# Influence of Node Mobility, Recharge, and Path Loss on the Optimized Lifetime of Wireless Rechargeable Sensor Networks<sup>\*,\*\*</sup>

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## ABSTRACT

Recently, a powerful lifetime improvement algorithm for mobile wireless sensor networks has been reported in the literature. It controls the communication activity between the sensor nodes and the sink node through the solution of a simple convex optimization problem. In this article, a systemic performance assessment of this algorithm is carried out, taking into consideration that: i) the energy storage devices of the sensor nodes are subjected to recharge via radiative wireless power transfer events, ii) the node mobility patterns are governed by the random waypoint, the random Gauss-Markov, and the reference point group models, iii) a two-slope distance-dependent propagation path loss prediction model governs the energy consumption and the amount of recharge delivered to the sensor nodes, and iv) recharge takes place via omnidirectional and directional radiation patterns. Proper modeling and a large number of computer simulation results are presented and discussed. The factorial analysis of variance is applied to analyze the results, measuring individual and interaction effects of the node mobility patterns, the path loss models and the recharge mechanisms on the optimized network lifetime. Among the reported findings, some are worth highlighting: i) different mobility patterns may result in considerably dissimilar performances of the adopted lifetime optimization strategy; ii) the adoption of the two-slope propagation loss model unveiled the need for developing efficient recharge mechanisms to cope with the potentially inefficient recharges that might happen when the target nodes are far away from the charger; iii) a poorly designed recharge mechanism might not bring sufficient lifetime improvement or sustained network operation.

# 1. Introduction

A wireless sensor network (WSN) is constituted of a few to hundreds or even thousands sensor nodes that are spatially distributed to measure some physical quantity or environmental condition, such as temperature, humidity, light, pressure, vibration and sound Akyildiz, Su, Sankarasubramaniam and Cayirci (2002); Arampatzis, Lygeros and Manesis (2005); Yick, Mukherjee and Ghosal (2008); Buratti, Conti, Dardari and Verdone (2009); Borges, Velez and Lebres (2014); Forster (2016). A sensor node typically contains a radio transceiver, a micro-controller unit, an interface with embedded or separate sensors and an energy provision that is usually made by means of a battery or a super-capacitor, properly managed by a dedicated system. The energy provision can also be partially or entirely realized by some form of environmental energy harvesting whose energy sources include solar, wind, vibration and radio-frequency (RF) signals Prauzek, Konecny, Borova, Janosova, Hlavica and Musilek (2018).

The range of applications of WSNs is wide, going from military, such as battlefield surveillance and distributed target detection, to industrial and consumer applications, such as control and process monitoring, health monitoring, telematics, intelligent transportation systems, earthquake and soil monitoring, glacial movement monitoring and wildlife monitoring Munir, Ren, Jiao, Wang, Xie and Ma (2007); Ekici, Gu and Bozdag (2006); Baronti, Pillai, Chook, Chessa, Gotta and Hu (2007); Tacconi, Miorandi, Carreras, Chiti and Fantacci (2010); Goel, Patel, Nagananda and Varshney (2018).

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The sensor nodes that forms a WSN typically use wireless links to communicate among themselves, or with one or more sink nodes to which the sensory information data is transmitted. A WSN may have nodes that do not change their positions over time, whereas a mobile WSN is characterized by the presence of mobile sink nodes, mobile sensor nodes or both Munir et al. (2007). The sink node can be a especial purpose device, or can be an ordinary network node or a cluster head Misra and Kumar (2016). Fixed and mobile WSNs probably will constitute an important part of, or will complement the fifth generation (5G) of communication networks. Moreover, it is well-known that the WSNs are the basic building blocks of the Internet of things (IoT) infrastructure.

Regarding the topology, a fixed or a mobile WSN can be deployed as a simple star network, or may form a multi-hop wireless mesh network. However, the dynamic topology of mobile WSNs imposes restrictions to the system design, for instance when developing routing and medium access control (MAC) protocols, and for establishing quality of service (QoS) control mechanisms. Nonetheless, mobility can be explored to improve coverage, to increase the network lifetime (or lifespan) and to handle energy control Munir et al. (2007).

Energy management is an important aspect to be considered when the lifetime of a WSN must be improved, mainly in mobile WSNs. This is owed to the fact that most of the sensor networks have their lifetime increased if the limited energy residual to the sensor nodes can be saved somehow. This is especially important if the sensor nodes' batteries cannot be replaced or if the replacement procedure is costly or difficult. However, when some sensor nodes deplete their energies, parts of the sensing field can no longer be monitored, and the network is considered dead. This is a huge problem in applications in which a long period of unattended operation must be avoided. Under the impossibility of replacing batteries in the field, the network lifetime can be improved or sustained by means of some energy harvesting scheme designed to recharge the batteries or super-capacitors of the sensor nodes, or even to allow for a battery-free operation of the network.

Among all available recharge mechanisms, wireless recharging techniques are of especial interest in this paper. These techniques are grouped into the so-called wireless power transfer (WPT) technology, a term that refers to any method of delivering power from one place to another without interconnecting wires Zeng, Clerckx and Zhang (2017). Among the WPT technologies, the radiative WPT plays a especial role in the case of fixed or mobile WSNs. It is a far-field RF power transfer technology in which the transmitter and the receiver are completely decoupled electrically. Power delivery can be achieved over distances varying from a few meters to kilometers Zeng et al. (2017). The RF received signal is converted into usable direct current (DC) via especial-purpose rectifiers. The joint task of receiving and rectifying the RF signal is made by a device called rectenna (the contraction of rectifying and antenna) Popović, Falkenstein, Costinett and Zane (2013); Zeng et al. (2017), which constitutes one of the most important parts of a radiative WPT system.

The application of wireless recharge mechanisms to wireless sensor networks gave rise to the term wireless rechargeable sensor network (WRSN) Jiang and Liao (2016); Jia, Chen, Deng, Wang and Aghvami (2017); Yoon and Noh (2018); Liu, Deng, Tian, Peng and Pei (2018); Zhong, Zhang, Ma, Kui and Gao (2018). Thus, a WRSN consists of sensor nodes that can harvest energy emitted from a single or multiple wireless power transmitters in order to recharge their batteries or super-capacitors, aiming at increasing or sustaining the network operation lifetime. A WRSN that has moving sensor nodes or sink nodes is referred to as a mobile WRSN, which is the focus of this paper.

Figure 1 depicts a possible architecture of a WRSN. The sensor nodes can reach the sink node via multi-hop links, or directly. The one-way RF transmissions with the purpose of recharging the nodes' batteries or super-capacitors are made by the recharge node, which in this illustration is the sink node itself. Multiple recharge nodes, fixed or mobile, can be adopted. Due to the propagation path losses, some nodes that are out of the reach of the charger may not receive enough recharge energy. The sensor network data is delivered to the end user or application via Internet connections, for example.

Due to the utmost relevance of prolonging the lifetime of mobile WRSNs, this work presents an extensive analysis of the effects of different signal propagation models, recharge mechanisms and node traveling patterns on this lifetime, when the network is optimized by means of the algorithm proposed in Guimarães, Sakai, Alberti and de Souza (2016), under the influence of battery recharge through radiative WPT mechanisms. Specifically, a systemic performance assessment of the lifetime optimization algorithm proposed in Guimarães et al. (2016) is carried out, taking into consideration that:

- 1. The energy storage devices of the sensor nodes are subjected to recharge via radiative wireless power transfer events.
- 2. The node mobility patterns are governed by the random waypoint (RWP), the random Gauss-Markov (RGM), and the reference point group (RPG) models.



Figure 1: A possible architecture of a wireless rechargeable sensor network with a single recharge node.

- 3. A two-slope distance-dependent propagation path loss prediction model governs the energy consumption and the amount of recharge delivered to the sensor nodes.
- 4. Recharge takes place via omnidirectional and directional antenna radiation patterns.

Proper background and modeling are reviewed in the case of items 1 and 2. With regard to item 3, new models are devised for the recharge and the energy consumption of the nodes. Regarding item 4, omnidirectional and a novel and simple directive beam recharge mechanisms are proposed. The overall performance assessment is supported by a large number of computer simulation results, which are statistically examined through the factorial analysis of variance. This analysis measured the individual and interaction effects of the node mobility patterns, the path loss models and the recharge mechanisms on the optimized network lifetime. Practical-appealing interpretations and design guidelines are drawn based on these results.

The remainder of the paper is organized as follows: Related research works are summarized in Section 2. Section 3 briefly describes the WSN lifetime optimization approach proposed in Guimarães et al. (2016). Section 4 is devoted to the review of the node mobility patterns considered throughout the paper. The models for path loss prediction, energy consumption of the sensor nodes and battery recharge are proposed in Section 5. Numerical results and discussions are given in Section 6. Section 7 concludes the article, also giving some directions for related research.

# 2. Related work

Considerable research initiatives aiming at prolonging the lifetime of wireless sensor networks have been reported in the last few years; see for example Pinto, Bolzani, Montez and Vargas Basaure (2012); Anastasi, Conti, Francesco and Passarella (2009); Zhang, Huang, Wang and Fang (2015); Luo, Jiang, Zhang, Wang, Zhang and Ren (2014); Rout and Ghosh (2013); Tashtarian, Hossein Yaghmaee Moghaddam, Sohraby and Effati (2015); Chen and Zhao (2005); Guimarães et al. (2016); Yetgin, Cheung, El-Hajjar and Hanzo (2017) and references therein. Likewise the present research, many of these initiatives deal with the energy spent during the task of communication among sensor nodes or between sensor nodes and sink nodes, since this is the most energy-consuming task of a node whose movement is not autonomous.

In Guimarães et al. (2016), a novel algorithm for lifetime improvement of WSNs has been proposed, grounded on the solid design guidelines established in Chen and Zhao (2005). From residual energy information reported by the sensor nodes, the sink node or another central processing entity dynamically optimizes the so-called communication activity levels of the mobile sensor nodes to save energy without sacrificing the sensory information data throughput. The activity level is defined in Guimarães et al. (2016) as representative of time or time-frequency portions of slots in a frame, during which the sensor node is scheduled to communicate with the sink. The lifetime improvement algorithm of Guimarães et al. (2016) is powered by a simple convex optimization Boyd and Vandenberghe (2004) problem whose solution controls the activity levels of the sensor nodes. Large lifetime improvements are reported in Guimarães et al. (2016), taking as references the non optimized network and an idealized greedy algorithm Chen and Zhao (2005) that uses both real-time channel state and residual energy information to handle the energy consumption of the nodes.

