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A memetic algorithm for optimal dynamic design of wireless sensor networks

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ABSTRACT

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

1. Introduction

Energy conservation probably constitutes the most important challenge in the design of wireless sensor networks (WSNs). These networks generally consist of a large number of low-power sensor nodes that communicate over short distances, and their energy resources are significantly more limited than in wired networks [1,25]. Their design should take into consideration these limitation and incorporate some operation scheduling so that sensor energy saving is optimized and the network's life span is maximized.

Another issue in WSN design is the connectivity of the network according to some specific communication protocol [25,19]. Cluster-based architectures with single-hop communication between sensors of a cluster are the most commonly used. In these cases, a selected clusterhead sensor collects all gathered information by the sensors in its cluster and sends it to a remote base-station (sink). Usually, connectivity issues include the number of sensors in each cluster (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 a clusterhead.

Finally, some issues that have to do with the physical characteristics of the network according to the relevant requirements of the specific application of the WSN have recently been included as major parameters in the design process of WSNs [7,8]. The purpose of the sensor network, which is the collection and possibly the management of measured data for some particular application, must not be neglected. This collection must meet some specific requirements, depending on the type of data that are collected. These requirements are turned into specific design properties of the WSN and play an important role in the design optimization of the WSN.

Most algorithms that lead to optimal topologies of WSNs towards power conservation, do not take into account the principles, characteristics and requirements of application-specific WSNs [9,21,11,4,6,29,22]. When these factors are considered, then the problem of optimal design and management of WSNs becomes much more complex [12,8,27,28].

It is clear that the problem of WSN design optimization that takes into account all the before-mentioned parameters, is a multi-objective optimization problem. There are several interesting approaches for tackling such problems. One of the most powerful heuristics that could be applied to our multi-objective optimization problem is based on Genetic Algorithms (GAs) [14]. The successful application of GAs in a sensor network design in Sen et al. [24] led to the development of several other GA-based application-specific approaches in WSN design. Most of these approaches used a single fitness function [26,13,15,2,3], but some of them considered Pareto optimality in the evaluation of fitness values [16], or even the use of memetic algorithms [17,23] or specifically designed evolutionary algorithms [18] and simulated annealing [5]. However, in most of these approaches, either very limited network characteristics are considered, or several application-specific requirements are not incorporated into the performance measure of the algorithm.

In our previous work [8], we considered an integrated GA approach, both in the direction of degrees of freedom of network characteristics and of application-specific requirements represented in the performance metric of the GA. The primary goal was to find the optimal operation mode of each sensor such that

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application-specific requirements are met and the energy consumption of the network is minimized. More specifically, network design was investigated in terms of active sensors placement, clustering and signal range of sensors, while performance estimation included, together with connectivity and energy-related characteristics, some application-specific properties like uniformity and spatial density of sensing points. Thus, the implementation of the proposed methodology resulted in a near-optimal design scheme, which specified the operation mode for each sensor.

More specifically, the optimization problem was defined by the minimization of the energy-related parameters and the maximization of sensing points' uniformity, subject to the connectivity constraints and the spatial density requirement. In order to combine all objectives into a single objective function (weighted sum approach), the optimization parameters were formed in such a way that all of them were minimized. In addition, the constraints were transformed into minimization objectives with the assignment of corresponding high value weights in the objective function. This led to the development of a single objective function that blended all objectives, as analyzed later in Section 3.

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

Memetic algorithms [20] introduce local search techniques at specific parts of a GA optimization process, with a goal to improve its performance. In this work, we develop and parameterize a memetic algorithm (MA) which hybridizes the GA system developed in Ferentinos and Tsiligiridis [8], the goal being to improve its performance by guiding the population formulation of the GA towards more intelligent decisions.

In the following Section we describe the WSN modeling approach and the parameters involved in the design problem. In Section 3, we briefly describe the GA approach that was originally used to develop the WSN design algorithm and the most important features of that algorithm are pointed out. In Section 4, we present the characteristics of the novel memetic algorithm approach and the initial experimentation towards the parameter-tuning of the algorithm. In Section 5, the design properties of the algorithm and its energy conservation capabilities are compared with those of the original GA-based design algorithm. Finally, in Section 7, some overall conclusions are drawn.

2. WSN design properties

2.1. WSN modeling

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

2.2. Design parameters

An evolutionary algorithm, like the one proposed here, requires the proper definition of some optimization criteria. In a design problem, these criteria constitute the design parameters that need to be optimized. In order for the optimization to be possible, it is required that these design parameters are explicitly defined and expressed mathematically. For the problem to be modeled properly in the optimization process, the actual inclusion of the appropriate parameters is as crucial as the correct mathematical formulation of the design parameters. In many studies, especially in WSN design, parameters that have to do with physical, application-specific characteristics of the WSN that is designed, are not included in the optimization process. In this way, the design procedure is limited to parameters that solely refer to communication restrictions and energy conservation.

In this work, in addition to connectivity and energy related parameters, we incorporate design parameters that have to do with the physical characteristics of the WSN, as these are related to the requirements of the network according to the real-life application that it is applied to. Therefore, three major sets of parameters that influence the performance of a specific design of a WSN that is used in some particular application are defined: the application-specific parameters, the connectivity parameters and the energy-related parameters. A more detailed description of the parameters of each set follows.

