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Energy Optimization of Wireless Sensor Networks for Environmental Measurements

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Abstract* – In this paper we propose an approach to optimal design of application-specific wireless sensor networks based on the optimization properties of genetic algorithms. Specific requirements for a precision agriculture application of sensor networks are taken into account by the genetic algorithm system, together with connectivity and energy conservation limitations. We develop an appropriate fitness function 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 normal sensor nodes. 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.

***Keywords* – Sensor network design, genetic algorithms, energy conservation, precision agriculture**

I. INTRODUCTION

Wireless sensor networks (WSNs) have been used in a wide range of applications. They usually consist of a large number of low-cost, low-power, multifunctional sensor nodes that are small in size and communicate in short distances [1]. Their structure and characteristics depend on their electronic, mechanical and communication limitations but also on the requirements of the specific application. The position of sensor nodes is usually not pre-determined, although the application can provide some guidelines and insights that can lead to the construction of an optimal design that satisfies application requirements and meets wireless network limitations.

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 [2]–[5] and several algorithms that lead to optimal topologies for power conservation have been proposed [6]–[11]. 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. 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 feasible or 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 were considered, or several requirements of the application cases were not incorporated in the performance measure of the algorithm. Here, a more integrated GA approach is proposed, 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.

II. NETWORK DESIGN

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 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, with WSNs belonging to the embedded, networked systems category.

Here, we consider an application that 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 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. Therefore, 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. 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 main 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 simple 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 (HSR) sensors cover a circular area with radius equal to 10 length units, while low signal range (LSR) 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, 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.

III. IMPLEMENTATION OF GA

GAs 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 each individual (i.e. possible network design) a performance metric.

A. GA Representation of the WSN

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 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, as shown in Fig. 1. Each position needs two bits for the encoding, thus, the length of each string 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.

B. Fitness Function

The fitness function is a weighted 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. The major issue in the development of a fitness function 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.

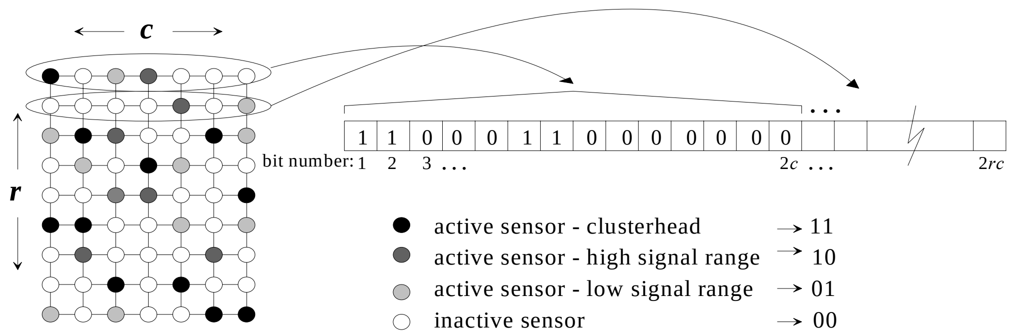


Fig. 1. Binary representation (on the right) of a randomly generated sample of a sensor network (on the left). Representation of the first row is shown.

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 that we used 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_{Si}, 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,…,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:

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

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:

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

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 be 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 simple sensors in its cluster, which was assumed to be equal to 15 for the application considered here. If *nfull* is the number of clusterheads (or clusters) that have more than 15 active sensors in their clusters and n_i is the number of sensors in the i-th of those clusters, then:

$$SCE = \begin{cases} \dfrac{\sum_{i=1}^{nfull} n_i}{nfull} & if \;\; nfull > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

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 *nout* is the number of active sensors that cannot communicate with their clusterhead and n is the total number of active sensors in the network, then:

$$SORE = \frac{nout}{n} \tag{4}$$

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 HSR or a LSR sensor, or whether it is inactive. The corresponding relevance factors for the energy consumption of the three active operating modes of the sensors are taken proportional to 20:2:1 respectively and zero for inactive. The Operational Energy (*OE*) consumption parameter was then given by:

$$OE = 20 \cdot \frac{nch}{n} + 2 \cdot \frac{nhs}{n} + \frac{nls}{n} \quad (5)$$

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

b) Communication energy. It 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 [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 μ=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.

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.

- $BC_i^{[t]}$ is the battery capacity of sensor i at measuring cycle t, taking values between 0 and 1, with 1 corresponding to full battery capacity and 0 to no capacity at all.

