Computer Networks 80 (2015) 89–108

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Distributed wireless power transfer in sensor networks with multiple Mobile Chargers ☆

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ARTICLE INFO

Article history:
Received 25 June 2014
Received in revised form 4 January 2015
Accepted 26 January 2015
Available online 4 February 2015

Keywords:
Sensor networks
Energy efficiency
Mobility
Distributed algorithms
Wireless power transfer
Wireless charging

ABSTRACT

We investigate the problem of efficient wireless power transfer in wireless sensor networks. In our approach, special mobile entities (called the Mobile Chargers) traverse the network and wirelessly replenish the energy of sensor nodes. In contrast to most current approaches, we envision methods that are distributed and use limited network information. We propose four new protocols for efficient charging, addressing key issues which we identify, most notably (i) what are good coordination procedures for the Mobile Chargers and (ii) what are good trajectories for the Mobile Chargers. Two of our protocols (DC, DCLK) perform distributed, limited network knowledge coordination and charging, while two others (CC, CCGK) perform centralized, global network knowledge coordination and charging. As detailed simulations demonstrate, one of our distributed protocols outperforms a known state of the art method, while its performance gets quite close to the performance of the powerful centralized global knowledge method.

1. Introduction and contribution

As wireless and portable mobile devices become pervasive, charging batteries for these devices has become a critical problem. Current battery charging technologies are dominated by wired technology, which requires a wired power plug to be connected to an electrical wall outlet. Existing wireless sensor networks are constrained by limited battery energy at a sensor node and can only remain operational for a limited amount of time. To prolong network lifetime, there have been many research efforts at all layers, from topology control, physical, MAC, and all the way up to the application layer. Despite these intensive efforts, the energy/lifetime of a wireless sensor network remains a performance bottleneck and is perhaps the key factor that hinders its wide-scale deployment.

Efficient wireless power transfer has been achieved through academic and industrial research by using technologies such as inductive coupling, electromagnetic radiation and magnetic resonant coupling [2]. Together with the research efforts on wireless power transfer, several international organizations, such as the *Wireless Power Consortium* (WPC, [3]) and the *Alliance for Wireless Power* (A4WP, [4]), aim at maximizing the use of these technologies. WPC, an open-membership cooperation of Asian, European, and American companies in diverse industries, including electronics manufacturers and original equipment manufacturers, is working towards the global standardization of wireless charging technology. A4WP, an independently operated organization composed of global wireless power and technology industry leaders, focuses on a new wireless power transfer technology that provides spatial freedom for charging of electrical devices

☆ A preliminary version of this paper appeared in [1].

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http://dx.doi.org/10.1016/j.comnet.2015.01.018
1389-1286/

in cars, on table tops and for multiple devices simultaneously. Commercial products utilizing wireless power transfer are already available on the market such as those in [5,6].

These technologies and organizations lead the way towards *a new paradigm* for wireless sensor networks; the Wireless Rechargeable Sensor Networks. Such networks 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 power transfer technologies are capable of charging 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 Wireless Rechargeable Sensor Networks can be performed passively from the perspective of sensor nodes and without the computational and communicational overhead introduced by complex energy management algorithms. Finally, Wireless Rechargeable Sensor Networks allow energy management to be studied and designed independently of the underlying routing protocol used for data propagation.

1.1. The problem

Let a Wireless Rechargeable Sensor Network comprised of *stationary* sensor nodes and *special mobile entities called the Mobile Chargers*. The Mobile Chargers have significant (yet finite) energy supplies, that are much larger than those of each sensor node, and are thus capable of charging the sensors in the network. We aim at designing and evaluating efficient protocols for the chargers' coordination and charging procedures in order to improve energy efficiency, prolong the lifetime of the network and also improve important network properties (such as the quality of network coverage and the robustness of data propagation).

In particular, we view the chargers' coordination as a distinct procedure, on top of the sensor nodes charging mechanism. Unlike other methods in the state of the art, we do not couple the chargers' coordination neither with the sensor nodes charging process nor with the underlying network energy information data propagation; actually, we wish to perform efficient coordinated wireless power transfer in a way which is agnostic of the network energy status, via adaptive techniques that *implicitly (based on the chargers' status) adapt to the network's energy evolution*.

Remark. We note that, although the wireless charging 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 charging necessitate the distinct investigation of special protocol design parameters.

Finally, we note that Mobile Charger optimization problems are (inherently) computationally hard e.g. in [7] we have formulated the wireless charging problem as the Charger Dispatch Decision Problem – CDDP, and showed that it is $\mathcal{NP}$-complete (via reduction from the Geometric Traveling Salesman Problem, G-TSP; see e.g. [8], p. 212).

1.2. Our contribution

While interesting research has been lately contributed to the wireless charging problem and particularly to the scheduling of a single 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 use (at most) local network information*. Also, unlike other multiple chargers state of the art approaches that opt for integration and coupling of the coordination and charging procedures, our methods distinguish the network operations in three separate levels: *the coordination procedure*, *the charging process* and *the routing mechanism*. We identify the necessity of this demarcation as an efficient approach to the design of more detailed and better fine-tuned charger protocols.

In particular, we propose and evaluate selected *alternative strategies for efficient charging* in stationary Wireless Rechargeable Sensor Networks via multiple Mobile Chargers. Our design provides concrete, different solutions to some *key issues (and the associated trade-offs)* of wireless charging which we identify, most notably

i. assuming a number of Mobile Chargers in the network, *in what way should they coordinate*,
ii. given that the Mobile Chargers have coordinated, *what are good trajectories for the chargers to follow*.

More specifically, (a) we first distinguish two fundamental network operations, *charger coordination* and *node charging*, (b) taking into account the capability of *both centralized and distributed processing* we design selected charger coordination alternatives that efficiently split the network area and assign subregions to the Mobile Chargers and (c) assuming *different levels of network knowledge* we design different charging traversal strategies employed by the chargers in their region of interest.

We provide four new coordination and charging protocols based on their network knowledge (from global to local and to absence of knowledge) and their processing ability (from distributed to centralized). The CC and DC protocols perform centralized and distributed coordination respectively with no network knowledge, the DCLK protocol performs distributed coordination with local knowledge and the CCGK protocol performs centralized coordination with global knowledge. Actually, we view the centralized coordination with global knowledge CCGK protocol as a kind of performance upper bound to which the two distributed, partial knowledge protocols are compared with.

2. Related work and comparison

Recently there has been much research effort in the field of Wireless Rechargeable Sensor Networks using *a single Mobile Charger*. In [9], 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 and carry out experiments on the prototype to evaluate its performance in small-scale networks of up to ten nodes. In [10], the authors introduce the necessary and sufficient conditions such that the wireless charging problem can be studied as an optimization problem, with the objective of maximizing the ratio of the Mobile Charger's vacation time over the network traveling time. In [7,11], the authors study the impact of the charging process to the network lifetime for selected routing alternatives by proposing protocols that locally adapt the trajectory of the Mobile Charger to several network properties. In [12], the authors co-locate the mobile base station on the Mobile Charger and minimize the energy consumption of the entire system while ensuring none of the sensor nodes runs out of energy. All above works are advancing the topic, but do not address the capability of a network to support more than one Mobile Chargers. Such a capability could be vital for the lifetime prolongation of large networks that consist of several thousand nodes (and thus their maintenance is not feasible using one single charger).

On the other hand, in the field of Wireless Rechargeable Sensor Networks using *multiple Mobile Chargers* there has been limited research effort. In [13] the authors introduce collaborative mobile charging, where Mobile Chargers are allowed to charge each other (in our case, the model is different since we do not address chargers charging each other). They investigate the problem of scheduling multiple Mobile Chargers which collaboratively charge nodes over one dimensional wireless sensor networks, to maximize the ratio of the amount of payload energy to overhead energy, such that no sensor runs out of energy but in contrast to our work, they restrict their algorithms only in line-graphs. In [14], the authors consider the minimum number of Mobile Chargers problem in a general 2-D network so as to keep the network running forever. They partition the sensor nodes in subsets such that any Mobile Charger, at each own period, visits its corresponding sensors, charges them and then gets back to the base station to charge it's own battery. In [15], the authors use Mobile Chargers for energy replenishment of robots in robotic sensor networks. Observing the discrepancy between the charging latency of robots and charger travel distance, they propose a tree-based charging schedule for the charger, which minimizes its travel distance without causing the robot energy depletion. They evaluate its performance and show its closeness to the optimal solutions. In [16,17] the authors nicely leverage concepts and mechanisms from NDN (Named Data Networking) to design energy monitoring protocols that deliver energy status information to Mobile Chargers in an efficient manner. They interestingly study how to minimize the total traveling cost of multiple chargers while ensuring no node failure and derive theoretical results on the minimum number of mobile vehicles required for perpetual network operations. They present a sophisticated heuristic algorithm and conduct simulations to demonstrate the effectiveness and efficiency of the proposed design but in contrast to our approach, they propose only one charging scheme of simple charger coordination and node selection procedures i.e., they do not really elaborate on the coordination aspect. Also, unlike our work, in both above approaches, the chargers' coordination is performed centrally and not distributively. That may not be considered realistic in large scale networks as it introduces high communication overhead (i.e., every charger has to propagate its status over large distances) and does not scale well with network size. We have chosen to compare with the protocol presented in [16], for comparison fairness in terms of similar model assumptions.

3. The model

Our model features three types of devices: stationary sensors, Mobile Chargers and one stationary Sink as illustrated in Fig. 1. We assume that there are N sensors of wireless communication range r distributed at random in a circular area (we investigate two cases, uniform distributions and non-uniform distribution) $\mathcal{A}$ of radius R and K Mobile Chargers initially deployed at the center of their area, i.e. at coordinates

$$(x,y) = \left(\frac{R}{2}\cos\left(\frac{\pi}{K}(2j-1)\right), \frac{R}{2}\sin\left(\frac{\pi}{K}(2j-1)\right)\right)$$

of the circular area (dots in Fig. 2a), where $j = 1, 2, \ldots, K$. Since the protocols run for a long time and the initialization happens only once, the initial position of the chargers is not a crucial parameter, i.e. it could be the center of the circular area as well. The Sink lies at the center of the circular area. In our model we assume that the Mobile Chargers do not perform any data gathering process.

