Efficient Information Dissemination in Wireless Sensor Networks using Mobile Sinks

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ABSTRACT

Wireless sensor networks constitute an emerging technology that has received recently significant attention both from industry and academia. On the one hand, there is an ever-widening range of attractive applications (e.g., disaster and environmental monitoring, wildlife habitat monitoring, target tracking, intrusion detection, security surveillance) sensor networks can be used for. On the other hand, sensor networks are self-organizing ad-hoc systems where optimized energy consumption is of paramount importance; therefore, relaying information between sensors and a sink node, possibly over multiple wireless hops, in an energy-efficient manner is a challenging task that preoccupies the research community for some time now.

Optimizing energy consumption in wireless sensor networks is of paramount importance. Sensors are tiny devices with sensing, processing, and transmitting capabilities; they are of low cost, but have a consequently low storage and computational capacity, and a limited energy supply. It is usually considered impossible or impractical (from a technical or economical point of view) to recharge their batteries; thus, they should be managed in such a way to ensure the unattended operation of the network for a long enough time period (e.g., several months).

There is a recent trend to deal with this problem by introducing mobile elements (sensors or sink nodes) in the network. The majority of these approaches assume time-driven scenarios. However, there are several real-life applications for which an event-based is more appropriate. In this paper we propose to adaptively move the sink node inside the covered region, according to the evolution of current events, so as to minimize the energy consumption of the dissemination of the event-related data. Both analytical and simulation results are given.

1.0 INTRODUCTION

Wireless sensor networks constitute an emerging technology that has received recently significant attention both from industry and academia. On the one hand, there is an ever-widening range of attractive applications (e.g., disaster and environmental monitoring, wildlife habitat monitoring, intrusion detection, security surveillance) sensor networks can be used for. On the other hand, sensor networks are self-organizing ad-hoc systems where optimized energy consumption is of paramount importance; therefore, relaying information between sensors and a sink node, possibly over multiple wireless hops, in an energy-efficient manner is a challenging task that preoccupies the research community for some time now.

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Sensors are tiny devices with sensing, processing, and transmitting capabilities; they are of low cost, but have a consequently low storage and computational capacity, and a limited energy supply. It is usually considered impossible or impractical (from a technical or economical point of view) to recharge their batteries; thus, they should be managed in such a way to ensure the unattended operation of the network for a long enough time period (e.g., several months).

Information gathering in sensor networks can follow different patterns, depending mostly on the specific needs of the applications. In a time-driven scenario all sensors send data periodically to the sink. As opposed to this, in the event-driven case sensors start communicating with the sink only if sensing an *event*, i.e., a situation that is worth reporting. Finally, in a query-driven scenario a sensor transmits its data only if the sink asks for it. Most of the research papers in the area address the time-driven scenario, and provide energy-efficient solutions for homogeneous networks, with sensors having constant and equal amounts of data to send in all parts of the covered region. However, there are a large number of applications (e.g., intrusion detection, seismic activity monitoring, animal movement tracking) where an event-driven approach is more appropriate. Hence, in our paper we address only this scenario.

As we noted before, energy efficiency is the main requirement for the operation of a sensor network. Sensors consume energy for sensing the field, for digitizing and processing the data, but the most penalizing task is by far the transmission of the information [1]. In the most commonly accepted power attenuation model [2], signal power falls as $d^{-\alpha}$, where d is the distance from the transmitter antenna and α is a constant dependent on the wireless transmission environment, typically between 2 and 4. Therefore, assuming that all receivers have the same power threshold for signal detection, typically normalized to one, the energy required to support communication between the two nodes is d^{α}. In such conditions it is straightforward to assert that by minimizing the distance between a sensor and a sink node we can efficiently reduce power consumption, both for single- and multi-hop communications (reducing the length of the multi-hop path results in fewer and/or shorter hops, i.e., less energy is needed to relay data to the sink).

Besides analyzing the general case of an event-driven scenario, we intend also to have a closer look on a specific example where events move inside the observed region following a correlated random walk model. There are several concrete use cases this example can be relevant for. In [3] authors show that animal movements can be described as a correlated random walk. A similar result is obtained in [4] for the specific case of caribous. Moreover, the model should fit intrusion detection and target tracking applications as well.

We propose sink moving strategies in this paper for both the single- and multi-hop event-driven WSNs. At first we examine how to replace the sink periodically when the sensor network is using single-hop communication. We evaluate the proposed sink relocating strategies through simulations. After that we analyze, both analytically and through simulations, the efficiency of adaptively moving the sink node so as to react to dynamic events that follow a correlated random walk mobility model in multi-hop WSNs.

The rest of this paper is organized as follows. In section 2.0 we present related work in the area of energy optimization and sink mobility. In section 3.0 we propose the sink moving strategies for the case of single-hop WSNs. In section 4.0 we describe the assumed network model, and calculate the overall energy requirement an event poses on the network, as well as the maximum energy consumption of a specific sensor in case of multi-hop WSNs. According to these analytical results, in we show how to find the optimal position of the sink inside the network so as to minimize overall or maximum energy consumption. We also present simulation results evaluating the performance of the proposed strategies, while section 5.0 concludes the paper.

2.0 RELATED WORK

There were many proposals recently targeting the energy efficiency of wireless sensor networks. Some approaches focused on energy conserving routing techniques, i.e., finding optimal routes in terms of consumed power, and balancing the energy consumption among all nodes [6], [7], [8], [9]. Others were based on topology control schemes, i.e, deploying sensor and sink nodes in an efficient way or reshaping the topology through dynamic power control of the participating sensors [10], [11], [12], [13], [14]. Clustering techniques are also widely employed; the network is divided into small clusters, a cluster head being responsible for aggregating and relaying towards the sink the information gathered from the sensors of its cluster [15],[16].

In all the above approaches the elements of the network are all considered static. However, there is a recent trend to explore mobility as a way of enhancing energy efficiency. In [17] sensors dynamically react to the environmental changes and move towards areas where events occur frequently. In [18] sensor mobility is exploited at the deployment phase, to eliminate coverage holes that are discovered through the use of Voronoi diagrams. Mobile sensors are also considered in [19] to provide an extension of a stationary sensor network.

Moving the sink node is also a widely explored solution. The approaches can be classified into three categories: random, predictable, and controlled mobility of the sink. In [20] the authors propose an architecture that builds on the *random mobility* of mobile agents, called data MULEs (Mobile Ubiquitous LAN Extensions), to collect sensor data in sparsely deployed networks. A similar approach, but for dense networks, is used by SENMA (SEnsor Networks with Mobile Agents) [21]; data is sent directly to the mobile agent that is flying above the sensor field, the transmission being triggered based on the estimated fading state of each sensor in its communication with the agent. [22] uses a random walk model for a mobile relay to theoretically derive parameters such as delay and data delivery ratio. A serendipitous movement of the sink nodes is also assumed in [23]. However, the authors propose an inversed scenario, where there is a single sensor that transmits data to a large number of mobile sinks. They describe the SEAD (Scalable Energy-efficient Asynchronous Dissemination) protocol to build and maintain an energy-efficient dissemination tree that covers all the sink nodes.

A *predictable mobility* solution is presented in [24]. The sink (called observer) moves along a predefined path, and pulls data from sensors in single-hop communication when arriving near to them. A predefined path of the sink is used in [5] as well. The authors show that moving the sink at the periphery of the covered circular region ensures energy-efficient operation; the approach is considerably different from other mobile sink solutions in that it assumes multi-hop communication between all the sensors and the sink.

