Adaptive design optimization of wireless sensor networks using genetic algorithms ☆

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Abstract

We present a multi-objective optimization methodology for self-organizing, adaptive wireless sensor network design and energy management, taking into consideration application-specific requirements, communication constraints and energy-conservation characteristics. A precision agriculture application of sensor networks is used as an example. We use genetic algorithms as the optimization tool of the developed system and an appropriate fitness function is developed to incorporate many aspects of network performance. The design characteristics optimized by the genetic algorithm system include the status of sensor nodes (whether they are active or inactive), network clustering with the choice of appropriate clusterheads and finally the choice between two signal ranges for the simple sensor nodes. We show that optimal sensor network designs constructed by the genetic algorithm system satisfy all application-specific requirements, fulfill the existent connectivity constraints and incorporate energy-conservation characteristics. Energy management is optimized to guarantee maximum life span of the network without lack of the network characteristics that are required by the specific application.
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1. Introduction

Wireless Sensor Networks (WSNs) generally consist of a large number of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate over short distances [1]. Their structure and characteristics depend on their electronic, mechanical and communication limitations but also on application-specific requirements. In WSNs, sensors are generally deployed randomly in the field of interest; however, there are certain applications which provide some guidelines and insights, leading to the construction of an optimal architecture in terms of network infrastructure limitations and application-specific requirements.

One of the major and probably most important challenges in the design of WSNs is the fact that energy resources are significantly more limited than in wired networks [1,2]. Recharging or replacing the battery of the sensors in the network may be difficult or impossible, causing severe limitations in the communication and processing time between all sensors in the network. Note that failure of regular sensors may not harm the overall functioning of a WSN, since neighboring sensors can take over, provided that their density is high. Therefore, the key parameter to optimize for is network lifetime, or the time until the network gets partitioned.

Another issue in WSN design is the connectivity of the network according to the selected communication protocol [2,3]. The most common protocol follows the cluster-based architecture, where single-hop communication occurs between sensors of a cluster and a selected clusterhead sensor that collects all information gathered by the other sensors in its cluster. 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, design issues that have been rather neglected in the research literature are those that depend on the particular application of WSNs. Energy and connectivity issues are certainly important in a WSN design, but one must not forget the purpose of the sensor network, which is the collection and possibly management of measured data for some particular application. This collection must meet specific requirements, depending on the type of data that are collected. These requirements are turned into specific design properties of the WSN, which in this work are called "application-specific parameters" of the network.

Several analyses of energy efficiency of sensor networks have been realized [2–5] and several algorithms that lead to optimal connectivity topologies for power conservation have been proposed [6–11]. However, most of these approaches do not take into account the principles, characteristics and requirements of application-specific WSNs. When these factors are considered, then the problem of optimal design and management of WSNs becomes much more complex.

A WSN designer who takes into account all the design issues discussed above obviously deals with more than one nonlinear objective functions or design criteria which should be optimized simultaneously (this problem is discussed in [12]). Thus, the focus of the problem is how to find many near-optimal non-dominated solutions in a practically acceptable computational time. There are several interesting approaches to tackling such problems, but one of the most powerful heuristics, which is also appropriate to apply in our multi-objective optimization problem, is based on Genetic Algorithms (GAs) [13]. GAs try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and by applying the principle of survival of the fittest. Their basic components are the representation of candidate solutions to the problem in a "genetic" form (genotype), the creation of an initial, usually random population of solutions, the establishment of a fitness function that rates each solution in the population, the application of genetic operators of crossover and mutation to produce new individuals from existing ones and finally the tuning of the algorithm parameters like population size and probabilities of performing the pre-mentioned genetic operators. The successful application of GAs in a sensor network design in [14] led to the development of several other GA-based application-specific approaches in WSN design, mostly by the construction of a single fitness function [15–18], but also by considering Pareto optimality in the evaluation of fitness values [19]. 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.

The novelty of this work stands in the development of 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 is 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 is investigated in terms of active sensors placement, clustering and signal range of sensors, while performance estimation includes, 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 results in an optimal design scheme, which specifies the operation mode for each sensor. The

ultimate objective of this research is to find a dynamic sequence of operation modes for each sensor, i.e. a sequence of WSN designs, which will lead to maximization of network lifetime in terms of number of data collection (measuring) cycles. This is achieved by implementing the algorithm repeatedly in order to develop a dynamic network design that adapts to new energy-related information concerning the status of the network after each measuring cycle or at predefined time intervals.

In the following section we describe the WSN modeling approach and the problem statement and complexity. In Section 3 we describe the GA approach that was used to develop the WSN design algorithm by analyzing the representation scheme that was used, the development of the fitness function that drives the evolution process of the algorithm and finally, the steps of the algorithm towards design optimization and further adaptation for energy conservation. In Section 4 we present the network design capabilities of the algorithm when it is applied on a set of sensors with full battery capacities. The procedure leads to an optimal design of the WSN, which is further used as the initial network in the sequence of runs in the dynamic algorithm. Its capability of sensor usage rotation and avoidance of using sensors with low-battery levels is shown in Section 5 where the algorithm is applied on the re-design of battery-constrained WSNs. Section 6 discusses the performance of the algorithm in adaptive design of WSNs during several consecutive measuring cycles, both at the levels of network characteristics, such as communication issues and application-specific requirements, as well as of energy-conservation characteristics, such as life-time maximization. Finally, in Section 7, some overall conclusions are drawn and trends of future work are stated.

2. Problem outline

The methodology of WSN design that we develop in this work, although general, takes into account several application-specific characteristics, such as those posed in the framework of precision agriculture, to show the performance of the developed algorithm. Precision agriculture refers to the approach of agricultural control and management based on direct chemical, biological and environmental sensing. Sensor networks play a vital role in that approach by maximizing the quantity, diversity and accuracy of information extracted from a WSN deployment. The parameters to be sensed include regular environmental parameters like temperature, humidity and solar radiation, as well as soil moisture, dissolved inorganics such as nitrogen and phosphorous species, and finally herbicides and pesticides. There are several sensing approaches that contribute to data collection, including remote sensing via satellites and airborne sensors, autonomous mobile systems and embedded, networked systems. WSNs belong to this last category.

2.1. WSN modeling

The salient features of the proposed WSN are the following: A square grid of 30 by 30 length units is constructed and sensors are placed in all 900 junctions of the grid, so that the entire area of interest is covered. The grid is applied to open field cultivation, where a length unit is an abstract parameter so that the developed system for optimal design is general enough. The length unit is defined as the distance between the positions of two neighboring sensor nodes in the horizontal or vertical dimension. Sensors are identical and may be either active or inactive. They are assumed to have power control features allowing manual or automatic adjustment of their transmit power through the base station. In this way, they are capable of transmitting in one of three supported signal ranges. Provided that a sensor is active, it may operate as a cluster-head 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).

We consider a cluster-based network architecture. There are several sophisticated clustering methodologies in the literature of WSNs towards energy saving [20–23]. However, our work tackles the energy saving issue through the optimization of the operating modes of sensors, thus a simple approach of clustering sensors in regular operating modes with their closest CH sensor is adopted for the formation of clusters in the network. Consequently, sensors are divided into clusters and in each cluster a sensor is chosen to act as a clusterhead. All sensors in regular operating modes in a cluster communicate directly (one-hope) with the closest clusterhead and this is how clusters are formed. Clusterheads communicate directly with the remote base station (single-hop transmission).

