General Network Lifetime and Cost Models for Evaluating Sensor Network Deployment Strategies

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Abstract—In multihop wireless sensor networks that are often characterized by many-to-one (convergecast) traffic patterns, problems related to energy imbalance among sensors often appear. Sensors closer to a data sink are usually required to forward a large amount of traffic for sensors farther from the data sink. Therefore, these sensors tend to die early, leaving areas of the network completely unmonitored and reducing the functional network lifetime. In our study, we explore possible sensor network deployment strategies that maximize sensor network lifetime by mitigating the problem of the hot spot around the data sink. Strategies such as variable-range transmission power control with optimal traffic distribution, mobile-data-sink deployment, multiple-data-sink deployment, nonuniform initial energy assignment, and intelligent sensor/relay deployment are investigated. We suggest a general model to analyze and evaluate these strategies. In this model, we not only discover how to maximize the network lifetime given certain network constraints but also consider the factor of extra costs involved in more complex deployment strategies. This paper presents a comprehensive analysis on the maximum achievable sensor network lifetime for different deployment strategies, and it also provides practical cost-efficient sensor network deployment guidelines.

Index Terms—Wireless sensor networks, data dissemination, linear programming, deployment strategies.

1 Introduction

Large-scale wireless sensor networks are an emerging technology that has recently gained attention for their potential use in many applications. Since sensors typically operate on batteries and are thus limited in their active lifetime, the problem of designing protocols to achieve energy efficiency to extend the network lifetime has become a major concern for network designers. Much attention has been given to the reduction of unnecessary energy consumption of sensor nodes in areas such as hardware design, collaborative signal processing, transmission power control policies, and all levels of the network stack. However, reducing an individual sensor's power consumption alone may not always allow networks to realize their maximum potential lifetime. In addition, it is important to maintain a balance of energy consumption in the network so that certain nodes do not die much earlier than others, leading to unmonitored areas in the network.

Previous research has shown that because of the characteristics of wireless channels, multihop forwarding between a data source and a data sink is often more energy-efficient than direct transmission. However, in sensor networks, where many applications require a many-to-one (convergecast) traffic pattern in the network, multihop forwarding may cause energy imbalance as all the traffic must be routed through the nodes near the data sink, thus creating a hot spot around the data sink or base station.[1] The nodes in this hot spot are required to forward a disproportionately high amount of traffic and typically die at a very early stage. If we define the network lifetime as the time when the first subregion of the environment (or a significant portion of the environment) is left unmonitored, then the residual energy of the other sensors at this time can be seen as wasted.

Despite the fact that many sensor deployment strategies have been considered to extend the network lifetime, there is no general framework to evaluate the maximum lifetime provided by these strategies and to evaluate their actual deployment cost (that is, monetary cost). Thus, there is no easy way to compare the advantages and disadvantages of these various deployment strategies. In this paper, we formulate the network lifetime problem and analyze the limits of network lifetime for different types of sensor network scenarios and corresponding network deployment strategies. Since applying a more complex strategy may introduce extra costs, we also provide a simple yet effective cost model to explore the cost trade-off for using advanced solutions. The main contributions of this paper are the following: 1) we propose a general framework for the analysis of the network lifetime for several network deployment strategies, and 2) we consider the extra costs associated with each deployment strategy to determine the best overall strategy for a given scenario.

The rest of this paper is organized as follows: Section 2 addresses related work. Section 3 presents several different sensor network deployment strategies. Our models for network lifetime and deployment cost are presented in

1. We do not differentiate between these terms in the rest of the paper.

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Section 4. Section 5 provides a detailed discussion of the optimal lifetime for the simplest deployment strategy and reveals trends that are common to the different deployment strategies. Section 6 compares several different sensor network deployment strategies in terms of normalized lifetime and cost for a target scenario. Finally, conclusions are provided in Section 7.

2 Related Work

The minimization of transmission energy in wireless sensor networks and in wireless networks in general has been studied extensively. If the transmission power cannot be adjusted, power consumption can be minimized by minimizing the number of hops between the source and destination. However, when the transmission power can be set according to the distance over which data is being transmitted, because received energy typically falls off with distance as $1/d^2$, it may be more energy efficient to send data over many short hops rather than fewer long hops. Several works have noted this and shown how to minimize energy consumption by appropriately setting the transmission power. Takagi and Kleinrock explored how to best set the transmission power in order to minimize interference and maximize throughput [1]. The problem of setting the transmission power to a minimal level that will allow a network to remain connected has been considered in several studies [2], [3]. In later work, some considered the importance of a fixed energy consumption per bit, independent of the transmission distance. Because of this overhead, there exists an optimal nonzero transmission range, at which energy efficiency is optimized [4], [5].

In the above-cited works, the goal was to minimize overall energy consumption, and a fixed network-wide transmission range was assumed. However, using such schemes may result in extremely unbalanced energy consumption among the nodes in sensor networks characterized by many-to-one traffic patterns. In addition to minimizing energy consumption, it may also be beneficial to distribute the energy among the nodes and to favor using those with greater energy resources so that the network lifetime may be maximized. Note that the network lifetime may be defined in a number of ways, including the time until the first node dies, the time when the first region of a sensor network is left unattended, etc. To accomplish this goal of lifetime maximization, load balancing through a combination of intelligent routing and transmission power control was studied in [6], where several heuristic routing costs were recommended for use in order to minimize and, at the same time, balance energy consumption. In [7], Chang and Tassiulas show how the optimal combination of several routing costs allows the network lifetime to be extended. In [8], Efthymiou et al. show how energy consumption can be balanced by distributing packets over several paths. The problem of finding the optimal routing to achieve the maximum network lifetime in a sensor network was studied as a constrained linear program optimization in [9], [10], and [11]. In this work, the authors find the maximum lifetime that could be achieved by any routing cost or balancing scheme. In [12], Perillo et al. show how transmission ranges can be optimally set and how traffic can be optimally distributed specifically in a many-to-one sensor network.

Aside from transmission range optimization for balancing energy across the sensors, several other sensor deployment strategies have been proposed to extend the network lifetime. For example, a mobile data sink roaming within the network can be deployed to balance the energy consumption. In [13], data mules are deployed in the network to pick up the data once they are close to the data source. Buffer requirements are the main focus of this study. In [14], Kim et al. focus on minimizing the cost for topology maintenance and communication between the mobile sinks and the data sources. In [15], the optimal sink mobility strategy is studied. Our generalized model is able to obtain the optimal assignment of communication load for the mobile-sink strategy, and our study focuses on the network lifetime improvement from this strategy. Therefore, detailed design considerations such as buffer size and the overhead for network maintenance are not considered here.

Multiple data sinks can also be deployed to collect data over a certain subregion of the entire area. In [16], the optimal assignment of communication load to multiple sinks is found using a method similar to electrostatic theory. In [17], an application using multiple Crossbow Stargates as virtual data sinks is implemented. Further deployment strategies that integrate data aggregation have also been considered. In LEACH [18], each sensor can serve as a cluster head, where data from neighboring sensors is aggregated, and sensors rotate their roles to evenly distribute the energy load. This can be considered as a multiple-sink strategy with data aggregation. We do not consider data aggregation in our model since data aggregation is application specific.

The deployment of extra relay nodes around the data sink can also be helpful in solving energy imbalance problems. In [19], Ergen and Varaiya compare the minimum energy consumption when the relay nodes' locations are predetermined and when they can be placed in any location. The authors provide a heuristic method to solve the latter problem. In [20], a similar mixed-integer nonlinear programming solution is provided to discover the optimal locations of relay nodes iteratively. In [21], Howitt and Wang attempt to balance energy consumption by requiring the sensors to send traffic to the next node along a chain to the base station and spacing sensors nonuniformly as a function of their distance to the data sink so that energy consumption is uniform for all nodes. In our work, we look at relay nodes simply as energy deposits. After we discover the optimal energy distribution map for the network, we can easily determine where energy is insufficient and thus determine where relay nodes should be placed and how much energy they should carry. Therefore, our solution is more general, and it is straightforward to apply.

