

Evolutionary Energy Management and Design of Wireless Sensor Networks

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Abstract—We present an evolutionary 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 regular 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 duration of the network without lack of the required by the specific application network characteristics.

Keywords—sensor network dynamic design; genetic algorithms; energy conservation; precision agriculture

I. 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. Sensor nodes are generally deployed randomly in the field of interest, however, there are certain applications of WSNs where the application itself can provide some guidelines and insights that can lead to the construction of an optimal architecture of sensor nodes that satisfies application requirements and meets wireless network limitations.

Energy conservation is a critical network limitation. Wireless sensors operate on limited power sources, making power conservation their major objective. Several analyses of energy efficiency of sensor networks have been realized [2]–[5] and several algorithms that lead to optimal topologies for power conservation have been proposed [6]–[11], but 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. This explains the use of several heuristic algorithms in application-specific WSN designs, capable of finding good solutions in complex search spaces where conventional analytical techniques are difficult to apply.

Genetic Algorithms (GAs) [12] are one of the most powerful such heuristics. Their successful application in a sensor network design in [13] led to the development of several other GA-based application-specific approaches in WSN design [14]–[17]. 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. Here, we propose a more 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. 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. Some preliminary results are presented in [18]. In addition, here we investigate the performance of the developed methodology in adaptive WSN design during several measuring cycles. The algorithm is applied dynamically and continuously redesigns the entire network so that energy conservation is achieved and maximization of life duration of the settlement is realized.

II. NETWORK DESIGN ISSUES

A. WSN for Precision Agriculture

The methodology of WSN design that we develop here is general but takes into account application-specific characteristics. We used a precision agriculture application, like for example, the measurement of soil temperature in a cultivation field, or the measurement of relative humidity, 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 the major role in that approach. In order to maximize the quantity, diversity and accuracy of information extracted from a precision agriculture

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WSN deployment, a variety of reliable, high-performance, and cost-effective sensor technologies are needed. An important issue that arises in precision agriculture is the type of parameters to be sensed, which, except for regular environmental parameters like temperature, humidity and solar radiation, may include soil moisture, dissolved inorganics such as nitrogen and phosphorous species, as well as 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.

The application considered here, concerns open field cultivation at an area of 30 by 30 length units, 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. The initial 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. Subsequently, the final goal 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 measuring cycles.

A further issue in a WSN for precision agriculture is the existence of some uniformity and spatial density conditions regarding sensors deployment, as these are determined by the requirements of the specific cultivation and the parameters that are being measured or monitored. These requirements, for the specific case considered here, are the highest possible uniformity of sensing points and a desired spatial density of 20 measuring points per 100 square units of cultivated area.

B. WSN Architecture

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. Sensors are identical and may be either active or inactive. They are capable of transmitting in one of three supported signal ranges. In the case that a sensor is active, it may operate as a clusterhead transmitting in the appropriate signal range so as to be able to communicate with the remote base station, or as a regular sensor transmitting in either high or low signal range, in the latter case consuming less power, as explained later, in section III-B. High signal range sensors cover a circular area with radius equal to 10 length units, while low signal range sensors cover a circular area with radius equal to 5 length units. Sensors are assumed to have power control features so as to adjust manually or automatically their transmit power whenever is needed, through the base station. Thus, regular sensors are divided into clusters and in each cluster a sensor is chosen to act as a clusterhead. Regular sensors communicate directly with the closest clusterhead, whereas clusterheads communicate with a remote base station. Single hop transmission is used in both cases. It is assumed that communication between clusterheads and the base station can always be achieved when required and that the base station can

communicate with every sensor in the field, meaning that every sensor is capable of becoming a clusterhead at some point.

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. However, the analysis of this operation is out of the scope of this work. After the application of the genetic algorithm, a specific operation mode is proposed for each sensor. The implementation of the proposed GA develops an optimal scheme specifying the operation mode for each sensor. Then, the algorithm is applied repeatedly in order to develop a dynamic network design that adapts to new energy-related information concerning the status of the network after each data collection (measuring) cycle or at predefined time intervals.

In the following Section we describe the GA approach that was used to develop the WSN design algorithm by analyzing the representation scheme that was used in the GA methodology, 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 IV-A we present the network design capabilities of the algorithm during the initial application on a set of sensor with full battery capacities. The optimal design obtained by that application of the algorithm was used as the initial network for the dynamic application of the algorithm. Its capability of sensor usage rotation and avoidance of using sensors with low battery levels is shown in Section IV-B where the algorithm is applied on the re-design of battery constrained WSNs. Finally, Section IV-C presents some preliminary results on the performance of the algorithm in adaptive design of WSNs during several consecutive measuring cycles, both at the levels of network characteristics (communication issues and application-specific requirements) as well as energy conservation characteristics (life-time maximization). At the end, some overall conclusions are drawn and trends of future work are stated.

