ENERGY-SAVING DESIGN ADAPTATION OF WIRELESS SENSOR NETWORKS WITH SOLAR RECHARGEABLE BATTERIES

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ABSTRACT

This paper presents an analysis on the capabilities of an algorithm for design adaptation of wireless sensor networks towards energy conservation. The application concerns environmental monitoring in a cultivation field that realizes the concepts of precision agriculture. The sensor system is enhanced with solar rechargeable batteries and the algorithm's performance on that enhanced approach is compared to the simple design optimization that includes normal batteries for the sensors. The comparison shows significant energy conservation capabilities and extension of the life span of the network. However, this improvement greatly depends on the duration of the measuring cycles of the network, a parameter that needs further investigation and tuning.

Keywords: Wireless sensor networks, precision agriculture, optimal design, energy management, genetic algorithms.

INTRODUCTION

Wireless sensors play a developing role in the realization of Precision Agriculture (PA). While their applications in agriculture and in the food industry are still rare (Wang et al., 2006), their uses across other areas promise successful applications in such high-technology fields as PA.

Particularly in open-field agricultural applications, where distances can be quite large, networks of such sensors can be structured to monitor the cultivation area. These wireless sensor networks (WSNs) usually consist of several low-cost multifunctional sensor nodes that are small in size and communicate across relatively short distances (Akyildiz et al., 2002). Even though they have low power consumption, they usually operate on limited power sources, making energy conservation a very significant factor in their design and operation.

Except for the obvious need for an optimal power management scheme that would maximize the life span of a WSN, another equally important matter that would make WSNs a useful tool for PA applications is the satisfaction of some prerequisite parameters set by the application itself. In other words, the WSN characteristics have to meet some criteria that would make its data collection useful to the user (grower). These criteria depend of course on the cultivation type, the measuring parameter and its properties, the characteristics of the cultivation site, etc. All these criteria can form some application-specific parameters that the designer of the network should take into account, along with the optimization of the energy conservation of the network.

This work describes such an approach to WSN design, which takes into account both energy-related parameters and application-specific parameters in the development of an algorithm for optimal design of WSNs for PA applications. It extends our initial effort (Ferentinos and Tsiligiridis, 2005) by using solar rechargeable batteries as an alternative power source for the wireless sensors. Optimal energy management remains an issue in this new approach, with solar energy making the entire dynamic optimal design of the network even more complicated.

BACKGROUND AND RELATED WORK

The WSN architecture used in this work consists of a square grid deployment with a 30 by 30 “length units” size, meaning that a total of 900 sensors are available in the junctions of the notional grid. Sensors are identical and may be either active or inactive. They are capable of transmitting in one of three supported signal ranges. In the case that a sensor is active, it may operate as a clusterhead transmitting in an appropriate signal range (CH sensor) that allows the communication with the remote base station (sink), or it may operate as a regular sensor transmitting in either high or low signal range (HSR/LSR sensor respectively). It is assumed that HSR-sensors cover a circular area with radius equal to 10 length units, while LSR-sensors cover a circular area with radius equal to 5 length units. Regular sensors are divided into clusters and in each cluster a sensor is chosen to act as a clusterhead. Regular sensors communicate directly with the closest clusterhead, whereas clusterheads communicate with a remote base station. Single hop transmission is used in both cases. It is assumed that communication between clusterheads and the base station can always be achieved when required and that the base station can communicate with every sensor in the field, meaning that every sensor is capable of becoming a clusterhead at some point.

