Strategies for Mitigating the Sensor Network Hot Spot Problem

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***Abstract*— In multi-hop wireless sensor networks that are characterized by many-to-one (convergecast) traffic patterns, problems related to energy imbalance among sensors often appear. When the transmission range is fixed for nodes throughout the network, the amount of traffic that sensors are required to forward increases dramatically as the distance to the data sink becomes smaller. Thus, sensors closest to the data sink tend to die early, leaving areas of the network completely unmonitored and causing network partitions. Alternatively, if all sensors transmit directly to the data sink, the furthest nodes from the data sink will die much more quickly than those close to the sink. Network lifetime can be improved to a limited extent by the use of a more intelligent transmission power control policy that balances the energy used in each node by requiring nodes further from the data sink to transmit over longer distances (although not directly to the data sink). However, transmission power control alone is not enough to solve the hot spot problem. Rather, policies such as data sink movement or data aggregation are necessary for the network to operate in an energy efficient manner. Since the movement of the data sink and the deployment of an aggregator node may be significantly more expensive than the deployment of an ordinary microsensor node, there is a cost tradeoff involved in both of these approaches. This paper provides an analysis of each of these policies for mitigating the sensor network hot spot problem, considering energy efficiency as well as cost efficiency.**

I. Introduction

Large scale wireless sensor networks are an emerging technology that have recently gained attention for their potential use in applications such as environmental sensing and mobile target tracking. 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 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 polices, and all levels of the network stack. However, reducing an individual sensor's power consumption alone may not always allow networks to realize their maximal potential lifetime. In addition, it is important to maintain a balance of power 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. Based on the power model of a specific sensor node platform, there exists an optimal transmission range that minimizes overall power consumption in the network. When using such a fixed transmission range in general ad hoc networks, energy consumption is fairly balanced, especially in mobile networks, since the data sources and sinks are typically assumed to be distributed throughout the area where the network is deployed. However, in sensor networks, where many applications require a many-to-one (convergecast) traffic pattern in the network, energy imbalance becomes a very important issue, as a hot spot is created around the data sink, or base station. 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.

Intuition leads us to believe that the hot spot problem can be solved by varying the transmission range among nodes at different distances to the base station so that energy consumption can be more evenly distributed and the lifetime of the network can be extended. However, this is only true to some extent, as energy balancing can only be achieved at the expense of using the energy resources of some nodes inefficiently [1]. We conclude from our study that transmission power control can alleviate the hot spot problem only to a limited degree, and alternative solutions are necessary for the network to operate in a more energy efficient manner.

In this paper, we formulate the transmission range distribution optimization problem and analyze the limits of network lifetime for uniformly deployed wireless sensor networks, which are easily obtained by using a practical energy-associated heuristic solution. However, as optimal transmission range distribution cannot fully solve the hot spot problem, we explore two alternative strategies: the employment of multiple data sink locations, implemented by using either a mobile data sink or several sinks deployed during the initial network deployment, and the formation of data aggregation clusters. We investigate the effectiveness of these techniques in combination with the optimization of transmission range distribution to determine their effectiveness in extending network lifetime. Since applying these strategies during network deployment may introduce extra costs, we explore the tradeoff between using these more advanced solutions and the cost, and we propose cost efficient suggestions for practical sensor deployments.

The rest of this paper is organized as follows. Section II addresses related work. Section III reviews the transmission power control problem and explores its effectiveness in mitigating the hot spot problem. Section IV investigates the effectiveness and cost efficiency of data sink movement and the deployment of multiple aggregator nodes, respectively, as alternative solutions to the hot spot problem. Section V concludes the paper.

II. Related Work

A. Transmission Range Optimization

Early work in transmission range optimization assumed that forwarding data packets towards a data sink over many short hops is more energy efficient than forwarding over a few long hops, due to the nature of wireless communication. The problem of setting transmission power to a minimal level that will allow a network to remain connected has been considered in several studies [2], [3]. Later, others noted that because of the electronics overhead involved in transmitting packets, there exists an optimal non-zero transmission range, at which power efficiency is maximized [4], [5]. The goal of these studies was to find a fixed network-wide transmission range. However, using such schemes may result in extremely unbalanced energy consumption among the nodes in sensor networks characterized by many-to-one traffic patterns. If we define sensor network lifetime as the model presented in [6], which is the network duration until the first node runs out of energy, this unbalanced energy consumption will greatly reduce the network lifetime.

An energy efficient routing scheme was proposed in [7]. The objective function of this scheme is to extend network lifetime by routing outgoing traffic intelligently. Iterative algorithms that are based on the formulation of the problem as a concurrent maximum flow problem are presented as well. Our transmission range distribution problem is similar to this energy efficient routing problem in many aspects. However, we propose a heuristic scheme that can easily be implemented rather than only providing an upper bound on network lifetime for specific topologies. Also, we extend the solution to alternative strategies rather than attempting to solve the problem using transmission range distribution alone.

B. Sensor deployment strategies

Several sensor deployment strategies exist that can help extend network lifetime. These strategies include the movement of data sinks [8], [9], [10], [11], [12], the deployment multiple base stations [13], and the formation of data aggregation clusters [14], [15], [16]. However, some of the research related to these strategies has primarily considered the case where the strategies are specifically chosen around the application requirements, while the others have focused only on the feasibility of the proposed solution while ignoring the fact that a more complex sensor deployment scheme may incur a larger financial cost. In this paper, not only do we investigate and compare the performance of each strategy using general terms such as normalized network lifetime, but we also propose some practical sensor deployment strategies from a cost efficient perspective.

