On optimal charger positioning in clustered RF-power harvesting wireless sensor networks

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Abstract

Wireless charging brings forward some new principles in designing energy efficient networks. A number of energy transmitters are placed in all over the network to recharge power constrained nodes. Since a few only nodes can remarkably benefit from the transmitter power emission, we organize the nodes in clusters and we propose an efficient localized algorithm as well as a centralized one to compute the charger position such that the cluster lifetime is maximized. Simulation results are presented to show the effectiveness of the approaches.

1 Introduction

A technology that has been recently developed takes advantage of the transmitted neighboring RF signals to harvest a small portion of energy. More specifically, a new type of antenna is used which can convert part of the received signal power to electricity. 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 [6]. However, this technology presents some major limitations mainly due to the low efficiency of the conversion unit [7]. First, the harvested power rapidly 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 distance, and third, there is a minimum received signal power corresponding to a maximum distance, below which no conversion is possible.

In this paper, we consider networks consisting of nodes which can acquire energy from energy transmitters (chargers). We assume that a charger periodically and omni-directionally transmits energy packets to the network. Due to the limitations of the harvesting technology, a few only nodes can substantially benefit from the energy data transmission whereas a possible use of multiple chargers in all over the network could considerably increase the operation costs. For these reasons we organize the network in clusters so that the majority of the nodes use short communication links and the most of communication burden falls onto the shoulders of the cluster heads. By using chargers close to these nodes we can alleviate their communication cost and, thus, extend the network lifetime.

However, the question that rises up is where to place a charger so that the network lifetime is prolonged as much as possible. We explain that this placement problem is a special case of the Weber problem and we propose a local search algorithm that finds a solution close to the optimal. The algorithm can operate in both centralized or distributed manner since it uses localized information and a number of successive small steps to gradually move the charger more efficient positions. We, also, present an exhaustive search algorithm that examines a big range of possible solutions exhibiting, however, higher computation cost.

2 Related work

RF-energy harvesting networks have been extensively studied from different research aspects. For a complete literature review the reader can refer to [7] and [2]. We cite, here, the most recent research activities closer to our work.

A placement and charging problem is examined in [10]. The authors assume that a set of candidate locations for placing chargers is given and they find a charger placement and a corresponding power allocation to maximize the charging quality. The problem is proved to be NP-Complete. Moreover, a wireless charger placement problem that that takes into account the electromagnetic radiation safety is tackled in [3]. Simulations show that in terms of charging utility, the proposed algorithm presents up to 45.7% better results compared to a previous approach.

In [4], the problem of cluster head recharging by the transmissions of the cluster members is examined. The authors formulate a power resource allocation problem to maximize the energy efficiency. The reverse problem is tackled in [9]. It is assumed that the cluster heads are equipped with solar panels and they use the solar energy to recharge the cluster members. A cluster head placement problem is examined which is proved to be NP-hard.

3 System model

We consider wireless sensor nodes powered by rechargeable batteries. Each node spends its energy by taking measurements utilizing its sensing module and by communicating with other nodes. The energy spent per bit is described by $\alpha_1 + \beta d^{2b}$ for the transmissions and by α_2 for the reception. α_1 is the energy/bit consumed by the transmitter electronics, β accounts for the energy dissipated in the transmit op-amp, α_2 is the energy consumed by the receiver electronics and b is the amplitude loss exponent.

We, also, assume that all the nodes take measurements periodically and generate the same amount of data D. The data is encapsulated in a packet of size p bits and it is transmitted to the sink or to a relay node. A node can transmit k packets per time period. A relay node is capable of aggregating multiple data in one packet. We set $k' = \lceil \frac{nkD}{p} \rceil$ the number of packets transmitted per time period by a relay node, where n is the number of communicating nodes (including the relay node itself).

We define as network lifetime the time until at least one node uses up its battery. Assuming that the nodes consume energy with constant rate, the node with the highest consumption sets an upper bound on the network lifetime.

The sensor nodes are equipped with an extra RF module capable of harvesting power from transmitted signals. A charger with omni-directional antenna is used to send energy packets to the network and recharge the nodes. We used the same energy harvesting model described in [11].

We split the transmission time in rounds where each round has two phases. During the first phase, named "Sensing data phase", the nodes communicate with the sink and transmit their sensing data. In the second phase, named "Energy data phase", we allow the transmission of energy packets. The transmission time is divided in S slots and we allow only one transmission per slot within the vicinity of a single node to avoid interference. We assume that the nodes are well synchronized using a precise time synchronization protocol [8]. 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.

