Efficient On-Demand Multi-Node Charging Techniques for Wireless Sensor Networks

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Abstract

This paper deals with energy transfer in wireless sensor networks (WSN) and explores efficient policies to perform simultaneous multi-node battery replenishment through a mobile charger (MC). An on-demand solution that takes advantage of this concept is proposed. It features the use of threshold-based tour launching (TTL), after appropriate request grouping, and a path planning strategy based on minimizing the number of stopping points in the charging tour. The proposed solution, called On-demand Multi-node Charging (OMC) is the first on-demand scheme that takes advantage of multi-node charging, and has several contributions. Contrary to existing solutions, that focus on shortening the charging delays, OMC groups incoming charging requests and optimizes the charging tour and the mobile charger energy consumption. Although slightly increasing the waiting time before nodes are charged, this allows taking advantage of multiple simultaneous charges and also reduces node failures. At the tour planning level a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes by maximizing the number of sensors that are charged at each stop. Given its NP-hardness, tour planning is approximated through a clique partitioning problem, which is solved using a lightweight heuristic approach. The proposed schemes are evaluated in offline and on-demand scenarios and compared against relevant state-of-the-art protocols. The results in the offline scenario show that the path planning strategy reduces the number of stops and the energy consumed by the mobile charger, compared to existing offline solutions. This is with further reduction in time complexity, due to the simple heuristics that are used. The results in the on-demand scenario confirm the effectiveness of the path planning strategy. More importantly, they show the impact of path planning, TTL and multi-node charging on the efficiency of handling the requests, in a way that reduces node failures and the mobile charger energy expenditure.

Keywords: Sensor networks, wireless energy transfer, mobile charger scheduling, magnetic resonance coupling

1. Introduction

Current applications of wireless sensor networks (WSNs) use tiny sensor motes that are powered by miniaturized on-board batteries with limited capacity. This scarceness in energy resources considerably constraints the network lifetime and makes energy efficiency a challenging objective to achieve. A plethora of energy conservation solutions have been proposed in the literature [1]. These solutions can only slow down the energy dissipation engendered by the network operations, but they are unable to guarantee their perpetual functioning. Energy harvesting solutions have been recognized as a sound alternative [2], where ambient energy such as solar, vibrational, wind energy, etc., is used to recharge the sensor nodes. However, the major drawback of these solutions is the high uncertainty associated with the harvested energy, which often shows an erratic behavior. For example; in solar harvesting systems, the energy output of the charger depends on the amount of solar radiations received at the panel, which varies with the time of the day and weather conditions. Research developments in wireless energy transfer technology opened up perspectives for more reliable and deterministic energy provision in WSNs. Kurs et al. [3] developed a new technique called magnetic resonant coupling that enables efficient and stable energy transfer between two devices through mid-range distances (e.g, 2 m). Furthermore, such wireless energy transfer is omnidirectional, i.e., it does not require a line of sight between the charging and receiving nodes. Recent research effort has been focusing on the concept of using a mobile charger that roves the network and charges the sensor motes wirelessly. In most existing solutions, the mobile charger is scheduled offline and deterministically, in order to carry out periodically the charging tour and visit every WSN node [4, 5, 6]. However, in many real-world applications the energy consumption of sensor nodes is highly dynamic. Consequently, offline solutions may lead to unnecessary visits of energy-rich nodes. This will not only result in a higher energy consumption of the mobile charger due to useless displacements, but it also causes high waiting times for those nodes with critical energy levels and possibly results in their exhaustion. Considering this shortcoming, some recent works proposed the use of on-demand approaches allowing the charger to serve requesting nodes only [7, 8, 9]. However, all the proposed approaches in this category are limited to charge a single node at a time. This may induce low performance of the mobile charger and make the approaches hard to scale up. Interestingly, Kurs et al. [10] proved that by properly tuning the magnetic resonance coupling, it is possible to perform a wireless energy transfer to *multiple* receivers simultaneously. Moreover, it has been empirically demonstrated that the overall output efficiency of charging multiple devices was better than that of charging each device individually.

Inspired by these new findings, we propose a novel *on-demand* wireless charging scheme for WSNs that considers the following challenges: i) avoiding node failure by ensuring a bounded charging delay for each requesting node, ii) optimizing the energy consumption of the mobile charger in terms of power transfer efficiency and traveling energy, iii) ensuring the scalability of the charging scheme with a high number of requesting nodes.

To address these challenges, we explore the use of *simultaneous multi-node charging* in on-demand scenarios. We use a simple but efficient scheduling of the charging operation via *threshold-dependent request grouping*. In addition, we propose a path planning strategy based on minimizing the stopping points in the charging tour.

The main contributions of our work are as follows:

- While simultaneous energy transfer has largely been used in off-line solutions, no on-demand approach uses it thus far. The present work investigates the use of simultaneous energy transfer in *on-demand* wireless charging. This has the advantage of improving the charging performance and assures higher scalability, as compared to charging based on one node at a time.

- We propose a novel on-demand charging solution that uses the concept of threshold-based tour launching (TTL). Contrary to existing schemes that focus on shortening the charging delays, we demonstrate that it is possible to delay the charging operation of requesting nodes to maximize the benefit from multi-node simultaneous charging without affecting the sensors' operations.

- To show that the proposed approach does not impact the sensor operations, we defined a new metric called cumulated failure time. We show that the latter is more relevant than the charging delay metric that is traditionally adopted by existing solutions.

- At the tour planning level of the proposed strategy, a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes, with the aim of maximizing the number of nodes that are charged at each stop. Giving the NP-hardness of the problem formulation, we approximate it to a clique partitioning problem, and a simple heuristic is proposed. The resulting charging algorithm is shown to have a cubic time complexity in the number of nodes, with a good approximation ratio.

- The proposed mechanisms are evaluated in offline and on-demand scenarios. First, and to illustrate the performance of the path planning strategy in terms of energy consumption in the presence of a high number of nodes, the strategy is compared to a recently proposed offline solution that is also based on multi-node simultaneous energy transfer. Afterwards, the whole solution including the threshold-based launching is evaluated in an on-demand scenario against NJNP [9].

The remainder is organized as follows. Sec. 2 summarizes the related work. Sec. 3 presents some general concepts and gives the problem statement. Sec. 4 introduces the proposed solution, while Sec. 5 and Sec. 6 describe each of its building blocks. Sec 7 analyses the computation complexity of the proposed algorithm, as well as the approximation ratio of the enclosed heuristics. Sec. 8 presents a thorough simulation study, evaluating the proposed techniques against state-of-the-art solutions. Sec. 9 concludes the paper.

2. Related Work

A rich body of work on wireless energy transfer using a mobile charger has appeared in the last few years. Li et al. [11] proposed a joint routing and charging scheme to prolong the WSN lifetime. Their key idea is to design a routing protocol that actively coordinates with the mobile charger to fully exploit the potential benefits of the adopted recharging strategy. Shu et al. [12] focus on minimizing communication delays in RFID-based wireless rechargeable sensor networks. To this end, they propose to optimally plan the path of the RFID reader. Depending on the assumed movement pattern of the latter, they propose an optimal solution for linear movement and a heuristic for a generic two-dimensional movement. The authors of [13] investigate the feasibility of bundling the wireless charger and the base station into a single mobile entity that collects data and charges sensor nodes at the same time. Hence, they present a model that jointly optimizes charging schedule and flow routing. These works depend on the routing and data collection operations, contrary to the solution that we propose here.

