A Memetic Algorithm for Dynamic Design of Wireless Sensor Networks

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***Abstract*—We present a memetic algorithm that dynamically optimizes the design of a wireless sensor network towards energy conservation and extension of the life span of the network, taking into consideration application-specific requirements, communication constraints and energy consumption of operation and communication tasks of the sensors. The memetic algorithm modifies an already successful genetic algorithm design system and manages to improve its performance. The obtained optimal sensor network designs satisfy all application-specific requirements, fulfill the existing connectivity constraints and incorporate energy conservation characteristics stronger than those of the original genetic algorithm system. Energy management is optimized to guarantee maximum life span of the network without lack of the network characteristics that are required by the specific sensing application.**

I. Introduction

ENERGY conservation probably constitutes the most important challenge in the design of wireless sensor networks (WSNs). These networks generally consist of a large number of low-power sensor nodes that communicate over short distances, and their energy resources are significantly more limited than in wired networks [1-2]. Their design should take into consideration these limitation and incorporate some operation scheduling so that sensor energy saving is optimized and life span of the network is maximized.

Another issue in WSN design is the connectivity of the network according to some specific communication protocol [2-3]. Cluster-based architectures with single-hop communication between sensors of a cluster are the most commonly used. In these cases, a selected clusterhead sensor collects all gathered information by the sensors in its cluster, and sends it to a remote base-station (sink). Usually, connectivity issues include the number of sensors in each cluster, because a clusterhead can handle up to a specific number of connected sensors, as well as coverage issues related to the ability of each sensor to reach some clusterhead.

Finally, some issues that have to do with the physical characteristics of the network according to the relevant requirements of the specific application of the WSN have recently been included as major parameters in the design process of WSNs [4-5]. The purpose of the sensor network, which is the collection and possibly the management of measured date for some particular application, must not be neglected. This collection must meet some specific requirements, depending on the type of data that are collected. These requirements are turned into specific design properties of the WSN and play an important role in the design optimization of the WSN.

Most algorithms that lead to optimal topologies of WSNs towards power conservation, do not take into account the principles, characteristics and requirements of application-specific WSNs [6-11]. When these factors are considered, then the problem of optimal design and management of WSNs becomes much more complex [5].

It is clear that the problem of WSN design optimization that takes into account all the before-mentioned parameters, is a multi-objective optimization problem. There are several interesting approaches to tackling such problems. One of the most powerful heuristics that could be applied in our multi-objective optimization problem is based on Genetic Algorithms (GAs) [12]. The successful application of GAs in a sensor network design in [13] led to the development of several other GA-based application-specific approaches in WSN design, mostly by the construction of a single fitness function [14-17], but also by considering Pareto optimality in the evaluation of fitness values [18]. However, in most of these approaches, either very limited network characteristics are considered, or several requirements of the application cases are not incorporated into the performance measure of the algorithm.

In our previous work [5], we considered an integrated GA approach, both in the direction of degrees of freedom of network characteristics and of application-specific requirements represented in the performance metric of the GA. The primary goal was to find the optimal operation mode of each sensor so that application-specific requirements are met and energy consumption of the network is minimized. More specifically, network design was investigated in terms of active sensors placement, clustering and signal range of sensors, while performance estimation included, together with connectivity and energy-related characteristics, some application-specific properties like uniformity and spatial density of sensing points. Thus, the implementation of the proposed methodology resulted in

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a near-optimal design scheme, which specified the operation mode for each sensor.

That GA-based algorithm was applied dynamically to obtain a dynamic sequence of operation modes for each sensor, i.e. a sequence of WSN designs, which leads to maximization of network lifetime in terms of number of data collection (measuring) cycles. This was achieved by implementing the algorithm repeatedly in order to develop a dynamic network design that adapted to new energy-related information concerning the status of the network after each measuring cycle or at predefined time intervals.

In this work, we develop a Memetic Algorithm (MA) [18] which hybridizes the GA system developed in [5], with a goal to improve its performance by guiding the population formulation of the GA towards more intelligent decisions.

