Adaptive, Limited Knowledge Wireless Recharging in Sensor Networks

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ABSTRACT

We investigate the problem of efficient wireless energy recharging in Wireless Rechargeable Sensor Networks (WRSNs). In such networks a special mobile entity (called the Mobile Charger) traverses the network and wirelessly replenishes the energy of sensor nodes. In contrast to most current approaches, we envision methods that are distributed, adaptive and use limited network information. We propose three new, alternative protocols for efficient recharging, addressing key issues which we identify, most notably (i) to what extent each sensor should be recharged (ii) what is the best split of the total energy between the charger and the sensors and (iii) what are good trajectories the MC should follow. One of our protocols (LRP) performs some distributed, limited sampling of the network status, while another one (RTP) reactively adapts to energy shortage alerts judiciously spread in the network. As detailed simulations demonstrate, both protocols significantly outperform known state of the art methods, while their performance gets quite close to the performance of the global knowledge method (GKP) we also provide, especially in heterogeneous network deployments.

1. INTRODUCTION

The last decade energy harvesting technologies have been effectively integrated into wireless sensor networks. A variety of ambient energy, such as mechanical, thermal, photovoltaic and electromagnetic energy, can be converted into electrical energy to recharge sensor batteries. However, as all these energy sources come from the external environment and their spatial-temporal profiles exhibit great variations, the strength of harvested energy is typically low, and especially sensitive to the environment dynamics. As there is generally a lack of a priori knowledge of energy profiles, such dynamics imposes much difficulty on the design of protocols that must keep sensors from running out of energy.

The technology of highly-efficient wireless energy transmission was proposed for efficient, non-radiative energy transmission over mid-range. The work in [15] 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% [12]. At present, commercial products utilizing wireless energy transmission have been available on the market such as those in [2], in [1] and in [3].

These technologies offer new possibilities for managing the available energy in WSNs and lead the way towards a new paradigm for wireless sensor networks; the Wireless Rechargeable Sensor Networks (WRSNs). WRSNs consist of sensor nodes that may be either stationary or mobile, as well as few mobile nodes with high energy supplies. The latter, by using wireless energy transmission technologies are capable of fast recharging [14] sensor nodes. 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 nodes 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 (WRSN) comprised of static sensor nodes and a single, special mobile entity called the Mobile Charger. The Mobile Charger has significant (yet finite) energy supplies, that are much larger than those of each sensor mote, and is thus capable of recharging the sensors in the network.

We aim at designing and evaluating efficient strategies for several critical aspects of the Mobile Charger’s configuration in order to improve energy efficiency, prolong the lifetime of the network and also improve important network properties.

We focus on the case where the sensor deployment is randomly heterogeneous, however our methods are general enough and perform very well in homogeneous deployments too. An underlying routing protocol is taking care of the data propagation from sensors to the Sink. Unlike other methods in the state of the art, we do not couple the charging process and the data propagation; actually, we wish to perform efficient wireless energy transfer in a way which is agnostic to the routing protocol, via adaptive techniques that (without knowing the routing protocol) implicitly adapt to any routing protocol.

Remarks. We note that, although the wireless recharge problem might look similar to other related research problems (such as aggressive data collection via mobile sinks), it admits special features that necessitate a direct approach, while the optimization of concrete trade-offs and the fine-tuning of design alternatives that arise in wireless recharging necessitate the distinct investigation of special protocol design parameters (like the extent of wireless recharging at each mote, the energy split between the charger and the motes etc.) mentioned above.

Finally, we note that such charger optimization problems are (inherently) computationally hard e.g. in [4] we have formulated the wireless recharge problem as the Charger Dispatch Decision Problem - CDDL, and showed that it is NP-complete (via reduction form Geometric Travelling Salesman Problem, G-TSP; see e.g. [8], p. 212).