III. GA METHODOLOGY AND FORMULATION

Genetic algorithms [12] belong to the evolutionary computation group of heuristic optimization techniques. They try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and applying the principle of survival of the fittest. Their basic components are the representation of candidate solutions to the problem in a “genetic” form, 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 mechanisms to produce new individuals from existing ones and finally the tuning of the algorithm parameters like population size and probabilities of performing some genetic operation.

The implementation of GAs in the application of optimal design and operation of WSNs incorporates two basic steps so that the algorithm is formulated for the specific application: the design representation, i.e. the encoding mechanism of the problem’s phenotypes into genotypes that GAs manipulate and evolve and the formulation of the fitness function that gives to

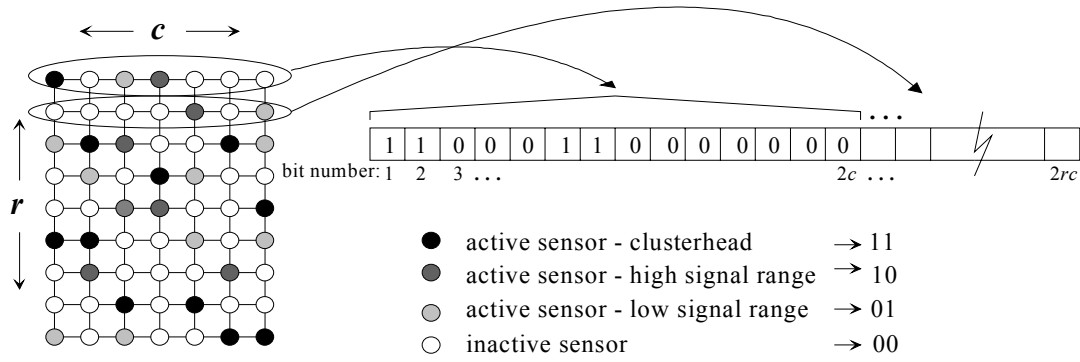


Figure 1. Binary representation (on the right) of a randomly generated sample of a sensor network (on the left). Representation of the first row is shown.

each individual (i.e. possible network design) a measure of performance. Both steps of the implementation of the algorithm are of major importance, as they drastically affect the performance of the final results and they are described in detail in the following subsections A and B. Subsection C describes the final algorithm that is dynamically applied to achieve adaptive design of the WSN towards continuous energy conservation. In addition, the types of crossover and mutation are of major importance to the performance of the GA optimization. Here, two types of the classical crossover defined in [19] were tested, the one-point and the two-point crossover, while 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 it is explained in Section IV.

A. 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).

A general grid of sensors has 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 a regular active sensor, operating in a low signal range (10), being a regular active sensor operating in a high signal range (01) and being an active clusterhead sensor (11). The grid junctions 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 each string is $2rc$. In the specific design problem analyzed here, the values of r and c are both equal to 30, thus the length of the GA strings are equal to 1800.

B. Fitness Function

In the case under investigation, the fitness function is a weighting function that measures the quality or performance of

a specific sensor network design. This function is maximized by the GA system in the process of evolutionary optimization. A fitness function must include and correctly represent all or at least the most important factors that affect the performance of the system. The first step is the decision on which factors are the most important ones. In the design of a WSN, there are some factors that concern communication issues of the network, as well as others that concern the characteristics of the specific application of the sensor network, that is, the environmental measurements in the precision agriculture application examined here. In the network characteristics, those factors include the connectivity of the sensors, the operational cost of the system depending on the types of the sensors and the communication cost of the system, depending on the distances between sensors that communicate with their corresponding clusterhead. In the application-specific characteristics, those factors include the existence of some uniformity and spatial density conditions regarding sensors deployment, as these are determined by the requirements of the environmental measurements application. As mentioned earlier, these requirements are the highest possible uniformity of sensing points and a desired spatial density of 20 such points per 100 square units of cultivated area.

The second step in the development of the fitness function is the decision on the importance of each parameter on the final quality measure of the network design. This importance is expressed by some weighting factor for each parameter in the final form of the fitness function and these weighting factors are usually based on experience. The final weights were such that network connectivity was given the highest importance, followed by energy consumption. In other words, connectivity characteristics of the network 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 a predefined maximum number of sensors.