In the following Section we describe the WSN modeling approach and the parameters involved in the design problem. In Section III we briefly describe the GA approach that was originally used to develop the WSN design algorithm and the most important features of that algorithm are pointed out. In Section IV we present the basic characteristics of the novel Memetic Algorithm approach and in Section V the network design capabilities of the algorithm are compared with those of the original GA-based design algorithm. Finally, in Section VI, some overall conclusions are drawn and trends of future work are stated.

II. WSN Design Issues

A. WSN Modeling

The WSN considered in this application is intended to cover a sensing area with a size of 30 by 30 length units. Sensors are placed on the junctions of a virtual grid that covers the entire area and has a grid step size of one length unit, thus there are 900 sensors all together. A length unit is an abstract parameter so that the optimal design algorithm is general enough. A cluster-based network architecture is used where sensors are partitioned into several clusters. Each sensor belongs to the cluster of its closest clusterhead sensor. All sensors are identical and may be either active or inactive. They are capable of transmitting in one of three supported signal ranges. Provided that a sensor is active, it may operate as a clusterhead transmitting at 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 at either high or low signal range (HSR/LSR sensor respectively).

B. Design Parameters

We propose an algorithm to dynamically design 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, the proposed algorithm tries to meet some embedded connectivity constraints and optimize some physical parameters of the WSN implemented by the nature of the specific application.

As mentioned in the Introduction, we consider three major sets of parameters that influence the performance of a specific design of a WSN that is used in some particular application. The first set is the application-specific parameters. In this work we consider a WSN that is intended to sense environmental variables in some rural area, so these application-specific parameters regard the deployment of sensors for that specific case considered here. They are: i) the highest possible uniformity of sensing points, and ii) 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.

The measure of uniformity of sensing points was estimated by the spatial mean relative deviation (*MRD*) of such points. The entire area of interest was divided into several overlapping sub-areas. Sub-areas are defined by four factors: two that define their size (length and width) and two that define their overlapping ratio (ratios in the two directions). All these factors are expressed in terms of the unit length of each direction. The larger the overlapping ratio is, the higher precision is achieved in the evaluation of uniformity, but also, the slower the algorithm becomes. In order to define *MRD*, the notion of spatial density (ρ) of sensing points was used. More specifically, ρ_{Si}, the spatial density of sensing points in sub-area S_i, was defined as the number of such points over the area of the i-th sub-area, i=1,2,…,N, where N is the number of overlapping sub-areas into which the entire area, say S, was divided. In addition, ρ_S, the spatial density of the entire area of interest, was defined as the total number of sensing points of the network over the total area of interest. Thus, *MRD* was defined as the relative measure of the deviation of the spatial density of sensing points in each sub-area from the total spatial density of such points in the entire area:

$$MRD = \frac{\sum_{i=1}^{N} \left| \rho_{S_i} - \rho_S \right|}{N \cdot \rho_S} \tag{1}$$

Low values of *MRD* correspond to high uniformity of sensing points. Acceptable values for our application example are of *MRD* up to 0.15-0.16.

In addition to uniformity and spatial density of sensing points as well as energy consumption of the WSN (both operational and communicational), two network connectivity issues were taken into account: i) A Sensors-per-Clusterhead Error (*SCE*) parameter was included to ensure that each clusterhead did not have more than a maximum predefined number of regular sensors in its cluster. This number is defined by the physical communication capabilities of the sensors as well as their data management capabilities in terms of quantity of data that can be processed by a clusterhead sensor. It was assumed to be equal to 15 for the application considered here. ii) A Sensors-Out-of-Range Error (*SORE*) parameter was included to ensure that each sensor can communicate with its clusterhead. This of course depends on the signal range capability of the sensor. 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.

Finally, the battery capacities of the sensors were taken into account by the introduction of the battery capacity penalty (*BCP*) parameter (more details can be found in [5]).