As discussed in the previous section, energy conservation has always been the major concern in the development of WSNs. Energy consumption of such networks concerns mainly two processes: i) operation of the sensors for data collection and possible data processing and aggregation, and ii) wireless communication between sensors. The first process, i.e. the operational energy consumption, refers to the energy that a sensor consumes during some specific time of operation and it basically depends on the operating mode of the sensor, i.e. whether it is active or inactive and in the former case, whether it operates as a clusterhead node, a HSR sensor or a LSR sensor. It was assumed that the energy consumption of a sensor operating in clusterhead mode is 10 times more than that of a regular sensor operating in HSR mode and 20 times more than that of a regular mode operating in LSR mode. Thus, the operational energy (E_{op}) consumption of the WSN at some specific configuration can be calculated by the equation:

$$E_{op} = 20 \cdot \frac{N_{CH}}{N_{act}} + 2 \cdot \frac{N_{HSR}}{N_{act}} + \frac{N_{LSR}}{N_{act}} \quad (1)$$

where, N_{CH}, N_{HSR}, N_{LSR} and N_{act} are the number of clusterheads, high signal range, low signal range and total active sensors in the network, respectively. The second process, i.e. the communication energy (E_{comm}) consumption, refers to the energy that is consumed due to communication between regular sensors and clusterheads. It mainly depends on the distances between the sensors and their clusterhead, in each cluster, as defined in Ghiasi et al., 2002, and is calculated by the equation:

$$E_{comm} = \sum_{i=1}^{c} \sum_{j=1}^{N_i} \mu \cdot d_{ji}^{k} \quad (2)$$

where, c is the number of clusters in the network, N_i is the number of sensors in the i-th cluster, d_{ji} is the Euclidean distance from sensor j to its clusterhead (of cluster i) and μ and k are constants, characteristic of the topology and application site of the WSN. For the specific PA application for open field monitoring considered here, the values of μ=1 and k=3 were chosen.

Energy efficiency of WSNs has been the major concern of several analyses on the design and management of WSNs (e.g., Slijepcevic and Potkonjak, 2001; Krishnamachari and Ordonez, 2003). As a result, several optimal design algorithms for power conservation have been proposed (Rodoplu and Meng, 1999; Chang and Tassiulas, 2000; Chiasi et al., 2002; Zhou and Krishnamachari, 2003). However, all these approaches do not take into account the principles, characteristics and requirements of application-specific WSNs, nor do they consider alternative power sources. When all these factors are taken into consideration, the problem of optimal design and energy management of WSNs becomes much more complex.

Solar energy is a type of environmental energy that can be greatly exploited in open-field cultivation applications of PA. By using solar cells, solar radiation can be used to produce electrical current, the amount of which is proportionate to the area of cells or the light intensity. However, solar cell efficiency is rather low, typically around 18% (Roundy et al., 2004). Solar energy has been recently incorporated into WSN applications, like the quite successful systems “ZebraNet” (Zhang et al., 2004), “Prometheus” (Jiang et al., 2005) and “Trio” (Dutta et al., 2006). These applications constitute Multiple Power Source (MPS) systems as their sensors can be powered by either batteries or solar cells. An important problem in such MPS systems is power fragmentation (Chou and Park, 2005), i.e., the requirement of a mechanism that should schedule dynamically the current source of power according to available battery capacities and alternative power supplies. This issue is avoided in our system by using solar energy to charge the batteries of the sensors instead of using it directly for operational purposes.

WSNs have been used in PA mainly in four areas (Wang et al., 2005): i) spatial data collection (Gomide et al., 2001; Lee et al., 2002; Mahan and Wanjura, 2004), precision irrigation (Damas et al., 2001; Evans and Bergman, 2003), variable-rate technology (Cugati et al., 2003) and supplying data to farmers

(Jensen et al., 2000; Flores, 2003). The WSN approach that is used here can be used as a theoretical tool to optimize network designs for all these areas of PA. As long as the adequate application-specific requirements are incorporated in the optimization algorithm, as explained in the following section, the algorithm takes them into account together with the other optimization parameters, like connectivity and energy conservation.

OPTIMAL DESIGN ALGORITHM

The overall problem that the proposed algorithm tries to solve is multi-objective. In general, the algorithm dynamically designs WSN topologies by optimizing energy-related parameters that affect the battery consumption of the sensors and thus, the life span of the network. At the same time, it tries to meet some embedded connectivity constraints and optimize some physical parameters of the WSN implemented by the nature of the specific PA application. The multiple objectives of the optimization problem are blended into a single objective function, the parameters of which are combined to formulate a fitness function that gives a quality measure to each WSN topology and it is optimized by the proposed algorithm.