Our contribution. While interesting research has been contributed to the wireless recharge problem and particularly to the scheduling of the mobile charger, most methods so far necessitate significant (in many cases even global) network knowledge (e.g. it is assumed that the charger knows the energy levels of all sensors in the network) and the solutions are centralized. On the contrary, our methods are distributed and adaptive, and use only local (or limited) network information. Also, unlike many state of the art approaches that opt for integration and coupling of the recharging and routing problems, our methods can be used together with any underlying routing protocol (since they adapt on it implicitly). Furthermore, our protocols dynamically and distributively adapt to network diversities, e.g. they cope well with heterogeneous node placement (while still behaving very well in the homogeneous case too).

In particular, we propose and evaluate selected alternative strategies for efficient recharging in static WRSNs via a single Mobile Charger. Our design provides concrete, different solutions to some key issues (and the associated trade-offs) of wireless recharging which we identify, most notably

- given that the energy the MC is finite, to what extent each sensor should be recharged,
- what should be the split of the total available energy between the charger and the sensors and
- what are good trajectories the MC should follow in order to charge the sensor motes.

More specifically, a) we first introduce a new network attribute, which we call node criticality, capturing both the energy consumption at the node over time and the traffic flow served by the node b) taking the node criticality of each sensor node into account, we suggest a particular amount of energy the sensor node should be recharged to when visited by the mobile charger c) for the trajectory followed by the mobile charger, we design three alternative strategies (GKP, LRP, RTP) assuming different levels of network knowledge (from global to limited and reactive); actually, we view the global knowledge protocol as a performance upper bound to which the two distributed, partial knowledge protocols are compared with.

One of our protocols (LRP) performs some distributed, limited sampling of the network status, while another one (RTP) reactively adapts to energy shortage alerts judiciously spread in the network. As detailed simulations demonstrate, both protocols significantly outperform known state of the art methods, while their performance gets quite close to the performance of the global knowledge method (GKP) we also provide, especially in heterogeneous network deployments.

2. RELATED WORK AND COMPARISON

Recently, there has been much research effort in WRSNs. In [17] the authors build a proof-of-concept prototype by using a wireless power charger installed on a robot and sensor nodes equipped with wireless power receivers, carry out experiments on the prototype to evaluate its performance in small-scale networks of up to ten nodes, and conduct simulations to study its performance in larger networks of up to a hundred nodes. Despite the fact that this paper nicely demonstrates the feasibility of a real, implemented WRSN, the simulations of the proposed heuristics are limited to a small number of sensor nodes in the network, an approach that is not convenient for highlighting the behaviour of the charging protocol in large scale networks.

In [16], the authors formulate an energy-constrained wireless charging problem, which maximizes the number of sensors wirelessly charged by a Mobile Charger. The paper proposes heuristic solutions based on the meta-heuristics of Particle Swarm Optimization but, in contrast to our approach, the model assumes extensive knowledge on the charger and the performance evaluation is limited to simulations on small-scale networks.

In previous work of our group in [4] the authors study the impact of the charging process to the network lifetime for selected routing protocols. They propose a mobile charging protocol that locally adapts the circular trajectory of the mobile charger to the energy dissipation rate of each sub-region of the network. They compare this protocol against several other trajectories by a detailed experimental evaluation. The derived findings demonstrate performance gains, but are limited to uniform network deployments, in contrast to our approach which focuses on heterogeneous node distributions.

Alternative versions of the problem have also attracted important research attention. In [20, 19] the authors consider the wireless recharging problem, using multiple mobile chargers. In this case, several other interesting aspects emerge, such as
the minimum number of chargers that suffice to cover the network area, inter-charger coordination etc. Another interesting
approach is presented in [7], where the charging process is conducted using another, RFID-based technology resulting in the
introduction of the charging delay notion and different modeling of the problem.