It is assumed that communication between clusterheads and the base station can always be achieved when required and that the base station is able to communicate with every sensor in the field, meaning that every sensor is capable of becoming a clusterhead at some point. In addition, it is assumed that traffic load is uniformly distributed among sensors in regular operating modes. Since clusterheads have to handle all traffic generated by and destined to the cluster, they have to transmit, receive and process a much larger amount of traffic than "regular sensors". Clusterheads need to perform long range transmissions to the base station, data collection and aggregation at specific periods including some computations, as well as coordination of MAC within a cluster. The problem becomes more complex in the cases of multi-hop transmissions, where clusterheads need to cover distances that are usually much greater than the "regular sensors" transmission range. Although the analysis of this operation is out of the scope of this work, the clear result is that clusterheads experience high energy consumption and exhaust their energy resources more quickly than "regular sensors" do.

2.2. Problem statement

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. 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, as it is shown in Section 3.

We identify three sets of parameters which dominate the design and the performance of a WSN for precision agriculture. 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.

The optimization problem is defined by the minimization of the energy-related parameters (say, objectives J_1, J_2 and J_3) and the maximization of sensing points' uniformity (objective J_4), subject to the connectivity constraints (say, constraints C_1 and C_2) and the spatial density requirement (constraint C_3) (see Table 1 for the exact correspondences). In order to combine all objectives into a single objective function (weighted sum approach), the optimization parameters are formed in such a way that all of them are minimized. Thus, objective J_4 is expressed by its dual objective, say J_4', which has to be minimized. Further, the penalization of the constraints C_1, C_2 and C_3 allows their transformation into objectives J_5, J_6, and J_7, respectively, which have to be minimized. Thus, a single objective function that blends all (obviously conflicting) objectives is of the form

$$f = \min \left\{ \sum_{\substack{i=1 \\ i \neq 4}}^{7} w_i J_i + w_4 J_4' \right\}. \qquad (1)$$

This form of objective function is suitable for the formulation of a numeric evaluation function [24] (namely a "fitness function" in the terminology of GAs), which gives a quality measure to each possible solution of the optimization problem. The

Table 1
Correspondences between objectives and optimization parameters

Objectives	Optimization parameters	Parameter symbols in GA methodology
J_1	Operational energy	*OE*
J_2	Communication energy	*CE*
J_3	Battery capacity penalty	*BCP*
J_4	Uniformity of measurements	–
J_4'	Mean relative deviation of measurement points	*MRD*
J_5	Sensors-per-CH error	*SCE*
J_6	Sensors out of range	*SORE*
J_7	Spatial density error	*SDE*

details of that formulation are presented in Section 3. What follows describes the mathematical representation of the optimization parameters in their "minimization" form.

1. *Application-specific parameters*: The main goal of a WSN used in precision agriculture is to take uniform measurements over the entire area of interest, so that an overall and uniform picture of the conditions of the area is realized. This has been achieved using the following two parameters:

(a) First, the measure of uniformity of measurements. The metric of the uniformity of measurement points that was used here was the Mean Relative Deviation (*MRD*). 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 measurements was used. More specifically, ρ_{Si}, the spatial density of measurements in sub-area S_i, was defined as the number of measurements over the area of the ith sub-area, $i = 1, 2, \ldots, N$, 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 measurements 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 measurements in each sub-area from the total spatial density of measurements in the entire area

$$MRD = \frac{\sum_{i=1}^{N} |\rho_{S_i} - \rho_S|}{N \cdot \rho_S}. \qquad (2)$$

Low values of *MRD* mean high uniformity of measurement points. Acceptable values for our application example are of *MRD* below 0.15.

(b) The second application-specific parameter of the fitness function was the Spatial Density Error (*SDE*) that was used to penalize network designs that did not meet the minimum required spatial density of measurement points that would suffice adequate monitoring of the measured variables (e.g., air or soil temperature, air or soil relative humidity, solar radiation, *etc.*) in the area of interest. The desired spatial density ρ_d was set equal to 0.2 measurement points per square length unit and the *SDE* factor was evaluated by

$$SDE = \begin{cases} \frac{\rho_d - \rho_s}{\rho_d} & \text{if } \rho_s < \rho_d, \\ 0 & \text{otherwise.} \end{cases} \qquad (3)$$

2. *Connectivity parameters*: A crucial issue in WSNs is the assurance that network connectivity exists and all necessary constraints are satisfied. Here, these necessary characteristics of the sensor network were taken into account by the inclusion of the following parameters in the fitness function:

(a) A Sensors-per-Clusterhead Error (*SCE*) parameter to ensure that each clusterhead did not have more than a maximum predefined number of sensors in regular operating modes 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. If *nfull* is the number of clusterheads (or clusters) that have more than 15 active sensors in their clusters and n_i is the number of sensors in the ith of those clusters, then

$$SCE = \begin{cases} \frac{\sum_{i=1}^{nfull} n_i}{nfull} & \text{if } nfull > 0, \\ 0 & \text{otherwise.} \end{cases} \qquad (4)$$

(b) A Sensors-Out-of-Range Error (*SORE*) parameter 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. If *nout* is the number of active sensors that cannot communicate with their clusterhead and n is the total number of active sensors in the network, then

$$SORE = \frac{nout}{n}. \tag{5}$$

3. *Energy-related parameters*: Energy consumption in a wireless sensor network, as explained earlier, is a crucial factor that affects the performance, reliability and life span of the network. In the optimization process during the evolutionary design of the sensor network, three different energy-related parameters were taken into account:

(a) Operational Energy (OE) consumption parameter, which refers to the energy that a sensor consumes during some specific time of operation. It basically depends on the operation mode of the sensor, that is, whether it operates as a CH, a HSR or a LSR sensor, or whether it is inactive. The corresponding relevance factors for the energy consumption of the three active operating modes of the sensors are taken proportional to 20:2:1, respectively and zero for inactive. The meaning is that the energy consumption of a sensor operating in CH mode is 10 times more than that of a sensor operating in HSR mode and 20 times more than that of a sensor operating in LSR mode. These relevant factors were used to simplify the analysis and did not necessarily represent accurately the real energy relations between the available operation modes of the sensors. Their exact values depend on electromechanical characteristics of the sensors and were not further considered in the analysis presented here. The *OE* consumption parameter was then given by

$$OE = 20 \cdot \frac{nch}{n} + 2 \cdot \frac{nhs}{n} + \frac{nls}{n}, \tag{6}$$

where, *nch*, *nhs* and *nls* are the number of CH, HSR and LSR sensors in the network, respectively.

(b) Communication Energy (*CE*), which refers to the energy consumption due to communication between sensors in regular operating modes and clusterheads. It mainly depends on the distances between these sensors and their corresponding clusterhead, as defined in [6]. It is depicted by

$$CE = \sum_{i=1}^{c} \sum_{j=1}^{n_i} \mu \cdot d_{ji}^{k}, \tag{7}$$

where c is the number of clusters in the network, n_i is the number of sensors in the ith 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 precision agriculture application for open field monitoring, the values of $\mu = 1$ and $k = 3$ were chosen.

