Tailoring Micro-solar Systems to Heterogeneous Wireless Sensor Networks

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Abstract. Energetic needs of wireless sensor networks (WSNs) have been thoroughly studied. Among the most important results, clustering protocols are able to reduce significantly energy consumption in these networks. In the last few years though, focus has also been put on energy harvesting for WSNs. With energy harvesting researchers aim to reach energy neutrality, which means the network only runs on harvested energy. Many papers propose design options for energy harvested WSN, but they only focus on ad-hoc solutions, homogeneous WSNs, or pose other limitations. In this paper we propose a new approach. We study the energetic need of a heterogeneous WSN clustered with a known algorithm (REECHD) through simulation, in order to calculate the minimum and ideal energy to harvest for a given network. Given that, we design an appropriate micro-solar power system to achieve energy neutrality.

1 Introduction

Wireless sensor networks (WSNs) are a fundamental part of what we call Internet of Things. Through WSNs we are able to generate data we have never been able to create before, both in terms of quality and quantity. Unfortunately, to achieve the most from this technology we need these networks to be deployed wherever the physical phenomenon to monitor happens, and we often need them to run for long periods. These factors lead researchers to consider energy one of the key constraints in WSNs [11]. Clustering algorithms have been introduced in WSNs to address this challenge. This approach organises the devices into sets (clusters). Each of them has a cluster head that gathers data from its nodes and communicates with other cluster heads in order to report data to a centralised data sink [10]. While clustering optimises nodes energy consumption, engineers introduced energy harvesting to provide wireless sensor nodes more energy. Micro-solar power systems are one of the most used harvesting techniques [8], due to the need to equip nodes with very compact components. Thanks to micro-solar power systems nodes can recharge their batteries using

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solar power, thus increasing network lifetime. Many efforts have been put in this field in order to get to the point where the network is able to perform its task with harvesting as its only energy supply: this result is called energy neutrality [3,4]. As we stress in Sect. 2, researchers achieved energy neutrality through ad-hoc designs. This poses constraints and limitation to WSN developers, in terms of hardware, software, number of nodes and network structure. To mitigate these limitations we propose a new approach to energy harvesting WSN design. We decide to base our work on widely-known and accepted clustering protocols for WSNs. This way, we achieve the best results in terms of energy consumption while maintaining a general purpose network architecture. Then, we study the energy supply the network needs to reach energy neutrality and we derive a suitable micro-solar power system. In Sect. 3 we define four different network configurations and we simulate REECHD protocol on them to measure their energy needs. Then, in Sect. 4 we use such information to design a solar harvesting system with the minimal dimensions of batteries and solar panels needed to achieve energy neutrality. In Sect. 5, we show how much energy the network needs to harvest to reach energy neutrality in the four networks aforementioned, as well as the necessary hardware. Finally, in Sect. 6 we show the implications of the result we achieved, and we propose some future works.

2 Related Works

In this section we analyse the current state of the art in terms of clustering algorithms, energy harvesting techniques, and the combination of these 2 features in WSNs.

2.1 Classic WSN Clustering Algorithms

Clustering is one of the most widely used techniques to improve the performance of WSNs. Clustering protocols aim to group network nodes into sets and select one node in each set (i.e. cluster) to be the cluster head (CH). The tasks of a CH are:

- receiving data sensed from the nodes of its cluster;
- optionally aggregate the received data;
- forward the data towards one or more base stations (BS), a node with high storage capabilities inside the network.

In the following, we describe some well-known clustering protocols for homogeneous and heterogeneous WSNs. A WSN is referred to homogeneous if all the nodes in it have the same capabilities (i.e. battery, transmission rate...). This is not the case in heterogeneous WSN, where nodes have different capabilities.

One of the first clustering protocols to appear in the literature is Low Energy Adaptive Clustering Hierarchy (LEACH) [7]. LEACH does not use the node residual energy to elect CHs. Instead, LEACH cluster election phase is based on a randomised algorithm which aims to evenly distribute the energy load between neighbour sensor nodes. Moreover, if a node gets the CH role, it can't be re-elected as CH in the next cluster election. The communication between CHs and the BS is single-hop.