Three sets of parameters which dominate the design and the performance of a WSN for PA are identified. The first set is the *application-specific parameters* which include two parameters regarding the deployment of sensors for the specific case considered here. These are the highest possible uniformity of sensing points and some desired spatial density of measuring points. The second set is the *connectivity parameters* which include an upper bound on the number of sensors that each clusterhead sensor can communicate with, and the fact that all sensors must have at least one clusterhead within their signal range. Finally, the third set refers to the *energy-related parameters* which include the operational energy consumption depending on the types of active sensors, the communication energy consumption depending on the distances between sensors that communicate with their corresponding clusterhead, and finally the battery energy consumption.

Genetic Algorithms (GAs) (Holland, 1975) were used for the optimization of the multiple objectives of the problem. GAs belong to the evolutionary computation group of heuristic optimization techniques. They try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and applying the principle of survival of the fittest. The methodology and formulation of GAs for some specific application incorporates three basic steps: (i) the problem representation, i.e. the encoding mechanism of the problem's phenotypes into genotypes that GAs manipulate and evolve, (ii) the formulation of the fitness function that gives to each individual (i.e. possible network design) a measure of performance, and (iii) the choice of the genetic operators and the selection mechanism used. These steps are of major importance, as they drastically affect the performance.

For the representation of WSN designs, binary encoding was used. Thus, each specific design was represented by a bit-string of zeros and ones using the following scheme: For a sensor placed at each of the $r{\cdot}c$ grid positions, there are four possibilities represented by a two-bit encoding scheme: being an inactive sensor (00), being a regular active sensor, operating in a low signal range (10), being a regular active sensor operating in a high signal range (01) and being an active clusterhead sensor (11). The grid junctions were encoded row by row in the bit string. Each position needs two bits for the encoding, thus, the length of an individual (GA string) was $2rc$. In the specific design problem analyzed here, the sizes of r and c were both equal to 30, thus the length of the individuals were equal to 1800.

The fitness function is a weighted function that measures the quality or performance of a specific sensor network design. This function is maximized by the GA system in the process of evolutionary optimization. A fitness function must incorporate all or at least the most important factors that affect the performance of the system. In the design of a WSN, these factors concern network connectivity issues, energy consumption issues and network characteristics issues, according to the specific PA application requirements. The connectivity issues include a parameter to ensure that no more than a maximum number of sensors are connected to each clusterhead (Sensors per Clusterhead Error parameter – *SCE*) and a parameter to ensure that each sensor is in range to its clusterhead (Sensors Out of Range Error parameter – *SORE*). The energy consumption issues include the operational and communication energy consumptions expressed by equations (1) and (2) and a third parameter related to the available battery capacities of sensors (Battery Capacity Penalty – *BCP*). Finally, the network characteristics issues include two application-specific parameters that have to be met by the designed network: a desired uniformity of measuring points, expressed by the Mean Relative Deviation parameter (*MRD*) where the smaller the value of *MRD*, the better the uniformity, and a desired spatial density of measuring points, expressed by a Spatial Density Error parameter (*SDE*). All these parameters are defined in such a way that they need to be minimized, and since GAs operate by maximizing a fitness function, the form of the fitness function or our design problem is given by the following equation:

$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + \alpha_4 \cdot SORE + \alpha_5 \cdot E_{op} + \alpha_6 \cdot E_{comm} + \alpha_7 \cdot BCP) \tag{3}$$

where, f is the fitness value of a specific WSN design and α_1-α_7 are weighting coefficients that determine the relative importance of each parameter in the equation.

The GA system maximized eq. (3) through the genetic operators of crossover, mutation and selection. Initially, full battery capacities were assumed for all sensors. After the initial optimal design was applied to the WSN, the batteries were updated according to the scheme described in the following section, and the algorithm was re-applied. Each such cycle or re-application of the design algorithm consisted a measuring cycle of the network. By re-applying the algorithm at the end of each measuring cycle, a dynamic system for design adaptation of the WSN was realized.