There are also several solutions that propose a *controlled mobility* of the sink nodes. In the AIMMS (Autonomous Intelligent Mobile Micro-server) system [25], [26] a mobile micro-server moves across the network, along a specific trail, to route data from the deeply embedded nodes. Its mobility is controlled in order to spend extra time (e.g., stop or slow down) in regions where there is a large amount of data to send or the communication channel is constrained. The idea of using mobile nodes for message ferrying is also considered in [27]; these nodes provide non-random proactive routes in highly-partitioned wireless ad-hoc networks.

An attempt to determine specific sink movements for energy optimization is presented in [28]. The authors argue that multi-hop communication results in the sensors neighboring the sink being depleted at a fast pace. Therefore, they propose to employ multiple sink nodes that periodically change their locations, and present an ILP (Integer Linear Programming) model to obtain the optimal positions of these sinks. A linear programming solution to determine the movement of the sink and its sojourn time in different points of the network is given in [29] as well. Both the sensors and the sink are placed on a bi-dimensional grid.

The sink moves along the grid, sojourns times in the specific grid points being calculated so as to maximize the network lifetime.

Finding the optimal position of the sink is addressed in [30] as well, even if mobility is not involved. The authors assume a time-driven scenario, where all sensors send data at a constant rate; the problem is how to deploy *n* sink nodes so as to ensure an energy-efficient operation of the network. [31] addresses the static deployment problem as well, as it proposes to find the optimal locations of multiple sinks in sparse networks of aggregator points that send data directly to these sinks.

In this paper we propose a solution that is significantly different from all the above approaches. We assume an event-driven scenario, where sensors that detect an event send data to the sink node in a single- or multi-hop manner. Our goal is to control the mobility of the sink so as to ensure an energy-efficient operation of the network. The sink node is alerted about the current events, estimates the evolution of these events, and decides about the optimal neighboring place where it should move so as to maximize network lifetime.

3.0 ADAPTIVE SINK MOBILITY IN EVENT-DRIVEN SINGLE-HOP WSNS

In this section we define adaptive mobility strategies for the sink node in case that the sensors use single-hop communication, so as to reduce the distance nodes have to send reports to. The solution perfectly fits the event-driven scenario, as the mobile sink can adapt and get closer to the nodes that are currently active, significantly reducing their energy consumption. It is also different from the existing controlled mobility solutions, as sensors do not wait to report until the sink gets close to them; thus, it can support delay-sensitive real-time applications. constraints, and is able to move anywhere inside the network. We also assume that nodes are able to adjust their radio power depending on their distance *d* from the sink. Although sensing also requires energy, this is far less than the energy used for communication; thus, we neglect it.

3.1 Minimizing average energy consumption

Let A be the set of active cluster heads (CHs) that have data to send to the sink. Let (x_0,y_0) denote the coordinates of the sink, and (x_i,y_i) the coordinates of the *i*th CH. Let d_i denote the distance between the sink and the *i*th CH. In the most commonly accepted attenuation model, signal power falls as d_i^{α}, where α is the attenuation exponent, with values ranging from 2 to 5. Thus, the energy needed for the *i*th CH to transmit data is

$$E_i = E_0 \cdot d_i^{\alpha}, \quad \alpha \in [2,5], \tag{1}$$

where E_0 is constant. The energy consumed by all the active cluster heads is $E = \sum_{i \in A} E_i$. To minimize the total (or average) energy consumption, the sink needs to be placed where this sum is the smallest, i.e.,

$$(x_0, y_0) = \arg\min_{(x,y)} E. \tag{2}$$

The idea here is that the network always spends the minimal energy for the communication between the active CHs and the sink. The total energy is minimal when

$$\left.\frac{\partial E}{\partial x}\right|_{x=x_0} = 0 \text{ and } \left.\frac{\partial E}{\partial y}\right|_{y=y_0} = 0, \tag{3}$$

where

$$\frac{\partial E}{\partial x} = \frac{\partial}{\partial x}\left(E_0 \sum_{i\in A} d_i^{\alpha}\right) = E_0\, \alpha \sum_{i\in A}(x-x_i)\left[(x-x_i)^2+(y-y_i)^2\right]^{\frac{\alpha-2}{2}} . \tag{4}$$

The partial derivative $\partial E/\partial y$ can be calculated similarly. Unfortunately, there is no closed form solution for (3); thus, it has to be solved using optimisation methods (for example some kind of gradient-based search [32]. In the following we will refer to this strategy as *minavg*.

3.2 Minimizing maximum energy consumption

The drawback of the minavg approach is that—although the total energy consumption is minimized—it can happen that the energy contributions of the sensors are rather uneven. In order to avoid this problem, the strategy introduced here minimizes the transmission energy for the most remote cluster head in the network. In other words, the maximum transmission energy is minimized, i.e.,

$$\max_{i\in A} E_i \rightarrow min\ . \tag{5}$$

Hence, energy consumption will be more balanced. As the transmission energy depends on the distance between the sensor and the sink, this strategy is equivalent with minimizing the maximum distance between the sink and every active CH in the network. Thus, the optimal location of the sink in this case is given by

$$(x_0, y_0) = \arg\min_{(x,y)}\left(\max_{i\in A}\sqrt{(x-x_i)^2+(y-y_i)^2}\right) . \tag{6}$$

The optimisation task is equivalent to the Minimal Enclosing Circle Problem, where the task is to find the minimum radius circle that encloses all points of a point set on the plane. There are several algorithms to solve this problem. E.g., it has been shown that it can be solved in O(n) time using the prune-and-search techniques for linear programming [33]. In the following we will refer to this strategy as *minmax*.

3.3 Minimizing relative energy consumption

Neither of the two previous strategies take into account the current energy levels of the sensor nodes; thus, they are not able to protect from depletion those cluster heads that have already sensed and reported many events and their batteries are getting exhausted. Nodes with little remaining battery power could be spared if the sink would move closer to them, while moving away from nodes with more remaining energy. One such possible strategy is when the maximum relative energy that a node has to spend on transmission is minimized, i.e.

$$\max_{i\in A}\frac{E_i}{E_{\text{rem},i}} \rightarrow min, \tag{7}$$

where $E_{rem,i}$ denotes the average remaining energy per node within the i*th* cluster. Note that we do not take into account the remaining energy of the current cluster head, but the total energy within the cluster.

By doing so we ensure a more balanced energy consumption in the network. The sink will not get close to a cluster full of energy, just because its CH is near of depletion; the CH should be changed instead. On the other hand, a cluster that is running out of energy will be spared even if its current CH is still in good shape. The CH will continuously monitor the energy level of the sensors in the cluster. An aggregated report on the cluster's energy level can then be passed to the sink, e.g., by piggybacking it on the normal reports sent by the active cluster heads; the sink can then use the information and adapt its movement accordingly. When the CH role is passed to a new sensor, the information about the remaining energy in the cluster is transmitted as well. The minimization problem is equivalent with the following:

$$(x_0, y_0) = \arg\min_{(x,y)} \left(\max_{i \in A} \frac{\sqrt{(x - x_i)^2 + (y - y_i)^2}^{\alpha}}{E_{\mathrm{rem},i}} \right). \tag{8}$$

For example, if there are two active CHs, with average remaining energies $E_{rem,1} = 60$ and $E_{rem,2} = 4$ units within the clusters respectively, the sink is at the optimal location if the first CH spends E_1=15 units of energy for transmission while the second one uses only E_2=1 unit. This is because in this case both of them would consume 25% of their average remaining energy. There is no closed form solution for finding the solution of (8); thus, it has to be determined using optimisation methods. We will refer to this strategy as *minrel*.