Table 1 provides a summary of these different approaches for balancing energy consumption and some representative protocols existing in the current literature. Despite the multitude of research investigating the aforementioned deployment strategies, there is no cross comparison among these strategies for situations when multiple options are available. In this paper, we fill this void by proposing a

TABLE 1
Comparison of Proposed Sensor Network Deployment Strategies

Strategy	Protocols
Routing/Transmission Power Optimization	[6] [7] [8] [9] [10] [11] [12]
Mobile Sinks	[13] [14] [15]
Multiple Base Stations	[16] [17] [18]
Non-uniform Sensor Deployment	[19] [20] [21]

general framework to determine the energy efficiency of a deployment strategy and providing a practical sensor deployment evaluation method that considers both energy and cost in determining the best solution for a particular target scenario.

3 Sensor Network Model

The sensor network hot-spot problem is one of the most important factors limiting the lifetime of conventional sensor networks with uniform node deployment, homogeneous sensors, and a single data sink. This hot-spot problem can be mitigated through several different deployment strategies to provide longer lifetime compared with the conventional deployment strategy, but the cost for these alternate deployment strategies may be prohibitive.

Our goal in this paper is twofold. First, for a given deployment strategy, we model the network so that we can determine the optimal lifetime possible for that particular deployment strategy. Then, in order to compare across different deployment strategies, we determine a normalized lifetime and the corresponding cost to achieve a given lifetime goal. This will enable sensor network designers to select the most cost-efficient solution to meet a particular lifetime goal for their sensor network.

We begin by discussing several different strategies for sensor network deployment and some assumptions we make in order to model the network for these different deployment strategies.

3.1 Deployment Strategy Options

Several key parameters can be used to describe sensor network deployment strategies. These parameters include the following:

1. *Sensor capabilities.* In some cases, sensors have a nonadjustable transmission power and, thus, a fixed transmission range, whereas in other cases, sensors equipped with more advanced transceivers may vary their transmission ranges by using different transmission powers.
2. *Base station options.* Some sensor networks are deployed with a fixed base station that cannot change its physical location. However, another deployment option is to utilize a mobile base station that changes its physical location over time. A third option is to deploy multiple base stations, where each base station can collect data from a portion of the network.
3. *Initial energy assignment.* The initial energy assignment for each sensor reflects how much freedom a sensor network deployment strategy has. When the deployment is in a controlled manner, nodes can be assigned different levels of initial energy depending on their locations and their roles in the network. For general sensor network deployments, however, we usually assume that the initial energy of all the sensors is the same. This might be true especially when sensors are manufactured in large quantities without differentiation.
4. *Sensor locations.* Similarly, the locations of sensors, relay nodes, and data sinks depend on how much freedom a sensor network deployment has. If the deployment is under full control, more sensors can be placed where energy is needed, and relay nodes can be placed in areas likely to receive the most traffic.
5. *Traffic generation pattern.* The traffic generation pattern is closely related to the sensing application. For environmental monitoring applications (for example, temperature monitoring), sensors may generate samples at the same rate. The traffic generation pattern is uniform in this type of network. For intruder detection applications where an intruder is expected to be detected at the farthest end from the base station, more traffic is expected to be generated at far distances. The traffic generation pattern is thus nonuniform in this case.

A good network deployment strategy should resolve energy imbalance while maintaining high energy efficiency. We list some potential sensor network deployment strategies in Table 2, labeled as DS_1 through DS_6. We do not intend to list every possible deployment strategy in Table 2 but rather merely to highlight some possible solutions to achieve both energy balance and energy efficiency.

The ultimate goal for sensor deployment is to provide a certain quality of service for a maximum lifetime using a minimum cost. Although the more complex deployment strategies listed in Table 2 may provide much longer network lifetimes, the extra cost of sensor hardware, base station hardware, and incurred deployment complexity may lead to a disproportionate increase in deployment cost. Although maximizing the network lifetime is most often the desired research goal, the ultimate goal for a real sensor network deployment plan is to reduce the network deployment cost per network lifetime without sacrificing the quality of service. Therefore, the cost must be considered along with the network lifetime during the analysis of different deployment strategies.

3.2 Assumptions

Our goal in this paper is to determine the maximum achievable sensor network lifetime for different network deployment strategies and to compare the cost of these different techniques. To obtain a true upper bound on the network lifetime, we have made several simplifications in our lifetime model. These assumptions enable us to evaluate these strategies at a high level.

First, we assume that the power consumption of sensor nodes is dominated by communication costs, as opposed to sensing and processing costs. This assumption is reasonable

TABLE 2
Sensor Network Deployment Strategies, Corresponding Scenarios, and Potential Difficulty/Extra Costs

Strategy	Scenario: {Traffic, Sensors, Energy, Sink}	Difficulty/Extra Costs
DS_1: Single static sink	{uniform, homogeneous, uniform, single/static}	
DS_2: Mobile data sink	{uniform, homogeneous, uniform, **single/mobile**}	Data sink mobility
DS_3: Multiple data sinks	{uniform, homogeneous, uniform, **multiple/static**}	Extra data sink deployment
DS_4: Non-uniform energy	{uniform, homogeneous, **non-uniform**, single/static}	Individual energy assignment
DS_5: Non-uniform placement	{uniform, **heterogeneous**, uniform, single/static}	Sensor/relay placement
DS_6: Non-uniform traffic	{**non-uniform**, uniform, uniform, single/static}	Case dependent

for many types of sensor nodes that require very little energy, such as pressure and temperature sensors. We also ignore the overhead that would typically be introduced by the routing layer. However, for long-lasting sensor networks with little or no mobility, route updates should be performed infrequently and should not significantly affect the overall power consumption in the network. We have also ignored any potential overhead at the MAC layer. Due to the scarce energy supplies in sensor nodes, TDMA scheduling is commonly proposed for use in the MAC layer of sensor networks. Because of the low data rates expected in many sensor network applications, even localized TDMA scheduling (as opposed to globally coordinated scheduling) should not induce much communication overhead in the form of collisions and necessary retransmissions. Furthermore, TDMA scheduling can eliminate most overhead introduced by idle listening and overhearing. As with the overhead associated with routing updates, the establishment of schedules can take place very infrequently and should not contribute significantly to overall power consumption. Finally, we assume that the channels are lossless. Although lossy channels will induce retransmissions for reliable data delivery, they have the same effect on all strategies and do not affect the relative lifetime performance of these strategies.

4 Generalized Lifetime and Cost Models

In this section, we propose a sensor network lifetime model that determines the maximum network lifetime and normalized lifetime for a given network deployment strategy. This model reveals the potential energy efficiency of a network deployment strategy. We also propose a deployment cost model that determines the overall monetary cost of a network deployment strategy. This model includes the extra costs associated with a more complex deployment strategy and can be used to evaluate whether the energy efficiency improvement of a deployment strategy is worth any extra costs that may be incurred.

Table 3 lists the parameters that we use in this paper, including those used in the general network model, the power model, the lifetime model, and the cost model.

4.1 Lifetime Model

We adopt as a common lifetime definition the time when the first sensor dies. This lifetime definition, proposed in [7], is widely utilized in the sensor network research field. An alternative lifetime definition that has been used is the time at which a certain percentage of total nodes run out of energy. This definition is actually quite similar in nature to the one we use here. In a well-designed network, sensors in a certain area exhibit similar behaviors to achieve energy balance. In other words, when one sensor dies, it can be expected that the neighbors of this node will run out of energy very soon since they will have to take over the responsibilities of that sensor. Therefore, in a well-designed network, there should be little or no difference in lifetime when using these two definitions.

