Efficient Energy Management in Wireless Rechargeable Sensor Networks*

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ABSTRACT

Through recent technology advances in the field of wireless energy transmission Wireless Rechargeable Sensor Networks (WRSN) have emerged. In this new paradigm for WSNs a mobile entity called Mobile Charger (MC) traverses the network and replenishes the dissipated energy of sensors. In this work we first provide a formal definition of the charging dispatch decision problem and prove its computational hardness. We then investigate how to optimize the trade-offs of several critical aspects of the charging process such as a) the trajectory of the charger, b) the different charging policies and c) the impact of the ratio of the energy the MC may deliver to the sensors over the total available energy in the network. In the light of these optimizations, we then study the impact of the charging process to the network lifetime for three characteristic underlying routing protocols; a greedy protocol, a clustering protocol and an energy balancing protocol. Finally, we propose a Mobile Charging Protocol that locally adapts the circular trajectory of the MC to the energy dissipation rate of each sub-region of the network. We compare this protocol against several MC trajectories for all three routing families by a detailed experimental evaluation. The derived findings demonstrate significant performance gains, both with respect to the no charger case as well as the different charging alternatives; in particular, the performance improvements include the network lifetime, as well as connectivity, coverage and energy balance properties.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Distributed Networks, Network Communications, Wireless Communication

General Terms

Algorithms, Experimentation, Performance

Keywords

Sensor Networks, Energy Efficiency, Mobility, Distributed Algorithms

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1. INTRODUCTION AND CONTRIBUTION

Wireless Sensor Networks (WSNs) are envisioned as large ad-hoc collections of very small autonomous devices, that can sense environmental conditions in their immediate surroundings while being highly restricted in terms of processing power, communication capabilities and energy reserves. The collected sensory data is disseminated to a static control center usually referred to as the *Sink*. WSNs by their very nature require specialised protocols that are able to cope with their particular features, most notably regarding energy efficiency in order to maximize the network lifetime. Towards this direction, several approaches have been studied over the past years for the fundamental problem of efficient data propagation. A taxonomy of these approaches would categorise them in main families of routing protocols, such as hop-by-hop data propagation schemes, clustering algorithms and energy balancing algorithms.

Each family of protocols has several characteristics that lead to different evolution of the network during its life cycle. For instance, in a hop-by-hop data propagation scheme sensor motes closer to the Sink act as relays for the motes lying further away. Therefore, a bottleneck effect emerges in areas closely around the Sink as the motes lying there also serve traffic from distant areas of the network. As a result, these motes deplete their energy at very high rates, thus resulting in a disconnected network. At the same time, motes at the periphery of the network have very high residual energy. Similarly, clustering algorithms tend to highly stress motes acting as cluster-heads. Although cluster-head rotation mechanisms have been proposed to cope with this issue, due to distant transmissions clustering algorithms still do not scale well with network size and high data generation rates. Finally, energy balance algorithms often make abstract assumptions in their models, particularly with respect to communication range. This way their implementations in real hardware, usually do not demonstrate the same desired characteristics as their theoretical analysis. Due to all these reasons, energy constrained WSNs very often reach the end of their lifetime with very high percentage of their total initial energy unused and with some motes having residual energy as high as 90% [17].

Recent advances in the fields of *wireless energy transmission* and batteries material offer new possibilities for managing the available energy in WSNs. In the first field, the technology of highly-efficient wireless energy transmission was proposed for efficient, non-radiative energy transmission over mid-range. The work in [4] and [16] has shown that through strongly coupled magnetic resonances, the efficiency of transferring 60 watts of power over a distance in excess of 2 meters is as high as 40%. Industry research also demonstrated that it is possible to improve transferring 60 watts of power over a distance of up to two to three feet with efficiency of 75% [7]. At present, commercial products utilizing wireless energy transmission have been available on the market such as that in [12].

In the second field, there is the new battery material for ultra-fast charging. Ultra-fast charging was recently realized in LiFePO4 by creating a fast ion-conducting surface phase through controlled off-stoichiometry [2]. It inherits and combines the advantages of both conventional Li-ion batteries and super-capacitors, that bring high energy density and can be charged as high as $400C^2$. This way, the time to fully charge a battery is shortened to few seconds.

These new technologies lead the way towards *a new paradigm for WSNs*; the Wireless Rechargeable Sensor Networks (WRSNs). WRSNs consist of sensor motes that may be either stationary or mobile, as well as few mobile motes with high energy supplies. The latter, by using wireless energy transmission technologies are capable of fast recharging sensor motes. This way, the highly constrained resource of energy can be managed in great detail and more efficiently. Another important aspect is the fact that energy management in WRSN can be performed passively from the perspective of sensor motes and without the computational and communicational overhead introduced by complex energy management algorithms. Finally, WRSNs allow energy management to be studied and designed independently of the underlying routing protocol used for data propagation.

The Problem. Let a Wireless Rechargeable Sensor Network consisting of a set of stationary sensor motes and a special mobile node called *Mobile Charger*. The sensor motes are deployed uniformly at random over a network area and propagate data to a *Sink* using a routing protocol P. The Mobile Charger has finite energy supplies, that are significantly greater than those of a single sensor mote, and is capable of recharging the sensors. The problem we study is identifying best possible configuration of the Mobile Charger in order to improve energy efficiency and to prolong the lifetime of the network. Such mobile charger configuration alternatives include the charging policy followed (i.e. whether to recharge motes fully or partially), the ratio of energy available to the charger over the energy initially deployed at the sensor motes, as well as the optimization of the network traversal by the charger e.g. finding which are the best trajectories the charger should follow.