SOLAR RECHARGING SCHEME

The initial implementation of WSNs described in Ferentinos and Tsiligiridis (2005) was enhanced with the inclusion of solar rechargeable batteries. The main difference of the new approach compared to the original battery scheme, as far as the modeling scheme is concerned, is that the battery update parameter has an additional positive term. This term compensates for the recharging of the batteries from solar radiation.

The original battery update scheme was depicted by the following equation:

$$BC_i^{[t]} = BC_i^{[t-1]} - BRR_i^{[t-1]} \tag{4}$$

where, $BC_i^{[t]}$ and $BC_i^{[t-1]}$ are the battery capacities of sensor i at the beginning of measuring cycles t and $t-1$ respectively, and $BRR_i^{[t-1]}$ is the battery reduction rate factor for sensor i that depends on its operating mode during measuring cycle $t-1$; for the four possible operating modes of clusterhead, HSR, LSR and inactive, that factor takes the values 0.2, 0.02, 0.01 and 0 respectively.

The battery update scheme concerns the last parameter of the fitness function that the GA system uses for the design optimization of the WSN (eq. (3)), namely the *BCP* parameter. This parameter is given by:

$$BCP^{[t]} = \sum_{i=1}^{N_{grid}} PF_i^{[t]} \cdot \left(\frac{1}{BC_i^{[t]}} - 1 \right) \tag{5}$$

where:

- $BCP^{[t]}$ is the battery capacity penalty of the WSN at measuring cycle t. It is used to penalize the use of sensors with low battery capacities, giving at the same time larger penalty values to operating modes that consume more energy (especially clusterhead mode)
- N_{grid} is the total number of available sensors
- $PF_i^{[t]}$ is a penalty factor of sensor i that takes different values according to the operation mode of sensor i. The values used here are proportional to the relevant battery consumptions of the sensor modes, namely, 20:2:1 for active sensor mode (CH, HSR and LSR respectively) and 0 for inactive. It provides different penalty weights according to the specific modes that these sensors are planned to have in the WSN of the next measuring cycle.

Thus, this parameter uses the battery update scheme so that battery capacities at each measuring cycle ($BC_i^{[t]}$) are evaluated.

The new scheme introduces a positive term in the battery update equation (4), namely the battery charging rate factor (*BCR*). This term incorporates the amount of battery capacity that is added to the sensors from the available solar radiation using some solar recharging mechanism. The hardware details of that mechanism are not examined in the work presented here, which focuses rather on the effect of that charging rate factor in the energy management and optimal design of the entire WSN.

Thus, the new battery update scheme is given by the equation:

$$BC_i^{[t]} = BC_i^{[t-1]} - BRR_i^{[t-1]} + BCR^{[t-1]} \tag{6}$$

where $BCR^{[t-1]}$ is the amount of battery capacity added to each sensor from solar radiation available during measuring cycle t-1. The values of $BRR_i^{[t-1]}$ were the ones used in the original update scheme, that is, 0.2, 0.02, 0.01 and 0 for clusterhead, HSR, LSR or inactive operating mode of sensor i during measuring cycle t-1.

The form of *BCR* depends basically on the duration of the measuring cycle of the network. More specifically, it depends on the measure of comparison between the measuring cycle and the charging period of the batteries. Since the charging period is actually a portion of the day (namely the daylight period), the form of the *BCR* factor depends on the size of the measuring cycle (*MC*) compared with daylight duration (*DL*). If l is the portion of the daily *DL* period that is covered in one *MC* (l can be greater than 1 if more than one *DL* periods are covered in a *MC*, i.e., if $MC > day \Rightarrow l \geq 1$), and m is the increase amount of battery capacity due to solar power supply in one daily *DL*, then *BCR* can be evaluated by:

$$BCR^{[t]} = l \cdot m \,. \tag{7}$$

The value of m does not depend on the operating mode of each sensor, thus *BCR* is the same for all sensors during some specific measuring cycle. Moreover, m depends on the size of solar cells, because larger cells yield quicker charging. Here, identical cells are considered for all sensors.