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 a uniform picture of the conditions of the area is realized. The metric of measurements uniformity 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 spatial density (ρ) of measurements was used. More specifically, ρ_{S_i} , the spatial density of measurements in sub-area S_i , was defined as the number of measurements over the area of the i -th sub-area, $i=1,2,\dots,N$, where N is the number of overlapping sub-areas into which the entire area 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:

$$MRD = \frac{\sum_{i=1}^N |\rho_{S_i} - \rho_s|}{N \cdot \rho_s} \quad (1)$$

Low values of *MRD* mean high uniformity of measurement points. The measure of sensing points uniformity was the first parameter of the fitness function.

The other application-specific parameter of the fitness function was a Spatial Density Error (*SDE*) factor 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 , as mentioned before, was set equal to 0.2 measurement points per square unit and the *SDE* factor was evaluated by:

$$SDE = \begin{cases} \frac{\rho_s - \rho_d}{\rho_d} & \text{if } \rho_s < \rho_d \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

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 including two separate 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 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, and it was assumed to be equal to 15 for the application considered here. If n_{full} 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 i -th of those clusters, then:

$$SCE = \begin{cases} \frac{\sum_{i=1}^{n_{full}} n_i}{n_{full}} & \text{if } n_{full} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

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. If n_{out} 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:

$$SORE = \frac{n_{out}}{n} \quad (4)$$

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 duration 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 consumption. It refers to the energy that a sensor consumes during some specific time of operation and it basically depends on the operation mode of the sensor, that is, whether it operates as a clusterhead, a high-signal range or a low-signal range 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 regular sensor operating in clusterhead mode is 10 times more than that of a sensor operating in high-signal range mode and 20 times more than that of a regular sensor operating in low-signal range 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 Operational Energy (*OE*) consumption parameter was then given by:

$$OE = 20 \cdot \frac{n_{ch}}{n} + 2 \cdot \frac{n_{hs}}{n} + \frac{n_{ls}}{n} \quad (5)$$

where, n_{ch} , n_{hs} and n_{ls} are the number of clusterheads, high-signal range and low-signal range sensors in the network, respectively.

b) Communication energy. It refers to the energy consumption due to communication between regular sensors and clusterheads. It mainly depends on the distances between the sensors and their clusterhead, in each cluster, as defined in [10]. It is depicted by the Communication Energy (*CE*) parameter:

$$CE = \sum_{i=1}^c \sum_{j=1}^{n_i} \mu \cdot d_{ji}^k \quad (6)$$

where, c is the number of clusters in the network, n_i is the number of sensors in the i -th cluster, d_{ji} is the Euclidean distance from sensor j to its clusterhead (of cluster i) and μ and k are constants, characteristic of the topology and application site of the WSN. For the specific 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 life of network's elements, i.e. 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) term. 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 (operation cycle) the battery capacity penalty term is given by:

$$BCP^{[t]} = \sum_{i=1}^{ngrid} PF_i^{[t]} \cdot \left(\frac{1}{BC_i^{[t]}} - 1 \right) \quad (7)$$

while BC_i is updated according to the operation mode of each sensor (clusterhead, high-range or low-range) during the previous time step (operation cycle) of the network's operation:

$$BC_i^{[t]} = BC_i^{[t-1]} - BRR_i^{[t-1]} \quad (8)$$

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 clusterhead mode).

- $ngrid$ is the total number of available sensor nodes.

- $PF_i^{[t]}$ is a penalty factor of sensor i that takes different values according to the operation mode of sensor i (as explained later). The values used here are proportional to the relevant battery consumptions of the sensor modes, namely, 20:2:1 for active sensor mode (clusterhead, high signal range and low signal range respectively) and 0 for inactive. It provides different penalty weights according to the specific modes that these sensors are planned to have in the WSN of the next measuring cycle. 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 a battery reduction rate term that depends on the operation mode of sensor i during the previous time step ($t-1$) 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 clusterhead, 0.02 for high-range and 0.01 for low-range operation modes and 0 for inactive sensors.

Thus, the final form of the fitness function f used by the genetic algorithm was:

$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + \dots + \alpha_4 \cdot SORE + \alpha_5 \cdot OE + \alpha_6 \cdot CE + \alpha_7 \cdot BCP) \quad (9)$$

where f is the fitness value of a specific WSN design. The weighting coefficients $\alpha_i : i = 1, 2, \dots, 7$ were used in the fitness function to determine the relevant importance of the corresponding parameters. The values of these coefficients were chosen based on experience about the importance of each parameter. First, weighting coefficients that resulted, in average, on the same importance of each parameter were estimated and after some rudimental experimentation, the final values that best represented the intuition about relevant importance of each parameter were set. These values were $\alpha_1=10^2$, $\alpha_2=10^4$, $\alpha_3=10^6$, $\alpha_4=10^5$, $\alpha_5=10$ and $\alpha_6=10^{-2}$. About the weighting coefficient of the BCP in particular (α_7), its value was determined after the other weighting factors were set. It should be noted that the BCP factor 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. It should also be noted that the final weights were such that network connectivity parameters were given the highest priority, followed by the energy consumption parameters. In other words, connectivity characteristics of the network 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 a predefined maximum number of sensors.