We denote by E_{total} the total available energy in the network. Initially,

$$E_{total} = E_{sensors} + E_{MC}(t_{init}),$$

where $E_{sensors}$ is the amount of energy shared among the sensor nodes and $E_{MC}(t_{init})$ is the total amount of energy that the Mobile Chargers have and may deliver to the network by charging sensor nodes. The maximum amount of energy that a single node and a single charger may store is E_{sensor}^{max} and E_{MC}^{max} respectively. Energy is split among the sensor nodes and the chargers as follows:

$$E_{sensor}^{max} = \frac{E_{sensors}}{N} \quad \text{and} \quad E_{MC}^{max} = \frac{E_{MC}(t_{init})}{K}.$$

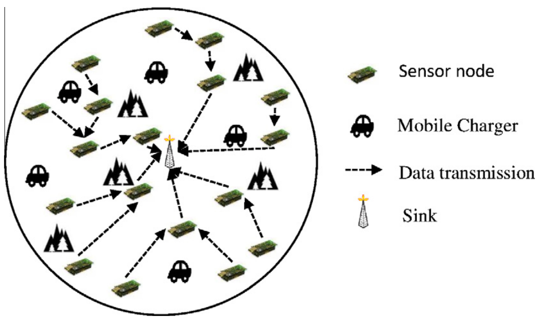
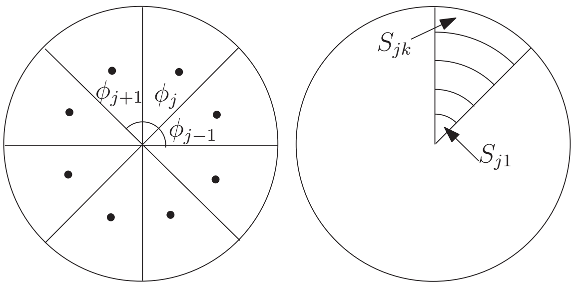


Fig. 1. The network.



(a) Slices. (b) Sectors.

Fig. 2. Network division in Slices and Sectors (in DCLK).

In our model the charging is performed point-to-point, i.e., only one sensor may be charged at a time from a 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, like gas or electric power needed for charger movement. We assume that the charging time is equal for every sensor and independent of its battery status.

We assume a quite heterogeneous data generation model. Each sensor node chooses independently a relative data generation rate $\lambda_i \in [a, b]$ (where a, b constant values) according to the uniform distribution $\mathcal{U}[a, b]$. Values of λ_i close to a imply low data generation rate and values close to b imply high data generation rate. The routing protocol operates at the network layer, so we are assuming appropriate underlying data-link, MAC and physical layers. We refer to [18,19] for greedy, single path, underlying routing protocol.

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. As usual, the power needed to transmit a message at distance d is roughly d^c where $2 \leqslant c \leqslant 6$ is a constant; for simplicity we take $c = 2$.

Placement heterogeneity. We virtually Slice the network into $2R/r$ co-centric rings and $2\pi/\phi$ Slices. A Sector is defined as the intersection of a specific ring and Slice. For example, in Fig. 2a the network is divided into 8 Slices ($\phi = \pi/4$) and Fig. 2b illustrates the separation of a Slice into Sectors. In this figure, the Slice contains 5 Sectors, resulting in a total of 40 Sectors in the network. 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 as shown in Fig. 2b. 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 $\mathcal{U}[1, b]$. We will refer to the number δ_{ij} as the relative density of Sector S_{ij}. Values of δ_{ij} close to 1 imply low relative density and values close to b imply high relative density. By combining the knowledge about the total number of sensors in the network N, together with the relative density δ_{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

$$\frac{A_{i'j'}}{A_{ij}} \frac{\delta_{ij}}{\delta_{i'j'}}.$$

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. An example of non-uniform network deployment is shown in Fig. 13.

4. Demarcated protocol phases

In contrast to other known works, we split the charging process in two phases, the *coordination phase* and the *charging phase*. The demarcation of the chargers' operations in phases allows us to focus on each aspect separately and fine-tune the protocols more precisely.

4.1. Coordination phase

A Mobile Charger's energy is consumed as it replenishes the energy of the sensor nodes. The energy dissipation rate among Mobile Chargers may not be the same, since the non-uniform generation rate of events can eventually lead to stressed network regions and burden some chargers more than others. For this reason, the Mobile Chargers periodically communicate with each other and deal out their charging regions fairly (for example, a weaker Mobile Charger in terms of energy should be assigned to a smaller network region). This coordination process can be achieved either in a *centralized* or a *distributed* manner.

In the centralized case the coordination is performed using information from all K chargers. We assume that the calculations for this type of coordination are performed by a computationally powerful network entity, e.g. the Sink. Centralized coordination is generally more powerful than distributed coordination, thus centralized protocols' performance serves as an upper bound on performance which the distributed methods are compared to. In the distributed case, a charger is informed about the status of its neighboring chargers resulting in a more secluded coordination between close chargers.

4.2. Charging phase

Charging traversal alternatives have been widely studied in the case of a single Mobile Charger. In our approach, where the charger's operation is dual, we give emphasis to the *amount of knowledge* possessed by protocols in terms of locality. In order to appropriately design the charging phase of a protocol we distinguish the protocol's knowledge amount among *global knowledge*, *local knowledge*, *no knowledge* and *reactive knowledge*.

In the case of global knowledge, we suppose that a Mobile Charger can use information from all over the network (sensor nodes and other chargers). Such an amount of knowledge makes the Mobile Charger powerful but it may be unrealistic in large networks and do not scale well with network size. On the contrary, in the more realistic case of local knowledge, a Mobile Charger is allowed to use limited information derived from its neighborhood. We consider a charger to be ‘‘blind’’ when it has no knowledge on the network and thus cannot use a sophisticated charging method. The reactive knowledge is a special case of real time acquisition of global knowledge, by receiving messages from a subset of nodes while the information refers to all set of nodes. Note that the amount of knowledge can also be diversified in the coordination phase, among the Mobile Chargers.

5. The protocols

We present four new Mobile Chargers protocols and another, state the art protocol [16] that we compare with. Protocol details are presented in short in Table 1.

5.1. Distributed Coordination protocol DC

5.1.1. Coordination phase

The DC protocol performs distributed coordination among chargers and assumes no network knowledge. We split the network area in Slices as shown in Fig. 2a and assign one Slice per charger. Angle ϕ_j corresponds to the central angle of jth charger's Slice. The chargers distributively define their Slice limits (i.e., the two radii that define the Slice), according to the size of the region each one can handle, w.r.t. their energy status. Each charger can shift their right and left Slice limits resulting in either a widening or a shrinkage of the region of interest. This task is performed distributively and each region limit movement is determined through a cooperation of each pair of adjacent Mobile Chargers. A limit movement of j's region is expressed as a change of ϕ_j. Fig. 3 depicts the coordination procedure. More specifically, Fig. 3a depicts the region of the Mobile Charger j before the coordination phase. Fig. 3b depicts the angle's change after the communication with the left and right neighbors ($\Delta\phi_j^l$ and $\Delta\phi_j^r$ respectively) during the coordination phase. Fig. 3c depicts the new angle i.e. the new region of the charger after the coordination phase.

Table 1
Protocol phase details.

Protocol	Coordination	Charging
DC	Distributed	No knowledge
CC	Centralized	No knowledge
DCLK	Distributed	Local knowledge
CCRK [16]	Centralized	Reactive knowledge
CCGK	Centralized	Global knowledge

The coordination process uses two critical charger parameters for definition of the region of interest, the charger's current energy level E_j and the charger's energy consumption rate since the last coordination ρ_j. The change $\Delta\phi_j^l$ of ϕ_j for the left Slice limit is defined by the following computation:

if $\min\{E_j, E_{j-1}\} = E_j$ **then**
$\quad \Delta\phi_j^l = -\phi_j \cdot \frac{|\rho_{j-1}-\rho_j|}{\max\{\rho_{j-1},\rho_j\}}$
else
$\quad \Delta\phi_j^l = \phi_{j-1} \cdot \frac{|\rho_{j-1}-\rho_j|}{\max\{\rho_{j-1},\rho_j\}}$
end if

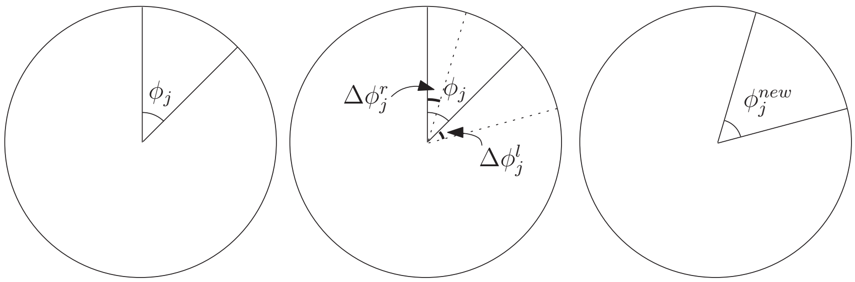
Similarly, the change $\Delta\phi_j^r$ of ϕ_j for the right Slice limit:

if $\min\{E_j, E_{j+1}\} = E_j$ **then**
$\quad \Delta\phi_j^r = -\phi_j \cdot \frac{|\rho_j-\rho_{j+1}|}{\max\{\rho_j,\rho_{j+1}\}}$
else
$\quad \Delta\phi_j^r = \phi_{j+1} \cdot \frac{|\rho_j-\rho_{j+1}|}{\max\{\rho_j,\rho_{j+1}\}}$
end if

The new angle (denoted by ϕ_j') is computed as $\phi_j' = \phi_j + \Delta\phi_j^l + \Delta\phi_j^r$. Note that, between two adjacent chargers j_1 and j_2, the change of their common Slice limit (i.e., the common radii) is $\Delta\phi_{j_1}^r = -\Delta\phi_{j_2}^l$ so that the charger with the lower energy level provides its neighbor with a portion of its region of interest. Also, it is their energy level that determines which charger should reduce its region of interest and the energy consumption rate that determines the size of the reduced area. The size of the angle change is not computed by considering the energy levels of the two chargers because energy consumption rate shows how quickly will this energy level be reduced. For example, if ρ_j is high then j's Slice is critical, causing a rapid reduction of E_j, independently of its current level. The above angle computations are performed simultaneously by all chargers.

5.1.2. Charging phase

During this phase, charger j traverses the network region it is assigned to (Slice defined by angle ϕ_j) and charges the corresponding sensor nodes. The CC protocol assumes no knowledge on the network. For this reason the path followed by the Mobile Charger is restricted to several naive alternatives (some presented in [7]). In our approach we use a ‘‘blind’’ scanning of the region where the Mobile Charger starts form the Sink and traverses an exhaustive path until it reaches the boundaries of the network area. The advantage of this movement is that due to its space filling attributes, the Mobile Charger covers the whole Slice and almost every node is charged, until the energy of the Mobile Charger is totally depleted. On the other hand, due to lack of knowledge, this movement is not adaptive, i.e., it does not take into account differences of the energy depletion rates of the network area caused by the underlying message propagation.



(a) Before the coordination. (b) During the coordination. (c) After the coordination.

Fig. 3. Distributed coordination.

5.2. Centralized Coordination protocol CC

The CC protocol performs centralized coordination among the chargers and assumes no knowledge on the network. In particular, the coordination process is able to use information from all Mobile Chargers (energy status, position, etc.), but is agnostic of the underlying network and sensor nodes attributes (energy status, position, etc.). This approach virtually partitions the network elements in two completely separate levels, the Mobile Chargers level and the sensor nodes level.

