Heuristic Dynamic Clustering in Wireless Sensor Networks for Environmental Sensing

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***Abstract*—We present a multi-objective optimization methodology for adaptive wireless sensor network design. The proposed approach takes into consideration application-specific requirements, connectivity constraints and energy conservation characteristics. The current work focuses on the dynamic clustering performed by the heuristic design algorithm and investigates the sophistication of the optimization methodology towards that aspect of network connectivity.**

***Index Terms*—Clustering, design methodology, genetic algorithms, wireless sensor networks**

I. Introduction

ONE of the major challenges in the design of Wireless Sensor Networks (WSNs) is the fact that energy resources are significantly more limited than in wired networks [1-2]. Recharging or replacing the battery of the sensors in the network may be difficult or even impossible, causing severe limitations in the communication and processing time between all sensors in the network. Thus, optimal energy management in such networks is of major importance. 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, another issue of equal importance, which is rather neglected in the majority of works in the literature, is the fact that some very exact physical characteristics of the network have to exist so that the sensing information gathered by the WSN is adequate and useful, from a practical point of view. These characteristics are defined by specific requirements that have to be met by the network, which depend on the exact application that the WSN is used into.

Usually, in environmental applications like the one considered in this work, the most important physical characteristic of the network is uniformity of measuring points. Environmental measurements have to be gathered with a certain degree of uniformity throughout the area of interest where the WSN is applied. In this way, it is guaranteed that all portions of the area are sensed at a similar degree. In addition, spatial density of sensing points is another physical characteristic that has some specific desired value depending on the type of sensing application.

We recently presented [12] an algorithm for the dynamic design of WSNs for energy conservation of sensors while taking into account some of the application-specific requirements of the network. In addition, the algorithm also takes into account the connectivity issues that arise in a wireless network scheme. These issues depend on the specific communication capabilities of sensors and the selected communication protocol. The most common protocol follows the cluster-based architecture, where single-hop communication occurs between sensors of a cluster and a selected clusterhead sensor that collects all information gathered by the other sensors in its cluster. Usually, connectivity issues include the number of sensors in each cluster, because a clusterhead can handle up to a specific number of connected sensors, as well as coverage issues related to the ability of each sensor to reach some clusterhead.

In this work, we investigate the clustering characteristics of the adaptive network topologies, as they are dynamically designed by the proposed algorithm. In addition, we take into account the uniformity of sensing points, energy conservation and network connectivity, which all constitute the driving forces in network design adaptation.

II. Problem Outline

A. Optimization Framework

The design optimization algorithm that was developed in [12] dealt with more than one nonlinear objective functions that had to be optimized simultaneously. These kinds of design problems are the subject of multiobjective optimization and can generally be formulated as follows:

$$\text{Minimize/maximize: } J_i(\vec{x},\vec{p}) \quad ; i = 1,2,\cdots,n \tag{1}$$

$$\text{subject to: } \begin{cases} C_j(x,\vec{p}) \geq 0 & ; j = 1,2,\cdots,m_1 \\ H_k(\vec{x},\vec{p}) = 0 & ; k = 1,2,\cdots,m_2 \\ x_r^{\min} \leq x_r \leq x_r^{\max} & r = 1,2,\cdots,s \end{cases} \tag{2}$$

where $\vec{x} = (x_1, x_2, \cdots, x_r, \cdots, x_s)$ is a design vector

Manuscript received February 10, 2006. This work was supported in part by the "PYTHAGORAS-II" research project which is co-funded by the European Social Fund and Greek national resources (EPEAEK II).

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and $\vec{p} = (p_1, p_2, \cdots, p_z)$ is a vector of fixed parameters.

The individual J_i objectives, the inequality constraints C_j and the equality constraints H_k are dependent on a vector $\vec{x}$ of design variables and a vector $\vec{p}$ of fixed parameters. In this case there are n objectives, s design variables, m_1 inequality constraints and m_2 equality constraints. In addition, the design variables may be bounded, assuming that $x_r \in \Re$. The problem is to minimize (or maximize) simultaneously all objectives J_i. The s-variable solution vector which satisfies all constraints and variable bounds is a feasible solution and the set of all such feasible solutions constitute a feasible variable domain space *S*. Obviously, in the above type of problems there is no single optimal solution, but rather a set of alternative solutions. These solutions are optimal in the wider sense that no other solutions in the search space are superior to them when all objectives are considered (Pareto optimal solutions). The decision vectors that are non-dominated within the entire search space are denoted as Pareto optimal and constitute the Pareto optimal front.

