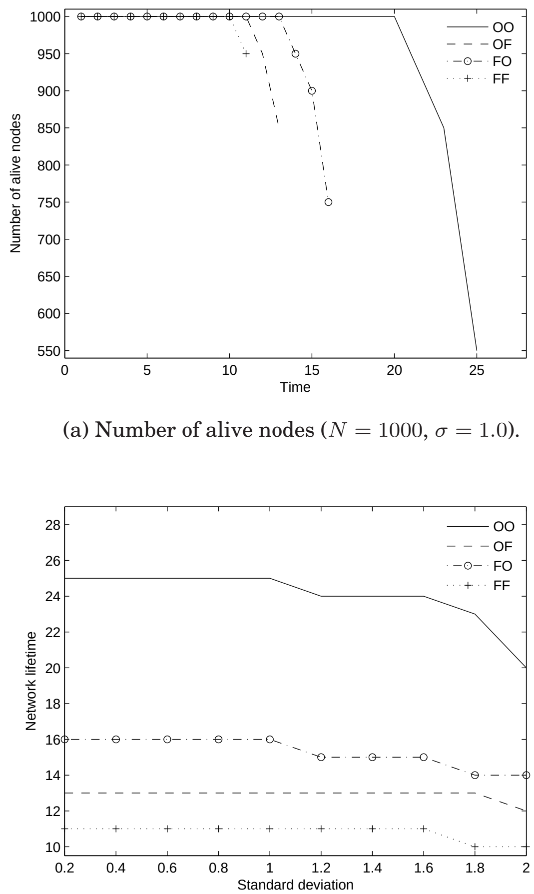
Table II. Parameter values for the test instances.

Parameter description	Value or distribution
Transmitter's exponential transmission rate	5.000
Poisson rate of locally-witnessed events	0.012
Poisson rate of locally-generated queries	0.050
Event lifetime distribution	Triangular $(0.1, 10.0, 19.9)$
Query lifetime distribution	Uniform $(0.1, 9.9)$
Energy expenditure during period τ	Truncated Normal $(c(n_\tau, a_\tau), \sigma^2)$
Maximum proportion of query failures (φ)	0.025
Minimum connectivity requirement (ρ)	0.99
Planning horizon ($\mathcal{T}$)	$\{1, 2, \ldots, 20\}$

The analytical approximations were coded in the C programming language and executed in Microsoft® Visual Studio® 2008 on a personal computer equipped with an Intel® Core™ 2 Duo CPU operating at 3.00GHz with 2.00 GB of RAM. For these test instances, the optimal solution of ($\mathbf{P}_2$) is an approximate solution because both $\Delta(n_\tau, a_\tau)$ and $\Psi(n_\tau, a_\tau)$ are evaluated using the approximations given in (9) and (5), respectively. Therefore, for computational expedience, problem ($\mathbf{P}_2$) can be solved by considering a subset of policy alternatives without significant effect on the solution quality. Consequently, we allow s_τ to assume only one of 20 integer values between 0 and N. Similarly, n_τ may assume one of 10 integer values between 0 and s_τ.

4.2. Results and Discussion

Figure 4a shows the effect of adjusting transmission range and sleep schedules on the number of alive nodes over time when $N = 1000$. When the transmission range and active/sleep decisions are fixed over time, the number of alive nodes in the network decreases rapidly. When either one of transmission range and active/sleep decisions is optimized for each period, the node failure rate is smaller than the case when the decisions are static. On the other hand, when the transmission range and the active/sleep schedules are optimized, the network lifetime increases, because nodes fail with a smaller rate over time. Additionally, when the transmission range and sleep



(a) Number of alive nodes ($N = 1000$, $\sigma = 1.0$).

(b) Network lifetime as a function of σ ($N = 1000$).

Fig. 4. Effect of optimal decisions on network lifetime.

schedules are optimized considering node failures, the network satisfies the QoS and connectivity requirements even after many nodes fail. Similar results are observed when $N \in \{600, 700, 800, 900\}$.

In Figure 4b, we first note that the maximum attainable lifetime for case OO dominates all other cases for each standard deviation value. Specifically, if none of the parameters are optimized (case FF), the maximum lifetime decreases by more than 50% (when $\sigma = 2$). Second, the network lifetime tends to be monotone decreasing (for $\sigma > 1$) in all cases. One possible explanation for this downward trend is that, as the variance of energy expenditure increases, a greater proportion of nodes can experience failure times that are significantly smaller than the mean failure time, thereby increasing the instances in which the connectivity and/or QoS constraints are violated early in the planning horizon.