All these parameters of different nature are taken into consideration in the design optimization algorithm presented in the following sections.

III. Original GA-Based Algorithm

In this section we briefly present the basic characteristics of the GA-based optimal design algorithm originally developed in [5]. Initially, the key elements of the GA approach are described, and then the dynamic optimization algorithm is presented.

A. Methodology of GA

The three main steps in the development of a GA are: i) the problem representation, i.e. the encoding mechanism of the problem's phenotypes into genotypes that GA manipulate and evolve, ii) the formulation of an appropriate fitness function that gives a quantitative quality measure of each possible solution, and iii) the choice of the genetic operators and the selection mechanism used.

The parameters of each WSN design that needs to be encoded in the representation scheme of the GA are the placement of the active sensors of the network, the operation mode of each active sensor, that is, whether it is a clusterhead or a "regular sensor", and in the case of a "regular sensor", the range of its signal (high or low). All these parameters can be distinguished by four states and thus can be encoded in a binary representation scheme by two bits for each sensor position. If there are x sensors in the WSN, each string in the GA population has a length of $2x$. As explained earlier, the sensors are on a grid deployment of size r x c, thus the length of the GA strings are $2\ r{\cdot}c$.

The fitness function incorporates all the parameters that influence the performance of the WSN design, which were described in the previous section. It is a weighted sum of all these parameters, with the values of the weighting coefficients α_i: i=1,2,…,7 determining the relevant significance of each parameter:

$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + \alpha_4 \cdot SORE + ... \\ ... + \alpha_5 \cdot OE + \alpha_6 \cdot CE + \alpha_7 \cdot BCP) \quad (2)$$

The values of these coefficients were determined based on experience about the importance of each parameter.

Two types of the classical crossover operator defined in [20] were tested, the one-point and the two-point crossover. The mutation type that was used was the classical one for binary representation, that is, the swapping of the bits of each string (0 becomes 1 and vice versa) with some specific low probability. Crossover is also applied with some specific probability. Both these probabilities are tuned after proper experimentation. The adopted selection mechanism was the roulette wheel selection scheme. The probability of selecting some individual to become a parent for the production of the next generation was proportional to its fitness value. In addition, in order to assure that the best individual of each generation was not destroyed by the crossover and mutation operators during the evolution process, "elitism" was included in the algorithm, meaning that the current best individual at each generation of the algorithm always survived to the next generation.

B. GA-based Dynamic Optimal Design Algorithm

The GA system is initially applied to sensors with full battery capacities. After obtaining an optimal WSN design, that design is applied to the sensors for an entire measuring cycle. Then, the battery capacities are updated and the GA is re-applied taking into account the updated battery values. A measuring cycle is defined as the time period during which a CH sensor loses 20% of its full battery capacity, while HSR and LSR sensors lose 2% and 1% respectively. It is assumed that inactive sensors do not consume any battery. The battery update and the re-application of the GA in each measuring cycle are performed during data collection of that measuring cycle. This is because battery capacities at the end of the cycle can be evaluated based on the developed model, without having to wait until the actual end of the measuring cycle. Thus, at the end of each measuring cycle, the next optimal WSN design has already been formed and it is then used for the next data measuring cycle.

IV. Memetic Algorithm Approach

The MA approach is incorporated into the dynamic optimal design algorithm. This means that the initial optimal WSN design (assuming full battery capacities for all sensors) is obtained by the original GA-based algorithm, as described in the previous section. Beginning from the second measuring cycle in the dynamic application of the design algorithm, the MA-based system performs the optimal design of the WSN.

Three battery level threshold values are introduced, one for each operating mode of the sensors (CHs, HSR and LSR modes). The idea is, at each measuring cycle to allow a sensor i to operate at some specific mode if and only if its battery level at the time is above the threshold value for that operating mode. Threshold values are adapted at each measuring cycle. More specifically, they are decreased according to some specific reduction schedule, as it is shown in the next section.