3.4 Simulation results

To evaluate the performance of the three mobile sink strategies, we compared them with the case when the sink is fixed and is deployed in the center of the network, and with the case when the sink moves randomly using the Random Waypoint Mobility model (originally proposed in [34]). We simulated the proposed sink relocation strategies using MATLAB. The network was modeled to be circle-shaped with radius (R) of 400 m, in which we randomly distributed 8000 sensors, using a uniform distribution model. The initial energy of every sensor was 2 J, E_0 was 1 nJ. The attenuation exponent α was chosen to be 3. Clusters were formed using the LEACH [35] algorithm, where in the initializing phase each sensor node declared itself as cluster head (CH) with a probability of 0.05.

The operation of the network is event driven. In our event radius model, an event is located in a single point in the network area, and all nodes within a distance of 20 m (called the sensing range, r) of this event are considered to be active. An event can occur in a uniformly distributed manner in the area. The time was split into equal periods (i.e., 10 sec) and we assumed that an event can be reported only at the beginning of the time period. The number of new events within a period was modeled as a Poisson-distributed random variable, with intensity parameter (λ) of 0.3. The duration of the event was geometrically distributed; thus, an existing event persisted in the next round with probability 0.9, having an average lifetime of 100 seconds. Every active sensor sends the same amount of data in a round, including the sensed attribute values as well as its ID and remaining battery power, and communicates with its cluster head directly. The sink can be relocated in each round; after determining the best position for the next step, according to the different strategies using eqs. (2),(6),(8), it moves there. Note, that the sink mobility is limited, i.e., the mobile sink can only move with finite maximum velocity (4 m/s). To inform the cluster heads about its current position, our solution assumes a periodic update message broadcasted by the mobile sink. An important power-saving factor is that only those CHs that have data to report listen to the update messages.

The area covered by operating sensors can be an important measure of efficiency from the application's point of view. Fig. 1(a) shows the area coverage as a function of time, in the case of all introduced strategies. Here we defined coverage as follows: if the energy level of all sensors within a cluster falls

below a certain critical threshold, it can happen that the elected cluster head will not be able to send its message to a far away sink. Thus, coverage of that area is lost, i.e., it is not assured that the sink node can be notified when an event appears in that particular area. Fig. 1(a) reveals that the randomly moving sink case is far less efficient than the other strategies. The fixed sink case is also considerably less effective than the adaptive strategies. For high area coverage values the difference between the three mobile strategies is not significant. However, the advantage of minimizing the average energy becomes more apparent at lower coverage values.

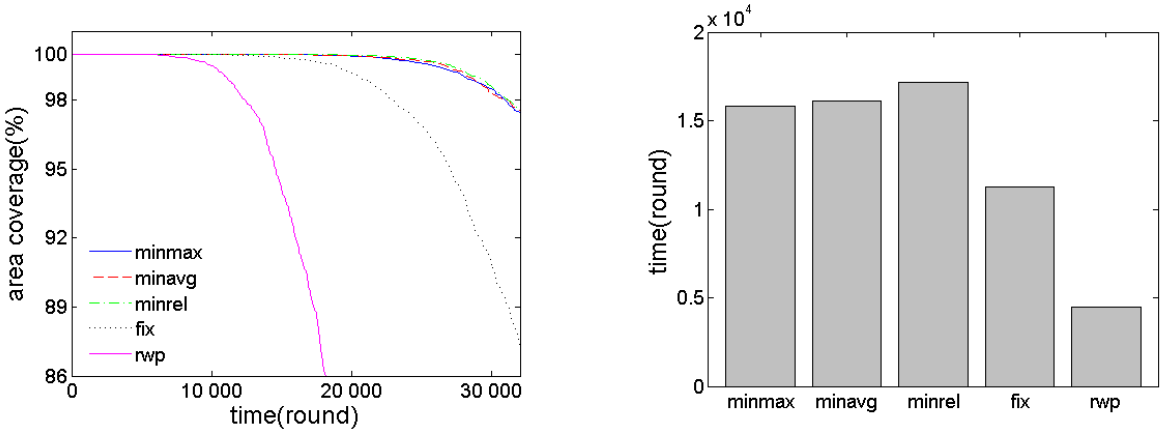

Fig. 1. (a): area coverage (left) and (b): average lifetime (right).

Fig. 1(b) shows the time elapsed until the area coverage falls below 100%. This can be seen as the lifetime of the network, if the application's requirement is so strict that even a single event loss cannot be tolerated. The network lifetime is the highest in case of *minrel*, while *minavg* and *minmax* have approximately the same performance, both well exceeding the lifetime obtained with a fixed or a randomly moving sink. It is also interesting to see how the five strategies affect the sensors located at different parts of the covered area. Fig. 2(a) shows the average energy consumption of a sensor in function of its distance to the center of the area. An obvious result is that the fixed strategy depletes the sensors in the least balanced manner. One can see that moving the sink randomly results in more balanced, but rather high energy consumption in the network. The most homogenous energy usage can be achieved by using the *minrel* strategy. Even if it causes higher energy usage compared to the other two mobile sink strategies, it still results in longer network lifetime, as it prevents sensors with low remaining energy from depletion.

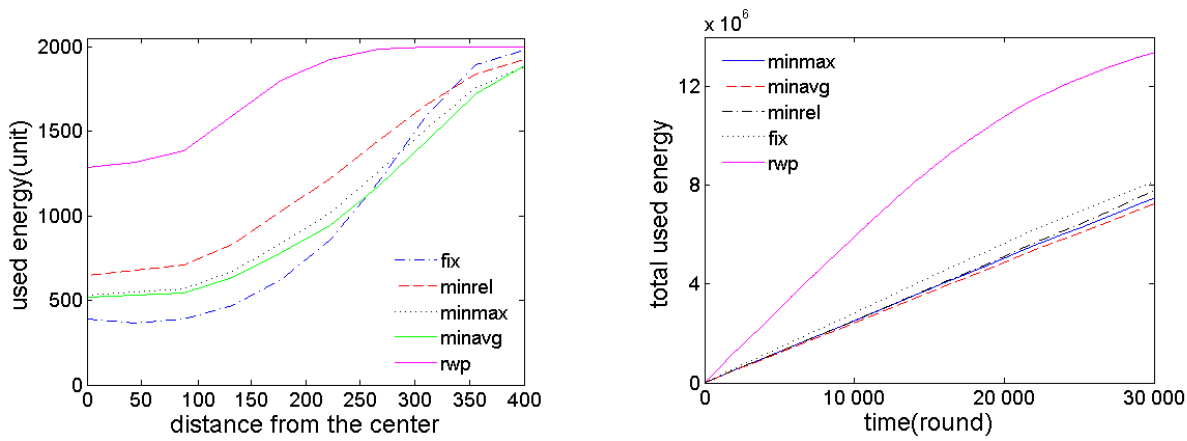

Fig. 2. (a): The energy consumption in function of the distance from the center (left), and (b): the total energy consumption (right).

Fig. 2(b) shows the amount of the total energy consumed by the network. Recall that the *minavg* strategy minimizes the total energy in every round; therefore, the total energy used by the network during its entire operation is also minimal. *Minrel* uses the most energy among the three adaptive strategies, but still less than the fixed or the randomly moving sink case. The latter consumes almost twice as much energy as the fixed sink case. In Fig. 3 we present the distribution of the sink coordinates after 500.000 simulation rounds. We can see that in the case of the *minmax* strategy the sink often resides near to the center, while in the *minrel* and the *minavg* case the distribution is more homogeneous. In the case of the *rwp* strategy the sink can be practically anywhere within the area.