III. Transmission Power Control

In this section, we review our study of the transmission range distribution optimization problem, which is solved by determining how a node should distribute its outgoing data packets over multiple distances, always using the minimum transmission power necessary to send over each distance. Given the energy constraints and data generation rate of each sensor node, the lifetime of the network, which we define to be the time at which the first sensor dies, can be maximized by using this optimal distribution. In typical sensor network applications, it may be true that the network can survive node failures as long as neighboring sensors can assume the failing nodes' responsibilities; however, we expect neighboring sensors to exhibit similar trends and attain similar lifetimes. Thus, we consider our definition of network lifetime valid even for such sensor network models. We refer to this problem as a transmission range distribution optimization problem rather than a transmission range optimization problem because we assume that nodes may send packets over multiple transmission ranges instead of setting a fixed transmission range. In our work, we have adopted the widely used power model from [14], where the amount of energy to transmit a bit can be represented as $E_{bit,tx} = E_{elec} + \epsilon d^{\alpha}$ and the amount of energy to receive a bit can be represented as $E_{bit,rx} = E_{elec}$. To obtain a true upper bound on network lifetime, we have made several simplifications in our network model. For a description of our model and assumptions, the reader is referred to [1].

In order to show the effectiveness of optimizing transmission range distribution, we provide simulation results that give the lifetime obtained using three different solutions: the optimal solution as found in [1], the optimal fixed transmission range solution and an energy-associated heuristic solution. In the second solution, we use the ideal energy efficient transmission range $d^* = \sqrt[\alpha]{\frac{2E_{elec}}{(\alpha-1)\epsilon}}$ from [4], [5], which is optimal in the absence of the sensor network hot spot problem. The third solution is obtained using our proposed energy-associated heuristic scheme. In this scheme, we assign routing costs to sensors to be the inverse of their residual energy. Link costs are set equal to a weighted sum of the energy consumed by the transmitting node and the receiving node, as given by Equation 1. Minimum cost routes are updated throughout the lifetime of the network through frequent routing updates. In all simulations, we use values of $E_{elec} = 50\ nJ/bit$ and $\epsilon = 100\ pJ/bit/m^2$, resulting in a value of $d^* = 32m$.

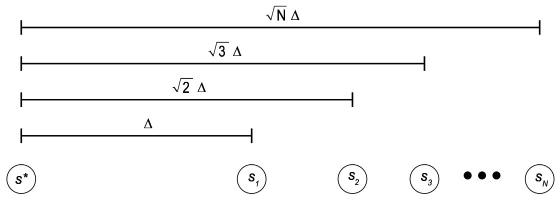


Fig. 1. One-dimensional modeling of a two-dimensional sensor field.

$$C_{link}(s_i, s_j) = \frac{1}{E_{res}(s_i)} E_{tx,bit}(s_i, s_j) + \frac{1}{E_{res}(s_j)} E_{rx,bit}(s_i, s_j) \quad (1)$$

For any given scenario, we can obtain the network lifetime L and the transmission distributions using these three schemes. Let us begin with a simple scenario, a densely deployed uniform two-dimensional field, as a case study. We modeled this deployment as a one-dimensional field with nonuniform spacing. With very dense sensor deployment, we can assume that sensors will always send their packets within an infinitesimally thin angle toward the data sink. Since the number of nodes N within the distance r from the data sink satisfies $N \propto r^2$ for two-dimensional networks, when mapped onto a one-dimensional space, the distance of a node to the data sink should be proportional to the square root of the node index, as shown in Figure 1.

The network lifetime performance using the three schemes are shown in Figure 2. Using a fixed network-wide transmission range results in a lower network lifetime, even when the optimal fixed transmission range is used. This illustrates the importance of varying the transmission range as a function of a node's location in the network. Because it incorporates two important goals of lifetime maximization – power minimization and energy balancing – the energy-associated heuristic routing scheme is able to achieve close to the lifetime obtained through the optimal transmission range distribution (the dotted line almost overlaps with the solid line in Figure 2). Using this scheme, minimum power routes are initially chosen, but as the nodes closest to the data sink start to deplete their energy resources, they are avoided as routers. However, even in the later stages of the network, the power minimization goal is not completely abandoned. Eventually, the routes converge to those that are found through the optimization, and only a small penalty is paid for not discovering the optimality of these routes early enough.

While transmission range distribution optimization and our heuristic scheme are somewhat effective in extending network lifetime compared to the scheme that uses a fixed transmission range, this improvement is limited because of the energy inefficiency forced on the sensors farthest from the data sink in order to evenly distribute the energy load among the nodes. In fact, in order to achieve near-optimal network lifetimes, it is only necessary to use a fraction of the energy available in the network. Consider the two-dimensional network used in

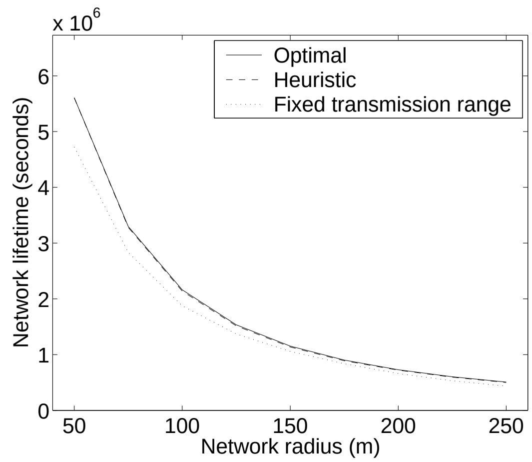


Fig. 2. Case study: network lifetime as a function of network radius for a two-dimensional deployment scenario.

