Assessing the cost of deploying and maintaining indoor wireless sensor networks with RF-power harvesting properties

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Abstract

Since Wireless Sensor Networks (WSNs) consist of nodes with limited power resources, methods that extend their energy lifespan are always in the spotlight. A potential method is the use of RF-power harvesting antennas which can absorb energy from radio frequency (RF) signals and transform a part of it into electricity. Dedicated energy transmitters (ETs) are used to emit power to the nodes. In this paper, we model the amount of harvesting energy as a function of several parameters such as the received power, the efficiency of the harvesting module and the transmission time. We consider a simple communication model that separates the ETs' transmissions with the node data transmissions to avoid interference whilst we allow multi-hop energy transfer between the nodes when it is achievable. However, the ultimate purpose of this paper is to examine whether the cost of the investment of using energy harvesting nodes can be covered by achieving a lower operation cost; that is longer and cheaper operation times and, thus, less frequent maintenance. We consider several scenarios with different node densities and transmitter populations. Simulation results show that the use of RF-energy harvesting nodes can save a significant amount of energy, while the cost of the investment can be (theoretically) covered in less than 7 years for dense networks.

1 Introduction

Wireless sensor networks are capable of periodically monitoring their vicinity and reporting important information about the integrity and security of their environment. The sensor nodes are usually powered by batteries and depending on how often they take measurements and communicate with other devices, their energy may be depleted fast. To tackle this problem, a new technology has been recently developed by harvesting energy from wireless transmitted signals. This technology uses a new type of antenna which can convert part of the received signal power to electricity. RF-power harvesting has been recently attracted a lot of attention due to its several energy-critical applications in the broad area of Internet of Things [28]. Some examples are healthcare applications [32], structural monitoring [10], and industrial applications [8]. All these applications take advantage of the ability of this technology to charge batteries by distance while the battery replacement may be a hard task since the nodes are often placed in inaccessible places or the cost of the replacement may be high.

Depending on the transmitted power and the distance between the transmitting source and the receiver, a node can harvest from some uW to some mW of power [13]. However, this technology is still new and presents some major limitations [17]. First, the harvested power dramatically decreases when the receiver is moving more than few meters away from the source. Second, the conversion efficiency is substantial only for a small range of distances. Third, there is a minimum received signal power, below which no conversion is possible, shortening the actual harvesting range. Finally, there are power losses due to leakage or discharging properties of the storage mediums.

Despite its weaknesses, wireless charging with dedicated ETs is a reliable way to charge low power consumption devices like WSN nodes, mainly due to the predictable and uninterrupted power supply. Other harvesting methods, like solar panels, exhibit higher energy gains (during sunlight), but the amount of energy depends on time, weather and seasonal conditions. Moreover, the solar radiation is in general case unpredictable and disappears at night. Another disadvantage is that panels take much space and require extra equipment like inverters and huge batteries to store the spare energy and present high installation costs as well. Due to these disadvantages the use of solar panels is considered impractical for indoor applications.

The energy transfer in RF-power harvesting is achieved either by taking advantage of the ambient RF signals transmitted by nearby primary devices or by dedicated chargers that continuously transmit energy beacons. Ambient harvesting has the advantage that does not require any additional equipment other than the harvesting module, however, the amount of harvesting power varies over time and it is much lower compared to dedicated chargers [3]. In this paper we consider dedicated and stationary ETs whose purpose is the periodic emission of RF signals. We model a network consisting of nodes and ETs taking into account the harvesting, communication and storage limitations described above. Unlike nodes whose power capacity is limited, the ETs are plugged into the power outlet and, thus, they have unlimited power resources. For simplicity reasons, we divide the time in rounds and every round includes two phases. The first phase allows the transmission of sensing data while the second phase is used for ET data transmissions. From now on we call the ET transmissions as "fake data" to distinguish them from node data transmissions.

Due to the fact that nodes that are closely to the ETs present high energy gains, we enhance our model by investigating whether these nodes could spend a spare part of their energy by transmitting some extra fake messages to their neighborhood. This action, known as *multi-hop energy transfer*, can extend the energy transfer range beyond the borders of the harvesting range of the ETs. We show that due to the current hardware limitations the performance gain is very limited for average or high distances.

In this paper, we consider the critical parameter of the *cost* in deploying and maintaining a network of nodes with RF-power harvesting capabilities. More specifically, we compute the capital and the operating expenditures focusing on indoor deployments. Taking into consideration the extra cost of the harvesting units, the cost of ETs, the cost of electricity, as well as the labor cost of maintaining a WSN (battery replacement), we introduce the *Minimum Reimbursement Time* problem. We particularly assess the time needed to cover the investment cost by an eventual reduced maintenance cost using a harvesting network. Since the maintenance cost is strongly connected with the network density, we examine a number of scenarios with different node and ET populations and we present extended simulation results. We extend the "Minimum Reimbursement Time" problem by introducing the problem of maximizing the coverage area whilst achieving the minimum possible reimbursement time.

The present paper extends our previous work [33] but it differentiates in the following ways: (a) the energy harvesting model is now more accurate, (b) a condition for networks consisting of nodes without batteries has been added, (c) the "Maximum Area Coverage" problem is introduced, (d) the position of the ETs is not fixed but it is computed based on the position of the nodes, (e) the simulation results derive by evaluating all the possible combinations between fake packet rate and number of ETs, and (f) the maximum number of ETs is increased from 8 to 16.

The contribution of this paper is threefold. First, we present the theoretical harvesting and communication background for RF-power harvesting networks and we provide conditions whether multi-hop energy transfer and node deployment without batteries are feasible. Second, we introduce the “Minimum Reimbursement Time” and the “Maximum Area Coverage” problems, to give some insights about (a) the scalability of the cost of a deployment consisting of RF-power harvesting devices, (b) how much of this cost can be covered by an eventual lower operating cost, and (c) finding upper bounds in terms of number of years for different node density deployments. Finally, extensive simulation results are conducted to evaluate the effectiveness of RF-power harvesting in terms of energy and cost savings.

The rest of the paper is organized as follows; Section 2 surveys the related work in the area of RF-energy harvesting WSNs. In Section 3 we present the energy harvesting and communication model while in Section 4 we give conditions to achieve multi-hop energy transfer and node deployment without batteries. In Section 5 we formulate the ‘Minimum Reimbursement Time” problem and we extend it by introducing the “Maximum Area Coverage” problem. Section 6 presents the theoretical and simulation results for different network scenarios, while Section 7 assesses the capital and operating costs. Finally, Section 8 concludes the paper and presents ideas for future work.

2 Related work

In the last few years there is an increased research effort for energy harvesting technologies due to the increased demand of power resources. The work of Basagni et al. [2] surveys all these technologies presenting their advantages and disadvantages. In the current paper we focus on RF-power harvesting which is frequently met in an indoor or outdoor environment since, nowadays, plenty of devices operate wirelessly, like television broadcasting, cell phones, Internet equipment etc..