Our Contribution. While considerable research efforts have been invested into energy-efficient scheduling of the mobile charger, proposed solutions in the literature so far require a global (or at best, a semi-global) knowledge of the state of the network. On the contrary, the solutions proposed in this paper is fully distributed and adaptive, and rely solely on local information. Furthermore, our proposed algorithm for the MC can be used in combination with any underlying routing protocol and adapts of the distribution of sensors in the network area.

More specific, we investigate alternative strategies for efficient recharging in WRSNs via a Mobile Charger. First, we identify several critical aspects of the charging procedure and the corresponding trade-offs. We provide a formal definition of the charging problem and prove that it is computationally hard. We then try to optimise each trade-off and, lastly, we investigate the impact of the charging process over three characteristic families of routing protocols. The trade-offs we have identified include: a) how the total available energy of the network should be split between sensor motes and the MC b) given that the energy the MC may deliver to the motes is finite, whether each sensor will be fully or partially charged (and to what extent) and c) what is the trajectory the MC should follow in order to charge the sensor motes. The implementation of the alternative strategies and their detailed simulation evaluation demonstrates significant performance gains with respect to several metrics such as network lifetime, connectivity and coverage, as well as energy balance properties.

2. RELATED WORK AND COMPARISON

The application of wireless energy transfer is a rather new technology and has not been analysed extensively in sensor networks. However, the idea behind WRSNs was first studied by Estrin et al. in [10]. The authors study the feasibility of extending the lifetime of a wireless sensor network by exploiting mobility. In particular, small percentage of network nodes which are autonomously mobile, search for new energy, recharge their batteries and deliver it to the rest network. In that paper the authors define the energy properties that a sensor network should have in order to be self-contained; that is, continue work forever. In [5] the authors analyse the problem of optimal scheduling in WRSN of both charger's path and sensor's sleeping policy for stochastic event capture. The maximization of the quality of monitoring is also studied. The work in [8] describes applications suited for wireless recharging sensor networks and analyse the advantages over classic sensor networks but also their limitations.

In [11] the authors consider a sensor network in which a mobile entity is employed which (in contrast to our approach) serves also as a data collector and as an energy transporter that charges the static sensors on its migration tour. They provide a two-step approach: in the first step the mobile entity selects the maximum number of anchor points such that the sensors located in these anchor points hold the least energy and meanwhile the tour length is no more than a threshold. In the second step they formulate a utility maximization problem on a flow-level network model in order to determine how to gather data from sensors. However this algorithm requires global information, thus making it not very practical in even medium-sized sensor networks.

In [19] the authors analyse again the possibility of practical and efficient joint routing and charging schemes. They propose a sensor network in which both a mobile charger and a base station appear. Each sensor sends data hop-by-hop to the Sink periodically using the Collection Tree Protocol (CTP). Also, measurements of other local properties such as energy level, consumption rate, etc. are piggybacked along with data and reported to the Sink. Then, the base station, according to sensors information, schedules future charging activities and commands the mobile charger through long range radio to execute the schedules. Authors show that the network lifetime is prolonged by the mobile charger which mostly moves in energy-minimum paths. However, each sensor has to send more data to the Sink and the charger has to know the location of each sensor a priori. Authors in [18] consider the scenario of a mobile charging vehicle periodically travelling inside the sensor network and charging the battery of each sensor node wirelessly. The necessary and sufficient conditions are introduced and the problem is studied as an optimization problem, with the objective of maximizing the ratio of the wireless charging vehicle's vacation time over the cycle time. However, in their model authors use global knowledge.

Overall, in all above methodologies the knowledge of the model is much stronger than ours allowing for off-line and/or centralized optimizations under high levels of network information. Also, in several of these approaches the charging problem is coupled together with routing, while in our method the charging policy implicitly adapts to any underlying routing policy.

Regarding the three families of routing protocols we use to investigate the impact of our methods, we refer to [15] for clustering, [6] for routing and [1, 3] for energy balanced data propagation.

3. THE MODEL

3.1 Deployment and energy model

Our model features three types of devices: static sensors, a mobile charger (MC) and one static Sink. We assume that there are N sensors uniformly distributed at random in a circular area of radius R. The communication range of sensors (we denote it by r) varies according to requirements of the underlying routing protocol. The network density is $\rho = \frac{N}{\pi R^2}$. The Sink S lies at the center of the circular area. In our model we assume that the MC does not perform any data gathering process. For simplicity we assume that all sensors have the same data generation rate of λ packets per unit time. Also we assume that E_{total} is the total available energy in the network and is constant. Initially, $E_{total} = E_{sensors} + E_{MC}^{init}$ where $E_{sensors}$ is the amount of energy shared among the sensor nodes and E_{MC}^{init} is the total amount of energy that the MC may deliver to the network by recharging sensors. At any given time the energy left to the MC for sensor charging is denoted as E_{MC}^{curr}. The maximum amount of energy that a single sensor may store is denoted as E_{sensor}^{max} and is the initial energy given to each sensor, i.e. $E_{sensor}^{max} = \frac{E_{sensors}}{N}$.