5.2.1. Coordination phase

Each Mobile Charger is assigned to a network region. Since the initial charger deployment coordinates are

$$(x, y) = \left(\frac{R}{2}\cos\left(\frac{\pi}{K}(2j-1)\right), \frac{R}{2}\sin\left(\frac{\pi}{K}(2j-1)\right)\right),$$

where $j = 1, 2, \ldots, K$, we can split the network area in Slices, as shown in Fig. 2a (example for $K = 8$ chargers), with one charger assigned to each Slice. When the coordination process is initialized, the region of each charger is computed. Each charger should be assigned to a region of size analogous to its current energy level, so that the energy dissipation among the chargers is balanced. In order to compute the size of the region of charger j, it suffices to compute the central angle ϕ_j corresponding to the charger's Slice. In particular

$$\phi_j = 2\pi \cdot \frac{E_j}{\sum_{j=1}^{K} E_j}, \quad \text{where } \sum_{j=1}^{K} \phi_j = 2\pi.$$

5.2.2. Charging phase

Since this protocol operates under the no knowledge assumption, the charging phase follows the same pattern with the DC protocol (Slice scanning).

5.3. Distributed Coordination Local Knowledge protocol DCLK

5.3.1. Coordination phase

The coordination phase follows the same pattern with the coordination phase of DC protocol (distributed ϕ_j angle computation).

5.3.2. Charging phase

The DCLK protocol operates with local knowledge assumption. The Slice corresponding to charger j is divided into k Sectors S_{jk} of the same width as shown in Fig. 2b. Charger j prioritizes its Sectors w.r.t. high number of sensor nodes with low level of residual energy.

Definition 1. E_{jk}^{min} is the lowest nodal residual energy level in the Sector S_{jk}.

Definition 2. $E_{jk}^{min+\Delta}$ is an energy level close to E_{jk}^{min}:

$$E_{jk}^{min+\Delta} = E_{jk}^{min} + \delta \cdot \frac{E_{sensor}^{max}}{E_{jk}^{min}}, \quad \delta \in (0, 1).$$

Definition 3. $N(S_{jk})$ is the number of nodes in Sector S_{jk} with residual energy between E_{jk}^{min} and $E_{min+\Delta}^{jk}$:

$$N(S_{jk}) = \sum_{e=E_{jk}^{min}}^{E_{jk}^{min+\Delta}} N(e),$$

where $N(e)$ is the number of nodes with energy level e.

Charger j charges Sector S_{jk} which maximizes the product

$$\max_{S_{jk}} \left\{ N(S_{jk}) \cdot (E_{sensor}^{max} - E_{jk}^{min}) \right\}.$$

The intuition behind this charging process is the grouping of nodes in each Slice and the selection of a critical group. A critical group is a Sector containing a large number of sensor nodes that require more energy than other nodes throughout the network.

5.4. Centralized Coordination Reactive Knowledge protocol CCRK *[16]*

The CCRK protocol acquires global knowledge in exchange for some in-network message aggregation. The Mobile Chargers obtain the most up-to-date energy information from sensor nodes and make decisions in real time. The energy information is aggregated by several special nodes in the network that act as representatives of partitioned network regions. We denote by S the number of the representative nodes.

5.4.1. Coordination phase

Mobile Chargers communicate with each other to know their positions. To avoid conflicts where multiple Mobile Chargers choose the same node for charge, the Sink stores and updates the availability of each node. The procedure is similar to that for shared memory access in operating systems, e.g. see [20], p. 125. The Sink maintains a 0–1 valued node list. Once a sensor node is chosen, its value is set to 1 (locked). Otherwise, it is 0. The value should be changed back from 1 to 0 when a Mobile Charger finishes charging that node. A Mobile Charger can simply communicate with the Sink, exclude nodes already selected by other Mobile Chargers, and notify the Sink of the status of nodes it chooses.

5.4.2. Charging phase

Two important metrics impact the charging order between node i and node i': the traveling time between node i to node i', and their residual lifetime L_i and $L_{i'}$. If node i' has a small $L_{i'}$ such that it would be dead if a Mobile Charger charges node i first, node i' should be visited first. In this protocol we use a weighted sum of traveling time from current node i to next node i' and the residual lifetime of node i',

$$w_{ii'} = \beta \cdot t_{ii'} + (1-\beta) \cdot L_{i'}.$$

$w_{ii'}$ is used to decide which node i' to charge next. A sensor node with a smaller weighted value should be visited at a higher priority. When $\beta = 1$, the algorithm reduces to nearest node selection that the Mobile Chargers always charge the closest node first regardless of battery deadlines; when $\beta = 0$, it picks the node with the earliest battery deadline first regardless of the traveling distance.

5.5. Centralized Coordination Global Knowledge protocol CCGK

The CCGK protocol, similarly to the CC protocol, performs centralized coordination. However, the assumption of global knowledge on the network further extends the Mobile Chargers' abilities. For this reason, it is expected to outperform all other strategies that use only local information, thus somehow representing a performance bound. The global knowledge assumption would be unrealistic for real large-scale networks, as it introduces large communication overhead (i.e., nodes and chargers have to propagate their status over large distances).

5.5.1. Coordination phase

Instead of using the same coordination process with the CC protocol, we integrate the global knowledge assumption in the coordination phase. As a result, the network is not partitioned in two separate levels (Mobile Chargers, sensor nodes) and the Mobile Chargers are allowed to use network information during this phase. Each Mobile Charger is assigned to a network region. The region of interest of charger j is a cluster of nodes. Node i belongs to the cluster of charger

$$j' = \arg\min_{j} \left\{ \left(1 + \frac{dist_{ij}}{2R}\right) \cdot \left(2 - \frac{E_j}{E_{MC}^{max}}\right) \right\},$$

where $dist_{ij}$ is the distance between node i and charger j and E_j the residual energy of charger j ($E_j > 0$). In other words, a node selects a charger which is close and has high amount of energy. If a charger's energy level is low, it may not be able to charge the node. Also, if the distance between the node and the charger is long, then the charger will waste a lot of energy for movement. Moreover, because of long distance, the traveling time is long too and thus, the node may die before the chargers arrives to its position.

The two factors of the product are normalized. That is to avoid elimination of the product from one possible zero factor, which may results in prioritizing the wrong charger. For example, for a node i if there is a charger j that has no energy then the factor $\frac{E_j}{E_{MC}^{max}}$ would be zero and the node would choose to belong to its cluster (since is chooses the charger with min product). In contrast, when the factor is of the normalized form $2 - \frac{E_j}{E_{MC}^{max}}$, then the value of the factor would be 2 (maximized) and thus the node would avoid this charger. For the distance factor the normalization is used in order to avoid the product to be eliminated as well. Thus, between two chargers that are close to the node, the latter should choose the charger with higher battery supplies.

Note that the centralized computation of the charger region in the CCGK protocol is more powerful compared to other methods, since it uses information about the distance among every charger with every node.

5.5.2. Charging phase

The global knowledge charging phase we suggest uses energy and distance in a ranking function. In each round the charger moves to the sensor in the corresponding cluster, that minimizes the product of each node's energy times its distance from the current position of the Mobile Charger. More specifically, in each moving step the charger j charges node

$$i' = \arg\min_{i \in C_j} \left\{ \left(1 + \frac{dist_{ij}}{2R}\right) \cdot \left(1 + \frac{E_i}{E_{sensor}^{max}}\right) \right\},$$

where E_i is the residual energy of sensor node i. In other words, this protocol prioritizes nodes with low energy and small distance to the Mobile Charger. Both of the two factors have the same weight in the product, i.e. there is no any dominant factor. The charger computes the product for each node (in its cluster) and selects to charge the one which minimizes the product.

6. Cost analysis

There are three kind of costs that are responsible for energy dissipation of the Mobile Chargers.

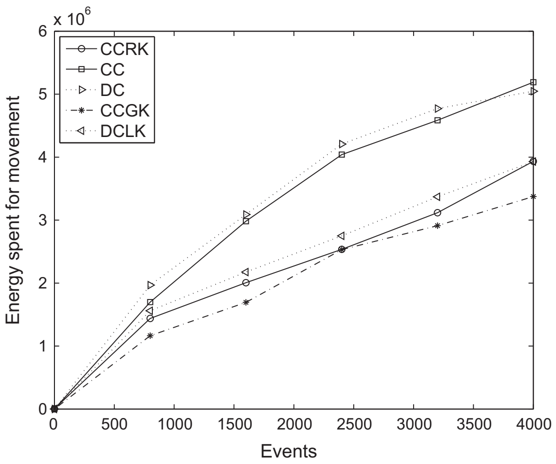
6.1. Movement cost

It refers to the amount of energy that Mobile Chargers dissipate for movement in order to charge sensor nodes. We assume that chargers have only one energy pool which is used both for movement and for charging.

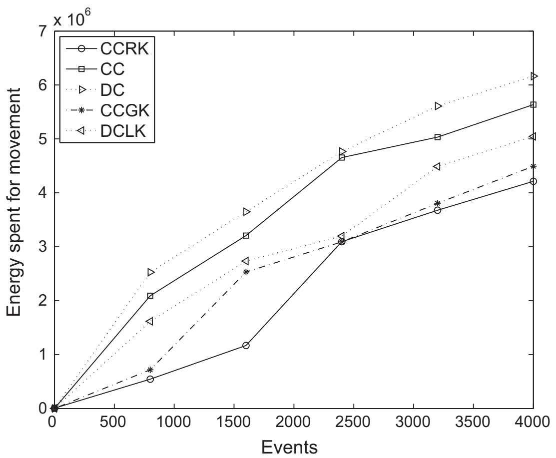
In our simulations we have not taken into account the movement cost directly, i.e. we do not calculate how much energy is spent for movement but we have calculated how much distance has each Mobile Charger traveled, which provides an estimation of the cost. More specifically, using the same assumptions for the Mobile Chargers with that in [21] (i.e. they carry high density battery packs (12 A, 5 V) and weight 20 lbs) and the battery calculator in [22] we provide in Fig. 4 an estimation of the energy spent for the Mobile Chargers' movement throughout the network for all protocols for both uniform and non-uniform network deployment. The DC and CC protocols which have a naive charging phase (slice scanning) spend high amount of energy for movement. In contrast, the CCGK and CCRK protocols which minimize the distance traveled also minimize the movement cost.

6.2. Charging cost

It refers to the amount of energy dissipated to charge sensor nodes. This cost can be distinguished in two kinds, the beneficial charging cost which is the energy obtained by sensor nodes and the wasted charging cost which is the energy wasted because of losses coming from the specific charging technology. In this paper we assume that there is no any energy loss during the charging procedure and the charging cost equals to beneficial energy cost.



(a) Uniform deployment.



(b) Non-uniform deployment.