Table III summarizes the average lifetime of 10 cases in which the standard deviation was varied between 0.2 and 2.0. The results illustrate the significant effect of optimized decisions and reveal that, for different network sizes, selecting the optimal transmission range and active/sleep decisions increases the average network lifetime significantly. For instance, in a network with 1000 nodes, the average lifetime of case OO is more than double that of case FF.

Table III. Average lifetime over 10 test instances.

N	OO	FO	OF	FF
600	27.4	17.1	12.9	10.9
700	27.8	13.6	13.3	10.5
800	18.6	15.3	10.8	10.8
900	26.9	13.4	12.9	10.5
1000	24.0	15.3	12.9	10.8

5. CONCLUSION

This paper has provided an optimization framework for maximizing the lifetime of a query-based wireless sensor network, subject to connectivity and quality-of-service constraints, by optimally selecting the transmission range, time-to-live counter and active/sleep schedules over a finite planning horizon. We have shown how to convert the nonlinear, mixed-integer programming model into a linearized version that can be more easily solved. An algorithm was developed to solve a special case of the model in which nodes never sleep. Additionally, we derived an improved approximation for the probability of network connectivity that explicitly accounts for the network's boundary effects. The computational results showed that the maximum network lifetime can be significantly prolonged by optimizing the operating parameters, irrespective of the variability of battery lifetime. However, as the variability of energy expenditure increases, the maximum attainable lifetime tends to decrease.

The general optimization framework is useful for two important reasons. First, it considers the simultaneous optimization of three important contributors to network energy consumption: the transmission range of sensors, the hop counter and the sleep schedules of sensor nodes. Second, problem ($\mathbf{P}_1$) is not restricted to the connectivity and quality-of-service constraints (Ψ and Δ, respectively) described herein. Indeed, the functions Ψ and Δ can be arbitrary, so long as functional values can be obtained analytically or numerically.

Despite these advantages, there remain opportunities for future improvements. First, it will be imperative to develop efficient algorithms for the most general lifetime maximization problem. The proposed linear model has the form of a knapsack problem with additional constraints and is, therefore, amenable to solution by a commercial solver, although obtaining the model parameters and solving the linear model requires significant computational time. For this reason, the current model does not scale well for very large-scale networks. While we developed an algorithm for the special case (when alive nodes never sleep), an algorithm is needed to reduce the size of the original model. Second, it will be instructive to develop a similar framework to handle networks with mobile nodes. The extension will undoubtedly lead to models with chance (probabilistic) constraints that ad significant complexity to the models. Finally, in our model we assume that the transmission range and event time-to-live counter are identical for all sensor nodes. In more general settings this assumption can be relaxed. However, it will require derivation of more sophisticated connectivity and QoS constraints and result in a more difficult optimization problem as the number of decision variables will increase substantially.

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REFERENCES

AHN, J. AND KRISHNAMACHARI, B. 2006a. Derivations of the expected energy costs of search and replication in wireless sensor networks. Tech. Rep. CENG-2006-3, Computer Engineering, University of Southern California.

AHN, J. AND KRISHNAMACHARI, B. 2006b. Fundamental scaling laws for energy-efficient storage and querying in wireless sensor networks. In *Proceedings of the 7th ACM International Symposium on Mobile Ad Hoc Networking and Computing*. 334–343.

AHN, J. AND KRISHNAMACHARI, B. 2007. Modeling search costs in wireless sensor networks. In *Proceedings of the 5th International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks*. 1–6.

AKYILDIZ, I. F., SU, W., SANKARASUBRAMANIAM, Y., AND CAYIRCI, E. 2002. Wireless sensor networks: A survey. *Computer Networks 38,* 4, 393–422.

AL-KARAKI, J. N. AND KAMAL, A. E. 2004. Routing techniques in wireless sensor networks: A survey. *IEEE Wireless Communications 11*, 6–28.

ANASTASI, G., CONTI, M., FRANCESCO, M. D., AND PASSARELLA, A. 2009. Energy conservation in wireless sensor networks: A survey. *Ad Hoc Networks 7,* 4, 537–568.

ANEJA, Y. P., CHANDRASEKARAN, R., LI, X., AND NAIR, K. P. K. 2010. A branch-and-cut algorithm for the strong minimum energy topology in wireless sensor networks. *European Journal of Operational Research 204,* 3, 604–612.

ATA, B. 2005. Dynamic power control in a wireless static channel subject to a quality-of-service constraint. *Operations Research 53,* 5, 842–851.