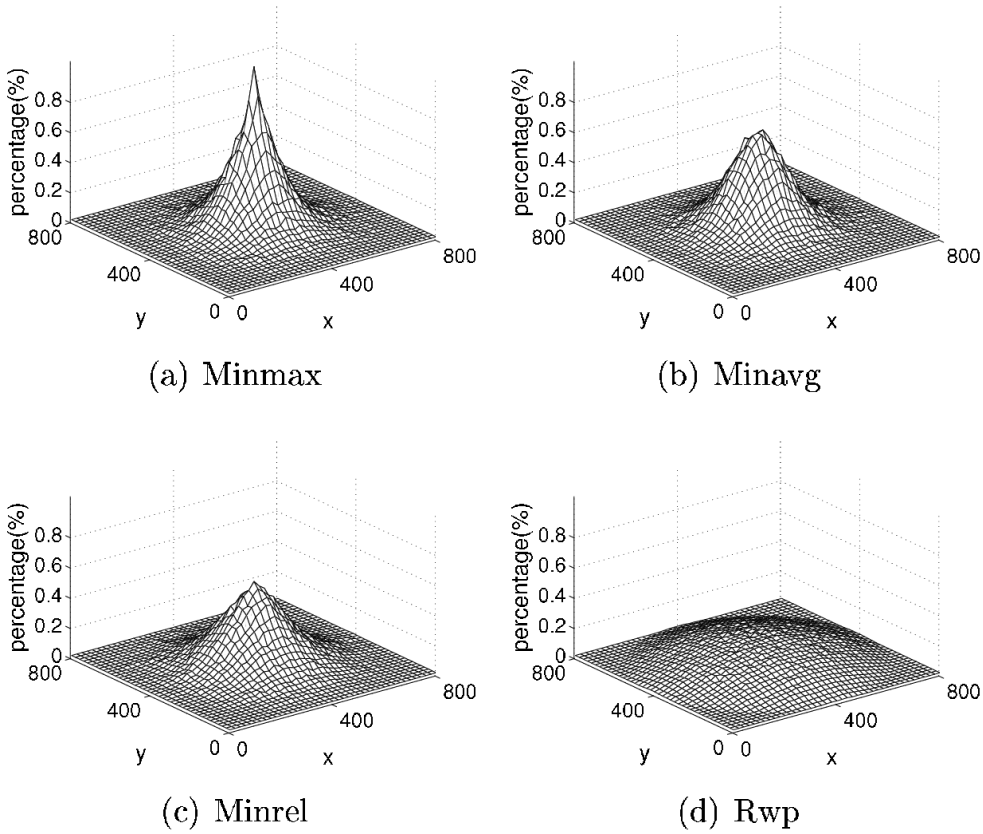

Fig. 3. Distribution of the sink location within the area.

4.0 ADAPTIVE SINK MOBILITY IN EVENT-DRIVEN MULTI-HOP WSNS

In this section we describe the assumed multi-hop network model, and calculate the overall energy requirement an event poses on the network, as well as the maximum energy consumption of a specific sensor. According to these analytical results, we show how to find the optimal position of the sink inside the network so as to minimize overall or maximum energy consumption.

4.1. Energy consumption in event-driven multi-hop networks

This section gives the description of our assumed network model as well as the analytical calculations on the energy requirements of network operation.

We assume a strongly connected network. There are N sensor nodes distributed evenly within a given area A, and a single sink node S is placed at location (x_S, y_S) to collect the data. The network is event-driven, i.e.,

whenever an *event* (Z) occurs at a particular location, all sensors that are within sensing range (r_0) become *active*. All active sensor nodes generate a message for the sink, and repeat it periodically, until the event persists. Since each node is only able to communicate with neighbors within its radio range ($r_f \geq r_0$), the message must be routed towards the sink hop-by-hop.

4.2 Events

From the abstract modeling point of view, we call an event any situation that is worth reporting to the sink (e.g., an intruder is sensed by the sensors within the monitored area). The events are random in space and time, and their location can change during their lifetime. In our model events are modeled as single points (or locations) within the sensor field. When taking only a snapshot of the system at a particular time instant, all existing events at that time are given by their location coordinates only.

As a result of multi-hop communication, sensors are communicating not only when they are sensing an event but also when they are forwarding the reports of other active sensors. In our model for the analytical calculations we assume ideal short path routing, that is, the sensors are deployed densely and evenly enough to find a straight linear path towards the sink. Thus, all sensors that are in between an active sensor and the sink node will also be active during the communication. denotes all active regions (marked as gray), assuming three events as an example.

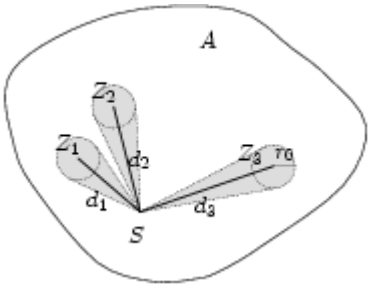

Fig. 4. Active sensor areas for three events.

4.3 Total energy

To calculate the overall energy requirement that an event poses on the network, we add up all the transmission energies for messages generated by sensors that were activated by the event. The distance between the event and the sink is denoted by d. From each sensing node a message passes through the network towards the sink, hop-by-hop. The total energy needed to report an event to the sink is directly proportional with the number of active sensors (N_s) that are sensing that event and the number of hops needed to reach the sink, on the average. Assuming a fixed hop length h (or equivalently, assuming a fixed radio transmission power for the nodes), the average hop count (k) can be calculated by approximating the average distance (l) of a sensing node from the sink and dividing it by the hop length (h). Since the average distance l can be well approximated by the event distance d, the hop count is given by $k=\lceil d/h \rceil$. Thus, the total energy needed to report an event is

$$E_{total} = N_s \overline{k}\, E_{hop}, \tag{9}$$

where E_{hop} is the energy required to pass a message at distance h in one hop. The number of sensing nodes (N_s) in our model is $r_0^2 \pi \rho$ with $\rho = N/A$. Since for a given path, $\lceil d/h \rceil \approx d/h + 0.5$ on the average, we approximate E_{total} by

$$E_{total} \approx \begin{cases} (d/h + 0.5) r_0^2 \pi \rho E_{hop}, & \text{if } h/2 < d \\ r_0^2 \pi \rho E_{hop}, & \text{if } d \leq h/2 \end{cases} . \tag{10}$$

In the approximation we calculated separately the case when the event is closer to the sink than half of the hop length, i.e., $d \leq h/2$. In this case all active sensors send the data to the sink directly.

Assume that there are I events on the sensor field instead of one. In this case, the total energy requirement of the whole network is given by

$$E_{total}^{SN} = \sum_{i=1}^{I} E_{total}^{i}, \tag{11}$$

where E_{total}^{i} is the energy required to report the ith event to the sink, and is given by (10).

4.4 Transit load and maximum energy

Sensors can sense an event and forward packets from other nodes at the same time. Furthermore, one sensor can be requested to forward (much) more than one packet towards the sink, even if it is far from any events to be sensed. This happens to sensors that are close to the sink node, and results in highly uneven load distribution, which plays a key role in our investigations.

The energy requirement of the most loaded sensor node (E_{max}) can be approximated as follows. Sensors that are only one hop away from the sink towards the event location (i.e., within area A_0 on Fig. 5) have to forward packets generated within the sensing range of the event (i.e., in A_1). Thus, the load on the last hop nodes is proportional to the ratio of A_1/A_0, i.e.,

$$E_{max} = \frac{A_1}{A_0} E_{hop} = \frac{2dr_0}{h^2} E_{hop}, \tag{12}$$

where

$$A_0 = \frac{\Delta\varphi}{2\pi} \left[(h + h/2)^2 - (h - h/2)^2 \right] \pi = \Delta\varphi h^2, \tag{13}$$

$$A_1 \approx \frac{\Delta\varphi}{2\pi} \left[(d + r_0)^2 - (d - r_0)^2 \right] \pi = 2\Delta\varphi d r_0. \tag{14}$$

Thus, E_{max} is a linear function of the distance d between the sink and the event location.