RF-energy harvesting networks have been extensively studied from different research aspects. [17] presents an overview of the RF-power harvesting networks including system architecture, RF energy harvesting techniques and existing applications. Then, it surveys the circuit design as well as the state-of-the-art circuitry implementations, and reviews the communication protocols specially designed for this type of networks. Soyata *et al.* [26], focus on design tradeoffs and process alterations to represent the diversity in the applications requiring wireless RF harvesting units. They, also, include an analysis of system combinations, and how to wake up units, active storage, and duty cycling play roles in the consumption and harvesting of RF energy.

Recent research studies on static charger scheduling strategies, mobile charger dispatch strategies, and wireless charger deployment strategies are additionally reviewed in [18]. New research challenges and opportunities on RF-power harvesting networks focusing on their practical implementations are presented in [20]. A broad based perspective on the present RF-power harvesting state-of-the-art to the researchers and application engineers dealing with wireless transfer of power is presented in [1]. A recent wireless power transfer implementation using beamforming and duty cycle optimization is proposed in [5]. The sensor node could stably maintain the stored energy at the distance of 2.6m away from the antenna array by joint circuit/physical/radio link layer design and optimization.

The problem of computing the optimal number of readers to cover an area with static or mobile RF-power harvesting RFIDs is studied in [12]. The authors propose an analytical model to determine the optimal distance between the readers. The work of Fuentes *et al.* [6] aims at bounding the minimum cumulative power that ETs need to inject into the network, such that the recipient nodes harvest sufficient power to operate. The authors show that the overall power decreases with the number of ETs and it is lower-bounded by the number of transmitters and the channel path-loss.

Pang *et al.* [22] examine the problem of finding the optimal number of chargers to replenish the energy of a set of sensors. The charger positioning problem has has been also studied as a problem of maximizing an objective function subject to a power budget [31]. The authors formulate an optimization problem and show that it is NP-Complete. A similar problem is studied in [7]. The authors propose a wireless charger placement problem definition that takes into account the electromagnetic radiation. The solution they propose guarantees that the electromagnetic radiation levels are safe for every location on the plane. The authors of [16], also, focus on the safety and security problems related to wireless power transfer and highlight their cruciality in terms of efficient and dependable operation of RF-based harvesting networks.

Finally, a promising method to extend the energy harvesting range is the use of multi-hop energy transfer [14, 21]. In [14], two-hop energy transfer has been experimentally tested. The findings show that the optimal position for maximizing the performance gain has been found to be when the intermediate node is closer to the source. In [21], sparse and dense network deployment cases are tested. The results show an average 2-hop performance gain of 6% to 12%. However, both experiments use devices very close to each other.

In this paper, we study the problem of cost in RF-power harvesting networks, a factor that has not yet been taken into account in the existing literature.

3 RF-power harvesting & communication models

3.1 Energy harvesting model

A number of ETs with omni-directional antenna and fixed positions is used to send fake packets and recharge nearby nodes. The nodes are equipped with an extra RF module capable of harvesting power from the transmitted signals. Multiple nodes can be simultaneously charged by a single ET [27].

The amount of power each node receives is affected by its distance from the transmission source and the environmental conditions. Eq. (1) describes the total amount of energy that can be harvested by a node i surrounded by T energy transmitters. The amount of power a node receives equals to the accumulated received power by the T transmitters [11].

$$E_{h_i} = \int_0^t \sum_{j=1}^{T} P_{rx}^{d_{ij}} f^{d_{ij}} \frac{\psi \cdot k'}{\theta} dt, \tag{1}$$

where t is the transmission time, $P_{rx}^{d_{ij}}$ is the received power at distance d_{ij}, $f^{d_{ij}}$ is the efficiency of the harvesting antenna for $P_{rx}^{d_{ij}}$, ψ is the packet size, k' is the number of fake packets transmitted per time unit and θ is the transmission data rate. Indeed, the number of fake packets (i.e., k') corresponds to the period of time a transmitter is active.

The received power at distance d is given by the following propagation model [29]:

$$P_{rx}^{d} = P_0 \frac{e^{2\sigma G}}{d^{2b}}, \tag{2}$$

where $e^{2\sigma G}$ has a log-normal distribution with a shadowing coefficient σ ($G \sim N(0,1)$). The term $1/d^{2b}$ accounts for the far-field path loss with distance d, where the amplitude loss exponent b is environment-dependent. P_0 is the received power at reference distance which can be experimentally found.

From the equations we have so far we can observe that the harvested energy depends on the distance between the nodes, the transmission source, the transmission duration, the communication frequency as well as the efficiency of the harvesting module f ($0 \leq f < 1$). This efficiency depends on the received power at the given distance and it can strongly affect the performance of the harvesting system. For example, the best efficiency of Powercast's commercial RF-harvesting module[1] is achieved when the input power is around 4mW (i.e., less than 1 meter distance while transmitting at 3W power). The efficiency remains high (>80%) for small distances but decreases a lot as the node is moving away from the transmitter. Consequently, in applications requiring a higher node density the distance between the nodes and the transmitters is lower, a fact that increases both received power and efficiency.

3.2 Communication model

The ETs send fake packets to the nodes to decrease their energy consumption. Obviously, the more the packets the higher the energy gain. Similarly to [30], we split the transmission time in rounds where each round has two phases (see Figure 1). During the first phase, named "Sensing data phase", the nodes communicate with the sink and transmit their sensing data. We allow two or more nodes transmitting at the same time, unless they are in the communication range of each other. We, also, assume a fair resource allocation model where all the nodes have the same opportunity to access the network. In the second phase, named "Fake data phase", we allow the transmission of fake packets. The transmitters can transmit fake packets at the same time during this phase. The higher the rate of fake packets the longer the "Fake data phase". If the two phases overlap each other, a number of nodes will interfere with the ETs. In other words, a very high fake packet rate could cause network problems like interference, collisions and delays.

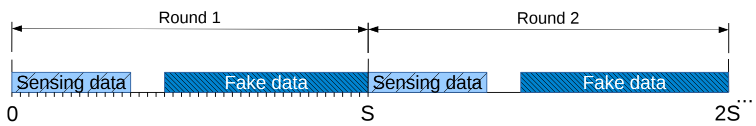


Figure 1: Transmission slots, phases and rounds.

The transmission time is divided in S slots and we allow only one data transmission per slot to avoid interference. However, a single time slot may be reserved by multiple ETs at the same time. We assume that the nodes are well synchronized using a precise time synchronization protocol [25]. Each time a node is ready to transmit a packet it switches to active mode while it remains in sleep mode if it is not transmitting. In sleep mode a node consumes much less energy but it can still harvest energy from the RF-harvesting antenna.