In our network model, a set of N_s sensors is deployed in a region in order to monitor some physical phenomenon. We refer to the complete set of sensors that has been deployed as $S = \{s_1 \dots s_{N_s}\}$. Sensor i generates traffic at a rate of r_i bps. All of the data that is generated must eventually reach a single data sink, labeled s_0. We adopt the power model in [18], where the amount of energy to transmit a bit can be represented as $E_{tx} = E_{elec} + \epsilon_{amp} d^{\alpha}$, and the amount of energy to receive a bit can be represented as $E_{rx} = E_{elec}$, where E_{elec} represents the electronics energy, ϵ_{amp} is determined by the transmitter amplifier's efficiency and the channel conditions, d represents the distance over which data is being communicated, and α represents the path loss exponent. The network scenario parameters also include the traffic generation rate r_i for each sensor, the distances d_{ij} between sensors, and the maximum transmission distance d^{max}.

4.2 Lifetime Optimization

The goal of our network lifetime model is to discover the maximum network lifetime L given a fixed deployment strategy and network scenario parameters. The model is able to determine this maximum by optimizing the amount of traffic that each sensor should distribute to the other sensors in order to balance energy consumption among the sensors. This traffic distribution is denoted by t_{ij}, indicating the amount of traffic that sensor i transmits to sensor j.[2]

During network lifetime L, sensor i will generate a total of $r_i L$ traffic. The first constraint of our problem, related to the conservation of data flow at all sensor nodes, is

2. Note that $t_{ii} = 0 \; \forall \, i$.

TABLE 3
Variables Used in Network Modeling Throughout this Paper

Variable	Description
Network Model	
N_s	Total number of sensors
s_i	Sensor i, $i \in \{1, \cdots, N_s\}$
s_0	Base station (single sink)
λ_a	Minimum sensor coverage density
λ_e	Energy density
A	Network area
r_i	Traffic generation rate of sensor i
e_i^{init}	Initial energy of sensor i
$e^{init,total}$	Total initial energy
d_{ij}	Distance between sensors i and j
d^{max}	Maximum transmission distance
Power Model	
E_{tx}	Energy consumption for each bit transmitted
E_{rx}	Energy consumption for each bit received
E_{elec}	Energy consumption from electronic overhead
ϵ_{amp}	Transmitter amplifier coefficient
α	Path loss exponent
Lifetime Model	
e_i	Energy consumption of sensor i
t_{ij}	Amount of traffic that sensor i forwards to sensor j
d_{ij}^t	Transmission distance between sensors i and j
L	Sensor network lifetime
$\tilde{L}$	Normalized sensor network lifetime
Cost Model	
C	Overall deployment Cost
C_s	Cost of sensors
C_e	Extra cost

$$\sum_{j=1}^{N_s} t_{ji} + r_i L = \sum_{j=0}^{N_s} t_{ij} \qquad \forall i \in \{1, \cdots, N_s\}. \tag{1}$$

Equation (1) states that the sum of all traffic received at sensor i and generated by sensor i must be transmitted to other sensors or to the data sink (s_0). The energy consumed by sensor i includes the energy required for both transmitting and receiving data and can be expressed as

$$e_i = \sum_{j=0}^{N_s} \Big(E_{elec} + \epsilon_{amp} (d_{ij}^t)^{\alpha} \Big) t_{ij} + \sum_{j=1}^{N_s} E_{elec} t_{ji}. \tag{2}$$

The second constraint, related to the initial energy at each sensor, e_i^{init}, is

$$e_i \le e_i^{init} \qquad \forall i \in \{1, \cdots, N_s\}. \tag{3}$$

The third constraint, related to the maximum transmission range d^{max} of each sensor, depends on the sensors' transmission power control capabilities. If the sensors can vary transmission power to accommodate the distance over which they must transmit, then the transmission power required to deliver a packet from sensor i to sensor j will be controlled in such a way that the transmission distance d_{ij}^t equals the physical distance:[3]

$$d_{ij}^t = d_{ij} \qquad \forall i \in \{1, \cdots, N_s\}, \forall j \in \{0, \cdots, N_s\}. \tag{4}$$

If nodes must use a fixed transmission range d^{max}, then the constraint simply becomes

$$d_{ij}^t = d^{max} \qquad \forall i \in \{1, \cdots, N_s\}, \forall j \in \{0, \cdots, N_s\}. \tag{5}$$

Note that if $d_{ij} > d^{max}$, then no traffic can be sent between sensors i and j, and the following constraint must be applied:

$$t_{ij} = 0 \qquad \forall (i, j) : d_{ij} > d^{max}. \tag{6}$$

The last constraint, related to the energy distribution at each sensor, depends on how freely energy can be assigned to each sensor. If energy can be freely assigned, then the total energy consumption of all sensors must simply satisfy

$$\sum_{i=1}^{N_s} e_i^{init} = e^{init,total}. \tag{7}$$

If sensors are initially assigned the same amount of energy, then

$$e_i^{init} = \frac{e^{init,total}}{N_s} \qquad \forall i \in \{1, \cdots, N_s\}. \tag{8}$$

The optimal network lifetime can be obtained using a linear programming approach that sets the constraints as in (1), (3), (4) (or (5)), (6), and (7) (or (8)) and sets the goal of maximizing L. The linear program finds the maximum lifetime L for a given scenario, and it also discovers the traffic distribution t_{ij}, indicating how this lifetime can be obtained through intelligent traffic distribution.

4.3 Normalized Network Lifetime

Although the lifetime L found in the previous section allows us to determine an absolute maximum time that the network can operate, this value is highly dependent on the network scenario parameters, including the network area, the required density of active sensors, the energy density, and the data generation rate. In order to obtain a more general understanding of the energy efficiency of different deployment strategies, we propose a normalized network lifetime $\widetilde{L}$, which measures how many total bits can be transported on the network per unit of energy. Similar sensing tasks should result in the same normalized network lifetime for a given sensor network deployment strategy.

A typical sensing task can be described as the requirement to monitor an area, providing a certain quality of

3. In many real radio transmitters that employ transmission power control, transmission power can only be set at a number of discrete levels, rather than at any arbitrary continuous value. However, these levels can be rather finely spaced, and we model the sensors as being able to set their transmission power arbitrarily to simplify analysis.

service, for a certain period of time. For example, suppose that we want to monitor the temperature of a region for one year with a temperature sample rate of once per hour. The design parameters of this task include the average traffic generation rate among active sensors ($\bar{r}$), the minimum sensor coverage density λ_a, the initial energy assigned to each node ($e^{\bar{init}}$), and the monitoring period or network lifetime (L). These parameters affect the absolute lifetime, and they should be factored out during the calculation of the normalized network lifetime. Note that energy efficiency of each deployment strategy is dependent on the area of the region being monitored, and so, we do not attempt to remove this factor.

In typical sensor networks, the network designer can calculate the minimum number of sensors that are required to cover an area for a given application and required quality of service. We denote this minimum sensor coverage density as λ_a. Sensors may be deployed more densely than the sensing application requires and allow their sensing activity to be rotated while maintaining the same sensing coverage goals [22], [23], [24], [25]. Once the network is fully covered, the network lifetime can be arbitrarily increased by simply putting more energy into the network. This can be realized by scaling up the deployed sensor density or increasing the initial energy per sensor. The network lifetime can also be increased by reducing the traffic generation rate $\bar{r}$ among active sensors. A normalized lifetime $\widetilde{L}$ that accounts for the total energy consumption by considering the above factors can be expressed as

$$\widetilde{L} = L\left(\frac{\bar{r}\lambda_a}{\lambda_e}\right), \tag{9}$$

where λ_a represents the minimum sensor coverage density, $\bar{r}$ represents the average bit rate among active sensors, λ_e represents the energy density of the network (that is, how much energy is available per unit area), and L is the lifetime achievable with the given scenario's parameters.

In terms of units, L is measured in seconds, $\bar{r}$ is measured in bits per second, λ_a is measured in the number of sensors per square meter, and λ_e is measured in Joules per square meter. $\widetilde{L}$ is thus measured in terms of bits per Joule, which explicitly indicates the energy efficiency of a particular deployment strategy for a given network scenario.