2.2.1. Application specific parameters

The main goal of WSNs for a wide variety of applications is the collection of uniform measurements over some specific area of interest, so that an overall and uniform picture of the conditions of the area is realized. The satisfaction or not of the demand on uniformity of measuring points has been taken into consideration using two design parameters: (a) the spatial mean relative deviation (*MRD*) of sensing points, representing the uniformity of those points, and (b) the desired spatial density of measuring points. Obviously, the *MRD* of sensing points has to be minimized (meaning that the uniformity is maximized), while the spatial density of sensing points has to be as close as possible to the desired value. For the *MRD* estimation, the entire area of interest was divided into several overlapping sub-areas. Sub-areas are defined by four factors: two that define their size (length and width) and two that define their overlapping ratio (ratios in the two directions). All these factors are expressed in terms of the unit length of each direction. The larger the overlapping ratio is, the higher precision is achieved in the evaluation of uniformity, but also, the slower the algorithm becomes. In order to define *MRD*, the notion of spatial density (ρ) of sensing points was used. More specifically, ρ_{S_i}, the spatial density of sensing points in sub-area S_i, was defined as the number of such points 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 sensing points of the network over the total area of interest. Thus, *MRD* was defined as the relative measure of the deviation of the spatial density of sensing points in each sub-area from the total spatial density of such points in the entire area:

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

Low values of *MRD* correspond to high uniformity of sensing points. Acceptable values for our application example are of *MRD* up to 0.15-0.17 [7,8].

For the desired spatial density of measuring points, a penalty factor namely the Spatial Density Error (*SDE*) was introduced 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 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:

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

2.2.2. Connectivity parameters

This set of design parameters includes two factors that try to ensure that the designed WSN satisfies two crucial connectivity issues: first, that each clusterhead does not have more than a maximum predefined number of sensors in its cluster, and second, that each sensor of the network can communicate with its clusterhead. The former issue is incorporated by the Sensors-per-Clusterhead Error (*SCE*) parameter, while the latter is incorporated by the Sensors-Out-of-Range Error (*SORE*) parameter. These parameters are penalizing factors. For the estimation of *SCE*, it was assumed that each clusterhead cannot be connected to more than 15 sensors. If n_{full} is the number of clusterheads 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:

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

For the estimation of *SORE*, the exact signal range capability of each sensor has to be defined. It was assumed that HSR-sensors covered a circular area with radius equal to 10 length units, while LSR-sensors covered a circular area with radius equal to 5 length units. 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:

$$SORE = \frac{n_{out}}{n} \tag{4}$$

2.2.3. Energy related parameters

This set of design parameters can be divided into two sub-categories. The first includes the parameters that are related to the energy consumption of the network, which are the operational energy (*OE*) consumption parameter and the communicational energy (*CE*) consumption parameter. The first one (*OE*) 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. 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. Thus, the *OE* consumption parameter was given by:

$$OE = 20 \cdot \frac{n_{CH}}{n} + 2 \cdot \frac{n_{HS}}{n} + \frac{n_{LS}}{n} \tag{5}$$

The second parameter (*CE*) 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 Ghiasi et al. [9]. It is depicted by:

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

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. The values of $\mu = 1$ and $k = 3$ were chosen for the current application.

The second sub-category includes a design parameter that takes into account the actual life span of the WSN based on the remaining battery capacities of the sensors. The maximization of the life duration of the network depends mainly on the remaining battery capacities of the sensors. The simple optimization of the operational and communicational energy consumption cannot ensure that operational load is spread evenly throughout the network. Thus, this energy conservation process must be regulated by taking into account complex relations of remaining battery capacities and operational modes of the sensors of the network. This was realized with 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:

$$BCP^{[t]} = \sum_{i=1}^{n_{grid}} PF_i^{[t]} \cdot \left(\frac{1}{BC_t^{[t]}} - 1 \right), \quad t = 1, 2, \ldots \tag{7}$$

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:

$$BC_i^{[t]} = BC_i^{[t-1]} - BRR_i^{[t-1]} \tag{8}$$

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 CH mode).
- n_{grid} 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.
- $BC_i^{[t]}$ 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.

Thus, the overall energy scheme that was developed here, is basically modeled by Eqs. (5)–(7). The inclusion of Eq. (7) gives the ability to the optimization process to perform sophisticated energy conservation towards the expansion of life duration of the network, rather than simple minimization of the energy consumption of the sensors. In this way, re-usage of sensors with low battery capacities is penalized, proportionally to their lack of battery and according to their intended operating mode.

3. Original GA-based algorithm

In this section we briefly present the basic characteristics of the GA-based optimal design algorithm originally developed in Ferentinos and Tsiligiridis [8]. Initially, the key elements of the GA approach are described, and then the dynamic optimization algorithm is presented.