4 Special cases

4.1 Multiple-hop energy transfer

Since some nodes which are very close to the transmitters may absorb more energy than they consume, we allow them to spend this extra amount of energy by transmitting some fake packets to their neighbors. In this way, we aim to extend the harvesting zone beyond the current harvesting range of the ETs. In fact, a node plays the role of the energy relay between the ET and its neighbors. All the node fake data transmissions take part during the second phase of a round. A node i can send fake packets within a round of τ time units if the extra harvesting energy it finally gets is equal

[1] http://www.powercastco.com

or higher than the energy cost of transmitting at least one fake packet:

$$E_{extra_i} l^i \geq P'_{tx} \frac{\psi}{\theta}, \tag{3}$$

where,

$$E_{extra_i} = \int_0^{t<\tau} dt \left(\sum_{j=1}^{T} P_{rx}^{d_{ij}} f^{d_{ij}} \frac{\psi \cdot k'}{\theta} - P_{tx} \frac{\psi \cdot k}{\theta} \right) - E_{rest}^{\tau}. \tag{4}$$

P_{tx} is the transmitted power of the nodes (for sensing data) and E_{rest}^{τ} is the energy cost for the rest of operations. l^i is a function which describes the energy loss due to discharge properties of the capacitor [9] and it is equal to $l^i = \lambda E_h^i$, where λ is the power loss factor ($0 < \lambda < 1$).

The total number of fake packets a node can send (i.e., k''_i) depends on how much energy a node harvests during the "Fake data phase" and it is given by Eq. (5). In order to technically achieve multi-hop energy transfer, we assume that the extra amount of energy is stored in a super-capacitor and it is used when the capacitor and the node battery energy levels are above a threshold.

$$k''_i = \left\lfloor E_{extra_i} l^i \frac{\theta}{\psi \; P'_{tx}} \right\rfloor. \tag{5}$$

4.2 Deployment without batteries

It is obvious that deploying an ET close to a node, the latter can operate without using batteries since the energy it harvests it is enough to operate for one round. In this case, an adequate amount of energy is stored in a super-capacitor and can be spent for the normal node activity or for transmitting multi-hop fake packets. A node i can operate without batteries when the following condition holds:

$$\int_0^{t<\tau} dt \left(\sum_{j=1}^{T} P_{rx}^{d_{ij}} f^{d_{ij}} \frac{\psi \cdot k'}{\theta} \right) l^i - \int_0^{t<\tau} P_{tx} \frac{\psi \cdot k}{\theta} - E_{rest}^{\tau} \geq 0. \tag{6}$$

From (2) and (6) we can compute the maximum node distance away from a charger and, thus, the minimum number of ETs in the network so that no batteries are required.

5 Reimbursement time & coverage problems

5.1 The minimum reimbursement time problem

In this section we formulate the minimum reimbursement time (MRT) problem as a function of the capital expenditures (CAPEX) and operating expenses (OPEX). MRT is a minimization problem of the time needed to cover the investment cost of deploying a WSN with harvesting capabilities.

Specifically, the CAPEX and the OPEX of deploying and maintaining a WSN with and without harvesting is compared. For each deployment, notated with D, we optimize MRT by minimizing the

“Reimbursement Ratio (RR)” as follows:

$$RR(D) = \min\left(\frac{CAPEX_D^{wh} - CAPEX_D^{woh}}{OPEX_D^{woh} - OPEX_D^{wh}}\right),$$

$s.t.$

$$CAPEX_D^{woh} = n(C_{nd} + C_b), \tag{7}$$

$$CAPEX_D^{wh} = n(C_{nd} + C_{rb} + C_{hu}) + T \cdot C_{st}, \tag{8}$$

$$OPEX_D^{woh} = n(C_{mnt} + C_b), \tag{9}$$

$$OPEX_D^{wh} = p(C_{mnt} + C_{rb}) + C_{el},\ p \leq n, \tag{10}$$

$$C_{mnt} = t_{mnt} C_{mh}, \tag{11}$$

$$C_{el} = T(C_{el_b} t_{el_b} + C_{el_r} t_{el_r}) \frac{P'_{tx} \psi\ k'}{\theta}, \tag{12}$$

$$OPEX_D^{woh} > OPEX_D^{wh}, \tag{13}$$

where wh and woh stand for “with harvesting” and “without harvesting” respectively. All the individual costs and times are defined in Table 1. Indeed, $RR(D)$ determines how much time is needed to cover the extra CAPEX with a reduced OPEX. The higher the difference between the OPEX with and without harvesting, the shorter the time of reimbursement.

Table 1: Costs and times that affect CAPEX and OPEX.

Cost/Time	**Definition**
C_{nd}	node cost
C_b	battery cost
C_{rb}	rechargeable battery cost
C_{hu}	harvesting unit cost
C_{st}	energy transmitter cost
C_{mnt}	maintenance cost to replace a battery
t_{mnt}	time to replace a battery
C_{mh}	man-hour cost
C_{el}	electricity cost of the stations
C_{el_b}	electricity cost in peak hours
C_{el_r}	electricity cost in off-peak hours
t_{el_b}	number of peak hours
t_{el_r}	number of off-peak hours

The CAPEX includes the cost of the nodes (with or without a harvesting unit), the batteries (rechargeable or not) and the ETs. On the other hand, the OPEX consists of the spare battery cost, the maintenance cost by a technician and the electricity cost of the stations in case of harvesting. The electricity cost depends on the packet rate of the stations and it is divided in the cost during the peak hours of the day and the cost during the off-peak hours of the day (typically during the night). The maintenance cost depends on how much time a technician spends to replace the battery and the man-hour cost.

Looking at Eq. (7), since the capital expenditures are constant for a given deployment (number of nodes and chargers), the reimbursement ratio is minimized by maximizing its denominator. Since $OPEX_D^{woh}$ is, also constant, the denominator is maximized by minimizing the operating costs when harvesting is applied. OPEX with harvesting is affected by the number of nodes that need maintenance (i.e., p) and the electricity cost (i.e. C_{el}) (see Eq. (10)). Apparently, the lower the p and the

C_{el}, the lower the reimbursement ratio. The higher the fake packet rate, the higher the harvested energy and, thus, the lower the probability of maintaining a node. On the other hand, a higher fake data packet rate increases the electricity cost and the total operating expenditures (see Eq. (12)). Hence, the MRT problem is transformed to a problem of finding a trade-off between electricity and maintenance cost.

5.2 The maximum area coverage problem

In correspondence with the MRT problem, we introduce the Maximum Area Coverage (MAC) problem as a function of the RR and the node density. MAC is a broader problem whose objective is, given a maximum set of nodes or budget, to maximize the covering area $\mathcal{A}$ while achieving the minimum possible RR. As *covering area* is defined an ubiquitous continuous convex area monitored by a set of nodes, positioning them in that way so that no coverage holes (uncovered spots) exist between them. A special case of covering area is a square area as the one presented in Figure 2. Assuming a quadratic node deployment, $\mathcal{A}$ is equal to $2nR_s^2$, where R_s is the sensing range of the nodes and a is the area side[2].

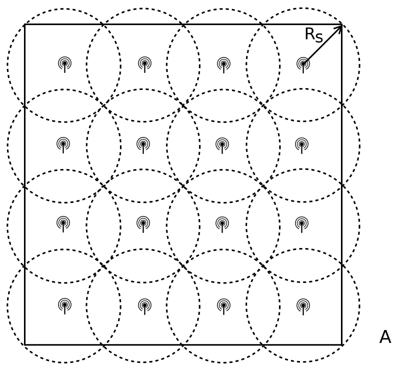


Figure 2: The maximum square area covered by 16 nodes using the quadratic node deployment.