C. Dynamic Optimal Design Algorithm

Having completed the steps of designing a representation scheme and forming the fitness function, the final genetic algorithm for optimal dynamic design of the WSN could be developed. The algorithm consisted of the following steps:

- 1) An initial population of randomly generated designs was formulated and a fitness value was assigned to each individual using (1) to (9).
- 2) Evolutionary optimization was performed through the GA operators of crossover, mutation and selection and the population was evolved until a predetermined maximum

number of generations was reached.

- 3) The best individual of the final population was stored as the optimal WSN design.
- 4) The optimal design (topology of the network and operation mode of each sensor) was applied to the WSN and a measuring cycle was initiated.
- 5) Using (8), the battery capacities of all sensor nodes were updated according to their operation mode in the optimal WSN of step 3. These would be their battery capacities at the next measuring cycle of the network.
- 6) Steps 1–3 were repeated, using the updated values of battery capacities. A new optimal WSN was found.
- 7) When current measuring cycle was completed, step 4 was applied, with the new optimal design.
- 8) Steps 5–7 were repeated, until the end of life-duration of the WSN.

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.

IV. RESULTS

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. Initially, a number of experiments was carried out to determine the most appropriate population size. Sizes from 100 to 1000 individuals in orders of hundreds were tested, as larger population sizes were very power-demanding, computationally speaking. The best performance was achieved with 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 $p_m = 0.005$.

Furthermore, 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

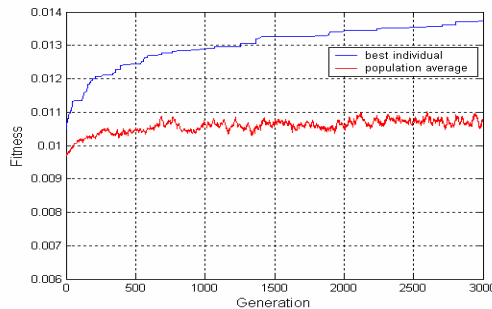


Figure 2. Evolution progress of the best individual (best fitness value) and the entire population (average fitness value) of the GA during the best run of the algorithm.

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. It was discovered that initial populations that contained active to inactive sensors ratio of 1:1 gave in average better results than initial populations that were generated randomly using uniform distribution (50/50 chances of having an 1 or a 0 in each bit of population strings), meaning that, because of the encoding scheme that was used, they contained active to inactive sensors in a ratio of 3:1. However, the best final result was achieved by an initial population of the 3:1 ratio.

The developed algorithm was tested in three ways and the results are shown in the three following parts of this section. First, the performance of the algorithm in designing initial optimal WSN topologies and sensor operation modes was examined. Thus, steps 1 to 7 of the algorithm, as presented in the previous section, were applied in a field of full battery capacity sensor nodes. Then, the battery capacity update term (8) was included and the integrated algorithm was tested off-line at some predetermined WSN designs with limited battery resources, that is, with specific limited or zero battery capacities at some sensor nodes. In that way, the algorithm's capability of avoiding low-battery nodes would be shown. Finally, the algorithm was applied dynamically to examine its performance on adaptive optimal topology and energy management that would lead to the maximization of the life-duration of the entire WSN.

A. Initial WSN Design

The algorithm was initially applied 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. 2, where both the fitness progress of the best individual found by the algorithm as well as the average fitness of the entire population

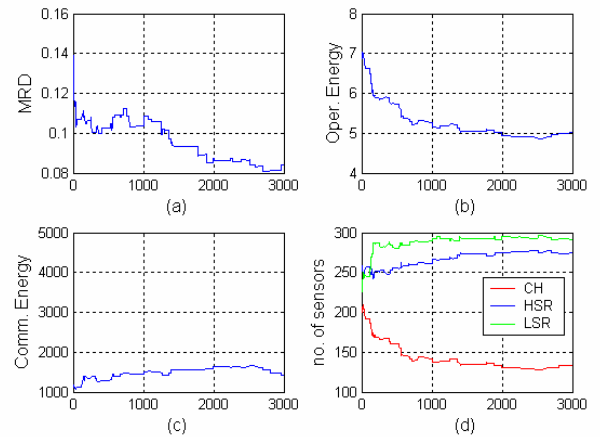


Figure 3. Evolution of WSN parameters during 3000 generations. (a) MRD values for estimation of uniformity of measurement point; (b) Operational energy consumption factor; (c) Communication energy consumption factor; (d) Number of active sensors for the three possible operation modes: CH: clusterhead, HSR: high signal range, LSR: low signal range