4.4 Cost Model

The normalized lifetime reflects the energy efficiency of different deployment plans. From the normalized lifetime, we can deduce the number of sensors that will need to be deployed in order to meet the sensing requirements, giving some indication of the cost to deploy the network. For a particular deployment strategy DS_i, given the sensing requirements and a target network lifetime goal L, we can calculate the number of required sensors N_s as follows:

$$N_s(DS_i) = \begin{cases} \min(\lambda_a A, \frac{L\bar{r}\lambda_a A}{\widetilde{L}e^{\bar{init}}}) & i = 1,2,3,5, \\ \lambda_a A & i = 4. \end{cases} \tag{10}$$

For deployment strategies DS_1, DS_2, DS_3, and DS_5, where each node has a uniform data generation rate $\bar{r}$ and a uniform initial energy $e^{\bar{init}}$, (10) determines the number of sensors that are needed based on the normalized lifetime $\widetilde{L}$, as well as the application quality of service (sensing density). For deployment strategy DS_4, (10) simply specifies that the minimum number of sensors that support the application quality of service (sensing density) should be deployed since unequal energy assignment can be used to ensure that the lifetime goal is met. In our cost analysis of strategies DS_1, DS_2, DS_3, and DS_5, we will assume that the application quality-of-service (sensing density) constraints are always met and that the network lifetime is the driving factor when determining how many sensors should be deployed.

More energy-efficient deployment strategies will have a higher normalized lifetime (that is, they will carry more traffic per unit of energy) and thus require a lower number of sensors $N_s(DS_i)$ to meet the target lifetime. Thus, the deployment cost from sensors $C_s(DS_i)$ is lowered. However, these complex strategies may have higher extra deployment cost $C_e(DS_i)$. Our cost model explores these extra costs that are often overlooked, and it enables the evaluation of different deployment strategies from a monetary cost perspective. The total cost for the sensors is $C_s(DS_i) = c_s N_s(DS_i)$, where c_s represents the cost of an ordinary microsensor, and the overall deployment cost $C(DS_i)$ becomes

$$C(DS_i) = C_e(DS_i) + C_s(DS_i). \tag{11}$$

This cost model is a simple yet effective method for allowing a network designer to compare different deployment strategies on an equal basis.

5 A Case Study for the Simplest Deployment Strategy: DS_1

We begin our study of the optimized network lifetime for the simplest, most common sensor network deployment scenario, DS_1 in Table 2. For this deployment strategy, the only option to reduce the effects of the hot-spot problem and maximize the network lifetime is to employ intelligent traffic distribution. Transmission power control can be used along with the optimal traffic distribution to achieve both energy efficiency and energy balance. Although it has been shown that the ideal energy-efficient transmission range for general ad hoc networks is $d^{opt} = \sqrt[\alpha]{\frac{2E_{elec}}{(\alpha-1)\epsilon_{amp}}}$ [5], this optimal transmission range is derived for networks in which traffic flows are assumed to be randomly distributed within the network rather than converging to a single base station as in sensor networks. Thus, this fixed optimal solution may not be suitable for many-to-one sensor networks. In this section, we show how setting optimal transmission ranges that vary with the sensors' positions in the network can help to balance energy consumption and lengthen network lifetime.

We start our study with a one-dimensional network deployment, which may occur in such applications as highway traffic congestion monitoring or boundary monitoring. In this network, nodes are separated by a distance of Δ, leading to the data sink, as depicted in Fig. 1. We assign nodes the same initial energy $e_i^{init} = 1$ Joule and the same

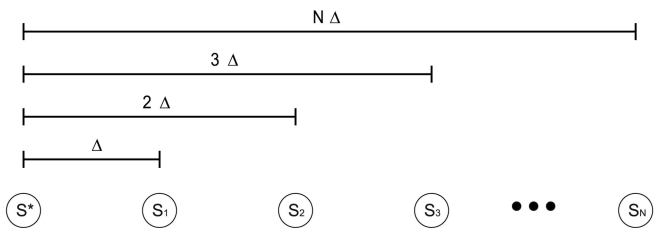


Fig. 1. A one-dimensional regularly spaced network topology. Nodes are equally spaced in this scenario.

traffic generation rate $r_i = 1$ bps. In all simulations and analysis, we use values of $E_{elec} = 50\ \mathrm{nJ/bit}$ and $\epsilon_{amp} = 100\ \mathrm{pJ/bit/m^2}$ [18].

We assume that nodes can adjust their transmit power large enough to transmit to sensors 100 m away (that is, $d^{max} = 100$ m). We solve a linear program with (1), (3), (4), (6), and (8) as the constraints and a goal of maximizing L. The linear program solution provides us with the maximum achievable network lifetime for this strategy. This lifetime is shown in Fig. 2 for various network radii.

In the optimal traffic distribution matrix, nodes that are very close to the base station simply transmit all of their traffic directly to the base station. Nodes at farther distances transmit most of their packets over multiple hops and send a smaller share of their packets directly to the base station over long distances. The traffic distribution matrix's solution is analyzed more thoroughly in [12].

To investigate the improvement that transmission power control provides, we compared its lifetime with the lifetime of a fixed transmission power scheme, which we found using an optimization program with (1), (3), (5), (6), and (8) as the constraints. The results are shown in Fig. 2. For each network radius, the optimal fixed transmission range was found using a brute-force search. Although it seems that transmission power control greatly improves energy efficiency, analysis shows that the improvements in Fig. 2 are a result of the inefficiency of the last-hop transmissions when transmission power control is not used. The sensors transmitting along the last hop have their power set unnecessarily high compared with the required level to reach the base station. To isolate the effect of this, we also propose and analyze a heuristic power control scheme in which nodes transmit using a fixed transmission power over most hops while using transmission power control for the last hop. To model this heuristic scheme, the constraint imposed by (5) must be modified as follows:

$$d_{ij}^t = \begin{cases} d^{max} & j \in \{1 \ldots N\}, \\ d_{ij} & j = 0. \end{cases} \tag{12}$$

The lifetime performance of this heuristic power control scheme is shown in Fig. 2. The optimal transmission distances d^{max} for each network radius are obtained through brute-force searches on all possible transmission ranges. The heuristic power control scheme performs somewhere between the optimal power control scheme and the fixed scheme.

If we take a closer look at the solutions for the fixed transmission range and heuristic power control schemes, we notice that when the first sensors die (those closest to the base station), there is still some energy left in the remaining nodes, especially those nodes far from the base station. The residual energy increases as the node distance to the base station increases since nodes at far distances have fewer packets to forward. In the optimal transmission power control scheme, we notice that most of the traffic is still sent over distances close to the ideal transmission distance d^{opt}, which has in a value of 32 m for our energy model. Sensors manage to increase the network lifetime by using their residual energy to transmit a greater share of their packets directly to the base station, lightening the load on the sensors closer to the base station. However, these transmissions are very energy inefficient, and only a few extra packets can be transmitted in this manner.

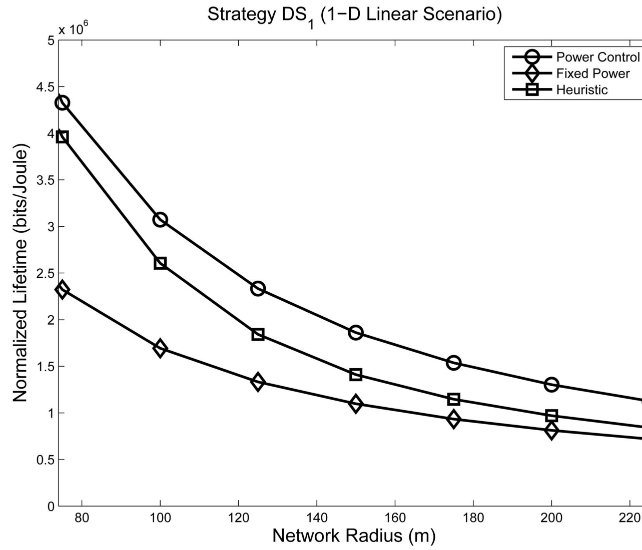


Fig. 2. Network lifetime as a function of the network radius for the optimal power control scheme, the fixed transmission power scheme, and the heuristic power control scheme in a one-dimensional scenario.