3.1. Methodology of GA

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

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

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

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

The values of these coefficients were determined based on experience about the importance of each parameter. This means that the designer has to initially decide on the relevant importance of these factors according to the specific WSN application. Here, the coefficient values of the original GA system were used [8]. The values of coefficients α_3 and α_4 were considerably high because the connectivity parameters were treated as constraints. The approach of Pareto optimality, as opposed to the weighted-sum single objective approach, was not considered because the system is supposed to run dynamically, thus at each measuring cycle a single optimal design has to be reached. Based on that optimal design, the following design is evaluated through the repetition of the MA optimization process. Based on the values of the weight coefficients, the designer of the fitness function decides on the way the optimal design at each measuring cycle is obtained.

Two types of the classical crossover operator defined in Goldberg [10] were tested, the one-point and the two-point crossover. The mutation type that was used was the classical one for binary representation, that is, the swapping of the bits of each string (0 becomes 1 and vice versa) with some specific low probability. Crossover is also applied with some specific probability. Both these probabilities are tuned after proper experimentation. The adopted selection mechanism was the roulette wheel selection scheme. The probability of selecting some individual to become a parent for the formation 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 incorporated in the algorithm, meaning that the current best individual at each generation of the algorithm always survived to the next generation.

3.2. GA-based dynamic optimal design algorithm

The GA system is initially applied to sensors with full battery capacities and then it is re-applied in an online operating mode. The process is the following: After obtaining an initial optimal WSN design, that design is applied to the sensors for an entire measuring cycle. Then, the battery capacities are updated and the GA is re-applied taking into account the updated battery values. A measuring cycle is defined as the time period during which a CH sensor looses 20% of its full battery capacity, while HSR and LSR sensors loose 2% and 1%, respectively. It is assumed that inactive sensors do not consume any battery. The battery update and the re-application of the GA in each measuring cycle are performed during data collection of that measuring cycle. So, even though the algorithm is quite time-consuming, it has plenty of time to optimize the WSN of the next measuring cycle during the data collection period. 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.

4. Memetic algorithm approach

The MA approach is incorporated into the dynamic optimal design algorithm, described in the previous sub-section, thus, it is applied online to dynamically re-design the WSN. The initial optimal WSN design (assuming full battery capacities for all sensors) is obtained by the original GA-based algorithm, as previously described. Beginning from the second measuring cycle in the dynamic application of the design algorithm, the MA-based system conducts the optimal design of the WSN.

The concept of the memetic algorithm is based on the introduction of some battery level threshold values for each operating mode of the sensors (denoted as T_{CH} for CH mode, T_{HSR} for HSR mode and T_{LSR} for LSR mode). The intention of these threshold values is to put specific constraints in the operation modes of each sensor, throughout the dynamic design of the network. The idea is, at each measuring cycle to allow a sensor i to operate at some specific mode if and only if its battery level at the time is above the threshold value for that operating mode. Threshold values are adapted at each measuring cycle, as explained in more details later on. Thus, the MA approach is materialized through two separate processes: (i) the local search, which consists of the checking of the battery level of each sensor against the corresponding threshold value and the "lowering" of its operating mode if necessary, and (ii) the appropriate update of the threshold values for each operating mode, according to some specific reduction scheme. The general block diagram of the MA-based dynamic design algorithm is shown in Fig. 1.

4.1. Local search

The main part of the MA is the local search that is performed in the generation of the population of the original GA. The term "local search" is used in its general context, concerning the optimization that is performed in each individual of the GA population in the following way.

First of all, some initial threshold values of battery levels for each of the three possible operating modes of the sensors are defined. During the design optimization process, when each individ-

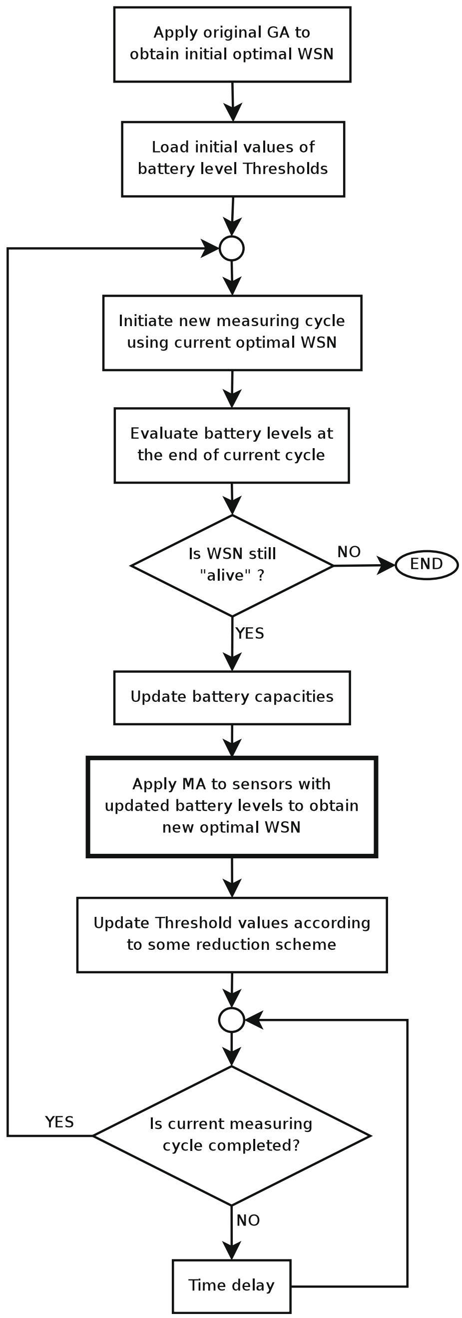

Fig. 1. Flow chart of the MA-based dynamic optimal WSN design algorithm.

ual of the population is generated, the operating mode of each sensor is checked according to the corresponding (based on its selected operating mode) threshold. If its battery level is below that threshold, its operating mode is changed to the lower mode (CH to HSR, HSR to LSR, LSR to inactive) until its corresponding threshold value becomes lower than (or equal to) its battery level. It should be noted that this local search procedure takes place not only in the generation of the initial population of the GA, but also in the generation of the population at each iteration of the GA. Its operation is shown in the pseudo-code presented in Fig. 2.