As a consequence, the number of data transmissions during the "Sensing data phase" determines the maximum (safe) number of energy packet transmissions. Assuming a time period equal to one round and k packet transmissions per round, it holds that $\frac{p}{dr}(k(N_{max}+1) + k' + k_e) \leq \tau$, where N_{max} is the maximum number of neighbors among the nodes in the network, k_e is the energy packets, dr is the data rate, and τ is the duration of the round. The higher the node density, the higher the number of neighbors and the lower the maximum possible transmissions of energy packets.

4 The optimal charger positioning problem

Finding the optimal charger position, the cluster lifetime is maximized. As it is defined in Section 3, the network lifetime is upper bounded by the node with the highest energy consumption. The most distant node to the CH, or the same the CH, set the lifetime upper bound. It practically means that in order to extend the lifetime, the charger must be placed somewhere that the CH gets enough energy to survive until one node dies, and at the same time, the most distant node (or multiple distant nodes) lasts as long as possible.

Given a group of n nodes the Optimal Charger Positioning problem (OCP) can be formulated as follows: find the best charger position $\mathcal{O}$ in the plane such that the maximum energy consumption in the cluster is minimized.

If I is the node with the highest consumption, we can distinguish two cases of the problem. First, if I is out of the harvesting range of the charger, the number of optimal charger positions is infinite. All these positions are located within a disk with center the coordinates of the CH and radius the maximum distance between the CH and charger (denoted by d_{CH}).

On the other hand, if I is in the harvesting range of the charger, then the problem is transformed to a Facility Location Problem (FLP) which in its general case is NP-hard [5]. The problem in FLP is to find facility positions that minimize the sum of transportation costs between those positions and a set of sites (nodes). A simple facility location problem is the Weber problem, in which a single facility is to be placed. In our case, as it is explained in the next section, the Weber point coincides with the center of the mass, since the maximum consumption is minimized when two or three diametrically opposed nodes have the same consumption.

5 Solutions for the OCP problem

5.1 Local Search algorithm

In this section we present "Local Search" (LS), an algorithm that computes the charger's position based on local information.

The input of LS is the CH position and the initial position of the charger. The CH is chosen based on two criteria; (a) to be reachable by all the nodes of the group and (b) to be connected with the sink. Every node that satisfies these two criteria can become the CH. In LS we choose as CH a node which is closer to the centroid of the plane, in order to balance the communication cost between the nodes and the CH. Another reason is to the centroid can be computed without much cost. In the centralized case it is the average of the coordinates of the nodes while in the distributed case it can be estimated using the nodes relative position [1].

As it has been already mentioned, the CH's consumption sets an upper bound on the network lifetime if it does not have enough energy to forward multiple packets by the nodes of the group. It means that the charger must not be located far away from the CH in order to stoke it with energy. The maximum charger distance away from the CH (i.e, d_{CH}) can be calculated by taking into account the cluster size as well as the consumption and the harvesting energy of the CH. Due to the limited size of this paper, we omit the detailed equations. Note that the distance between the CH and the most distant node I is, also, involved in the equations. Hence, the optimal charger position is always found in a disk $\mathcal{A}$ with radius d_{CH} and center the coordinates of the CH. d_{CH} is, also, upper bounded by the maximum harvesting range. We have narrowed down the search space for the charger to a disk $\mathcal{A}$. However, the number of solutions in $\mathcal{A}$ remains infinite.

Based on the fact the harvesting energy is higher the closer we move to a receiver, we make two observations. First, since harvesting power depends on distance, if we move the charger towards the most distant node I the communication cost remains the same but the harvesting energy is getting higher. It means that the closer we move to distant nodes the total consumption is reduced. The second observation is that moving towards a distant node we reduce its consumption but, at the same time, we increase the consumption of other nodes located at the opposite direction from where we move to. However there is an optimal point $\mathcal{O}$ where at least two or three nodes present the same (maximum) consumption C_{max}. If w is the number of nodes with equal consumption, then all w nodes are enclosed in a minimum (weighted) circle $\mathcal{C}$ with center $\mathcal{O}$ and radius (weight) C_{max}. However, it is known that a minimum enclosing circle can be drawn by computing maximum three points (or two if the points are on the same straight line with the center of the circle). Therefore, $\mathcal{O}$ can be computed by finding three (or two) only nodes with equal weight.

