# Heuristic Design and Energy Conservation of Wireless Sensor Networks for Precision Agriculture

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*Abstract: A heuristic optimization algorithm for adaptive wireless sensor network design and energy management for precision agriculture is presented. The algorithm takes into account application-specific requirements, communication constraints and energy conservation characteristics. Genetic algorithms are used as the optimization tool of the developed system and an appropriate fitness function is developed to incorporate many aspects of network performance. It is shown that optimal sensor network designs constructed by the genetic algorithm system satisfy all application-specific requirements, fulfill the connectivity constraints and incorporate energy conservation characteristics. Energy management is optimized to guarantee maximum life duration of the network without lack of the network characteristics required by the precision agriculture application.*

*Keywords: Wireless sensor networks, genetic algorithms, optimal design, energy management*

## 1. Introduction

Precision agriculture refers to a set of technologies that introduce the concept of local variation into the large-scale mechanization, which is essential to large fields. With the determination of soil conditions and plant development, these technologies can lower the production cost by fine-tuning seeding, fertilizer, chemical and water use, and potentially increasing production and lowering costs. These can be achieved through 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 Wireless Sensor Network (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.

WSNs usually consist of a large number of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate in short distances (Akyildiz *et al.*, 2002). Their structure and characteristics depend on their electronic, mechanical and communication limitations but also on the requirements of the specific application. One of the most important network limitations is energy conservation. Wireless sensors operate on limited power sources therefore, their main focus is on power conservation through appropriate optimization of communication and operation management. Several analyses of energy efficiency of sensor networks have been realized (Slijepcevic and Potkonjak, 2001; Krishnamachari and Ordónez, 2003; Trigoni *et al.*, 2004; Mhatre *et al.*, 2005) and several algorithms that lead to optimal topologies for power conservation have been proposed (Rodoplu and Meng, 1999; Heinzelman *et al.*, 2000; Chang and Tassiulas, 2000; Chmielewski *et al.*, 2002; Zhou and Krishnamachari, 2003). However, most of the proposed approaches do not take into account the principles, characteristics and requirements of the specific application that sensor networks are used for.

In this work, a novel approach of WSN design and energy management is proposed, which considers not only energy and communication characteristics of the network, but also application-specific characteristics and requirements. These different in nature optimization items are combined with the use of the heuristic optimization methodology of Genetic Algorithms (GAs) (Holland, 1975).

## 2. WSN Architecture for Precision Agriculture

The precision agriculture application concerns the collection of environmental measurements on an open-field area with some specific cultivation 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, that is, an adaptive WSN design, which will lead to maximization of network lifetime in terms of number of measurement cycles.

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. A cluster-based network architecture in which sensors are partitioned into several groups is considered. 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 in an appropriate signal range (CH sensor) that allows the communication with the remote base station (sink), or it may operate as a simple sensor transmitting in either high or low signal range (HSR/LSR sensor respectively). It is assumed that HSR-sensors cover a circular area with radius equal to 10 length units, while LSR-sensors cover a circular area with radius equal to 5 length units. Simple sensors are divided into clusters and in each cluster a sensor is chosen to act as a clusterhead. Simple 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.

## 3. GA Methodology

GAs belong to the evolutionary computation group of heuristic optimization techniques. They try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and applying the principle of survival of the fittest. Their basic components are the representation of candidate solutions to the problem in a "genetic" form (genotype), the creation of an initial, usually random population of solutions, the establishment of a fitness function that rates each solution in the population, the application of genetic operators of crossover and mutation to produce new individuals from existing ones and finally the tuning of the algorithm parameters like population size and probabilities of performing the pre-mentioned genetic operators.

GAs have been successfully applied to sensor network design in several works (e.g., Sen *et al.*, 1998; Turgut *et al.*, 2002; Jin *et al.*, 2003; Aldosari and Moura, 2004). However, in most of these approaches, either very limited network characteristics are considered, or several requirements of the application cases are not incorporated into the performance measure of the algorithm. In this work, we propose 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 set in this research is to find the optimal operation mode of each sensor so that application-specific requirements are met and energy consumption of the network is minimized. More specifically, network design is investigated in terms of active sensors placement, clustering and signal range of sensors, while performance estimation includes, together with connectivity and energy-related characteristics, some application-specific properties like uniformity and spatial density of sensing points. Thus, the implementation of the proposed methodology results in an optimal design scheme, which specifies the operation mode for each sensor.