Overall, in the majority of the 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. For this reason, we have chosen to compare with the protocols presented in [4] and [17], in order to be fair in
terms of the model assumptions. Our strategies here significantly extend the ones in [4] via also taking into account the traffic
served by a node (not just its energy levels). This gives rise to completely new configurations of the Mobile Charger (one
based on a limited network knowledge and a reactive one) that significantly outperform (especially in heterogeneous settings)
the ones in [4]. A qualitative exposition of some ideas in this paper will be presented as a poster in DCoSS 2013.

3. THE MODEL

We consider a plane sensor network, in which the sensors and the Sink node are static. We abstract the network by a graph
$G(V,E)$, where $V = \{v_1,v_2,...,v_n\}$ denotes the set of nodes (sensors), and $E \subseteq V^2$ represents the set of edges (wireless links).
An edge between two nodes in the graph exists if the distance between the corresponding sensors in the network is less than
or equal the transmission range $r$.

Without loss of generality, we assume that network deployment area is a circle of radius $D$. We virtually slice the network
into $M = D/R$ co-centric Rings and $N = 2\pi/\phi$ Slices. A Sector is defined as the intersection of a specific Ring and Slice. For
example, in Fig. 1 the network is divided into 12 Slices ($\phi = \pi/6$) where each Slice contains 10 Sectors, resulting in a total of
120 sectors in the network.

Placement heterogeneity. We consider random instances of the following quite general model of non-uniform deployment:
Denote by $S_{ij}$ the sector corresponding to the intersection of Slice $i$ and Ring $j$. Let $b > 1$ be an arbitrary constant. Each
sector $S_{ij}$ chooses independently a number $\delta_{ij} \in [1,b]$ according to the uniform distribution $U[1,b]$. We will refer to the
number $\delta_{ij}$ as the relative density of sector $S_{ij}$. Values of $\delta_{ij}$ close to 1 imply low relative density and values close to $c$
imply high relative density. By combining the knowledge about the total number of sensors in the network $n$, together with
the relative density $\delta_{ij}$ and the area $A_{ij}$ of every Sector, we compute the number of nodes $n_{ij}$ deployed in sector $S_{ij}$ by
the following formula:

$$n_{ij} = \frac{n}{\sum_{i',j'} \frac{A_{i',j'}}{A_{ij}} \frac{\delta_{i',j'}}{\delta_{ij}}}$$

where $n = \sum_{i,j} n_{ij}$. Finally, we scatter $n_{ij}$ nodes in the area corresponding to sector $S_{ij}$. The fraction of the actual densities
of two sectors $S_{ij}$ and $S_{i',j'}$ is exactly $\frac{A_{i',j'}}{A_{ij}} \frac{\delta_{i',j'}}{\delta_{ij}}$. Furthermore, if all Sectors have the same relative density (i.e. $\delta_{ij} = \delta_{i',j'}$, for
all $i',j'$), we get the uniform deployment.

Each sensor node knows its location, has a unique ID and belongs to exactly one Sector. Each node can identify in which
Slice it belongs to. This information can be disseminated through a set-up phase initiated by the Sink during which the
position of the Sink and the IDs of the nodes in neighbouring Slices are diffused. Our protocols operate at the network
layer, so we are assuming appropriate underlying data-link, MAC and physical layers. The nodes’ memory is assumed limited
and each node chooses independently a relative data generation rate $\lambda_i \in [c,d]$ (where $c,d$ constant values) according to the
uniform distribution $U[c,d]$. Values of $\lambda_i$ close to $c$ imply low data generation rate and values close to $d$ imply high data
generation rate. We consider two types of data transmission: a) single-hop transmission (cheap in terms of energy and slow)
between two neighboring nodes and b) direct transmission (expensive in terms of energy and fast) where the node that holds
the data transmits directly to the Sink. We assume that the energy spent at a sensor when transmitting data messages is proportional
to the square of the transmitting distance and only energy spent during transmissions is counted (for simplicity).