The "threshold approach" is incorporated into the original GA system in the following way:

When each individual of the population is formed, the operating mode of each sensor is checked according to the corresponding (according to its selected operating mode) threshold. If its battery level is below that threshold, its operating mode is changed to the lower mode (CH → HSR → LSR → inactive) until its corresponding threshold value becomes lower than (or equal to) its battery level. In this way, a local search procedure is introduced in the population of the GA, leading to the development of a Memetic Algorithm.

Fig. 1 shows the general block diagram of the MA-based dynamic design algorithm, while Fig. 2 presents the detailed operations of the MA approach, in pseudocode form.

V. Results

The MA approach to the dynamic optimization of WSN designs was compared to the original GA-based system, during 15 consecutive measuring cycles of the WSN. The fine-tuned parameters of that GA system (i.e., probabilities of crossover and mutation and population size) are kept the same in the MA. The additional parameters that are expected to influence the performance of the MA system are the initial values of the three battery-level thresholds and their reduction schemes. For this initial comparison presented here, some arbitrary initial values were applied and the following reduction scheme was used for all three thresholds:

$$T^{[t+1]} = (1 - RR) \cdot T^{[t]} \quad (3)$$

Where T is a specific threshold of the indicated measuring cycle and RR is the reduction rate which is equal to 0.2 for the case of the CH threshold and 0.1 for the other two cases (HSR and LSR thresholds). Further investigation of these parameters is going to be the next step in the continuation of this work.

A. Network Characteristics

The first comparison concerns the network characteristics that have to do with the application-specific requirements. It is very important that the values of these characteristics are kept within certain acceptable limits. Fig. 3 shows the progress of the values of uniformity level (MRD), operation energy consumption and communication energy consumption, for both the GA-system and the MA-system, during the examined 15 measuring cycles. In both cases, the adaptive WSN designs kept the MRD values quite low during all measuring cycles. In general, the MRD values of the WSNs designed by the MA-system are a little higher (lower uniformity), but they are constantly kept below 0.16, which is a very reasonable value. The general trend of increase in the values of MRD is reasonable as more and more energy limitations are introduced into the network as time passes. In the case of operational energy consumption

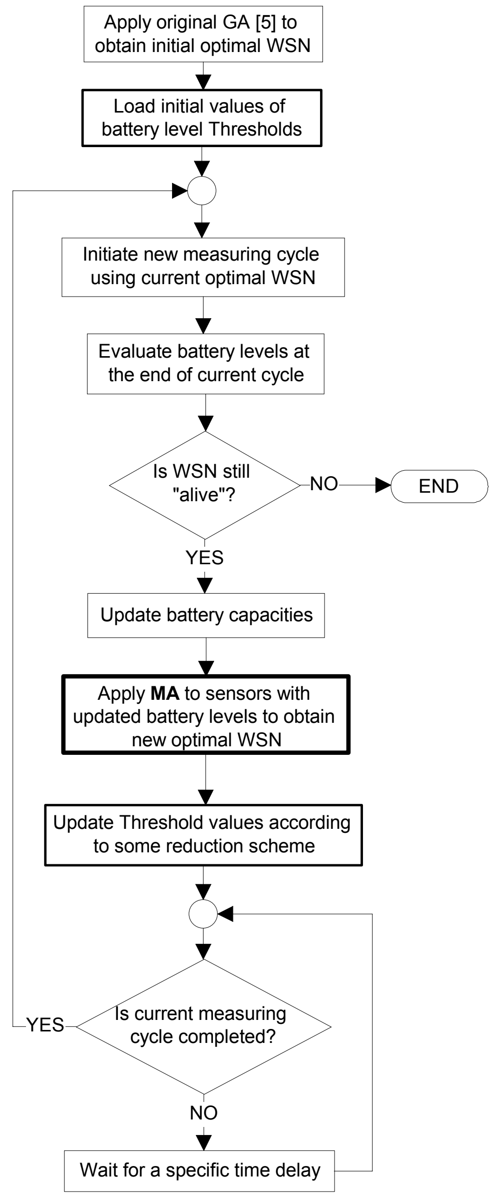

Fig. 1. Flow chart of the MA-based dynamic optimal WSN design algorithm.