Assume again that there are more than one event at a time. In this case, using (12) we can identify for each event Z^i (i=1,...,I) the most heavily loaded sensor with energy requirement E_{max}^{i}. By comparing these highly loaded sensors on the sensor field, we get the highest energy requirement by

$$E_{max}^{SN} = \max_{1 \leq i \leq I} E_{max}^{i}. \tag{15}$$

This energy load is on the sensor that is close to the sink and in the direction towards the most distant event Z^j, that is given by

$$j = \arg\max_{1 \le i \le I} d(Z^i, S). \tag{16}$$

We should note, that here we neglected the fact that one sensor could take part in relaying messages of more than one event at a time. However, since the most loaded sensors are on the line between the event and the sink, we basically neglect only the case when there are two or more events directly behind each other.

4.5 Optimal sink location

The so-called facility location is a classical problem of operations research that has also been examined in the computational geometry community. The task is to position a point in the plane (the *facility*, which is the sink in our case) such that the distance between the facility and given points (active sensors) is minimized or maximized. The optimal facility location is NP-hard, thus, the problem is usually solved using either a hill-climbing heuristic or linear programming.

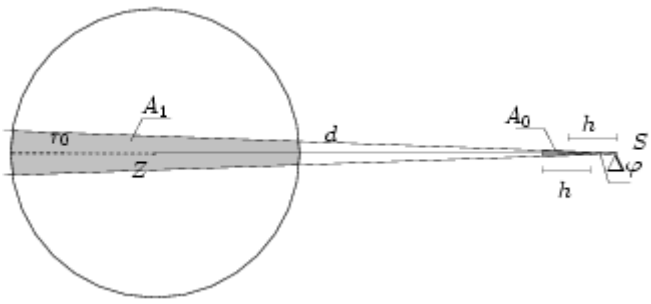

Fig. 5. Approximating maximal load

4.5.1 Minimizing total energy

In our case, the first idea is to place the sink node so as to minimize the overall energy consumption of the network. Since there can be more than one event at a time, the task is to minimize E_{total}^{SN} given by (11). Since the energy requirement of reporting an event is proportional to the event distance d_i (see (10)), this is equivalent to minimize the sum of event distances, i.e.,

$$\sum_{i=1}^{I} \max(h/2, d_i) \to \min, \tag{17}$$

where the maximum means that there is no gain when moving closer to a particular event than the half of the hop length. Practically, this is the location that gives the minimal average distance from the events. There is no closed formula to find this location, but the problem can be solved numerically.

4.5.2 Minimizing maximum energy

The problem with the total energy minimization approach could be that—altough the overall energy consumption is minimized—it can happen that the energy contributions of the sensors are rather uneven. In order to avoid this problem, one would think of minimizing the transmission energy for the most heavily loaded sensor in the network. Hence, energy consumption will be more balanced. As the maximal traffic load depends on the biggest event distance from the sink node (see (12) and (15)), this strategy is equivalent with that of minimizing the maximum event distance from the sink, i.e.,

$$\max_{1 \le i \le I} d_i \to \min. \tag{18}$$

This minimization task is equivalent to the Minimal Enclosing Circle Problem, where the task is to find the minimum radius circle that encloses all points of a point set on the plane. There are several algorithms to solve this problem. For example, it has been shown that it can be solved in $O(n)$ time using the prune-and-search techniques for linear programming [33].

4.6 Adaptive sink mobility

The optimal positioning of the sink, presented in the previous section, is specific only to a given snapshot of events that are present in the network. Moreover, in a real application the sink cannot usually move directly to the optimal position, it can only take a step towards it in a certain period of time. Therefore, to continuously optimize energy consumption in the case of dynamically evolving events, we should give efficient strategies for adaptive sink mobility. The specific application area we focus on is the so-called intrusion detection and tracking task.

4.6.1 Target detection and tracking

The goal of intrusion detection and tracking is to detect intruders (or targets) entering the observed area, to estimate their initial position and to track the position estimate as the target moves. To localize the target, the readings of a certain minimum number of nodes have to be combined. In our approach, all nodes sensing the target report their (timestamped) readings to the sink node, which combines them to obtain the desired estimates. This approach imposes significant communication overhead when the target is far away from the sink.

4.6.2 Event model

Our chosen model here is basically an *intruder movement* model. We assume that intruders appear (uniformly and independently) on the boundary of the area described by a Poisson process of fixed rate λ, and start their own independent movement in the field. Let t_0 be the starting time of the intruder at $Z_0=Z(t_0)$. In each unit of time it makes a step of fixed length l. What is varying is the direction of the step. The direction of the first step, denoted by θ, is uniformly choosen in $[-\pi/2,\pi/2]$. This is the main direction the intruder follows. Each further step has length l and the direction angle is choosen uniformly from $[\theta-\sigma,\theta+\sigma]$, where $\sigma\in[0,\pi]$ is the (only) free parameter of the model. This σ determines how closely the intruder follows the originally choosen direction θ. It is clear that if $\sigma=0$, then the movement follows a straight line, while $\sigma=\pi$ is a random walk without any direction preference.

Let Z_k denote the event position at the kth step (at time t_k). The evolution of the intruder's trajectory is thus

$$Z_{k+1} = Z_k + l\,\underline{e}_{\theta_{k+1}}, \tag{19}$$

where e_j denotes the (unit) vector of $(\cos\varphi,\sin\varphi)$. The coordinates of Z_{k+1} are thus given by

$$x_{Z_{k+1}} = x_{Z_k} + l\cos\theta_{k+1}, \tag{20}$$

$$y_{Z_{k+1}} = y_{Z_k} + l\sin\theta_{k+1}. \tag{21}$$

The intruder leaves the network when it steps outside of the sensor field boundary.

4.6.3 Sink relocation decision

To reduce the communication overhead and thus prolong the network lifetime, we give in this section two sink relocation algorithms.

What we want to maximize is the network lifetime. To achieve this, we have two ways to proceed: (1) to minimize the total energy spent in the next round, or (2) to minimize the maximum energy load on a sensor in the next round. We do this by moving the sink node to the best possible location within reach. We assume that the sink makes a relocation decision (SRD) periodically, i.e., it calculates the optimal position where the energy consumption is minimal, and moves there.

4.6.3.1 Minimizing the total energy

The task here is to minimize the total energy spent in the next round given by (11), i.e.,

$$E_{total}^{SN}(s) = \sum_{i=1}^{I} E(Z_{k+1}^{i}, s), \tag{22}$$

where the energy function E(Z,s) is given by (10), and the notation emphasizes that this energy depends on the event location z and sink location s. Thus, the optimal sink location is given by

$$s_{opt} = \arg\min_{s} E_{total}^{SN}(s). \tag{23}$$

The problem is that we do not know the exact position (Z_{k+1}) of the event(s) in the next step. What we can do is to approximate its future location using prediction based on the past observations (see later).

4.6.3.2 Minimizing the maximum energy

The maximal energy spent in the next round, E_{max}^{SN}, is given by (15), i.e.,

$$E_{max}^{SN} = \max_{1 \le i \le I} E\left(Z_{k+1}^{i}, s\right), \tag{24}$$

where the energy function E(z,s) is given by (12).