As far as recharge is concerned, not much can be found in the literature when seeking for simple and mathematically tractable models in the context of the wireless power transfer technology, with the exception of the recent model proposed in He, Chen, Jiang, Yau, Xing and Sun (2013). This model was empirically constructed based on real field measurements that were used to tune a free-space propagation path loss formula. Since then, this model is being widely used in many research works related to the wireless power transfer technology, for instance in Jiang and Liao (2016); Li, Fu, Chen, Chi and h. Zhu (2015); Shu, Yousefi, Cheng, Chen, Gu, He and Shin (2016); Fu, Cheng, Gu, Chen and He (2016); Suo, Yao, Zhang and Li (2016).

In Zeng et al. (2017), the linear and nonlinear behaviors of the rectifier at the energy receiver are explored by means of several communication and signal processing optimization techniques, aiming at maximizing the DC output power delivered to the load. Although this reference is not targeted at any specific recharge model, its content brings relevant information capable of feeding the development of analytical recharge models that take into account the linear and nonlinear characteristics of the RF-to-DC conversion process.

## 3. Reference lifetime optimization problem

In this section, the lifetime optimization problem solved by the algorithm proposed in Guimarães et al. (2016) is concisely described. Only the information needed to establish the notation and give a self-contained character to this article is presented. The reader is invited to refer to Guimarães et al. (2016) in order to obtain detailed information on the steps of such algorithm, which basically defines the information handled by the optimization problem and describes how this information flows in the sensor network as time elapses.

It is assumed in Guimarães et al. (2016) that the sensor nodes move, but not autonomously. Hence, most of their energies are spent during communication with the sink node. In order to manage communication for controlling the energy consumption, the parameter activity level is coined in Guimarães et al. (2016). It represents the fraction of time or time-frequency slots, within a frame, that is assigned to a sensor node for communication purposes. The aim of the lifetime optimization strategy devised in Guimarães et al. (2016) is to determine, dynamically, the optimum activity levels for all sensor nodes, simultaneously, so that the network lifetime is maximized. This is accomplished by solving the convex optimization problem

minimize 
$$f_0[\mathbf{s}_f(k)] = w_1 \max\{\mathbf{s}_f(k)\} + w_2 \max\{\mathbf{s}_f(k) - \mathbf{b}_f(k)\}, \quad f = 1, 2, ..., F$$
  
subject to 
$$\mathbf{x}_f(k) \ge 0$$
$$\mathbf{1}^T \mathbf{x}_f(k) = 1$$
$$\mathbf{s}_{f+1}(k) = \mathbf{s}_f(k) - \mathbf{b}_f(k) \circ \mathbf{x}_f(k).$$
(1)

This optimization problem seeks for a balance between minimizing the unused residual energy available to the sensor nodes, and the energy spent to report sensory information to the sink, for the *k*-th optimization event (or optimization realization) that spans F communication frames, k = 1, ..., K.

All boldface characters in Problem (1) denote *N*-dimensional vectors, with *N* being the number of sensor nodes. The objective function  $f_0[\mathbf{s}_f(k)]$  is formed by the weighted sum of  $\max{\{\mathbf{s}_f(k)\}}$ , which is the maximum of the wasted energies residual to the nodes in the *k*-th optimization event at the end of the *f*-th frame, for f = 1, ..., F, and  $\max{\{\mathbf{s}_f(k)-\mathbf{b}_f(k)\}}$ , which is the maximum discounted residual energies computed by subtracting the potential (achievable) maximum energy consumption of the sensor nodes,  $\mathbf{b}_f(k)$ , from their residual energies,  $\mathbf{s}_f(k)$ , in the *f*-th frame of the *k*-th optimization event. The discrete-time events associated to the optimized network operation are indexed by t = f + (k - 1)F = 1, 2, ..., KF; a discrete-time event corresponds to a single communication frame.

The roles of the weights  $w_1$  and  $w_2$  in Problem (1), with  $(w_1, w_2) \in [0, 1]$  and  $w_1 + w_2 = 1$ , are as follows: when  $w_1/w_2 > 1$ , the optimization acts in favor of equalized residual energies, i.e. the sensor nodes tend to have almost equal residual energies over time; when  $w_2/w_1 > 1$ , the optimization tends to assign high activity levels to nodes with better channels and high residual energies, sometimes even disabling those nodes under bad channels and low residual energies. Thus, if  $w_2/w_1 > 1$  the residual energies over time are not completely equalized. It is shown in Guimarães et al. (2016) that when  $w_2/w_1 > 1$  the lifetime improvements are larger than in the case of  $w_1/w_2 > 1$ , at the cost of residual energies not completely equalized throughout the network operation. In other words, when  $w_2/w_1 > 1$  the instant when the first node ceases its operation due to insufficient stored energy Guimarães et al. (2016)). When  $w_1/w_2 > 1$ , the lifetime improvement is smaller, but all sensor nodes have almost the same amount of residual energies over time.

The constraints in Problem (1) have the following roles in each optimization event  $k: \mathbf{x}_f(k) \ge 0$ , where  $\ge$  denotes element-wise inequality, means that the smallest number of slots assigned to a sensor node is zero. The vector  $\mathbf{x}_f(k)$ , which is a variable of the optimization problem, contains the activity levels that will be assigned to the sensor nodes during the *F* frames subsequent to the *k*-th optimization event. The constraint  $\mathbf{1}^T \mathbf{x}_f(k) = \sum_{n=1}^N x_{n,f}(k) = 1$ , with  $x_{n,f}(k)$  being the *n*-th element of  $\mathbf{x}_f(k)$ , means that the activity levels assigned to the sensor nodes in a given frame must add to 1. The residual energies available to the (f + 1)-th frame are dummy optimization variables computed as the residual energies at the beginning of the *f*-th frame, minus the energy consumptions during the *f*-th frame, that is,  $\mathbf{s}_{f+1}(k) = \mathbf{s}_f(k) - \mathbf{b}_f(k) \circ \mathbf{x}_f(k)$ , with the symbol  $\circ$  denoting the Hadamard product (element-wise multiplication).

The optimization variables obtained from the k-th optimization event are the activity level matrix

 $\mathbf{X}(k) = [\mathbf{x}_1(k), \mathbf{x}_2(k), \dots, \mathbf{x}_F(k)]$ 

that contains the optimized activity levels to be assigned to the sensor nodes, and the residual energy matrix

 $\mathbf{S}(k) = [\mathbf{s}_1(k), \mathbf{s}_2(k), \dots, \mathbf{s}_{F+1}(k)]$ 

that contains the theoretical (not necessarily actual) values of the residual energies of all sensor nodes. The optimization input parameters are the number of sensor nodes, N; the optimization span, F; the initial energy levels of the batteries,  $\mathbf{s}_1(1)$ ; and the estimated maximum consumed energies in the first F frames, which are stored in the matrix  $\mathbf{B}(1) = [\mathbf{b}_1(1), \mathbf{b}_2(1), \dots, \mathbf{b}_F(1)].$ 

Each column of the maximum consumption matrix  $\mathbf{B}(k + 1)$  that will be used as input to the optimization event k + 1 is updated according to the equation  $\mathbf{b}_f(k + 1) = [\mathbf{s}_f(k) - \mathbf{s}_{f+1}(k) + \mathbf{r}_f(k)] \circ [1/\mathbf{x}_f(k)]$ . This update is made from the assigned activity levels and the actual residual energies associated with the k-th block of F frames, where  $\mathbf{s}_f(k)$  and  $\mathbf{r}_f(k)$  contains the residual and recharge energies, respectively, whose values are informed by the sensor nodes to the sink node, where Problem (1) is meant to be solved, to feed each optimization event.

A recharge matrix is defined in Guimarães et al. (2016) according to  $\mathbf{R}(k) = [\mathbf{r}_1(k), \mathbf{r}_2(k), \dots, \mathbf{r}_F(k)] \in \mathbb{R}^{N \times F}$ , with  $\mathbf{r}_f(k)$  representing the amount of energy delivered to the sensor nodes' batteries or super-capacitors during recharge. The instants of recharge and the amount of charge transferred to the nodes depend on the energy harvesting method and the associated technology. For instance, recharge may occur very frequently if the energy harvesting is from a continuously-transmitted RF signal, opportunistically in the case of solar energy harvesting, or defined according to when and how often a recharge device transmits an RF signal for the specific purpose of WPT.

## 4. Node mobility models

In this section, the well-known mobility models random waypoint, random Gauss-Markov and reference point group Roy (2016); Camp, Boleng and Davies (2002) are shortly described in order to enlighten their main features and differences. These models can mimic quite different traveling patterns, which contributes with distinct scenarios for the optimized wireless rechargeable sensor network analyzed herein.

#### 4.1. Random waypoint

The random waypoint (RWP) is one of the most common mobility models used for *ad hoc* network evaluation Roy (2016); Bettstetter, Resta and Santi (2003); Hyytiä and Virtamo (2007); Son, Minh, Sexton and Aslam (2014); Kumar and Dave (2014). It is a simple and straightforward stochastic model in which a pause time happens between changes in the node's direction of movement, speed, or both. When the model execution is started, the mobile node stays in a location for a certain period of time, which corresponds to the pause time. Once this pause time expires, the node starts traveling towards a random destination within the simulated network area, at a selected speed that is uniformly distributed between minimum and maximum predefined values. Upon arrival at the destination, the process is re-initiated with a new pause time and repeated during the whole simulation execution.

Figure 2(a) depicts a traveling pattern of a single node under the RWP model, and Figure 2(b) shows a surface plot that can be interpreted as the empirical probability distribution of the node position. The traveling pattern graph was constructed from  $4 \times 10^3$  simulation steps, and the surface plot was constructed from  $5 \times 10^5$  steps. The node started at a randomly chosen point and traveled with a speed uniformly distributed between 0 and 1 unit per simulation step, and a maximum pause time of 1 simulation step.

In most of the performance investigations that adopt the RWP mobility model, the nodes are initially uniformly distributed on the simulation area. However, as demonstrated in Camp et al. (2002), this initial uniform distribution may



**Figure 2:** Traveling pattern of a node under the RWP model for  $4 \times 10^3$  steps (a), and surface plot of the node position for  $5 \times 10^5$  steps (b).

result in misinterpretations regarding some network performance evaluations. In order to avoid such misinterpretations, it is recommended to discard a number of initial steps from the total simulation execution steps to ensure that the node distribution reaches its steady state. This number is recommended to be around 1000 in Camp et al. (2002), and around 500 in Roy (2016).