### 3.1. Representation scheme and genetic operators

The variables that are included in the WSN representation 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 simple sensor, and in the case of a simple 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 simple active sensor, operating in a low signal range (10), being a simple 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. Each position needs two bits for the encoding, thus, the length of each sting is $2 \cdot r \cdot c$. 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.

The types of crossover and mutation are of major importance to the performance of the GA optimization. Two types of the classical crossover operator (Goldberg, 1989) were tested, the one-point and the two-point crossover. The mutation type that was used was the classical one for binary representation, that is, the swapping of the bits of each string (0 becomes 1 and *vice versa*) with some specific low probability. Crossover is also applied with some specific probability. Both these probabilities are tuned after proper experimentation, as it is explained in Section 4. The adopted selection mechanism was the roulette wheel selection scheme (Goldberg, 1989).

### 3.2. Fitness function

The fitness function is a weighting function that measures the quality or performance of a solution, in this case 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. 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.

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*). Low values of *MRD* mean high uniformity of measurement points. Details on the exact methodology of calculating the *MRD* factor can be found in Ferentinos and Tsiligiridis (2005). 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 $\rho_d$, was set equal to 0.2 measurement points per square unit and the *SDE* factor was evaluated as shown in Ferentinos and Tsiligiridis (2005).

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: i) A Sensors-per-Clusterhead Error (*SCE*) parameter to ensure that each clusterhead did not have more than a maximum predefined number of simple sensors in its cluster. This number was assumed to be equal to 15 for the application considered here. ii) 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.

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:

i) The Operational Energy consumption parameter (*OE*), which 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 HSR or a LSR sensor. The corresponding relevance factors for the energy consumption of these three operating modes of the sensors are taken equal to 20, 2 and 1 respectively, meaning that the energy consumption of a simple sensor operating in clusterhead mode is 10 times more than that of a sensor operating in HSR mode and 20 times more than that of a simple sensor operating in LSR mode.

ii) The Communication Energy parameter (*CE*), which refers to the energy consumption due to communication between simple sensors and clusterheads. It mainly depends on the distances between the sensors and their clusterhead, in each cluster, as defined in Ghiasi *et al.* (2002).

iii) The Battery Capacity Penalty parameter (*BCP*). 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 its battery in order to perform its vital operations, like sensing, communication, data aggregation if the sensor is a clusterhead, etc. 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 can be evaluated (Ferentinos and Tsiligiridis, 2005).

The final fitness function used by the genetic algorithm was:

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

where *f* is the fitness value of a specific wireless sensor network design. The values of the weighting factors $a_1$ to $a_7$ were chosen based on experience about the importance of each parameter, after experimentation.