Thus, we have to minimize $E_{\max}^{SN}(s)$. To do this, first we need an estimate of Z_{k+1}.

4.6.4 Forecast

There are many sophisticated ways to predict the next position of the moving event based on our assumed correlated random movement model. Since the event prediction is not the main scope of this paper, here we use the simplest first order approximation for demonstration, i.e., the estimate $\hat{Z}_{k+1}$ is given by

$$\hat{Z}_{k+1} = Z_k + l\underline{e}_{\theta_k}, \tag{25}$$

that is, we basically assume that the last step is repeated again without any directional change.

4.6.5 Strategies

4.6.5.1 Mintotal

As argued before (see(17)), the total energy minimization is equivalent with minimizing the sum of event distances. By substituting (17) into (15) using (14), the best position for the sink node in the next round—assuming that the sink can only move at limited speed—is given by

$$S_{k+1}^{total} = \arg \min_{s \in \mathcal{C}_{S_k, r_v}} \sum_{i=1}^{I} \max(h/2, d(\hat{Z}_{k+1}^i, s)), \tag{26}$$

where r_v is the maximum distance the sink node can move within one round. We call this strategy as *mintotal*.

4.6.5.2 Minmax

To minimize the maximum energy consumption, by substituting (26) into (25) we have to solve

$$\hat{E}_{max}^{SN}(s) = \max_{1 \le i \le I} E\left(\hat{Z}_{k+1}^i, s\right) \to \min . \tag{27}$$

Since this minimization is equivalent with that of minimizing the maximum event distance from the sink (see(19)), we have

$$S_{k+1}^{max} = \arg \min_{s \in \mathcal{C}_{S_k, r_v}} \left\{ \max_{1 \le i \le I} d(\hat{Z}_{k+1}^i, s) \right\}. \tag{28}$$

In the following, we call this strategy as *minmax*.

4.7 Implementation issues

4.7.1 Routing

In our analytical investigations we assumed that the multi-hop communication is supported by an ideal short path routing mechanism; the sensors were considered to be deployed densely and evenly enough to find a straight linear path towards the sink. However, in a real world scenario there are many factors that make such an ideal routing impossible; sensors are not that densely deployed, the depletion of some sensors after a while may result in "white holes" in the area, etc. Therefore, in order to implement in a simulator our proposed adaptive mobility strategies, we had to use a more realistic routing mechanism, that takes into account all these factors.

We considered a distributed routing solution, where there is no central authority to select the end-to-end route and inform the participating nodes about it. It is up to the nodes to decide locally to whom the packet should be handed over. The question is, how to choose the next hop among the neighbors within radio range. We applied the GOAFR routing algorithm [36]. The GOAFR routing combines the greedy and the face algorithms. The greedy algorithm always picks the neighbor closest to the sink to be next node for routing. However, it certain situations it can occur that no neighbor is closer to the sink than the current node, for example if there is a hole in the sensor field, as shown in Fig. 6). In this case the routing switches to the face algorithm, and passes around the hole on its border. When it is possible, the routing switches back to the greedy algorithm.

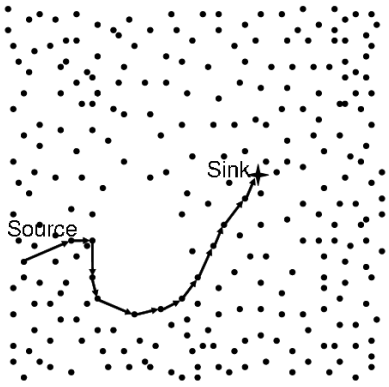

Fig. 6. The route between the sink and the reporting node.

4.7.2 Updates related to sink relocation

If sensors want to send data to the sink, they have to know its position when geographical greedy routing is concerned. Moving the sink node has a negative side-effect on the energy consumption: sensors should be alerted about the changed position of the sink through location update messages. Therefore, having an efficient and power saving update mechanism is essential for a viable data gathering strategy.

Our solution assumes a periodical update message sent out by the mobile sink. However, there are several factors that make this mechanism power-friendly. First, sensors do not relay update messages among them; the sink node has the ability to cover the entire region through a single broadcast message, updating each sensor directly. Note that the sink does not have power limitations; thus, it can afford such a costly update mechanism. Moreover, if needed, dedicated powered relay nodes can be deployed in the region to forward these update messages.

Besides eliminating multi-hop update relaying, an important feature is that only sensors that sensed an event listen to the update messages. When a reporting sensor receives the update, it sends its data towards the advertised location, incorporating the sink coordinates in its message as well. Hence, intermediate relaying nodes do not have to listen to the periodic updates of the sink.

It is important, that all the data packets that are sent by a sensor have to arrive to the sink before it moves away. This can be ensured if the sink stays in its advertised position for a certain (guaranteed) period of time, also included in the update message. We assume that data delivery is fast enough to fit safely into this guaranteed time period.

4.7.3 Communicating neighbors

In our model we assumed that only a specific receiver node, chosen by the routing mechanism, has to listen to the transmission of the sender; none of the other neighbors within radio range have to waste energy on overhearing, i.e., on receiving packets that are not meant for them. This can be achieved, for example, by using the free sleep-schedule feature of the S-MAC protocol [37]. Using S-MAC, an idle sensor goes to sleep for some time; then it wakes up, and listens to see if any other node wants to talk to it. All nodes are free to choose their own listen/sleep schedules. These schedules are exchanged by broadcasting them to all the immediate neighbors. This ensures that all neighboring nodes can talk to each other even if they have different schedules. For example, if node A wants to talk to node B, it just waits until B is listening. Hopefully, the other neighbors will be in sleep mode that time; thus, they do not waste energy for listening to the transmission of node A. If more nodes are in listening mode, the use of short RTS/CTS (Request-To-Send/Clear-To-Send) packets can help to further reduce overhearing (see [37] for more details).

4.8 Simulation results for Multi-hop WSNs

We simulated the proposed sink relocation strategies using MATLAB. We assumed that the covered region is a circular area of radius R=1000m, in which we randomly distributed 10.000 sensors, using a uniform distribution model. Both the sensing range and the maximum communication range of each sensor were fixed to 80 m, the hop length h being 80m. At the beginning of a simulation run each sensor was loaded with 1000 units of energy. The cost of receiving a packet was 1 unit. The cost of sending one packet depended on the transmission distance d (E_{Tx}~d^{α},α = 3); the transmission consumed 1 unit of energy for d=h=80m. Events occurred at uniformly chosen random locations on the periphery of the area. The probability of a new event occurring in a simulation round followed a binomial distribution with a parameter of 0.03. The direction θ of the first step taken by an event was uniformly chosen between 0 and π. For each further step the direction angle was uniformly chosen between [θ-π/4,θ+π/4]. Both the events and the sink moved with a speed of 40m/round. By evaluating (26) and (28) the next position of the sink can be determined with arbitrary precision. The network was considered to be alive until there was an event the sink was not informed about.

First, we present an example on how the events are reported to the sink through multi-hop routing. Fig. 7 shows a snapshot of the network with five simultaneous events being reported. Around each event we marked the circular area containing the sensors that observed that event. All those sensors start to send data to the sink on multi-hop wireless paths that might overlap near to the sink node. Note that overlapping is more probable if events are far from the current location of the sink; nodes on such an overlapping segment will have an increased load as they have to relay data from several sensors. This load, however, is different from the theoretically computed one in section 4.1 as we simulate a discrete network, with a finite number of sensors spread inside the covered region. Nevertheless, results show that the proposed adaptive sink mobility strategies are efficient also in the simulated discrete cases.