Three facts are evident about the proposed modification. First, that it is applied to the phenotype of the design problem and not the genotype of the optimization process of the GA. Second, that the investigation on the appropriate level of reduction of the operating mode of the modified sensors resembles some kind of search operation. Third, that the modification always leads towards the direction of a local improvement, without any assurance that this would result into a generally better solution. These two principles justify the "local search" characterization of the proposed hybridization of the original GA, leading to the development of a memetic algorithm.

4.2. Threshold update schemes

Threshold values of battery levels for each of the three possible operating modes of the sensors (T_{CH}, T_{HSR} and T_{LSR}) are initialized at the beginning of the design optimization process. These initial values are used for the local search part of the MA during the first measuring cycle of the WSN. After that, and at each measuring cycle, threshold values are updated according to some specific reduction scheme. The purpose of this reduction is to make threshold values less rigorous as time passes by and as battery levels of the sensors get lower.

There are three parameters that determine the reduction scheme of each threshold: the initial value at the beginning of the optimization process, the reduction formula and the reduction rate. The developed optimization algorithm incorporates the ability to use a different reduction scheme for the thresholds of each operating mode during the optimization process. However, this could lead to the requirement of extensive parameter exploration during algorithm tuning, thus it should be used only in cases where the same reduction scheme for all three thresholds does not lead to satisfactory design optimization results. Fig. 3 depicts this general aspect of thresholds reduction by showing the general reduction of the local search effect on the operation modes of sensors through time. Obviously, sensors with battery levels above the upper area of the graph are not affected by the MA, as they keep their original operating modes.

Thus, the three threshold values (T_{CH}, T_{HSR} and T_{LSR}) can be updated with one of the following ways:

(i) geometric reduction:

$$T^{[t+1]} = (1 - RR) \cdot T^{[t]} \tag{10}$$

where T represents any of the three types of threshold and t is some specific measuring cycle. The constant RR is the reduction rate parameter, which together with the initial value of each threshold constitute the parameters of exploration during the tuning of the MA.

(ii) linear reduction:

$$T^{[t+1]} = T^{[t]} - RR \tag{11}$$

and (iii) no update, where thresholds are kept constant over time.

5. Results

The performance of the MA approach to the dynamic optimization of WSN designs was compared to that of the original GA-based system, during 15 consecutive measuring cycles of the WSN. The fine-tuned parameters of the GA system (after extended experimentation) were kept the same in the MA. Thus, the probability of crossover was equal to 0.8 and the probability of mutation equal to 0.001, while the population size was equal to 300 individuals. The additional parameters that were expected to influence the performance of the MA system were, as explained in the previous section, the initial values of the three battery-level thresholds and their reduction scheme (reduction formula and reduction rate). Several experiments were performed with different combinations of these three tuning parameters of the MA. The exploration ranges for the initial values of the thresholds and the reduction rates, for each operating mode, are shown on Table 1. All three reduction formulas were explored in each testing case. The differently tuned

```
Set population size M;  Set max # of generations G;
Generate random initial population of M WSN designs
Load values of thresholds for current measuring cycle m: T1(m), T2(m),T3(m)
ively)
ating mode: CH, HSR, LSR
m
 to om+1 // om=4 means "inactive"
LOCAL SEARCH" modifications
l in current population
al
pecific probabilities
offspring to form current population
tion (Optimal_WSN_design)

// (for CH, HSR and LSR modes, respect
*** PART "LOCAL SEARCH" STARTS HERE ***
for om = 1 to 3   // i.e., for each oper
   for each sensor i of operating mode o
      if Batteryi < Tom(m), then
         "reduce" oper. mode of sensor i
      end if
   end for i
end for om
*** PART "LOCAL SEARCH" ENDS HERE ***
Update current population according to "
for t = 1 to G
   Evaluate parameters or each individua
   Assign fitness value to each individu
   Perform Crossover and Mutation with s
   Re-apply part "LOCAL SEARCH"
   Replace old population with modified
end for t
return best individual in current popula
```

Fig. 2. Pseudocode of the MA used in the dynamic optimal design algorithm (bold box in Fig. 1).