6 Evaluating RF-energy harvesting network scenarios

6.1 Evaluation parameters & methodology

In this section we evaluate the proposed model by presenting theoretical and simulation results. We assume three types of scenarios with 256, 100, and 36 nodes respectively. We call the three scenarios, "Dense", "Normal", and "Sparse" respectively. The nodes as well as the transmitters are placed on a square grid-based terrain with 50 meters side. We assume that the transmitters are located at a slightly different height level to avoid blocking and shadow loss effects [20]. We vary the number of ETs from 1 to 16 with an increment of 1 as well as the fake packet rate and we measure (a) the number of interfering nodes, (b) the energy consumption, and (c) the percentage of nodes that need maintenance. Due to the presence of random values, we run each instance 100 times and the average results are presented.

[2] since $2R_s\sqrt{n} = \sqrt{2}a$ and $a^2 = \mathcal{A}$.

Regarding the node and ET characteristics, we consider the following values (summarized in Table 2): $P_{tx} = 65$mW, $\psi = 127$ bytes, $\theta = 250$Kbps, $k = 1/30$, $\tau = 30$ secs, $P_{rest} = 0.15$mW, $P_0 = 10$mW, $\sigma = 1$, and $b = 1$. $R_c = 30$m and $R'_c = 100$m are the transmission ranges of the nodes and stations, respectively. 5% energy loss between recharges is considered ($\lambda = 0.95$). Node parameters correspond to Mica2 sensor nodes [24] using a Zigbee communication module at 915MHz. Regarding the harvesting efficiency we used the values provided by Powercast for P2110B model (version 1.1) operating at the same frequency. The values used for the propagation/shadowing model correspond to indoor communication only [23].

Table 2: List of variables and their definition.

Variable	**Definition**
E_h	Harvesting energy
T	Number of ETs
P_rx^d	Received power at distance d
f^d	Harvesting efficiency at distance d
ψ	Packet size
k	Data packets per time unit
k'	Fake data packets per time unit
k''	Number of extra fake data packets (transmitted by the nodes)
θ	Data rate
P_0	Received power at reference distance
σ	shadowing coefficient
b	Path-loss exponent
G	Environment-dependent random variable
τ	Round length
$l(\cdot)$	Energy loss function
P_{tx}	Transmission power of the nodes
P_{rest}, E_{rest}^t	Power / Energy spent for the rest of operations for t time units
R_c	Communication range

6.1.1 Energy transmitter placement

The position of the transmitters is a parameter that heavily impacts the harvesting energy. The optimization of their position can lead to better performance and, thus, lower operating cost. However, this particular optimization problem has been proven to be NP-Complete and approximation algorithms have been proposed to tackle it [15, 4, 11, 31, 7]. Since in this paper we assume that all the nodes consume the same amount of energy per round and they have equal distances with each other, we compute the transmitter positions by minimizing the average distance between the transmitters and the nodes while keeping as many nodes as possible within the transmitters' harvesting range. A similar approach is presented in [31].

Figure 3 shows a depiction with the position of the ETs (X's), the grid of nodes (dots) as well as the nodes consumption (color) during a single round. A scenario with 100 nodes is used. Each plot corresponds to 2, 4, 6 and 8 ETs respectively. The theoretical maximum number of fake packets is used. We can see that nodes close to the ETs have a very low or even zero consumption. On the contrary, nodes close to the borders of the terrain or nodes far from the transmitters exhibit the highest consumption since they do not harvest almost any energy.

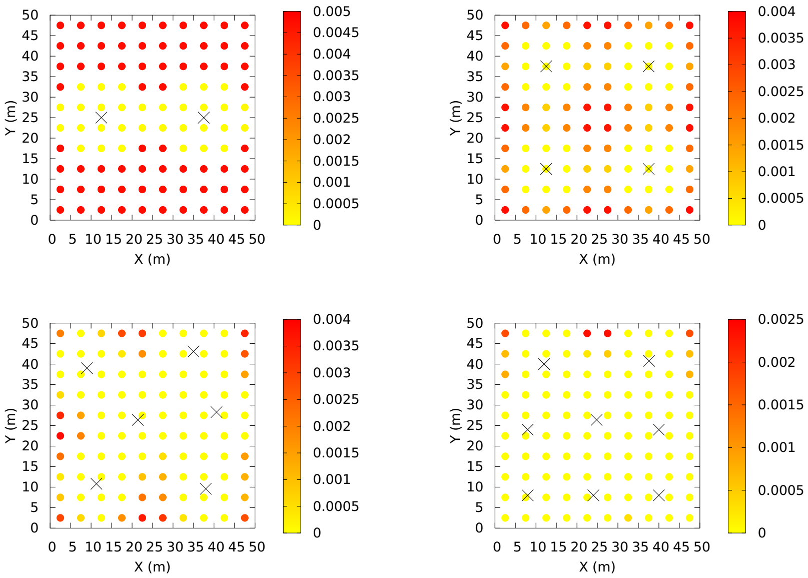


Figure 3: A grid with 100 nodes and 2, 4, 6 or 8 ETs respectively.

6.2 Consumption

Figure 4 illustrates the average energy consumption for the three scenarios when 4 ETs are used. As it is expected, the energy consumption decreases as the fake packet rate increases. We, also, observe that interference little affects the energy cost since, on average, harvesting covers part or all the energy loss. The average consumption is almost 3 times lower than the consumption without harvesting considering the theoretical maximum fake packet rate.

6.3 Maintenance

Figure 5 shows the empirical cumulative distribution function (CDF) of the percentage of the remaining energy level in the network for one year of operation. 100% on the X axis means that a node harvests at least equal amount of energy compared to what it consumes. On the other hand, 0% indicates the proportion of nodes whose remaining energy level is above 0. We can observe that more than half of the nodes do not consume any energy for all the three scenarios. The other half has a remaining energy level of about 25-75% of the maximum, while all the nodes have an energy level above 0.

6.4 Multi-hop energy transfer

Figure 6 presents the theoretical number of extra fake packets transmitted by a node during one round located at different positions away from an ET. The results obtained using Eq. (5). They show that the number of multi-hop packets is very limited when the distance between the participants is high but it highly increases as we move the node closer to the transmitter. We mention that no extra packets were sent with the highest tested distance (i.e., 8m) which means that the multi-hop energy transfer is applicable only for below average harvesting ranges.