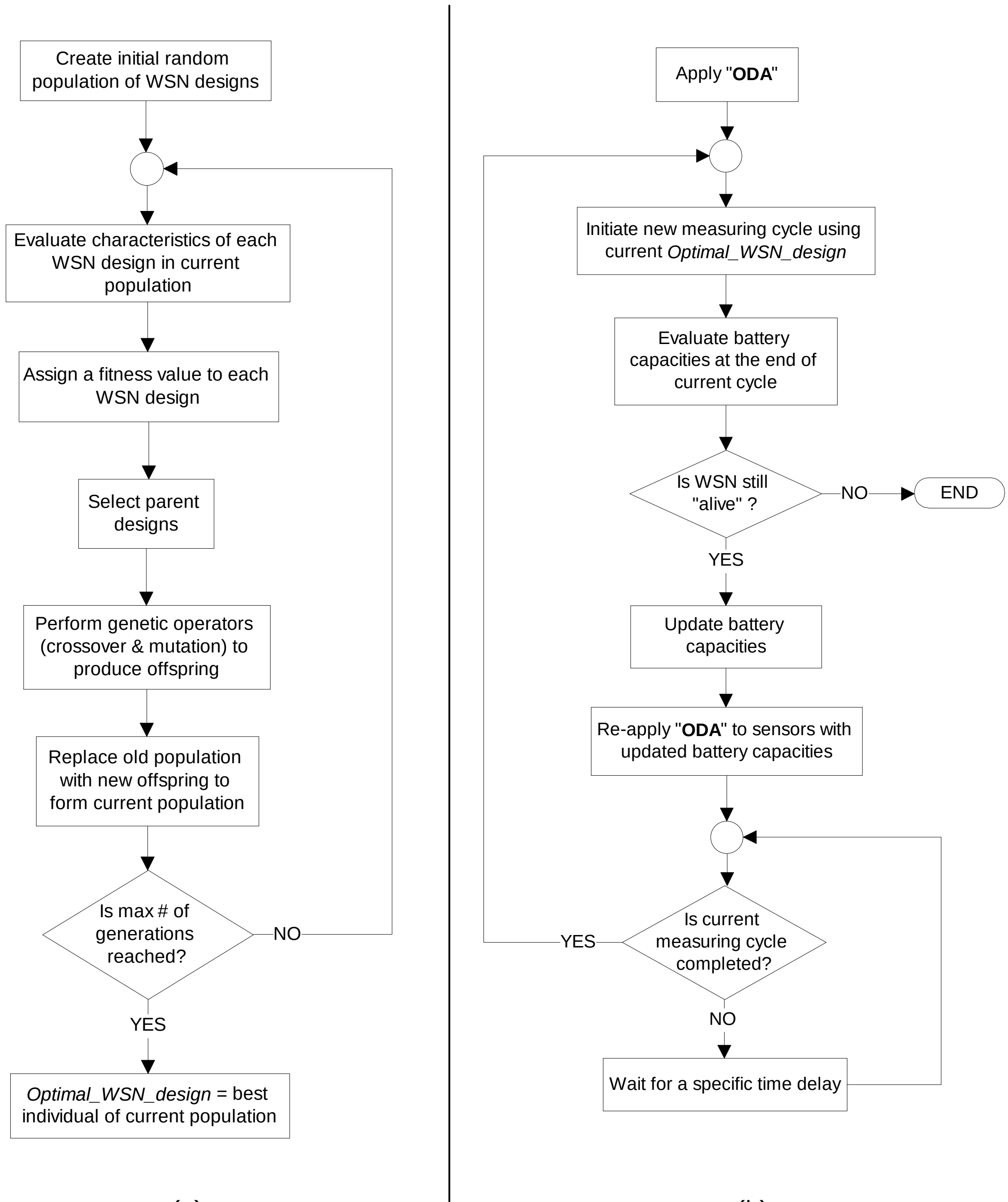
### 3.4. Dynamic optimal design algorithm

Having completed the development of a representation scheme and forming the fitness function, the dynamic genetic algorithm for optimal adaptive design of the WSN could be developed. The algorithm consisted of two parts: the Optimal Design Algorithm (ODA), which is applied to a set of sensors with specific battery capacities (Fig. 1a), and the Dynamic Optimal Design Algorithm (DODA), which updates the battery capacities of the sensors and reapplies the optimal design algorithm accordingly (Fig. 1b).

## 4. Results

GAs are stochastic algorithms and thus incorporate 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. 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.




(a) (b)

Figure 1. Flow charts of the optimal WSN design algorithm (ODA) (a) and the dynamic optimal WSN design algorithm (DODA) (b)

### 4.1. 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). Table 1 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, HSR and LSR 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.

### 4.2. Dynamic design performance

The adaptation capabilities of the algorithm towards energy conservation but also towards connectivity sustainability and nursing of application-specific requirements were examined by the dynamic application of the algorithm to a sequence of measuring cycles. According to the energy consumption scheme introduced in Section 3.2, if a static clustering algorithm was used, the life duration of the WSN would have been five measuring cycles. The optimal design "GA1" presented in Table 1 was used as the starting design in the dynamic application of the algorithm, which was tested during 15 consecutive measuring cycles. A comparison of some preliminary results with those of static clustering on the initially optimal WSN ("GA1") presented in previous work (Ferentinos *et al.*, 2005) showed clear evidence of the energy conservation that is performed by the adaptive design of the algorithm. Here, the focus is on the analysis of the effect of the adaptation factor concerning energy conservation of the dynamically applied algorithm. The variability of this effect is determined by the weighting factor of the *BCP* parameter in the fitness function of the GA ($\alpha_7$), which from now on we call Energy Conservation Factor (*ECF*). The algorithm performed a trade-off between the satisfaction of the performance measures (uniformity,

| | "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 |
| $CE \cdot 10^3$ | **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 | - | - | - | - |

Table 1. WSN designs parameter values. 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;

spatial density, connectivity) and energy conservation. After some experimentation with several values of *ECF* in orders of 10, it was found that a reasonable trade-off is performed for *ECF* values between 0.01 and 10.

Fig. 2 shows that the uniformity level (*MRD*) and the communication energy consumption of the WSN are highly influenced by the value of *ECF*. The adaptive WSN designs with *ECF* equal to 0.1 and 0.01 (especially the latter) kept the *MRD* values quite low during all measuring cycles. There is a small general trend of increase in the value of *MRD*, but this is reasonable as more and more energy limitations are introduced into the network as time passes. Similarly, in the case of communication energy consumption of the WSNs, the adaptive design with *ECF* = 0.01 preserved the best values during the entire testing period, with values very close to the initial consumption of the network.