Energy imbalance becomes a more severe problem in two-dimensional (2D) networks since sensor locations are more densely concentrated further from the base station. In the optimal solution using transmission power control, more packets are transmitted over long inefficient distances to use up the energy of sensors far from the base station. Fig. 3 compares the performance of the optimal transmission power control scheme, the fixed transmission power scheme, and the heuristic transmission power control scheme for two-dimensional grid networks. The performance of the heuristic scheme is very close to that of the optimized power control, especially when the network radius is large. More discussion about optimal transmission power control for 2D networks can be found in [12].

From the results in this section, it is obvious that a good sensor network deployment strategy should strive to achieve energy efficiency and energy balance simultaneously. On one hand, it should allow nodes to transmit their packets using the optimal transmission range as much as possible. On the other hand, a good strategy should simultaneously allow nodes to use up all of their energy. However, transmission power control alone cannot achieve both goals. In the next section, we will evaluate alternative strategies that can be used to resolve energy imbalance, and we will investigate how well they meet both goals.

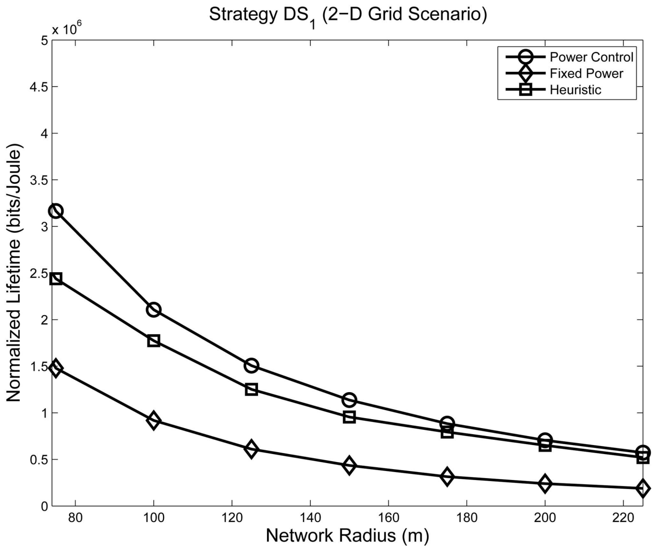


Fig. 3. Network lifetime as a function of the network radius for the optimal power control scheme, the fixed transmission power scheme, and the heuristic power control scheme in a 2D scenario.

6 Comparison of Different Deployment Strategies

In the previous section, we showed that optimal traffic load distribution with transmission power control is not very effective in extending the network lifetime in some scenarios. However, for deployment strategy DS_1, this is the only option for extending the network lifetime. In this section, we investigate how well each of the other strategies listed in Table 2 improves the network lifetime. We will evaluate these strategies using the general normalized lifetime and deployment cost models, defined in Section 4.

When determining the normalized lifetime for each deployment scenario, we use an arbitrary sample scenario that is manageable in terms of memory and processing for solving the linear programs. In the sample scenario, $N_s = 180$ nodes are deployed in a disc with a radius of 250 m, and sensors send traffic at a rate of $\bar{r} = 1$ bps. The total energy assigned to the sensors is 180 Joules. The network parameters for the sample scenario are summarized in Table 4. Once the values of $\widetilde{L}$ have been determined for each deployment strategy via the analysis of this sample scenario, they can be used to compare the cost efficiency of different deployment strategies for a larger scale target scenario. For each deployment strategy, we find the normalized lifetime with and without transmission power control. For the scenarios without transmission power control, we perform a brute-force search over all possible fixed transmission ranges so that we find an upper bound for that scenario using any transmission power.

TABLE 4
Network Parameters for the Sample Scenario

Parameter	Value
Network Radius	250 m
N_s	180
λ_a	$\frac{180}{\pi 250^2}/m^2$
$e^{init,total}$	180 J
λ_a	$\frac{180}{\pi 250^2}J/m^2$
$\bar{r}$	1 bit/sec

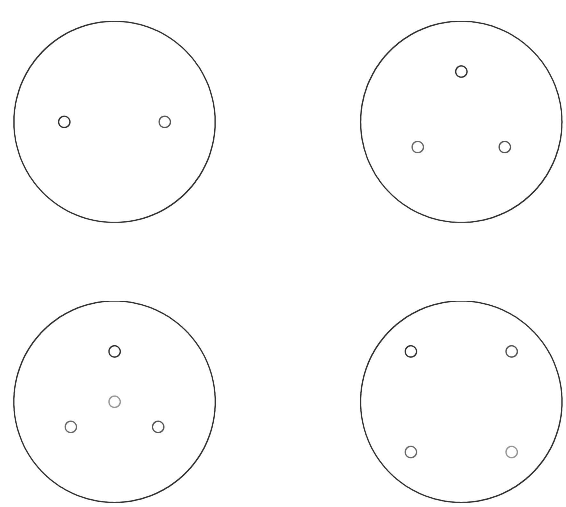


Fig. 4. Sink locations can be presumed to be in a symmetric pattern. The pattern for less than five sinks can thus be determined as shown.

6.1 Deployment Strategy DS_1: Single Static Sink

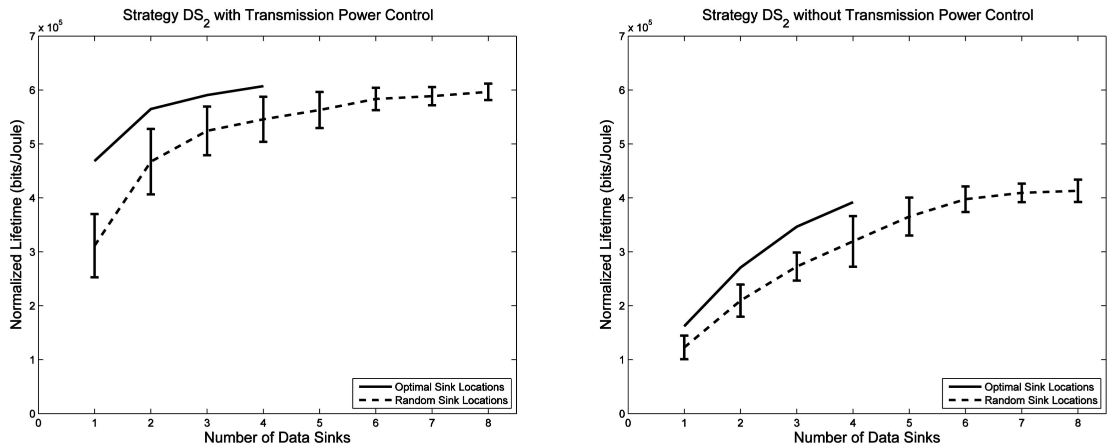
The effectiveness of using transmission power control and optimal traffic distribution with deployment strategy DS_1 has been fully studied in Section 5. The normalized lifetime for a 2D network utilizing the parameters in the sample scenario (Table 4) was found to be 4.69×10^5 bits/J when using transmission power control and 1.62×10^5 bits/J when not using transmission power control.

6.2 Deployment Strategy DS_2: Mobile Data Sink

In this section, we analyze the effectiveness of a mobile data sink for extending the network lifetime. Suppose that the mobile data sink stops at a given number N_l of data sink locations, and all of the active sensors report to this sink when it stops at a new location.[4] For small values of N_l such as 2, 3, and 4, we assume that the optimal sink locations form a symmetric pattern, as shown in Fig. 4. To find the optimal locations, we can use a brute-force search, slowly varying the distances between the base stations and the center of the deployment region, while finding the maximum lifetime achievable for each set of sink locations. For values of N_l larger than four, it is more difficult to determine the optimal base station locations. Therefore, we resort to random location deployment.[5]

During the period that the data sink is at each of the locations, the data flow at each sensor should be balanced. To account for this, several modifications must be made to our model's constraints. We will refer to the time during which each data sink location l is operational as L_l. The

4. We ignore the travel time for a data sink to change its location.
5. We can assume that the optimal pattern would be able to achieve a lifetime comparable to the upper bound seen in the simulations utilizing randomly chosen locations.