the simulations of this section. Figure 3 shows how network lifetime increases with the total energy used in the network for different scenarios, when the energy consumption of each individual sensor node is limited to $1\ J$. If energy is to be allocated among the nodes in any way in order to maximize network lifetime (i.e., if only the total energy consumption, but not individual energy consumption, is limited), network lifetime should increase proportionally with the energy consumed. This lifetime is illustrated by the dotted line in the figure. With the individual energy consumption constraints imposed by our assumption of uniform node distribution and equal energy allocation, however, the obtainable lifetime, illustrated by the solid line in Figure 3, is found to be only a fraction of this. The shape of the energy-lifetime curve implies that when all of the network energy is completely used, network lifetime improvement is minimal and energy is being used inefficiently. Furthermore, this inefficiency becomes worse as the network grows. In brief, the energy inefficiency is caused primarily by nodes far from the data sink sending traffic directly to the data sink rather than using multiple hops. For a more detailed description of the reasons for this inefficiency, the reader is referred to [1].

Finally, we observe the effect of setting a maximum transmission range on network lifetime. Figure 4 illustrates the obtainable lifetime as a function of network radius for various maximum transmission ranges in a two-dimensional network. Limiting the maximum transmission range severely affects network lifetime, especially for large network radii. The optimal transmission range distribution compensates for high energy drain in the nodes surrounding the base station by requiring the furthest nodes to send over longer distances. If transmission range limitations prevent these transmissions from being realized, it becomes very difficult to balance energy appropriately. Thus, we observe that the hot spot problem becomes even worse when considering the realistic limitations of transmission range.

In summary, the simulation results in this section show that

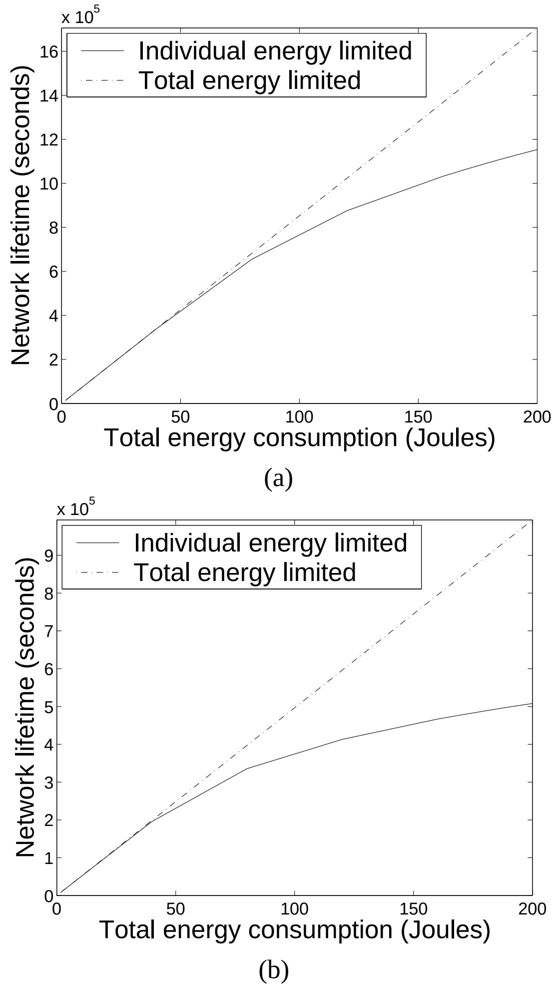


Fig. 3. Lifetime vs. percentage of the total energy consumed in the network for a two-dimensional sensor field with a radius of $150m$ and with a radius of $250m$.

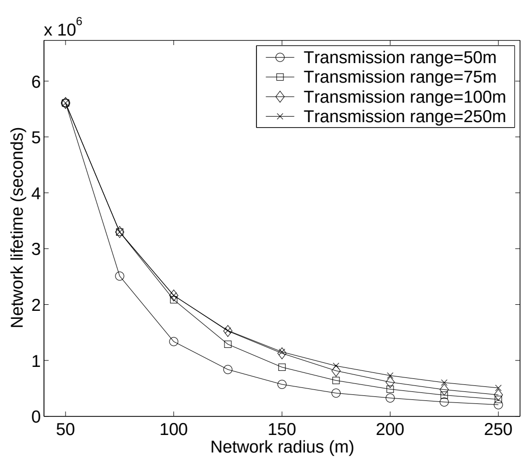


Fig. 4. Network lifetime as a function of network radius for various maximum transmission ranges in two-dimensional network deployments.

while optimizing the transmission range distribution increases network lifetime when compared to using a fixed network-wide transmission range, this optimal lifetime comes with a cost of using the energy inefficiently, especially in very large networks. While using nonuniform deployment is the simplest solution to the problem, this may lead to poorer sensing capabilities in the regions farthest from the data sink. Furthermore, this may be impossible in some applications. With this motivation, we explore alternative strategies for improving the lifetime of many-to-one wireless sensor networks in the next section of this paper.