BEHDANI, B., SMITH, J., AND XIA, Y. 2013. The lifetime maximization problem in wireless sensor networks with a mobile sink: MIP formulations and algorithms. *IIE Transactions 45,* 10, 1094–1113.

BEHDANI, B., YUN, Y., SMITH, J., AND XIA, Y. 2012. Decomposition algorithms for maximizing the lifetime of wireless sensor networks with mobile sinks. *Computers and Operations Research 39,* 5, 1054–1061.

BELLAVISTA, P., CORRADI, A., AND MAGISRETTI, E. 2005. Comparing and evaluating lightweight solutions for replica dissemination and retrieval in dense MANETs. In *Proceedings of the 10th IEEE Symposium on Computers and Communications*. 43–50.

BETTSTETTER, C. 2002. On the minimum node degree and connectivity of a wireless multihop network. In *Proceedings of the 3rd ACM International Symposium on Mobile Ad Hoc Networking and Computing*. 80 – 91.

BETTSTETTER, C. 2004. On the connectivity of ad hoc networks. *The Computer Journal 47,* 4, 432 –447.

CERULLI, R., DEDONATO, R., AND RAICONI, A. 2012. Exact and heuristic methods to maximize network lifetime in wireless sensor networks with adjustable sensing ranges. *European Journal of Operational Research 220,* 1, 58–66.

CHEN, I. R., SPEER, A. P., AND ELTOWEISSY, M. 2011. Adaptive fault tolerant QoS control algorithms for maximizing system lifetime of query-based wireless sensor networks. *IEEE Transactions on Dependable and Secure Computing 8,* 2, 161–176.

CHEN, P., O'DEA, B., AND CALLAWAY, E. 2002. Energy efficient system design with optimum transmission range for wireless ad hoc networks. *IEEE International Conference on Communications 2*, 945–952.

CHIASSERINI, C. F., GAETA, R., GARETTO, M., GRIBAUDO, M., MANINI, D., AND SERENO, M. 2007. Fluid models for large-scale wireless sensor networks. *Performance Evaluation 64,* 7-8, 715–736.

CPLEX 2011. IBM ILOG: CPLEX. http://www.ilog.com/products/cplex.

DEGIRMENCI, G., KHAROUFEH, J. P., AND BALDWIN, R. O. 2013. On the performance evaluation of query-based wireless sensor networks. *Performance Evaluation 70,* 2, 124–147.

DENG, J., HAN, Y. S., CHEN, P., AND VARSHNEY, P. K. 2004. Optimum transmission range for wireless ad hoc networks. *Electrical Engineering and Computer Science 2*, 1024–1029.

DIETRICH, I. AND DRESSLER, F. 2009. On the lifetime of wireless sensor networks. *ACM transactions on Sensor Networks 5,* 1, 1–39.

DIGGLE, P. 2003. *Statistical Analysis of Spatial Point Patterns*. Arnold, London.

FLAMMINI, F., GAGLIONE, A., OTTELLO, F., PRAGLIOLA, A. P. C., AND TEDESCO, A. 2010. Towards wireless sensor networks for railway infrastructure monitoring. In *Electrical Systems for Aircraft, Railway and Ship Propulsion (ESARS)*. 1–6.

GAO, Q., BLOW, K. J., HOLDING, D. J., MARSHALL, I. W., AND PENG, X. H. 2006. Radio range adjustment for energy efficient wireless sensor networks. *Ad Hoc Networks 4,* 1, 75–82.

GUNGOR, V. C. AND HANCKE, G. P. 2009. Industrial wireless sensor networks: Challenges, design principles, and technical approaches. *IEEE Transactions on Industrial Electronics 56,* 10, 4258–4265.

HA, R. W., HO, P. H., SHEN, X. S., AND ZHANG, J. 2006. Sleep scheduling for wireless sensor networks via network flow model. *Computer Communications 29,* 13-14, 2469–2481.

HERRING, C. AND KAPLAN, S. 2000. Component-based software systems for smart environments. *IEEE Personal Communications 7,* 5, 60–61.

HOCHBAUM, D. S. 1995. A nonlinear knapsack problem. *Operations Research Letters 17,* 3, 103–110.

KRISHNAMACHARI, B. AND AHN, J. 2006. Optimizing data replication for expanding ring-based queries in wireless sensor networks. In *Proceedings of the 4th International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks*. 1–10.