The estimation of *BCR* using the parameters l and m makes the comparison of *MC* with the duration of the day unnecessary. Thus, by just varying the value of l, several different scenarios of battery update schemes can be investigated. These scenarios are not defined in terms of the duration of *MC* because that duration has been already defined in terms of battery consumption and not in an absolute time measure (a *MC* is defined as the period during which the battery capacity of a clusterhead sensor is reduced by 20% of its full capacity and it is assumed that this period is constant throughout the experiment).

However, a possible problem in the analysis of dynamic application of the proposed algorithm for WSN design could arise in the case where $MC \neq$ day, because then l is different for each *MC*. In order to avoid this complication, for the moment it is assumed that MC = day and thus l = 1. Therefore, the investigation of different dynamic schemes of the values of l with possible inclusion of real or simulated solar radiation data and different *MC* sizes is left for future work.

For the value of *BCR* in the battery update scheme of eq. (6), two different cases were considered:

Scenario 1: l=1, so from eq. (7), $BCR = m$. In this case, it does not matter how long the *DL* period is; it is derived by the value of m.

Scenario 2: $MC = \frac{1}{3} day$ and $DL = \frac{1}{3} day$ with the two periods coinciding. Then, *BCR* is a periodic step function with the value of m for one *MC* and 0 for the following two measuring cycles, while its period is three measuring cycles (Fig. 1).

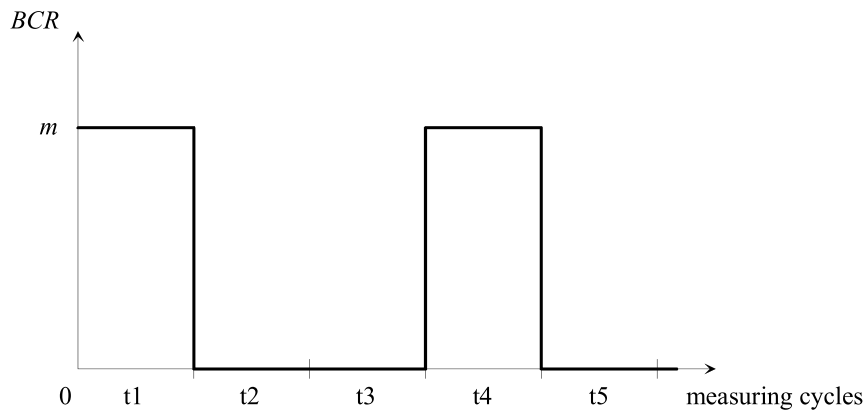

Fig. 1. Step function representation of the *BCR* factor for the second scenario of battery recharging scheme.

It should be noted that obviously a sensor with full battery capacity cannot be further charged, even during the existence of solar radiation. The investigation of the performance of the proposed algorithm in dynamic application of the WSN design process, in these two different battery recharging scenarios, is presented in the following section.

RESULTS ON DYNAMIC APPLICATION OF WSN DESIGN

The proposed WSN design algorithm was tested dynamically using the two previously described versions of battery update scheme. The value of *m*, in addition to the size of the solar cells that it was assumed to be the same for all sensors as mentioned in the previous section, also depends on the available amount of solar radiation during each daylight period (*DL*). To compensate variations between different periods, an average radiation amount was considered throughout the dynamic application of the algorithm, thus a constant value of *m* was used. Specifically, it was assumed that in an entire daily daylight period, a sensor's battery was charged by an amount of 2% of its original full battery capacity, that is $m = 0.02$.