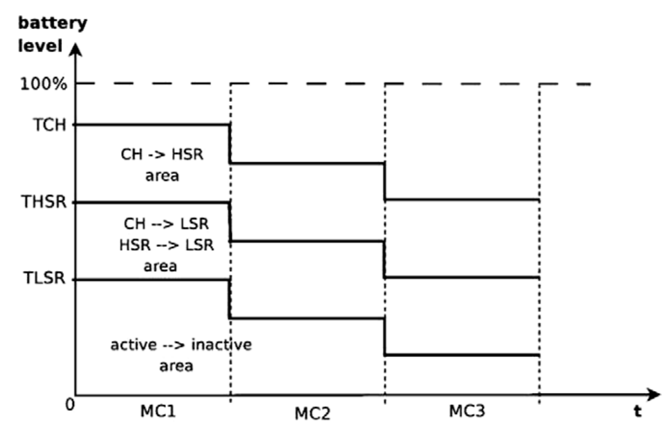

Fig. 3. Thresholds update through time and corresponding local search results (changes in operating modes of sensors). On the *x*-axis are the consecutive measuring cycles (MC).

memetic algorithms were compared to each other against several performance metrics and tests. The MA parameters that gave the best results were the following: initial threshold values of $T_{CH} = 0.8$, $T_{HSR} = 0.6$ and $T_{LSR} = 0.4$ with *geometric* reduction formula, using reduction rates of 0.2, 0.1 and 0.1 for CH, HSR and LSR operating modes, respectively. These parameter values were used in the MA that was eventually compared to the original GA system. What follows in the rest of this section is the comparison of the MA with these parameter values, with the original GA approach for WSN dynamic design optimization.

5.1. Network characteristics

The first comparison concerns the network characteristics that have to do with the application-specific requirements. It is very important that the values of these characteristics are kept within certain acceptable limits. Fig. 4 shows the progress of the values of uniformity level (*MRD*), operation energy consumption and communication energy consumption, for both the GA system and the MA system, during the examined 15 measuring cycles. In both cases, the adaptive WSN designs kept the *MRD* values quite low during all measuring cycles. In general, the *MRD* values of the WSNs designed by the MA system are a little higher (lower uniformity), but they are constantly kept below 0.17, which is a very reasonable value. The general trend of increase in the values of *MRD* is reasonable as more and more energy limitations are introduced into the network as time passes by. The GA system is more energy efficient in terms of operational energy consumption and the MA system in terms of communication energy consumption. It should be noted that spatial density of sensing points was not presented in these graphs because the required value was constantly met throughout the entire testing period. In addition, no communication faults occurred throughout the adaptive design processes of both the GA- and MA-systems. In general, it is evident that application-specific characteristics of the WSNs designed by both approaches are similar.

Table 1
Ranges of MA parameters during algorithm tuning.

Parameter	Minimum	Maximum	Step
T_{CH}	0.6	0.9	0.1
T_{HSR}	0.4	0.7	0.1
T_{LSR}	0.2	0.5	0.1
RR_{CH}	0.1	0.2	0.05
RR_{HSR}	0.05	0.15	0.05
RR_{LSR}	0.05	0.15	0.05

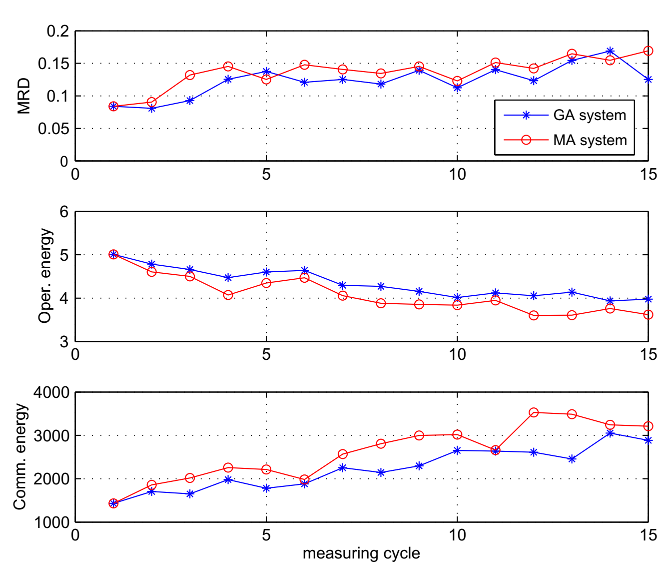

Fig. 4. Basic network characteristics of WSN designs during 15 measuring cycles for both system (GA and MA).

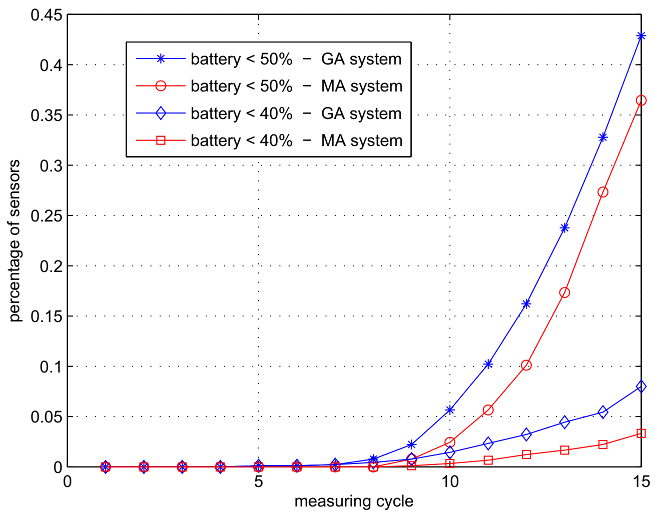

Fig. 5. Percentages of sensors with battery capacities below 50% and 40% of full battery capacity at the end of each measuring cycle, for both design optimization systems.