To our knowledge, Xi et al. [4] were the first to investigate the use of simultaneous multi-node wireless charging technology in WSNs. The proposed approach relies on a fixed charging path formed by a set of stopping points. The latter represents the centers of hexagonal cells that partition the deployment field. The solution's goal is to minimize the energy consumption of the mobile charger by optimizing the stop durations at each cell center. In [14], the authors identify optimal velocity control of the mobile charger as a key design objective and propose a near optimal solution. Fu et al. [15] proposed a new charging strategy that optimizes the overall charging delay using similar charging technology. However, all the existing solutions that employ simultaneous multi-node charging are based on a static offline scheduling, and the charging operation is performed periodically over the entire network. This makes such solutions unpractical in most WSN applications where the operating circumstances are highly dynamic and unpredictable. In fact, a mobile charger that adopts offline scheduling tends to make unnecessary visits to some nodes with a sufficient energy level. This considerably degrades the charger's efficiency in terms of energy consumption and induces additional delays in serving the energy-hungry nodes, thus leading to the exhaustion of their batteries.

In an attempt to deal with the limitations of offline approaches, some research efforts proposed the use of on-demand wireless charging. For example, Jiang et al. [16] provide an on-demand strategy that serves the requesting nodes while maximizing the network covering utility. This metric is defined to reflect the WSN effectiveness in terms of event monitoring. In [17], the notion of energy synchronization is proposed in an attempt to jointly optimize charging delays and traveling energy. The work in [9] is a prominent effort in the area of on-demand wireless charging. The authors provide an analytical study of on-demand mobile charging under the discipline of *"Nearest Job Next with Preemption"*. Also, best practices are suggested to implement NJNP-based wireless charging in real-world scenarios. Our approach departs from existing on-demand charging solutions in three respects: i) it allows simultaneous multi-node charging with the objective to achieve better performance, especially in large-scale networks, ii) it takes into account a new performance metric (average nodes failure time) instead of the charging delay, which better reflects the efficiency of on-demand charging strategies in real-world deployments. iii) it adopts an online path planning mechanism that optimizes both power transfer efficiency and traveling energy.

3. Preliminaries

3.1. Wireless Power Transfer Technologies for WSNs

The concept of Energy harvesting through wireless power transfer (WPT) is not new [18]. Nevertheless, its application remained unsuccessful until the early nineties, when different WPT technologies were proposed with the emergence of consumer electronics and electrical vehicles. WPT technologies can be classified as follows [19]:

- **Inductive coupling:** it is based on magnetic field induction that generates a voltage when hitting the charged device circuit. Due to its simplicity and safety, this technology is approved by the Wireless Power Consortium, and commercialized in a large variety of products. However, the major drawback of inductive coupling resides in its poor efficiency for energy transfer even for short distances, which requires the charger and the receiver to be in contact. This makes it impractical for use in WSNs.

- **Electromagnetic (EM) radiation:** it uses electromagnetic waves as a medium for energy transfer. Most technologies of this category rely on 915 MHz ISM bands which suffer from low energy transfer capability, like in the *PowerCast* solution [20]. Moreover, potential health hazard to humans from EM radiations restricts the use of this technique on ultra low-power sensor nodes that can function under 10 mW, e.g., [21].

- **Magnetic resonant coupling:** similarly to inductive coupling, magnetic resonant coupling relies on the magnetic field for power transfer. Its principle consists in making a couple of coils (at the sender and the receiver) operate at the same resonance frequency for strong coupling via magnetic resonance induction. This technology was developed by Kurs et al. [3], and experiments demonstrated the possibility to power a 60 W device from a distance of 2 m with an energy transfer efficiency of 40%. Furthermore, the authors proposed an enhancement allowing simultaneous power transfer to multiples devices [10]. They showed that proper tuning of the coupled resonators enables a better power transfer efficiency than for a single charged device. Therefore, this technique allowed a significant performance enhancement over the previously mentioned technologies in terms of received power and charging distance. This opens up new possibilities for wireless charging in WSNs, especially in applications that require medium or high deployment density such as WSNs for military/border surveillance, or smart cities [22].

Giving the usefulness of magnetic resonant coupling for those WSN applications, as well as its scalability enabled by multiple simultaneous charging, we decide to use this technology in this paper. Nevertheless, we underline that the proposed model and solutions are not exclusively related to magnetic resonant coupling, but apply to all charging technologies where the mobile charger can perform simultaneous wireless charging of multiple nodes. For the current technology, multiple simultaneous charging with magnetic resonant coupling is only efficient in applications of medium to high deployment density (i.e., short distances between the charger and the nodes), but not in applications with sparse deployment such as [23]. However, abstracting from the limitations of present charging technology, our solution can take advantage from any future technology that may offer better efficiency of multi-node charging over longer distances. This will extend the application range of our charging strategy to low-density WSNs as well. In the rest of the paper, the employed charging technique is referred to as Multi-node Wireless Charging (MWC).

3.2. Problem Statement

We consider a network with a mobile charger (MC) and a set of static sensor nodes that are randomly scattered over a two-dimensional deployment area. Each sensor is equipped with an onboard battery of limited capacity. Nodes send out charging requests to the MC when their energy level falls below a certain threshold. Dealing with routing request is out of the scope of this work, but similarly to data, the necessary communication scheme for this operation can be performed using state-of-the-art routing protocols for mobile destination [24]. Furthermore, the time needed for request delivery is assumed to be negligible compared to the MC's travel and charging time. The MC maintains a service queue to store the received charging requests that are served according to the adopted on-demand charging strategy. Here, by *serving* a request we mean that the charger travels to the requesting node and replenishes its energy supply. As emphasized earlier, we assume the use of MWC technology for power transfer between the MC and the visited nodes. This means that the MC has the ability to simultaneously charge several nodes if more than one requesting nodes is located within its charging radius.

Contrary to offline approaches, where the charging operation is triggered periodically taking into account every node in the network, on-demand charging exhibits highly dynamic properties in both the *temporal* dimension, i.e., the arrival time of a new charging request, and in the *spatial* one, i.e., the location of requesting nodes. These yield additional design challenges compared to offline approaches that mainly focus on optimizing the path of the charging tour. In fact, the design process of on-demand mobile charging must consider the following challenges to guarantee efficiency for the requesting nodes and the mobile charger:

- **Bounded charging delays**: for requesting nodes, charging delays measure the time from when these send out their charging requests to when their energy supply is replenished. An efficient charging strategy ensures that each requesting node can be served within a limited charging delay, so as to prevent its battery exhaustion. It is worth mentioning that, contrary to all existing on-demand solutions, the one proposed herein does not target the minimization of the charging delay. Instead, its objective is to keep the delay sufficiently low in order to mitigate node's failures due to battery depletion. Our new approach to deal with the energy delay metric is further detailed in Sec. 4.

- **Optimized MC's energy consumption**: from the mobile charger perspective, achieving an efficient charging scheme requires optimization in its energy consumption. This includes the energy spent to recharge the requesting nodes (*charging energy*), in addition to the *traveling energy* necessary to visit those nodes. As shown in Sec. 5, optimizing the MC's energy consumption can positively or negatively influence the charging delay of the requesting nodes, depending on the employed technique. Hence, it is vitally important to consider this challenge in the early design stages of the on-demand charging strategy. Yet, existing solutions either neglect it to the detriment of other utility metrics [9, 16], or consider it as a secondary objective that amounts to reducing the traveling energy by minimizing the length of the charger's path.

- **Scalability**: Most WSN applications envisage a large-scale deployment over a widely-extended area with high number of nodes. A viable charging process must ensure scalable performance when used in such application scenarios, especially when the requesting load becomes heavy. One trivial solution to enhance scalability in on-demand wireless charging is to rely on cooperation of multiple mobile chargers, similarly to [25]. However, the scalability objective becomes more challenging with the use of a single charger.