(c) *Battery life*. An important issue in WSNs is self-preservation of the network itself, that is, the maximization of the life span of the sensors. Each sensor consumes energy from some battery source in order to perform its vital operations, like sensing, communication, data aggregation if the sensor is a clusterhead, etc. Battery capacity of each sensor of the network was taken into account in the design optimization process by the introduction of a Battery Capacity Penalty (*BCP*) parameter. Since the operation mode of each sensor is known, its Battery Capacity (*BC*) can be evaluated at each time. Thus, when the design optimization algorithm is applied at a specific time t (measuring cycle), the *BCP* parameter is given by

$$BCP^{[t]} = \sum_{i=1}^{ngrid} PF_i^{[t]} \cdot \left(\frac{1}{BC_i^{[t]}} - 1 \right), \quad t = 1, 2, \dots \tag{8}$$

Note that BC_i is updated according to the operation mode (CH, HSR or LSR) of each sensor i, during the previous measuring cycle $t - 1$ of the network

$$BC_i^{[t]} = BC_i^{[t-1]} - BRR_i^{[t-1]}. \tag{9}$$

In the above:

- $BCP^{[t]}$ 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 CH mode).
- *ngrid* is the total number of available sensor nodes.
- $PF_i^{[t]}$ is the Penalty Factor assigned to sensor i. The values it takes are given 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 modes (CH, HSR and LSR, respectively) and 0 for inactive. They provide different penalties according to the specific modes of the sensors in the WSN of the following measuring cycle. However, as it is explained in the next section, further exploration of the optimal relevance values needs to be performed.

- $BC_i^{[t]}$ and $BC_i^{[t-1]}$ are the Battery Capacities of sensor i at measuring cycles t and $t-1$, respectively, taking values between 0 and 1, with 1 corresponding to full battery capacity and 0 to no capacity at all.
- $BRR_i^{[t-1]}$ is the Battery Reduction Rate that depends on the operation mode of sensor i during the measuring cycle $t-1$ and reduces its current battery capacity accordingly, using the percentage of the relevance factors for the energy consumption of the operating modes of the sensor as follows: 0.2 for CH, 0.02 for HSR 0.01 for LSR operation modes and 0 for inactive sensors.

2.3. Problem complexity

By considering the connectivity constraint of the optimization problem which upper bounds the number of allowed sensors per cluster in the WSN topology (15 sensors in our case), the problem is equivalent to finding the Minimum Degree Spanning Tree (MDST) over the active sensors of the WSN, which is NP-hard [25]. In other words, deciding whether there exists a spanning tree whose degree is upper-bounded by a number, say D, is equivalent to finding the MDST.

The information on the Euclidean distances of the active sensors reduces the problem to a Minimum Weight Spanning Tree (MWST). In the case where all nodes are placed on a two-dimensional plane and the weights of the edges between two nodes correspond to the Euclidean distances, the degree of a MWST is upper-bounded by 6 [26]. However, the other constraints of our optimization problem (e.g., all active nodes other than clusterheads have degree equal to 1, energy requirements, etc.), might not allow the construction of a connected MWST. Therefore, the problem still needs to be solved in the context of the MDST, which as we mentioned above, is NP-hard.

3. Methodology of GA

The methodology and formulation of GAs for some specific application incorporates three basic steps: the problem representation, i.e. the encoding mechanism of the problem's phenotypes into genotypes that GAs manipulate and evolve, the formulation of the fitness function that gives to each individual (i.e. possible network design) a measure of performance, and finally the choice of the genetic operators and the selection mechanism used. These steps are of major importance, as they drastically affect the performance of the final results and they are described in detail in the following Sections 3.1–3.3, respectively. Section 3.4 presents the algorithm that is dynamically applied to achieve adaptive design of the WSN towards continuous energy conservation.

3.1. WSN representation

The variables that are included in the WSN representation are those that give all the required information so that the performance of a specific network design can be evaluated. These variables 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).

Each individual in a GA population specifies the composition and arrangement of sensors encoded as a vector of genes. Fig. 1 shows an example individual which represents a grid of sensors with r rows and c columns. 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 an active sensor operating in a low-signal range (10), being an active sensor operating in a high-signal range (01) and being an active clusterhead sensor (11). The grid junctions are encoded row by row in the bit string, as shown in Fig. 1. Each position needs two bits for the encoding, thus, the length of an individual (GA string) is $2rc$. In the specific design problem analyzed here, the sizes of r and c are both equal to 30, thus the length of the individuals are equal to 1800.

3.2. Fitness function

In the case under investigation the fitness function is a weighting function that measures the
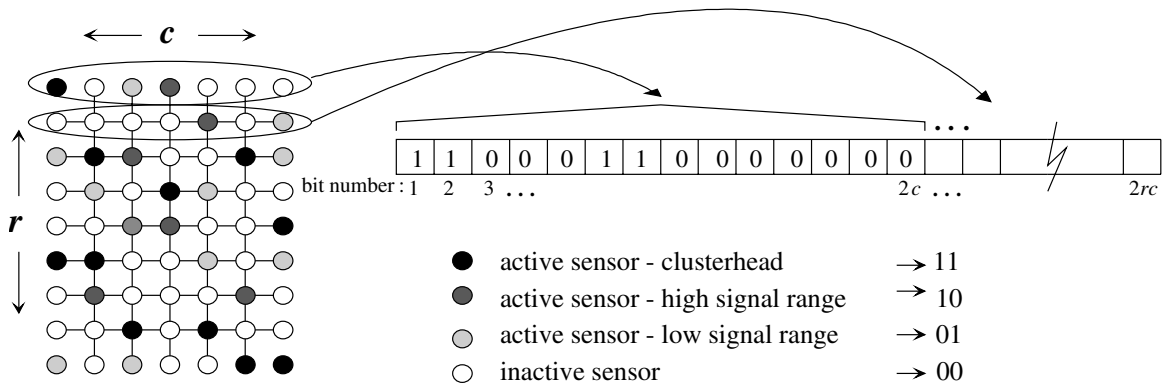
Fig. 1. Binary representation (on the right) of the location and state of sensors in a randomly generated WSN (on the left). Representation of the first row is shown.

quality and the 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 include and correctly represent all or at least the most important parameters that affect the performance of the WSN design. Having described these parameters (Section 2), the next issue is the decision on the importance of each parameter on the final quality and performance measure of the network design. The final form of the weighting linear fitness function f of a specific WSN design is given by

$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + \alpha_4 \cdot SORE$$
$$+ \alpha_5 \cdot OE + \alpha_6 \cdot CE + \alpha_7 \cdot BCP). \quad (10)$$

The significance of each parameter is defined by setting appropriate weighting coefficients α_i: $i = 1, 2, \ldots, 7$ in the fitness function that will be maximized by the GA. The values of these coefficients were determined based on experience about the importance of each parameter. First, weighting coefficients that resulted, in average the same importance of each parameter were determined (first column of Table 2) and after some rudimental experimentation, the final values that best represented the intuition about relevant importance of each parameter were set (second column of Table 2). As can be seen in Table 2, the final weights were such that network connectivity parameters (weights α_3, α_4) were treated as constraints, in the sense that all sensors should be in range with a clusterhead and no clusterhead should be connected to more than the predefined maximum number of sensors. There was no need for an increase of the *SDE* weight value because all GA-generated designs seemed to meet

Table 2
Weighting coefficients of GA fitness function

Weighting coefficient	"Equal importance" values	Final values
α_1	10^2	10^2
α_2	10^4	10^4
α_3	2	10^6
α_4	10^3	10^5
α_5	10	10
α_6	5×10^{-3}	10^{-2}

that specific constraint (i.e. the desired spatial density of measurement points). Note that the coefficients were determined based on normalization with respect to the value of α_5 which is set equal to 10. It should be noted that the *BCP* parameter was not taken into account in the optimization of the initial design of the WSN, as it was assumed that all sensor nodes had full battery capacities at the beginning. The final value of α_7 was the result of a trade-off between energy management optimization and network characteristics optimization, particularly of the characteristics concerning the application-specific properties of the WSN, as it is further explained in Section 4.

3.3. Genetic operators and selection mechanism

The types of crossover and mutation are of major importance to the performance of the GA optimization. Two types of the classical crossover operator defined in [27] 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, as explained in Section 4.

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.