Another characteristic of the RWP model that might potentially cause misinterpretations about its influence in some network performance metric is the concentration of node positions around the center of the analyzed area Roy (2016); Bettstetter et al. (2003), as can be concluded from Figure 2(b). For an example related to the present context, if the sink node is located at the center of the area, the overall energy consumption of the network under the RWP model, compared with a uniform distribution pattern, will be smaller due to the higher probability of nodes closer to the sink.

#### 4.2. Random Gauss-Markov

It is reasonable to consider that the velocity of a mobile node traveling to a destination can only be changed within a short time span, due to physical restrictions. In other words, the future location and velocity of a node are generally correlated with its past and current locations, and with velocity Kumar and Dave (2014). In order to mimic this behavior, the random Gauss-Markov (RGM) mobility model was proposed Roy (2016); Liang and Haas (2003). Its name derives from its root in the Gauss-Markov random process (Rasmussen and Williams, 2006, Appendix B).

Although the RGM was initially proposed for simulating wireless personal communication service (PCS) networks, it has been used for simulating *ad hoc* network protocols due to its ability to capture the correlation of a mobile node's velocity in time and adapt to different levels of randomness through a model tuning parameter Kumar and Dave (2014). Initially, speed and direction values are assigned to each node and, at fixed time intervals, node movement occurs by updating these values. If a node moves within a certain distance of the edge of the area, it is forced away by modifying its mean direction. This approach is used to ensure that nodes do not remain near an edge for a long period of time.

Figure 3(a) exemplifies the traveling pattern of a mobile node under the RGM model, and Figure 3(b) shows the corresponding surface plot for the node location. The numbers of steps used were the same used to plot Figures 2(a) and 2(b), respectively. Differently from the RWP model, in the RGM there is no concentration of nodes throughout the analyzed area as time elapses, giving to this model a more evenly-distributed node position character, as can be concluded from Figure 3(b).

## 4.3. Reference point group

The reference point group (RPG), sometimes referred to as reference point group mobility (RPGM) Roy (2016); Hong, Gerla, Pei and Chiang (1999), is part of a set of models that have been widely applied for performance evaluation of *ad hoc* networks Aung, Seet, Zhang, Xie and Chong (2015); Kumar and Dave (2014); Jayakumar and Ganapathi (2008). Each node, which is member of a group of nodes, follows the movement of a lead node that determines the group's motion behavior, including its speed, direction, and acceleration. Basically, a group motion vector is used to calculate the group motion, directly impacting the movement of its corresponding group of nodes. Each node randomly



**Figure 3:** Traveling pattern of a node under the RGM model for  $4 \times 10^3$  steps (a), and surface plot of the node position for  $5 \times 10^5$  steps (b).

moves around its own predefined reference point, updating its location according to the group's logical center. As the individual reference points move, the updated reference points are combined with a random motion vector, resulting the motion of each node around its individual reference point. Individual nodes are not subjected to pause times while the group is moving, pausing only when the group reference point reaches a destination, which makes all group nodes pause for the same period of time.

A traveling pattern under the RPG model is depicted in Figure 4(a), which shows the tracks of 10 nodes moving together as a group. The corresponding surface plot for the node locations is shown in Figure 4(b). The number of steps for each node was set to  $1.5 \times 10^3$  to plot Figure 4(a), and  $5 \times 10^4$  to plot Figure 4(b).

It is important to highlight that the RWP model is used to generate both the movement of the lead node for each group and the random motion of each individual node within the group, which however does not necessarily confer to the node distribution of the RPG the same characteristics of the RWP. This can be noticed by comparing the individual WPT node movement pattern illustrated in Figure 2(a) with respect to the group of nodes under the RPG model in Figure 4(a), as well as the associated surface plots. It can be noticed that the node distribution is more uniform in the RPG than in the RWP, with a common characteristic of a lower number of nodes traveling close to the area boundaries. The node distribution of the RPG becomes more similar to the RWP as the size of the group is increased, or the aggregation of its members is decreased, or both.



**Figure 4:** Traveling pattern of a group of 10 nodes under the RPG model for  $1.5 \times 10^3$  steps (a), and surface plot of the node position for  $5 \times 10^4$  steps per node (b).

The RPG model can emulate a variety of mobility behaviors. Some examples are presented in Hong et al. (1999),

highlighting three different applications, namely: in-place, overlap and convention, which can represent group mobility in battlefield, disaster recovery, and convention scenarios, respectively. The RPG model can also be used to model a herd movement, for instance to assess a mobile wireless sensor network applied to wildlife monitoring.

## 5. Path loss, energy consumption and recharge

In the present context, the RF signal propagation loss (path loss for short) accounts for the signal attenuation from the sensor nodes to the sink, and from the WPT transmitter to the sensor nodes. It affects the energy consumption of the nodes and the amount of charge delivered to them, which eventually affects the performance of the optimization Problem (1), and the network lifetime itself. In this section, the proposed mathematical models for the energy consumption and the recharge, as well as the proposed recharge mechanisms are described, preceded by a short review about the two-slope propagation path loss model on which the proposed ones are grounded. The energy consumption and the recharge models are affected by the propagation losses, while the recharge mechanism that governs the way in which the wireless power transfer events take place is influenced by the recharge model.

## 5.1. The two-slope path loss model

The planning and deployment of any wireless communication system demand the knowledge of the propagation characteristics of the environment, mainly in terms of the large-scale path loss. The knowledge about it is needed to determine link budgets and margins, and as input to some process during the system operation.

Many path loss models are derived from, or are based on the log-distance law Rappaport (2002)(Guimarães, 2009, pp. 200-206), for instance the Stanford University Interim (SUI) model Katev (2012); Sulyman, Nassar, Samimi, Mac-Cartney, Rappaport and Alsanie (2014). A distance-dependent loss model aims at estimating the area-mean received power level, which is the signal power averaged over obstacle-dependent fluctuations, so that only the part associated to the distance-dependent signal attenuation is retained. The log-distance law dictates that the area-mean received power falls off linearly with the logarithm of the distance between the transmitter and the receiver, following a single slope whose inclination is determined by the environmental characteristics, and whose initial value is determined by the carrier frequency.

The importance of the log-distance path loss model goes even beyond, for instance when it is applied in more elaborated models for coverage prediction in cellular-like communication systems. Thanks to its low complexity and accuracy, it is widely used in analyses requiring that the path loss and related information are taken into account, additionally carrying simple mathematical tractability.

A generalization of the above path loss model dictates that the distance-dependent area-mean received signal power may fall off according to multiple slopes. For instance, the multi-slope path loss law has been put into focus in Zhang and Andrews (2015), where it has been demonstrated that the analysis of metrics related to a wireless network can be severely impacted if such a model is adopted, resulting in conclusions that significantly depart from those in which the conventional single-slope law is considered. This is specially true in dense networks Zhang and Andrews (2015), e.g in the future 5G cellular systems and sensor networks with close apart sensor nodes.

Recently, it has been emphasized that the two-slope path loss model accurately represents the WSN propagation environment Kurt and Tavli (2017). Moreover, it has been shown that this model adheres to measurements in indoor Andrade and Hoefel (2010) and outdoor Abbas, Sjöberg, Karedal and Tufvesson (2015); Cheng, Henty, Stancil, Bai and Mudalige (2007); Masui, Kobayashi and Akaike (2002) environments. Hence, it is important to adopt a two-slope propagation law in the context of a mobile WRSNs.

The two-slope path loss model has its root in the two-ray flat earth model Bullington (1977); Lee (1982), or simply two-ray model, which has been found in Xia, Bertoni, Maciel, Lindsay-Stewart and Rowe (1993) to suitably represent the signal attenuation in real scenarios departing from the original idealized assumptions. In the two-ray model, transmitter and receiver are in line-of-sight condition and lay on a flat-earth surface such that a single reflected path towards the receiver is formed besides the line-of-sight one. Two path loss regions separated by a breakpoint can be distinguished: before the breakpoint the received signal power varies severely due to destructive and constructive combination between the direct and the reflected rays, whereas after the breakpoint it decreases linearly with the logarithmically-scaled distance Xia et al. (1993). The single breakpoint, in this case, is the distance  $d_c$  from the transmitter in which the first Fresnel zone touches the ground Xia et al. (1993). This distance is sometimes referred to as the critical distance Zhang and Andrews (2015) or Fresnel distance Cheng et al. (2007), and is given approximately

by  $d_c \approx 4h_t h_r / \lambda$ , where  $h_t$  and  $h_r$  are the transmit and the receive antenna heights (taking into account the heights of their supporting structures), respectively, and  $\lambda$  is the carrier wavelength, all in meters.

It has been demonstrated in Perera, Williamson and Rowe (1999) that the breakpoint might happen closer to the transmitter due to the presence of obstacles that hit the first Fresnel zone at a distance that can be far below  $d_c$  Cheng et al. (2007); Masui et al. (2002). Hence, the breakpoint may be at, or even before the distance

$$d_{\rm bp} \approx \frac{4(h_{\rm t} - h_{\rm avg})(h_{\rm r} - h_{\rm avg})}{\lambda},\tag{2}$$

where  $h_{\text{avg}} < h_{\text{r}}$  is the average height of the obstacles located in-between transmitter and receiver (Masui et al., 2002, Eq. (2)).

Based on the above concepts, the two-slope path loss model dictates that the area-mean received signal power, in dBm, at a distance d from the transmitter is given by

$$P(d) = \begin{cases} P_0 - 10 \log\left(\frac{d}{d_0}\right)^{\epsilon_1}, \ d \le d_{\rm bp} \\ P_0 - 10 \log\left(\frac{d_{\rm bp}}{d_0}\right)^{\epsilon_1} - 10 \log\left(\frac{d}{d_{\rm bp}}\right)^{\epsilon_2}, \ d > d_{\rm bp} \end{cases},$$
(3)

where  $\epsilon_1$  and  $\epsilon_2$  are the environment-dependent dimensionless loss exponents or loss coefficients,  $d_{bp}$  is the breakpoint measured from the transmitter, in meters, and  $P_0$  is the area-mean received power, in dBm, at an unobstructed reference distance  $d_0$  from the transmitter, in meters, such that  $\lambda \ll d_0 < d_c$ . For example, using the simplified form of the Friis' free-space signal loss equation (Guimarães, 2009, p. 200),

$$P_0 = 10 \log \frac{P_{\rm t} G_{\rm t} G_{\rm r} (\lambda/4\pi d_0)^2}{0.001},\tag{4}$$

where  $P_t$  is the power delivered to the transmit antenna, in watts, and  $G_t$  and  $G_r$  are the transmit and receive antenna dimensionless gains, respectively.