4. Solution Overview

We propose a new on-demand charging scheme that aims at improving the scalability by relying on MWC for power transfer, which is scalable and enables the simultaneous charging of multiple nodes. Nevertheless, the high dynamics exhibited by requesting nodes in terms of locations and request time make it less probable for the mobile charger to find a subset of requesting nodes that are close enough to be charged simultaneously. This complicates the use of MWC in on-demand scenarios. The objective is to explore the available design choices that better integrate MWC into an on-demand charging strategy, and to maximize its benefit. The employed techniques must also optimize the MC's traveling and charging energy consumption, without neglecting the solution performance in terms of bounded charging delays.

From the perspective of requesting nodes, we think the efficiency of an on-demand charging strategy is *not necessarily achieved by minimizing the charging delay*. A more flexible definition of this efficiency is *the prevention node's failures by serving requesting nodes before their battery depletion*. Hence, the time available for the mobile charger to serve a given requesting node is equivalent to the period between request issuing and battery exhaustion. This period depends on the requesting node's energy consumption and becomes longer if this node experiences low communication and sensing loads after issuing the request. Previous on-demand charging solutions do not take into account this variance in terms of charging delay requirement and tend to minimize it for every requesting node. Although this may help prevent battery exhaustion for energy-hungry nodes, it imposes unnecessary constraints on the mobile charger strategy for serving other nodes that can tolerate a longer charging delay. The consideration of such unnecessary constraints may foster the use of some greedy charging approaches that negatively influence other performance metrics such as the MC's traveling and charging energy.

The objective of charging delay optimization is relaxed in our approach to maximizing the benefit from MWC power transfer, subject to preventing nodes' batteries depletions. Hence, the MC is no longer constrained to start the charging process immediately upon receiving the first request. Instead, the MC waits and keeps on collecting additional requests for a period that ends when a predefined threshold is reached. This waiting period is intended to enable the collection of the maximum number of requests, which allows for a more efficacious simultaneous multi-node power transfer during the charging tour. Driven by these considerations, we build the charging strategy on charging tours that are triggered based on a waiting threshold. The choice of this threshold and its impact on the solution's performance is discussed in Sec. 5. Each time the waiting threshold is reached, the mobile charger proceeds to the second step, which consists in the so called *charging path planning*. In this step, the MC computes an optimized charging path represented by a set of stopping locations, along with their corresponding stop durations.

While a conventional on-demand strategy may choose, at each round, the next optimal charging position to serve one or a subset of the existing requests without the need for path planning, the MC in the proposed approach considers all requests received before starting the charging tour. Moreover, charging is performed without preemption, i.e., any request that may arrive during the charging tour will not be served until the next round. This is for the sake of fairness and to avoid penalizing some waiting nodes upon the reception of new requests that better meet optimal criteria. These facts justify the need for an online path planning mechanism that seeks to optimize the charging of the requesting nodes within each round, while adapting to the dynamic nature of the charging requests.

The planned path is intended to ensure the MC ability to serve all requesting nodes before their battery depletion. In addition, it must optimize the energy expenditure related to charger movement and charging energy. To this purpose, we propose a design that takes benefit from MWC power transfer through computing a charging path with the *minimum number of stopping points*. The advantage of minimizing of the number of stop locations in the charging path is twofold. First, it allows maximizing the number of nodes that are simultaneously charged at each stop. This reduces the overall amount of energy spent by the mobile charger to charge all the requesting nodes. Second, it helps reduce the length of the charging path, as well as the energy and time needed to stop and resume movement. This contributes to limiting the delays consumed by the mobile charger to serve the requesting nodes, and reduces the energy expenditure associated with the MC mobility.

Once the charging path is calculated, the MC starts visiting requesting nodes and charging their energy supplies, following the computed schedule. Meanwhile, It continues receiving possible charging requests from other nodes in the network. Upon finishing the current tour, the mobile charger begins a new charging round if its queue contains new requests with at least one being below the waiting threshold.

5. Threshold-based Tour Launching (TTL)

As emphasized earlier, the proposed charging solution seeks to collect as many requests as possible, so as to group them in the upcoming charging tour. For this, the mobile charger needs a mechanism to decide about the time to launch a new charging tour. The choice of a suitable time for tour launching represents an important design challenge that considerably affects the solution performance in terms of charging delays and energy consumption. If the charging tours are carried out frequently, the service delay experienced by the requesting nodes is reduced. However, a low number of nodes would be served in each tour and this reduces the possibility for the MC to find subsets of requesting nodes that can be charged simultaneously via MWC. As a result, the mobile charger efficiency in terms of traveling and charging energy consumption is expected to be rather low. On the other hand, prolonging the waiting time, so as to serve a higher number of nodes in each charging tour, leads to a higher energy consumption efficiency due to simultaneous charging and traveling path optimization, but it increases the service delay, which may result in node's failures due to battery exhaustion. Thus, the decision mechanism by which the MC chooses the launching time of subsequent charging tours needs to balance the energy consumed by the MC and the time spent to charge requesting nodes.

A simple but efficient strategy for such decision mechanism is to rely on a characteristic value that may reflect the state of requesting nodes or that of the mobile charger's queue. A new charging tour is launched when this value reaches a predefined threshold. Depending on the application requirements, the threshold definition can be either fixed or adaptive. For example, one could use the MC's waiting time since the reception of the first request as a tour launching metric. In this case, the MC may launch a new tour when this time reaches a given threshold value, say T. However, the use of a fixed temporal threshold is not convenient in dynamic WSNs, where the generation of charging requests varies considerably with time and location. In fact, whenever the time threshold is exceeded, the MC may undertake a new charging tour even for a single requesting node. This may lead to an unsatisfactory performance in terms of energy consumption and traveling path planning.

To cope with this, our solution relies on an adaptive threshold that allows the mobile charger to monitor the energy level of the requesting nodes battery. The mechanism uses two energy thresholds, L_c and L_r with $L_c < L_r$ and the following procedure applies to each WSN node. When the energy level of any of the nodes falls below L_r, this node sends a *request* message to the MC. When the battery level decreases below the second threshold L_c, the node then issues an ALERT message, indicating that it has reached a critical battery condition. The MC keeps collecting requests and starts a new charging tour as soon as it receives the first ALERT message, at which point all the nodes that have issued a request are served (charged) by the MC using path planning and multi-node charging for each stop location. The use of these two thresholds allows the mobile charger to prolong the request collection phase in an attempt to maximize the benefit of MWC power transfer, without neglecting the time needed to serve requesting nodes before their battery depletion. Hence, scheduling charging tours based on battery criticality threshold will help the MC to adapt its charging strategy to the varying rates of charging requests. This tends to reduce energy consumption, while preventing node's failures due to long charging delays.

6. Minimum-Stop Path Planning

The path planning phase is executed each time the mobile charger decides to launch a new charging tour.

Its objective is to schedule a charging strategy that allows the MC to recharge the set of nodes from which a request was received before tour launching. Specifically, the goal is to find optimal stop locations and the corresponding stop durations that minimize the total energy consumed by the mobile charger. The energy optimization technique must take into account the objective of preserving a bounded charging delay in order to prevent node's failures due to battery depletion. For this purpose, we formulate the path planning calculation as a minimum stop planning (MSP) problem that computes a charging path allowing to recharge requesting nodes with a minimum number of stops. As emphasized earlier, minimizing the number of stops is expected to maximize the number of nodes that are charged simultaneously using MWC power transfer. This allows decreasing the energy consumed in power transfer. Furthermore, planning a charging path with a reduced number of stops helps decrease the distance traveled by the mobile charger, which also reduces the traveling energy and limits the charging delays.