3.4. Dynamic optimal design algorithm

Having completed the development of a representation scheme and forming the fitness function, the dynamic genetic algorithm for optimal adaptive design of the WSN could be developed. The algo-

rithm consisted of two parts: the Optimal Design Algorithm (ODA), which is applied to a set of sensors with specific battery capacities (Fig. 2), and the Dynamic Optimal Design Algorithm (DODA), which updates the battery capacities of the sensors and reapplies the optimal design algorithm accordingly (Fig. 3). Both algorithms as well as all simulations presented in the following sections were implemented in Matlab.

Some of the issues that have to be clarified follow.

1. Optimal WSN design algorithm:
   - The size of the population is a parameter of exploration that is further discussed in the next section.
   - In the assignment of a fitness value to each individual, specific weighting coefficients are used in (10) (Table 2).
   - The probability of selection of parent individuals is proportional to their fitness value.

```
Set population size M; Set max # of generations G;
Generate random initial population of M WSN designs
for t=1 to G
   Evaluate parameters for each individual in current popul. using (2)-(8)
   Assign fitness value to each individual using (10)
   for i=1 to M/2
      Select 2 parent individuals (according to fitness values)
      Crossover the 2 individuals with probability p_c
      Store the 2 output offspring
   end for i
   for i=1 to M
      Mutate offspring i with probability p_m
   end for i
   Replace old population with new offspring to form current population
end for t
return best individual in current population (Optimal_WSN_design)
```

Fig. 2. Pseudocode of the optimal WSN design algorithm (ODA).

```
Apply "ODA"
while WSN is "alive"
   Initiate new measuring cycle using current Optimal_WSN_design
   Evaluate battery capacities at the end of current cycle, using(9)
   Update battery capacities using(9)
   Re-apply "ODA" to sensors with updated battery capacities
   Wait until current measuring cycle is completed
end while
```

Fig. 3. Pseudocode of the dynamic optimal WSN design algorithm (DODA).

- The genetic operators of crossover and mutation are applied with specific probabilities, as it is explained in the next section.
2. Dynamic optimal design algorithm:
   - The measuring cycle is defined as the period of time during which a clusterhead sensor consumes 20% of its full battery capacity.
   - The steps of "battery capacities update" and "re-application of the optimal WSN design algorithm" are performed during data collection of the 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.
   - The life span of the network, which is referred to as "WSN is alive" in the pseudocode, defines the application time of the dynamic algorithm. The network, i.e. the set of sensors in the field, is considered to be "alive" if the set of sensors with battery capacities above zero is such that some operational WSN can be designed and applied to the next measuring cycle.

The number of iterations performed by the algorithm in a single measuring cycle are in the order of $G \cdot l \cdot M^2$, where G is the number of generations of the GA, l is the bit-string length and M is the population size. If n is the total number of available sensors in the WSN design, then obviously the computational complexity of the algorithm is O(n), as only the l parameter depends on n ($l = 2 \cdot n$).

4. GA experimentation and initial WSN design

GAs have a number of parameters that are problem specific and need to be explored and tuned so that the best algorithm performance is achieved. These parameters are the population size, the probabilities of crossover and mutation and the type of crossover. In the beginning, a number of experiments were carried out to determine the most appropriate population size. Sizes from 100 to 1000 individuals in orders of hundreds were tested. The best performance, by means of maximizing the corresponding fitness function, was achieved with a population size of 300 individuals. Then, several explorations were performed with probabilities of

crossover ranging from 0.3 to 0.9 for both one-point and two-point crossover types and probabilities of mutation ranging from 0.0001 to 0.01. The results led to the use of one-point crossover with probability $p_c = 0.8$ and probability of mutation $p_m = 0.005$.

GAs incorporate stochastic operations during the optimization process while the quality of the randomly generated initial population drastically affects the final performance. Thus, in any exploration and then further application of the algorithm that are presented, several runs were tested with different random initial populations. Average results over the several runs as well as the best solutions achieved by each set of parameters were used to draw conclusions.

The developed algorithm was tested in three ways and the results are shown in the current and the following two sections. First, the performance of the algorithm in designing initial optimal WSN topologies and sensor operation modes was examined. Thus, "ODA" was applied in a field of full battery capacity sensor nodes. Then, the battery capacity update term was included and the integrated algorithm was tested off-line in some predetermined WSN designs with limited battery resources, that is, with specific limited or zero battery capacities at some sensor nodes, so that its capability of avoiding low-battery nodes would be shown. Finally, "DODA" was applied dynamically to examine its performance on adaptive optimal topology and energy management that would lead to the maximization of the life span of the entire WSN.

The algorithm was started, having available all sensor nodes of the grid at full battery capacities. The three initial populations that gave the best results after 3000 iterations of the GA were recorded (abbreviated as "GA1", "GA2" and "GA3", starting from the fittest design). The evolution progress of the best GA run is shown in Fig. 4, where both the fitness progress of the best individual found by the algorithm as well as the average fitness of the entire population at each generation are plotted. The optimization in the entire GA population can be seen from the general increase of the average population fitness, despite the numerous fluctuations caused by the search process through the genetic operators of crossover and mutation.

The optimization performed by the GA evolution process can also be seen by the progress of the values of some of the parameters of the WSN designs found during the evolution. These parameters are
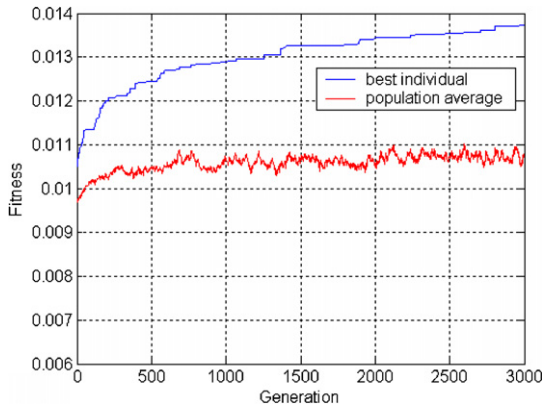
Fig. 4. Evolution progress of the best individual (best fitness value) and the entire population (average fitness value) of the GA during the two best runs of the algorithm.

shown in Fig. 5 for the best run of the GA which led to the "GA1" design. More specifically, plot (a) shows the evolution of *MRD* which represents uniformity of measurement points (the lower the value of *MRD*, the better the value of the achieved uniformity), plot (b) shows the evolution of the operational energy consumption (*OE*), plot (c) shows the evolution of the communication energy consumption (*CE*), while plot (d) shows the number of clusterheads (lower line), high-signal range (middle line) and low-signal range sensors (upper line) in the sensor networks as they evolved during optimization.

The optimization process can easily be observed by the evolution of WSN characteristics as shown in these graphs. The conducted experiments showed that in cases where the initial random designs suffered with communication limitation issues, the algorithm at the beginning of the evolution was always trying to find designs that at least satisfied the communication and the application-specific constraints. Afterwards, the other parameters like energy issues and clustering were optimized with the best possible minimization of operation energy consumption factor, the decrease of clusterheads existence, the increase of low-signal range sensors existence and so on. Details on all sensor network characteristics for the three GA-generated designs can be seen in Table 3. A comparison with the performance and characteristics of some additional designs can be found in [28]. Comparison results favored the GA-generated designs in all aspects of performance evaluation, that is, energy consumption, connectivity and application-specific characteristics.