HEED [17] is another well-known clustering protocol which aim to produce clusters with the same size. HEED uses node residual energy to perform CH election in the election phase. Then, neighbour nodes become member nodes by joining the least costly (usually the closest) CH. In the steady phase each member node sends a message to its CH. Then, CHs forward the messages to the BS. It is worth to mention that HEED algorithm prevents two nodes within the same transmission radius to simultaneously become CHs. HEED introduces the notion of "round" as a grouping of subsequent TDMAs. A TDMA is the time between a node starting to collect data and the data reaching the BS.

A problem which affects HEED is the cost of the CHs election phase, which can decrease the lifetime of the nodes by depleting their energy too fast. ER-HEED [15] aims to improve the performance of HEED by rotating the CHs role inside clusters. Clusters are initially formed through a classical HEED election and formation phase, while in the next rounds each CH choose the next CH as the cluster member node with the highest energy left. HEED cluster head election has to be repeated only if a sensor node inside a cluster depletes its battery completely. ER-HEED rotation algorithm makes it more effective in terms of network lifetime of HEED.

Rotated Unequal HEED (RUHEED) [1] produces unequal-sized clusters by decreasing the competition radius of nodes near to the BS, thus reducing the hot-spot problem. Moreover, it adds a rotation phase after cluster election and formation. Rotation occurs when the current CH designates the next CH among its cluster members basing on their residual energy. The node with the highest residual energy becomes the next CH. Rotation avoids re-election of the CHs, reducing the communication overhead and thus postponing the death of the network. Cluster election and cluster formation take place when any of the sensors dies.

DEEC (distributed energy-efficient clustering algorithm for heterogeneous WSNs) [12] is a clustering protocol which takes into account the energy heterogeneity of the network. In fact, the probability of each node to become CH is based on the ratio between the residual node energy and the whole network average energy. Thus, nodes with both high residual and initial energies have more chances to become CHs.

REECHD [10] is another clustering algorithm for heterogeneous WSNs. A peculiarity of REECHD is that it considers the transmission rate of the nodes in the CH leader election. In particular, the election process considers the average transmission rate of the node to estimate the extent of work it induces on its neighbours. In fact, nodes with higher transmission rates induce less work on neighbours and thus they should have a higher probability of becoming CH. On the other hand, nodes with low transmission rates should have less probability of becoming CH. That is because they generate little intra-traffic communication inside their cluster when they are not CH.

2.2 WSN Energy Harvesting Techniques

Energy harvesting in WSNs is performed through a number of different sources. These include solar, wind, thermal, vibration, and more ([2]).

In our study we decide to focus on solar energy because it is the most popular harvesting source ([9,14,18], and many others), due to its efficiency, relatively low costs and ease of use.

For example, the authors of [14] present a detailed case study of a harvested energy WSN using solar energy to achieve energy independence. They provide a systematic approach to building micro-solar power subsystems for WSN nodes. While doing this, they also stress the challenges involved in the development of harvested energy WSN powered by solar energy, as panel dimensions, battery capacity, geographic position, time of the day and time of the year.

2.3 Clustering Algorithms for Energy Harvesting WSNs

MENC (Multi-hop Energy Neutral Clustering [16]) is a multi-hop clustering protocol for energy harvesting WSNs, with the goal of perpetual network operation. To achieve that, MENC analyses the energy consumption of intra-cluster and inter-cluster communication to find the best energy neutrality constraints. By respecting such constraints, every node can work in an energy neutral state, thus achieving perpetual network operation. The protocol mathematically derives the minimum network data transmission cycle thanks to convex optimisation techniques in a scenario of maximal network information gathering. In addition of ensuring perpetual network operation, MENC also improves the network throughput with respect to traditional clustering protocols for non-harvesting WSNs.