We assume a single, mobile charger (MC) that traverses the network and wirelessly charges sensor nodes when getting
appropriately close to them. We assume that $E_{\text{Total}}$ is the total available energy in the network (at the sensors and at the
charging is denoted as Mobile Charger may deliver to the network by recharging sensors. At time \( t \) the energy left to the Mobile Charger for sensor charging is denoted as \( E_{MC}(t) \) and the current residual energy of node \( v_i \) as \( E_i(t) \). 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. \( E_{sensor}^{max} = E_{sensor} \). In our model the charging is performed point-to-point, i.e. only one sensor may be charged at a time from the Mobile Charger by approaching it at a very close distance so that the charging process has maximum efficiency. The time that elapses while the Mobile Charger 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 proportional to the battery level of each sensor.

Regarding the three families of routing protocols we use to investigate the impact of our methods, we refer to [11] for clustering, [9, 5] for greedy, single path routing and [13, 6] for energy balanced data propagation.

4. NODE CRITICALITY: A NEW NETWORK ATTRIBUTE

In order to develop efficient protocols for the Mobile Charger and address the corresponding trade-offs, we introduce a new attribute that captures a node’s “importance” in the network, under any given routing protocol. This new attribute relies on two factors, a) the traffic served by the node and b) the energy consumed by the node.

The need for combining these two factors emerges from the fact that the traffic served by a node captures different aspects than its energy consumption rate. A node may consume a large amount of energy either because it serves a high network flow, or because its transmissions have high cost (e.g. long range transmissions) (or both). The purpose of the attribute is to indirectly prioritize the nodes according to their flow rate and energy consumption; a node serving high traffic and/or having low residual energy should be recharged at higher energy level.

We denote as \( c_i(t) \) the criticality of node \( v_i \) at time \( t \), with

\[
c_i(t) = f_i(t) \cdot \rho_i(t).
\]

Given the time \( t_{MC} \) when the last charging of the node occurred,

\[
f_i(t) = 1 - \frac{\text{generation rate of node } v_i}{\text{traffic rate of } v_i \text{ since } t_{MC}} = 1 - \frac{\lambda_i}{\lambda_i + \frac{m_i(t)}{t - t_{MC}}}
\]

is the normalized traffic flow served by node \( v_i \), where \( m_i(t) \) is amount of traffic (number of messages) that \( v_i \) has processed (received and forwarded) towards the Sink by time \( t \) since time \( t_{MC} \), and

\[
\rho_i(t) = \frac{\text{energy consumed since last charging}}{\text{max node energy since } t_{MC}} = \frac{E_i(t_{MC}) - E_i(t)}{E_i(t_{MC})} = 1 - \frac{E_i(t)}{E_i(t_{MC})}
\]

is the normalized energy consumption by time \( t \), since the last charging. The criticality is thus a number in [0, 1] which captures the importance of a given node by taking into account its flow rate, its energy consumption, its possible special role in the network and its influence to the routing protocol; nodes serving high traffic (large \( m_i(t) \)) and/or having consumed a lot of energy (low \( E_i(t) \)) have high criticality \( c_i(t) \) at time \( t \) and are “prioritized” by the Mobile Charger.

5. MOBILE CHARGER CONFIGURATION

5.1 Charging extent

A straightforward charging policy (such as in [4]) follows the rationale that the amount of energy the Mobile Charger delivers to node \( v_i \) is proportional to the residual charging energy of the Mobile Charger. This approach takes into account the energy dissipation rate of the Mobile Charger but neglects the energy evolution in the network and the fact that some nodes are more important than others, due to their location, generation rate, special role in the network, etc. In other words, by adopting that charging policy, the energy of every node is replenished in the same way, with the absence of any energy levels based on node diversity.

In this work we use the criticality attribute as a measure of the level that a node \( v_i \) should be charged.

**Definition 1.** Let \( e_{MC}(t) = \frac{E_{MC}(t)}{E_{MC}(t_{init})} \) denote the ratio of the Mobile Charger’s residual energy at time \( t \) over the total amount of energy that the Mobile Charger was provided at the network initialization at time \( t_{init} \).