5. Performance on battery-constrained WSNs

The algorithm was applied on specific initial WSN designs with sensor nodes of various battery capacities, in order to show the quality of decisions that the algorithm makes on the operation modes of the sensors for the next measuring cycle. Table 4
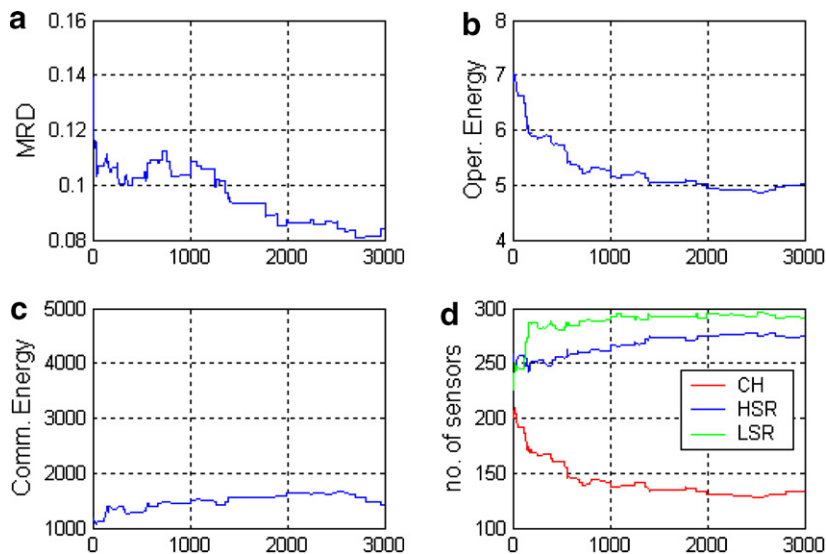

Fig. 5. Evolution of WSN parameters during 3000 generations. The initial population has 3:1 ratio of active to inactive sensors. (a) *MRD* values for estimation of uniformity of measurement point; (b) operational energy consumption parameter; (c) communication energy consumption parameter; (d) number of active sensors for the three possible operation modes (CH, HSR, LSR).

Table 3
WSN designs parameter values

	"GA1"	"GA2"	"GA3"
MRD	**0.0840**	0.1018	0.1141
SDE	0	0	0
OE	5.0086	**4.6827**	4.9711
CE × 10³	**1.4323**	1.6422	1.4965
OOR	0	0	0
OCC	0	0	0
Active	699	602	622
CH	133	105	117
HSR	275	222	247
LSR	291	275	258
CH/Active	0.19	**0.17**	0.19
HSR/Active	0.39	0.37	0.40
LSR/Active	0.42	**0.46**	0.41
Fitness	**0.0137**	0.0136	0.0131

Parameter values for the three GA-generated wireless sensor network designs. OOR: Out-of-Range sensors (sensors that cannot communicate with some clusterhead); OCC: Over-Connected Clusters (clusters with more than 15 sensors).

Table 4
Initial WSN design scenarios

Battery capacity (%)	Scenario I (%)	Scenario II (%)	Scenario III (%)
0	15	15	15
10	0	30	30
50	30	33	0
70	33	0	0
100	22	22	55

Percentages of sensors' battery levels over all available sensors, for the three examined scenarios.

shows the three scenarios that were used for the initial designs as far as the battery capacities of the sensors are concerned. Battery capacities were given as a percentage of the full battery capacity offered at the beginning of the initial measuring cycle, whereas in each scenario, the number of sensors with the

specified battery capacity was given as a percentage of the total number of sensors (900). In all three scenarios, 15% of the sensors were considered having zero battery capacities. The construction of these scenarios was based on the percentages of operating modes of the sensors in the best GA-generated optimal design (namely, the "GA1" design). In Scenario I, the values of 0%, 50%, 70% and 100% battery capacity levels are taken equal to the percentages of CH, HSR, LSR and inactive operating modes respectively, in "GA1", over all 900 sensors. The rest two scenarios were obviously produced in a similar way (see Table 4).

The algorithm was run several times for each scenario for 3000 generations in each run and the average results are shown in Tables 5 and 6. Both tables represent average rates of used (active) sensor nodes of the proposed by the algorithm WSN designs. Table 5 shows the average percentages and standard deviations (values in the parentheses) of the sensors of each initial battery capacity that were active or used as clusterheads in the proposed designs of the next measuring cycle, for all three scenarios. We do not explicitly include HSR and LSR usage of sensors in these results because these operating modes are quite similar. We investigate usage of active sensors in general, which is an important parameter, and from these active sensors, we further present usage of the CH operating mode, because clusterheads drastically differ in energy consumption from sensors in regular operating modes, and therefore their usage and re-usage are of major importance. Thus, for example, in "Scenario I", 78% of the sensors with 50% battery capacity were active in the new WSN design of the next measuring cycle, while 14% of the 50% battery capacity sensors were used as clusterheads in that new design. Similarly, in "Scenario III", only 3% of the sensors with 10% battery capacity were used as clusterheads in

Table 5
Battery-capacity usage as active sensors and clusterheads

Battery capacity (%)	Scenario I		Scenario II		Scenario III	
	Active sensors (%)	Clusterheads (%)	Active sensors (%)	Clusterheads (%)	Active sensors (%)	Clusterheads (%)
0	0 (0)	0 (0)	0 (0.4)	0 (0)	0 (0.3)	0 (0)
10	–	–	70 (2.3)	5 (1.5)	67 (1.9)	3 (0.9)
50	78 (1.1)	14 (2.5)	78 (1.4)	19 (2.3)	–	–
70	78 (1.5)	17 (1.1)	–	–	–	–
100	78 (3.2)	16 (1.6)	77 (2.4)	21 (2.5)	78 (1.7)	22 (1.1)

Average percentages (std's) of specific battery levels of sensors used as active sensors in general or clusterheads in the WSN of the next measuring cycle, for the three examined scenarios.

Table 6
Active sensors and clusterheads battery-capacity distributions

Battery capacity (%)	Scenario I		Scenario II		Scenario III	
	Active sensors (%)	Clusterheads (%)	Active sensors (%)	Clusterheads (%)	Active sensors (%)	Clusterheads (%)
0	0 (0)	0 (0)	0 (0.1)	0 (0)	0 (0.1)	0 (0)
10	–	–	33 (0.8)	12 (3.5)	32 (0.5)	8 (1.9)
50	36 (0.6)	32 (5.5)	39 (0.4)	50 (2.9)	–	–
70	38 (0.6)	42 (3.1)	–	–	–	–
100	26 (1.0)	26 (2.8)	27 (0.7)	38 (3.5)	68 (0.5)	92 (1.9)

Average distribution (percentages and std's) of active sensors and clusterheads in the WSN of the next measuring cycle over existing battery levels of sensors, for the three examined scenarios.

the new WSN, while 22% of the full battery capacity sensors were used as clusterheads in the same WSN. As can be seen, there was no case where some sensor with no battery capacity was used in any of the proposed designs, in any scenario. The avoidance of using sensors with low-battery capacities is not evident in Scenario I (the battery level distribution of 0/50/70/100 did not help towards that), but it can be seen in both Scenarios II and III, especially in the percentages that represent clusterhead usage. It is evident that sensors with high-battery capacities were preferred over low-battery ones, especially in the case where these sensors served as clusterheads in the new design.

A different approach of presenting the usage of sensors in the WSN of the next measuring cycle according to their previous battery capacities is used in Table 6. In that table, the average percentages (and standard deviations in the parentheses) of active nodes or clusterheads in each scenario's design of the next measuring cycle that used specific initial battery capacity sensors are presented. For example, in Scenario II, 33% of the active nodes of the new WSN design of the next measuring cycle had 10% battery capacity, 39% had 50% battery capacity and 27% had full battery capacity, or, in Scenario III, 8% of the sensors chosen to serve as clusterheads in the WSN design of the next measuring cycle had 10% battery capacity while 92% of the

clusterheads had full capacity. The complete avoidance of using sensors with no battery is evident here too, while the preference in sensors with high-battery capacities can be seen, mainly in Scenarios II and III where the battery distributions were more problematic.