In [19] the authors study the relation between WSN clustering algorithms and the presence of energy harvesting nodes. More specifically, assuming a clustered network and a certain number of energy harvesting nodes, they manage to obtain the optimal position for cluster heads and energy harvesting nodes.

These and many other works focus on the development of ad-hoc clustering algorithms for harvested WSNs. This ends in a lack of generality in the field.

Also, in [3] authors analytically calculate the minimum energy harvesting requirement for nodes in a generic clustered WSN, but they limit their study to homogeneous WSNs.

In our study, instead, we assume a fixed clustering algorithm on a generic heterogeneous WSN. Given that all the nodes are energy harvesting nodes, we derive which kind of batteries and solar panel a node needs to guarantee energy neutrality for that given network.

3 Scenario

We want to measure the energy we need to harvest to reach energy neutrality on four different network configuration. To do this, we use the REECHD [10] algorithm to cluster each network then for every node we get the maximum and average energy consumption over all the Rounds until first node dies. The energy depleted is the energy needed by each node for communication, network synchronisation, and data collection, aggregation and forwarding to the BS.

We choose REECHD because it is one of the most optimized algorithms, and because it is based on the well known MIT radio model [7]. The MIT model calculates the transmission and reception energy consumed in sending and receiving a data packet of k bits over a distance d as follows:

$$E_{Tx}(k, d) = k(E_{elec} + E_a d^n) \tag{1}$$

$$E_{Rx}(k) = k(E_{elec}) \tag{2}$$

where $E_{elec} = 50\,\text{nJ/bit}$ is the energy consumption of a sensor transceiver circuit and E_a is the sensor amplification energy which depends on the distance between a sender node and a receiver. When $d < d_0 = 75\,\text{m}$, E_a becomes $E_{fs} = 10\,\text{pJ/bit/m}^2$ while when $d \geq d_0 = 75\,\text{m}$ E_a becomes $E_{mf} = 0.0013\,\text{pJ/bit/m}^4$.

First, we define four different networks where nodes are deployed on a fixed size square area. Nodes are not mobile i.e. they are stationary, while the BS is located at the centre of the area.

- $hWSN_1$ Area 100 m × 100 m, 100 nodes;
- $hWSN_2$ Area 200 m × 200 m, 100 nodes;
- $hWSN_3$ Area 500 m × 500 m, 100 nodes;
- $hWSN_4$ Area 1000 m × 1000 m, 100 nodes.

We vary the Area size and keep the number of nodes fixed, to lower the density of the network and increase the average distance between the nodes. Moreover, we consider two different scenarios for each area: one in which the data sensed from the sensors is not aggregated when sent to other nodes toward the BS, and another where such data is aggregated. An aggregation value equal to 0 means that all messages are sent to the BS, whereas an aggregation value of 1 results in only one message sent to the BS (due to data compression).

In $hWSN_1$ nodes are uniformly distributed inside the network, while in $hWSN_2$, $hWSN_3$ and $hWSN_4$ the same nodes are deployed after different linear changes of coordinates. Due to the large size of the networks, instead of implementing the REECHD protocol on top of hardware sensors we use a Java based simulation tool specifically designed to run clustering protocols in hWSNs networks. The parameters used to simulate the four scenarios described at the top of this section are listed in Table 1.

After the simulation, we have all the data we need to define the minimum hardware requirements as shown in the next section. Table 2 shows the energy depleted by the nodes of network $hWSN_1$ with no aggregation and nodes competition radius set to 25 m. E_{max} is the maximum energy while $E_{average}$ is the average energy depleted by that node for each Round.