Fig. 4. Energy spent for Mobile Chargers' movement over time.

6.3. Communication cost

It refers to the amount of energy dissipated by a charger in order to get informed about the energy status of the sensor nodes. This cost depends on two quantities. The first one is the number of messages that Mobile Chargers send and receive and the second one is the distances between the sensor nodes and the Mobile Chargers since the message transmission cost is analogous to the square of the distance.

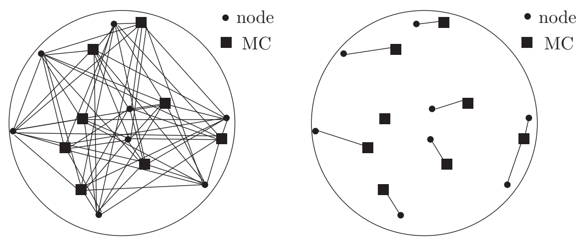
The communication cost is based both on coordination and on charging procedure. An analysis of the communication cost of our proposed protocols is provided below.

6.3.1. CCGK

- Coordination phase: The chargers are informed about the energy status of all sensor nodes. In this case, the number of messages of each charger is $O(N)$ and the total number of messages is $O(KN)$. Also, the transmission distances between a charger and a node may vary ($\in [0, 2R]$) A relevant small scale example of eight nodes and eight chargers is depicted in Fig. 5a.
- Charging phase: Each Mobile Charger receives messages about energy status of each node that belong to its group and thus, the total number of messages is $O(N)$. The transmission distances are relatively small, since it is a factor that affects the cluster construction. Fig. 5b depicts an example according to the charging phase of the protocol.

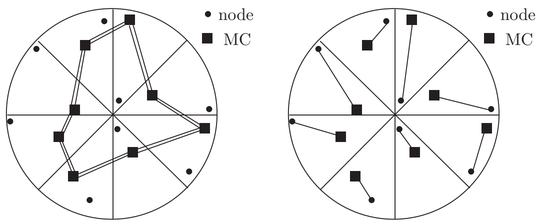
6.3.2. DCLK

- Coordination phase: Each Mobile Charger communicate with its two adjacent chargers. Thus, the total number of transmitted messages is $O(K)$. Also, the distances between the adjacent chargers are relatively small as depicted in Fig. 6a.
- Charging phase: Each Mobile Charger is informed about the energy status of the sensor nodes that belong to its Slice at each time period. The expected amount of nodes in each Slice is $\frac{N}{K}$ since there are K Slices, one for each



(a) Coordination phase. (b) Charging phase.

Fig. 5. Messages of CCGK protocol.



(a) Coordination phase. (b) Charging phase.

Fig. 6. Messages of DCLK protocol.

charger. Thus, the total number of messages is $O(K\frac{N}{K}) = O(N)$. However, this number of messages is not transmitted at each time slot as in CCGK but at each time period. In order to provide local knowledge, Slice size should be small enough. Considering that the network radius is R, we assume that in local knowledge the distance between a node and a charger should exceed this value. Since there are K Slices, each Slice has an central angle $A = \frac{2\pi}{K}$ (in radians). The length of an arc of a central angle A is $\ell = \frac{2\pi RA}{2\pi} = RA$. Thus, the distance is $\ell = R\frac{2\pi}{K}$. In order to ensure that the maximum node-charger distance in each Slice is at most R, the following inequality should hold:

$$\ell \leqslant R \Rightarrow R\frac{2\pi}{K} \leqslant R \Rightarrow K \geqslant 2\pi.$$

As a result, the distances in local knowledge are in $[0, R]$. Fig. 6b depicts the communication distances between the nodes and the chargers in charging phase.

6.3.3. CC

- Coordination phase: Each Mobile Charger sends to the Sink its available energy and receives the value of its angle. The number of messages is $O(K)$ and the distances are in $[0, R]$.
- Charging phase: The chargers obtain no network knowledge and perform “blind” scanning. Thus there is not any communication cost.

6.3.4. DC

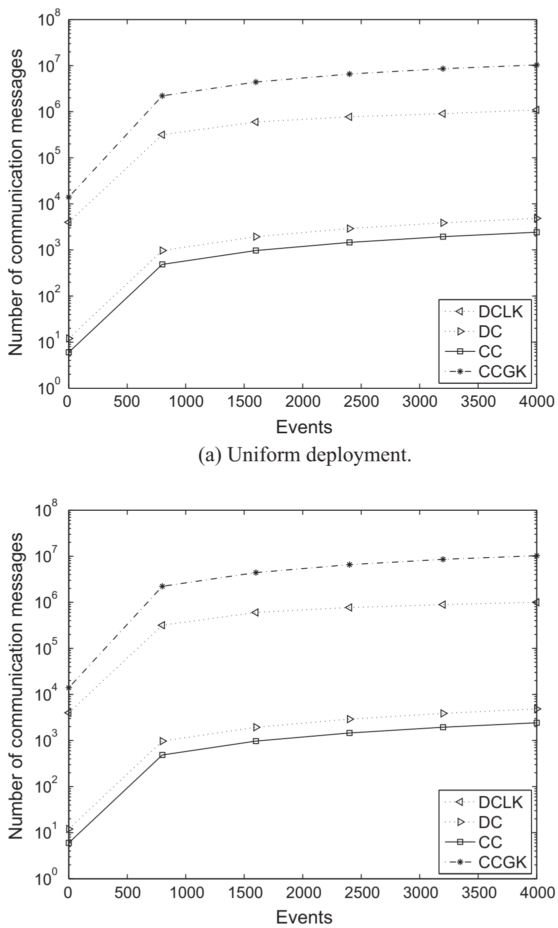
- Coordination phase: Each Mobile Charger communicates with its two adjacent chargers. Thus, the number of transmitted messages is $O(K)$. Also, the distances between the adjacent chargers are relatively small.
- Charging phase: The chargers obtain no network knowledge and perform “blind” scanning. Thus there is not any communication cost.

It is clear that the lower the knowledge level is, the lower the communication cost becomes, since both the number of messages and the distances between nodes and chargers are reduced. Thus, in our simulation results we can make useful conclusions about protocols e.g. if two protocols achieve the same performance on a specific metric, the protocol with lower knowledge level is considered more efficient.

We conducted simulations to verify the above analysis on the number of messages that are send and received by the Mobile Chargers. Fig. 7 depicts the amount of messages that are spent by all Mobile Chargers throughout our simulations for both uniform and non-uniform network deployment. As shown in this figure, the DC and CC protocols which use no network knowledge achieve the lower number of messages sent throughout the simulation. The CCGK protocol achieves higher number of messages than the DCLK protocol since each Mobile Chargers communicates with each sensor node in the coordination phase. Also, the cost of each message is higher because the distances between nodes and chargers are larger.

7. Experimental evaluation

The simulation environment for conducting the experiments is Matlab 7.11. The Sink is placed at the center $(x, y) = (0, 0)$ of the circular deployment area. The number of sensors is set to 2000 and the number of chargers to 6. We simulate experiments of 4000 generated events. For statistical smoothness, we apply several times the deployment of nodes in the network and repeat each experiment



(a) Uniform deployment.

(b) Non-uniform deployment.

Fig. 7. Number of messages over time.

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 [23,24] 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.

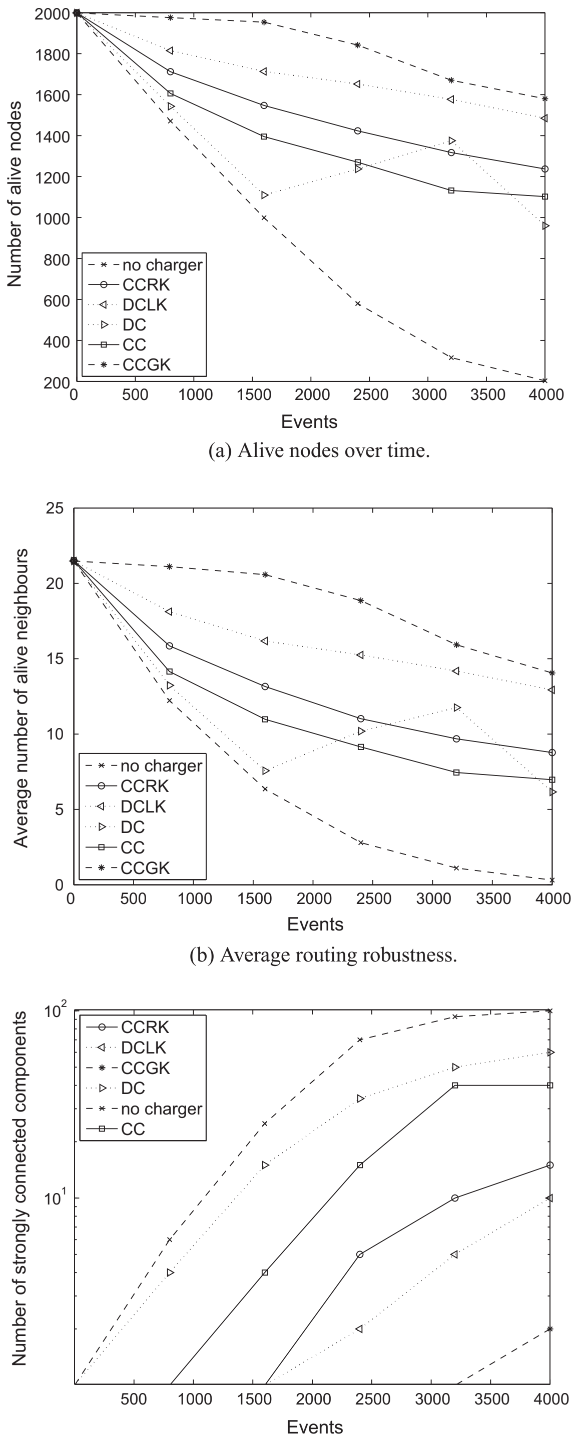
We focus on the following performance metrics: (a) *alive nodes over time*, that is the number of nodes with enough residual energy to operate, during the progress of the experiment, (b) *connected components over time* which indicates the number of strongly connected components of the network graph throughout the experiment, (c) *routing robustness* and *average routing robustness*, in terms of the nodes' average alive neighbors during the progress of the experiment, (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 and (e) *distance traveled* per Mobile Charger and *total distance traveled* by all chargers.

In this paper, we aim at designing energy efficient protocols for both uniform and non-uniform network deployments. Our main goal is to manage the available energy efficiently. In all simulations that are performed in this section, we assume that the energy is dissipated only for charging purposes, i.e. we do not take into consideration the movement and communication cost. The total energy of the Mobile Chargers is transferred to sensor nodes through our proposed recharging protocols.

7.1. Uniform network deployment

7.1.1. Protocols' impact on network properties

(i) The application of charging protocols results in a great reduction in the overall death rate of the network (in terms of *alive nodes* over time), as shown in Fig. 8a. The CCGK as expected outperforms all other protocols and rather serves as an upper bound of their performance. The power of CCGK comes from the great amount of knowledge it assumes



(a) Alive nodes over time.