TABLE I. WSN DESIGNS PARAMETER VALUES

	“GA1”	“GA2”	“GA3”	Rand1	Rand2	Rand3	Rand4
MRD	0.0840	0.1018	0.1141	0.5513	0.3333	0.1815	0.1541
SDE	0	0	0	0.0944	0	0	0
OE	5.0086	4.6827	4.9711	2.5276	3.4021	6.5550	8.2474
CE · 10 ³	1.4323	1.6422	1.4965	1.3882	8.8816	1.7896	0.9610
OOR	0	0	0	29	5	0	0
OCC	0	0	0	4	2	0	0
Active	699	602	622	163	378	591	679
CH	133	105	117	9	39	161	248
HSR	275	222	247	78	167	224	209
LSR	291	275	258	76	172	206	222
CH / Active	0.19	0.17	0.19	0.05	0.10	0.27	0.36
HSR / Active	0.39	0.37	0.40	0.48	0.44	0.38	0.31
LSR / Active	0.42	0.46	0.41	0.47	0.46	0.35	0.33
Fitness	0.0137	0.0136	0.0131	-	-	-	-

OOR: out of range sensors (sensors that cannot communicate with some clusterhead); OCC: over-connected clusters (clusters with more than 15 sensors); Active: active sensors;

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 sensor network designs found during the evolution. These parameters are shown in Fig. 3, for the same run of the GA as before. Specifically, in these graphs, 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. Experiments with varying ratios of active to inactive sensors in the random initial populations of designs of the GA 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 constraints as well as the application specific constraints. After these constraints were satisfied, then 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.

Table I summarizes all the sensor network characteristics for the three GA-generated designs as well as some random

generated designs, for comparison. Random network designs were generated (“Rand1” to “Rand4”) with several different numbers of active sensors and percentages of clusterheads, high signal range and low signal range sensors, as shown in the corresponding rows of the table. Values in bold represent the best values for each parameter, while networks that did not satisfy the communication constraints (i.e., networks with sensors out of range or clusters with more than 15 sensors) were not considered in that comparison of values. It can be seen, not only from the fitness values but also from the parameters values, that network designs “GA1” and “GA2” have the overall best performance, with very good values of uniformity of sensing points, low energy consumption both for operation and communication issues and rational ratios of clusterhead nodes over total active nodes (17-19%). Designs “Rand1” and “Rand2” do not satisfy the communication constraints, as they both have some sensors that cannot communicate with some clusterhead and also have some clusters with more than 15 active sensors, which is the maximum number of sensors a clusterhead can handle. Design “Rand3” has a rather high value of *MRD* (0.1815) and does not achieve a satisfactory uniformity of measurement points and it also has high values of both operational and communication energy consumption. Design “Rand4” achieves better value of uniformity than “Rand3” (*MRD* = 0.1541), which is still much worse than that of the GA-generated designs and it also has very high operational energy consumption.

B. Performance on Battery-Constrained WSNs

The algorithm was applied on specific initial WSN designs

TABLE III. BAT-LEVEL USAGE AS ACTIVE SENSORS AND CLUSTERHEADS

Battery level (%)	Scenario I		Scenario II		Scenario III	
	active sensors	cluster heads	active sensors	cluster heads	active sensors	cluster heads
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 II. INITIAL WSN DESIGN SCENARIOS

Battery level (%)	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%

Exact percentages of sensors' battery levels over all available sensors, for the three examined scenarios

TABLE IV. ACTIVE SENSORS AND CLUSTERHEADS BATTERY-LEVEL DISTRIBUTIONS

Battery level (%)	Scenario I		Scenario II		Scenario III	
	active sensors	cluster heads	active sensors	cluster heads	active sensors	cluster heads
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

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 II shows the three scenarios that were used for the initial designs as far as the battery capacities of the sensors are concerned. In all three scenarios, 15% of the sensors were considered having zero battery capacities. The algorithm was run several times for each scenario for 3000 iterations and the average results are shown in Tables III and IV. Both tables represent average rates of used (active) sensor nodes of the proposed by the algorithm WSN designs.

Table III shows the average percentages and standard deviations (values in the parentheses) of the sensors of each initial battery level that were active or used as clusterheads in the proposed designs of the next measuring cycle, for all three scenarios. For example, the values 78 and 14 in the 50% battery level cells of "Scenario I" mean that 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 the new WSN, while 22% of the full battery capacity sensors were used as clusterheads in the same WSN. As it 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 of higher 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 IV. In that table, the average percentages (and standard deviations in the parentheses) of total active nodes or total clusterheads in each scenario's design of the next measuring cycle that used each initial battery level 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

TABLE V. WSN DESIGN MAIN CHARACTERISTICS

	MRD		OE		CE · 10 ³	
	avg.	std.	avg.	std.	avg.	std.
Initial 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

capacity. The complete avoidance of using sensors with no battery is evident here too, while the preference in sensors with larger battery capacities can be seen, mainly in scenarios II and III where the battery distributions were more "difficult".