An important issue in the off-line testing of the developed system (as well as in the dynamic application of the algorithm examined later) is the conservation of the application-specific WSN characteristics, while the system tries to avoid the usage of sensors with no-battery or low-battery capacities. For this reason, direct comparison with the LEACH model [8] or other models appearing in the literature, needs considerable attention so as to avoid furnishing misleading results. It should be noted that even better energy-conservation usage could be achieved by the developed algorithm, but limitations of application-specific parameters and communication constraints, limit that ability. As it is shown in Table 7, the values of uniformity and operational and communication energy consumptions of the proposed designs were kept quite close to the optimal values of the original WSN design. This becomes even more important, considering the fact that in all three scenarios, 15% of the available sensors had no battery capacity and they were completely avoided by the design algorithm. In addition, in all three cases, all communication

Table 7
WSN design main characteristics

	MRD		OE		CE $\times 10^3$	
	Avg.	Std.	Avg.	Std.	Avg.	Std.
Initial optimal WSN	0.0840	–	5.0086	–	1.4323	–
Scenario I	0.1227	0.0088	5.1516	0.0950	1.6953	0.1591
Scenario II	0.1555	0.0116	5.0047	0.3136	2.0106	0.2202
Scenario III	0.1594	0.0115	5.3593	0.1729	1.8045	0.1031

Design characteristics of initial optimal WSN design and designs of the next measuring cycle, for the three examined scenarios.

constraints were met and spatial densities of measuring points were kept within the appropriate range.

6. Adaptive design performance

The self-organizing (adaptation) capabilities of the algorithm towards energy conservation but also towards connectivity sustainability and nursing of application-specific requirements were examined by the dynamic application of the algorithm to a sequence of measuring cycles. As described in Section 2, battery consumption during one measuring cycle was set to 20% of the total (full) battery capacity for sensors operating as clusterheads, 2% for high-signal range sensors and 1% for low-signal range sensors, while there was no battery consumption for sensors that were inactive during some measuring cycle. Therefore, if a static clustering algorithm was used, the life span of the WSN would have been five measuring cycles. It should be noted here that the duration of a measuring cycle was set large enough to better demonstrate the way the proposed algorithm operates in avoiding low-battery sensors and maximizing life span of the entire network. In addition, the necessary setup time for network re-configuration and updating was not taken into account. The performed simulations try to give an approximation of lifetime duration of the WSN in terms of the number of measuring cycles.

The optimal design "GA1" was used as the starting design in the dynamic application of the algorithm, which was tested during 15 consecutive measuring cycles. A comparison of some preliminary results with those of static clustering on the initially optimal WSN ("GA1") presented in previous work [28] showed clear evidence of the energy conservation that is performed by the adaptive design of the algorithm. Here, we focus on the analysis of the effect of the adaptation factor concerning energy conservation of the dynamically applied algorithm. The variability of this effect is determined by the weighting factor of the BCP parameter in the fitness function of the GA (α_7), which from now on we call Energy-Conservation Factor (ECF).

6.1. Adaptation analysis and performance

The dynamic adaptation of WSN design by the developed algorithm during several measuring cycles was based not only on the conservation of energy that would lead to the maximization of the life span of the network, but also on the conservation of the performance characteristics of the WSN, like measurement uniformity and spatial density, faultless connectivity, and minimization of operating and communication costs. The algorithm performed a trade-off between the satisfaction of these performance measures and energy conservation. The proper adjustment of the ECF parameter could give dynamic design capabilities that would "prefer" either the energy-conservation part or the network performance part. Because of the fact that this trade-off is not stable and depends on the user's preference and the specific demands of the application that the sensor network is used to, only a suitable range can be suggested for the specific WSN design. After some experimentation with several values of ECF in orders of 10, it was found that a reasonable trade-off is performed for ECF values between 0.01 and 10.

The final analysis of the energy-conservation characteristics of the adaptive design process that is presented in Section 6.2 was based on an application of the algorithm with ECF parameter equal to 0.1, which kept a balance between energy conservation and network performance. Here, in the presentation of the network performance characteristics during 15 consecutive measuring cycles, three representative applications of the algorithm are shown, with ECF equal to 10, 0.1 and 0.01, that is, its "boundary values" and the value that is considered the most appropriate, as explained before. In Fig. 6 it can be seen that the uniformity level (MRD) and the communication energy consumption of the WSN are highly influenced by the value of ECF. The adaptive WSN designs with ECF equal to 0.1 and 0.01 (especially the latter) kept the MRD values quite low during all measuring cycles. There is a small general trend of increase in the value of MRD, but this is reasonable as more and more energy limitations are introduced into the network as time passes. Similarly, in the case of communication energy consumption of the WSNs, the adaptive design with $ECF = 0.01$ preserved the best values during the entire testing period, with values very close to the initial consumption of the network. It should be noted here that spatial density of sensing points was not presented in the graphs of Fig. 6 because all approaches gave zero penalty values of SDE during the entire testing period. In addition, no
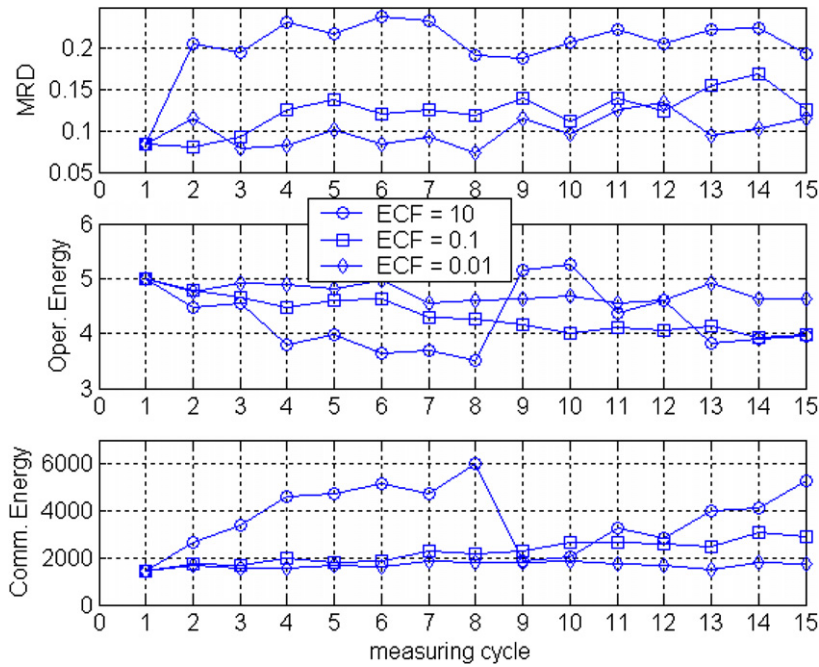
Fig. 6. *MRD*, *OE* and *CE* performance measures of the WSNs over the testing period of 15 measuring cycles for three different values of the *ECF*.
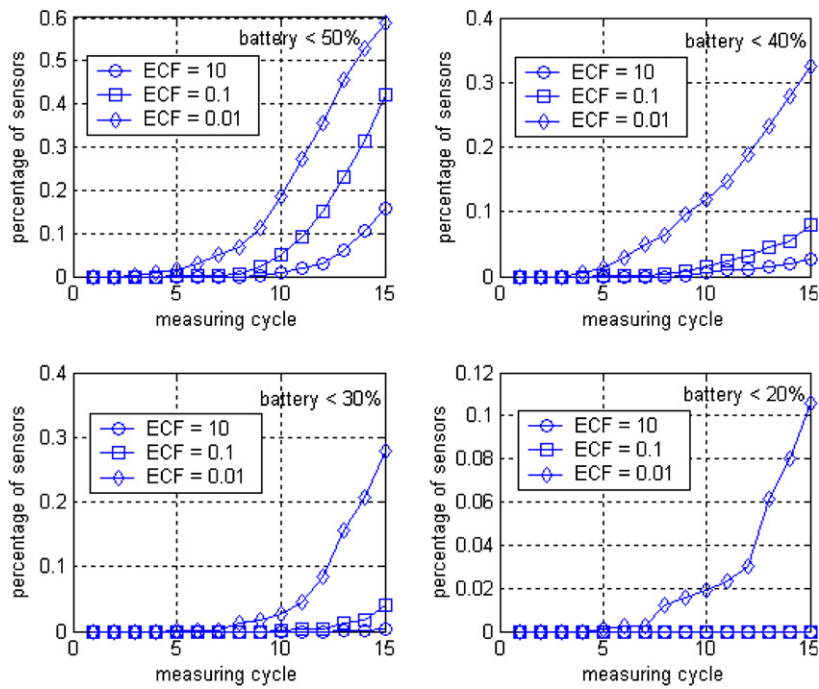