(b) Average routing robustness.

(c) Graph connected components over time.

Fig. 8. Various metrics for uniform deployments.

and from the robust centralized coordination of the Mobile Chargers. The DCLK protocol, with limited network knowledge is an efficient distributed alternative, since it manages to achieve a performance close to the upper bound and outperform the reactive CCRK protocol. CC and DC protocols which assume no network knowledge are outperformed by other protocols. Note that the upward curve of the DC protocol after 1500 generated events indicates a temporary starvation, after which the chargers revive some of the dead nodes when passing by areas with high amounts of dead nodes.

The CCGK protocol achieves the lowest death rate since it computes which node to charge next based on both its distance from the node and on the energy status of the node. In contrast, CC and DC protocols use just the distance property for the relevant choice, so the weak nodes that are also far away from the charger may deplete their energy. DCLK protocol separates each Slice into Sectors and the charger chooses to charge the nodes of the most critical Sector. This procedure may incur higher traveling distance since it may change Sectors more often than the CCGK protocol which minimizes the covered distance each time (see Fig. 12).

(ii) *Routing robustness* is critical for wireless sensor networks, as all data collected have to be sent to the Sink. Path breakage occurs frequently due to node failure, mobility, or channel impairments, so the maintenance of a path from each node to a control center is a challenging task. A way of addressing the routing robustness of a wireless sensor network is by counting the number of its alive neighbors over time for each node. This can be seen as an implicit measure of network connectivity. For our protocols, the average number of alive neighbors is depicted in Fig. 8b. A more detailed evolution of the network's routing robustness is depicted in Fig. 9. The average routing robustness follows the same pattern as the death rate of nodes in the network. This is natural, since more dead nodes in the network result in loss of neighbors for each node. In Fig. 9 we can see that in the no charger case the black bar (representing number of neighbors <7) is increasing, while the white bar (number of alive neighbors >16) is rapidly decreasing. On the other hand, CCGK, CCRK and DCLK protocols achieve reliable routing robustness.

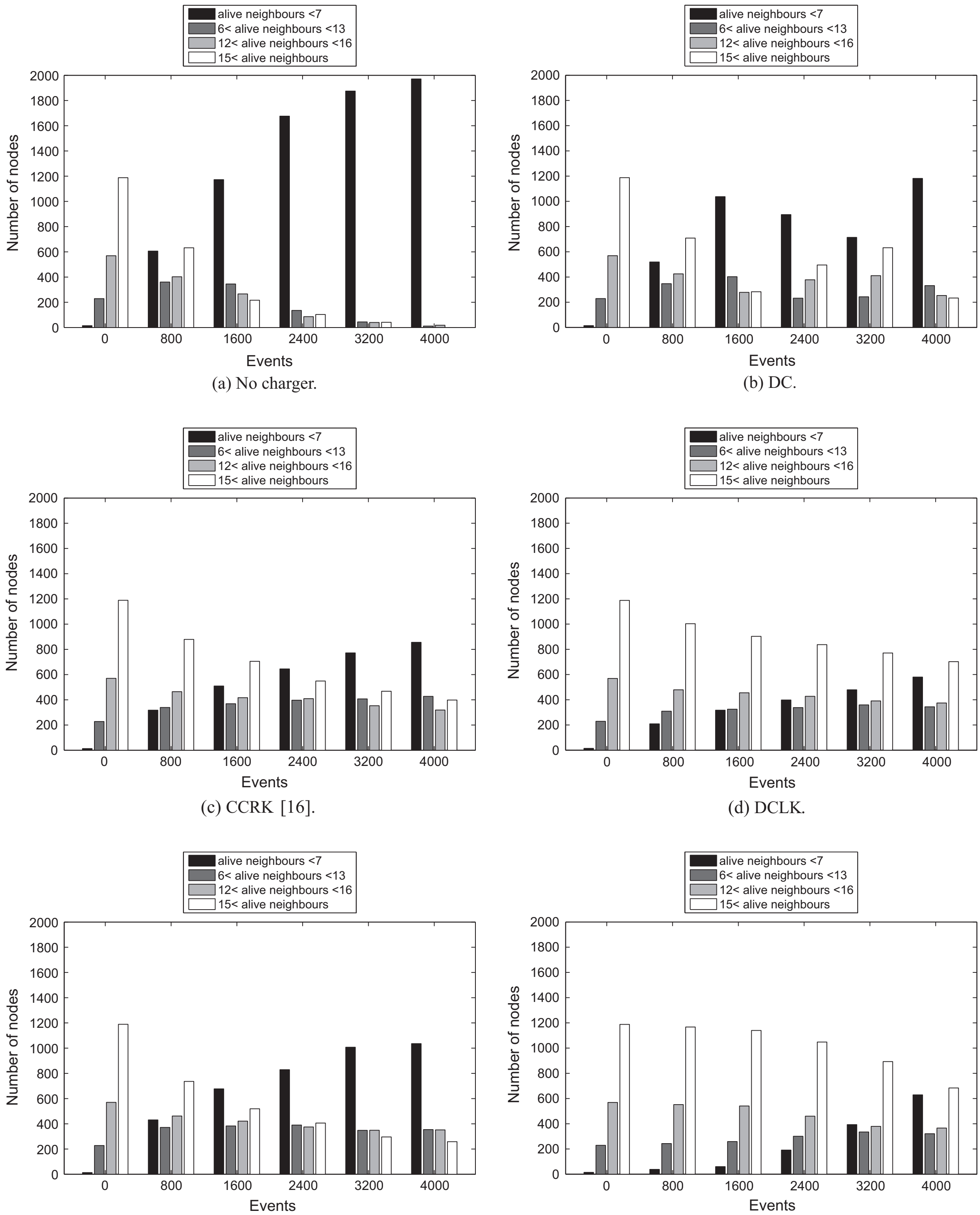
(iii) Similarly to the routing robustness, the number of *strongly connected graph components* is an overall measure of connectivity quality in a wireless sensor network. Disconnected components are unable to communicate with each other and support efficient data propagation, resulting in high data delivery failures. A strategy of improving data delivery latency is the maintenance of a small number of connected components in the network. High numbers of components may lead to isolation of critical nodes, thus loss of important information. Fig. 8c depicts the evolution of the number of network components throughout the experiments. As we noted earlier, DC and CC protocols lead to a higher node death rate in comparison to CCRK and DCLK protocols, a fact that results in early disconnections and sharp increase of connected components. The powerful CCGK maintains a single strongly connected component for much longer.

(iv) *Point coverage* problem regards the assurance that some selected points in the network are covered by an adequate number of sensors and is an important aspect in numerous wireless sensor networks functionalities (e.g. localization, tracking, etc.). A point that is covered by k sensors is called k-covered. In Fig. 10 we can see the coverage ageing of 1000 randomly selected points scattered throughout the network. We examine how many points are <2-covered, 2-covered, 3-covered and >3-covered for 4000 generated events. Each bar in the plot represents a number of the covered points. In the no charger case, the number of <2-covered points is increasing in contrast to the number of >3-covered points that is decreasing. CCGK, DCLK and CCRK protocols improve the network coverage by reducing the rate that the coverage of >3-covered points is decreasing. The absolute difference of the number of <2-covered and >3-covered points, between different time instances, is not increasing quickly, compared to the no charger case.

7.1.2. The impact of knowledge

An important fact that comes up from the observation of the aforementioned metrics is that the CC and DC protocols are outperformed by their improved alternatives, CCGK and DCLK. The CC protocol, which uses a strong, centralized computation in order to calculate the regions of interest for the chargers, is outperformed even by the DCLK protocol that employs distributed computation (but assumes more knowledge on the network). This leads to the conclusion that the nature of the coordination procedure is less significant than the design of the charging traversal, when the latter relies on a greater amount of knowledge. Of course, when assuming the same amount of knowledge, the coordination procedure is still important (e.g. CC vs DC).

Also, the comparison between CCGK and CCRK protocols enlighten us about the size of the impact for acquiring knowledge on the network w.r.t. energy cost. The CCRK protocol is provided with global knowledge on the network but (in contrast to CCGK) the information maintenance relies on an underlying message propagation mechanism which is dissipating node and charger energy. As shown by the experimental evaluation, the degradation from global knowledge to local knowledge assumption (DCLK) is more efficient than a costly acquisition of global knowledge. This is why, although in our simulations we do not calculate the communication cost between the chargers and the nodes, we calculate the cost of the node-to-node communication. This cost is similar to the one introduced by the underlying routing protocol that is used by the nodes for data propagation. However, in the CCRK protocol, the representative nodes communicate with the nodes in their group more frequently, in order to collect their important status information and thus, they are dissipating their energy with a higher rate. This may lead to a higher node death rate, higher number of connected components, etc. This communication overhead is the reason of the worse CCRK performance compared to DCLK.



(a) No charger.

(b) DC.

(c) CCRK [16].

(d) DCLK.