IV. Sensor network deployment strategies

Since energy imbalance due to the many-to-one traffic pattern is the root cause of energy inefficiency and corresponding restricted network lifetime for sensor networks, we must either compensate energy imbalance among the nodes in order to improve network lifetime or alter the many-to-one traffic pattern. To compensate for the energy imbalance, we must either assign more energy to nodes around hot spots or deploy more nodes around hot spots. However, it may not always be feasible to compensate for the energy imbalance by using these solutions, especially when sensors are randomly deployed and sensors are manufactured to be of the same capabilities. Therefore, in this section, we focus on the latter category of solutions. To alter the many-to-one traffic pattern, several strategies can be applied, including mobile data sinks, multiple data sinks and clustering approaches. In addition, since alternative deployment strategies may incur extra cost, we study these strategies from the perspective of both energy efficiency and cost efficiency.

A. Normalized Lifetime

Before we discuss these specific strategies, we first define a general metric, normalized network lifetime, to describe the efficiency of a network deployment plan. In short, normalized network lifetime $\widetilde{L}$ measures how many total bits can be transported on the network per unit of energy. For a given network scenario, we are able to find the optimal lifetime L^{opt}. This lifetime can be arbitrarily increased by simply increasing the energy density in the network (either by scaling up the deployed sensor density or the average energy per sensor). Also, since we assume that protocols that manage the amount of traffic sent (e.g., [17], [18], [19], [20]) may be used so that the density of active sensors does not necessarily correspond to the density of deployed sensors, lifetime can similarly be increased by decreasing the required active sensor density. Similarly, lifetime can be increased by reducing the bit rate among active sensors. To account for these factors, the normalized network lifetime $\widetilde{L}$ is given as

$$\widetilde{L} = L^{opt}\left(\frac{R_a\lambda_a}{\lambda_e}\right) \tag{2}$$

where λ_a represents the density of active sensors, R_a represents the average bit rate among active sensors, λ_e represents the energy density of the network (we assume uniform distribution of energy), and L^{opt} is the maximum lifetime achievable with the given parameters.

B. Strategy 1: Moving the Data Sink Location

Since intelligent transmission power control policies require inefficient operation to maximize network lifetime, we must solve the hot spot problem by altering the many-to-one traffic pattern. One solution is to allow the data sink to move within the network. Two scenarios in which this is possible are

1) a network that employs a mobile data sink (e.g., a robot), and
2) a network in which multiple aggregator-capable nodes are deployed, only one of which collects all of the data in the network at a given time[1]. This can be seen as a virtual mobile data sink scenario.

These two scenarios are similar from the network routing perspective since during a given period, all data is sent to a single data sink. Although lifetime improvement is one metric that we are interested in, we must realize that these strategies require extra implementation costs compared to schemes utilizing a single static sink. The extra costs may be associated with the energy and extra hardware required to move a data sink, or the hardware costs of deploying extra data sinks. Furthermore, there may be certain energy costs incurred by the microsensors themselves, as additional protocols are needed to advertise the identity and location of the data sinks (however, these can be made arbitrarily small and we ignore their effect in this work). When exploring these schemes and the lifetime extension that can be gained from their use, one should carefully consider these cost tradeoffs for practical sensor deployment.

In addition to moving the data sink's location, network lifetime can always be increased by simply deploying more sensors in the network. While this does not solve the hot spot problem and some data will still be sent over inefficient routes, as shown in the previous section, at least *more* data can be sent. In this section, we analyze the tradeoff between the costs associated with additional sensor deployment and those associated with utilizing multiple data sinks. If the tradeoff is balanced optimally, a desired network lifetime can be obtained for a minimum total cost.

1) Lifetime Improvement: To find the value of $\widetilde{L}$ (given in bits per Joule) of a scheme utilizing multiple data sinks for a given number of data sink locations N_l, we ran lifetime optimization programs while varying the data sink locations. In these simulations, only one data sink operated at a given time, and all of the active sensors reported to this sink during this time. The sensors were deployed in a two-dimensional rectangular grid and were again subject to the same power model as in the previous section. The transmission range of each node was limited to $75m$.

First, we must determine the optimal data sink locations. Although we conjecture that the data sinks should be located where the average distance between sensors and the data sink is minimum, it becomes difficult to find the location pattern for more than four data sinks. Therefore, we only show the lifetime performance of the optimal data sink locations for up to 4 data sinks, and we focus on the lifetime improvement for random data sink deployments. Figs. 5(a) and 5(b) show plots of the normalized lifetime $\widetilde{L}(N_l)$ as a function of the number of data sink locations N_l for a $150m$ radius network and a $250m$ radius network, respectively. Plots of $\widetilde{L}(N_l)$ using randomly chosen data sink locations are given by the solid lines with standard deviation bars in these figures, and the optimal positioned data sinks are plotted by dashed lines.[2]

With the random data sink deployment, the network lifetime shows an improvement of about 67% for the $150m$ radius network and 91% for the $250m$ radius network when using three data sink locations instead of just one. This improvement increases to 86% for the $150m$ radius network and 121% for the $250m$ radius network for six locations. However, using more than six data sink locations does not provide significant lifetime improvement since the hot spot problem is already effectively solved at this point. The simulation results show that larger gains in network lifetime can be obtained as the network size grows. This is because the hot spot problem becomes worse as the network becomes larger.