Therefore, in the first scenario, during each *MC* a sensor looses either 20%, 2%, 1% or none of its full battery capacity according to its operating mode (CH, HSR, LSR or inactive, respectively) and gains 2% from solar radiation. In the second scenario, during each *MC* a sensor looses again either 20%, 2%, 1% or none of its full battery capacity, and gains 2% from solar radiation every third measuring cycle, while during the other two cycles it does not gain any battery capacity.

The design algorithm for both battery recharge scenarios was applied for 15 consecutive measuring cycles, starting from an initial optimal design that assumed full initial battery capacities for all available sensors. The results of both applications of the algorithm were compared to those of the original battery update scheme without solar recharging batteries (Ferentinos and Tsiligiridis, 2005).

Fig. 2 shows the comparison between the original battery update scheme (normal case) and scenario 1 described before (solar recharging). The two columns of graphs correspond to the investigation of sensors that have battery capacities below the level of 50% of their initial full capacity after each measuring cycle. The plots of the first row show the percentages of sensors (among all 900 available sensors) that remain after measuring cycle with battery capacities above the specific levels (50% and 30%), for both the original battery update scheme and the update scheme of scenario 1. The second row contains graphs showing the difference (in absolute number of sensors) between the two cases, that is, how many more sensors have battery capacities below those levels in the original case than in scenario 1, while the bottom graphs show the relative improvement of the update scheme of scenario 1, in terms of existing sensors in the original update scheme with battery level below either 50% or 30%. In other words, a value of 1 means that all sensors with battery < 50% in the original case, have battery > 50% in scenario 1, while a value of 0.5 means that half of there sensors have battery > 50% in scenario 1. Similarly, Fig. 3 compares the original battery update scheme with scenario 2 described before.

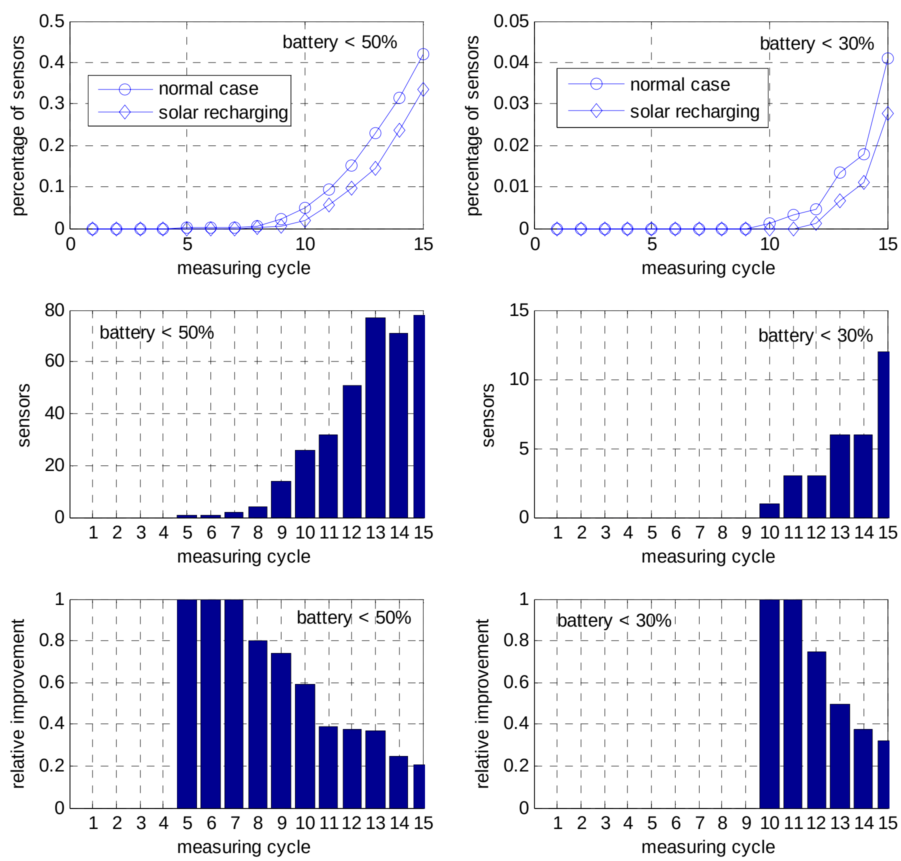

Fig. 2. Percentages of sensors with battery capacities below 50% and 30% of full battery capacity at the end of each measuring cycle, for original battery update scheme and solar recharging scenario 1, absolute differences of two cases (in numbers of sensors) and relative improvement over the original (normal) case.