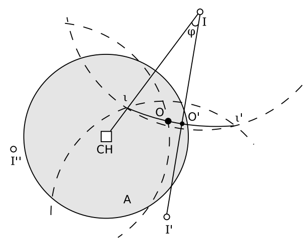

Figure 1: Example with the positions of three distant nodes, the intermediate charger positions and the optimal position on the plane.

Next, we describe how LS works in order to find a solution close to $\mathcal{O}$. Let us assume that the best solution found by LS is at point O. The algorithm works by evaluating successive charger positions with a step of ϵ, where ϵ is a small number. As it is shown in Figure 1 the charger which is initially located next to the CH, is starting moving towards I which is the most distant node and the node that presents the highest consumption. At every single point the algorithm checks if the consumption of the rest of the nodes is higher than or equal to the consumption of I. A node that satisfies this condition, let say at point ι, is the second point I' needed to define $\mathcal{C}$. If multiple nodes have higher consumption than I, the node with a consumption closer to that of I is selected. We must mention here that three subcases exist. First, if I, I' and CH are on the same straight line, no other node is needed to be found since $\mathcal{C}$ can be defined by two points (I and I'). Second, if multiple nodes exhibit the same consumption with I, it means that all these nodes belong in $\mathcal{C}$, and thus more than three points have already been found. Third, if no node I' is found, then ι is located at the intersection point of the border of $\mathcal{A}$ and the straight line defined by nodes CH and I.

At point ι the algorithm has found a solution for OCP problem, but it may not be the optimal. For example in Figure 1 if the charger moves right, the energy consumption can be improved. The algorithm's next objective is to detect a third point by moving on an arc $\overset{\frown}{\iota, \iota'}$ that connects the intersection points of the two circles with centers the coordinates of I and I', and radii $\overline{I, \iota}$ and $\overline{I', \iota}$, respectively. The energy consumption of I and I' is equal for all points on $\overset{\frown}{\iota, \iota'}$ since in fact $\iota\iota'$ is the diagonal of the (weighted) square $\iota I \iota' I'$ with a (weighted) side of $E_c^{I_\iota}$. The arc can be defined by points ι, ι' and O'. O' is the intersection point of the arc and the straight line $\overline{I, I'}$. At this point I and I' present the same consumption and $\overline{I, O} + \overline{O, I'} = \overline{I, I'}$. Similarly to the previous steps, the charger is moving on the arc $\overset{\frown}{\iota, \iota'}$ with step ϵ until a third node I'' with higher than or equal consumption to that of I and I' is found. Note that the same three subcases may also exist here. Since I'' is detected, the best position has been found.

It is obvious that the lower the ϵ the closer the solution to the optimal point. We must note that there is no other $\mathcal{O}$ defined by I, I', and I'' since $\mathcal{O}$ is the center of the mass of the triangle $II'I''$ which is unique.

Property 1 *The maximum traveling distance of the charger is less than or equal to* $\overline{CH, I}$.

We omit the proof of the previous property due to the limited size of the paper.

The computation cost of the approach mainly depends on the step ϵ and the number of nodes. Apparently the lower the ϵ the more the iterations of the algorithm. If z is the number of iterations to find O, then the longest run of the algorithm is $\frac{z(n-1)}{\epsilon}$. z depends on the distance between CH and the most distant node.

In the distributed version of LS, the charger needs to communicate with the nodes before each step ϵ and to decide its movement through the nodes relative position and RSSIs. This means that the total number of exchange messages is proportional to the number of nodes and the step ϵ. Since $2(n-1)$ messages need for each step, the total number of messages is upper bounded by $\frac{2z(n-1)}{\epsilon}$.

5.2 Brute force algorithm

In this section we describe "Brute force" (BF), a simple exhaustive algorithm that examines a very wide range of possible solutions. BF divides $\mathcal{A}$ in square bits of equal size with a side of ϵ'. For every bit it assigns a point in the middle of the square. Subsequently, it checks every single point to find the minimum possible maximum consumption for all the nodes in the group.

Similar to Local Search, the lower the ϵ' the higher the precision of the best solution. BF guarantees that its best solution is $\frac{\sqrt{2}\epsilon'}{2}$ far from the optimal and, unlike LS, this solution does not depend on the nature of the harvesting module. BF's complexity depends on ϵ' and the number of nodes. Unlike Local Search, BF always checks all the possible solutions which are equal to $\frac{\pi d_{CH}^2}{\epsilon'^2}$. Hence, its complexity is $\mathbb{O}(\frac{\pi d_{CH}^2}{\epsilon'^2}n) = \Omega(\frac{\pi d_{CH}^2}{\epsilon'^2}n)$.