The next two figures (Fig. 3 and 4) show the effect of *ECF* to the available energy of the sensors of the WSN during the period of the dynamic application of the algorithm. Fig. 3 shows the percentage of sensors that have battery capacity below certain levels at the end of each measuring cycle, with the three *ECF* values discussed before. Similarly, Fig. 4 shows the corresponding percentages of sensors with battery capacity above certain levels. Except for the indication that appropriate energy management of the WSN is achieved, these graphs also show that the *ECF* parameter seems to play an important role in the life duration of the network too, especially in the "lower energy bound" of the network, as it seems that the influence of *ECF* to the sensors with large battery capacities is limited (Fig. 4).

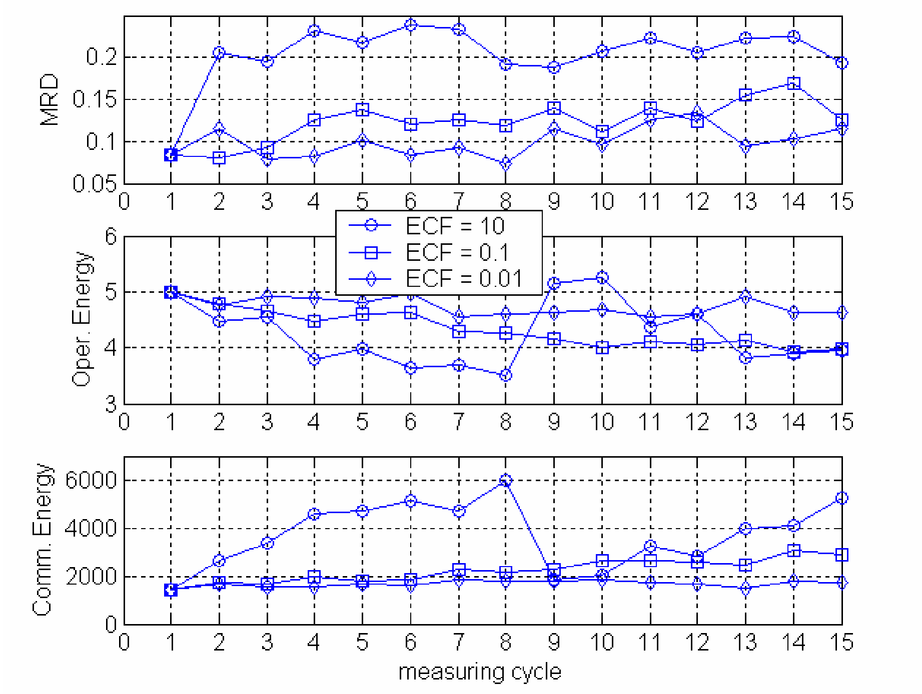



Figure 2. *MRD*, *OE* and *CE* performance measures of the WSNs over the testing period of 15 measuring cycles for three different values of the *ECF*.