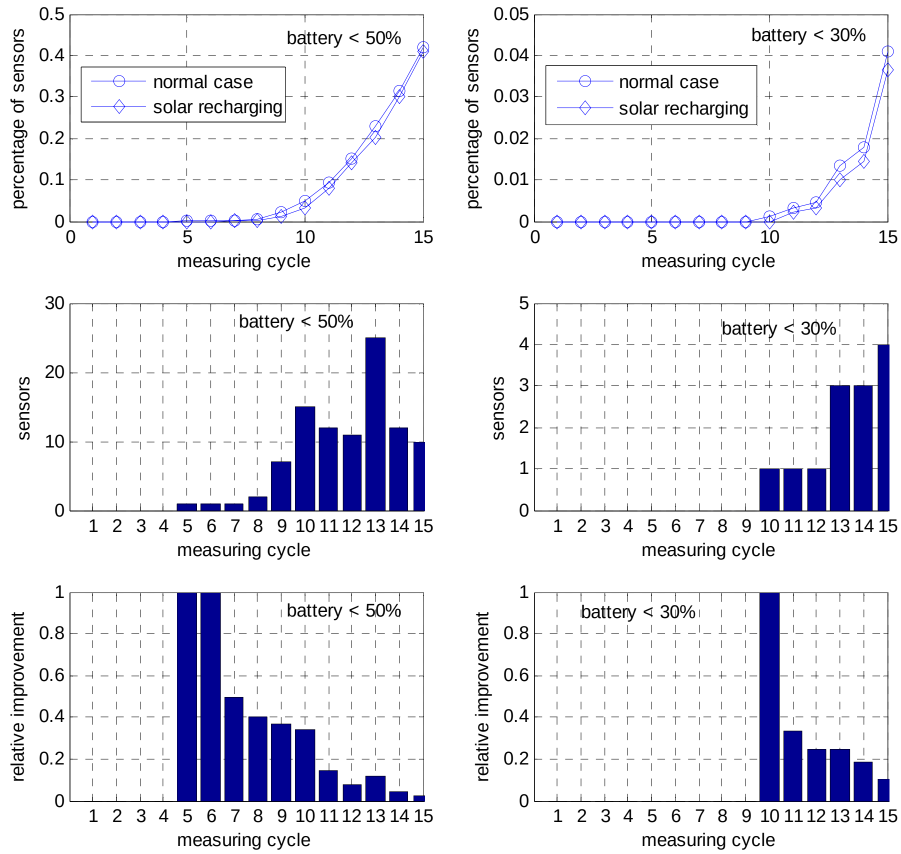

Fig. 3. Percentages of sensors with battery capacities below 50% and 30% of full battery capacity at the end of each measuring cycle, for original battery update scheme and solar recharging scenario 2, absolute differences of two cases (in numbers of sensors) and relative improvement over the original (normal) case.

From these graphs it can be seen that in general, energy conservation was improved with the inclusion of solar rechargeable batteries. The battery recharging scheme of scenario 1 achieved much better improvement over the original battery update scheme than that of scenario 2. That was of course something rather expected, as recharging was taking place at each measuring cycle. However, this scenario can be realistic only if power consumption of sensors is considered quite low, because of the way a measuring cycle is defined, by specific amounts of energy consumption of sensors at the available operating modes. In addition, the improvement rate is much more normal in the case of scenario 1 with the constant recharging, while in scenario 2 there are increments of improvement during the measuring cycles of battery recharging.