For transmitting and receiving a message, we assume that the radio module dissipates an amount of energy proportional to the message size. To transmit a k-bit message, the radio expends $E_{\tau}(k) = \epsilon_{trans} \cdot k$ and to receive a k-bit message, the radio expends $E_R(k) = \epsilon_{recv} \cdot k$ where ϵ_{trans} and ϵ_{recv} are constants that depend on the radio module and the transmission range of the sensors. As usual, the power needed to transmit a message at distance d is roughly d^{α} where $2 \leq \alpha \leq 6$ a constant; for simplicity we take $\alpha = 2$.

3.2 Charging Model

In our model the charging is performed point-to-point, i.e. only one sensor may be charged at a time from the MC by approaching it at a very close distance so that the charging process has maximum efficiency. The time that elapses while the MC moves from one sensor to another is considered to be very small when compared to the charging time; still the trajectory followed (and particularly its length) is of interest to us, since it may capture diverse cost aspects. We assume that the charging time is equal for every sensor and independent of its battery status.

4. THE CHARGER DISPATCH DECISION PROBLEM

Below we give a formal definition for the decision version of the problem we consider.

DEFINITION 1 (CDDP). *Suppose that we are given a set S of sensors each one capable to store E units of energy and for each sensor $s \in S$ a list L_s of pairs $(t_s^j, e_s^j), j \geq 1$ in which t_s^j corresponds to the time that the j-th message of s was generated and e_s^j the energy that the sensor used to transmit it. We are also given an $|S| \times |S|$ matrix D, where $D_{i,j}$ is the distance*[1] *between sensors i and j and a mobile charger M which can charge a sensor in one time unit to its initial energy. The charger dispatch decision problem (CDDP) is to determine whether there is a feasible schedule for M to visit the sensors so that no message is lost due to insufficient energy.*

Notice that we neglect to include energy needed by sensors in order to receive messages. Moreover, the messages a sensor s might receive by other nodes are included in each L_s. Thus we suppose that these messages are generated by the sensor itself. This allows the consideration of different routing policies in a unified manner.

We show that the general version of the CDDP is NP-complete.

THEOREM 1. *CDDP is NP-complete.*

PROOF. We first note that, given a certain walk W of the charger visiting sensors in S, we can verify whether this walk is sufficient so that no message is lost, i.e. no message x is generated on a sensor s such that x is the j-th message of s and s has less than e_s^j available energy at time t_s^j. In particular, this can be done in $O(T \cdot |W|)$ time, where T is the total number of events generated in the network. Therefore CDDP $\in$ NP.

For the hardness part we use the Geometric Travelling Salesman Problem (G-TSP in short, see [9], page 212). Let $P \subseteq \mathbb{Z} \times \mathbb{Z}$ and $B \in \mathbb{N}$ be the input of G-TSP. We now transform this into an input for CDDP as follows: We use a set S of $|S| = |P|$ sensors and set $D_{i,j}$ equal to the Euclidean distance between the i-th and j-th point in P. Furthermore,

[1]Notice that if we assume that the charger moves with constant speed v then the time needed to travel between i and j is $\frac{D_{i,j}}{v}$.

for each sensor $s \in S$ we define its event list to be $L_s = \{(0, E), (\frac{B}{v}, 1)\}$, where v is the charger's speed. That is, two events happen in each sensor s, namely one at time 0 depleting all the energy available in s and one at time $\frac{B}{v}$ requiring energy 1. Notice that a solution to this instance of the CDDP problem would provide an answer to G-TSP, which means that G-TSP $\leq_m$ CDDP. This completes the proof. $\square$

5. TRADE-OFFS OF THE CHARGING PROCESS

In order to properly understand and investigate the charging process we first analyse several of its aspects and specify their inherent trade-offs.

5.1 Energy percentage available to charger

In order to be fair in our evaluation, we assume that the total available energy to the network E_{total} is finite and same in all cases. This way, we will be able to investigate whether the energy efficiency is increased (and to what extent) with and without the introduction of the MC and the charging process to the network. This particular trade-off consists in how much energy (in terms of the total energy available) should the MC be initially equipped with. On the other hand, more energy to the MC leads to better online management of energy in the network. However, since $E_{total} = E_{sensors} + E_{MC}^{init}$, more energy to the MC also means that the sensor motes will initially be only partially charged. Therefore, it will be more likely that they run out of energy before the MC charges them leading to possible network disconnection and low coverage of the network area. In order to determine the optimal energy amount available to charger as a percentage of E_{total}, we conduct experiments for various ratios between $E_{sensors}$ and E_{MC}^{init}.

A key conclusion is that a rather modest percentage of energy at the MC is a wise strategy (see section 7.2 and Fig 3), with a 20% percentage value being the best choice.

5.2 Full versus partial charging

Each time the MC visits a mote a straightforward strategy would be to fully charge that mote. This way the MC would maximize the time interval of revisiting the mote before it runs out of energy. However, as the network operates, energy is dissipated in motes due to data propagation and in the MC due to the recharging process. Therefore, the MC will have increasingly less energy to distribute to more and more motes.

Another approach is to judiciously spread the precious available energy to as many motes as possible in order to extent the network lifetime. Following this rationale, the amount of energy the MC delivers to a mote i is proportional to the residual charging energy of the MC. More formally, MC charges a mote until its energy becomes

$$e_i \approx \frac{E_{MC}^{curr}}{E_{MC}^{init}} \cdot E_{sensor}^{max} \qquad (1)$$

In order to determine the best strategy we conduct detailed experiments comparing the full charging strategy against our adaptive, partial charging strategy.