Fig. 7. Percentages of sensors with battery capacities below 50%, 40%, 30% and 20% of full battery capacity at the end of each measuring cycle, for three different *ECF* values.

communication faults occurred throughout the adaptive design processes.

Fig. 7 shows the effect of *ECF* to the available energy of the sensors of the WSN during the period

of the dynamic application of the algorithm. It presents the percentage of sensors that have battery capacity below certain levels at the end of each measuring cycle, with the three *ECF* values discussed before. Except for the indication that appropriate energy management of the WSN is achieved (as it is analyzed in the next section), these graphs also show that the *ECF* parameter seems to play an important role in the life span of the network too. Relevant analysis on remaining sensors with battery capacities *above* certain percentage-levels indicated similar effects on the conservation of energy resources.

6.2. Energy-conservation characteristics

As mentioned before, the analysis of the energy-conservation characteristics of the adaptive design process that is presented here was based on an application of the algorithm with *ECF* parameter equal to 0.1, which kept a balance between energy conservation and network performance. The graphs in Fig. 8 show the frequencies of sensor usages over the dynamic application of adaptive WSN design (15 measuring cycles), i.e. the number of measuring cycles during which each sensor was used. The three possible usages of clusterhead, high-signal range and low-signal range are shown in graphs (a)–(c), respectively, while graph (d) shows the number of measuring cycles during which each sensor was active, in general. For example, in the usages of just 10 sensors which are shown in Fig. 9 for convenience (sensor numbers 501–510), it is clear that, sensor number 503 for example, was used once as a clusterhead node during the entire period of 15 measuring cycles (graph (a)), five times as a high-signal range sensor (graph (b)), and seven times as a low-signal range sensor (graph (c)). Thus, it has been used as an active sensor during 13 measuring cycles (graph (d)).

In average, all sensors were used for 1.6 measuring cycles as clusterheads (0.7 standard deviation), for 4.0 measuring cycles as HSR sensors (1.8 std), for 4.7 measuring cycles as LSR sensors (1.8 std) and in general, they were active for 10.3 measuring cycles in average (1.7 std). The average values show the general tendency to avoid repeatedly using the
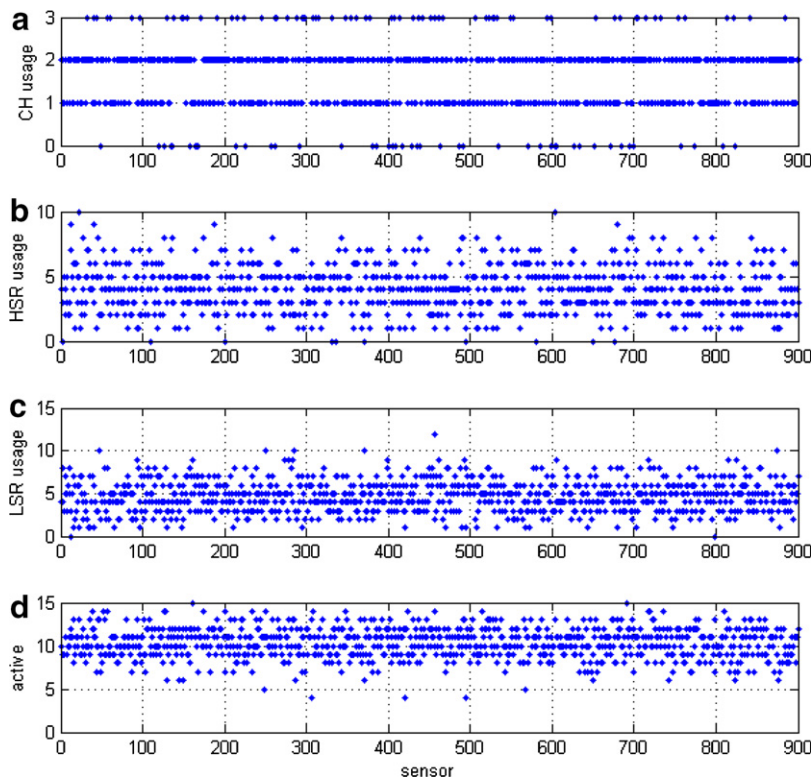

Fig. 8. Frequency of usage of each sensor of the network, over all measuring cycles. (a) Usage as clusterhead node, (b) usage as high-signal range sensor, (c) usage as low-signal range sensor, (d) general usage (independent of operating mode).
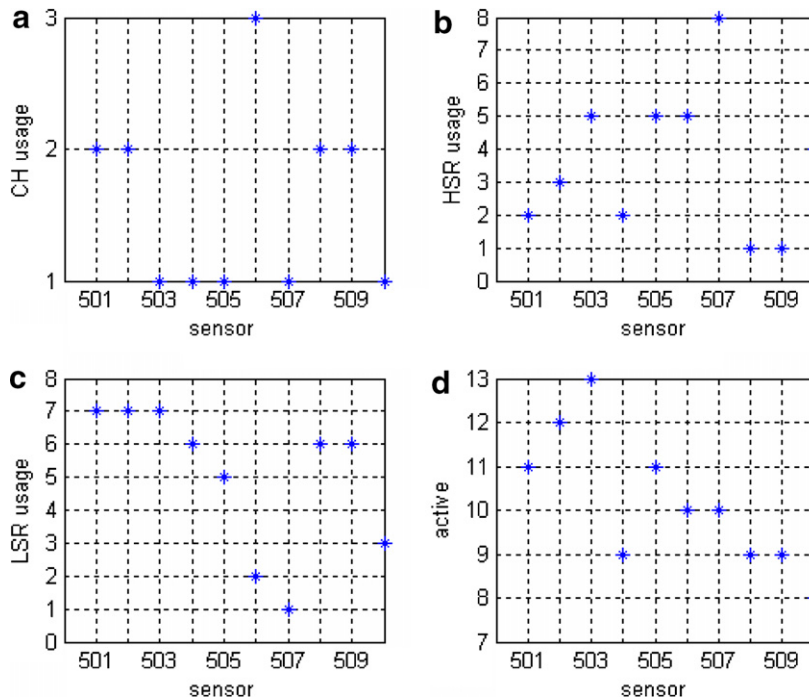
Fig. 9. Detail of Fig. 8, for sensor numbers 501 to 510. Explanation of graphs is the same as that of Fig. 8.

same sensors, especially as clusterheads. In addition, the algorithm manages to avoid the repetitive use of the same sensors in HSR mode in a larger degree than in LSR mode, which is reasonable. The actual plots of course provide more information on the performance of the dynamic application of the algorithm than the average values, especially the plots considering clusterhead usage and usage in general (active nodes).