In addition to energy conservation, the connectivity characteristics of the WSN designs together with their characteristics concerning the application-specific requirements were of interest. Like in the case of the original battery update scheme without rechargeable batteries, in both scenarios of solar rechargeable batteries, connectivity constraints were always met during all 15

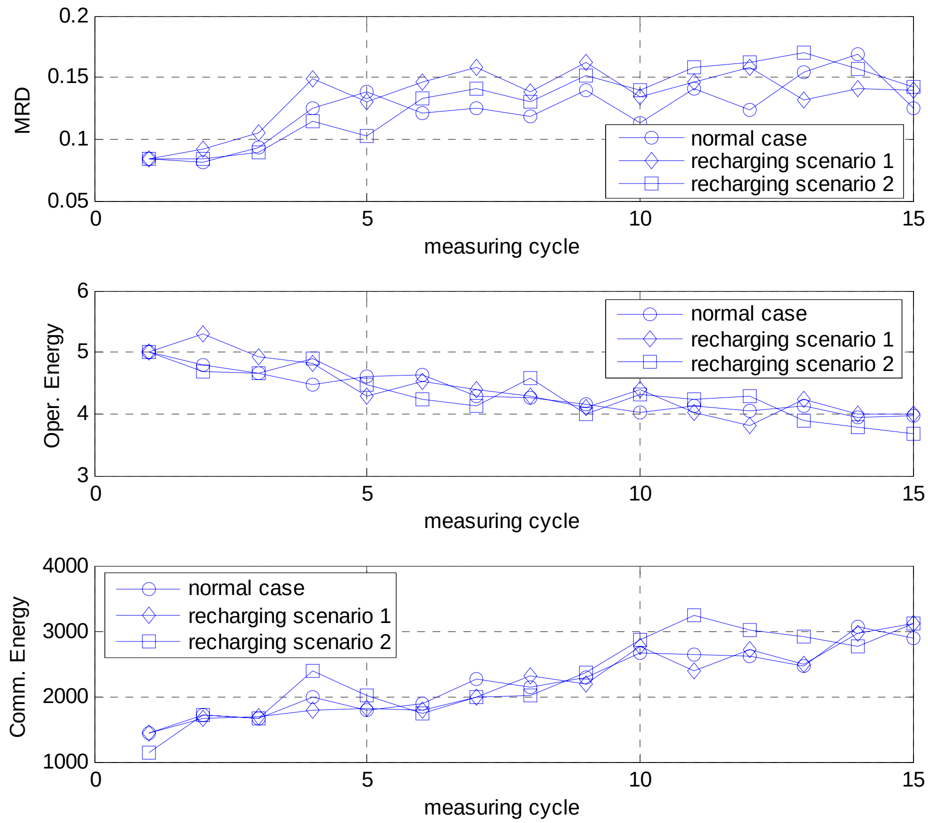

Fig. 4. Network characteristics (uniformity (MRD), operational energy and communication energy) over the testing period of 15 measuring cycles for the original battery update scheme (normal case) and the two battery recharging scenarios.

consecutive measuring cycles. In addition, the spatial density requirement was also met and uniformity was kept at levels similar to those of the original battery update scheme (Fig. 4). Finally, from the graphs of Fig. 4 it can be deduced that the recharging schemes did not play a significant role in the evolution of the characteristics of the WSNs during the dynamic designing optimization process.

CONCLUSIONS

An algorithm for dynamic WSN design optimization was tested in three different battery update schemes: the case where normal batteries were assumed and two scenarios with the inclusion of solar rechargeable batteries. The comparisons on the energy conservation capabilities of the algorithm towards the extension of the life span of the network showed that the inclusion of rechargeable batteries was sufficiently accommodated by the algorithm and significant improvement was achieved. However, the duration of the measuring cycles of the system proved a parameter that greatly influences the performance of the algorithm and should be further investigated. Finally, it was shown that the algorithm performs adequately in the new recharging schemes as far as the network characteristics are concerned, while each specific battery recharging scheme does not seem to influence the evolution of these characteristics throughout the continuous process of the network design optimization.

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