Our basic result is that partial recharging is more efficient than the full case (see section 7.1 and Fig 2).

6. TRAVERSAL STRATEGIES OF THE MOBILE CHARGER

6.1 Global knowledge traversal strategy

The global-knowledge charger we study is an on-line solution that in each round minimizes the product of each sensor's energy with its distance from the current position of the charger. More specifically, in each moving step the global charger minimizes the following product:

$$P = min\left\{\left(1 + \frac{E_{curr}}{E_{init}}\right) \cdot \left(1 + \frac{dist_{curr}}{2R}\right)\right\} \qquad (2)$$

where E_{curr}, E_{init} and $dist_{curr}$ are respectively tge current energy, initial energy and distance of each sensor, with the minimum taken over all sensors in the network (or at least a large part of it). Since this strategy requires a global knowledge of the state of the network, it is expected to outperform all other strategies, thus somehow representing a performance bound. However, it would not be suitable for real life networks as it introduces great communication overhead (i.e. every mote has to propagate its residual energy to the MC) and does not scale well with network size.

6.2 Spiral traversal strategy

Starting from the Sink, the MC traverses a path which forms a set of concentric circles, centered around the Sink but with increasing radii. Thus it forms a spiral until it reaches the boundaries of the network area. Then the MC follows the same path towards the opposite direction. The advantages of this movement is that due to its space filling attributes, the MC covers the whole network and almost every node is charged, until the energy of MC is totally depleted. On the other hand, this movement is not adaptive, i.e. it does not take into account differences to the energy depletion rates of each subregion of the network caused by the underlying routing protocols, such as bottleneck areas.

6.3 Diameter traversal strategy

Starting from the Sink, located at the center of the circular network area, the MC arbitrarily chooses a direction and moves towards the perimeter of the network moving along the corresponding diameter. Once it has reached the edge of the network area, the MC traverses the perimeter of the network area for an angle of d degrees, i.e. it moves over $\frac{d}{2\pi}2\pi R = dR$ length along the perimeter. Then, it starts moving again along the new corresponding diameter until it reaches the opposing edge of the network area. This procedure is repeated until there is no energy left in MC for charging. In order for the areas that the MC charges not to overlap, in every step d is chosen uniformly at random from the interval of $(0, 90]$ degrees. By following this trajectory pattern the MC manages to charge sensors that lie both close to and far from the Sink. However, although simple, it is also a non-adaptive strategy as well. An instance of the diameter traversal strategy is depicted in Fig. 1

6.4 Random walk traversal strategy

In a simple, blind random walk, each next move of the MC is random and stochastically independent of the previous ones. Furthermore, given that the current node is i, the probability of moving to any neighbouring node j is $p_{i,j} = \frac{1}{deg(i)}$. This method is very robust, since it probabilistically guarantees that eventually all network regions and nodes will be visited, but it may become inefficient on networks with bottleneck areas, or under routing protocols with special nodes (like clustering protocols) or nodes that serve a lot of traffic, as in the case of multi-hop data propagation.

6.5 Our adaptive circular traversal strategy

Given the symmetric geometry, uniform density and uniform data generation rate of the network, we propose that the MC follows a circular trajectory around the Sink. The radius of the trajectory varies and adapts to the energy depletion rates of each subregion of the network. Let S be the set of these sensors where $|S| = 2\pi R_{MC} \cdot \rho$. Let, also, e_i denote the current residual energy of node i. Starting from the Sink, the mobile charger traverses a path which forms a set of concentric circles, centred around the Sink with varying (increasing or decreasing) radii. While at a given distance from the Sink, the MC records the mean value of the energy of the sensors lying on the corresponding circular trajectory; we denote this value by $\overline{E}_{current}$. Accordingly, the MC keeps record of the mean value of the energy of the sensors lying on its previous circular trajectory; we denote this value by $\overline{E}_{previous}$. Based on these two values, the MC tries to optimize its trajectory in terms of recharging the nodes that deplete their energy faster.

The algorithm is shown below:

while $E_{MC}^{curr} > 0$ **do**
  $E_{tmp} = 0$
  for every $i \in S$ **do**
    $E_{tmp} += e_i^c$
    Charge until $e_i \approx \frac{E_{MC}^{curr}}{E_{MC}^{init}} \cdot E_{sensor}^{max}$
  end for
  $\overline{E}_{current} = \frac{E_{tmp}}{|S|} = \frac{\sum e_i}{|S|}$
  if $\overline{E}_{current} \approx \overline{E}_{init}$ **then**
    if $\overline{E}_{previous} \geq \overline{E}_{current}$ **then**
      Keep direction
    else
      Change direction
    end if
  end if
end while

The MC commences traversing the network from the first center of the network area by setting $R_{MC} = 1$, i.e. it will first visit the nodes that lie one hop away from the Sink. Once all corresponding sensors are charged, i.e. the nodes the MC encounters have $e_i \simeq E_{sensor}^{max}$, the MC increases its radius R_{MC} by visiting nodes that are two hops away from the Sink. By comparing the values of $\overline{E}_{current}$ and $\overline{E}_{previous}$ the MC is able to figure out whether it moves towards areas that are stressed by the routing protocol or not. More specifically, if $\overline{E}_{current} < \overline{E}_{previous}$, then the MC assumes it is moving towards a stressed area of the network. Otherwise, if $\overline{E}_{current} > \overline{E}_{previous}$, then it assumes it is moving away from the stressed areas and therefore should change direction.