(a) (b)

Fig. 5. Normalized lifetime versus number of data sinks deployed for the sample scenario (a) with transmission power control and (b) without transmission power control. Increasing the number of sink locations improves the lifetime until a certain threshold is met and the hot-spot problem has been effectively solved.

amount of traffic sent from sensor i to sensor j during the time when sink location l is active will be denoted as t_{ijl}. The conservation of flow constraints become

$$\sum_{j=1}^{N_s} t_{ijl} + r_i L_l = \sum_{j=0}^{N_s} t_{ijl} \quad \forall i \in \{1, \cdots, N_s\}, \forall l \in \{1, \cdots, N_l\}. \tag{13}$$

Meanwhile, the energy consumption of each sensor should be defined as

$$e_i = \sum_{j=0}^{N_s} \sum_{l=1}^{N_l} \Big(E_{elec} + \epsilon_{amp} (d_{ij}^t)^\alpha \Big) t_{ijl} + \sum_{j=1}^{N_s} \sum_{l=1}^{N_l} E_{elec} t_{jil}. \tag{14}$$

The goal of the linear program is now to maximize $\sum_{l=1}^{N_l} L_l$.

Note that sensors are required to send their traffic in a timely manner. Although we do not consider packet delay in our analysis, we make a fundamental underlying assumption that the data must reach its destination before the data sink moves to a new location. Otherwise, a node could simply hold the data until the base station moves to a nearby location, and the lifetime could be made arbitrarily high.

Figs. 5a and 5b show plots of the normalized lifetime $\widetilde{L}$ as a function of the number of data sink locations N_l with and without transmission power control, respectively. Plots of $\widetilde{L}$ using optimal data sink locations are given by the solid lines, and plots of $\widetilde{L}$ using randomly chosen data sink locations are given by the dashed lines with standard deviation bars.

The use of DS_2 with random data sink deployment and transmission power control improves the network lifetime by 92 percent to 5.97×10^5 when using eight data sink locations instead of just one. However, the normalized lifetime flattens out at about eight data sink locations since the hot-spot problem is already solved effectively at this point. When transmission power control is not available, the use of eight data sink locations improves the lifetime 237 percent to 4.13×10^5. However, the improvement again flattens out at eight data sink locations.

Although the normalized lifetime of DS_2 for a large number of sink locations is higher than that of DS_1 (and thus, the required number of sensors is lower), a mobile data sink may be much more expensive than a stationary data sink used in DS_1. This cost may affect the overall desirability when we compare and evaluate the different deployment strategies.

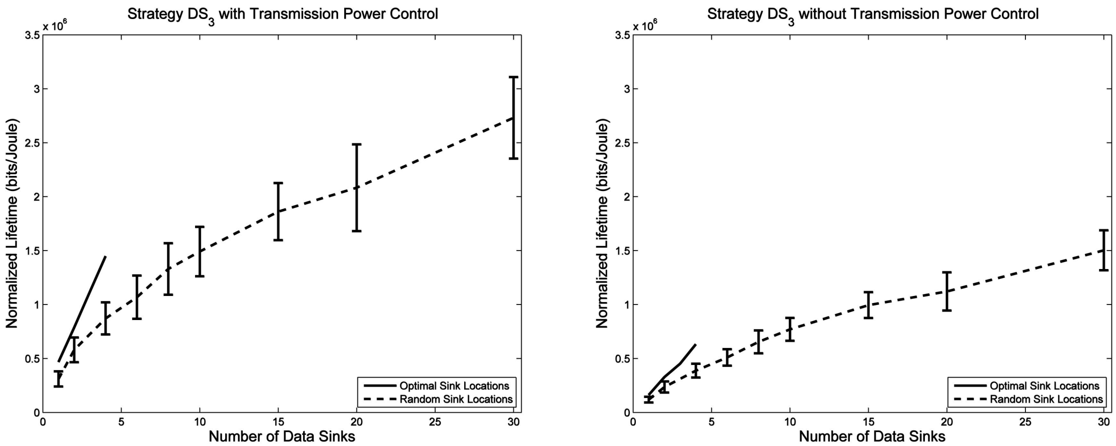
6.3 Deployment Strategy DS_3: Multiple Data Sinks/Clustering

In a clustering approach, multiple aggregator-capable nodes are deployed, and each sink collects data from only a portion of the sensor network for the entire network lifetime. Previous work in this area deals primarily with homogeneous networks, in which any of the deployed nodes is capable of acting as cluster head. Although this may be the case in some network scenarios, it can be expected that data aggregation will require more powerful processors and, thus, more expensive sensor nodes, resulting in the deployment of heterogeneous networks. In this section, we consider such heterogeneous networks, where cluster heads are actually data sinks that are more capable (for example, they contain larger batteries, more processing power and memory, and possibly a second radio to link back to a central base station) and significantly more expensive than ordinary microsensors. In our model, a sensor may send its traffic to whichever cluster head it chooses.[6]

This deployment strategy also requires a modification of the first constraint in our network lifetime model. Since we have multiple data sinks, we can no longer refer to a single sink s_0. Rather, we will refer to the data sinks as $S^* = \{s_{N_s+1}, \ldots, s_{N_s+N_l}\}$. Equation (1) should be modified as follows:

$$\sum_{j=1}^{N_s} t_{ji} + r_i L = \sum_{j=1}^{N_s+N_l} t_{ij} \qquad \forall i \in \{1, \cdots, N_s\}. \tag{15}$$

6. The chosen cluster head is typically but not necessarily the closest cluster head.



(a) (b)

Fig. 6. Normalized lifetime versus the number of cluster heads deployed (a) with transmission power control and (b) without transmission power control. Large gains in the network lifetime can be achieved when even a few extra cluster heads are deployed, especially when their locations are optimized. Random sink locations can provide lifetime improvement, but it is not as large as that obtained using the optimal sink locations. When power control is unavailable, the gap between random sink locations and optimal sink locations is greatly reduced.

The energy consumption of each sensor can be described as

$$e_i = \sum_{j=1}^{N_s+N_l} \Big(E_{elec} + \epsilon_{amp}(d_{ij}^t)^\alpha\Big)t_{ij} + \sum_{j=1}^{N_s} E_{elec}t_{ji}. \tag{16}$$

Using the sample scenario, we find the relationship between the normalized lifetime and the number of data sinks that are deployed, as shown in Figs. 6a and 6b for schemes with and without transmission power control, respectively. The normalized lifetime is given for optimal cluster head placement,[7] as well as random placement. As expected, when more cluster heads are deployed, the hot-spot problem is reduced, and the network lifetime improves. In the most extreme case, so many data sinks are deployed that every sensor can find a data sink just one hop away. The hot-spot problem is completely solved in this case. When transmission power control is used, the normalized lifetime is found to be 3.11×10^5 bits/J for a single base station and increases to 2.73×10^6 bits/J for 30 base stations. When transmission power control is not applied, increasing the number of randomly deployed data sinks from 1 to 30 increases the normalized lifetime from 1.19×10^5 bits/J to 1.50×10^6 bits/J.

Note that the performance of DS_3 is better than that of DS_2 since on the average, traffic is forwarded over much shorter distances (to the closest data sink rather than the single global data sink). Another potential advantage of clustering is that it may better accommodate certain scheduling schemes. The cluster heads can serve as local controllers for scheduling, which brings additional advantages over the single-sink uniform deployment strategy. However, unlike the assumed fixed extra cost for a mobile data sink, the extra cost of this strategy is more likely to have a linear relationship with the number of data sinks deployed. Therefore, a proper number of data sinks must be chosen according to the cost ratio of data sinks and normal sensors.

7. Again, optimal cluster head location patterns are only achievable for a small number of cluster heads through brute-force searching.