**Definition 2.** Let \( \Delta E_i(t) = E_i(t_{MC}) - E_i(t) \) denote the amount of energy that node \( v_i \) has consumed by time \( t \), since the last charging (occurred at time \( t_{MC} \)).

Node \( v_i \) will be charged until its energy becomes

\[
E_i(t + t_c) = E_i(t) + c_i(t) \cdot e_{MC}(t) \cdot \Delta E_i(t)
\]
where \( t_c \) is the time needed (considered negligible) for the charging of \( v_i \) and

\[
\frac{c_i(t) \cdot e_{MC}(t) \cdot \Delta e_i(t)}{E_{MC}(t)} = \left( 1 - \frac{\lambda_i}{\lambda_i + \frac{\mu_i(t)}{E_{MC}(t)}} \right) \cdot \frac{E_{MC}(t)}{E_{MC}(t_{\text{init}})} \cdot \frac{(E_i(t_{\text{MC}}) - E_i(t))^2}{E_i(t_{\text{MC}})}
\]

We notice that \( v_i \)'s charging is not a fraction of its maximum or initial energy but a fraction of the consumed energy since the last charging. In other words, a sensor that consumed a lot of energy since its last charging will be charged at a higher level; this level is also higher when the sensor has high criticality and when the energy left at the charger is high.

## 5.2 New protocols

We introduce three protocols for the trajectory followed by the mobile charger. These protocols assume different levels of network knowledge (from global to limited and reactive). Actually, the global knowledge method can not be considered realistic in large scale networks and rather serves as an upper bound on performance which the other methods are compared to.

### 5.2.1 Global Knowledge Protocol GKP

The global-knowledge charger we suggest is an on-line method that uses criticality as a ranking function. In each round the charger moves to the sensor that minimizes the product of the negation of each node’s criticality times its distance from the current position of the Mobile Charger. More specifically, in each moving step the global charger minimizes the product

\[
\min_i \left\{ \left( 2 - c_i(t) \right) \cdot \left( 1 + \frac{\text{dist}_i}{2D} \right) \right\}
\]

where \( \text{dist}_i \) is the distance of each sensor from the Mobile Charger and \( D \) is the network radius, with the minimum taken over all sensors in the network (or at least a large part of it). In other words, this protocol prioritizes nodes with high criticality and small distance to the Mobile Charger. Since this protocol requires a global knowledge of the state of the network, it is expected to outperform all other strategies that use only local or limited network information, thus somehow representing an on-line centralized performance upper bound. However, it would not be suitable for large scale networks as it introduces great communication overhead (i.e. every mote has to propagate its criticality to the Mobile Charger) and does not scale well with network size.

### 5.2.2 Limited Reporting Protocol LRP

The Sink is informed about the status of some representative nodes scattered throughout the network and is able to provide the Mobile Charger with some guidance. In other words, this protocol distributively and efficiently “simulates” the global knowledge protocol. We assume that the Sink can transmit to the Mobile Charger wherever in the network the latter might be. The protocol follows a limited reporting strategy, since it exploits information from the whole network area but from a limited number of nodes. The nodes of each Slice periodically run a small computation overhead algorithm in order to elect some special nodes, the reporters of the Slice; in particular, each node becomes a reporter independently with some appropriate probability (thus, the number of reporters is binomially distributed). The reporters act as the representatives of their Slice and their task is the briefing of the Sink about their criticality.

The percentage of the nodes that will act as reporters brings off a trade-off between the representation granularity of the network and the communication overhead on each message propagated in the network. If we set a large percentage of reporters, the Sink will have a more detailed knowledge of each Slice’s overall criticality but the message overhead will highly increase, since each message should carry the Slice reporter’s current criticality. On the contrary, if we set a small percentage of reporters, the overhead will be tolerable, but the representation of a Slice will be less detailed.