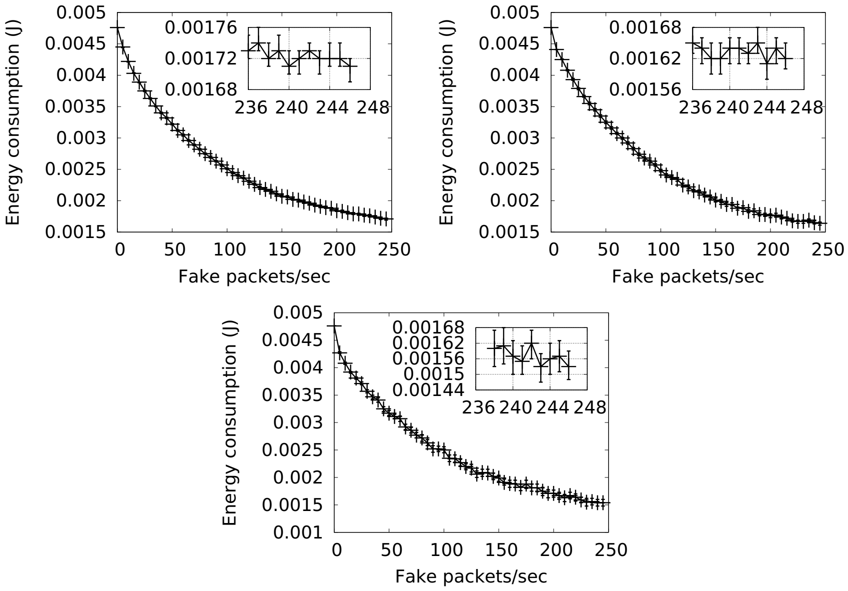


Figure 4: Energy consumption in relation with the number of fake packets/sec for the dense, normal and sparse scenario respectively (4 energy transmitters are used).

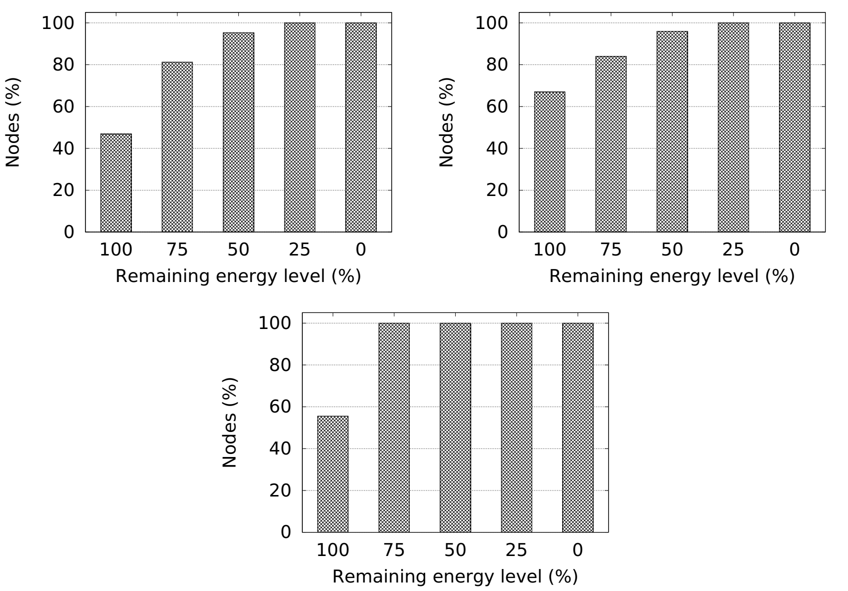


Figure 5: Empirical CDF of the remaining energy level in the network for the dense, normal and sparse scenario respectively (4 ETs are used)

6.5 Node deployment without batteries

Figure 7 depicts the energy consumption of a node for a single round. Variable number of data packet rates and node distances were tested. The results show that the maximum distance that satisfies

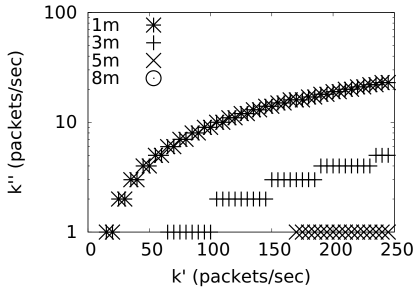


Figure 6: Number of multi-hop packets for different node distances and different fake packet rates.

Eq. (6) varies from 3 to 3.5 meters. Indeed, in order to cover an area of 50x50 square meters, more than 100 ETs are needed which is unacceptable both in terms of investment cost and in terms of installation feasibility. Hence, based on the node parameters considered in the present paper, it is infeasible to retain in operating condition a network consisting of nodes without batteries.

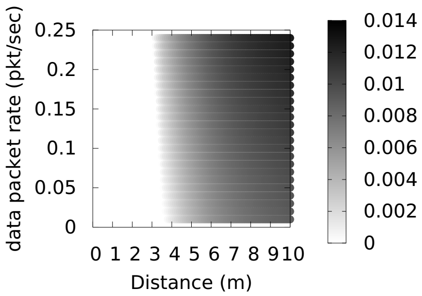


Figure 7: Node energy consumption (gradient) for different node-ET distances and data packet rates.

7 Assessing capital and operating costs

7.1 Evaluation parameters & methodology

In this section, we solve the MRT and MAC problems and we present numerous results. The polynomial nature of the two problems allows us to examine all the possible combinations of fake packet data rate and ETs for each instance of the problem. Indeed, approximately up to 16x250 combinations per instance of the problem are examined. The exhibited values represent the optimal average solutions for each examined scenario. In order to evaluate OPEX and CAPEX, the following values are used for the parameters of Table 1. All the costs are in Euros. C_{nd}=50[3], C_b=1, C_{rb}=1.5, C_{hu}=30, C_{st}=100[4], t_{mnt}=10 min[5], C_{mh}=35[6], C_{el_b}=0.1636 per KWh, C_{el_b}=0.1150 per KWh, t_{el_b}=16h, and

[3] Approximate TelosB node price for a big bulk order.

[4] The prices provided by http://www.mouser.fr/

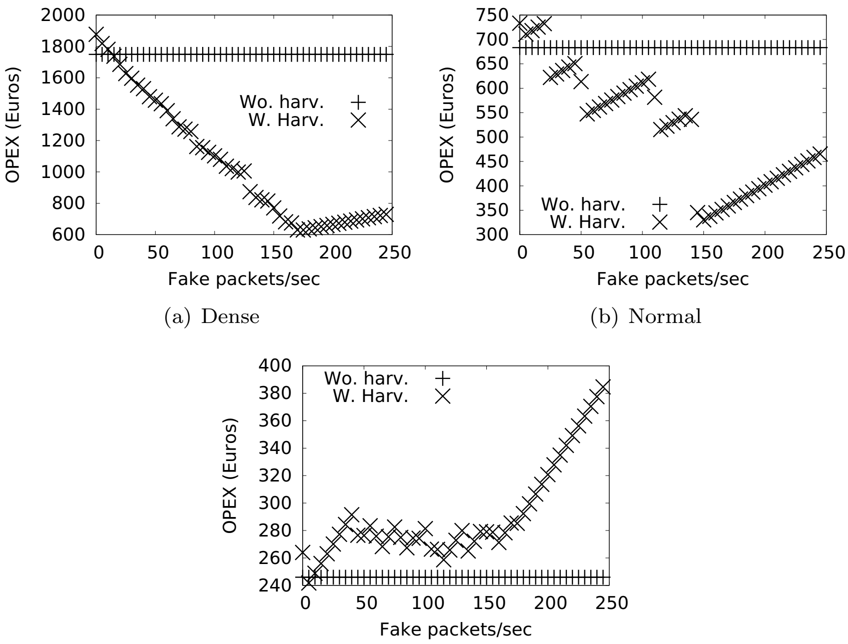
[5] Approximate average time to unscrew the node box, change the battery, screw the box back and move to the next node.