From these plots, the following remarks can be made about the dynamic design performed by the proposed algorithm:

- All available sensors eventually become active at some point, with the vast majority of them being used more than 5 times during the 15 measuring cycles (in average, each sensor was used around 10 times).
- No sensor was used more than three times as a clusterhead during the 15 measuring cycles, with the vast majority of them being used just once or twice in that operating mode.

A similar representation that includes the time factor of the re-use of sensors at each operating mode is shown in the graphs of Fig. 10. The three available operating modes as well as the general use of sensors are shown, while the number of sensors that are used in each operating mode for specific times during the dynamic application of the algorithm is shown for each measuring cycle. More specifically, graph (a) shows the number of sensors in each cycle that had not yet been used as clusterheads, as well as those that had been used once, twice and three times. It can be seen that the third reuse in most of those few sensors that were used three times as clusterheads, was clearly delayed. In a comparison of graphs (b) and (c), the slight preference in earlier re-use of sensors in low-signal range than in high-signal range is shown. The general patterns of all these graphs give a clear indication that some energy-conservation optimization is performed in the adaptive design of the WSNs. Of course, it should not be forgotten that this optimization is restricted by the concurrent optimization of the rest performance parameters of the WSN.

Table 8 shows the distribution of operating modes of the sensors at each of the 15 measuring cycles tested, as well as the average number of sensors that each clusterhead coordinates respectively (standard deviations in the parentheses). It can be seen that the number of active sensors remains constant after the first three measuring
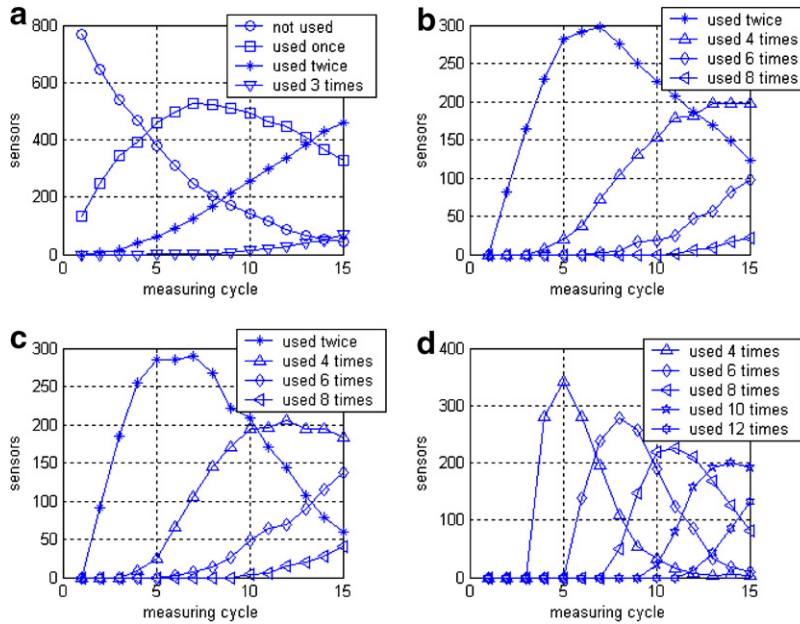
Fig. 10. Number of sensors that were used for specific times (or not used) over the testing period of the adaptive design at each measuring cycle, as clusterhead nodes (a), in high-signal range operating mode (b), in low-signal range operating mode (c), and as active nodes in general (d).

cycles, and the same holds for the allocation of the active nodes into HSR and LSR operating modes, while there is a slight decrease in the number of CH sensors, which leads to the general increase of the average number of active sensors coordinated by each clusterhead. However, these average values are much smaller than the actual capability of clusterhead sensors (15 sensors), which leads to the conclusion that less clusterheads could be used, but the energy conservation of the operat-

ing cost of such a design would have been neglected by the increase in communication energy consumption.

Fig. 11 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. It is clear that the percentage of sensors with battery capacity below 40% is kept very

Table 8
Distribution of operating modes of sensors and average clustering

| Measuring cycle	CHs	HSR	LSR	Total active	Inactive	Avg. sensors/CH (std's)
1	133	275	291	699	201	4.26 (1.80)
2	125	273	302	700	200	4.60 (2.08)
3	119	276	298	693	207	4.82 (2.03)
4	98	253	258	609	291	5.21 (2.23)
5	107	229	292	628	272	4.87 (2.11)
6	103	235	264	602	298	4.84 (2.26)
7	93	237	278	608	292	5.54 (2.38)
8	91	234	275	600	300	5.59 (2.14)
9	88	227	287	602	298	5.84 (2.25)
10	83	220	293	596	304	6.18 (2.44)
11	86	238	276	600	300	5.98 (2.89)
12	84	234	281	599	301	6.13 (2.53)
13	87	224	287	598	302	5.87 (2.74)
14	75	225	262	562	338	6.49 (2.78)
15	82	219	296	597	303	6.28 (2.35)
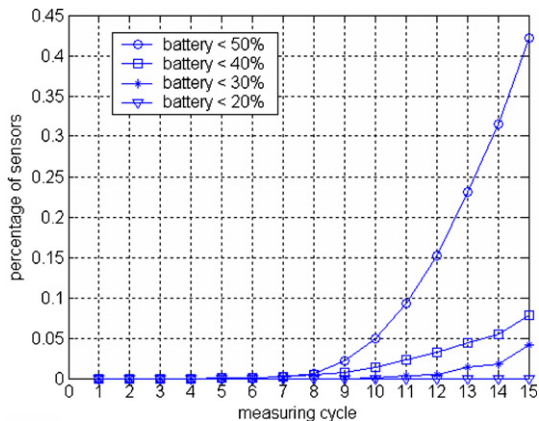
Fig. 11. Percentages of sensors with battery capacities below certain values (as percentages of full battery capacity) at the end of each measuring cycle of the adaptive WSN design.

low during the 15 measuring cycles, even while at the end of the 15th measuring cycle there is no sensor with battery capacity below 20%. Corresponding results on the analysis of remaining sensors with battery capacities *above* certain percentage-levels also showed high conservation of energy resources.

7. Conclusions

In this paper, we presented an algorithm for the optimal design and dynamic adaptation of application-specific WSNs, based on the evolutionary optimization properties of genetic algorithms. A fixed wireless network of sensors of different operating modes was considered on a grid deployment and the GA system decided which sensors should be active, which ones should operate as clusterheads and whether each of the remaining active normal 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 so that an integrated optimal WSN was designed. From the evolution of network characteristics during the optimization process, we can conclude that it is preferable to operate a relatively high number of sensors and achieve lower energy consumption for communication purposes than having less active sensors with consequently larger energy consumption for communication purposes. In addition, GA-generated designs compared favorably to random designs of sensors. Uniformity of sensing points of optimal

designs was satisfactory, while connectivity constraints were met and operational and communication energy consumption was minimized.

We also showed that dynamic application of the algorithm in adaptive WSN design can lead to the extension of the network's life span, while keeping the application-specific properties of the network close to optimal values. The algorithm showed sophisticated characteristics in the decision of sensors' activity/inactivity schedule as well as the rotation of operating modes (clusterhead or "regular sensor" with either high or low-signal range), which led to considerable energy conservation on available battery resources.

Future work will deal with the development of heuristic methodologies for optimal routing of dynamically selected clusterhead sensors, through some multi-hop communication protocol.

Acknowledgements

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