From Equation (3) it is clear that P(d), in dBm or equivalent logarithmic unit, is a piecewise linear function of the logarithmically-scaled distance d. The name two-slope path loss model derives from this fact. If P(d) and  $P_0$  are expressed in watts or equivalent linear quantity, then Equation (3) becomes

$$P(d) = \begin{cases} P_0 \left(\frac{d_0}{d}\right)^{\epsilon_1}, d \le d_{\rm bp} \\ P_0 \left(\frac{d_0}{d_{\rm bp}}\right)^{\epsilon_1} \left(\frac{d_{\rm bp}}{d}\right)^{\epsilon_2}, d > d_{\rm bp} \end{cases}$$
(5)

In practice, the loss exponents  $\epsilon_1$  and  $\epsilon_2$  are determined through a non-trivial segmented regression procedure applied to local-mean received power measurements made in the coverage area of the network (Guimarães, 2009, pp. 200-206). The local-mean power is the received signal power averaged over multipath fading signal fluctuations so that only the obstacle-dependent part, usually referred to as shadowing, is retained. The estimated loss exponents are then plugged into Equation (3) or Equation (5) for path loss prediction within that specific area, or within areas that are similar in terms of morphology.

#### 5.2. Proposed energy consumption model

The energy consumption of a sensor node during communication with the sink node, or with another node of the network, is proportional to the transmit power necessary to guarantee a target bit error rate at the receiver, which in turn depends on the path loss, and on the devices' physical layer specifications. Assume that this target error rate is achieved if the area-mean received signal power is  $P(d) = P_{\text{target}}$ , with P(d) obtained from the two-slope model in Equation (5) applied to the link between a sensor node and the intended receiver.

Thus, the energy consumed by a sensor node located at a distance d from the sink node is directly proportional to  $P_0$ , i.e., from Equation (5), it is directly proportional to  $P_{\text{target}}(d/d_0)^{\epsilon_1}$  for  $d \leq d_{\text{bp}}$ , and directly proportional to  $P_{\text{target}}(d_{\text{bp}}/d_0)^{\epsilon_1}(d/d_{\text{bp}})^{\epsilon_2}$  for  $d > d_{\text{bp}}$ . Assuming that  $P_{\text{target}}$  is maintained constant for a fixed target error rate, for instance via power control, and that  $d_0 = 1$  meter without loss of generality, then it is proposed that the *n*-th element

 $b_{n,f}(k)$  of the *f*-th column  $\mathbf{b}_{f}(k)$  forming the maximum consumption matrix  $\mathbf{B}(k)$  that feeds Problem (1) in the *k*-th optimization event is computed according to the energy consumption model

$$b_{n,f}(k) = \begin{cases} \Omega \left[ d_{n,f}(k) \right]^{e_1}, \, d_{n,f}(k) \le d_{\rm bp} \\ \Omega \, d_{\rm bp}^{e_1} \left[ \frac{d_{n,f}(k)}{d_{\rm bp}} \right]^{e_2}, \, d_{n,f}(k) > d_{\rm bp} \end{cases}, \tag{6}$$

where  $\Omega$  is a hardware-dependent and battery-dependent proportionality constant that accounts for the proper conversion from transmit power into consumed energy, and  $d_{n,f}(k)$  is the distance of the *n*-th sensor node to the sink at the time instant associated to the *f*-th frame and *k*-th optimization event.

When a computer simulation needs to be executed under the two-slope energy consumption model described by Equation (6), the constant  $\Omega$  can be configured to scale-down the network lifetime as well, avoiding prohibitively large simulation execution times. Such a scaling has been made to generate the numerical results presented later on, in Section 6.

#### 5.3. Proposed recharge model

A simple and well-accepted empirical recharge model is proposed in He et al. (2013), as a variant and tuned version of the model considered in Yeager, Powledge, Prasad, Wetherall and Smith (2008). The model devised in He et al. (2013) is based on a curve fit to measurements taken from a short-distance WPT testbed. The curve used in the fitting process was a parametrized version of the Friis' free-space loss formula. According to this model, the recharge power, in watts, available to a sensor node at a distance d from the wireless power transmitter is

$$P_{\rm r}(d) = \frac{P_{\rm t}G_{\rm t}G_{\rm r}\eta}{L_{\rm p}} \left[\frac{\lambda}{4\pi(d+\beta)}\right]^2,\tag{7}$$

where  $P_t$  is the power delivered to the charger's transmit antenna, in watts,  $G_t$  and  $G_r$  are the dimensionless transmit and receive antenna gains, respectively,  $\lambda$  is the carrier wavelength in meters,  $\eta$  is the rectifier efficiency of the rectenna,  $\beta$ is a parameter used to adjust the Friis' free-space formula in short distance transmissions, the constant 2 is the singleslope loss exponent, and  $L_p$  is the dimensionless antenna polarization loss that accounts for using transmit and receive antennas in different polarizations for the electric field Yeager et al. (2008).

Motivated by Kurt and Tavli (2017), where it is emphasized that a two-slope path loss model better fits the WSN propagation scenario, herein a two-slope recharge model is devised by adapting the single-slope recharge model given in Equation (7) to the two-slope path loss Equation (5). This adaptation becomes quite straightforward after noticing that the influence of  $\beta$  in Equation (7) is relevant only for distances below 10 meters, as can be observed in Figure 5. Without loss of generality, in this figure the quantities  $20 \log \left[ 1 / 4\pi (d + \beta) \right]$  and  $20 \log (1 / 4\pi d)$  are plotted for the value of  $\beta = 0.2316$  given in He et al. (2013).



**Figure 5:** The effect of the correction factor  $\beta$  on the recharge model in Equation (7).

The adoption of  $\epsilon_1 = 2$  in Equation (5) allows for the empirical value of  $\beta = 0.2316$  given in He et al. (2013) to be applied only to the first slope, since the breakpoint often occurs above 10 meters in real propagation scenarios. The RF-to-DC conversion efficiency  $\eta = 0.125$  He et al. (2013) can be directly applied to both slopes.

Hence, it is proposed that the recharge power, in watts normalized to a 1 ohm load, delivered to a sensor node located at a distance d from the wireless power transmitter is determined from

$$P_{\rm r}(d) = \begin{cases} \frac{GP_0\eta}{L_{\rm p}} \left(\frac{d_0}{d+\beta}\right)^2, \ d \le d_{\rm bp} \\ \frac{GP_0\eta}{L_{\rm p}} \left(\frac{d_0}{d_{\rm bp}}\right)^2 \left(\frac{d_{\rm bp}}{d}\right)^{\epsilon_2}, \ d > d_{\rm bp} \end{cases}, \tag{8}$$

where the loss exponent  $\epsilon_2$  is kept as a variable to maintain the model degree of freedom with respect to the rate of decay of the slope after the breakpoint. Notice that if  $\epsilon_2 = 2$ , it turns out that the proposed two-slope recharge model in Equation (8) becomes equivalent to the single-slope model in Equation (7).

It is informative to mention that the experimental RF-to-DC conversion efficiency  $\eta = 0.125$  reported in He et al. (2013) is below the one of Yeager et al. (2008) ( $\eta = 0.3$ ), but it is within the RF power-dependent efficiency ranges reported in Valenta and Durgin (2014) and specified by the data-sheets of commercial radiative WPT devices Powercast Corporation (2017).

The dimensionless gain  $G \ge 1$  in Equation (8) modifies  $P_0$  to account for the azimuthal antenna radiation pattern adopted in the wireless power transmitter (which can be co-located with the sink node), as follows: G = 1 means that an omnidirectional antenna is used, i.e. no power concentration towards the sensor nodes is achieved, whereas G > 1represents a radiated power concentration produced by a directive single antenna or a directive antenna array. One must be aware that, here, the use of G = 1 and G > 1 for an omnidirectional and a directional antenna, respectively, is not meant to comply with actual antenna specifications. Instead, it is meant to allow for obtaining a relative measure of the radiated power concentration capability of these two devices, which suffices for the purpose of comparing their influences on the recharge effectiveness.

Using Equation (8) one can compute the recharge energy eventually delivered to the sensor node's battery or super-capacitor, which is directly proportional to the time interval over which the power  $P_r(d)$  is available to the node. Moreover, the recharge energy is directly proportional to the power  $P_0$  (referenced to the distance  $d_0$  from the charger) and to the charger antenna directivity expressed in terms of the gain G, and is inversely proportional to the antenna polarization loss  $L_p$  and to the distance d from the charger to the sensor node. Additionally, the effective amount of charge delivered to the battery or super-capacitor depends on the specific characteristics of these devices. Hence, a proportionality constant  $\Omega'$  must be defined for the recharge model, but shall not be the same as  $\Omega$ , which is the one used to scale the energy consumption for scalling the network lifetime; see Equation (6). Thus, again assuming  $d_0 = 1$  meter without losing generality, the recharge energies stored in the elements  $r_{n,f}(k)$  of the recharge vector  $\mathbf{r}_f(k)$  (see Section 3) for the *n*-th sensor node in the *f*-th frame of the *k*-th optimization event can be determined according to the two-slope recharge model

$$r_{n,f}(k) = \begin{cases} \Omega' G\left(\frac{1}{d_{n,f}(k) + \beta}\right)^2, \, d_{n,f}(k) \le d_{\rm bp} \\ \Omega' G\left(\frac{1}{d_{\rm bp}}\right)^2 \left(\frac{d_{\rm bp}}{d_{n,f}(k)}\right)^{\epsilon_2}, \, d_{n,f}(k) > d_{\rm bp} \end{cases}$$
(9)

In the energy consumption model defined by Equation (6) and by the recharge model proposed in Equation (9), the proportionality constants  $\Omega$  and  $\Omega'$ , respectively, are jointly set to keep consumptions and recharge energies within relative reasonable values from the practical standpoint, or to scale these quantities to provide control on the network lifetime from the perspective of computer simulations, or for other analyses requiring such scalings.