[6] Approximate man-hour labor cost in France as provided by Eurostat.

t_{el_r}=8h[7].

In this section, we assume that the battery capacity is enough to provide power to a node for one year without harvesting. We consider that a technician maintains the network every 6 months after the first year. When harvesting is used, some nodes may last for 1, 2 or more years, which means that different number of nodes is maintained every six months. For example, in the first year, all the batteries which cannot last more than 1.5 years are replaced. The second maintenance includes the replacement of the batteries which cannot last 6 months more and so on. However, batteries replaced after the first year, will still need to be replaced again during the next maintenances. We keep track of battery replacements within the first 4 years and we compute the expenses per maintenance visit as well as the average results within these 4 years. After 4 years, all the batteries have been replaced except of the nodes that harvest more energy than they consume.

7.2 Operating expenditures



(a) Dense (b) Normal

(c) Sparse

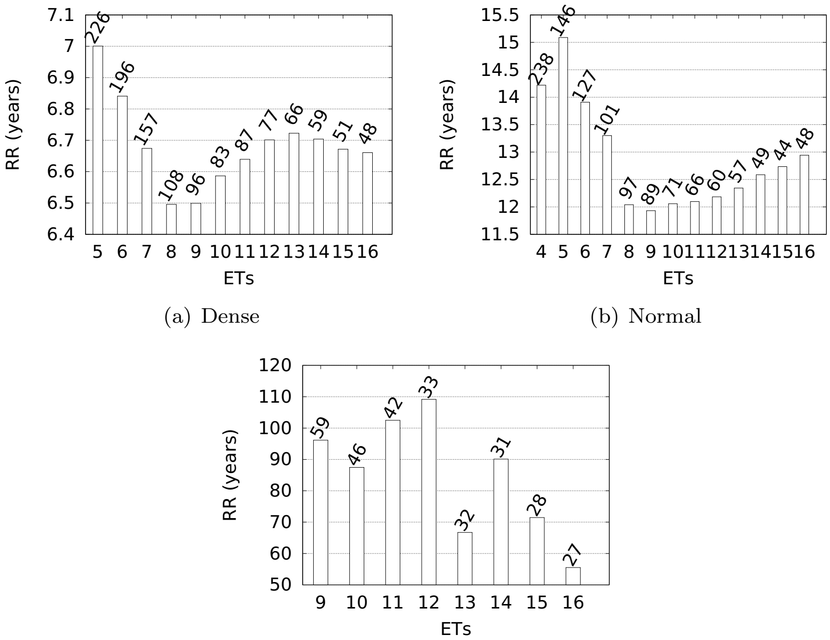
Figure 8: OPEX of the first year in relation with the number of fake packets/sec for the dense, normal and sparse scenario respectively (4 ETs are used).

Figure 8 presents the OPEX of the first maintenance when 4 ETs are used. For the dense scenario, we see that the best result is achieved when approximately 170 packets/sec are transmitted. At that point, the OPEX with harvesting is almost 3 times lower than the cost without harvesting. In the second scenario, the cost presents a zig-zag shape which is explained as follows. As the packet rate increases more and more nodes save more energy. It means that at certain levels of packet rate an amount of nodes lying on the same distance away from the stations will have enough energy to

[7]The values are available on EDF website.

operate more than 1.5 years and, thus, the OPEX massively decreases. In the meantime between these specific levels of packet rate, the OPEX slightly increases due to the increased electricity cost. The combination of the reduction of the consumption and the increase of the electricity cost causes the zig-zag effect. Concerning the sparse scenario, the OPEX with harvesting hardly exceeds the OPEX without harvesting, which means that the CAPEX will take long time to be covered. The OPEX's of the next maintenances present the same behavior.

7.3 Reimbursement Ratio



(a) Dense (b) Normal

(c) Sparse

Figure 9: RR per scenario and per number of ETs.

Figure 9 depicts the average RR (throughout the 4 years) for the three evaluated scenarios. To test all the possible combinations between the number of ET and fake packet rates, we vary the number of ET from 1 to 16 with an increment of 1 and the fake packet rate from 1 to the theoretical maximum. The best fake packet rate instance is displayed on the top of every bar of the graph. The results show that: (a) the best RR is achieved when 8-9 or 16 ETs are placed for the three scenarios respectively. Indeed, due to the square shape of the terrain, the node area can be more efficiently covered using ET populations of power of two. (b) The higher the density, the shorter the RR. As it was shown by the theoretical results, as more nodes are placed close to the ETs, less nodes need maintenance which results to a lower RR. Simulations performed with denser networks presented an even lower RR (see Figure 10). (c) The cost of deploying the sparse RF-power harvesting network cannot be covered in a reasonable amount of time. Indeed, more than 50 years are needed to cover the investment cost of the evaluated sparse network which is unacceptable and infeasible. (d) The higher the number of ETs, the lower the best fake packet rate. This happens due to the fact that the increased CAPEX of placing more ETs must be covered by reducing the OPEX which implies to lower electricity cost and, thus, lower number of fake packets.

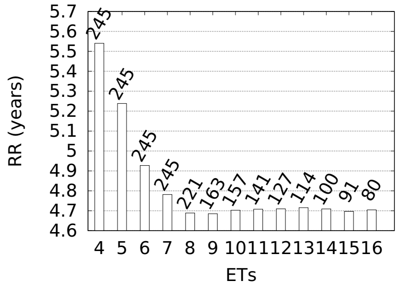
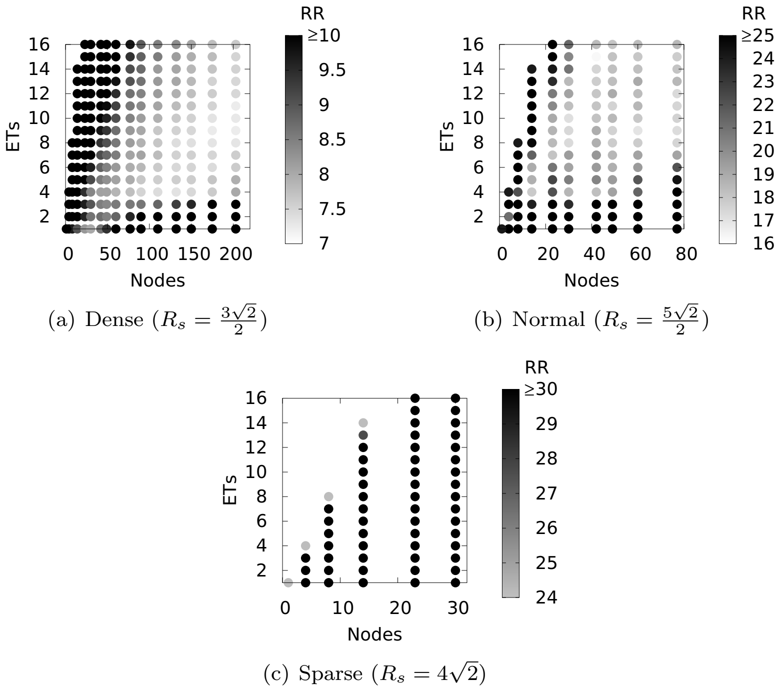


Figure 10: RR over the best packet rate instance for a very dense scenario (1 node/m^2).