6.1. Problem Formulation

The MSP problem is formulated as follows. Let $\mathcal{N}$ be the set of n requesting nodes from which a charging request was received by the MC at the time when a decision is made to launch a new charging tour., i.e., $|\mathcal{N}| = n$. Each node, i, has a *power reception disk*, D_i. The latter is defined as the set of possible locations where a mobile charger can stop by and charge the node. D_i is centered at the node i position with a radius equal to the maximum energy transfer distance of the mobile charger, denoted by, r_c. We consider all potential stop regions, R_j, from where the mobile charger can simultaneously charge a different set of nodes. To clarify the concept of stop regions, let us consider the example in Fig. 1 that illustrates a scenario of three nodes represented by their respective power reception disks. Depending on the location of each node, its power reception disk may (or may not) intersect with other node's power reception disks. For example, the power reception disks of nodes 1 and 2 intersect, thus the resulting stop regions for these nodes are R_1,R_2 and R_3. R_1 and R_3 are the regions from where the mobile charger can charge either node 1 or 2, while R_2 is the region where both nodes can be charged simultaneously. For node 3, only one region R_4 can be defined and it is equivalent to its power reception disk. This is because the latter does not intersect with any other region in the network. Generally speaking, each region R_j is either resulting from the intersection of several node's power reception disks, or equals an entire node's power reception disk if this latter does not intersect with any other region. In our model, each geometric region R_j is associated with the set of nodes that can be charged from that region, say, $\mathcal{N}_j$. This is defined as,

$$\mathcal{N}_j = \bigcup_{i=1}^{n} \{i | R_j \cap D_i \neq \emptyset\}. \tag{1}$$

Obviously, the union of all regions' representative sets $\mathcal{N}_j$ is equal to the set of nodes in the network, i.e., $\mathcal{N} = \bigcup_{j=1}^{m} \mathcal{N}_j$, where m is the number of regions.

Since the number of nodes that can be charged from a given region, R_j, is unrelated to the *MC* position (provided it is inside the region), the region's centroid (s_j) is chosen to be the stop location of the mobile charger when R_j belongs to the charging path. For the ease of presentation, the terms stop region and stop location are used interchangeably.

Given the calculated sets $\mathcal{N}_j$, $j \in 1, \cdots, m$, of possible stop regions, we define an $n \times m$ matrix, $A = [a_{ij}]$, as follows:

$$a_{ij} = \begin{cases} 1 & \text{if node } i \in \mathcal{N}_j \\ 0 & \text{otherwise .} \end{cases} \tag{2}$$

Minimizing the number of stop locations that allows to recharge the n requesting nodes is equivalent to solving the following optimization problem:

$$\begin{aligned} \min \quad & \sum_{j=1}^{m} x_j \\ \text{subject to} \quad & \sum_{j=1}^{m} a_{ij} x_j \geq 1 \qquad \forall i \in \{1, \cdots, n\} \\ & x_j \in \{0, 1\}, \end{aligned} \tag{3}$$

where x_j is a binary decision variable that is equal to 1 if region R_j belongs to the minimum stop path, and to 0 otherwise. Also, the n inequality constraints ensures that every node must belong to at least one stop region in the minimum stop path. (3) is a Binary Integer Linear Programming (BILP) problem, which is known to be NP-hard. In the next section, this problem is solved through a simple heuristic allowing to find a charging path with a small number of stop locations.

6.2. MSP algorithm for Path Planning

Finding the optimal solution by solving the BILP defined in (3) is NP-hard, and thus it cannot be achieved with an acceptable computing time for a high number

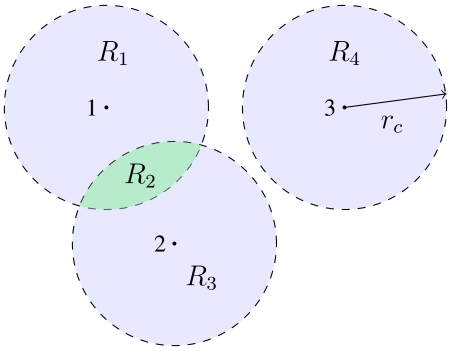

Figure 1: Illustrative example of stop regions.

of requesting nodes. In on-demand charging scenarios, the mobile charger needs to perform the path planning phase frequently and cannot afford costly and complex computations. To deal with this problem, we propose a Minimum Stop Planning (MSP) algorithm. The objective is to compute a charging path with a small number of stop locations, using low complexity mechanisms that scale well with an increasing number of requesting nodes.

The main idea is to transform the MSP problem into a clique partitioning problem, and to take advantage of a simple but efficient heuristic to find a reduced number of stop locations in the charging path. The problem is reformulated as follows. Let $G(V, E)$ be the undirected graph where each node in the network is represented by a vertex in the set V. An edge between two vertices is activated iff the power reception disks of the corresponding nodes intersect. The clique partition problem applied to $G(V, E)$ consists in finding the minimal number of cliques that partition the graph, where each clique represents a subset of V such that every two vertices in this subset are connected by an edge. Although also this clique partitioning is NP-hard, in the literature there exist several heuristics that achieve a near-optimal result in polynomial time. In the proposed algorithm, we use the popular heuristic proposed by Tseng et al. in [26] (see Appendix A).

The intuition behind partitioning graph G into a number of cliques is that when a set of nodes forms a clique, it is highly probable that a single intersection region exists between their power reception disks. Thus, the algorithm considers this region as stop region from where the mobile charger can charge all the nodes in the clique. As a result, finding a minimum number of stop locations where the mobile charger can stop and charge all requesting nodes is equivalent to computing a minimum number of cliques. However, it is possible that a set of nodes form a clique but their power reception disks do

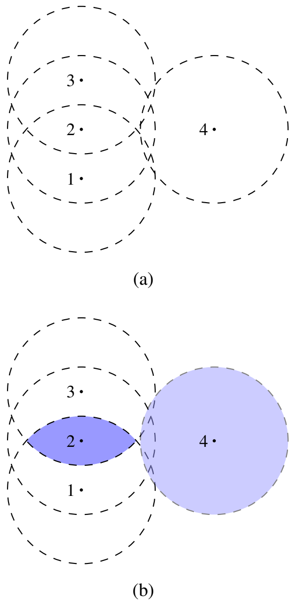

Figure 2: An example of a 4-nodes clique. (a) No common intersection region exist for all nodes. (b) Two stop regions are identified after isolating node 4.

not intersect in a single common region. Fig. 2(a) illustrates an example of four nodes represented by their power reception disks. Following the proposed model, these nodes form a clique, but no common intersection region exist between their power reception disks. When such a special case is met, MSP proceeds iteratively to find a minimal set of stop regions from which the nodes of this clique can be charged. It starts by isolating a single node from the clique and checks if the resulting new clique has a common intersection region. If this is the case, the algorithm considers two stop regions; namely, the intersection region of the new clique and the power reception disk of the isolated node. Otherwise, if no common intersection is found in the new clique, the algorithm proceeds to the next iteration by isolating a higher number of nodes. Fig. 2(b) shows that by isolating node 4 from the clique, a common intersection region can be found for the remaining nodes (dark blue region on the left). The algorithm considers, for this case, two stop regions (colored regions).

The minimum stop path produced by the algorithm is defined by the set Π, that includes all stop regions related to each clique of the graph G. Upon obtaining Π, the MSP algorithm computes the best path allowing the MC to travel around the calculated stop positions in order to charge all nodes. For this, we apply a Polynomial Time Approximation Scheme (PTAS) for the Traveling Salesman Problem (TSP) on the set Π. The aim is to obtain a minimum-length charging path that includes all the calculated stop positions.

Finally, the last step of the MSP algorithm consists in calculating the stop durations so that the MC can fully charge the nodes within each stop region. This duration, which is calculated upon the MC arrival to each stop location, depends on the nodes' battery levels and on the distance of these nodes from the stop location. It is calculated as follows.