#### 5.4. Proposed recharge mechanisms

It is self-explanatory that recharge can improve the network lifetime, and that the amount of improvement is expected to be larger if dying nodes receive more recharge instead of those with low depleted batteries. Moreover, the more frequent the recharge events are, the higher will be the lifetime. On the other hand, the recharge rate should be kept as small as possible, just enough for prolonging the network life to a certain desired extent, or aiming at its sustained operation He et al. (2013). The number, intensity and due moments of recharges depend on the energy availability in the charger node, and sometimes depend on external restrictions as well. For instance, if sensor nodes are deployed in a hazardous area, or attached to the body of animals for wildlife monitoring, the recharge events will be governed by when and how often a device carrying the WPT transmitter, like an airplane or a drone, pass over the hazardous sensor field or through the herd while emitting RF recharge signals.

The overall recharge process should be also optimized for, or matched to the expected mobility pattern of the nodes in case of mobile WRSNs. For instance, if node movements better fit to the RPG model, efficient recharges can be delivered to a large number of nodes if somehow it is guaranteed that they are close to the charger at the moment of triggering the recharge transmissions. On the other hand, if the node mobility is well represented by the RWP model, a charger placed at the center of the sensor field seems to bring benefits to the recharge mechanism, since nodes will be mostly concentrated close to the charger. If nodes are evenly moving throughout the sensor field, as happens when the RGM model is considered, a node selection approach for WPT with directive antenna radiation pattern can play a strong role. Hence, it can be concluded that the dynamics of the WPT events may vary tremendously from case to case, and that numerous recharge mechanisms can be developed and optimized to specific scenarios Sangare, Xiao, Niyato and Han (2017).

To establish consistency with the above comments, two recharge mechanisms are proposed herein with respect to the WPT antenna radiation pattern, as illustrated in Figure 6. An omnidirectional pattern is considered in Figure 6(a), meaning that all sensor nodes receive some recharge whose amount will depend on their distances to the WPT transmitter. For this scenario, the dimensionless gain in the recharge power Equation (8) is G = 1.

Owed to the fact that the omnidirectional WPT has an intrinsic low efficiency, significant amelioration can be achieved by concentrating the radiated power towards the energy receiver. This concentration can be achieved through sophisticated antenna array beam steering, or simply by using a directive single antenna or an antenna array. Hereafter, the beam directivity is generally referred to as beam-forming. Beam-forming increases the irradiated power density on the sensor node antenna, increasing the recharge power delivered to the energy storage device. For this scenario, G > 1 in Equation (8). Figure 6(b) illustrates the recharge mechanism with beam-forming, considering for simplicity that the radiated power is the same in all directions inside the beam, yielding a cone-shaped radiation pattern.

The antenna gain (Balanis, 2005, p. 66) is the product of its radiation efficiency  $\xi$  and its directivity D, that is,  $G = \xi D$ . For the sole purpose of relative measurements regarding the two aforementioned WPT mechanisms, it is assumed without loss of generality that the WPT transmit antenna has a radiation efficiency of 100%. In this case, the gain of the directive antenna can be approximately determined from the half-power beam-width  $\varphi_{bw}$ , in radians, through (Balanis, 2005, pp. 51-66)

$$G = \frac{4\pi}{\varphi_{\rm bw}^2}.$$
(10)

For example, if  $\varphi_{bw} = \pi/2$  radians, it means that the directive antenna delivers  $4\pi/(\pi/2)^2 \approx 5.09$  more power to the sensor nodes than the omnidirectional antenna.

In the proposed beam-forming recharge mechanism, the direction of the cone-shaped beam during a given recharge transmission is determined according to the sensor node demanding stronger recharge, which hereafter is referred to as the recharge-hungry node (the one marked with a cross in Figure 6(b), for example). This node is determined by monitoring the nodes' residual energies, which is an information already available to the central node for communication activity optimization according to Problem (1). In each optimization event, the recharge-hungry node is the one with the smallest residual energy. According to the recharge-hungry node position, only the sensor nodes located inside the area defined by  $\varphi_{bw}$  in Figure 6(b) are hit by the recharge transmissions.

From the perspective of computer simulations of this directive recharge mechanism, given the recharge-hungry node coordinates in vector form,  $\mathbf{p}_{\text{rh}} = [x_{\text{rh}}, y_{\text{rh}}]^{\text{T}}$ , two points  $\mathbf{p}_1 = [x_1, y_1]^{\text{T}}$  and  $\mathbf{p}_2 = [x_2, y_2]^{\text{T}}$  equidistant from  $\mathbf{p}_{\text{rh}}$  by the angle measure  $\varphi_{\text{bw}}/2$  are determined. Then, a two-dimensional cone (Boyd and Vandenberghe, 2004, p. 25) whose boundaries pass through these points is defined as follows: the *n*-th sensor node belongs to the cone if the node position  $\mathbf{s}_n = [x_n, y_n]^{\text{T}}$  satisfies the equation  $\mathbf{s}_n = \theta_1 \mathbf{p}_1 + \theta_2 \mathbf{p}_2$ , for any constants  $\theta_1 \ge 0, \theta_2 \ge 0$ .

As an attempt to improve the wireless power transfer efficiency when beam-forming is used, recharge is temporarily held over if the recharge-hungry node is not in a good channel condition. In terms of modeling, assume that a number of recharges are scheduled throughout the network operation. The recharge-hungry node is identified in all optimization events occurring during each scheduled recharge, but the corresponding recharge is enabled only if this node is



**Figure 6:** Pictorial representation of the proposed recharge mechanisms: (a) omnidirectional antenna at the charger; (b) beam-forming at the charger, where  $\varphi_{bw}$  is the half-power antenna beam-width. The dots represent nodes distributed at random positions inside the square areas. The node marked with a cross is the one towards which the beam is directed in a given recharge event. In this figure it is considered that the charger is co-located with the sink node.

experiencing a low channel attenuation with respect to the charger. If not, the recharge trigger instant is postponed by an appropriate number of frames, when it is eventually enabled independently of the channel attenuation. The delayed recharge transmission is redirected to the possibly new recharge-hungry node. It is expected that the probability of having a recharge-hungry node in a bad channel condition for receiving the recharge transmission both at the scheduled and at the delayed recharge instants will be small, as long as the node positions at these instants are uncorrelated.

Specifically, the attenuation-dependent delayed recharge mechanism works by enabling a recharge scheduled to  $t = t_r$  only if the recharge-hungry node is at a distance below the two-slope path loss breakpoint  $d_{bp}$ ; otherwise the this recharge is postponed by  $\Delta_{t_r}$  frames. The choice of  $\Delta_{t_r}$  goes as follows: it is conjectured that if the recharge-hungry node is located beyond the breakpoint in a given  $t_r$ , it will be located below the breakpoint in  $t_r + \Delta_{t_r}$  with high probability, if it is guaranteed that the correlation between the sensor node distances to the sink in  $t_r$  and  $t_r + \Delta_{t_r}$  is small. To analyze this correlation, here it is defined the parameter decorrelation frame span, which is the frame index in which the Pearson correlation coefficient of the sensor node distance to the sink node drops below a given threshold. The threshold was set to  $1/e \approx 0.368$ , which is a common value adopted in the context of the decorrelation distance Jalden (2010); Abbas et al. (2015), which is a similar parameter typically applied to characterize signal propagation in wireless communication systems. The Pearson correlation coefficient was measured by means of the sample autocovariance function of the node distances to the sink, whose biased (but asymptotically unbiased) estimator Chatfield (2003) is

$$R(i) = \frac{1}{T} \sum_{j=1}^{T-i} (d_j - \hat{\mu}_d) (d_{j+i} - \hat{\mu}_d), \tag{11}$$

where  $\hat{\mu}_d$  is the sample mean of the distances from the sensor node to the sink node, and *T* is the number of distance values. The normalized sample autocovariance function R(i)/R(0) is plotted in Figure 7 for a realization of each mobility pattern with  $2.5 \times 10^4$  steps ( $T = 2.5 \times 10^4$  distance values). From this figure it can be seen that the decorrelation frame span is around 28, meaning that  $\Delta_{t_r} > 28$  guarantees a low correlation between the node positions in  $t_r$  and in  $t_r + \Delta_t$ .

In practice, the channel attenuation needed for the operation of the delayed recharge mechanism can be obtained from the RSSI (received signal strength indication) information retrieved from the sensor nodes Benkic, Malajner, Planinsic and Cucej (2008). This RSSI-based method is simple, but inaccurate due to the inherent inaccuracy of any theoretical attenuation model used to map the RSSI level onto the actual channel attenuation. However, what is needed in the present directive recharge mechanism is only relative and indirect measures of attenuations, not necessarily accurate, just for a simple classification. For instance, the recharge transmission could be enabled if the recharge-hungry node is experiencing an RSSI level above the average RSSI retrieved from all nodes.



**Figure 7:** Normalized autocovariance function of the distance between a sensor node and the sink node computed throughout 25000 steps; the first 500 are shown. The decorrelation frame span is 28, for which R(i)/R(0) = 1/e.

Notice that the above approach for recharge-hungry node identification and recharge via beam-forming is in agreement with Zeng et al. (2017), where it is stated that: i) from the perspective of maximizing the overall energy transfer efficiency, the sensor nodes that have the best channel conditions should be scheduled for WPT; ii) to avoid battery depletion of the nodes and hence prolong the network lifetime, higher priority should be given to those nodes with low residual battery energy and high energy consumption demands.

The mechanism illustrated in Figure 6(b) is also aligned with one of the challenges stated in Zeng et al. (2017), where it is suggested the use of a simple beam-forming technique called retrodirective amplification. It applies to a multi-antenna array, which upon receiving a signal from any direction, transmits a signal response back towards the same direction without the need of knowing the source direction Re, Podilchak, Constantinides, Goussetis and Lee (2016); Zeng et al. (2017). The retrodirective amplification could be employed in the lifetime optimization approach considered herein, since the charger node could retrodirect the sensory information data received from a sensor node.

## 6. Numerical results

This section reports numerical results aiming at assessing the effects of the node traveling patterns, path loss models and recharge mechanisms on the lifetime of WRSNs optimized via the solution of Problem (1).

## 6.1. Simulation setup

Computer simulations have been conducted using Matlab, assuming that the sensor nodes move randomly within an area of  $100 \times 100 \text{ m}^2$ , with a reflecting boundary, according to the RWP, the RGM and the RPG models described in Section 4. The Pymobility Library Panisson (2012), which is a Python software package for simulating mobility and contact models, has been used to generate the random movements of the nodes according to the above mobility models. The same velocity (0.9 to 1.1 units/step) and pause time (0 steps) have been adopted for all mobility models. The randomness tuning parameter of the RGM has been set to 0.99 to keep a high correlation between steps. The aggregation parameter of the RPG has been set to 0.2 to mimic the movement of some herd. It has been considered N = 10 nodes for not polluting unnecessarily some graphs and to speed-up the time-consuming replicated experiments related to the statistical analysis of variance. The sink node, which is also the WPT transmitter, was placed at the center of the network area. The sensor nodes communicate with the sink according to a star topology.