LIU, J., JIANG, X., HORIGUCHI, S., AND LEE, T. T. 2010. Analysis of random sleep scheme for wireless sensor networks. *International Journal of Sensor Networks 7,* 1, 71–84.

MAINWARING, A., CULLER, D., POLASTRE, J., SZEWCZYK, R., AND ANDERSON, J. 2002. Wireless sensor networks for habitat monitoring. In *Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications*. 88–97.

MANN, C. R., BALDWIN, R. O., KHAROUFEH, J. P., AND MULLINS, B. E. 2007. A trajectory-based selective broadcast query protocol for large-scale, high-density wireless sensor networks. *Telecommunication Systems 35,* 1-2, 67–86.

MANN, C. R., BALDWIN, R. O., KHAROUFEH, J. P., AND MULLINS, B. E. 2008. A queueing approach to optimal resource replication in wireless sensor networks. *Performance Evaluation 65,* 10, 689–700.

MILENKOVIC, A., OTTO, C., AND JOVANOV, E. 2006. Wireless sensor networks for personal health monitoring: Issues and an implementation. *Computer Communications 29,* 13-14, 2521 – 2533.

MIRANDA, H., LEGGIO, S., RODRIGUES, L., AND RAATIKAINEN, K. 2007. An algorithm for dissemination and retrieval of information in wireless ad hoc networks. In *Proceedings of the 13th International Euro-Par Conference (Euro-Par 2007)*. 891–900.

MISHRA, A., GONDAL, F. M., AFRASHTEH, A. A., WILSON, R. R., MOFFITT, R. D., KAPANIA, R. K., AND BLAND, S. 2006. Embedded wireless sensors for aircraft/automobile tire structural health monitoring. In *2nd IEEE Workshop on Wireless Mesh Networks*. 163–165.

NIYATO, D., HOSSAIN, E., AND FALLAHI, A. 2007. Sleep and wakeup strategies in solar-powered wireless sensor/mesh networks: Performance analysis and optimization. *IEEE Transactions on Mobile Computing 6,* 2, 221–236.

PAPADIMITRIOU, I. AND GEORGIADIS, L. 2005. Maximum lifetime routing to mobile sink in wireless sensor networks. In *Proceedings of the 13th IEEE Software, Telecommunications and Computer Networks (SoftCOM) Conference*. Split, Croatia.

RODERO-MERINO, L., ANTA, A. F., LÓPEZ, L., AND CHOLVI, V. 2010. Performance of random walks in one-hop replication networks. *Computer Networks 54*, 781–796.

SARKAR, M. AND CRUZ, R. L. 2004. Analysis of power management for energy and delay trade-off in a wlan. In *Proceedings of the Conference on Information Sciences and Systems*.

SCHURGERS, C. AND SRIVASTAVA, M. B. 2001. Energy efficient routing in wireless sensor networks. In *IEEE Military Communications Conference*. 357–361.

SINHA, A. AND CHANDRAKASAN, A. P. 2001. Dynamic power management in wireless sensor networks. *IEEE Design and Test of Computers Magazine 18,* 2, 62–74.

TURKOGULLARI, Y. B., ARAS, N., ALTINEL, I. K., AND ERSOY, C. 2010. Optimal placement, scheduling, and routing to maximize lifetime in sensor networks. *Journal of Operational Research Society 61,* 6, 1000–1012.

WELSH, M. 2004. Harvard Sensor Networks Lab: Volcano monitoring. http://fiji.eecs.harvard.edu/Volcano.

XING, X., WANG, G., WU, J., AND LI, J. 2009. Square region-based coverage and connectivity probability model in wireless sensor networks. In *5th International Conference on Collaborative Computing: Networking, Applications and Worksharing*. 1–8.

YE, W., HEIDEMANN, J., AND ESTRIN, D. 2004. Medium access control with coordinated adaptive sleeping for wireless sensor networks. *IEEE/ACM Transactions on Networking 12,* 3, 493–506.

YUN, Y. AND XIA, Y. 2010. Maximizing the lifetime of wireless sensor networks with mobile sink in delay-tolerant applications. *IEEE Transactions on Mobile Computing 9,* 9, 1308–1318.

YUN, Y., XIA, Y., BEHDANI, B., AND SMITH, J. 2013. Distributed algorithm for lifetime maximization in delay-tolerant wireless sensor network with mobile sink. *To appear in IEEE Transactions on Mobile Computing*.

ZHANG, Z., MAO, G., AND ANDERSON, B. 2010. On the effective energy consumption in wireless sensor networks. In *IEEE Wireless Communications and Networking Conference (WCNC)*. 1–6.