Let s_j be one of the stop locations in the calculated charging path. The MC simultaneously charges all the nodes that are reached by its charging radius. The received power $p_i(s_j)$ by a sensor node i located at a distance $d_{i,j}$ from this stopping point is:

$$p_i(s_j) = \mu(d_{i,j}) p_t, \tag{4}$$

where p_t denotes MC's transmission power for wireless recharging, and $\mu(d_{i,j})$ reflects the efficiency of the wireless energy transfer operation using MWC. The value of this efficiency is always smaller than 1 and polynomially decreases with the distance separating the charging node and the mobile charger [10]. To fully charge a node battery of capacity σ_i, the received power at this node needs to be accumulated during a charging time, $t_i(s_j)$, such that:[1]

$$t_i(s_j) = \frac{\sigma_i}{p_i(s_j)}. \tag{5}$$

Since the mobile charger needs to charge all the nodes covered by the current stop point before moving to the next one, the stop duration, $t(s_j)$, of the mobile charger is:

$$t(s_j) = \max_{i \in \mathcal{N}_j} (t_i(s_j)). \tag{6}$$

Algorithm 1 summarizes the main steps of the proposed On-demand Multi-node Charging (OMC) scheme including the the collection of charging requests, threshold-based tour launching (TTL), and minimum stop path planning (MSP).

7. OMC Algorithm Analysis

In the following, we analyze the computation complexity of the OMC algorithm and demonstrate that it runs in polynomial time with respect to the number of

Algorithm 1 On-demand Multi-node Charging (OMC).

1: threshold = FALSE
2: **while** NOT threshold **do**
3: Receive msg from nodes in set $\mathcal{N} = \{i(x_i, y_i)\}, i = \{1, .., n\}$
4: **if** msg == ALERT **then**
5: threshold = TRUE
6: **else**
7: Add msg to queue
8: **end if**
9: **end while**
10: $\mathcal{D} = \emptyset$
11: **for** $i = 1$ to `length`(queue) **do**
12: Compute D_i of node $i(x_i, y_i)$
13: $\mathcal{D} = \mathcal{D} \cup D_i$
14: **end for**
15: Calculate graph $G(V, E)$ given $\mathcal{D}$
16: Find minimum number λ of cliques in G(V,E) using the heuristic of Tseng et al in appendix
17: $\Pi = \emptyset$
18: **for** every clique $C_j, j = 1$ to λ **do**
19: Find the set $\mathcal{S}_j$ of k stop regions using iterative routine, $k \geq 1$
20: $\Pi = \Pi \cup \mathcal{S}_j$
21: **end for**
22: $\Pi' =$ ordered set by applying TSP PTAS on Π
23: **for** each s in Π' **do**
24: Go to s
25: Calculate the stop duration $t(s)$ using Eqs. (4)-(6)
26: Charge neighboring nodes for $t(s)$ seconds
27: **end for**

requesting nodes. In addition, we show through simulation experiments that the used heuristics for clique partitioning makes it possible to deal with the NP-hardness of the optimal BILP solution, while keeping the number of stop locations close to the minimum.

7.1. Computation Time complexity

To calculate the computation time complexity of OMC (Algorithm 1), we assume the worst case where the mobile charger receives the first ALERT message after all the nodes have sent a charging request. Thus, the number of requests received at the mobile charger will be equal to the total number of nodes n. In such situation, the MC starts by executing the first block (lines $1-9$) that consists in verifying wether the received request is an ALERT message or not. This implies a complexity of $\mathcal{O}(n)$. In the second step (lines $10-15$), the MC calculates the power reception disk for each requesting node and constructs the graph $G(V, E)$ based on the intersection of each disk with the others. Given n power reception disks, mutual intersection verifications can be done in $n(n-1)/2$ steps with a complexity of $\mathcal{O}(n^2)$.

Concerning the complexity of the clique partitioning heuristic (line 16), we also consider the worst case where the graph resulting from the second step is complete and contains $n(n-1)/2$ edges. The result of the heuristic will be then one clique. For this case, and following the steps detailed in the Appendix, the mobile charger starts by searching in $n(n-1)/2$ edges

[1] A linear model is assumed for the charging time, i.e., nonlinearities in the charging process are neglected in this study.

the one with the vertices having the maximum number of common neighbors. When found, the corresponding two vertices will be combined into one vertex, and the resulting graph will contain $n-1$ vertices and $(n-1)(n-2)/2$ edges. Following a similar rationale, the computations in the i^{th} iteration will entail a complexity of $(n-i+1)(n-i)/2$, which represents the number of edges in that iteration. Since the algorithm ends when the graph contains no edges (i.e., $i = n$), the total number of iterations is n. Consequently, the overall complexity of the clique partitioning heuristic is obtained by summing the computation complexity along the n iterations:

$$\sum_{i=1}^{n} \frac{(n-i+1)(n-i)}{2} = \mathcal{O}(n^3). \quad (7)$$

The forth step (lines $17-21$) is only executed if the resulting clique, which in our case has n vertices, does not have a common intersection region for all the nodes' reception disks. In this case, the routine starts searching for two stop regions instead of one, by choosing one node and isolating it. This will take a maximum of n iterations. If the two stop regions are not found, the MC iteratively chooses two nodes and isolates them, and so on. The heuristic terminates when finding two intersecting regions or by isolating $n-1$ nodes in one iteration. Hence, the maximum number of computations for this step is $\mathcal{O}(n^2)$. Finally, once the stopping regions are obtained, a quasilinear heuristic for Euclidean TSP in $\mathbb{R}^2$ is used to compute the shortest path that covers all the stop regions. It has been shown in [27] that such a scheme has a complexity of $\mathcal{O}(n(\log(n))^{\mathcal{O}(c)})$ with an approximation ratio of $1+1/c$. In our algorithm, we set $c = 2$.

As a result, we conclude that the computing time complexity of OMC is dominated by the clique partitioning heuristic, which leads to a polynomial time complexity of $\mathcal{O}(n^3)$ for the whole algorithm.

7.2. *Clique Partitioning Heuristic: Approximation Ratio*

The polynomial time complexity of our charging algorithm has been essentially achieved by using a clique partitioning heuristic that allows overcoming the NP-hardness when calculating the minimum number of stop locations within a BILP formulation. In order to show that the enhancement in the computation complexity preserves a good approximation ratio to the optimal number of stop locations, we performed simulation experiments to compare, for different numbers of requesting nodes, the number of stop locations found by an optimal BILP solver and by the adopted clique partitioning heuristic. As shown in Fig. 3, the ratio between the heuristic and the optimal solutions remains within the interval $[1.33, 1.38]$. For example, with $1,000$ requesting nodes, the optimal number of stop locations is 173, while the clique partitioning heuristic resulted in 238 stops, i.e., in an approximation ratio of 1.37.

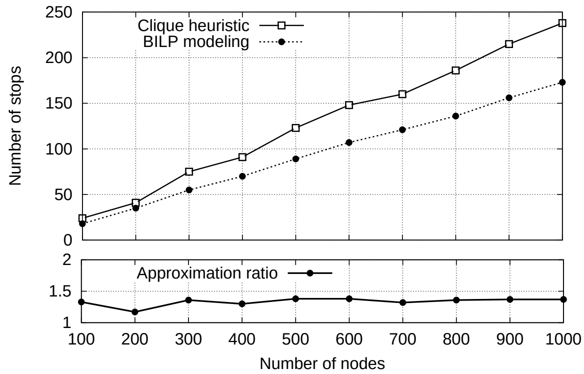

Figure 3: Approximation of clique partition heuristic.

8. Performance Evaluation

The performance evaluation is conducted in two stages. First, the proposed strategy is simulated in offline scenarios, where each experiment considers a fixed number of requesting nodes for which a charging tour is planned and executed. The objective is to evaluate the effectiveness of minimum stop planning (MSP) neglecting the dynamics of charging request arrivals. In the second stage, the entire OMC scheme (including TTL) is evaluated in on-demand scenarios, and its performance is compared to a popular solution from the literature.