In order to maintain a small set of reporters for each Slice (for communication overhead purposes) we propose that Slice \( i \) which contains \( n_i \) nodes elects

\[
k_i = \frac{n_i}{n} \cdot \kappa_{\text{total}}
\]

reporters, with the global number of reporters being

\[
\kappa_{\text{total}} = h \frac{D}{r} \log n, \text{ where } h = 1 - \frac{a}{b}
\]

is a network density heterogeneity parameter. Clearly, a highly heterogeneous deployment (large \( b \) compared to \( a \)) will necessitate a higher number \( \kappa_{\text{total}} \) of reporters. Also, \( \kappa_{\text{total}} \) must be large in large networks with many sensors. Each node periodically with probability \( p_i \) becomes a reporter. In order to have an expected number of \( k_i \) reporters in Slice \( i \) we need:

\[
k_i = n_i \cdot p_i \Rightarrow p_i = \frac{n_i}{n} \cdot \kappa_{\text{total}} \Rightarrow p_i = \frac{\kappa_{\text{total}}}{n}
\]

### 5.2.3 Reactive Trajectory Protocol RTP

In this protocol, a node \( v_i \) is propagating an alert message to its neighbours each time its energy drops below a set of some crucial limits. The messages are propagated for some hops and are stored at every node passed, in order for a tree structure rooted at \( v_i \) to be formed that can be detected by the Mobile Charger when passing through some tree node. Every node can
We use criticality as a measure of the gradual expansion of the tree, since its value depicts both the importance of the node in the network and its energy consumption rate. We propose a strategy of message propagations that aims at covering a relatively large area of the network, while keeping energy consumption due to communication overhead low.

More specifically, each node $v_i$ can alter among $\left\lceil \log \left( \frac{n D}{r} \right) \right\rceil$ alert levels which determine the characteristics of the $v_i$’s rooted tree. We denote as $al_i$ the current alert level of node $v_i$. The tree rooted at $v_i$ is formed in a way that the degree $= al_i - 1$ and the depth $= 2^{al_i - 1} - 1$. The duration of each successive alert level is increased by a constant ratio from the previous level:

$$al_i = \left\{ \begin{array}{ll} 1 & \text{if } 0 \leq c_i(t) < 0.5 \\
 2 & \text{if } 0.5 \leq c_i(t) < 0.75 \\
 \vdots & \vdots \\
 \left\lceil \log \left( \frac{n D}{r} \right) \right\rceil & \text{if } 1 - \frac{1}{2^{\left\lceil \log \left( \frac{n D}{r} \right) \right\rceil}} \leq c_i(t) < 1 \\
 \end{array} \right.$$  

$$= \left\{ \mu \mid \mu \in \left[ 1, 2, ..., \left\lceil \log \left( \frac{n D}{r} \right) \right\rceil \right] \right\}$$

with $1 - \frac{1}{2^{\mu - 1}} \leq c_i(t) < 1 - \frac{1}{2^{\mu}}$

where $1 - \frac{1}{2^{\mu - 1}} = \sum_{j=1}^{\mu-1} \frac{1}{2^j} \quad 1 - \frac{1}{2^{\mu}} = \sum_{j=1}^{\mu} \frac{1}{2^j}$.

The Mobile Charger alters its state between a patrol mode and a charging mode. When in patrol mode, it follows a spiral patrol trajectory centered at the Sink and does not charge any nodes until notified that the area traversed is low on energy. When so notified by a node in such an area, it pauses the patrol mode and enters the charging mode, in which it follows a different trajectory in order to accomplish the charging process in this area. If the Mobile Charger detects simultaneously different trees, then by a check on the depth of each structure it can decide which is the most critical. After the completion of the charging process the Mobile Charger resumes the patrol mode.

The reactive traversal can be an efficient, adaptive solution for dynamic networks such as networks with varying event generation rate per Slice.