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. The main difference between the developed system and other energy-management systems of WSNs, like LEACH for example [20], is that together with energy conservation, our system keeps on taking into account the application-specific parameters of the design, as well as the existent communication issues and constraints. 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 V, 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, especially if someone thinks 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 constraints were met and spatial densities of measuring points were kept within the appropriate range.

C. Dynamic Design Performance

The self-organizing 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 III-B, 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 duration 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 (defined by the battery consumption of clusterhead sensors) to better demonstrate the way the proposed algorithm operates in avoiding low-battery sensors and maximizing life duration of the entire network. In addition, the necessary setup time for network re-configuration and updating was not taken into account.

The algorithm we present is mainly driven by application-specific requirements, while the other objectives are also taken into account. The main difference between our approach and

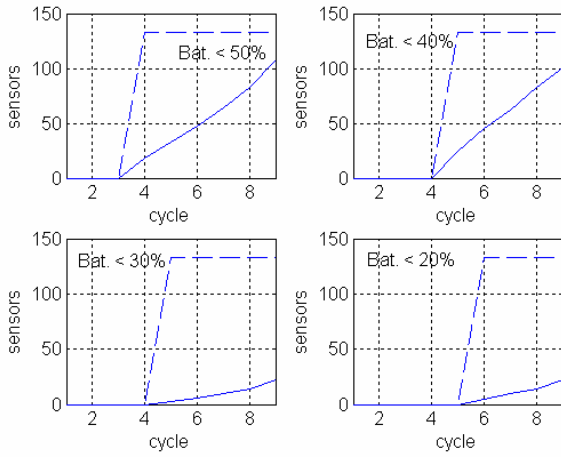


Figure 4. Number of sensors (over all 900 sensors) with battery capacities below certain levels after each measuring cycle. Solid lines: average numbers of dynamic algorithm application. Dashed lines: numbers of application of static clustering.

the LEACH approach [20] is that our algorithm searches globally the “energy management” space taking always into account the application-specific characteristics of the WSN design, while in LEACH each node makes its decision about whether to be a clusterhead or not independently on the other nodes in the network and more importantly, the algorithm does not take into account any application-specific characteristics. The only global information that LEACH uses is the desired percentage of clusterheads in the network. In our approach, that percentage is a parameter to be optimized. This is because in application-specific WSNs such a parameter is not solely determined by communication issues and thus it cannot be determined a priori.

The performed simulations try to give an approximation of lifetime duration of the WSN. The optimal design “GA1” presented in Table I was used as the initial WSN in the dynamic procedure. Primarily, the algorithm was tested during 8 consecutive measuring cycles and the results were compared with those of static clustering on the initially optimal WSN

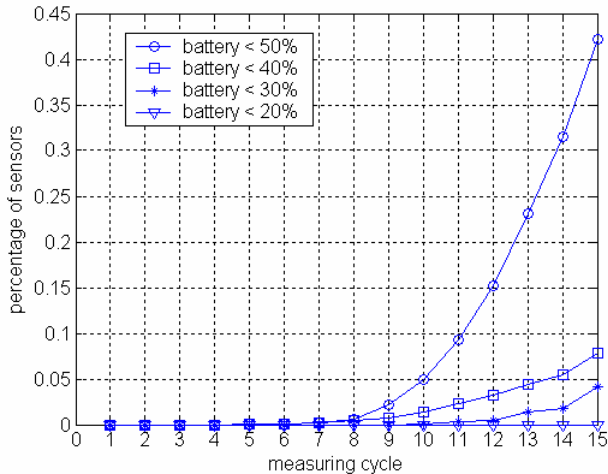


Figure 5. Percentages of sensors with battery capacities below certain values (as percentages of full battery capacity) at the end of each measuring cycle of the adaptive WSN design

TABLE VI. WSN DESIGN MAIN CHARACTERISTICS

cycle	MRD	OE	CE · 10 ³
1	0.0840	5.0086	1.4323
2	0.0803	4.8124	1.6782
3	0.0883	4.8153	1.6573
4	0.0894	4.8134	1.5821
5	0.0892	4.8058	1.5861
6	0.0996	4.7210	1.7167
7	0.0896	4.8005	1.5900
8	0.0767	4.9838	1.6062

(“GA1”). Average results from two runs of the algorithm were used. Fig. 4 shows the average number of sensors (solid lines) during the dynamic application of the algorithm that have battery capacities below certain levels (from 50% to 20% of full capacity). These numbers are over all available sensors, not only the sensors used in WSN designs during each measuring cycle. The ninth cycle shown in the graphs represents the estimated values after the end of the final measuring cycle with the last designed WSN. The corresponding numbers of sensors during application of static clustering, as explained before, are shown in dashed lines. The gain in overall energy conservation can be shown in these graphs.