8.1. *Performance of MSP in Offline Scenarios*

Offline mobile charger scheduling has been largely dealt with in the literature, and many solutions based on MWC have been proposed. However, some of them, due to their assumptions such as static flow routing and nodes' fixed transmission rates, are limited to a specific application context [4]. The most related and recent work that can be compared to our solution in an offline scenario is the one by Fu et al. [6], which we call hereafter Minimum Charging Time (MCT). Similarly to our approach, MCT employs multi-node simultaneous charging and aims at optimizing the charging path (stopping locations) without prior assumptions on the network operations.

8.1.1. Simulation Settings

In offline scenarios, the mobile charger considers a fixed number of nodes that need to be charged periodically. Hence, the performance in such case is unrelated to the MC strategy for tour launching and solely depends on the effectiveness of the path planning strategy in terms of charging and traveling energy drained by the MC.

To evaluate the performance of the proposed minimum stop planning (MSP) algorithm, a set of nodes with different battery capacities ($\sigma_i \in [25, 50]$ J) is considered. The energy consumed in charging operations is computed using the experimental measurements on the efficiency of simultaneous wireless energy transfer [10]. By undertaking a curve fitting on these experiment results, the equation that computes the energy efficiency transfer $\mu(d)$ as a function of the distance between the mobile charger and charged node is: $\mu(d) = -0.0958d^2 - 0.0377d + 1.0$. Assuming $p_t = 5$ W (MC transmission power), and a minimum received power threshold allowing a sensor node to be charged of $p_{\min} = 1$ W. The maximum charging range for the mobile charger following the previous equation would be, $r_c = 2.7$ m. Furthermore, to reflect mobility in a realistic environment, the motion characteristics of the Pioneer 3DX robot are considered for the mobile charger MC [28]. Hence, to travel from a charging point to another, the MC increases its traveling speed with an acceleration of $a = 0.3$ m/s^2. If the maximum velocity $v_{\max} = 2$ m/s is reached, the MC keeps traveling with this constant speed before decelerating to stop at the destination. To measure the energy consumed by the MC for traveling along the charging path, we use the study presented in [29] on the Pioneer 3DX robot. There, it has been experimentally shown that the traveling power consumption varies linearly with the robot speed following the equation: $p_{\text{travel}} = 7.4v + 0.29$. Finally, in the following graphs, 95% confidence intervals are shown as vertical lines around the plotted average points.

8.1.2. Results for Low and Medium Scale Networks

In the following, the performance of MSP is compared against MCT [6] by varying the network size from 10 to 100 nodes. For each simulation scenario, the nodes are randomly deployed within a square area of 25×25 m^2.
Fig. 4 shows the number of stop locations on the charging paths for MSP and MCT. As shown, the number of stop locations with MSP increases very slowly with the number of nodes. It remains low compared to the number of charged nodes in the network (25 stops for 100 nodes). In contrast, the number of stops in MCT increases linearly but much faster than MSP and reaches high values for higher number of charged nodes. In fact, since MCT only focuses on optimizing the charging energy, the mobile charger tends to visit each node individually to perform the charging operations from shorter distances. This explains the high number of stops in MCT. In MSP, minimizing the number of stop points makes it possible to optimize the charging energy, but in a different way. In fact, rather than minimizing the charging energy by enhancing the efficiency of energy transfer, MSP tends to maximize the number of nodes that can be charged simultaneously in order to reap the full benefits of simultaneous multi-node charging technology. This is shown in Fig. 5, where MSP is shown to consume more energy for charging the nodes, but the measured values stay relatively close to MCT that consumes a near-optimal charging energy, as demonstrated in [6]. Moreover, the plots show a similar rise shape for an increasing number of nodes, and it is worth noting that the difference between MCT and MSP in this figure is smaller than that in the previous one.

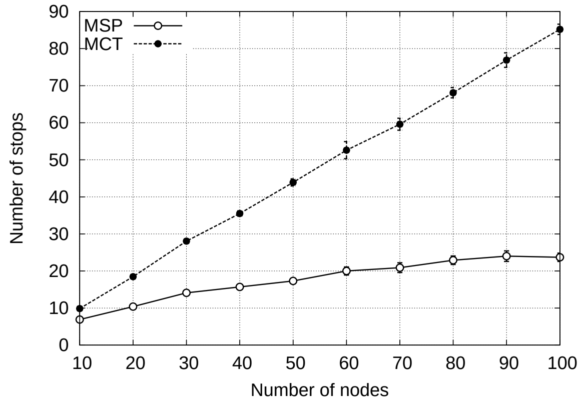

Figure 4: Number of stop locations *vs* network size.

From Fig 6, we see that MSP considerably reduces the traveling energy *vs* MCT. This is due to the low number of stops of MSP, which helps reduce the length of charging paths and, in turn, the energy expenditure for traveling. Also, minimizing the number of nodes in the charging path optimizes the motion of the MC, which then drains less energy (note that a higher number of stops entails a higher energy consumption for the MC due to repeated accelerations and decelerations, and high dynamics in traveling speed).

Fig. 7 illustrates the total energy consumed by the mobile charger for both charging nodes and traveling around the path. We remark that for a relatively low number of nodes ($n \leq 20$), the two schemes con-

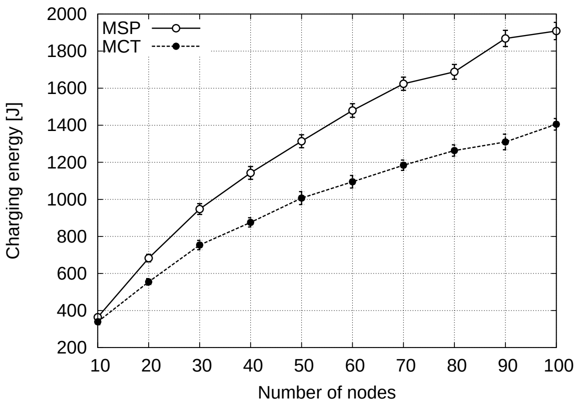

Figure 5: Charging energy *vs* network size.

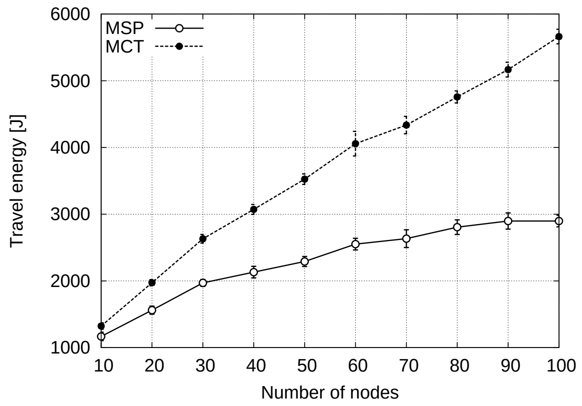

Figure 6: Travel energy *vs* network size.

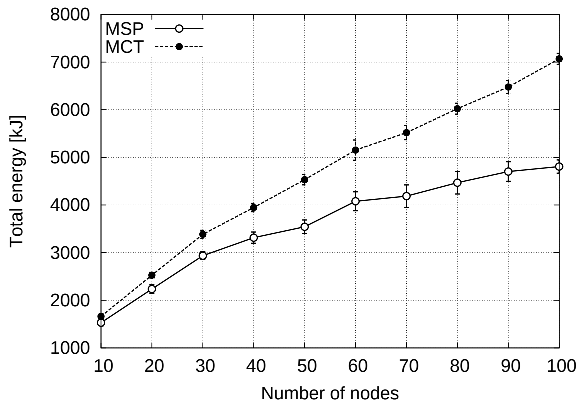

Figure 7: Total energy *vs* network size.

sume almost the same amount of energy. However, this amount becomes higher as the number of nodes increases. This is explained by the fact that the optimization on charging energy in MCT cannot compensate for the high traveling energy expenditure due to charging a high number of nodes. Consequently, we conclude that for large-scale networks, and when using simultaneous multi-node recharging, the total energy expenditure of the mobile charger is more impacted by the traveling energy than by the charging one, and that our technique effectively tackles this fact.