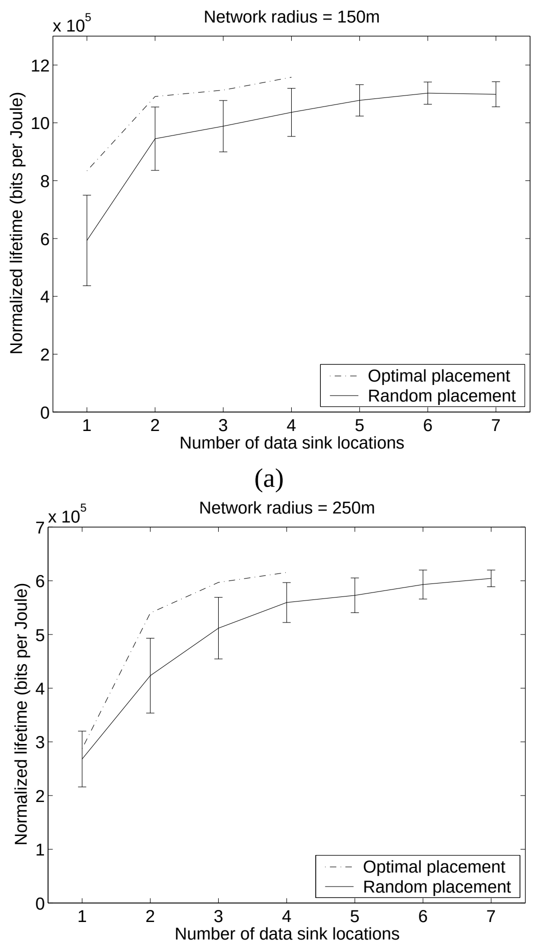
2) Cost Analysis: As shown in these figures, moving the data sink provides longer network lifetime. However, there are extra costs associated with this strategy, specifically the cost of deploying aggregator nodes or moving the data sink. Thus, when these costs are very high, it is wise to simply deploy more sensors and use their energy inefficiently. However, when these extra costs are low, it makes sense to deploy more aggregator nodes or move the data sink multiple times. Given a desired network lifetime L, if we deploy a network with N_l data sink locations, we can calculate the number of sensors $N_s(L, N_l)$ that are required to be deployed in order to achieve lifetime L. If we denote the cost of data sink deployment for a scheme using N_l data sink locations as $C_{ds}(N_l)$ and the cost of deploying one sensor as C_s, the total cost C of deploying such a sensor network to operate for a lifetime of L can be expressed as

$$C(L, N_l) = C_{ds}(N_l) + C_s N_s(L, N_l) \tag{3}$$

where $N_s(L, N_l)$ represents the number of sensors necessary to achieve the lifetime L for a configuration using N_l data sinks. $N_s(L, N_l)$ can be found by rearranging Equation 2, using the relationship $\lambda_e = \frac{N_s * E_s}{A}$ (where E_s represents the

[1]This scenario may occur if an aggregator node needs a complete picture of the network in order to make any decisions. These aggregator nodes could conceivably collect all data in their region and forward these data to another aggregator node for analysis; however, this would be extremely costly for the aggregator nodes and we cannot assume that they are *completely* unconstrained by energy. Furthermore, unless these aggregator nodes can communicate directly with each other on another channel, this data will need to be forwarded between aggregator nodes by the ordinary microsensors in the network.

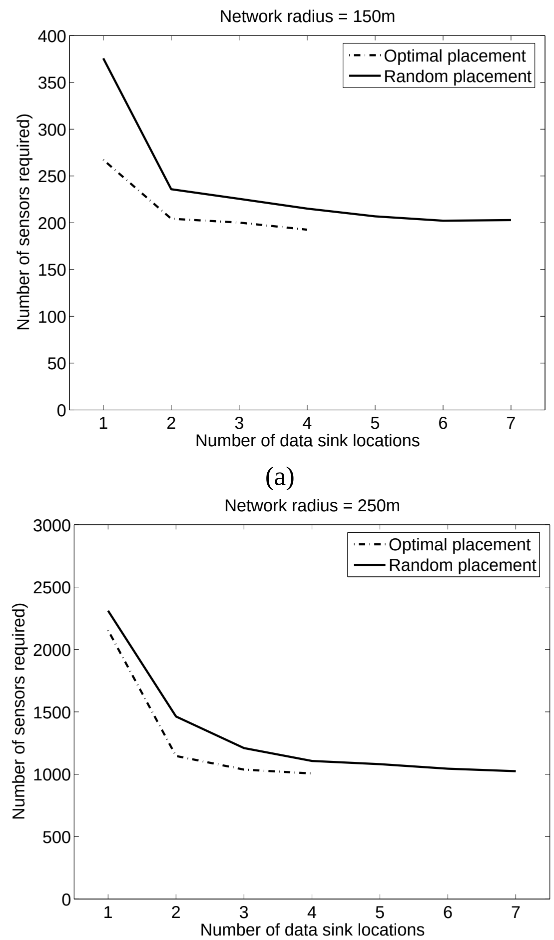
[2]The optimal lifetime for scenarios with more than four data sink locations is hard to determine since the optimal pattern of the data sink locations is not obvious. Nevertheless, we can assume that the optimal pattern would be able to achieve a lifetime comparable to the upper bound seen in the simulations utilizing randomly chosen locations.



(a)

(b)

Fig. 5. Normalized lifetime vs. number of data sinks deployed for networks with a radius of $150m$ (a) and $250m$ (b). Increasing the number of sink locations improves lifetime until a certain threshold is met and the hot spot problem has effectively been solved. Much larger gains in network lifetime can be achieved for a given number of data sink locations for a larger network, since the hot spot problem becomes worse.