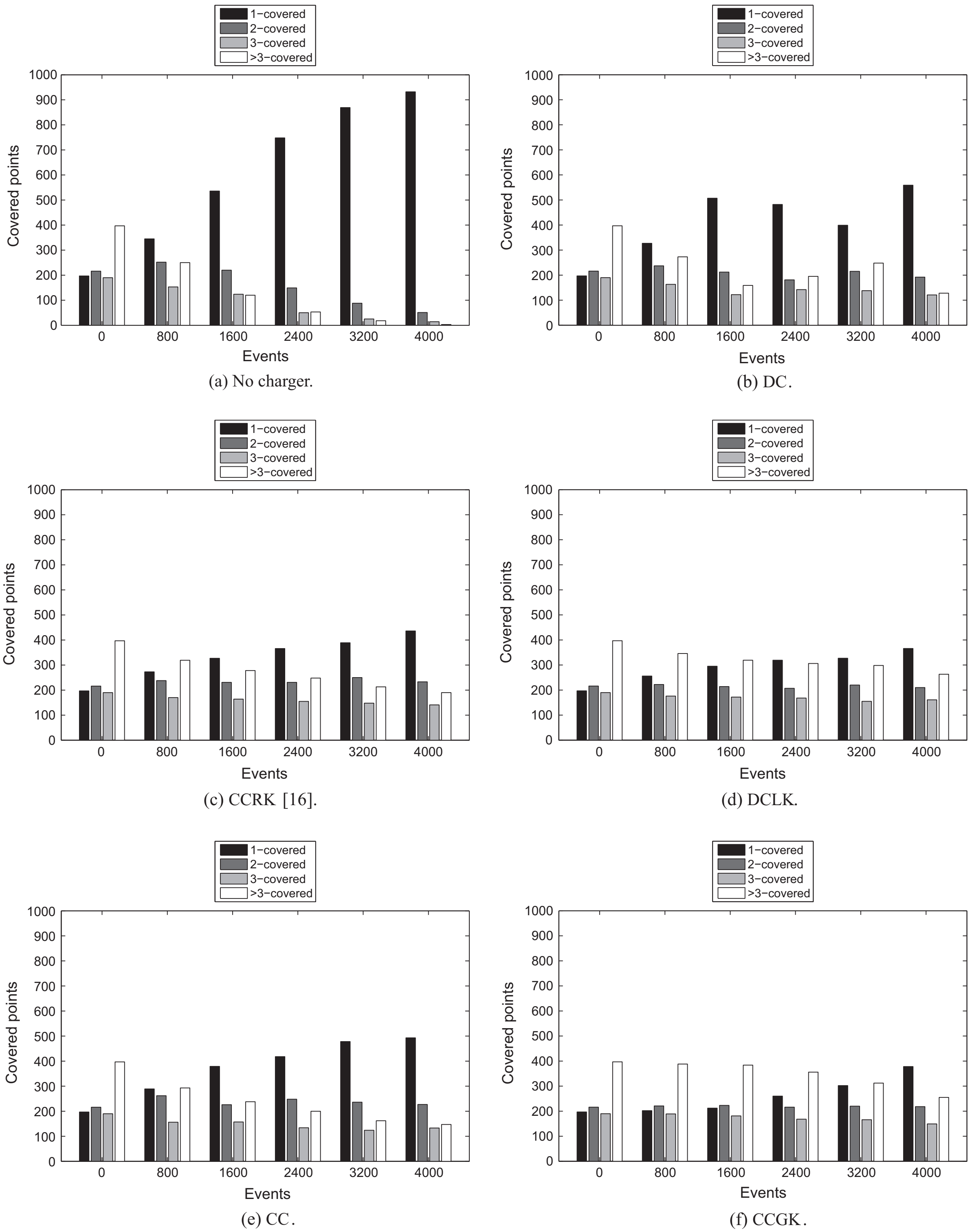
(e) CC.

(f) CCGK.

Fig. 9. Routing robustness for uniform deployments.

7.1.3. Traveling distance

Traveling distance of the Mobile Chargers indirectly reflects the efficiency of the coordination procedure and the charging process. Although the investigation of traveled distance does not display the impact on crucial network parameters, it can lead to useful conclusions about

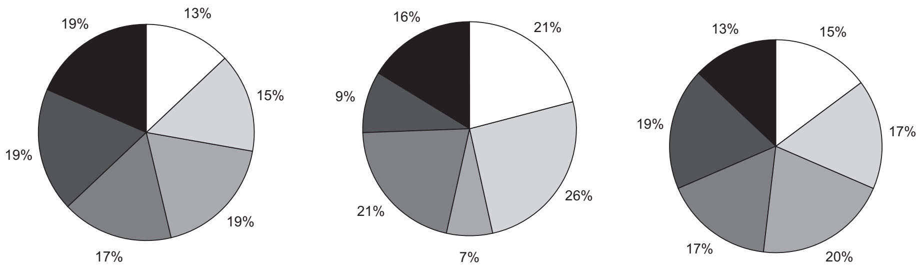


(a) No charger. (b) DC. (c) CCRK [16]. (d) DCLK. (e) CC. (f) CCGK.

Fig. 10. Coverage ageing for uniform deployments.

the balance of the chargers activity. Also, traveling distance can be associated with relevant cost for movement as presented in Section 6.1.

Fig. 12 depicts the total distance traveled by all (six) Mobile Chargers in the network. It is clear that CCGK, CCRK and DCLK protocols achieve the required charging



(a) CCGK. (b) DC. (c) CCRK [16]. (d) DCLK. (e) CC.

Fig. 11. Distance traveled per Mobile Charger for uniform deployments.

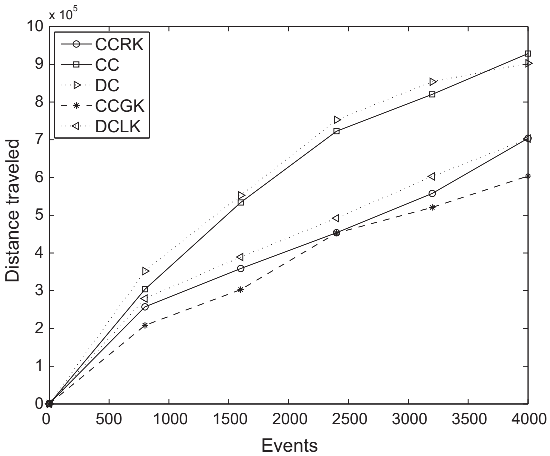


Fig. 12. Distance traveled by Mobile Chargers for uniform deployments.

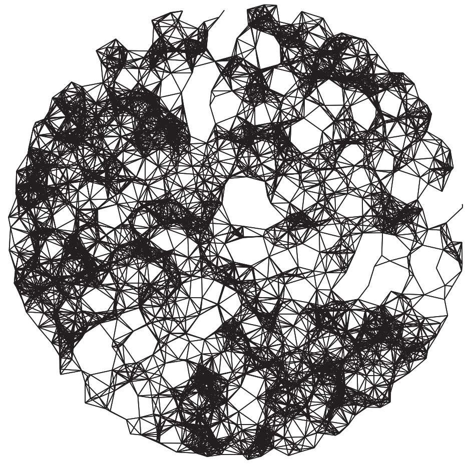


Fig. 13. Non-uniform deployment.

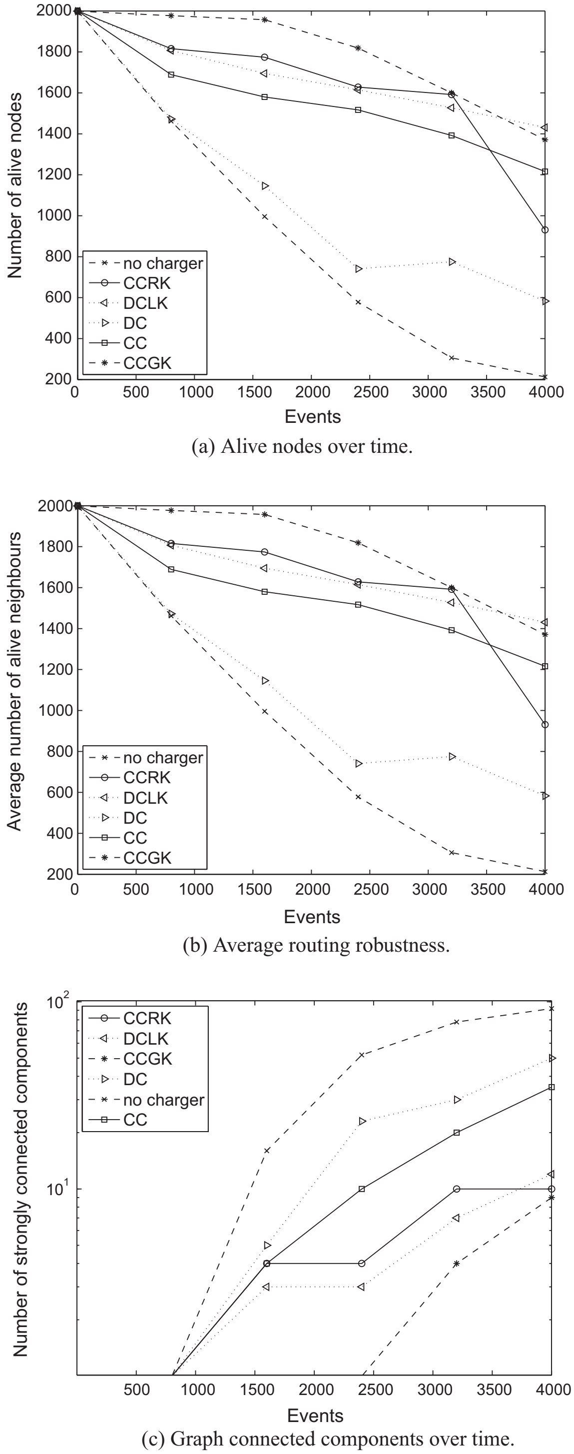
process by traveling less distance than DC and CC protocols. Fig. 11 is comprised of five piecharts, one per protocol. A piechart consists of Slices, the size of which is proportional to the distance traveled by the corresponding charger. We observe that in contrast to DC and CC protocols, CCGK, CCRK and DCLK protocols achieve balanced distribution of traveled distance among the chargers.

7.2. Non-uniform network deployment

We examine the performance of our protocols in networks where the deployment of the sensor nodes is non-uniform (follows the heterogeneous placement described in Section 3). This scenario is more realistic in large scale, real-life, sensor networks. The protocol's performance over the various metrics share some similarities with the uniform case.

7.2.1. Protocol's impact on network properties

(i) *Alive nodes over time*. As shown in Fig. 14a, the most powerful protocol, CCGK, still outperforms all other protocols. Furthermore, the number of alive nodes in the DCLK protocol decreases with a very low rate indicating that the protocol's charging process that partitions the Slices into Sectors and charges the nodes of the most critical Sector, achieves a balanced energy consumption between the sensor nodes. The



(a) Alive nodes over time.

(b) Average routing robustness.

(c) Graph connected components over time.

Fig. 14. Various metrics for non-uniform deployments.

DC protocol, which assumes no network knowledge and has a distributed coordination procedure, achieves the worst performance, which in the non-uniform case is even worse, since it is quite close to the no charger protocol. Also, the number of alive nodes in the CC protocol is much higher than in the DC protocol. Since both protocols are not using any knowledge, the difference in their performance is due to the coordination procedure, which in CC is centralized and in DC is distributed.