The scalability of a wireless recharging scheme for an increasing number of nodes should not only be measured in terms of its energy efficiency. It is important to also consider the complexity entailed in the computation of charging path and stop durations. The entity responsible for these calculations in rechargeable WSNs is the MC. Although the latter is assumed to be more powerful in terms of computing and memory capacity compared to the sensor nodes, the computing overhead of the charging path and stop durations needs to remain acceptable to make the solution practical. In Fig. 8, the time to compute the charging path and stop durations is shown. The experiments are performed on a desktop computer with an Intel Core i3 CPU and 4 GB of RAM, running Windows8. As it can be noted, MCT is very demanding in terms of computing time. For example, calculating the charging path for 100 nodes takes longer than $7,000$ s, while the MSP calculation time did not exceed 10 s. This considerable gap is due to the difference in the two approaches to compute the charging path. MCT solves a linear programming optimization problem where the number of variables increases exponentially with the number of nodes. Instead, MSP uses a low-complexity heuristics that scales with the problem size.

8.1.3. Results for Large-Scale Networks

To better demonstrate the scalability of MSP in large-scale networks, we vary the number of charged nodes from 100 to $1,000$. The nodes are randomly deployed in a square area of 100×100 m^2. Due to the high complexity of MCT, we were unable to execute it within an acceptable computing time. As shown in Fig. 9, the total energy consumption of MSP increases smoothly as the number of charged nodes increases, which demonstrates the good scalability of our scheme in large-scale sensor networks.

8.2. Solution Performance in On-Demand Scenarios

8.2.1. Simulation Settings

Next, the performance of the entire OMC charging algorithm is studied in the context of on-demand charging scenarios. Each experiments considers a WSN with a different number of nodes that varies from 50 to 500. To emulate a sensible energy consumption model, we simulate an event-based sensing application where events are periodically generated and detected by a random

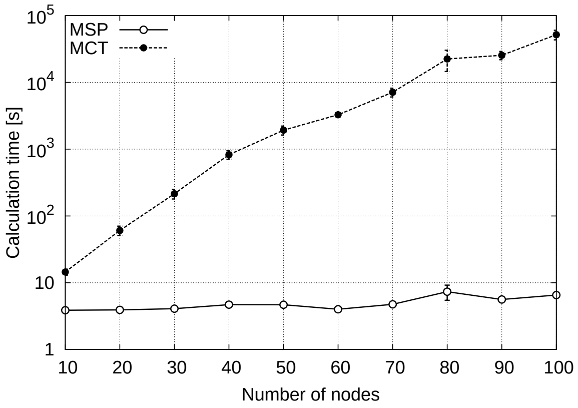

Figure 8: Computing time *vs* network size.

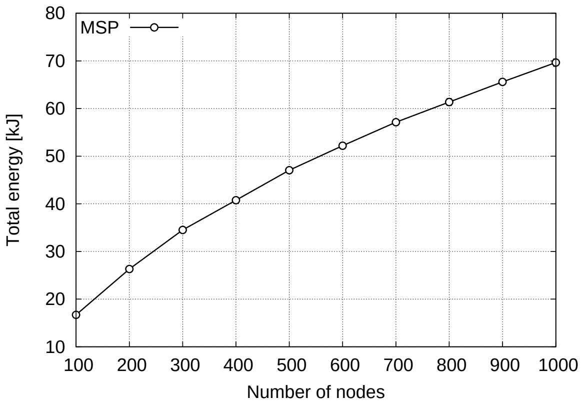

Figure 9: MSP performance in large scale networks.

subset of sensors. Energy is consumed as a result of communication and sensing operations. The number of nodes participating in the event detection and reporting is proportional to the total number of nodes in the WSN. This allows us to study the scalability of OMC with respect to a higher charging request load and an increasing network size. The energy consumption models for motion and energy consumption are the same as those considered in the offline scenario.

Since none of the existing on-demand charging solutions uses multi-node simultaneous power transfer, the proposed scheme is compared against a popular approach and our own variation of it. The two schemes are: i) Nearest Job Next with Preemption (NJNP) [9], ii) a modified version of NJNP, with added MWC capabilities (called MWC-NJNP). NJNP was shown to achieve near optimal charging delays using point to point wireless power transfer. It prioritizes the requesting node located at the nearest position from the MC. Moreover, the MC is forced to preempt its motion towards the next scheduled node if a new request from a closer node is received meanwhile. In MWC-NJNP, the MC charges all the requesting nodes within its power transmission range upon arriving to the scheduled node. In the following, OMC, NJNP and MWC-NJNP are compared in terms of energy consumption and ability to serve the requesting nodes within a bounded delay. For this, we define a new metric that measures the total failure time due to battery exhaustion. We believe that this metric better reflects the service quality of on-demand charging techniques (see our discussion in Sec. 3.2) than the traditionally adopted average charging delay. Energy and delay metrics are measured for a simulation duration of 500 seconds.

8.2.2. Results and Discussion

Fig. 10 depicts the total energy consumption, including charging and traveling energy, for the three strategies. This figure shows that MWC-NJNP enhances the MC's performance in terms of energy consumption. This is mainly due to the reduction in charging energy obtained through MWC, while NJNP charges each node individually, even when requesting nodes are close enough to be simultaneously charged. The figure clearly shows that OMC outperforms, not only NJNP, but also MWC-NJNP. This is explained as follows:

- In MWC-NJNP, the mobile charger starts charging as soon as the first request is received (in order to reduce as much as possible the charging delay). This lowers the number of requesting nodes to be charged in the MC's queue and makes it difficult to group them into subsets to take advantage of simultaneous charging. On the other hand, the adoption of a request collection period, along with threshold-based tour launching of OMC increases the number of requesting nodes in the MC's queue. This provides more aggregation opportunities and a better exploitation of MWC.

- In MWC-NJNP, the mobile charger tends to stop by a location that is close to the next scheduled node only. This prevents the MC from covering other requesting nodes that could be simultaneously charged, and leads to additional traveling and charging energy consumption. In OMC, the stop positions computed through MSP allow the MC to cover the maximum number of requesting nodes within each stopping point. This plays an important role in the optimization of charging and traveling energies.

- The greedy approach of MWC-NJNP forces the MC to proceed with serving any request, even if

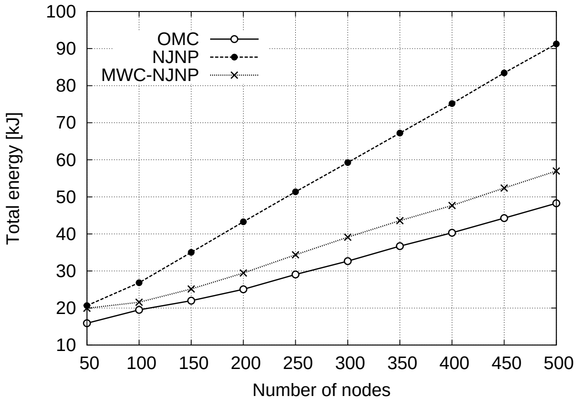

Figure 10: MC's energy consumption *vs* number of requesting nodes.