7.4 Maximum coverage area



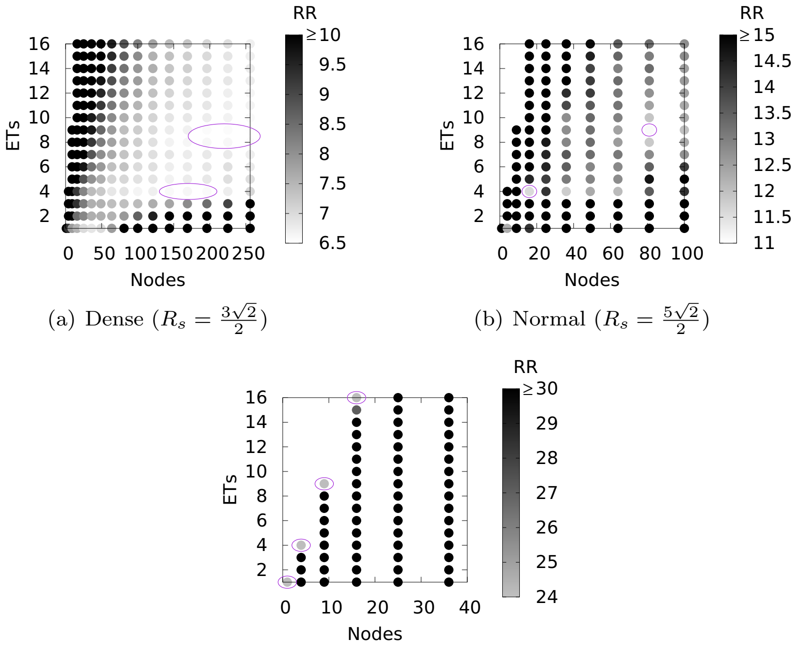
(a) Dense ($R_s = \frac{3\sqrt{2}}{2}$)

(b) Normal ($R_s = \frac{5\sqrt{2}}{2}$)

(c) Sparse ($R_s = 4\sqrt{2}$)

Figure 11: Best RRs for different node and ET populations (triangular deployment).

One of the observations of the previous set of simulations is that the node density is the most important factor in maintaining RF-power harvesting WSNs. Moreover, as introduced in Section 5.2, given a set of nodes there is a maximal area covered by the nodes where the RR is minimized. Since the node deployment method affects the problem solution, we consider the two most common



(a) Dense ($R_s = \frac{3\sqrt{2}}{2}$)

(b) Normal ($R_s = \frac{5\sqrt{2}}{2}$)

(c) Sparse ($R_s = 4\sqrt{2}$)

Figure 12: Best RRs for different node and ET populations (quadratic deployment).

deployment methods; the triangular and the quadratic. It has been proven that the triangular deployment maximizes the coverage area [19], decreasing however the network density.

Figures 11 and 12 present the RR achieved for 3 different node densities with variable number of nodes and ETs. The first set of figures correspond to the triangular node deployment and the second one to the quadratic deployment. It is obvious that the same area is covered by different number of nodes for each of the deployment methods entailing a different CAPEX. However, in this section we assess whether the triangular or the quadratic method is more efficient in terms of reimbursement ratio. The results show that although the quadratic deployment needs higher number of nodes to cover the corresponding area, it achieves better results than the triangular deployment.

Concentrating on the quadratic results we can conclude that the larger the deployment, the lower the reimbursement ratio. More specifically, for the dense scenario, the best RR is approximately 6.5 years and it is achieved when 256 nodes are placed (2,304 m^2). Similar performances are achieved by other node populations (marked with ellipses). For the normal scenario, the best performance is achieved when 81 nodes are placed, a number that corresponds to an area of 2,025 m^2. For both dense and normal density scenarios, the optimal number of ETs is 4, 8 or 9. On the other hand, the sparse scenario presents a different behavior since the best solution is achieved when the number of nodes coincides with the number of ETs. The maximum coverage area is 1,024 m^2.

8 Conclusion & future work

Wireless sensor networks consisting of nodes with RF-energy harvesting capabilities were considered in this paper. A number of ETs was used to periodically recharge the nodes. We modeled the energy consumption of the nodes and we showed that it mainly depends on the distance between the nodes and the transmitters as well as on the number of fake packet transmissions. We gave another dimension to our problem by introducing the problem of minimizing the reimbursement time of the investment and the problem of maximizing the coverage area with the minimum CAPEX-OPEX ratio. Theoretical and simulation results showed that a network with RF-energy harvesting nodes saves up to the two thirds of the consumed energy compared to the case where no harvesting is used. In terms of cost, the findings showed that the current technology encourage the use of RF harvesting only for networks with higher node density. In the future, we plan to use a multi-hop communication model for data delivery and consider the case where both nodes and ETs transmit packets with variable rate.

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References

[1] A. Banerji, T. Datta, G. Bandyopadhyay, S. K. Biswas, A. Banerji, and A. Banerji. Wireless transfer of power: Status and challenges. In *2016 International Conference on Intelligent Control Power and Instrumentation (ICICPI)*, pages 251–257, Oct 2016.

[2] Stefano Basagni, M Yousof Naderi, Chiara Petrioli, and Dora Spenza. Wireless sensor networks with energy harvesting. *Mobile Ad Hoc Networking: Cutting Edge Directions, S. Basagni, M. Conti, S. Giordano, and I. Stojmenovic, Eds. Hoboken, NJ: John Wiley & Sons, Inc*, pages 703–736, 2013.

[3] M. Majid Butt, Ioannis Krikidis, Amr Mohamed, and Mohsen Guizani. *Energy Management in Wireless Cellular and Ad-hoc Networks*, chapter RF Energy Harvesting Communications: Recent Advances and Research Issues, pages 339–363. Springer International Publishing, Cham, 2016.

[4] T. C. Chiu, Y. Y. Shih, A. C. Pang, J. Y. Jeng, and P. C. Hsiu. Mobility-aware charger deployment for wireless rechargeable sensor networks. In *Network Operations and Management Symposium (APNOMS), 2012 14th Asia-Pacific*, pages 1–7, Sept 2012.

[5] K. W. Choi, L. Ginting, P. A. Rosyady, A. A. Aziz, and D. I. Kim. Wireless-powered sensor networks: How to realize. *IEEE Transactions on Wireless Communications*, 16(1):221–234, Jan 2017.