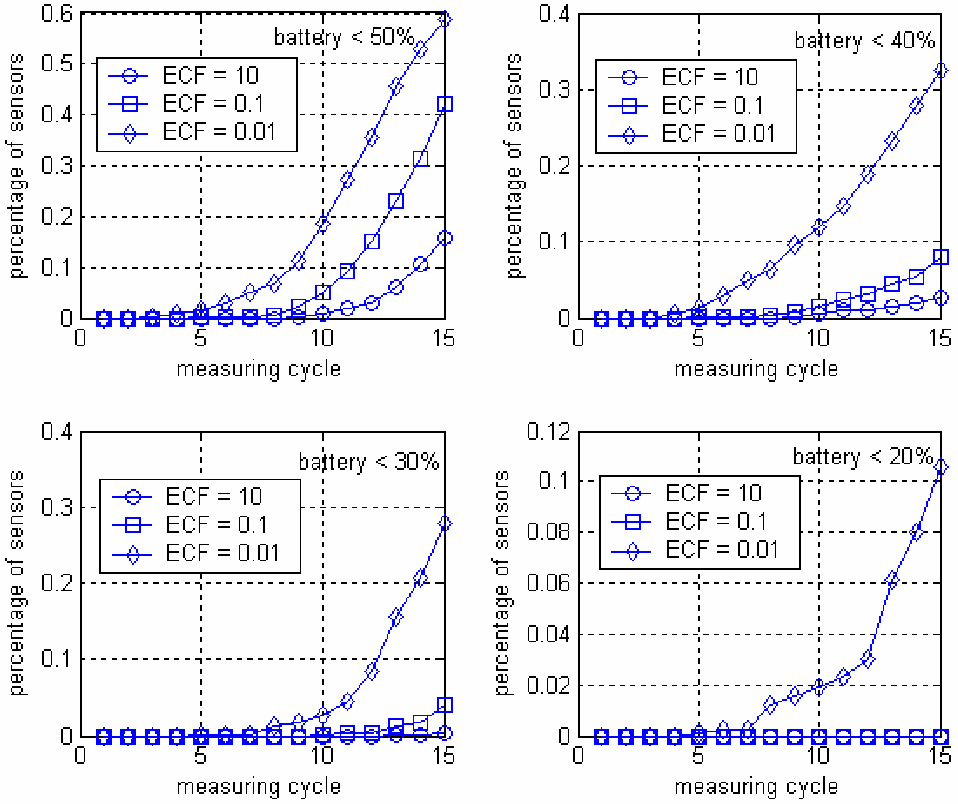



Figure 3. Percentages of sensors with battery capacities below 50%, 40%, 30% and 20% of full battery capacity at the end of each measuring cycle, for three different *ECF* values.

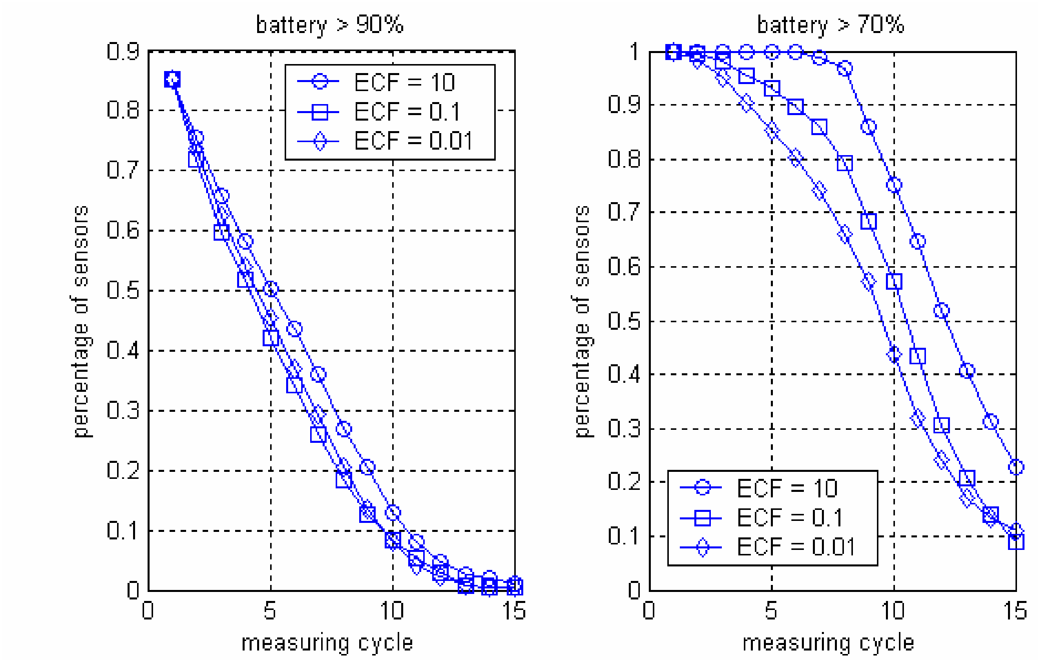



Figure 4. Percentages of sensors with battery capacities above 90% and 70% of full battery capacity at the end of each measuring cycle for three different *ECF* values.

## 5. Conclusions

In this paper, an algorithm for the optimal design and dynamic adaptation of application-specific WSNs was developed and applied in precision agriculture. The algorithm was based on the heuristic optimization properties of genetic algorithms. A fixed wireless network of sensors of different operating modes was considered on a grid deployment and the GA system decided on which sensors should be active, which ones should operate as clusterheads and whether the remaining active normal nodes should have high or low signal range. During optimization, parameters of network connectivity, energy conservation as well as application requirements were taken into account so that an integrated optimal WSN was designed. It was shown that GA-generated designs compared favorably to random designs of sensors. Uniformity of sensing points of optimal designs was satisfactory, while connectivity constraints were met and operational and communication energy consumption was minimized. Furthermore, it was shown 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.

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