It is noteworthy to mention that the scalability of the adopted lifetime optimization approach with respect to the number of nodes has already been demonstrated in Guimarães et al. (2016), wiping out the need for verifying it again in this article.

The first 500 node mobility steps in each simulation run have been discarded so that the mobility pattern reached the steady-state node distribution Roy (2016). Each mobility scenario has been evaluated under the single-slope path loss model with loss exponents  $\epsilon_1 = \epsilon_2 = 2$ , and under the two-slope model with  $\epsilon_1 = 2$  and  $\epsilon_2 = 4$ , with the breakpoint firstly set to  $d_{bp} = 30$  meters from the sink node, and later to  $d_{bp} = 45$  meters. Six optimization spans were assessed in the case of no recharge: F = 1, 5, 10, 20, 30, 40; see Problem (1). A single representative optimization span F = 10 was adopted in the case of recharge, as will become clear later on in this section. The half-power beam-width in the

directive recharge mechanism was set to  $\varphi_{bw} = \pi/2$  radians, which corresponds to a directivity relatively easy to be accomplished in practice.

The reference WRSN lifetime optimization algorithm devised in Guimarães et al. (2016) has been implemented in the Matlab software. Problem (1), which is the core of the algorithm, has been evaluated using the CVX, a system that works under the Matlab environment for modeling and solving convex optimization problems Grant and Boyd (2008). The weighting factors of the objective functions in Problem (1) were set to  $w_1 = 0$  and  $w_2 = 1$ , which is the configuration that yields larger lifetime improvements, but poses more challenges to the recharge mechanism due to possibly larger discrepancies among the nodes' residual energies during the network operation in comparison with other values of the weights Guimarães et al. (2016). The influence of other weights in the performance of the lifetime optimization has been fully explored in Guimarães et al. (2016).

In regard to the ANOVA, the factorial design analysis Montgomery (2013) was applied to measure individual and interaction effects of the node mobility patterns, the path loss models and the recharge mechanisms on the network lifetime. Shortly, a factorial design is a strategy for planning an experiment in a proper way such that the data collected allow for detecting which input variables (factors) and which interactions between them are the most influential to the desired performance metrics. Replicated experiments are carried out and the responses collected from all replications are used to evaluate the effect of each factor and their iterations through statistical tests, which in turn can determine whether the output is significantly dependent of the input or not, and to which extent. A general linear model that represents the effect of each factor (main effect analysis) and their interactions (interaction analysis) is then established. An F-test is used to compare the fits from different linear regression models. If the P-value associated to the overall F-test is less than a specific significance level, it means that the regression model is capable of explaining the response variable better than the mean of the responses. The model fit quality is also measured by the coefficient of determination Hahn (1973),  $R^2$ . The closer  $R^2$  is to 1, more precisely the model explains the data.

The factorial analysis was firstly applied to the WSN without recharge. Then, representative system configurations were chosen for assessing the network lifetime when recharge is present. The factorial analysis has been carried out under the ANOVA general linear model, using the Minitab 16, which is a software tool with focus on statistical computing and visualization Minitab, Inc. (2010); Lesik (2009), considering the standard significance level of 5%. The number of experiment replications for the factorial analysis was chosen as 10, which was enough to guarantee the desired confidence with respect to the tests, reliably evidencing the differences among the impact of the analyzed factors and their interactions Montgomery (2013).

As far as the lifetime optimization performance metrics are concerned, the average of the residual energies of all sensor nodes at the end of the simulation execution time has been used herein, since we are mostly interested in relative lifetime measurements. The absolute network lifetime seems to be more appropriate, but the time spent to wait for the network death can be a limiting issue in computer simulations. This problem is aggravated in the case of replicated experiments needed for a reliable statistical analysis of variance. To alleviate this problem, it would be reasonable to modify some system variable that influence the lifetime in order to anticipate the network death (for instance, the energy consumption of the nodes can be scaled up). However, different network scenarios in terms of signal propagation characteristics, node mobility patterns and recharge mechanisms can lead to quite different behaviors of the residual energies over time, making it cumbersome to set the appropriate scaling factor for each scenario. Nonetheless, a single lifetime scaling factor can be set, and simulations can be halted at a given reference time, so that the network lifetime can be indirectly quantified, in relative terms, by the average energy residual to the sensor nodes at this time. The average residual energy at the simulation stop time is hereafter referred to under the acronym ARESST.

The number of steps chosen for the mobility models, which determines the simulation stop time frame index, also influences the accuracy of the network simulations. To find the proper number of steps, firstly the following conservative criterion has been adopted: using  $2.5 \times 10^3$  steps, which is enough for the mobility model to reach the steady state, the number of times that a sensor node visited each of the  $31 \times 31$  cells dividing the analyzed area for each model was counted, similar to what has been made in Roy (2016). An average of at least 95% of the cells were visited in random executions of the RWP model. In the case of the RGM model, 100% of the cells were visited, a consequence of its uniform node distribution. In the case of the RPG model, almost 100% of the cells were visited during  $2.5 \times 10^3$  steps, on average, a consequence of its more evenly node distribution compared to the RWP; see Figure 4(b). Cells not visited are located next to the area boundaries with higher probabilities for the RWP and RPG models. Thus,  $2.5 \times 10^3$  steps would be enough to assess the network lifetime in the absence of recharge.

However, when recharge is applied the simulation execution time has to be increased to accommodate several recharge events during the analyzed time. This is because the recharge efficiency depends largely on the node mobility

model, on the recharge mechanism, and on the node positions when each recharge is triggered. To illustrate this behavior, Figure 8 shows the normalized residual energies of N = 10 sensor nodes moving according to the RGM model during  $2.5 \times 10^3$  frames, for the recharge mechanisms described in Subsection 5.4, which are the WPT with omnidirectional radiation, and the WPT with beam-forming subjected or not to delayed transmissions. The corresponding regression lines and coefficients of determination are also given. Two random realizations of the RGM model are shown. In Figure 8(a), the first recharge trigger occurred as scheduled (in  $t_r = 800$ ), and the second recharge trigger was delayed 100 frames from the scheduled  $t_r = 1600$  in the case of beam-forming. In Figure 8(b), both triggers occurred as scheduled. The disturbances on the residual energies caused by the recharge events can last tens or even hundreds of frames, preventing recharge transmissions very close apart if it is intended that their influences do not overlap. As a consequence, few recharge events could be accommodated within  $2.5 \times 10^3$  frames.

Hence, it is mandatory to increase the number of recharge events to reduce the variability of the recharge effectiveness in a given scenario. Hereafter, 9 recharge events have been scheduled during  $8.8 \times 10^3$  frames. To maintain consistence, this number of frames has been also adopted in the case of no recharge. By doing so, the chance of occurring a single small recharge or a large number of inefficient recharges during the observation interval is reduced, thus reducing the variability of the ARESST. Additionally, given the large variability observed between different realizations of the same scenario, here the lifetime analyses were made based on repeated experiments via the ANOVA full factorial design.



**Figure 8:** Effect of the recharge mechanisms on the evolution of the residual energies of 10 sensor nodes in the optimized network under the RGM mobility model, for two executions of the experiment. The different line colors are meant to distinguish the different sensor nodes. Recharges are around 1/3 and 2/3 of the observed interval.

The two-slope recharge model defined in Section 5 was subjected to the following procedure: the 9 recharge events were triggered at integer multiples of 800 frames, i.e. the instants of recharge initiation were  $t_r = z800$ , for z = 1, 2, ..., 9. No recharge occurred during the last interval corresponding to 1600 frames out of the total of  $8.8 \times 10^3$  frames, preventing disruptions on the residual energies at the end of the simulation interval, which could cause erroneous ARESST measurements and analyzes.

Each recharge transmission remained active during 50 frames, meaning that the amount of recharge delivered to the charge storage device (battery or super-capacitor) depended upon the channel condition and the node position during these 50 frames, as described in Subsections 5.3 and 5.4. To mimic the increase of the charge delivered to the charge storage device with time, not taking into account the charge characteristics of any particular device, the recharge increase law was made linear within the 50 frames, if a fixed distance to the charger is considered. Obviously, the actual charge increase law was dependent of the node movement pattern while each WPT transmission was active.

When the omnidirectional (omni, for short) recharge was enabled, the recharge trigger instants were kept fixed at integer multiples of 800 frames. This was also the case of the directional recharge via beam-forming without delayed transmissions (beam, for short). When the directional recharge via beam-forming and delayed transmissions (beam, for short) was enabled, the scheduled recharge was enabled in each  $t_r$ , and the eventual delayed recharge occurred at  $t_r + \Delta_{t_r}$ , with  $\Delta_{t_r} = 100$  frames.

All energy levels were normalized with respect to the maximum. The scaling constant  $\Omega$  in the energy consumption model of Equation (6) was adjusted to  $2.1 \times 10^{14}$  to force the optimized network death to occur just after  $8.8 \times 10^3$ 

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Parameter	Value or attribute
Weights in Problem (1)	$w_1 = 0, \ w_2 = 1.$
Simulation steps	$8.8 \times 10^3$ steps, with and without recharge.
Number of nodes	10 nodes.
Velocity	0.9 to 1.1 units/step.
Mobility models	RWP, RGM and RPG.
Pause time (RWP, RPG)	0 steps.
Path loss models	Single-slope ( $\epsilon_1 = \epsilon_2 = 2$ ) and two-slope ( $\epsilon_1 = 2, \epsilon_2 = 4, d_{bp} = 30$ m).
Proportionality constants	$\Omega = 2.1 \times 10^{14}$ in Equation (6); $\Omega' = 2 \times 10^{17}$ in Equation (9).
Optimization span $F$	Without recharge: 1, 5, 10, 20, 30, 40 frames; with recharge: $F = 10$ .
WRSN topology	Star, over a square area of $100 \times 100 \text{ m}^2$ .
Replications for ANOVA	10 replications.
Statistical significance level	5%.
Recharge mechanisms	One omnidirectional (omni) and two directional (beam and beam-wait);
	The directional radiation pattern has $\varphi_{bw} = \pi/2$ rad;
	Nine recharge events up to the stop time, each lasting 50 frames.
Performance metric	Average residual energy at the simulation stop time (ARESST).