Table 1. Simulation parameters

Simulation parameters	
Parameters	Values
Network grid	$100 \times 100, 200 \times 200$
	$500 \times 500, 1000 \times 1000$
BS	$(50, 50)$, $(100, 100)$
	$(250, 250)$, $(500, 500)$
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{mp}	0.0013 pJ/bit/m^4
Homogeneous T_x rate	2000
Homogeneous energy	1 J
Heterogeneous T_x rate	(500...2000)
Heterogeneous energy	(1...4 J)
R_0	25 m, 50 m, 125 m, 250 m
Number of nodes	100
Aggregation rate	0,1

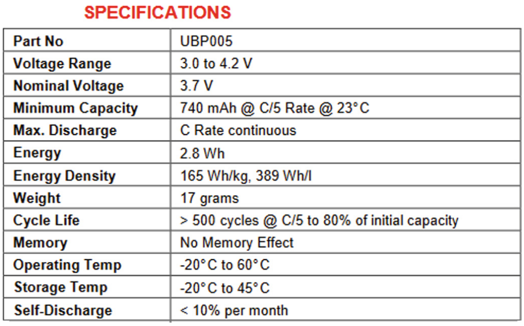
Table 2. Extract of the energy depleted by the nodes of a hWSN

ID	Coordinates (m, m)	E$_{\max}$ (J)	Rate	E$_{\max}$ (J)	E$_{\text{average}}$ (J)
n_1	(12.380, 39.037)	1	2000	$2.11 * 10^{-3}$	$1.55 * 10^{-3}$
n_2	(8.780, 57.928)	1.596	1626	$2.92 * 10^{-2}$	$3.3 * 10^{-3}$
n_3	(44.465, 51.654)	1	2000	$4.58 * 10^{-2}$	$2.89 * 10^{-3}$
n_4	(68.603, 92.540)	2.232	1965	$1.52 * 10^{-2}$	$2.41 * 10^{-3}$
...	...	...	...	...	...

4 Energy Harvesting Model

In this section, we give the details about the harvesting model we define starting from the metrics we get from the simulation of our four scenarios. We choose photo-voltaic, i.e. solar panels, as the source of our harvesting.

To perform a real-life study of our scenario, we first need to define the actual time duration of a simulation round. We fix such time to 30 s, thus having 2880 samples per day for each sensor. Knowing this, we can compute a node daily energy depletion $E_n daily$ as $E_n average$ multiplied by 2880. We choose to consider the nodes average consumption. This is enough for our case since we assume no more than a full week without solar irradiation. Each sensor has to be equipped with an output regulator, an electric energy storage (i.e. the rechargeable UBP053048/PCM Ultralife Batteries of Fig. 1), an input regulator and a solar panel with a slope angle of 0°. The energy which is needed to store into each battery is computed as the product of $E_n daily$ and 7 divided by the output regulator efficiency (in our case, 50%), divided by the maximum discharge percentage for the batteries (fixed to 80% of initial capacity) as shown in Fig. 1. Finally, we can compute the minimum amount of energy the solar panel have to output in order to achieve the neutral energy consumption goal. This is the ratio between the energy to store into each battery and the input regulator efficiency (fixed to 70%) divided by the batteries conversion efficiency which is equal to 99%.



SPECIFICATIONS

Part No	UBP005
Voltage Range	3.0 to 4.2 V
Nominal Voltage	3.7 V
Minimum Capacity	740 mAh @ C/5 Rate @ 23°C
Max. Discharge	C Rate continuous
Energy	2.8 Wh
Energy Density	165 Wh/kg, 389 Wh/l
Weight	17 grams
Cycle Life	> 500 cycles @ C/5 to 80% of initial capacity
Memory	No Memory Effect
Operating Temp	-20°C to 60°C
Storage Temp	-20°C to 45°C
Self-Discharge	< 10% per month

Fig. 1. UBP053048/PCM Ultralife battery specifications.

5 Results

In this section we show the results of our study. To get our results, we start from existing climatic historical data available on the internet[1]. We need this data to estimate the average number of sunny days over the months of one year.

It is worth mentioning that we measure the minimum hardware requirements starting from the maximum energy needs we get from the simulations (see Sect. 3). In fact, not all the nodes have the same energy needs. Nodes near the BS, for instance, usually deplete their energy faster because they have to forward data from the lower levels of the network. So, considering the highest energy needs we get from each simulation, we can ensure that every node receives a sufficient energy input from its harvester (i.e. the solar panel).