[6] R. G. Cid-Fuentes, M. Y. Naderi, K. R. Chowdhury, A. Cabellos-Aparicio, and E. Alarcn. On the scalability of energy in wireless rf powered internet of things. *IEEE Communications Letters*, 20(12):2554–2557, Dec 2016.

[7] H. Dai, Y. Liu, A. X. Liu, L. Kong, G. Chen, and T. He. Radiation constrained wireless charger placement. In *IEEE INFOCOM 2016 - The 35th Annual IEEE International Conference on Computer Communications*, pages 1–9, April 2016.

[8] K. Das, P. Zand, and P. Havinga. Industrial wireless monitoring with energy-harvesting devices. *IEEE Internet Computing*, 21(1):12–20, Jan 2017.

[9] Y. Diab, P. Venet, H. Gualous, and G. Rojat. Self-discharge characterization and modeling of electrochemical capacitor used for power electronics applications. *IEEE Transactions on Power Electronics*, 24(2):510–517, Feb 2009.

[10] Ruisi Ge, Hong Pan, Zhibin Lin, Na Gong, Jinhui Wang, and Xiaowei Chen. Rf-powered battery-less wireless sensor network in structural monitoring. In *2016 IEEE International Conference on Electro Information Technology (EIT)*, pages 0547–0552, May 2016.

[11] S. He, J. Chen, F. Jiang, D. K. Y. Yau, G. Xing, and Y. Sun. Energy provisioning in wireless rechargeable sensor networks. *IEEE Transactions on Mobile Computing*, 12(10):1931–1942, Oct 2013.

[12] Shibo He, Jiming Chen, Fachang Jiang, David K. Y. Yau, Guoliang Xing, and Youxian Sun. Energy provisioning in wireless rechargeable sensor networks. *IEEE Transactions on Mobile Computing*, 12(10):1931–1942, October 2013.

[13] A.S.M. Zahid Kausar, Ahmed Wasif Reza, Mashad Uddin Saleh, and Harikrishnan Ramiah. Energizing wireless sensor networks by energy harvesting systems: Scopes, challenges and approaches. *Renewable and Sustainable Energy Reviews*, 38:973 – 989, 2014.

[14] K. Kaushik, D. Mishra, S. De, S. Basagni, W. Heinzelman, K. Chowdhury, and S. Jana. Experimental demonstration of multi-hop rf energy transfer. In *24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 538–542, Sept 2013.

[15] J. H. Liao and J. R. Jiang. Wireless charger deployment optimization for wireless rechargeable sensor networks. In *Ubi-Media Computing and Workshops (UMEDIA), 2014 7th International Conference on*, pages 160–164, July 2014.

[16] Q. Liu, K. S. Yildirim, P. Paweczak, and M. Warnier. Safe and secure wireless power transfer networks: challenges and opportunities in rf-based systems. *IEEE Communications Magazine*, 54(9):74–79, September 2016.

[17] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han. Wireless networks with rf energy harvesting: A contemporary survey. *IEEE Communications Surveys Tutorials*, 17(2):757–789, 2nd quarter 2015.

[18] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han. Wireless charging technologies: Fundamentals, standards, and network applications. *IEEE Communications Surveys Tutorials*, 18(2):1413–1452, Secondquarter 2016.

[19] M. Ma and Y. Yang. Adaptive triangular deployment algorithm for unattended mobile sensor networks. *IEEE Transactions on Computers*, 56(7):946–847, July 2007.

[20] D. Mishra, S. De, S. Jana, S. Basagni, K. Chowdhury, and W. Heinzelman. Smart rf energy harvesting communications: challenges and opportunities. *IEEE Communications Magazine*, 53(4):70–78, April 2015.

[21] D. Mishra, K. Kaushik, S. De, S. Basagni, K. Chowdhury, S. Jana, and W. Heinzelman. Implementation of multi-path energy routing. In *25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, pages 1834–1839, Sept 2014.

[22] Y. Pang, Z. Lu, M. Pan, and W. W. Li. Charging coverage for energy replenishment in wireless sensor networks. In *Proceedings of the 11th IEEE International Conference on Networking, Sensing and Control*, pages 251–254, April 2014.

[23] S. Y. Seidel and T. S. Rappaport. 914 mhz path loss prediction models for indoor wireless communications in multifloored buildings. *IEEE Transactions on Antennas and Propagation*, 40(2):207–217, Feb 1992.

[24] Victor Shnayder, Mark Hempstead, Bor-rong Chen, Geoff Werner Allen, and Matt Welsh. Simulating the power consumption of large-scale sensor network applications. In *Proceedings of the 2Nd International Conference on Embedded Networked Sensor Systems*, SenSys '04, pages 188–200, New York, NY, USA, 2004. ACM.

[25] P. Sommer and R. Wattenhofer. Gradient clock synchronization in wireless sensor networks. In *Information Processing in Sensor Networks, 2009. IPSN 2009. International Conference on*, pages 37–48, April 2009.

[26] T. Soyata, L. Copeland, and W. Heinzelman. Rf energy harvesting for embedded systems: A survey of tradeoffs and methodology. *IEEE Circuits and Systems Magazine*, 16(1):22–57, Firstquarter 2016.

[27] B. Tong, Z. Li, G. Wang, and W. Zhang. How wireless power charging technology affects sensor network deployment and routing. In *Distributed Computing Systems (ICDCS), 2010 IEEE 30th International Conference on*, pages 438–447, June 2010.

[28] Le-Giang Tran, Hyouk-Kyu Cha, and Woo-Tae Park. Rf power harvesting: a review on designing methodologies and applications. *Micro and Nano Systems Letters*, 5(1):14, Feb 2017.

[29] M. Z. Win, P. C. Pinto, and L. A. Shepp. A mathematical theory of network interference and its applications. *Proceedings of the IEEE*, 97(2):205–230, Feb 2009.

[30] C. Zhang and G. Zhao. Wireless powered sensor networks with random deployments. *IEEE Wireless Communications Letters*, PP(99):1–1, 2017.

[31] S. Zhang, Z. Qian, F. Kong, J. Wu, and S. Lu. P3: Joint optimization of charger placement and power allocation for wireless power transfer. In *2015 IEEE Conference on Computer Communications (INFOCOM)*, pages 2344–2352, April 2015.

[32] Y. Zhang, F. Zhang, Y. Shakhsheer, J. D. Silver, A. Klinefelter, M. Nagaraju, J. Boley, J. Pandey, A. Shrivastava, E. J. Carlson, A. Wood, B. H. Calhoun, and B. P. Otis. A batteryless 19 muw mics/ism-band energy harvesting body sensor node soc for exg applications. *IEEE Journal of Solid-State Circuits*, 48(1):199–213, Jan 2013.

[33] Dimitrios Zorbas, Patrice Raveneau, and Yacine Ghamri-Doudane. Assessing the cost of rf-power harvesting nodes in wireless sensor networks. In *2016 IEEE Global Communications Conference (GLOBECOM)*, Washington, DC, USA, Dec 2016.