of the WSNs, the GA-system results in designs with lower consumptions, while the MA-system seems to give lower consumptions in the case of communication energy consumption. It should be noted that spatial density of sensing points was not presented in these graphs because the required value was constantly met throughout the entire testing period. In addition, no communication faults occurred throughout the adaptive design processes of both the GA and MA systems. In general, one could say that application-specific characteristics of the WSNs designed by both approaches are similar.

```
Set population size M; Set max # of generations G;
Generate random initial population of M WSN designs
Load values of thresholds for current measuring cycle m: T_1^[m], T_2^[m], T_3^[m]
  (for CH, HSR and LSR modes respectively)
*** PART "LOCAL SEARCH" STARTS HERE ***
for om=1 to 3   // i.e., for each oper. mode: CH, HSR and LSR
   for each sensor i of operating mode om
      if Battery_i < T_om^[m], then
         "reduce" oper. mode of sensor i to om+1  // om=4 means "inactive"
      end if
   end for i
end for om
*** PART "LOCAL SEARCH" ENDS HERE ***
Update current population according to "LOCAL SEARCH" modifications
for t=1 to G
   Evaluate parameters for each individual in current population
   Assign fitness value to each individual
   Perform Crossover and Mutation with specific probabilities
   Re-apply part "LOCAL SEARCH"
   Replace old population with modified offspring to form current population
end for t
return best individual in current population (Optimal_WSN_design)
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Fig. 2. Pseudocode of the MA used in the dynamic optimal design algorithm (bold box in Fig. 1)

B. Energy Saving

Another important feature of the dynamic application of the optimal design algorithms is the energy saving characteristics of the designs, which lead to the extension of the life span of the networks. Figure 4 shows the percentage of sensors (over the entire grid of 900 sensors) with battery capacities below certain percentage-levels after each measuring cycle, based on the assumption that all sensors had 100% battery capacity at the