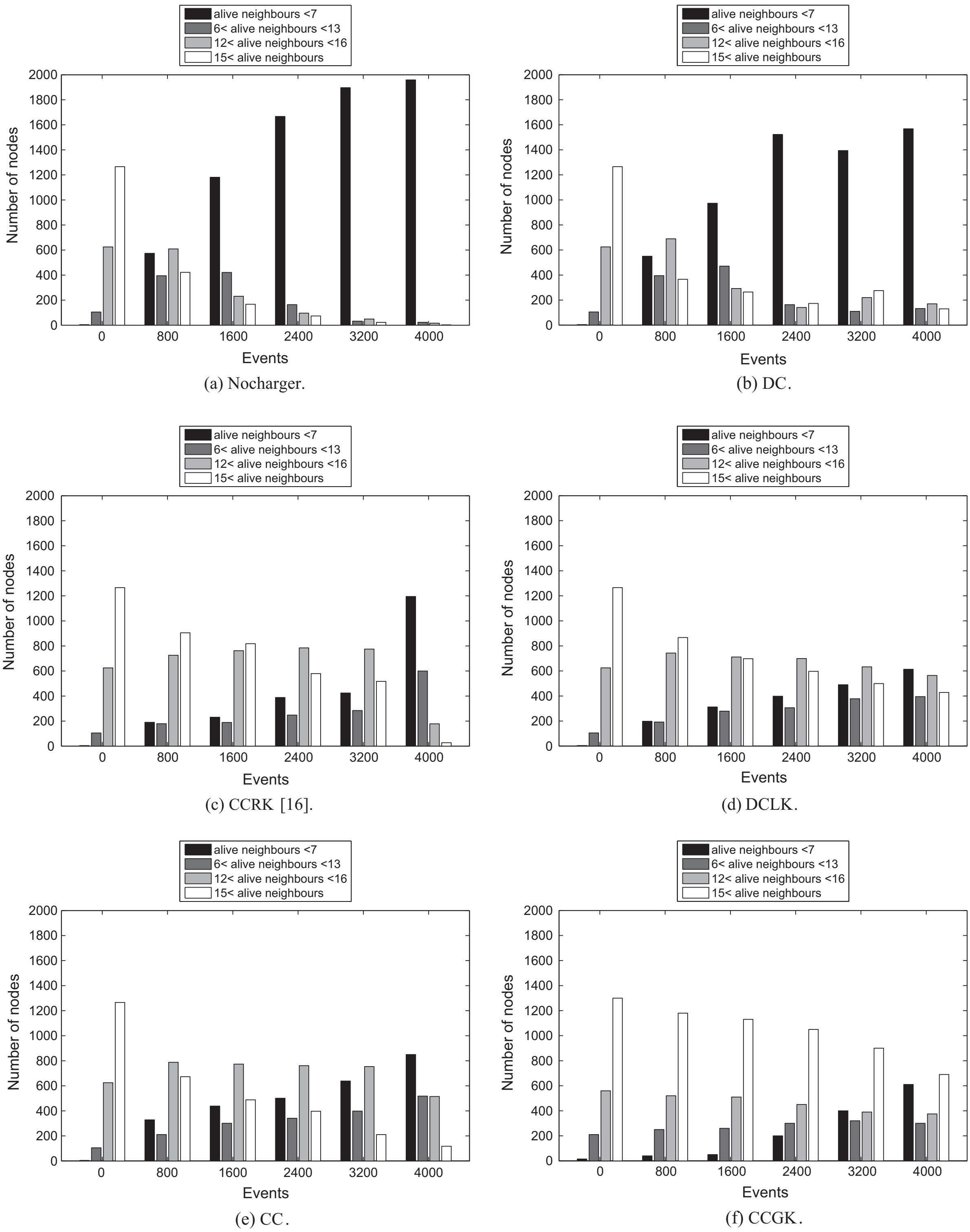
(ii) *Routing robustness*. The average routing robustness, as shown in Fig. 14b, follows the same pattern with the lifetime of the network, indicating that the higher the level of knowledge is, the more reliable the provided routing robustness becomes. In Fig. 15, a detailed evolution of the routing robustness is provided. The no charger case results in the worst performance (the black bar increases rapidly) as the number of generated events is increasing. In contrast, the CCGK protocol achieves the best performance since it maintains high robustness. DCLK and CCRK protocols also achieve high robustness by maintaining a high number of alive neighbors (>12-alive neighbors as well as >16-alive neighbors) and a low increase on black bar (which represents <7-alive neighbors).

(iii) *Strongly connected components*. This metric is the one affected the most by the non-uniform node deployment. As shown in Fig. 14c, the difference between the protocols' performance is similar to the uniform case, i.e., the order of the protocols based on their performance is the same. Four of the protocols begin to increase the number of connected components after some time (and not earlier as in the uniform case) but they achieve similar number of components at the end of the simulation. This indicates that the number of components increases with higher rate. Also, the CCGK, CCRK and DCLK protocols begin to increase the number of components earlier than in the uniform case (and with a higher rate).

(iv) *Point coverage*. In the non-uniform network deployment, there may be some parts of the network that are more sparse than others and the points belonging in these areas will be uncovered earlier, i.e., there will not be any alive nodes to collect their generated data. As shown in Fig. 16, the three protocols that assume large amount of network knowledge, manage to keep a high point coverage level, i.e., the black bar depicting the number of points covered by <7 nodes is not increasing with a high rate. More specifically, the CC and CCRK achieve better performance than in the uniform case. In contrast, DC and no charger are not able to maintain good coverage levels and increase the black bar rapidly. The increase on the DC protocol is higher than the corresponding increase in the uniform case.

7.2.2. Impact of knowledge

The following observation in the uniform case is also valid in the non-uniform case. The higher the amount of knowledge is, the better the protocol's performance achieved (for the same coordination procedure). This is natural since protocols with higher knowledge amounts exploit more efficiently the network resources.

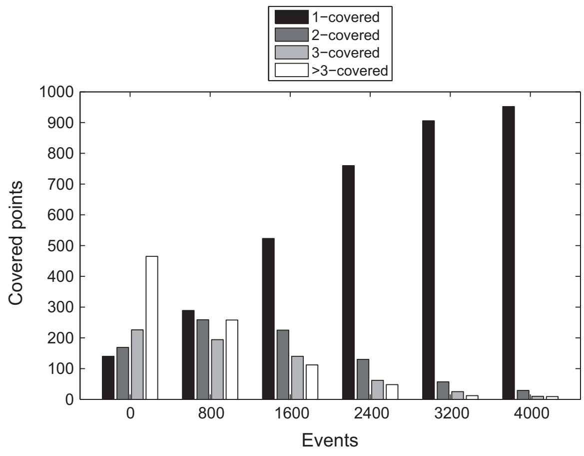


(a) Nocharger. (b) DC. (c) CCRK [16]. (d) DCLK. (e) CC. (f) CCGK.

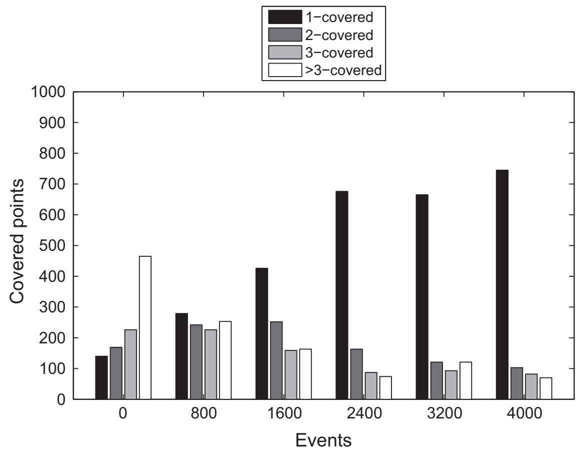
Fig. 15. Routing robustness for non-uniform deployments.

7.2.3. Traveling distance

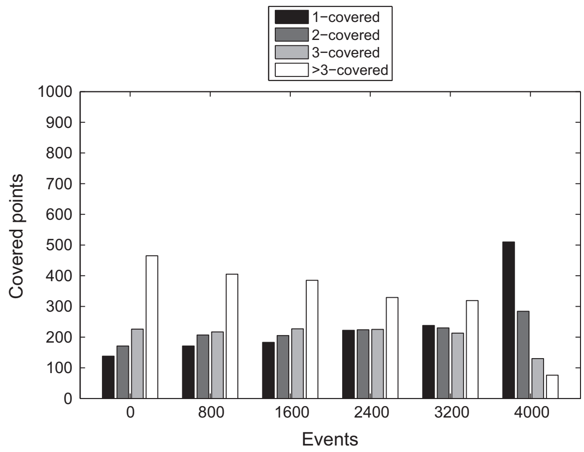
In the non-uniform case, (similarly to the uniform), when using the CC and DC protocols that are not exploiting any network knowledge, there are some Mobile Chargers that cover much longer distance than others. As shown in Fig. 18 the total distance traveled by all Mobile Chargers



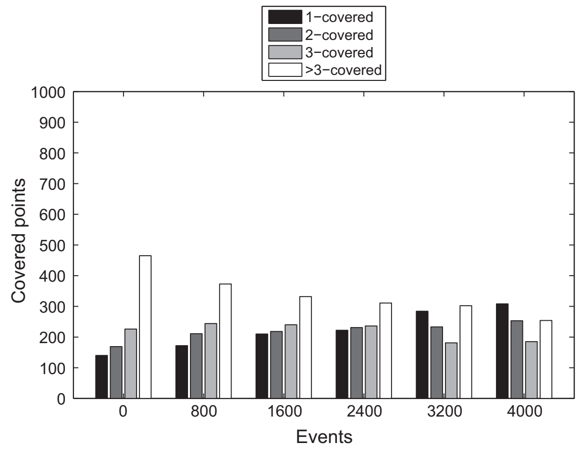
(a) No charger.



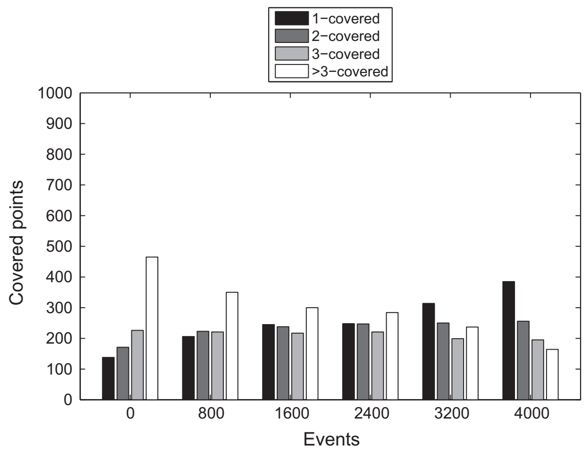
(b) DC.



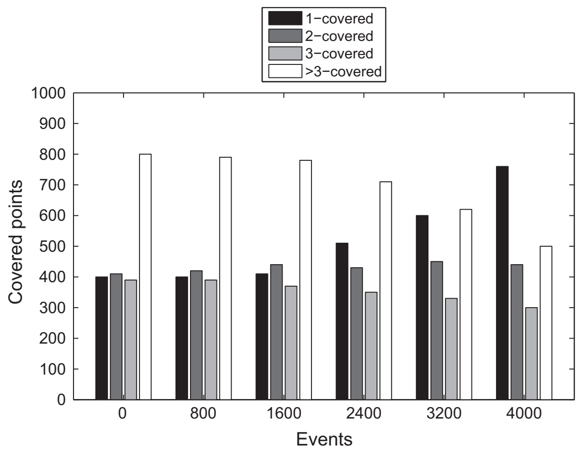
(c) CCRK [16].



(d) DCLK.