By looking at Table 3, we observe that both 100 × 100 and 200 × 200 scenarios have similar energy needs in order to reach neutral energy consumption. In particular, they need a 10 cm × 10 cm panel with a peak power of 1 Wp both when the aggregation is equal to 1 (A) and when it is equal to 0 (NA). Differently, if we consider the 500 × 500 scenario we can appreciate a big difference between the A and NA cases. In fact, the former is way less energy-hungry of the latter, which needs a three times bigger solar panel and eight times more batteries to achieve neutral energy consumption. Finally, in the 1000 × 1000 case, we can see that we need a

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[1] http://re.jrc.ec.europa.eu/pvg_tools/en/tools.html.

solar panel of 1,16 m^2 area and a 24 batteries pack for each sensor. This makes clear that the long distances between the nodes affects the energy need in disproportionate way, raising the minimum energy harvesting requirements to 31,78 Wh.

It is clear that the amount of harvested energy is much more than the actual need of the nodes. One of the reasons is that there are times of the day with no or few energy output from the harvester (i.e. at night). The graphs in Figs. 2, 3, 4 and 5 show the gap between the energy output and the energy not captured.

Table 3. Solar panels area needed for each node, according to the network configuration. A denotes an aggregation rate of 1, NA denotes an aggregation rate of 0.

Network	Power (Wp)	Area (cm^2)	Batteries	Energy
$hWSN_1$ NA	1	100	1	2,8
$hWSN_1$ A	1	100	1	2,8
$hWSN_2$ NA	1	100	1	2,8
$hWSN_2$ A	1	100	1	2,8
$hWSN_3$ NA	9	900	8	22,4
$hWSN_3$ A	3	300	1	2,8
$hWSN_4$ NA	116	11600	24	67,2
$hWSN_4$ A	35	3500	11	30,8

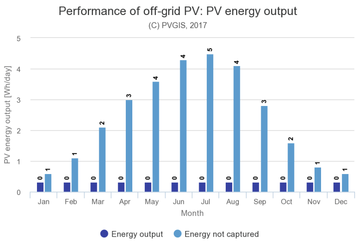

Fig. 2. 100 × 100 with an aggregation rate of 0.

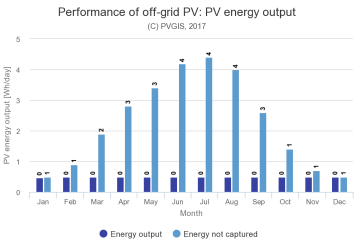

Fig. 3. 200 × 200 with an aggregation rate of 0.

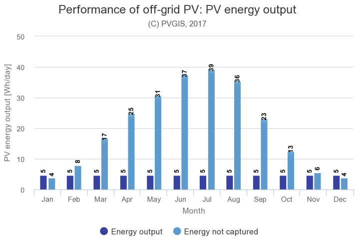

Fig. 4. 500 × 500 with an aggregation rate of 0.

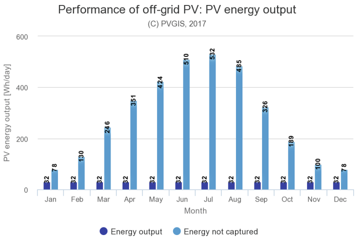

Fig. 5. 1000 × 1000 with an aggregation rate of 0.

6 Conclusions

In this work, we studied the energetic needs of four different hWSNs clustered with the same algorithm (REECHD) in order to compute the amount of energy to harvest so that they could reach an energy neutrality state. To do this, we found the actual energy consumed from each node during the network life cycle thus we used such information to determine the minimum amount of energy to harvest for reaching our goal. As a future work, we propose to extend our approach to different energy harvesting sources (piezoelectric, wind, ...), and to measure performances on testbeds with real hardware and advanced software frameworks as [5,13] or [6]. Moreover, we want to collect enough data from other scenarios as a base to develop a solid analytical model able to calculate hWSNs energy harvesting needs for any given network.

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