beginning of the first measuring cycle, for the designs produced by both GA and MA systems. It is clear that the MA-system performs better than the GA-system in energy conservation of sensor power resources, as at specific measuring cycles, fewer sensors have battery capacities below certain values in the case of MA-designed WSNs. Something similar can be seen in Fig. 5, where percentages of sensors with battery capacities above certain levels are shown. Again, in most cases, the MA-designed networks have more sensors with battery capacities above certain levels, even though in very high capacities, the performances of both systems are quite similar.

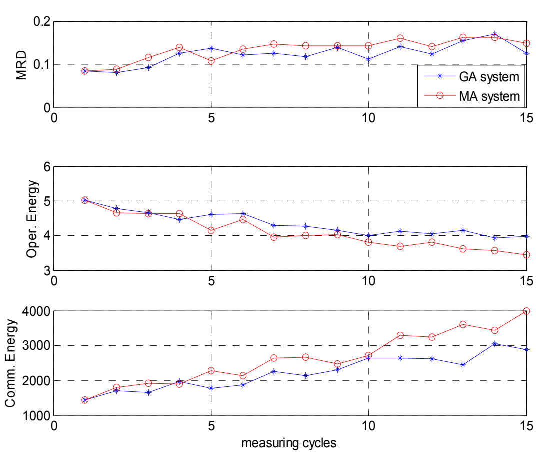

Fig. 3. Basic network characteristics of WSN designs during 15 measuring cycles for both systems (GA and MA).

An indication of the sophistication of a design algorithm towards energy saving and intelligent scheduling of the operation modes of sensors during dynamic network design, can be seen in the degree of re-usage of each sensor at some specific operating mode. Figures 6 and 7 show the number of sensors that were used at each measuring cycle in CH and HSR operating modes respectively, for some specific number of times (or not used at all). In the case of CH usage, it is clear that in the case of the MA-designed networks, more sensors were used once as CHs while less were used twice or three times, making the MA-based

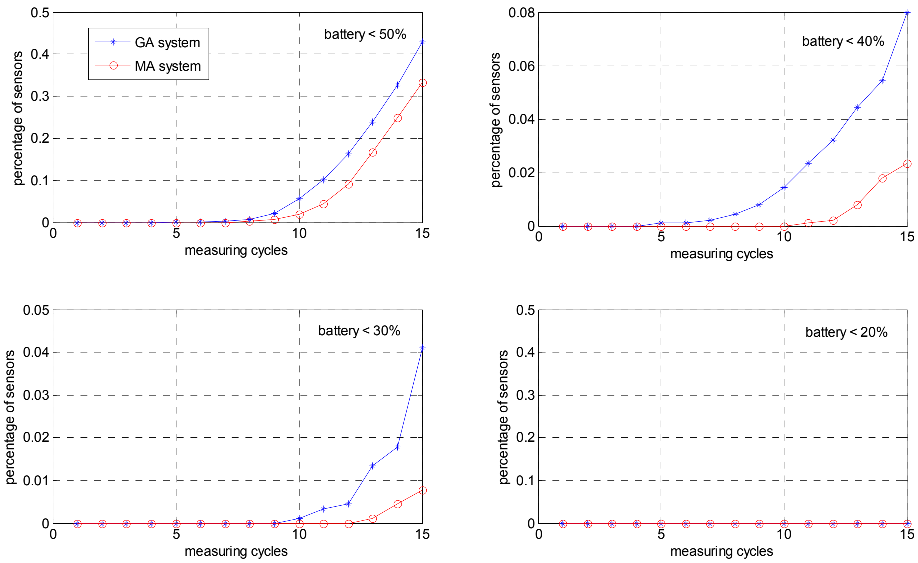

Fig. 4 Percentages of sensors with battery capacities below 50%, 40%, 30% and 20% of full battery capacity at the end of each measuring cycle, for both design optimization systems.

algorithm more sophisticated than the GA-based one (Fig.

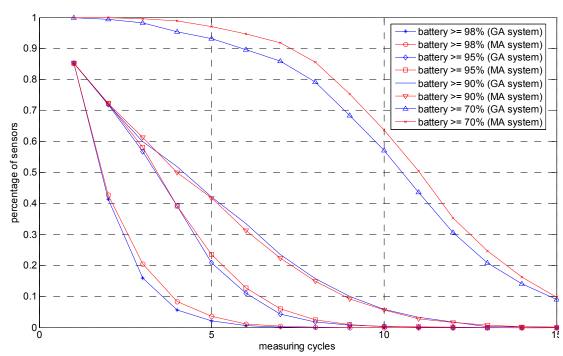

Fig. 5. Percentages of sensors with battery capacities above 98%, 95%, 90% and 70% of full battery capacity at the end of each measuring cycle, for both design optimization systems.

6). Similar but not so strong results are shown in the HSR usage (Fig. 7). This behavior also explains the better energy conservation achieved by the MA-based design algorithm that was shown before.