6. EXPERIMENTAL EVALUATION

We compare our protocols to two state of the art approaches, the limited knowledge protocol LKP presented in [4] and the GreedyPlus protocol presented in [17].

6.1 Experimental set-up

The simulation environment for conducting our experiments is Matlab 7.11.0. For statistical smoothness, we apply 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.

Before we deploy the nodes as described in Section 3 and in order to come up with a heterogeneous network topology that will be connected with high probability, we deploy a portion of the nodes (defined by the connectivity threshold discussed below) uniformly at random in order to establish connectivity. Since two nodes communicate with each other if their euclidean distance is at most $r$, the generated network topology by this first set of nodes is in fact an instance of the Random Geometric Graph model. In [10, 18] it is shown that the connectivity threshold for an instance of the RGG model is $r_c = \sqrt{\frac{\pi n}{2}}$. This is the connectivity threshold according to which the initial nodes are deployed.

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) **connected components over time** which indicates the number of strongly connected components of the network graph throughout the experiment, c) **network criticality map**, which is a spatial depiction of the whole network in terms of energy dissipation and flow traffic, after the generation of a number of events, d) **routing robustness** and **average routing robustness**, in terms of the nodes’ average alive neighbours during the progress of the experiment.
6.2 Protocol parameters

6.2.1 Percentage of $E_{\text{total}}$ available to the charger

This particular trade-off consists in how much energy (of the total available) should the MC be initially equipped with. On the one hand, more energy to the MC leads to better on-line management of energy in the network. However, since $E_{\text{total}} = E_{\text{sensors}} + E_{\text{MC} (t_{\text{init}})}$, more energy to the MC also means that the sensor motes will initially be only partially charged. Therefore, they may run out of energy before the MC charges them leading to possible network disconnection and low coverage of the network area.

To investigate this trade-off, we conducted a comparison among several percentages of initial energy given to the charger. More specifically, we investigate the cases of 20%, 30%, 50%, 70%, and 80% of the total energy to be given to the MC, both for the LRP and for RTP (Figs. 2a and 2b correspondingly). It is clear that providing the MC with more than 30% of the total energy is negatively affecting the life evolution of the network, in both protocol cases. On the other hand, a smaller percentage of energy at the charger (like 20%) leads to worse results, since the recharging potential is limited. We thus adopt a 30% percentage in the following.
6.2.2 $\kappa$total of the LRP

The total number of nodes that act as reporters is a fundamental parameter of the LRP. High numbers of reporters provide the MC with a detailed information about the current state of the Slices’ criticality but require more messages for the propagation of the reporters’ state, resulting in higher energy consumption throughout the network. On the other hand, whereas a small number of reporters decreases the number of message exchanges, poor detail of the Slice’s representation may disorientate the MC and guide it to Slices where the energy to be provided is not truly needed (in comparison to other Slices).

In order to figure out possible good values for $\kappa_{\text{total}}$ that maximize the LRP performance we carry out a comparison operating the protocol between several reporter numbers. Fig. 3a depicts the number of alive nodes of the network after 6000 events, for various percentages of reporters over the total number of nodes in the network. In the particular setting the formula for $\kappa_{\text{total}}$ yields $\kappa_{\text{total}} = 5\%$. Then we try to experimentally validate the suitability of this $\kappa_{\text{total}}$ choice. It is obvious that if the protocol defines the number of reporters to be less than 5% of the network nodes, the granularity of the Slice representation is poor, resulting in reduced network lifetime. Similarly, for numbers greater than 5% of the network nodes, the lifetime is also reduced, due to the higher message exchange overhead (over total traffic) in Fig 3b. Thus, we set the reporters to a 5% percentage.