6.4 Deployment Strategy DS_4: Nonuniform Energy Assignment

In strategy DS_4, we loosen the initial energy constraint and allow each sensor to be deployed with a different value of initial energy. In this strategy, (1), (3), (4), (6), and (7) are used as the constraints for the linear program. The lifetime performance of nonuniform energy assignment for various network radii is shown in Fig. 7. Compared to the results shown in Fig. 3, in which optimal traffic distribution is the only option, the normalized lifetime improves from 4.69×10^5 bits/J to 9.09×10^5 bits/J for the sample scenario when using transmission power control. The normalized lifetime increases from 1.62×10^5 bit/J to 7.25×10^5 bit/J when transmission power control is not used. Figs. 8a and 8b show the optimal energy assignment map for nodes at different distances to the base station, along with an interpolated polynomial function, for schemes using

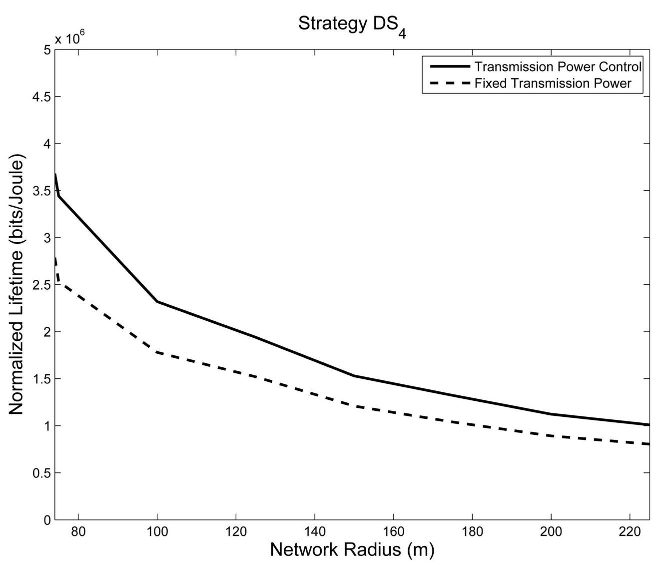
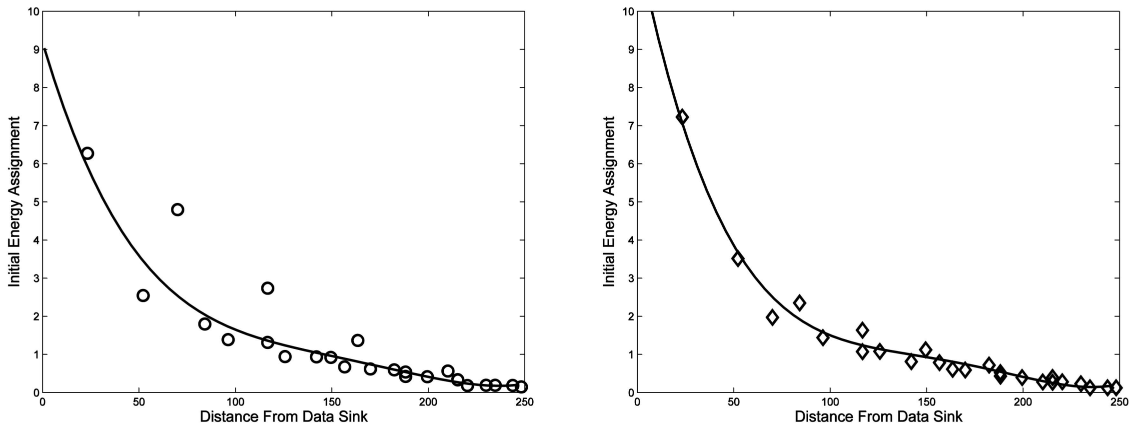


Fig. 7. Normalized lifetime as the network radius varies for the nonuniform energy assignment strategy.



(a) (b)

Fig. 8. Energy distribution map for the sample scenario (a) with transmission power control and (b) without transmission power control. Nodes closest to the base station should be assigned the most energy. The assignment can be approximated using a polynomial function.

transmission power control and not using transmission power control, respectively.

Intelligent energy assignment seems to be a good choice for sensor network deployment. However, this strategy is inherently difficult since energy must be assigned differently for individual nodes at different locations. When sensor deployment is performed in a random manner, this becomes almost impossible. However, deployment strategy DS_5 (nonuniform sensor placement) is very similar in nature to DS_4, and its use seems more realistic. We will omit further discussions of DS_4 and focus on strategy DS_5 in the remainder of this paper.

6.5 Deployment Strategy DS_5: Nonuniform Relay/Sensors

If we assume that all sensors must be deployed with equal initial energy, we may deploy more relay/sensor nodes according to the energy maps shown in Fig. 8, achieving the same goal of providing more energy at particular points in the network. The normalized lifetime obtained using this approach is equivalent to that calculated for DS_4.

6.6 Deployment Strategy DS_6: Nonuniform Traffic Generation

In certain sensor networks, more traffic may be generated at distances farther from the base station. For example, in sensor networks designed for intruder detection, the sensors in the network periphery may provide the most important data, as these sensors notify the application when an intruder has entered the network area. The majority of the work for nodes closest to the base station is to forward the traffic, rather than to generate it. In this type of traffic generation pattern, the hot-spot problem is automatically alleviated. Consider an extreme case in the one-dimensional scenario in Fig. 1. If only sensor N_s, the sensor furthest from the data sink, generates traffic, the traffic will be forwarded hop by hop to the data sink. Choosing the next hop closest to the optimal transmission range will be the most energy-efficient forwarding method, and the energy imbalance trends seen in other deployment strategies will not exist.

Data aggregation can be considered a variation of nonuniform traffic generation as well. As data are forwarded to the base station, sensors may perform some processing and aggregate their data with the received data before forwarding. Even if the data generation rate is uniform within the network, data aggregation actually transforms it into a nonuniform traffic generation pattern. Again, this helps to reduce the hot-spot problem.

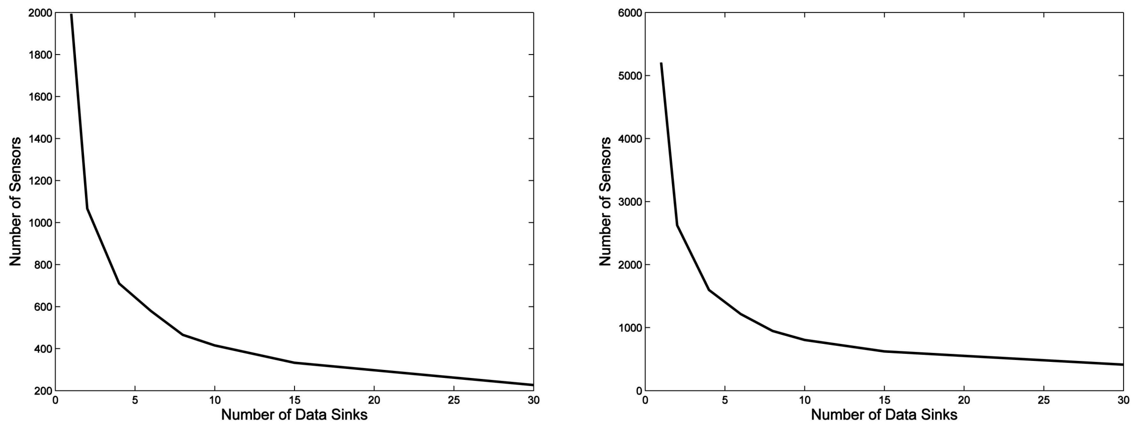
However, in sensor networks where areas closer to the data sink are more of interest for monitoring, more traffic is generated around the data sink. This actually aggravates the hot-spot problem. All of the strategies mentioned earlier can be applied to alleviate the problem, and our model is still applicable to these scenarios. However, these scenarios are essentially different from the previous scenarios. Therefore, we will not compare the performance of this strategy with that of the previous strategies.

6.7 Cost Comparison of Deployment Strategies

Now that we have analyzed the normalized lifetime of the different deployment strategies, in this section, we analyze the cost efficiency of the deployment strategies for a chosen target scenario. In our target scenario, we wish to monitor a disc with a radius of 250 m with sensors that send traffic at an average rate of $\bar{r} = 100$ bps. The sensors are activated with a density of 0.001 $\mathrm{sensors/m^2}$ and are deployed with an initial energy of $e^{init} = 1{,}000$ J. The target network lifetime L is one year. The network parameters for the target scenario are summarized in Table 5.