Table 1Simulation setup.

steps, as previously explained. This value of  $\Omega$  was determined based on the mobility model that yielded the smallest network lifetime, which is the RPG.

The constant  $\Omega'$  in the recharge model of Equation (9) was set to  $2 \times 10^{17}$ , allowing for the recharge events to be minimally perceived, visually, in the situation of less recharge efficiency, which corresponds to the omnidirectional WPT approach. The initial energy levels available to the sensor nodes were made equal to one another, i.e. their normalized values were set to 1. This value corresponds to a full-charged battery. Naturally, a given recharge event never fills the batteries above their initial energies. Table 1 summarizes the simulation setup.

## 6.2. Results considering no recharge

As a consequence of applying the full factorial analysis,  $3 \times 2 \times 6 \times 10 = 360$  experimental runs were executed in the case of no recharge. These numbers refer to 3 mobility models, 2 path loss models, 6 values of the optimization span F, and 10 replications of each experiment. It means that Problem (1) was executed  $360 \times (\text{simulation stop time})/F = 360 \times 8800/F$  times, yielding  $3.168 \times 10^6$  executions for F = 1 and  $7.92 \times 10^4$  executions for F = 40. For reference, it took approximately two and a half hours to run 10 replications for 8800 steps of a given mobility model in a computer Asus K43E, Intel Core is 2410M - 2.3 GHz, 6 GB RAM DDR3 1333 MHz, running Windows 7 Home Basic, service pack 1, and Matlab version R2010b. Approximately the same measurement applies when recharge is applied.

All results presented in this section related to the factorial analysis are statistically significant at the significance level of 5%, since P-values equal to zero (the best possible) resulted for all factors and interactions. The coefficient of determination for the ANOVA general linear model fit was  $R^2 = 0.9877$ , further contributing to assure that the present analysis is statistically trustworthy, even to be used for predictions on the response variable (the metric ARESST).

A first set of results obtained from the analysis of variance is presented in Figure 9. Effect plots like these can help better understand how the response variable is affected by each of the factors (mobility models, path loss models and optimization span). The reference value identified by the dashed lines is the overall average of the responses, i.e., it is the mean response produced by the factors altogether. If a response line lies parallel to this average, it means that switching between factors does not cause any statistically significant change to the response; otherwise, if a response line has some inclination with respect to this average, it means that different factors cause statistically significant changes to the response. If the response value is above the reference, the impact on the response is in favor of increasing it with respect to the average effect of all factors; otherwise it is in favor of decreasing it with respect to the average.

Figure 9(a) shows that the RWP mobility model is responsible for the highest ARESST, which translates into the highest network lifetime. This is justified by recalling that the RWP traveling pattern tends to concentrate nodes around the center of the network area; see Figure 2(b). Lower average energy consumptions result due to the higher number of nodes closer to the sink node, which corresponds to lower transmission powers, eventually yielding a higher ARESST and a higher lifetime as a consequence. The RGM produces an intermediate lifetime, whereas the ARESST achieved with the RPG is way below the overall average. The lower ARESST yielded by the RGM with respect to the RWP is credited to the fact that, in the RGM, nodes tend to walk evenly across all available area, staying more often within the area of higher attenuation (beyond the breakpoint) in comparison with the RWP; see Figure 3(b). The smaller ARESST produced by the RPG when compared with the RGM apparently contradicts the expected outcome: the RPG should yield higher ARESST, since the presence of nodes closer to the area boundaries in the RPG (which would correspond to higher energy consumption) is less probable than in the case of the RGM; see Figures 3(b) and 4(b). Thus, it can be concluded that the grouping of nodes in the RPG penalizes more the ARESST than how much this metric is improved due to the less probable presence of nodes close to the area boundaries.

From Figure 9(b) it can be seen that the two-slope path loss model produces a smaller ARESST when compared with the single-slope model, which is explained by the fact that nodes moving within the area located beyond the two-slope breakpoint tend to spend more energy to compensate for the higher attenuation induced by the loss exponent  $\epsilon_2 > \epsilon_1$ , combined with the larger distances from the sink. However, from the interaction plot presented in Figure 10(a), it can be seen that the RWP is less sensitive to the switching of the path loss model than the RGM and the RPG, since it is more likely that a small number of nodes in the RWP will be under the combined bad conditions of larger distances from the sink and a larger loss exponent, yielding non significant discrepancy in the energy consumption with respect to the single-slope scenario. From Figure 10(a) one can also observe that the impacts of the mobility models on the ARESST are less different from each other if the single-slope path loss model is adopted. Nonetheless, the RWP maintains the highest ARESST, followed by the RGM and then the RPG.

The effects of the optimization span F on the ARESST are depicted by the main effect plot in Figure 9(c), and by the interaction plots in Figures 10(b) and 10(c). Generally speaking, from these plots it can be concluded that large values of F are undesirable from the perspective of lifetime improvement, except in the case of the RPG model, for which any F yields approximately the same, but the lowest ARESST. Nevertheless, one must recall that a smaller F means that the optimization Problem (1) is solved more frequently, increasing the computational burden of the central processing node. From Figures 9(c), 10(b) and 10(c) it can be additionally concluded that any F around 5 to 10 is an appropriate choice, as far as the network lifetime is concerned, for any mobility model and any path loss model. A value of F in this range produces the highest ARESST if the single-slope path loss model is adopted along with the RWP mobility model.

Specifically in the cases of Figures 9(c) and 10(c), it can be seen that the ARESST increases slightly for F up to  $\approx 10$ , and then reduces monotonically as F increases above  $\approx 10$ . This happens when the mobility models are considered altogether (Figure 9(c)), and when the mobility models RWP and RGM are separately considered for the purpose of identifying interactions (Figure 10(c)). The reduction of the ARESST above  $F \approx 10$  is credited to the fact that past information on residual energies produces an estimated consumption matrix **B** (see Section 3) progressively less correlated with the actual ones as F increases, reducing the performance of the lifetime optimization process. The small improvement in the ARESST when F increases up to around 10 is due to the fact that when F is very small, from Guimarães et al. (2016) it can be concluded that the energy consumption of the nodes tend to become approximately equal to one another, which is similar to using  $w_1 = 1$  and  $w_2 = 0$ , a situation in which the lifetime is penalized. As F increases, the consumptions tend to become more dissimilar, as happens when  $w_1 = 0$  and  $w_2 = 1$ , which improves the network lifetime up to the point in which the low correlation between the estimated and the actual energy consumptions becomes dominant, making the ARESST curve trend to go downwards.

Regarding the ARESST associated with the RPG mobility model in Figure 10(c), it can be seen that it practically does not change with F. Since in this model all nodes are moving close to each other, they have approximate energy consumptions. As a consequence, the effectiveness of the lifetime optimization is drastically reduced, since a small margin remains to control these consumptions. Hence, any variation of the ARESST with F becomes nearly imperceivable.

Finally, it can be seen that the interaction lines in all plots in Figure 10 are not completely parallel to each other, which means that there are some sort of interaction effects with respect to the analyzed factors. An interaction means that the presence of a given factor influences the response caused by another one differently from the main effect of the latter alone. In other words, an interaction exists when the effect of one factor changes depending on the level or

presence of another factor.



**Figure 9:** Main effect plots for the average residual energy at the simulation stop time (ARESST), without recharge, according to the mobility model (a), the path loss model (b), and the optimization frame span (c). The dashed lines identify the overall average response.

## 6.3. Results considering recharge

The factorial analysis about the mobile WRSN lifetime with recharge took into account the following:

- The two-slope path loss model was chosen for being the most challenging from the perspective of lifetime improvement, as well as for being representative of the WRSN propagation environment Kurt and Tavli (2017).
- All mobility models (RWP, RGM and RPG) have been analyzed, since the assessment of their influences on the network lifetime is one of the targets in this article.
- The optimization span in Problem (1) was chosen as F = 10 frames, which corresponds to a value that is favorable to the WRSN lifetime improvement, as demonstrated in Subsection 6.2.
- All recharge mechanisms (omni, beam and beam-wait) described in Subsections 5.4 and 6.1 have been considered, since their influences on the network lifetime is another target in this article.
- The optimized lifetime inferred via the ARESST was the performance metric adopted.

The total number of experiments in the full factorial analysis was  $3 \times 1 \times 1 \times 3 \times 10 = 90$ . These numbers refer to 3 mobility models, 1 path loss model, 1 value of the optimization span *F*, 3 recharge mechanisms, and 10 replications. As a consequence, Problem (1) was executed  $90 \times (\text{simulation stop time})/F = 90 \times 8800/10 = 7.92 \times 10^4$  times.

Likewise the case of no recharge, all results given in the present subsection related to the factorial analysis are statistically significant at the significance level of 5%, since P-values equal to zero were obtained for all factors and interactions. The coefficient of determination resulted from the ANOVA general linear model fit was  $R^2 = 0.8019$ .



**Figure 10:** Interaction plots for the average residual energy at the simulation stop time (ARESST), without recharge, according to the path loss model and the mobility model (a), the optimization frame span and the path loss model (b), the optimization frame span and the mobility model (c).

Figure 11 shows the main effect plots for the ARESST according to the recharge mechanism in part (a), and the mobility model in part (b). From Figure 11(a) it can be seen that the recharge mechanisms with directional beam at the charger (beam and beam-wait) produce larger network lifetimes (larger ARESSTs) when compared with the omnidirectional transmission (omni). This is an expected outcome, since a directional WPT is more efficient than its omnidirectional counterpart. However, the directional transmission with controlled delay (beam-wait) surprisingly did not bring advantage over the directional transmission without controlled delay (beam), a behavior that is explored a little further ahead.

Comparing Figure 9(a) with Figure 11(b), it can be concluded that the impact of the mobility model on the network lifetime without recharge is analogous to the one in which recharge is applied. However, the difference between the maximum and the minimum ARESST in the former case is larger then in the latter due to the different impacts of the recharge mechanisms in each mobility pattern.