6.3 Results in non-uniform deployments

We study the effect of our charger strategies, on the number of alive nodes over time, the energy/flow balance of the network, the routing robustness and the number of strongly connected components over time in non-uniform network deployments.

i) The overall death rate (in terms of alive nodes over time) of the network is vastly reduced, as shown in Fig. 4a. The performance of both the LRP and the RTP approaches the performance of the GKP, powerful charger. We note that our traversal strategies outperform both the LKP of [4], which seems to be less adaptive, when used in non-uniform deployments, and the GreedyPlus.

ii) Fig. 5 depicts the criticality map of the network over time, for each one of the chargers. More specifically, we present graphically the spatial evolution of energy dissipation combined with flow traffic information in the network after 4,000 event generations. Nodes with low criticality values are depicted with bright colours. In contrast, nodes with high criticality values are depicted with dark colours. The centralized global knowledge charger GKP, as expected, outperforms all other chargers and achieves a balanced overall network criticality while the local knowledge LKP of [4] creates a ring consisted of low criticality nodes, since the underlying routing protocol is the energy balance $E_i$, where nodes in the middle of the network radius suffer both from long-range transmissions and high flow rate from outer nodes. This ring is a cause of imbalance, in contrast to our proposed charger schemes in Figs. 5c, 5d, where the overall network criticality is more balanced.

iii) Routing robustness is critical for sensor networks, as information collected needs to be sent to remote control centers. Path breakage occurs frequently due to node mobility, node failure, or channel impairments, so the maintenance of a path from each node to a control center is challenging. A way of addressing the routing robustness of a sensor network is by considering for each node the number of its alive neighbors over time, which can be seen as an implicit measure of network connectivity. The average number of alive neighbors is depicted in Fig. 4b. Our LRP and our RTP achieve high robustness, outperforming the LKP and GreedyPlus and approaching the GKP performance.

iv) The number of strongly connected graph components is also an overall measure of connectivity quality in a sensor network. Disconnected components are unable to communicate with each other and sometimes even with the Sink, resulting in high data delivery failures. Maintaining a small number of connected components in the network, can also improve data delivery latency. High numbers of components may lead to isolation of critical nodes, thus loss of important information. Fig. 4c depicts the evolution of the number of network components throughout the experiments. As we noted earlier, the LKP of [4] has a high node death rate, a fact that results in early disconnections and sharp increase of connected components. Our LRP maintains a (single) strongly connected network. The performance of LKP and GreedyPlus is characterized by an increasing number of connected components.
Overall, our proposed protocols extend several network attributes, approach the performance of the global powerful knowledge protocol and significantly outperform the LKP which was designed with a focus on uniform deployments, and the GreedyPlus in which the MC requires frequent updating, hence increased energy consumption due to message transmissions throughout the whole network.

7. CONCLUSIONS

In this work we have studied the problem of efficient wireless energy recharging in Wireless Rechargeable Sensor Networks, in which a Mobile Charger traverses the network and wirelessly replenishes the energy of sensor nodes. We first identify and investigate some critical issues and trade-offs of the MC’s configuration, such as (a) the energy level each sensor should be recharged to (b) the best split of the total available energy between the charger and the sensors and (c) which trajectories are good for the MC to follow.

To capture the diverse dynamics in the network (for both the energy consumption and the traffic flow) we introduce the new network attribute of node criticality; nodes with high criticality are “prioritized” by the charger. This also gives rise to alternative traversal strategies for the charger; in particular, we suggest three new protocols assuming different levels of network knowledge: a centralized global knowledge method, a limited knowledge protocol that performs a distributed sampling of the network conditions and a reactive method based on the judicious propagation of alert levels in the network.

We note that, in contrast to most current approaches, our methods are distributed and adaptive, and use only limited network information; also, we do not couple recharging with routing, since our methods can be used together with any underlying routing protocol.

For future research, we plan to address the cases of multiple chargers and/or mobile sensor nodes. Also, compare the performance of potential new protocols to other centralized solutions for the charger’s configuration; this may include directly addressing the charger’s trajectory length and associated cost. Finally, we plan to also implement selected protocols in small/medium scale real experiments (e.g. with robotic elements and wireless recharge technology).

8. REFERENCES