Due to the centralized nature of the algorithm and its high computation cost, it makes it viable only for small networks or for comparison purposes.

6 Evaluation & discussion of the results

We assume a scenario with a square terrain of 25 meters side (fixed) and variable number of nodes randomly and uniformly scattered on the terrain. We measure the maximum energy consumption of the nodes (displayed as "Consumption") for one round and the execution time of the algorithms. Due to the presence of random values, we run each instance 50 times and the average results are presented. The 95% confidence intervals are, also, shown when it is feasible.

Regarding the node and station characteristics, we consider the following values (see [11] for details): $p = 127bytes$, $D = 256bits$, $dr = 250Kbps$, $k = 1$ packet, $k_e = 150$ packets/sec, $\tau = 30sec$, $P_{tx}G_T = 3W$, $R_h = 12m$ (max. harvesting range), $R_c = 40m$ (max. communication range), $G_R = 6dBi$, $\lambda = 0.3279m$, $\sigma = 0.01$, $\rho = 1m$, $\alpha_1 = 50nJ$, $\alpha_2 = 50nJ$, $\beta = 100pJ$, and $b = 2$. We assume four transmission levels when $d < 10, 10 \leq d < 20, 20 \leq d < 30$, and $d > 30$. The steps ϵ and ϵ' are both equal to $0.05m$. Node parameters correspond to Mica2 sensor nodes using a Zigbee communication module at 915MHz. Regarding the transmitting station and the harvesting efficiency we used the values provided by Powercast corporation for P2110B model operating at the same frequency. k, k_e and node densities are chosen in that way so that no interference exists. The experiments were carried out on an Intel i7 2.5GHz CPU with 16GB RAM running Linux.

Figure 2 illustrates the range of solutions provided by BF and the best solution found by LS for a scenario with 20 nodes. The left figure pictures disk $\mathcal{A}$ centered at CH whereas the color represents the maximum consumption. The tiny squares stand for the position of the nodes. We can observe that the best solutions are gathered in an eye-shaped area while the consumption

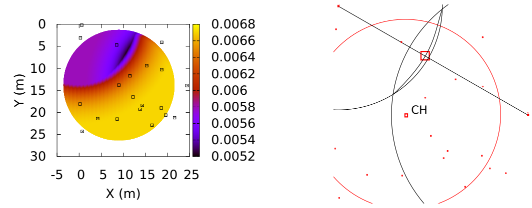

Figure 2: The range of solutions provided by BF and the best solution found by LS for a scenario with 20 nodes.

gradually increases as we move away from it. On the right figure, the solution found by LS is depicted. The tiny squares represent the nodes and the best solution is drawn with a slightly bigger square. We can see that the solution is on the arc which connects the two circles (arcs here) centered at I and I' respectively. Here, no node I'' was found, so the best solution is also located on the line which connects the I and I'.

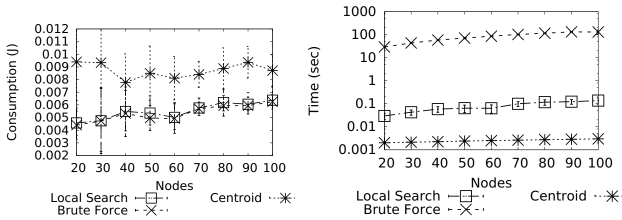

Figure 3: Maximum energy consumption (left) & execution time (right) for variable node populations.

Finally, the results of the comparison between LS, BF and "Centroid" are figured in Figure 3. "Centroid" represents the centroid of the cluster and it is the solution with the minimum computation cost. Its performance is 20-40% lower to that of BF and LS which exhibit similar results in terms of consumption. However, the computation cost of BF is 100 to 1000 times higher than that of LS.

7 Conclusion & Future work

In this paper, we introduced the problem of the optimal charger placement in RF-energy harvesting networks organized in clusters. We proposed both localized and a centralized algorithms with good approximation to the optimal. Simulation results showed that the centralized algorithm exhibits a slightly better performance in terms of energy consumption but it presents high computation cost. In the future, we plan to investigate the problem of finding the optimal number of chargers so that budget and network lifetime requirements are met.

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