(a)

(b)

Fig. 6. Number of sensors required vs. number of data sinks deployed for networks with a radius of $150m$ (a) and $250m$ (b). The required sensor density is inversely proportional to normalized lifetime.

initial energy of a single sensor node and A represents the area of the network), and substituting L for L_{opt}.

$$N_s(L, N_l) = \frac{L R_a \lambda_a A}{\widetilde{L}(N_l) E_s} \tag{4}$$

Consider the scenario in which we would like to plan a sensor network to operate for 1 year with sensors activated at a density of 0.0001 $sensors/m^2$ and sending data at a rate of 1 bit per second. All sensors initially contain 1 Joule of energy as they are deployed, and the cost of a sensor is fixed at a single unit. Using the data from Figure 5 and applying Equation 4, we have plotted the number of sensors that are required to be deployed in a network with a radius of $150m$ in Figure 6(a) and a network with a radius of $250m$ in Figure 6(b). Recall that we have assumed that the data sinks are unconstrained by energy. The actual energy consumption of the data sink was found to be 11.1 Joules and 30.0 Joules for the $150m$ radius network and the $250m$ radius network, respectively. These are reasonable values to assume for several data sink nodes.

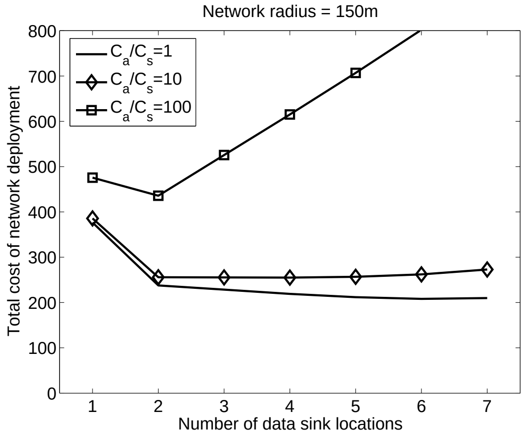
a) Deployment of Multiple Aggregator Nodes: After we determine the number of sensors and data sinks that are required to complete a sensing task, we can calculate the cost of each deployment plan and determine which plan is the best. The choice of the best plan depends on the cost ratio $\frac{C_a}{C_s}$ of the aggregator node and the normal sensor. In the case that we are deploying multiple static aggregator nodes, the cost function $C^s_{ds}(N_l)$ should be linear and depend on the cost C_a of an aggregator node.

$$C^s_{ds}(N_l) = C_a N_l \tag{5}$$

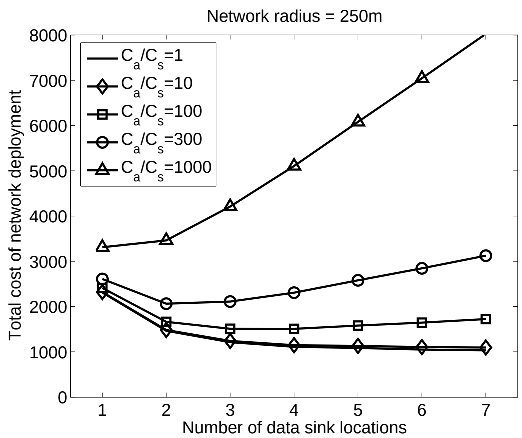
Using Equations 3 and 5, the total cost of deploying a network for the multiple data sink scenario is given as

$$C^s(L, N_l) = C_a N_l + C_s N_s(L, N_l) \tag{6}$$

and plotted in Figures 7(a) and 7(b) for a $150m$ radius network and a $250m$ radius network, respectively. Note that the cost of deploying a network with a single static data sink is given as



(a)



(b)

Fig. 7. Network deployment cost vs. number of data sinks deployed for networks with a radius of $150m$ (a) and $250m$ (b). When the relative cost of an aggregator node is high, it is most cost efficient to increase network lifetime by scaling up the number of sensors deployed. When the cost is relatively low, however, there is an optimal number of aggregator nodes that should be deployed so that the network deployment is optimally cost efficient. The most cost efficient number of aggregator nodes increases as the cost of an aggregator node becomes smaller and the network becomes larger.

the cost value when the number of data sink locations equals 1 (i.e., $C^s(L,1)$). As the figures show, for a very high relative cost of an aggregator node, it is most cost efficient to simply increase the number of sensors deployed even in spite of the energy inefficiency caused by the hot spot problem. However, for lower relative costs, it is cost efficient to use two or more data sink locations. However, the returns eventually diminish as the hot spot problem becomes solved and a finite optimal number of deployed data sink nodes exists.

b) Deployment of a Mobile Data Sink: We will now consider the scenario in which a mobile base station is deployed, using the same approach as above. If there is a cost associated with each movement of the mobile station, the problem can be modeled similarly as the scenario in which multiple data sinks are deployed. More likely, however, the most significant costs associated with a mobile data sink's deployment are the hardware necessary for the base station to

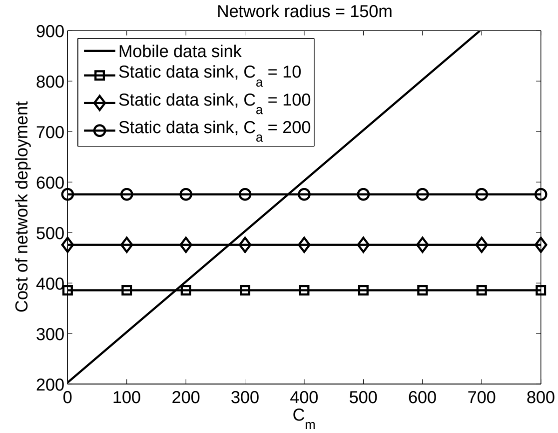


Fig. 8. Cost of deploying a network with a mobile and with a static base station for a network with a radius of $150m$.