An important issue is the performance of dynamically designed WSNs as far as the application-specific characteristics as well as the communication and operation energy consumptions are concerned. As it was specifically mentioned before, maximization of the battery life of the WSN was one of several other parameters of the optimization process. Table VI shows the average values of the three main characteristics of the dynamically designed WSNs through the 8 investigated measuring cycles, i.e. uniformity measure (*MRD*), operation energy consumption and communication energy consumption. It can be seen that values were kept very close to the optimal values of the initial WSN design.

The positive results of the comparison with a static clustering approach led to the additional testing of the algorithm on adaptive design during 15 consecutive measuring cycles, again starting from the initial optimal design “GA1”.

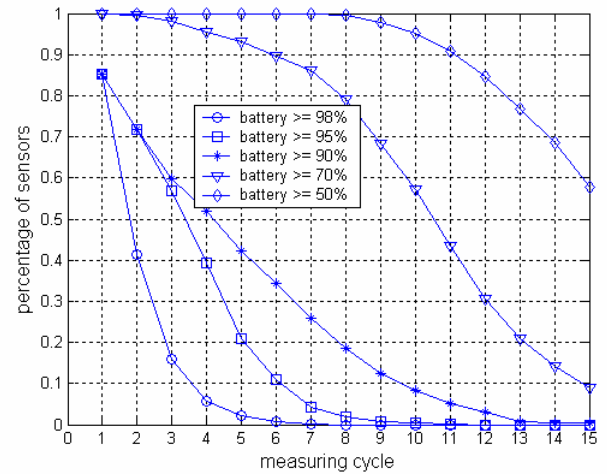


Figure 6. Percentages of sensors with battery capacities above certain values (as percentages of full battery capacity) at the end of each measuring cycle of the adaptive WSN design

Fig. 5 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. Similarly, Fig. 6 shows the percentage of sensors with battery capacities above certain percentage-levels after each measuring cycle during the application of the algorithm to the dynamic WSN design. The first of these two figures shows that the percentage of sensors with battery capacity below 40% is kept very low during the fifteen measuring cycles while even at the end of the fifteenth measuring cycle there is no sensor with battery capacity below 20%. The high conservation of energy resources is better shown in Fig. 6 where the reduction of battery capacities at specific levels is shown. It is shown that there are still some sensors with almost full battery capacity after several measuring cycles (after 11 cycles, if “almost full battery” refers to 95% of maximum battery level, or after 7 cycles if it refers to 98%) while the rate of reduction of sensors with battery capacity above certain levels gets smaller for battery levels below 90%.

In average, during these 15 measuring cycles, all sensors were used for 1.6 measuring cycles as clusterheads (0.7 standard deviation), for 4.0 measuring cycles as high signal

range sensors (1.8 std), for 4.7 measuring cycles as low signal range 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 of avoiding using repeatedly the same sensors, especially as clusterheads. In addition, the algorithm manages to avoid the repetitive use of the same sensors in “high signal range” mode in a larger degree than in “low signal range” mode, which is reasonable.

Similar conclusions can be drawn from the graphs of Fig. 7, which include the time factor of the re-use of sensors at each operating mode. 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 been used yet 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