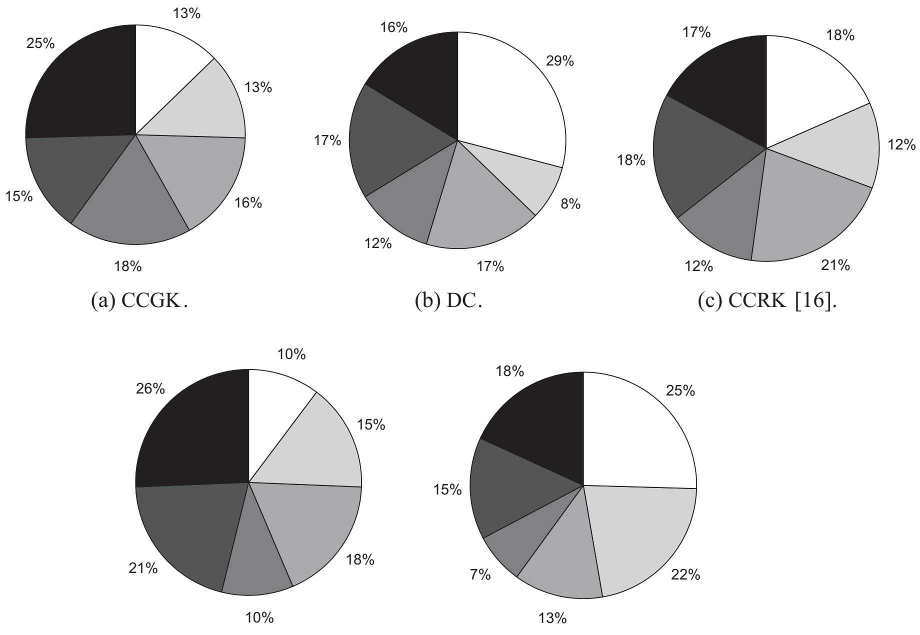
(e) CC.



(f) CCGK.

Fig. 16. Coverage ageing for non-uniform deployments.

for each protocol, is higher that the corresponding distance traveled in the uniform network deployment. Despite the fact that the nodes are non-uniformly deployed, the distribution of the total distance traveled among all Mobile Chargers is quite similar to the corresponding distribution of the uniform case. As is shown in Fig. 17, the CCGK, CCRK



(a) CCGK. (b) DC. (c) CCRK [16].

(d) DCLK. (e) CC.

Fig. 17. Distance traveled per Mobile Charger for non-uniform deployments.

and DCLK protocols perform a more balanced distribution of total traveled distance between the chargers than the CC and the DC protocols. As we can see, CC and DC not only lead to an unbalanced distribution of traveled distance among the Mobile Chargers (Fig. 17) but also have larger traveled distance compared to other protocols (Fig. 18).

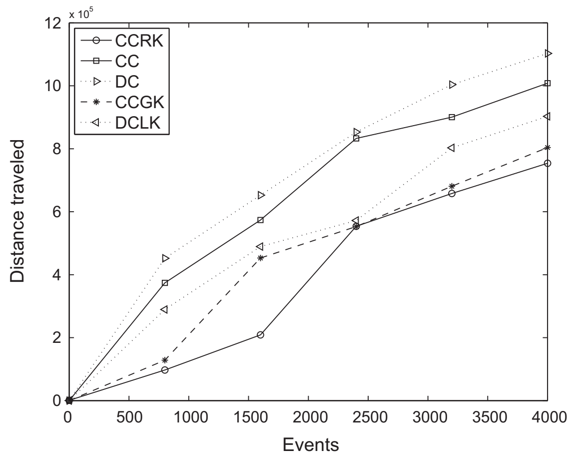


Fig. 18. Distance traveled by Mobile Chargers for non-uniform deployments.

7.2.4. Summary of differences between impact on uniform and non-uniform node deployment

We compared the protocols both on networks with uniform node deployment and on networks with non-uniform node deployment too. The simulation results demonstrated that the protocols' performance on the various metrics on the two networks have a lot of similarities. In general, in most metrics the ordering of the protocols by their performance is the same. Differences exist mostly on the exact values of the metrics. More specifically, the differences in each metric are the following. In the *alive nodes over time* metric, the CCRK protocol achieves better performance in the non-uniform case than in the uniform one throughout almost the whole experiment. After that, the death rate is very high. Also, in this time interval it outperforms the DCLK protocol while in the uniform case the DCLK always achieves a better performance. In the *average routing robustness* metric, the differences are the same as with the previous metric since these two metrics are related. In the *routing robustness* metric, the DC, DCLK and CC protocols show great differences. In the non-uniform case, the DC and DCLK achieve inefficient routing robustness while the CC achieves better performance. In *strongly connected components* metric (non-uniform case), the no charger and DC protocols improve their performance since they keep one connected component for long time. In contrast, in the uniform case, the same protocols increase the number of connected components since the beginning of the experiment. Unlike the above protocols, the CCGK, CCRK and DCLK protocols, start to increase the number of components earlier than in the uniform case. Furthermore, in the *point coverage* metric, in the non-uniform case, the DC protocols increase the uncovered points with a higher rate compared to the uniform case. On the contrary, the CC and CCRK protocols, manage to keep more nodes alive to cover the points than in the uniform case. Comparing the *distance traveled* metric, in the non-uniform case all protocols cover longer distance than that in the uniform case. Also, in the uniform case the CCGK protocol has covered the shortest distance while in the non-uniform case the CCRK has the shortest traveled distance. Finally, on the distribution of total traveled distance between chargers there is not any remarkable difference between the performance on the two types of node deployment.

7.3. Conclusions and future work

In this work we have studied the problem of efficient wireless power transfer in Wireless Rechargeable Sensor Networks. In such networks, Mobile Chargers traverse the network and wirelessly replenish the energy of sensor nodes. We first identify and investigate some critical issues and trade-offs of the Mobile Chargers configuration (i) what are good coordination procedures for the Mobile Chargers to perform and (ii) what are good trajectories for the Mobile Chargers to follow. In contrast to most current approaches, we envision methods that are distributed and use limited network information. We propose four new protocols for efficient charging assuming different levels of network knowledge (from global to local and no network knowledge), and different processing (from centralized to distributed).

For future research, we plan to investigate the impact of different execution periods of the coordination phases. Another future research direction is the case of collaborative charging (as nicely addressed in [13]), where Mobile Chargers are allowed to charge each other. This model variant may lead to new protocols for charger configuration. Also, recent advances in magnetic resonant coupling shows that multiple nodes can be charged at the same time. This enables us to consider new design alternatives for the charging problem. Moreover, we intend to investigate which is the optimal number of chargers in order to achieve efficient energy usage in the network. Finally, we plan to implement selected protocols in small/medium scale real experiments (e.g. with robotic elements and wireless charging technology).

Acknowledgements

We wish to thank the anonymous reviewers for their detailed, helpful comments.

This research was partially supported by (a) the EU/FIRE IoT Lab project – STREP ICT-610477 and (b) the European Social Fund (ESF) and Greek National Funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) – Research Funding Program: Thalis-DISFER, Investing in knowledge society through the European Social Fund.

References

[1] A. Madhja, S. Nikoletseas, T.P. Raptis, Efficient, distributed coordination of multiple mobile chargers in sensor networks, in: Proceedings of the 16th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM), 2013.
[2] L. Xie, Y. Shi, Y. Hou, A. Lou, Wireless power transfer and applications to sensor networks, IEEE Wireless Commun. 20 (4) (2013) 140–145.
[3] The Wireless Power Consortium. <http://www.wirelesspowerconsortium.com/>.
[4] Alliance for Wireless Power. <http://www.a4wp.org/>.
[5] Powercast. <http://www.powercastco.com/>.
[6] Broadcom Corporation. <http://www.broadcom.com/>.
[7] C.M. Angelopoulos, S. Nikoletseas, T.P. Raptis, C. Raptopoulos, F. Vasilakis, Improving sensor network performance with wireless energy transfer, in: International Journal of Ad Hoc and Ubiquitous Computing, Inderscience Publishers, 2014.
[8] M.R. Garey, D.S. Johnson, Computers and Intractability, W.H. Freeman and Company, 1979.
[9] Y. Peng, Z. Li, W. Zhang, D. Qiao, Prolonging sensor network lifetime through wireless charging, in: Proceedings of the 31st IEEE Real-Time Systems Symposium (RTSS), 2010.
[10] Y. Shi, L. Xie, Y.T. Hou, H.D. Sherali, On renewable sensor networks with wireless energy transfer, in: Proceedings of the 30th IEEE International Conference on Computer Communications (INFOCOM), 2011.
[11] C.M. Angelopoulos, S. Nikoletseas, T.P. Raptis, Wireless energy transfer in sensor networks with adaptive, limited knowledge protocols, Comput. Networks 70 (2014) 113–141.
[12] L. Xie, Y. Shi, Y.T. Hou, W. Lou, H.D. Sherali, S.F. Midkiff, Bundling mobile base station and wireless energy transfer: modeling and optimization, in: Proceedings of the 32nd IEEE International Conference on Computer Communications (INFOCOM), 2013.
[13] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging for sensor networks, in: Proceedings of the 9th IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS), 2012.
[14] H. Dai, X. Wu, L. Xu, G. Chen, S. Lin, Using minimum mobile chargers to keep large-scale wireless rechargeable sensor networks running forever, in: Proceedings of the 22nd International Conference on Computer Communications and Networks (ICCCN), 2013, pp. 1–7.
[15] L. He, P. Cheng, Y. Gu, J. Pan, T. Zhu, C. Liu, Mobile-to-mobile energy replenishment in mission-critical robotic sensor networks, in: Proceedings of the 33rd IEEE International Conference on Computer Communications (INFOCOM), 2014.
[16] C. Wang, J. Li, F. Ye, Y. Yang, Multi-vehicle coordination for wireless energy replenishment in sensor networks, in: Proceedings of the 27th IEEE International Parallel & Distributed Processing Symposium (IPDPS), 2013.
[17] J. Li, C. Wang, F. Ye, Y. Yang, Netwrap: an NDN based real time wireless recharging framework for wireless sensor networks, in: Proceedings of the 10th IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS), 2013, pp. 173–181.
[18] O. Gnawali, R. Fonseca, K. Jamieson, D. Moss, P. Levis, Collection tree protocol, in: Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems (SenSys), 2009.
[19] D. Efstathiou, A. Koutsopoulos, S. Nikoletseas, Analysis and simulation for parameterizing the energy-latency trade-off for routing in sensor networks, in: Proceedings of the 13th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM), 2010.
[20] A. Tanenbaum, Modern Operating Systems, third ed., Prentice Hall, 2007.
[21] C. Wang, J. Li, F. Ye, Y. Yang, Recharging schedules for wireless sensor networks with vehicle movement costs and capacity constraints, in: Proceedings of the 11th IEEE International Conference on Sensing, Communication, and Networking (SECON), 2014.
[22] Battery Calculator. <http://www.evsource.com/battery_calculator.php/>.
[23] P. Gupta, P. Kumar, Critical power for asymptotic connectivity in wireless networks, Stochastic Anal., Control, Optim. Appl. (1998).
[24] M. Penrose, Random Geometric Graphs, Oxford University Press, 2003.

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