move. In other words, there may be a single cost associated with the deployment of a mobile base station (which we will define as C_m), which accounts for its deployment and all subsequent movements throughout the field. As our simulation results have shown, only several movements are needed to significantly improve lifetime over the scenario of a static data sink. We will say that the mobile data sink moves N_m times throughout the lifetime of the network. The cost $C^s(L,1)$ of deploying a network with a static data sink is just a special case of the first scenario.

$$C^s(L,1) = C_a + C_s N_s(L,1) \tag{7}$$

Meanwhile, the cost of deploying a mobile data sink is simply

$$C^m(L,N_m) = C_m + C_s N_s(L,N_m) \tag{8}$$

The cost of deploying a mobile data sink and the cost of deploying a static data sink (for several values of C_a) are plotted in Figure 8 (a) for a $150m$ radius network. We used $N_m = 7$ for these simulations (i.e., the data sink moves 7 times during the data gathering) since out simulation results showed that network lifetime does not increase significantly beyond this point. To interpret this plot, consider a network where a mobile data sink has a cost of 300. The total cost of deploying as network with a mobile data sink is approximately 503, as indicated by the diagonal solid line. Now consider the deployment of a network with a static sink. If the cost of the static sink is 100, the total cost of network deployment, considering the extra sensor that must be added to compensate for the inefficiency caused by the hot spot, is approximately 476. In this case, it makes sense to deploy a network with a static data sink. However, if a static sink costs 200, then it is wiser to deploy a static data sink since its cost rise to 576. A network planner can use this data when deciding if it is more cost efficient to deploy a static or mobile data sink.

C. Strategy 2: Clustering Approach

In the network deployment plans outlined in the previous section, only one node serves as the data sink for the entire network at one time, even if multiple aggregator-capable nodes have been deployed. In this section, we consider a clustering approach in which multiple aggregator-capable nodes are deployed and each sink collects data from only part of the sensor network for the entire network lifetime. Such clustering schemes have been proposed for wireless sensor networks in [14], [15], [16]. Previous work in this area deals primarily with homogeneous networks, in which any of the deployed nodes is capable of acting as cluster head. In this section, we consider heterogeneous networks, where nodes equipped with the capability of acting as cluster head (e.g., those with larger batteries, more processing power and memory, and possibly a second radio to link back to a central base station) are significantly more expensive than ordinary microsensors. In our model, a sensor may send its traffic to whichever cluster head it chooses (typically, but not necessarily, the closest cluster head). The analysis methods in this section are very similar to those in the previous section.

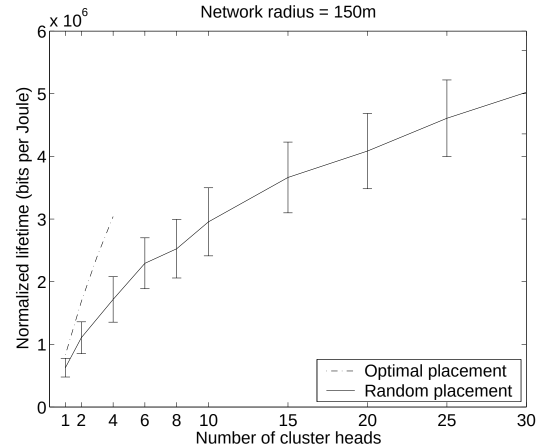
1) Lifetime improvement: We used similar simulation parameters and the same deployment pattern as in the previous section to find the relationship between the normalized lifetime (again given in bits per Joule) and the number of cluster heads that are deployed. The results are shown in Figures 9(a) and 9(b) for a $150m$ radius network and a $250m$ radius network, respectively. In both figures, the normalized lifetime is given for optimal cluster head placement as well as random placement. As expected, when more cluster heads are deployed, the network lifetime improves significantly in both cases. It is obvious that for a smaller network, fewer number of cluster heads are enough to solve the "hot spot" problem, and the figures verify this.

2) Cost Analysis: We can find the number of sensors $N_s(L, N_c)$ that need to be deployed to achieve a lifetime L when N_c cluster heads are deployed, as we did in the previous section when we considered the necessary number of sensors when N_l data sink locations are used. For the scenario in which we plan a sensor network to operate for one year with active sensors sending data at 1 bit per second and activated at a density of 0.0001 $sensors/m^2$, the required number of sensors are shown in Figures 10(a) and 10(b), respectively.

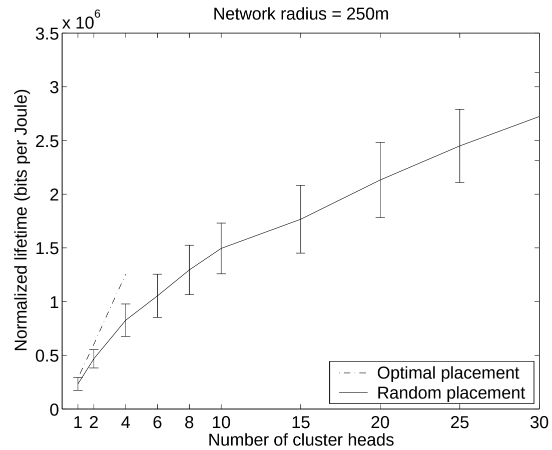
If the cost of a cluster head node is C_a, the total cost of deploying a heterogeneous clustering network is

$$C(L, N_c) = C_a N_c + C_s N_s(L, N_c) \tag{9}$$

This cost is plotted in Figures 11(a) and 11(b) for a $150m$ radius network and a $250m$ radius network, respectively. As expected, the most cost efficient number of cluster heads deployed becomes larger as the price of a cluster head becomes smaller. Also, for the same cost of a cluster head, more cluster heads should be deployed in the larger network than in the smaller network since the hot spot problem is worse in large networks.