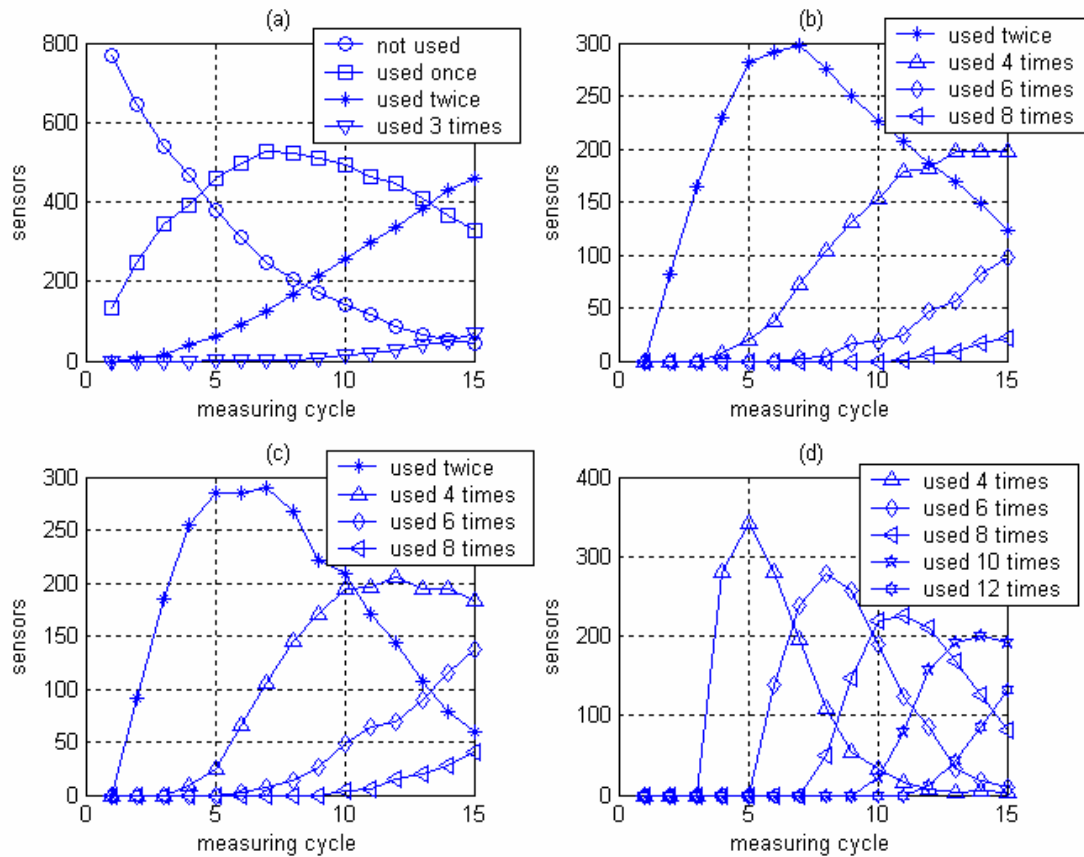


Figure 7. Number of sensors that were used for specific times (or not used) over the testing period of the adaptive design at each measuring cycle, as clusterhead nodes (a), in high signal range operating mode (b), in low signal range operating mode (c), and as active nodes in general (d)

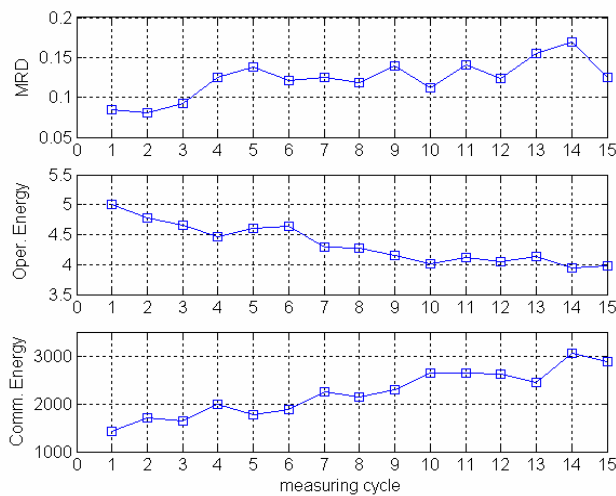


Figure 8. Values of performance measures of the WSNs over the testing period of 15 measuring cycles

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.

As mentioned before, it is very important that the values of the adaptive sensor networks characteristics are kept within certain acceptable limits, as these are defined by the application-specific requirements. Fig. 8 shows the progress of the values of uniformity level (*MRD*), operation energy consumption and communication energy consumption. The adaptive WSN designs 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. Something similar happens in the case of communication energy consumption of the WSNs, with values being kept very close to the initial consumption of the network. It should be noted here that spatial density of sensing points was not presented in these graphs because penalty values of *SDE* were zero during the entire testing period. In addition, no communication faults occurred throughout the adaptive design process.

V. CONCLUSIONS

In this paper, we presented an algorithm for the optimal design of application-specific WSNs, based on the evolutionary optimization properties of genetic algorithms. Identical sensors were considered on a grid placement and the GA system decided on which sensors should be active, which ones should operate as clusterheads and whether the remaining active regular 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 deployments and 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 extension of network's life duration, 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 signal range or low signal range), which led to considerable energy conservation on available battery resources.

Future work will deal with further analysis on dynamic WSN design. More specifically, we will focus on the investigation of the importance of the adaptation factor concerning energy conservation of the dynamically applied algorithm, which is defined by the weighting coefficient of the "battery capacity penalty" parameter in the fitness function of the genetic algorithm. Furthermore, at a different level of design, we will investigate heuristic methodologies for optimal routing of dynamically selected clusterhead sensors, through some multi-hop communication protocol.

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