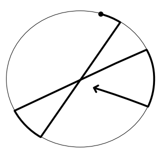


Figure 1: Diameter traversal strategy

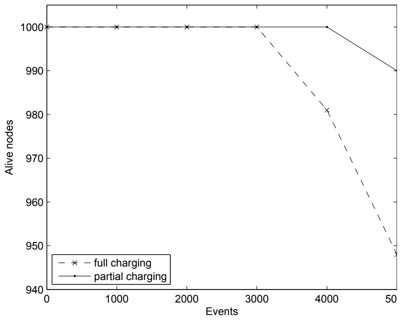
7. EXPERIMENTAL EVALUATION

Our simulation environment for conducting the experiments is Matlab 7.11.0. The Sink is placed at the center (0,0) of the circular deployment area. For statistical smoothness, we apply several times the deployment of nodes in the network and repeat each experiment 100 times. For each experiment we simulate large numbers of data propagations and the average value is taken. The statistical analysis of the findings (the median, lower and upper quartiles, outliers of the samples) demonstrate very high concentration around the mean, so in the following figures we only depict average values.

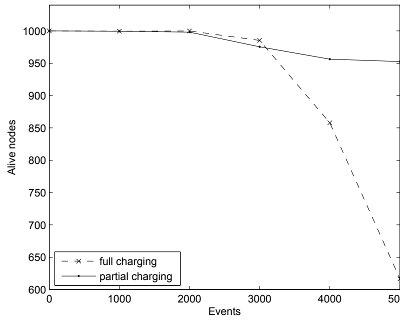
Since the N sensors are uniformly distributed in the circular area $\mathcal{A}$ of radius R, we apply a well known connectivity threshold, in order to maximize the probability that the produced random instances are connected. More strictly, since $\mathcal{A} \subset \mathbb{R}^2$, an instance of the *random geometric graphs model* $\mathcal{G}(\mathcal{X}_N; r)$ is constructed as follows: select N points $\mathcal{X}_N$ uniformly at random in $\mathcal{A}$. The set $V = \mathcal{X}_N$ is the set of vertices of the graph and we connect two vertices if their euclidean distance is at most r. In [13, 14] it is shown that the connectivity threshold for $\mathcal{G}(\mathcal{X}_N; r)$ is $r_c = \sqrt{\frac{\ln N}{\pi N}}$. In this paper we consider random instances of $\mathcal{G}(\mathcal{X}_N; r)$ of varying density, by selecting $r = \sqrt{\frac{c \ln N}{\pi N}}$, for different values of $c > 1$, which guarantees that the produced random instance is connected with high probability. Throughout the experiments we fix the parameter c to higher values for the Greedy routing protocol because it is more prone to early disconnections.

Since the network is dense enough, we assume that each transmission costs r^2 in terms of energy, where r is the transmission range of a sensor node. Since the sensors are uniformly distributed and the event generation is also uniform, the average number of hops needed for an event to travel from the source node to the Sink is $\frac{R}{2} \cdot \frac{1}{r}$. Consequently, the average energy spent for the routing of an event a source node to the Sink is $r^2 \frac{R}{2r} = \frac{rR}{2}$, and for the overall energy spent in the network we have $E_{total} = \frac{\mu r R}{2}$, where μ is the number of the events. We provide the network with $E_{total} = \frac{h \mu r R}{4}$, for $h > 1$, in order to prevent some nodes from dying during the experiments.

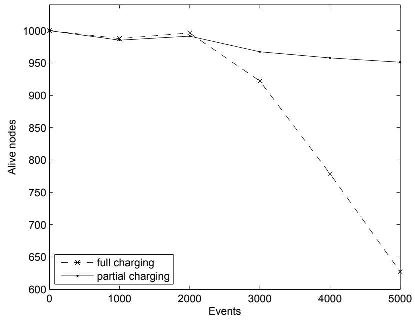
We focus on the following performance metrics: a) **alive nodes over time**, that is the number of nodes with enough residual energy to operate, during the progress of the experiment, b) **network energy map**, which is a depiction of the whole network in terms of spatial aspects, after the generation of a number of events, c) **connectivity over time**, in terms of the nodes' average degree during the progress of the experiment and d) **coverage ageing**, that is the average coverage number (number of sensors having the point in their range) of 1000 randomly selected points in the network over time. At first we investigate the above mentioned charging trade-offs and traversals by using the alive nodes over time as our lead metric. Then, in the light of these results, we apply the best possible configurations on the MC's parameters and conduct a detailed experimental analysis of the MC's impact of the charging process to each of the underlying routing protocols.



(a) Greedy protocol



(b) E_i protocol



(c) LEACH protocol

Figure 2: Alive nodes over time for full and partial recharging. The MC is provided with 40% of the total energy.

7.1 Full versus partial charging

The first trade-off to be investigated is at which level should the sensor motes be charged by the MC. We compare two possible strategies: a) full charging of the nodes and b) partial charging of the nodes using our approach mentioned at section 5.2. At this stage we arbitrarily set the initial energy of the MC to be 40% of E_{total}. This ratio will be investigated individually and optimised later on. The results on the life evolution of the network are shown in Fig. 2. Our partial charging strategy outperforms the full charging strategy, after a specific number of generated events, in all three routing protocols. This behaviour is the outcome the fact that the MC is spending more energy in sensor charging when following the full charging strategy. Thus, the MC's energy is consumed earlier, resulting to a sharp increase in the node death rate.