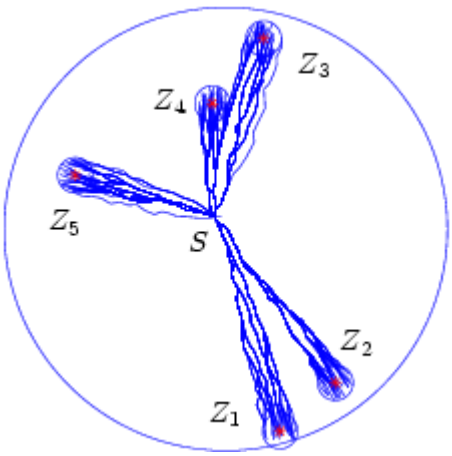

Fig. 7. Routes between the sink and the reporting nodes.

In Fig. 8 (a) we present the trajectories of 100 events that entered the region. We can observe that the different parts of the region were affected by these events in a homogeneous manner. Note that these events were not simultaneous ones, but appeared and disappeared according to our simulation model. In Fig. 8 (b) we show a histogram on the frequency of simultaneous events during an entire simulation run. One can see that in most of the time there were either no events at all, or only a single one. Two simultaneous events were present in 27% of the time, while three or more events were very rare.

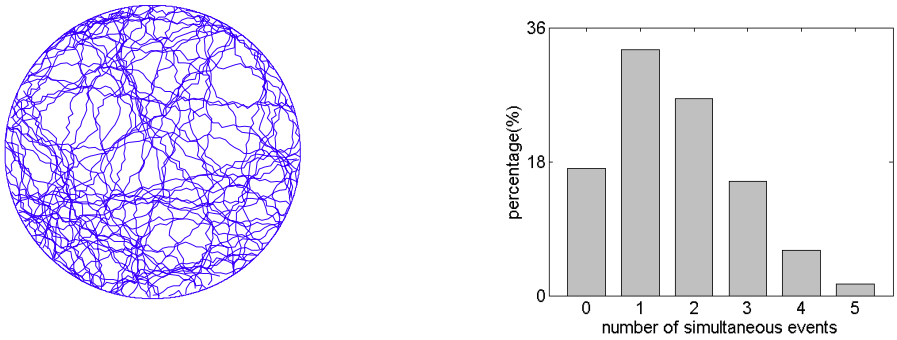

Fig. 8. (a): Trajectories of 100 events (left), and (b): the number of simultaneous events in the simulation (right).

Until now we have seen how the events move inside the covered region. However, it would be interesting to point out the areas the sink moves more frequently during a long simulation period. Fig. 9 shows the distribution of the sink coordinates after 30.000 simulation rounds, for the *minmax* (left) and the *mintotal* (middle) mobility strategies, respectively. We can see that in the *minmax* case the sink often resides near the center of the region, while in the *mintotal* case the distribution is more homogeneous. This is because in the *mintotal* strategy if there are several events nearby in a specific area, they will attract the sink even if there is another distant event, isolated in an opposite area, which will be negatively affected. On the other hand, in the *minmax* approach the isolated distant event is more strongly protected.

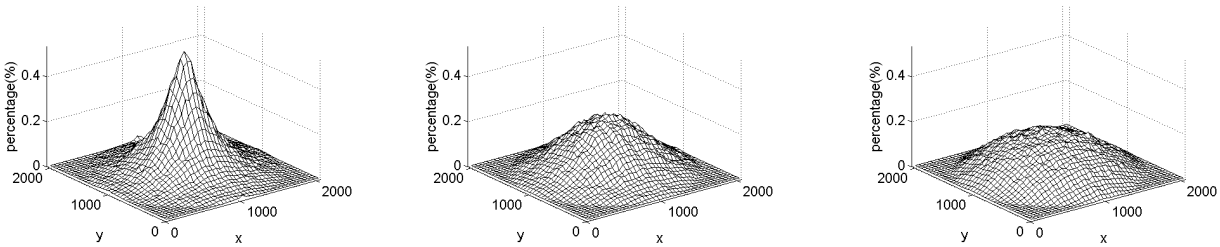

Fig. 9. Histogram of sink positions for the *minmax* (left), *mintotal* (middle) and *rwp* (right) strategies.

It is quite straightforward to assert that by adaptively moving the sink we can increase the energy efficiency of the network. However, we should be able to quantify this improvement compared to other solutions. In order to do so, we consider three other approaches. The first one, called *fix*, assumes the sink to be static, and located in the center of the covered area. The second one, called *circular*, proposes to move the sink along the periphery of the network, with a constant speed, independently of the occurred events. We consider this approach as authors in [5] argue in favor of it as being the optimal solution for lifetime elongation. However, they analyzed a time-driven scenario, as opposed to our event-driven model. Finally, the third approach, called *rwp* considered the sink to follow a random waypoint mobility model, again independently of the current events. The sink randomly chooses a point in the area, and goes towards it with a constant speed of 40m/round; upon reaching it, it chooses a new direction.

The distribution of the sink coordinates in the *rwp* case is shown in Fig. 9 (right). We can see that the *rwp* strategy ensures an even more homogeneous distribution than the *mintotal* case.

Now let us compare the total energy consumption in the network for the five different strategies. Fig. 10 presents the results obtained for one specific simulation run, for the same succession of events in the five

cases. On the *x*-axis we present the number of rounds completed in the simulation. A curve ends in the figure if the network died for that specific strategy, i.e, the sink could not be informed about an event, because of the neighboring sensors, or those necessary to relay the report, being depleted. We can see that by positioning the sink in the middle of the network we consume less energy in overall than by moving the sink along the periphery. However, nodes around the sink deplete their batteries rapidly, and the network dies. On the other hand, we can see that the *circular* strategy consumes significantly more energy than both of our proposals. Note also that there is practically no difference between our two solutions in terms of overall energy consumption. This is mainly due to the fact that in the majority of the cases there are very few (0 to 2) simultaneous events in the region; thus, even if the sink moves to different locations, as shown in Fig. 9, the overall power consumption will not differ significantly. Finally, moving the sink randomly inside the area consumes less energy than moving it on the periphery, but it is still less efficient than the adaptive strategies. By repeating the simulation several times, for different successions of events, we obtained similar shapes for all the curves, the only difference being in when the network dies in the different cases, a parameter that greatly depends on the occurred events.

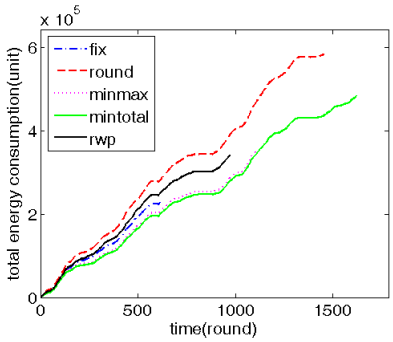

Fig. 10. Total energy consumption of the five strategies.

Fig. 11 presents the average lifetime of the network for the different strategies. We ran the simulation 10 times, and considered the network to be alive until one of the events was unobserved by the sink (either there were no sensors to detect it, or the information could not be relayed to the sink). We can see that the *mintotal* strategy outperforms all the other solutions, ensuring 16% longer lifetime than the *circular* strategy, and nearly 150% longer than the *fix* case. In Fig. 12 we see the average energy consumption of the entire network per round, for the five different strategies. We considered only those rounds where at least one event was present in the region, and stopped the calculus when the first sensor died, for each of the strategies. We ran 10 times the simulation, and calculated a cumulated average. It can be seen that our two adaptive strategies consume the less energy; they are around 30% better in average than the *circular* strategy, and around 15% better the case of the randomly moving sink.