5.2. Energy conservation

Another important feature of the dynamic application of the optimal design algorithms is the energy saving characteristics of the designs, which lead to the extension of the life span of the networks. 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, for the designs produced by both GA- and MA-systems. It is clear that the MA system performs better than the GA system in energy conservation of sensor power resources, as at specific measuring cycles, fewer sensors have battery capacities below certain values in the case of MA-designed WSNs. Something similar can be seen in Fig. 6, where percentages of sensors with battery capacities above certain levels are shown. Again, in most cases, the MA-designed networks have more sensors with battery capacities above certain levels, even though in very high capacities, the performances of both systems are quite similar.

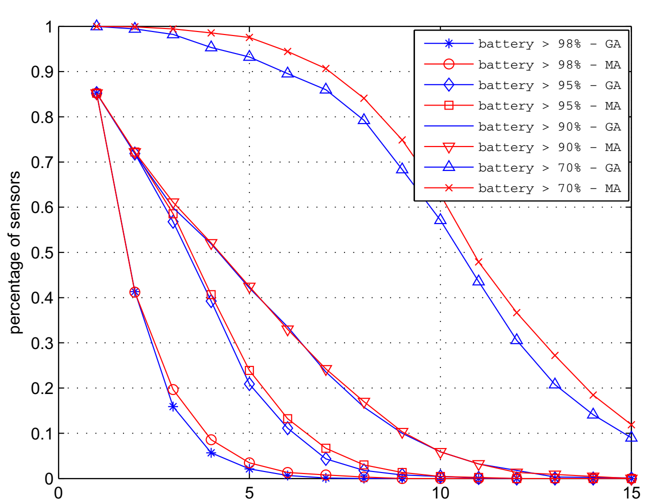

Fig. 6. Percentages of sensors with battery capacities above 98%, 95%, 90% and 70% of full battery capacity at the end of each measuring cycle, for both design optimization systems.

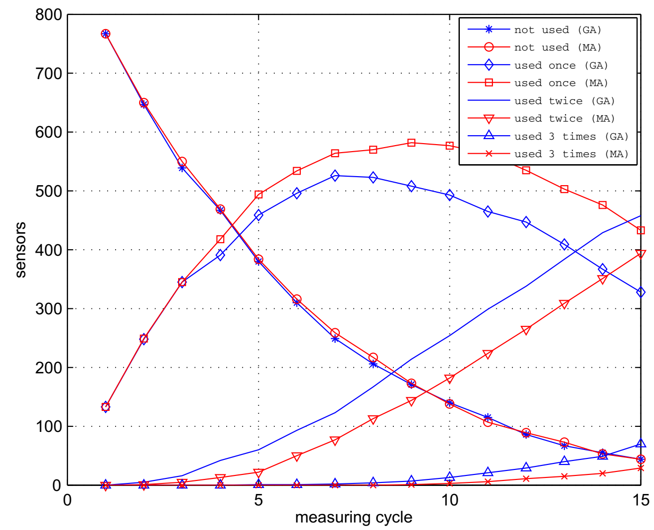

Fig. 7. Number of sensors that were used as CHs for specific times (or not used) over the testing period of the dynamic design at each measuring cycle, for both GA- and MA-systems.

An indication of the ability of a design algorithm towards energy saving and intelligent scheduling of the operating modes of sensors during dynamic network design, can be seen in the degree of re-usage of each sensor at some specific operating mode. Figs. 7 and 8 show the number of sensors that were used at each measuring cycle in CH and HSR operating modes, respectively, for some specific number of times (or not used at all). In the case of CH usage, it is clear that in the case of the MA-designed networks, more sensors were used once as CHs while less were used twice or three times, making the MA-based algorithm more "intelligent" than the GA-based one (Fig. 7). Similar but not so strong results are shown in the HSR usage (Fig. 8). This behavior also explains the better energy conservation achieved by the MA-based design algorithm that was shown before.

Finally, Fig. 9 shows the average battery levels of sensors operating at specific modes during each measuring cycle. Again, the superiority of the MA approach is obvious in all cases, where average battery levels are higher than those of the GA-based system's designs, especially as time progresses in the testing period of the 15 measuring cycles.

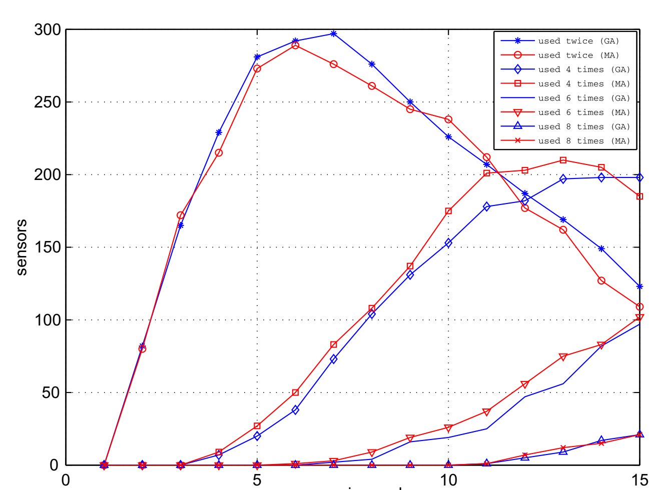

Fig. 8. Number of sensors that were used in HSR mode for specific times (or not used) over the testing period of the dynamic design at each measuring cycle, for both GA- and MA-systems.