7.2 Energy available to the charger

The next trade-off to be investigated is the optimal amount of total energy given to the charger with respect to the total energy of the network E_{total}. We conducted a comparison among several percentages of initial energy given to the charger. More specifically, we investigate the cases of 20%, 40%, 60%, and 80% of the total energy to be given to the MC, using our partial charging strategy, since it is found to be more efficient. The results are shown in Fig. 3.

It is clear that providing the MC with more than 40% of the total energy is negatively affecting the life evolution of the network, for all three routing protocols. This result comes from two facts. First, as $E_{total} = E_{sensors} + E_{MC}^{init}$, the more is the energy of the MC and the less is the initial energy of the nodes, resulting in a faster node death rate. A second corollary effect is that if the MC is provided with a high amount of energy, then it can not fast enough to distribute the whole amount of energy to the network, resulting in high residual energy at the MC by the time the network becomes disconnected.

7.3 Traversals comparison

Following the clarification of the previous questions, which resulted in an optimized configuration of our charger (20% initial MC energy, partial charging strategy), comes an experimental comparison of the aforementioned possible traversal strategies of the MC.

More specifically, Fig. 4 shows the impact on the life evolution of the network for each of the proposed strategies. The global knowledge charger outperforms, as expected, all the other chargers, until its energy is depleted. Given LEACH as the underlying routing protocol, the energy of the global knowledge charger is consumed earlier than our charger, resulting in a faster node death. The spiral charger, aside for the Greedy protocol, has a rather unstable impact on the number of alive nodes over time. This is explained by the distribution of the more stressed nodes over the network, for each routing protocol. More specifically, if we apply a greedy routing, the nodes closer to the Sink tend to be more used, and the spiral charger's impact is positive, since these nodes are charged very frequently at the spiral traversal. On the contrary, for the E_i and LEACH protocols, where more distant nodes are stressed, the charging frequency is reduced, due to the spiral traversal. Our charger's performance is very close to the global knowledge charger in all three cases. In the LEACH case it actually becomes more efficient after a specific amount of events, since the global knowledge charger depletes its energy earlier.

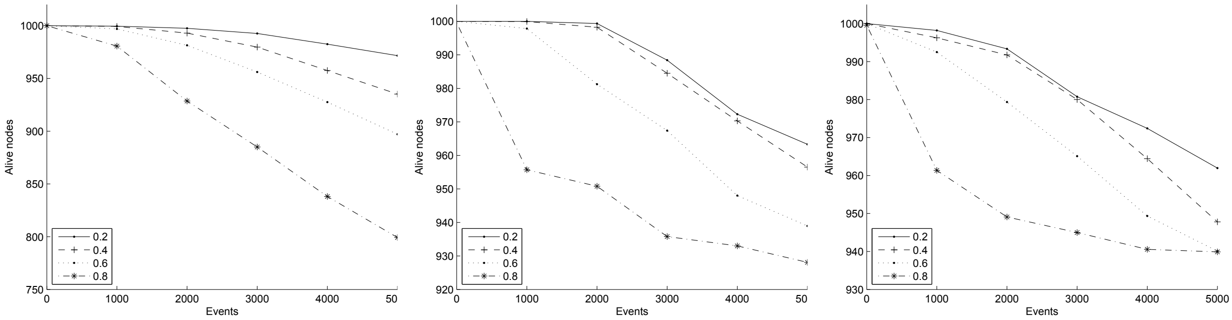
	Greedy	E_i	LEACH
global knowledge	48974	64330	57458
spiral	64167	64167	64167
random walk	181135	222462	222447
diameter	152252	172734	173169
our charger	42412	37856	38641

Table 1: Distance travelled by chargers

The *distance travelled* by each charger during the experiment is given in Table 1. The random walk and diameter chargers are not only inefficient at managing the network energy but they also cover the greatest distance. Our charger travels significantly less distance than the spiral and the global knowledge charger.

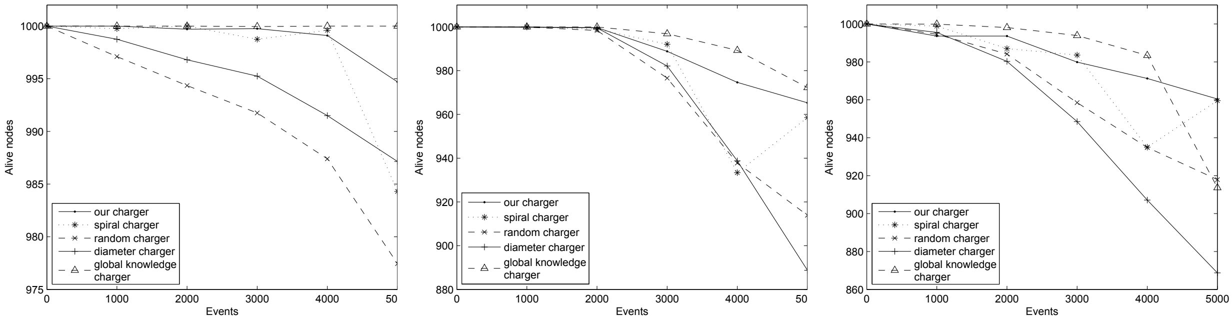
7.4 Overall improvements on the routing protocols

After the line of experiments conducted, we are able to identify various parameters of the MC in order to achieve high performance. Following the previous results, the MC will be provided with 20% of the network's total energy, using our partial charging strategy and our adaptive traversal. We study the effect of our charger on the three routing protocols, on the number of alive nodes over time, the energy



(a) Greedy protocol (b) E_i protocol (c) LEACH protocol

Figure 3: Alive nodes over time for various MC initial energy percentages. Partial recharging is used.