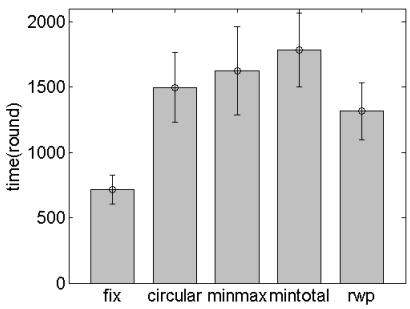

Fig. 11. The average lifetime of the network for all five strategies.

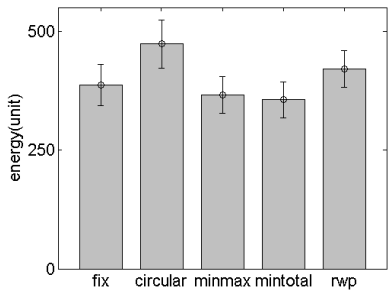

Fig. 12. The average energy consumption in a round for all five strategies.

It is also interesting to see how the five strategies affect the sensors located at different portions of the covered area. Fig. 13 shows the average energy consumption of a sensor in a single round in function of its distance to the center of the area. We divided the total energy consumption of a sensor with the number of rounds it was alive, and calculated the average of this value for all the sensors located at the same distance form the center. The final averages were obtained after running the simulation 10 times. An obvious result is that the *fix* strategy depletes aggressively the sensors located close to the center. It can also be seen that the *circular* strategy ensures the most homogeneous energy consumption of the sensors. However, our two strategies consume less energy than the *circular* solution in all the areas of the network, which explains the resulting lifetime elongation. Sensors near the periphery consume less energy for all the strategies, as they are rarely selected to relay messages of other nodes.

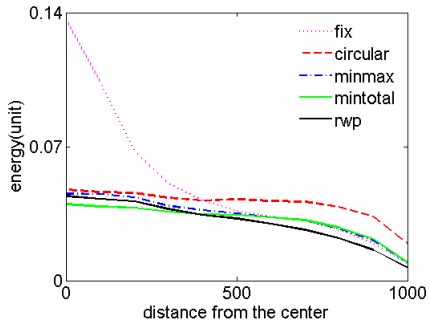

Fig. 13. The average energy consumption of the sensors as as function of the sensors' distance from the center of the sensor field.

Finally, in Fig. 14 we present the remaining energy of the sensors in different areas of the covered region, after the network has died; an area is completely black if the corresponding sensors have 100% of their initial energy still available. The values are averages calculated over 10 simulations. It can be observed again that the *fix* strategy depletes the sensors around the center, while the *circular* one makes use of nearly all the sensors in a comparable way. Our two solutions conserve more energy in the network than the *circular* strategy, while still ensuring a longer network lifetime. As the results for *minmax* and the *mintotal* cases were quite similar, we have chosen to chow only one of them.

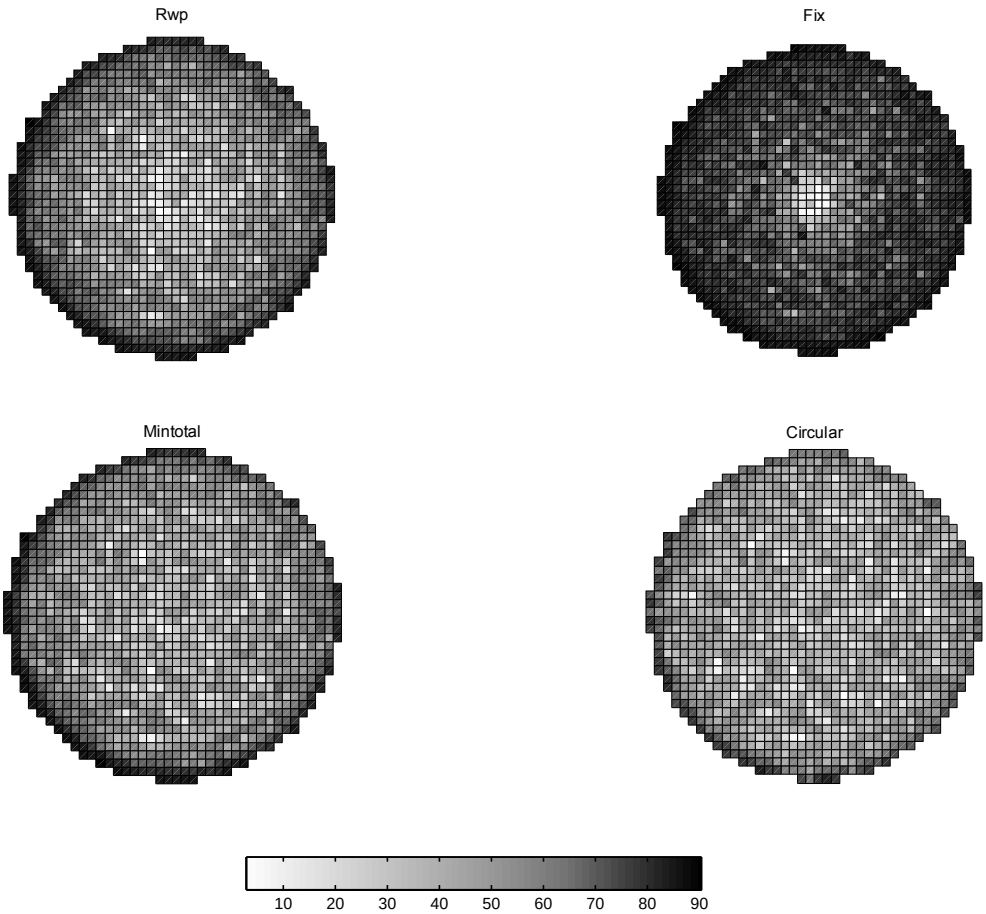

Fig. 14. The remaining energy in the network.

5.0 CONCLUSION

Enhancing energy-efficiency is primordial in a wireless sensor network. There are several techniques to achieve that, e.g., by using energy-aware routing protocols, topology control schemes, or clustering mechanisms. Many recent papers propose to use mobile sinks to reduce energy consumption. However, they usually assume a time-driven scenario.

In this paper we presented the idea of adaptively moving the sink of a single-hop clustered sensor network, in order to decrease the amount of energy required for communication, and hence prolong the lifetime of the network. We introduced three different strategies for moving the sink: *minavg*, *minmax*, and *minrel*. The first one minimizes the average energy required for the communication, the second one minimizes the maximum energy consumption among active cluster heads, while the third one minimizes the relative energy consumption by taking into account the remaining battery power of the nodes in the active clusters. We presented simulation results and a performance evaluation. The results have shown that all the three proposed adaptive sink relocation strategies perform significantly better than the fixed or randomly moving sink case. Among them, the *minrel* strategy turned out to be the most efficient one, as long as the network lifetime is concerned.

For the case of multi-hop WSNs we presented the analytical foundations of two sink relocation strategies: one optimizes the overall energy consumption in the network (*mintotal*), the other minimizes the energy

consumption of the most loaded sensor (*minmax*). We showed through simulations that both strategies ensure a network lifetime of around 150% longer than in case of a fixed sink, and consume about 30% less energy than the *circular* strategy that moves the sink along the periphery of the network. Even if this *circular* strategy ensures a more homogeneous depletion of the sensors, the network dies more rapidly due to the increased overall energy consumption. Our adaptive strategies perform significantly better than the case of a randomly moving sink as well, both regarding network lifetime and energy consumption.

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