(a)

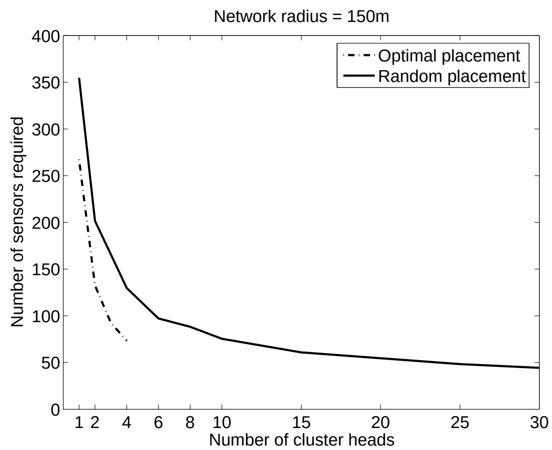


(b)

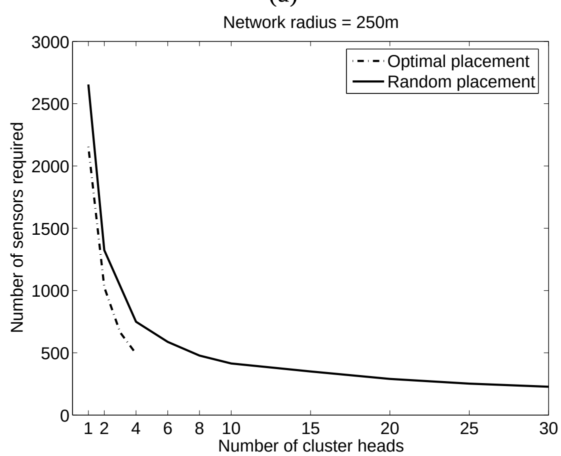
Fig. 9. Normalized lifetime vs. number of cluster heads deployed for networks with a radius of $150m$ (a) and $250m$ (b). Very large gains in network lifetime can be achieved when even a few extra cluster heads are deployed, especially when their locations are optimized.

V. CONCLUSIONS

We have studied multiple strategies that can compensate for the hot spot problem seen in sensor networks using many-to-one traffic patterns. First, we found the optimal transmission range distribution that allows the lifetime of sensor networks to be maximized. Based on this model, we revealed the upper bound of the lifetime of a typical scenario and demonstrated the inability to make good use of the energy of nodes furthest from the base station, even when utilizing the optimal distribution and our quasi-optimal heuristic routing scheme. Thus, varying the transmission power of individual nodes cannot alone solve the hot spot problem. In addition to transmission power control, we have investigated several alternative strategies for solving the hot spot problem and analyzed the gains that can be obtained from their use. Specifically, we have considered the deployment of multiple base stations, where each node aggregates all of the network's data at one time, the deployment of a mobile robot, and the use of a clustering hierarchy, where heterogeneous sensors are deployed, some of which can act as data aggregators/compressors. When analyzing the use of each strategy, we also considered the necessary extra costs incurred and show how the network

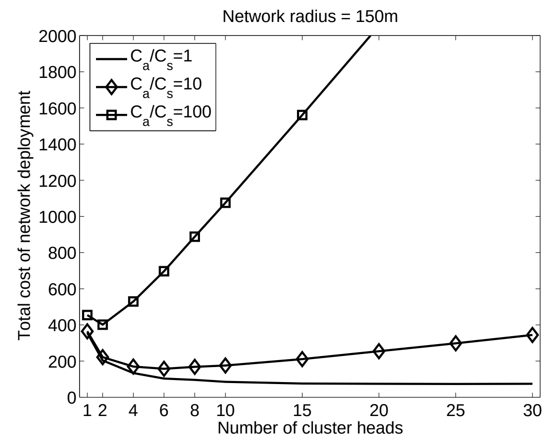


(a)

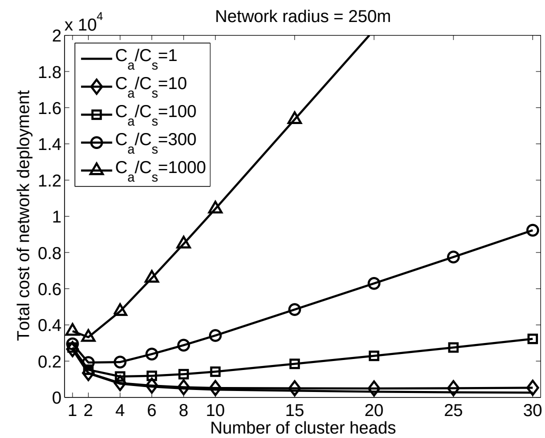


(b)

Fig. 10. Number of sensors required vs. number of data sinks deployed for networks with a radius of $150m$ (a) and $250m$ (b). The required sensor density is inversely proportional to normalized lifetime.



(a)



(b)

Fig. 11. Network deployment cost vs. number of cluster heads deployed for networks with a radius of $150m$ (a) and $250m$ (b). The most cost efficient number of cluster heads increases as the cost of an cluster head becomes smaller and the network becomes larger.

configuration can be optimized for cost efficiency in each case.

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