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

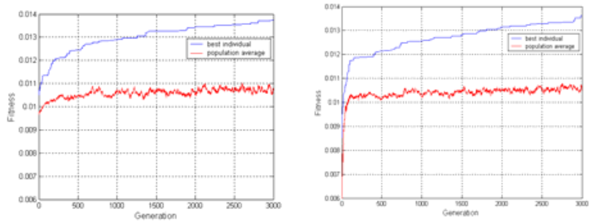
$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + ... \\ + \alpha_4 \cdot SORE + \alpha_5 \cdot OE + \alpha_6 \cdot CE + \alpha_7 \cdot BCP) \quad (8)$$

where f is the fitness value of a specific WSN design. The weighting factors $\alpha_i : i = 1,2,...,7$ were used in the fitness function to determine the relevant importance of the corresponding parameters. The values of these factors were chosen based on experience about the importance of each parameter after experimentation. First, weighting factors that resulted on the same importance of each parameter were estimated and after some experimentation, the final values that best represented the intuition about relevant importance of each parameter were set. It should be noted that we did not include the *BCP* parameter in the results presented in this work. The algorithm was applied to the optimal design of sensors with full battery capacities. Its dynamic application for adaptive optimal design is presented in future work [18], where the reduction rate of battery capacities is also explained in more detail.

C. Optimal Design Algorithm

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

1) An initial population of randomly generated designs was formulated. The size of the population was a parameter of exploration, as explained in the next section.
2) Using (1) to (7), the characteristics of each individual were evaluated.
3) A fitness value was assigned to each individual, using (8) with specific weighting factors, based on experience. The best fitness value and the corresponding individual, as well as the average fitness of the entire population were stored



(a) (b)

Fig. 2. Evolution progress of the best individual (best fitness value) and the entire population (average fitness value) of the GA during two runs.

4) The individuals that would form the parents of the next generation were selected with probability proportional to their fitness value.
5) Crossover was performed between couples of the parent individuals, with specific probability. In addition, mutation in the form of changing the value of some bit was applied to the new population, with specific probability.
6) The population was replaced by the new population and steps 2–5 were repeated until a predetermined maximum number of generations was reached.

The individual with the maximum fitness value represented the optimal WSN design estimated by the algorithm.

IV. RESULTS

There are some problem specific parameters of GAs that have to be tuned initially, like population size, the probabilities of crossover and mutation and the type of crossover. The explorations led to the use of the following parameters for the final GA: a population of 300 individuals, one-point crossover with probability $p_c = 0.8$ and probability of mutation $p_m = 0.005$. In addition, because GAs are stochastic algorithms sensitive to the quality of the initial population, in all explorations and then further application of the algorithm, several runs were tested with different random initial populations.

A. Evolution of Network Parameters

The three initial populations that gave the best results after 3000 iterations of the GA were recorded (abbreviated as “GA1”, “GA2” and “GA3”, started from the fittest design). The evolution progress of the two best GA runs 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 at each generation are plotted. The general optimization in the entire GA population can be seen from the general increase of the average population fitness in both graphs, despite the numerous fluctuations caused by the search process through the genetic operators of crossover and mutation.

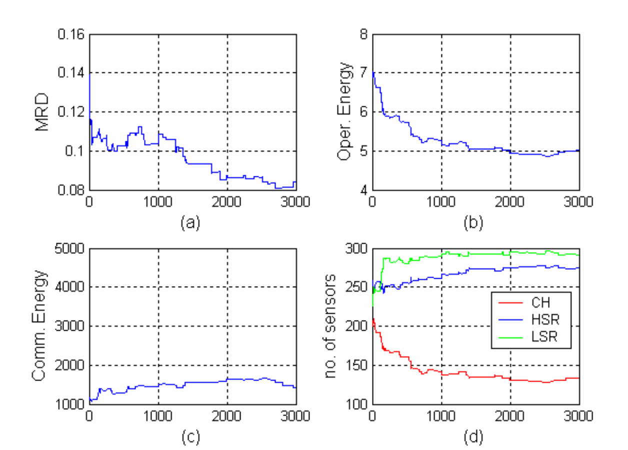


Fig. 3. Evolution of WSN parameters during 3000 generations. (a) MRD values for estimation of uniformity of measurement point; (b) Operational energy consumption factor; (c) Communication energy consumption factor; (d) Number of active sensors for the three operation modes.

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 best GA run. More 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.

B. Design Comparisons

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, 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 point, 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

Table I. WSN designs parameters values (OOR: out-of-range sensors, OCC: over-connected clusters)

	"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	N/A	N/A	N/A	N/A

communicate with some clusterhead and also have some clusters with more than 15 sensors, which is the maximum number of sensors a clusterhead can handle. Design "Rand3" has a 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.

V. CONCLUSIONS

In this paper, we presented a genetic algorithm system for the optimal design of WSNs for a precision agriculture application. 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 rest 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. Evolution of several characteristics of the network was shown during the GA optimization process and it can be concluded 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.

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