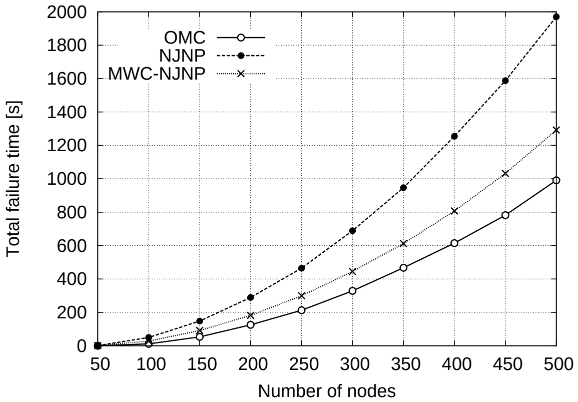

Figure 11: Total node's failure time *vs* number of requesting nodes.

the position of the nearest requesting node is relatively far. This usually results in a "zigzag" movement of the MC across the WSN, e.g., when receiving a new request from a node located in the vicinity of its initial position. Conversely, the charging tours in OMC make it possible to prevent these undesired back-and-forth movements and shorten the total traveled distance.

Finally, we notice that the energy consumption of OMC increases sublinearly with the network size and the charging request load. This demonstrates the good scalability of the proposed on-demand scheme in terms of energy consumption.

Concerning the total failure time, we notice a considerable improvement in OMC compared to NJNP and MWC-NJNP (Fig. 11). The gap between OMC and the other schemes becomes larger for higher number of nodes. This confirms the fact that the objective of minimizing charging delays, traditionally adopted in existing on-demand schemes, is practically inefficient. For example, NJNP and MWC-NJNP prioritize the nearest requesting nodes in order to optimize the overall charging delay. Consequently, all requesting nodes that are located in the MC's vicinity will see their requests served in a short time, even if they do not need such a prompt recharge. This entails that farther nodes will be penalized by waiting longer times, which causes their failure due to battery exhaustion. The TTL mechanism of OMC forces the mobile charger to proceed in a new charging tour as soon as one of the requesting nodes sends an ALERT message, without considering new requests. This guarantees a bounded charging delay for all requesting nodes and avoids battery depletion failures.

8.3. *Design Choice for TTL Thresholds*

The practical design of OMC relies on a TTL mechanism that uses the nodes' energy level thresholds L_r and L_c to trigger charging requests and ALERT messages. These thresholds influence the behavior of the mobile charger and of the requesting nodes, and their choice considerably impacts the solution performance. However, L_c has a more important role as compared to L_r, since it determines when the MC stops collecting requests and starts a new charging tour. Consequently, a judicious approach that we adopt consists in fixing the value of the charging request threshold L_r, and empirically choosing a suitable L_c, so as to obtain a suitable tradeoff between competing performance objectives.
The empirical calculation of L_c for a given network scenario can be attained through numerical simulation. For example, Fig. 12 shows simulation results for a sensor network of 50 nodes. L_r is fixed to 30% (expressed as a percentage of the battery capacity) and L_c is varied from 10% to 26%. The performance of OMC is then measured in terms of MC's average energy draining rate (EDR) per unit of time, and average node failure probability (NFP). As expected, EDR decreases with an increasing L_c. In fact, $L_c << L_r$ means that we allow for collection of a high number of requests before starting a new charging tour. When a new tour is launched, we then have an opportunity of aggregating more nodes, thus increasing the charging efficiency (or equivalently decreasing EDR). The tours, on the other hand, will tend to start late because of a longer request collection period. Also, they will last longer as a large number of nodes is to be charged, implying the visit of many locations. This has the impact of increasing NFP, since requesting nodes have a long time to wait before being served. As L_c increases and gets closer to L_r, the

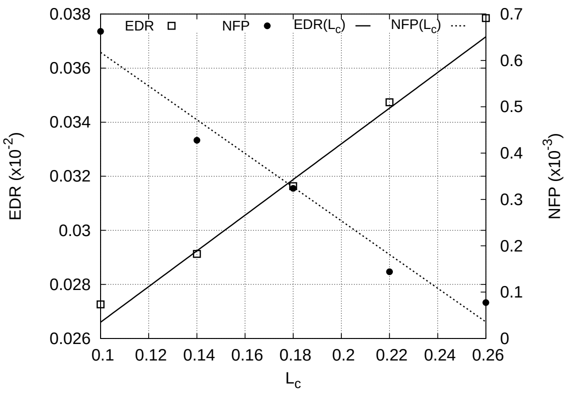

Figure 12: L_c variation impact on EDR and NFP.

number of collected requests decreases too, which implies the following facts: 1) the tours will take a shorter amount of time (NFP decreases) and 2) a smaller number of nodes will be charged within each tour, resulting in fewer aggregation opportunities (EDR increases).
One sensible way to pick the L_c value that optimizes both EDR and NFP consists in using multi-objective optimization approaches [30]. For this, we apply curve fitting to the simulation results in order to derive the functions expressing EDR and NFP in terms of L_c. As shown in Fig. 12, the resulting curves are linear, since $\text{EDR}(L_c) = a_1 L_c + b_1$, and $\text{NFP}(L_c) = a_2 L_c + b_2$, with $a_1 = 0.066$, $b_1 = 0.020$, $a_2 = -3.636$ and $b_2 = 0.981$. Minimizing EDR and NFP simultaneously implies their combination in an objective function to be minimized considering a weight factor $w > 0$. The latter encodes the designer's preference for one of the metrics. As an example of suitable objective functions, we adopt the quadratic sum formula used in the *least square optimization* method, as follows: $f = (\text{EDR})^2 + w(\text{NFP})^2$. Here, the designer may choose $w > 1$ if NFP metric is preferred. Otherwise w needs to be less than 1, if a preference is accorded to EDR.
As a result, the optimal L_c value is the one that minimizes the objective function f :

$$L_c = -\frac{a_1 b_1 + w a_2 b_2}{(a_1)^2 + w(a_2)^2} \tag{8}$$

9. Conclusions

Scheduling of a mobile charger that performs wireless charging of sensor nodes has been considered in this paper, exploiting multi-node power transfer and devising a new scheme for on-demand scenarios. Our technique is based on grouping the charging requests and appropriately launching and planning the charging tours. For the tour launching, threshold-based tour launching (TTL) has been proposed, whereas for the tours, a new path planning strategy has been presented, based on minimizing the number of stopping points. Compared to previous on-demand solutions, the proposed technique postpones the launching of the tours in an attempt to maximize aggregation opportunities for requesting nodes, for their simultaneous charge. We numerically found that this has a very positive impact on energy efficiency and reduces failures due to battery depletion. As a drawback, the waiting time increases slightly, but this can be well tolerated as long as the nodes receive energy before their batteries drain out of energy. A new performance metric is defined to clarify this aspect. At the tour planning level of the proposed strategy, a new modeling approach is used. It leverages simultaneous energy transfer to multiple nodes by maximizing the number of sensors that are charged at each stop. As the problem is NP-hard, we model it through a clique partitioning approach, which is solved through lightweight heuristics. The resulting charging algorithm is shown to run in a cubic time complexity with respect to network size, while ensuring a good approximation to the minimum number of stops.

The proposed scheme has been evaluated by extensive simulations in offline and on-demand scenarios, and its different parts have been compared to relevant solutions from the literature. Simulation results show that the proposed path planning strategy reduces the number of stops in the charging tours and the energy consumed by the mobile charger, while also being computationally efficient. The results in the on-demand scenario demonstrate the effectiveness of the path construction strategy, TTL, and multi-node charging, in reducing node failures, as well as the total energy consumed by the mobile charger. Clear improvements against state-of-the-art solutions have been demonstrated.

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Appendix A. Clique Partitioning Algorithm [26]

1. Pick the edge (p, q) which has the maximum number of common neighbors (a vertex is a common neighbor of an edge if it is connected with both vertices of the edge).
   - Tie-breaking: select p and q such that the sum of node degrees is maximum;
   - If the graph has no edges, then Stop.
2. Cluster p and q into a clique.
3. Delete edges from p and q that are not connected with their common neighbors.
4. Combine p and q in the original graph and call it r.

5. If vertex r is isolated, Goto 1.
   - Else pick an edge s which includes r as a vertex and which has the maximum number of common neighbors.
6. Rename r and s as p and q.
7. Goto 3.