(a) Greedy protocol (b) E_i protocol (c) LEACH protocol

Figure 4: Alive nodes over time for various MC traversals, partial recharging and 20% initial energy.

balance of the network, the average connectivity over time and the coverage ageing.

The overall death rate (in terms of *alive nodes* over time) of the network is vastly reduced in all three protocols, as shown in Fig. 5.

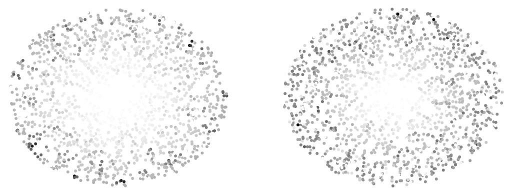
Figs. 6,7,8 depict the energy map of the network over time. More specifically, we present graphically the spatial evolution of energy dissipation in the network after 5.000 event generations. Nodes with high energy dissipation are depicted with dark colours. In contrast, nodes with high residual energy are depicted with bright colours. The *energy balance property* is crucial for the networks lifetime, since early disconnections are avoided and nodes tend to die in a uniform manner.

For all three protocols, we observe that the use of our charger improves the energy balance property. For the Greedy protocol, the stressed nodes closer to the Sink are used very frequently, thus their energy is depleted quickly. Using the charger, not only do the inner nodes not die that fast, but the network's energy in total is more balanced. For the E_i and LEACH protocols, in which more distant nodes tend to be overused, the energy dissipation is higher at the distant form the Sink nodes. The use of charger has a similar effect with the Greedy case, balancing the network by charging more distant from the Sink nodes.

Connectivity is critical for sensor networks, as information collected needs to be sent to remote control centres. This is only possible if there is a path from each node to that centre.

(a) Without charger (b) With charger

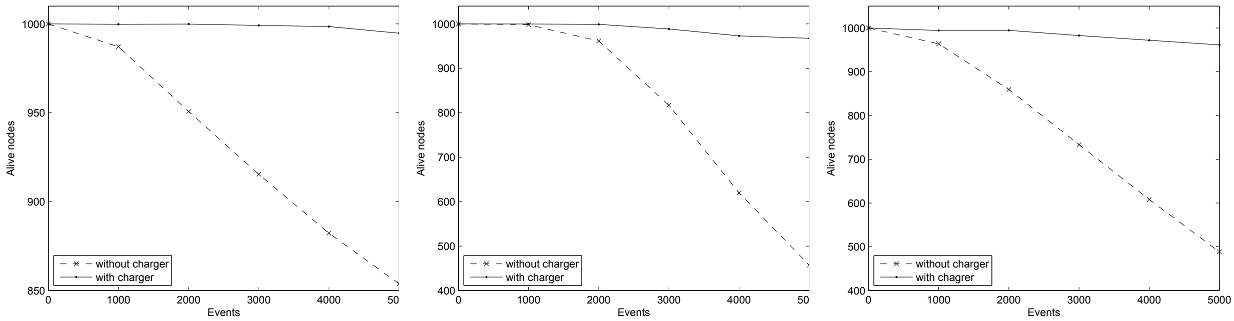
Figure 6: Energy map for Greedy protocol.



(a) Without charger (b) With charger

Figure 7: Energy map for E_i protocol.

The connectivity of a sensor network is usually studied by



(a) Greedy protocol (b) E_i protocol (c) LEACH protocol

Figure 5: Alive nodes over time with and without charger.

(a) Without charger (b) With charger

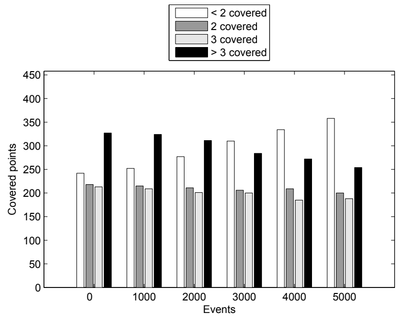
Figure 8: Energy map for LEACH protocol.

considering a graph associated with that network. As far as connectivity is concerned, the average node degree over time is depicted in Fig. 9. We observe that the degree number degradation follows a pattern identical to the node death rate in Fig. 5.

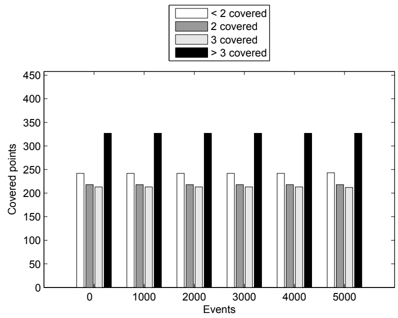
Point *coverage* problem is regarding how to ensure that each of some selected points in the network are covered by enough sensors. Coverage is an important aspect in sensor networks (e.g. localization, data accuracy etc.). A point that is covered by k sensors is called k-covered. The coverage ageing of 1000 randomly selected points in the network is shown in Figs 10, 11, 12. We examine how many points are $\leq 1, 2, 3, > 3$ covered for 5000 generated events. Each bar in the plots represents the number of the covered points. We observe that during the experiment without charger, the number of $\leq$ 1-covered points is increasing and the number of $>$ 3-covered points is decreasing. The use of the charger is improving the coverage ageing of the selected points. More specifically, we observe that the absolute difference of the number of $\leq$ 1-covered points and $>$ 3-covered points, between different time instances of the experiment, is not increasing quickly, compared to the experiment without the charger.