Figure 11(b) shows that, in general, the RWP mobility model benefits from the recharges more than the RGM, which in turn benefits more than the RPG, taking into account the overall effect of the recharge mechanisms. On the other hand, the interaction plot in Figure 12 unveils that the RWP benefits equally from any recharge mechanism, which is approximately the same situation achieved by the RGM. The lifetime improvement attained under the RPG mobility model is considerably larger when the directional recharge is applied. This is explained by the fact that when the recharge is directed to a given node, it efficiently hits the other ones with high probability, since in this model the nodes move close to each other. This behavior does not happen in the case of the RWP and the RGM models. Such a result is also intuitively satisfying if analyzed from another viewpoint: although the solution of the optimization Problem (1) tends to equalize less the energy consumption of the nodes over time if  $w_1 = 0$  and  $w_2 = 1$ , when a recharge-hungry node is identified its residual energy is not too distinct from the energy residual to the other nodes, meaning that an efficient recharge mechanism is the one that, ideally, is capable of transferring the same amount of energy to all sensor nodes. It is noteworthy to mention that this is a particular situation owed to the behavior of the

optimized network according to the solution of the Problem (1).

From the interaction plot in Figure 12 it can also be seen that the inferiority of the beam-wait recharge mechanism with respect to the beam recharge mechanism is more apparent in the case of the RPG model. Again recalling that in this model the nodes move close to each other, if the recharge-hungry node is beyond the breakpoint, it is more likely that all of them will remain in this situation after  $\Delta_{t_r}$  frames. Additionally, due to the nonlinear signal propagation loss, if the nodes altogether move away from the WPT transmitter, the recharge penalty is larger than the benefit achieved when they move the same amount towards the WPT transmitter, which justifies the performance penalty of the beam-wait with respect to the beam mechanism.



**Figure 11:** Main effect plots for the average residual energy at the simulation stop time (ARESST), with recharge, according to the recharge mechanism (a), and the mobility model (b). The dashed lines identify the overall average response.



**Figure 12:** Interaction plots for the average residual energy at the simulation stop time (ARESST), with recharge, according to the mobility model and the recharge mechanism.

The inefficiency of the beam-wait recharge mechanism in the specific situation considered in Figure 11(a) can be explained by firstly recalling, from Subsection 5.4, that this mechanism was developed under the conjecture that, if the recharge-hungry node is located beyond the breakpoint in a given recharge trigger instant  $t_r$ , it will be located below the breakpoint in  $t_r + \Delta_{t_r}$  with high probability, as long as  $\Delta_{t_r}$  is made larger than the decorrelation frame span. In fact, once the recharge-hungry node is located in a bad channel condition (beyond the path loss breakpoint  $d_{bp} = 30$  m), it is more likely that it remains in this condition after  $\Delta_{t_r}$  instead of switching to a good channel condition (below  $d_{bp}$ ). In other words, the decorrelation frame span guarantees low distance correlation, but does not guarantee sufficient distance change to produce switching from a bad to a good channel situation. Since the area of the circle defined by the breakpoint ( $\pi \times 30^2 \approx 2827$  m<sup>2</sup>) is significantly smaller than the area outside this circle ( $100^2 - \pi \times 30^2 \approx 7163$  m<sup>2</sup>), a distance change enough for a node to move from a bad channel condition. Moreover, although the node movement direction is evenly distributed, from the nonlinear recharge model in Equation (9) it can be concluded that a position

change distancing a node from the WPT transmitter reduces the recharge power more than it is increased by the same position change towards the transmitter.

In order to support the arguments regarding the influence of the areas associated to bad and good channel conditions on the efficiency of the beam-wait recharge mechanism, a factorial analysis was made to measure the impact of the breakpoint distance on the ARESST, for  $d_{bp} = 30$  m and  $d_{bp} = 45$  m. Figure 13(a) shows the main result, from where it can be concluded that the breakpoint distance has a considerable impact on the network lifetime improvement produced by the beam-wait mechanism. This important result also prompts a potential application of the beam-wait recharge in shadowed propagation scenarios, where the local-mean received power fluctuates due to the presence of obstacles between the WPT transmitter and the sensor nodes (Guimarães, 2009, p. 202). In such scenarios, the probability of encountering a non-shadowed channel after  $\Delta_{t_r}$  frames will be high if the recharge-hungry node is found under such channel condition at the scheduled recharge moment.

Figure 13(b) and Figure 14 complement Figure 13(a). The former carries some similarity with Figure 11(b); thus, similar conclusions apply. However, it is worth highlighting that the ARESST has been noticeably improved from Figure 11(b) to Figures 13(b) in the case of the RGM and the RPG mobility models, what did not happen in the case of the RWP. This outcome means that a significant positive impact of an increased breakpoint distance can be attained if the node mobility pattern follows the RGM and the RPG models. This fact is even more evident from the interaction plots given in Figure 14. These last three sets of results have been generated under a coefficient of determination  $R^2 = 0.79$ , and null P-value; thus, they are statistically significant.



**Figure 13:** Main effect plots for the average residual energy at the simulation stop time (ARESST) with recharge via the beam-wait recharge mechanism, under different breakpoint distances (a), and mobility models (b). The dashed lines identify the overall average response.



**Figure 14:** Interaction plots for the average residual energy at the simulation stop time (ARESST), with beam-wait recharge mechanism, according to the mobility model and different breakpoint distances.

# 7. Conclusions and opportunities for further research

In this article, the lifetime of a mobile wireless rechargeable sensor network was assessed when the nodes moved according to the random waypoint, the random Gauss-Markov or the reference point group mobility models. A recently-proposed convex optimization approach, in which the communication activity levels of the sensor nodes with the sink node are controlled to save energy, was applied to maximize the network lifetime under the influence of recharge via radiative wireless power transfer events. The recharge was modeled to take into account factors that mostly influence the end-to-end recharge efficiency. The mobility and the recharge models were coupled with a two-slope propagation loss prediction model. The main conclusions obtained from the present research are summarized in the sequel:

- It has been shown that different mobility patterns may result in considerably different performances of the adopted lifetime optimization approach. Among the analyzed mobility models, the random waypoint potentially produces the highest lifetime, closely followed by the random Gauss-Markov. The reference point group model, which is particularly useful for mimicking the movement of herds in wildlife monitoring sensor networks, for example, unveiled to be the worst case in terms of lifetime improvement. On the other hand, it carries the largest potential for lifetime improvement when subjected to recharge.
- The two-slope propagation loss prediction model emphasizes the need for developing efficient recharge mechanisms to cope with the potentially inefficient recharges that might happen when the intended nodes are far away from the charger, i.e., when they are affected by the normally larger path loss associated to the second slope of the loss model. The omnidirectional recharge transmission unveiled to be quite inefficient and should be avoided in the case of the reference point group mobility model, unless this inefficiency is compensated for by high-power recharge transmissions, which is feasible when there is no hard power constraint on the wireless power transfer emitter. Both the omnidirectional and the directional recharge mechanisms produced comparable lifetime improvements in the case of the random waypoint and the random Gauss-Markov models. Thus, in the context of the network lifetime optimized according to the solution of Problem (1), there is no strong reason for directing the beam of the wireless power transfer emitter if these two models apply to the application.
- Perhaps the most important lesson learned from the present research, concerning a wireless rechargeable mobile sensor network, is that a poorly designed recharge mechanism might not bring significant lifetime improvement or sustained network operation. On the contrary, it has been shown that the recharge strategies must be properly designed, taking into account not only the aspects of the wireless power transfer technology, but also the node mobility pattern and the propagation loss model that better fits to the sensor field environment.
- In general, the node mobility patterns, the path loss models and the recharge mechanisms influence, into variable extents, the performance of the lifetime improvement method. Thus, these factors must be modeled and analyzed together, as targeted and made in this article. Moreover, it has been demonstrated that are some sort of interaction effects with respect to the analyzed factors, meaning that the effect of a factor changes depending on the presence of another one.

The present work opens a number of related research opportunities, for instance:

- Adaptation of the wireless power transfer model described in Zeng et al. (2017) to the mobile wireless rechargeable sensor network scenarios considered in this paper, as a refinement of the proposed two-slope recharge model. This refinement, though not straightforward, could bring insights on the network lifetime optimization from the perspective of the maximization of the wireless power transfer efficiency.
- Implementation of a testbed to validate the proposed two-slope recharge model described in Subection 5.3. The use of commercial wireless power transfer devices, like the one described in Powercast Corporation (2017), could be a starting initiative.
- Implementation of the lifetime optimization algorithm proposed in Guimarães et al. (2016) in a real wireless sensor network, hopefully adding the recharge mechanism developed as a consequence of the previous opportunity. The simulation of the network on a specific simulation tool could be a starting point to refine the project and to validate it before implementation.

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- Analysis about the effect of other wireless radiative recharge mechanisms, for instance with multiple fixed or mobile charge nodes. The determination of the single recharge-hungry node could also be converted into the determination of a larger number of recharge-hungry nodes, as an attempt to produce more efficient recharges with the adaptive beam-forming approach. For instance, the infinitely possible beam directions could be discretized into a reasonable number of superimposed candidate beams, such that the selected direction for transmission would be the one with the largest number of nodes having the lower residual energy combined with the smallest distance from the wireless power transmitter. The search for the recharge-hungry nodes and the verification of their distances to the charger would be respectively made by means of the residual energies already available to the central processing node for the purpose of lifetime optimization, and by means of the relative received signal strength indicator information.
- Investigation of the impact of the directional recharge mechanism with delayed transmissions (the so-called beam-wait, for short) on the mobile wireless rechargeable sensor network when the nodes are subjected to local-mean received power variations (shadowing) in addition to the distance-dependent area-mean multi-slope propagation loss.
- Investigation on how the present lifetime improvement of mobile wireless rechargeable sensor networks may affect or is affected by scheduling, as discussed, for instance, in (Cecílio and Furtado, 2014, Chap. 5) regarding channel access for communication in ordinary wireless sensor networks, or in Suo et al. (2016); Sangare et al. (2017); Xu, Liang, Jia, Xu, Li and Liu (2018); Zhong et al. (2018) with respect of recharge scheduling.
- Although the conclusions reported herein refer only to the radiative wireless power transfer technology, it should be emphasized that the methodology adopted to devise the models and to generate the results, as well as to perform the statistical analyses, can be adapted to wireless sensor networks supported by other energy harvesting techniques. Thus, an analysis similar to the one made here, but assuming other energy harvesting strategy, also represents an opportunity for additional contributions to the field.

# **CRediT** authorship contribution statement

**Dayan Adionel Guimarães:** Conceived the main ideas and models associated to the research, participated in the original draft preparation, and contributed in discussions and proofreading. **Edielson Prevato Frigieri:** Participated in the original draft preparation, executed the experiments and simulations and contributed in discussions and proofreading. **Lucas Jun Sakai:** Executed the experiments and simulations and contributed in discussions and proofreading.

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#### Influence of mobility, recharge and path loss on the optimized lifetime of WRSNs



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