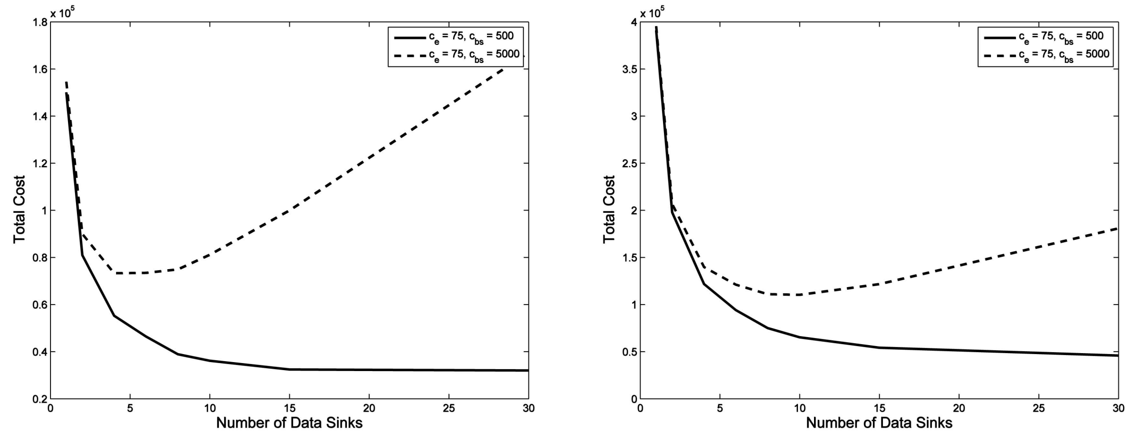
TABLE 5
Network Parameters for the Target Scenario

Parameter	Value
Network Radius	250 m
λ_a	0.001 $/m^2$
$e^{\bar{init}}$	1000 J
$\bar{r}$	100 bit/sec
L	1 year



(a) (b)

Fig. 9. Number of sensors required to meet the target scenario lifetime (a) when using transmission power control and (b) when not using transmission power control for the multiple-data-sink deployment strategy.



(a) (b)

Fig. 10. Total cost of deployment for the target scenario (a) when using transmission power control and (b) when not using transmission power control for the multiple-data-sink deployment strategy.

We compare the cost efficiency of several deployment strategies under two cost scenarios. In both scenarios, the cost of a normal microsensor is assumed to be $75 per unit [26]. In the first cost scenario, the base stations are relatively cheap units ($500 per unit) such as simple Crossbow Stargate nodes [27]. In the second cost scenario, the base station becomes a much more expensive unit ($5,000 per unit) such as a high-power laptop or a custom-designed base station.

When analyzing the cost efficiency of DS_2, we assume a large number of movements by the data sink and use the normalized lifetime obtained from using eight data sink locations, as it seems to be fairly close to an asymptotic bound. For strategy DS_3, before comparing the strategy as a whole, we must find the optimal number of sink locations to use for a given cost model. The number of sensors required for our target scenario when using strategy DS_3 is plotted in Figs. 9a and 9b for schemes with and without transmission power control, respectively. The total costs for both cost scenarios are plotted in Figs. 10a and 10b. As expected, when data sinks are cheaper, it is more cost-efficient to deploy more of them. As a representative set of solutions, we will consider the use of eight data sinks and 30 data sinks in our cost analysis.

The number of sensors required to meet the target lifetime for different deployment strategies when using transmission power control and not using transmission power control is summarized in Tables 6 and 7, respectively. We can see that in Cost Scenario 1, when the base station is relatively cheap, it is wise to use a clustering approach with many base stations, and DS_3 with $N_l = 30$ becomes the most cost-efficient approach. When sensors become much cheaper than base stations, it becomes more effective to use a single base station and deploy more sensors, and thus, DS_5 becomes the most cost-effective. For such a scenario, nonuniform sensor deployment is the best option. If this is not possible, then a clustering approach with fewer data sinks is the next best option. After this, if the difference in costs between DS_1 and DS_2 is enough to make up for the hidden costs of DS_2 not shown here (those that are difficult to quantify in a general sense, such as the cost to manually move the data sink or the extra cost of adding robotics to the data sink), then DS_2 should be used. As a last resort, DS_1 can be used.

Although the normalized lifetime for some strategies is higher than others, when considering the extra cost of these strategies, they become less desirable than some of the less energy-efficient strategies. A complete evaluation of

TABLE 6
Cost Evaluation for the Two Cost Scenarios with Transmission Power Control

	DS_1	$DS_2, N_l = 8$	$DS_3, N_l = 8$	$DS_3, N_l = 30$	DS_5
$N_s(DS_i)$	1322	1038	466	227	681
Cost Scenario 1					
c_s	\$75	\$75	\$75	\$75	\$75
c_{e1}	\$500	\$500	\$500$\times$ 8	\$500$\times$ 30	\$500
C_1	\$99626	\$78353	\$38923	**\$32006**	\$51607
Cost Scenario 2					
c_s	\$75	\$75	\$75	\$75	\$75
c_{e1}	\$5000	\$5000	\$5000$\times$ 8	\$5000$\times$ 30	\$5000
C_2	\$104130	\$82850	\$74920	\$167010	**\$56110**

TABLE 7
Cost Evaluation for the Two Cost Scenarios without Transmission Power Control

	DS_1	$DS_2, N_l = 8$	$DS_3, N_l = 8$	$DS_3, N_l = 30$	DS_5
$N_s(DS_i)$	3820	1499	947	412	854
Cost Scenario 1					
c_s	\$75	\$75	\$75	\$75	\$75
c_{e1}	\$500	\$500	\$500$\times$ 8	\$500$\times$ 30	\$500
C_1	\$286990	\$112930	\$75030	**\$45900**	\$64540
Cost Scenario 2					
c_s	\$75	\$75	\$75	\$75	\$75
c_{e1}	\$5000	\$5000	\$5000$\times$ 8	\$5000$\times$ 30	\$5000
C_2	\$291490	\$117430	\$111030	\$180900	**\$69040**

different strategies should be performed from both an energy and a cost perspective. Although these conclusions sound straightforward, our method provides a quantification on the overall cost, and thus, a clear method for making a decision between several potential strategies.

7 Conclusions

In this paper, we proposed a general network lifetime model and a general deployment cost model to evaluate multiple sensor network deployment strategies. In our study, we have made the following observations:

1. Most sensor network deployment strategies can be generalized and have their maximum achievable lifetime found using a linear programming model. Their differences lie in the freedom of deployment parameters and the constraints on the network parameters.
2. A good sensor network deployment strategy is one that achieves both energy balance and energy efficiency.
3. Energy imbalance becomes worse when the network size increases, and when the network goes from one to two dimensions. The maximum achievable lifetime decreases accordingly.
4. Contrary to intuition, the strategy of transmission power control is not sufficient to resolve both energy imbalance and energy inefficiency. The limited lifetime improvement from transmission power control is mainly due to energy savings from nodes close to the data sink.
5. A good strategy should allow sensors to send most of their traffic at the general optimal transmission range (32 m in this paper).
6. The strategy of mobile-data-sink deployment has some limitations on lifetime improvement, whereas the strategy of deploying multiple data sinks can continue to improve the network lifetime as more sinks are added until the subnetworks become one-hop networks.
7. The strategy of nonuniform energy assignment achieves both energy efficiency and energy balance simultaneously. However, it is inherently difficult to apply in practice.
8. Although more intelligent strategies may have better lifetime performance, the cost of these strategies

must be fully considered because once the quality of service of a network is satisfied, the cost becomes the primary concern for a practical sensor deployment plan.

Thus, this paper has made the following contributions. First, we propose a general lifetime model that can be applied to many sensor network deployment strategies with little or no modifications. Second, we reveal the general lifetime trends for different deployment strategies. Finally, we propose a general method to compare the normalized lifetime and cost for different strategies, which provides practical suggestions for real sensor deployment.

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