8. CONCLUSIONS AND FUTURE WORK

We investigate diverse energy efficiency aspects of the recent paradigm of Wireless Rechargeable Sensor Networks (WRSNs), in which a mobile charger traverses a WSN and transfers energy to sensor motes in a wireless manner. The ability to add energy to the network during its evolution probably strengthens the power of the model; however a careful investigation of alternative configurations of the charging process is necessary to fully exploit the potential benefits and identify the extent of possible improvements.



(a) Without charger

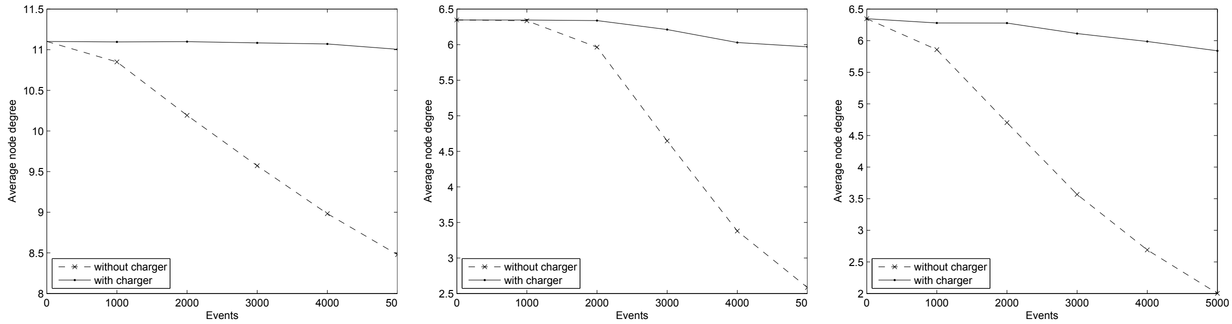


(b) With charger

Figure 10: Coverage ageing for greedy protocol.

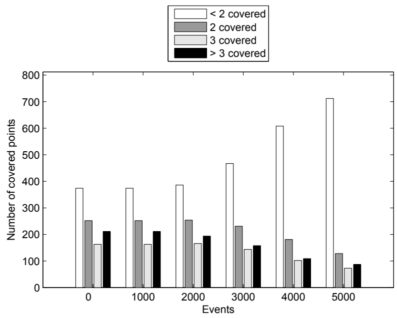
In this work, we first provide a formal definition of the wireless recharging problem and prove that it is computationally hard. We then investigate three key aspects of recharging: a) whether motes should be recharged fully or partially (and to what extent) b) what is the best split of total available energy between the motes and the mobile charger c) what is the trajectory the charger should follow.

For each of these issues we investigate (via detailed simulations) several alternatives and identify best options in each case. Overall, we show that the best strategy is partial recharge of the motes, by a charger with a moderate frac-

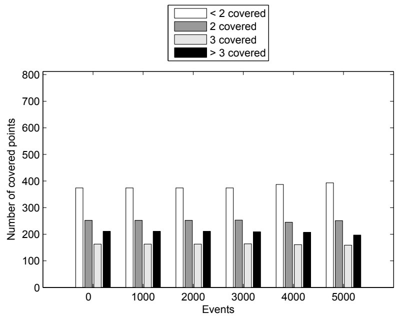


(a) Greedy protocol (b) E_i protocol (c) LEACH protocol

Figure 9: Average node degree over time with and without charger.

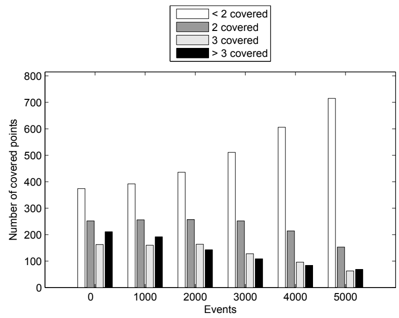


(a) Without charger

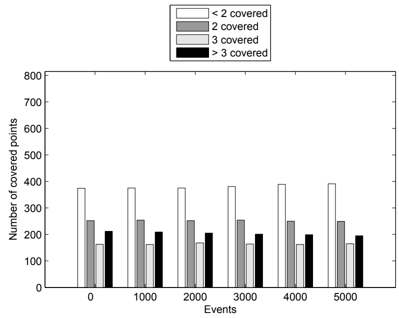


(b) With charger

Figure 11: Coverage ageing for E_i protocol.



(a) Without charger



(b) With charger

Figure 12: Coverage ageing for LEACH protocol.

tion of the total available energy, which follows a circular trajectory around the Sink of a radius which locally adapts to spatial variations of energy in the network. In particular, our simulation findings suggest significant performance gains with respect to various metrics such as network lifetime, connectivity and coverage as well as energy balance.

Future research directions include the design and rigorous analysis of efficient approximation algorithms with provable performance guarantees. In this respect, we note that the reduction used in Theorem 1 for proving the computational hardness of the problem is not preserving the approximation ratios (i.e. known efficient algorithms for the geometric TSP problem may not be very efficient for the charging problem), so this task seems quite challenging.

We also plan to study charging policies in non-uniform network deployments; this may actually lead to new algorithms for the mobile charger policy.

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