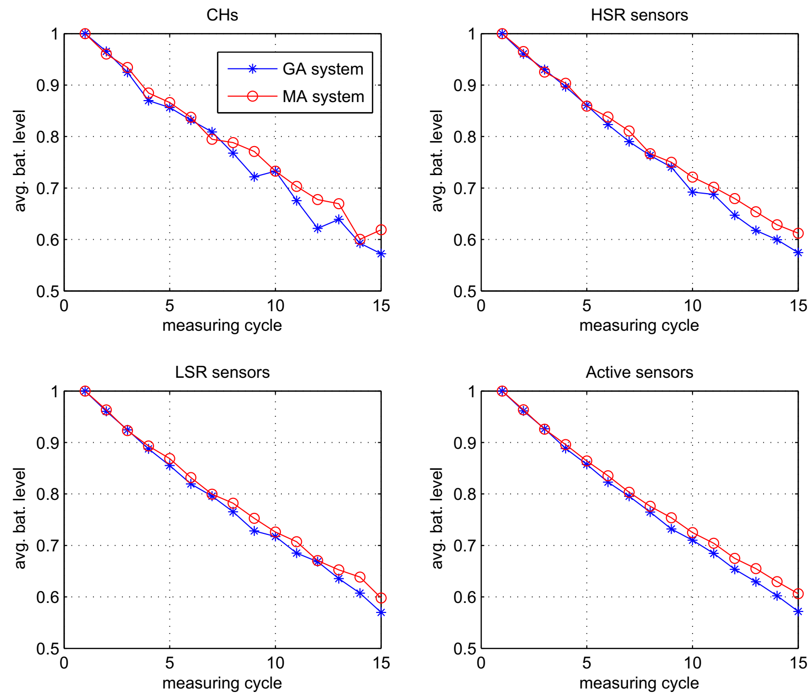

Fig. 9. Average battery levels of sensors operating at specific modes during each measuring cycle, for both GA- and MA-systems.

6. Discussion

The presented results show that the hybridization of the original GA with the local search operation using the suggested thresholds, brought some improvement in the performance of the WSN design process, mainly in the energy conservation aspect of the design. This implies that the original GA was probably consuming resources in several "bad" candidate solutions that assigned high-demand operating modes to sensors with relatively low battery capacities. These candidate solutions were modified by the MA, making the overall fitness of the population of each generation higher in average, giving an extra assistance to the optimization process. Thus, some degree of "intelligence" was incorporated into the genetic optimization process, leading to the presented performance improvement.

An additional advantage is that the performance improvement was achieved without any major increase in the computational complexity of the algorithm. The additional computations are not time consuming; they do not involve any additional fitness function evaluations and they just increase the iterations of the algorithm by some multiple of the number of active sensors in the WSN, keeping the computational complexity of the MA in the $O(n)$, like the original GA (n being the number of sensors in the WSN design). Finally, the MA achieved similar to the GA convergence time. Thus, the main difference was in the quality of the results and not in the speed that these results were obtained.

7. Conclusions

A memetic algorithm for the dynamic optimal design of WSNs is proposed. A fixed wireless network of sensors of different operating modes was considered on a grid deployment and the MA system decided which sensors should be active, which ones should operate as clusterheads and whether each of the remaining active nodes should have high or low signal range. During optimization, parameters of network connectivity, energy conservation as well as application requirements were taken into account. Extended experimentation with the tuning parameters of the MA was performed so that the best parameter values were obtained. The performance of the WSNs designed by the tuned MA system was compared to that of networks designed by a genetic algorithm system that has been previously developed. The MA system showed considerable improvement in energy conservation of the network resources over the already successful performance of the GA system, while the application-specific characteristics of the sensor networks were kept close to optimal values.

The satisfactory performance of the algorithm during the dynamic network design process makes it a valuable tool for design optimization towards maximization of the life span of WSNs, especially in cases where satisfaction of some application-specific requirements is a necessity. In addition, it was shown that appropriate manipulation of the population of the GA (something that was introduced by the proposed local search scheme) can lead to performance improvement. The investigation of this approach and its possible use in other (similar or not) applications of genetic algorithms, needs further research and can lead to the development of more advanced memetic algorithms.