Finally, Fig. 8 shows the average battery levels of sensors operating at specific modes during each measuring cycle. Again, the superiority of the MA approach is obvious in all cases, where average battery levels are higher than those of the GA-based system's designs, especially as time goes by in the testing period of the 15 measuring cycles.

VI. Conclusions

A Memetic Algorithm for the dynamic optimal design of WSNs is proposed. A fixed wireless network of sensors of different operating modes was considered on a grid deployment and the MA system decided which sensors

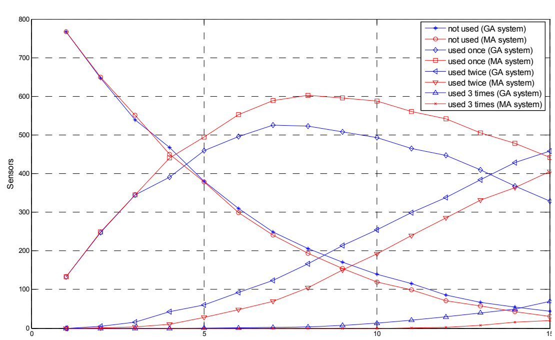

Fig. 6. Number of sensors that were used as CHs for specific times (or not used) over the testing period of the dynamic design at each measuring cycle, for both GA and MA systems.

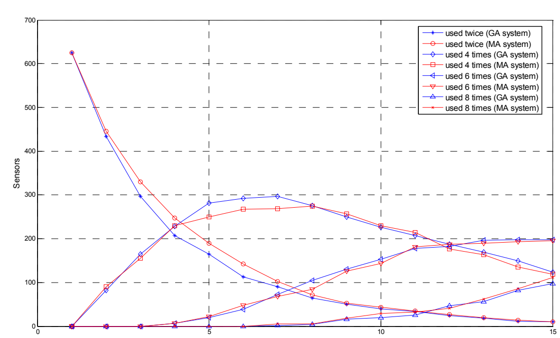

Fig. 7. Number of sensors that were used in HSR mode for specific times over the testing period of the dynamic design at each measuring cycle, for both GA and MA systems.

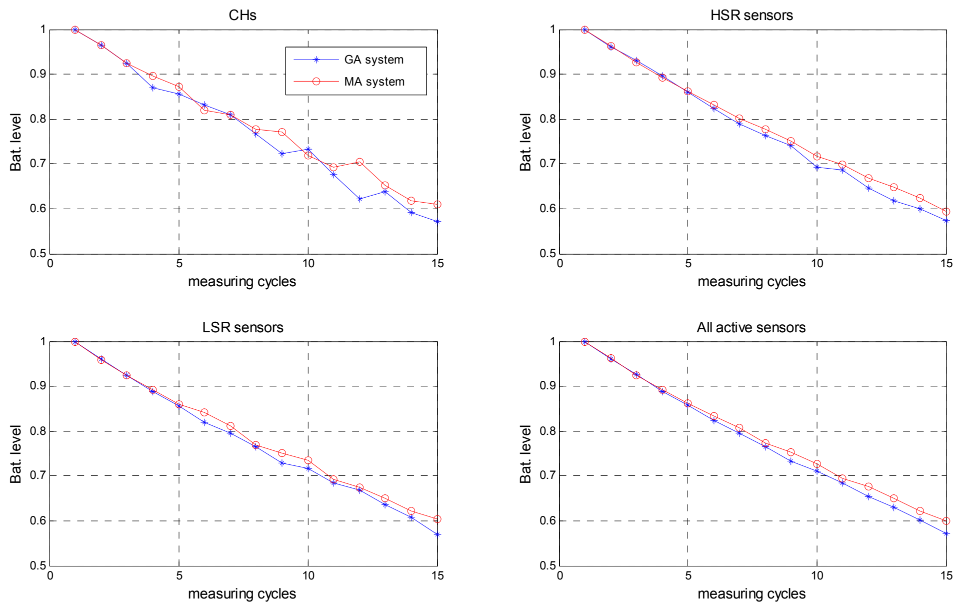

Fig. 8 Average battery levels of sensors operating at specific modes during each measuring cycle, for both GA and MA systems.

should be active, which ones should operate as clusterheads and whether each of the remaining active nodes should have high or low signal range. During optimization, parameters of network connectivity, energy conservation as well as application requirements were taken into account. The performance of the WSNs designed by the MA-system was compared to that of networks designed by a genetic algorithm system that has previously been developed. The MA-system showed considerable improvement in energy conservation of the network resources over the already successful performance of the GA-system, while the application-specific characteristics of the sensor networks were kept close to optimal values.

Future work will deal with the experimentation and fine tuning of the parameters that could improve even more the performance of the MA, that is, the initial values of the battery-level thresholds for each operating mode of the sensors, as well as the nature of the reduction schemes of those thresholds.

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