References

[1] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, Computer Networks 38 (2002) 393–422.
[2] S.A. Aldosari, J.M.F. Moura, Fusion in sensor networks with communication constraints, in: Information Processing in Sensor Networks (IPSNG04), Berkeley, CA, 2004, pp. 26–27.
[3] A. Bari, S. Wazed, A. Jaekel, S. Bandyopadhyay, A genetic algorithm based approach for energy efficient routing in two-tiered sensor networks, Ad Hoc Networks 7 (4) (2009) 665–676.
[4] J.-H. Chang, L. Tassiulas, Energy conserving routing in wireless ad hoc networks, in: Proceedings of the IEEE INFOCOM 2000, Tel Aviv, Israel, 2000, pp. 22–31.
[5] J. Chen, X. Chao, Y. Xiao, Y. Sun, Simulated annealing for optimisation with wireless sensor and actuator networks, Electronics Letters 44 (20) (2008) 1208–1209.
[6] D.J. Chmielewski, T. Palmer, V. Manousiouthakis, On the theory of optimal sensor placement, AIChE Journal 48 (5) (2002) 1001–1012.
[7] K.P. Ferentinos, T.A. Tsiligiridis, Evolutionary energy management and design of wireless sensor networks, in: Proceedings of the Second IEEE Conference on

Sensor and Ad Hoc Communications and Networks (SECON 2005), Santa Clara, CA, 2005.
[8] K.P. Ferentinos, T.A. Tsiligiridis, Adaptive design optimization of wireless sensor networks using genetic algorithms, Computer Networks 51 (4) (2007) 1031–1051.
[9] S. Ghiasi, A. Srivastava, X. Yang, M. Sarrafzadeh, Optimal energy aware clustering in sensor networks, Sensors 2 (2002) 258–269.
[10] D.E. Goldberg, Genetic Algorithms in Search: Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.
[11] W.B. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy-efficient communication protocol for wireless microsensor networks, in: Proceedings of the 33rd Hawaii International Conference on System Sciences, Maui, Hawaii, 2000.
[12] W.B. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communications 1 (4) (2002) 660–670.
[13] G. Heyen, M.-N. Dumont, B. Kalitventzeff, Computer-aided design of redundant sensor networks, in: Escape 12, The Aague, The Netherlands, 2002.
[14] J.H. Holland, Adaptation in Natural and Artificial Systems, University of Michigan Press, Ann Arbor, MI, 1975.
[15] S. Jin, M. Zhou, A.S. Wu, Sensor network optimization using a genetic algorithm. in: Proceedings of the Seventh World Multiconference on Systemics, Cybernetics and Informatics, Orlando, FL, 2003.
[16] D. Jourdan, O. de Weck, Layout optimization for a wireless sensor network using a multi-objective genetic algorithm, in: IEEE Semiannual Vehicular Technology Conference, Milan, Italy, 2004.
[17] A. Konstantinidis, K. Yang, H.-H. Chen, Q. Zhang, Energy-aware topology control for wireless sensor networks using memetic algorithms, Computer Communications 30 (2007) 2753–2764.
[18] A. Konstantinidis, K. Yang, Q. Zhang, An evolutionary algorithm to a multi-objective deployment and power assignment problem in wireless sensor networks, in: IEEE GLOBECOM 2008, New Orleans, LA, 2008.
[19] B. Krishnamachari, F. Ordnez, Analysis of energy-efficient, fair routing in wireless sensor networks through non-linear optimization, in: Proceedings of the IEEE Vehicular Technology Conference Fall, vol. 5. Orlando, FL, 2003, pp. 2844–2848.
[20] P. Moscato, On evolution, search, optimization, genetic algorithms and martial arts: towards memetic algorithms, in: Caltech Concurrent Computation Program (C3P) 826, California Institute of Technology, 1989.
[21] V. Rodoplu, T.H. Meng, Minimum energy mobile wireless networks, IEEE Journal on Selected Areas in Communications 17 (8) (1999) 1333–1344.
[22] P.K. Sahoo, J.-P. Sheu, K.-Y. Hsieh, Power control based topology construction for the distributed wireless sensor networks, Computer Communications 30 (2007) 2774–2785.
[23] A.-A. Salehpour, A. Afzali-Kusha, S. Mohammadi. Efficient clustering of wireless sensor networks based on memetic algorithm, in: Proceedings of the Fifth International Conference on Innovations in Information Technology (ITT 2008), Al Ain, United Arab Emirates, 2008, pp. 450–454.
[24] S. Sen, S. Narasimhan, K. Deb, Sensor network design of linear processes using genetic algorithms, Computers & Chemical Engineering 22 (3) (1998) 385–390.
[25] S. Slijepcevic, M. Potkonjak. Power efficient organization of wireless sensor networks, in: Proceedings of the IEEE International Conference on Communications, vol. 2, Helsinki, Finland, 2001, pp. 472–476.
[26] D. Turgut, S.K. Das, R. Elmasri, B. Turgut, Optimizing clustering algorithm in mobile ad hoc networks using genetic algorithmic approach, in: IEEE GLOBECOM 2002, Taipei, Taiwan, 2002.
[27] M. Younis, K. Akkaya, Strategies and techniques for node placement in wireless sensor networks: a survey, Ad Hoc Networks 6 (4) (2008) 621–655.
[28] J.H. Zhang, J.M. Chen, Y.X. Sun, Transmission power adjustment of wireless sensor networks using fuzzy control algorithm, Wireless Communications and Mobile Computing 9 (6) (2009) 805–818.
[29] C. Zhou, B. Krishnamachari, Localized topology generation mechanisms for wireless sensor networks, in: IEEE GLOBECOM 2003, San Francisco, CA, 2003.