However, even when solving an optimal design problem with contradictory criteria, the final solution should be based on some quantitative expression of the relative preferences. A traditional way of solving the pre-described minimization problem is to reduce it to a scalar problem of the form:

$$\min J = \sum_{i=1}^{n} w_i J_i \quad ; w_i \geq 0 \ \ with \ \sum_{i=1}^{n} w_i = 1 \qquad (3)$$

The weighted sum method parametrically changes the weights among objective functions to obtain an appropriate set of solutions which may approximate the Pareto front in objective space. This method offers a valuable approach in the optimal design problem with contradictory objectives, particularly in the case of a large-scale multi-objective optimization problem in which it is impossible to find all Pareto-optimal solutions. Thus, the focus of the problem is how to find many near-optimal non-dominated solutions in a practically acceptable computational time. There are several interesting approaches to tackling such problems, but one of the most powerful heuristics, which is also appropriate to apply in our multi-objective optimization problem, is based on Genetic Algorithms (GAs) [13]. GAs try to imitate natural evolution by assigning a fitness value to each candidate solution of the problem and by applying the principle of survival of the fittest. Their basic components are the representation of candidate solutions to the problem in a "genetic" form (genotype), the creation of an initial, usually random population of solutions, the establishment of a fitness function that rates each solution in the population, the application of genetic operators of crossover and mutation to produce new individuals from existing ones and finally the tuning of the algorithm parameters like population size and probabilities of performing the pre-mentioned genetic operators.

B. *WSN Modeling and Design Objectives*

The sensing area under investigation consists of a square of 30 by 30 length units. A virtual grid of those dimensions is constructed and sensors are placed in all 900 junctions of the grid, so that the entire area is covered. A length unit is an abstract parameter so that the optimal design algorithm 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. We consider a cluster-based network architecture in which 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).

The primary goal of the algorithm is to find the optimal operation mode of each sensor so that application-specific requirements are met and energy consumption of the network is minimized. More specifically, network design is investigated in terms of active sensors placement, clustering and signal range of sensors, while performance estimation includes, together with connectivity and energy-related characteristics, some application-specific properties like uniformity and spatial density of sensing points. Thus, the implementation of the proposed methodology results in an optimal design scheme, which specifies the operation mode for each sensor. The ultimate objective of this work is to investigate the dynamic clustering of the WSN during the application of the optimal design algorithm. This is achieved by implementing the algorithm repeatedly in order to develop a dynamic network design that adapts to new energy-related information concerning the status of the network after each measuring cycle or at predefined time intervals.

C. *Optimal Design Methodology*

Three sets of parameters which dominate the design and the performance of a WSN for the specific environmental sensing application were identified. The first set is the *application-specific parameters* which include two parameters regarding the deployment of sensors for the specific case considered here. These are the highest possible uniformity of sensing points and some desired spatial density of measuring points. The second set is the *connectivity parameters* which include an upper bound on the number of sensors that each clusterhead sensor can communicate with, and the fact that all sensors must have at least one clusterhead within their signal range. Finally, the third set refers to the *energy-related parameters* which include the operational energy consumption depending on the types of active sensors, the communication energy consumption depending on the distances between sensors that communicate with their corresponding clusterhead, and finally the battery energy consumption.

The optimization problem is defined by the minimization of the energy-related parameters (say, objectives J_1, J_2 and J_3) and the maximization of sensing points' uniformity (objective J_4), subject to the connectivity constraints (say, constraints C_1 and C_2) and the spatial density requirement (constraint C_3) (see Table I for the exact correspondences). Thus, the objectives are:

$$\min J_i \; ; i = 1,2,3 \;\; and$$
$$\max J_4$$
$$subject\ to\ C_i ; i = 1,2,3$$

In order to combine all objectives into a single objective function (weighted sum approach), the optimization parameters are formed in such a way that all of them are minimized. Thus, objective J_4 is expressed by its dual objective, say J'_4, which has to be minimized. Further, the penalization of the constraints C_1, C_2 and C_3 allows their transformation into objectives J_5, J_6 and J_7, respectively, which have to be minimized. Thus, a single objective function that blends all (obviously conflicting) objectives is of the form:

$$f = \min\left\{ \sum_{\substack{i=1 \\ i\neq 4}}^{7} w_i J_i + w_4 J'_4 \right\} \tag{4}$$

This form of objective function is suitable for the formulation of a numeric evaluation function [14] (namely a "fitness function" in the terminology of GAs), which gives a quality measure to each possible solution of the optimization problem.

The measure of uniformity of sensing points was evaluated by the spatial mean relative deviation (*MRD*) of such points. 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_{Si}, the spatial density of sensing points in sub-area S_i, was defined as the number of such points 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, 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:

$$MRD = \frac{\sum_{i=1}^{N} \left| \rho_{S_i} - \rho_S \right|}{N \cdot \rho_S} \tag{5}$$

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

TABLE I
CORRESPONDENCES BETWEEN OBJECTIVES AND OPTIMIZATION PARAMETERS

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

In addition to uniformity and spatial density of sensing points as well as energy consumption of the WSN (both operational and communicational), two network connectivity issues were taken into account in the formulation of the fitness function: i) A Sensors-per-Clusterhead Error (*SCE*) parameter was included to ensure that each clusterhead did not have more than a maximum predefined number of regular sensors in its cluster. This number is defined by the physical communication capabilities of the sensors as well as their data management capabilities in terms of quantity of data that can be processed by a clusterhead sensor. It was assumed to be equal to 15 for the application considered here. ii) A Sensors-Out-of-Range Error (*SORE*) parameter was included to ensure that each sensor can communicate with its clusterhead. This of course depends on the signal range capability of the sensor. It is assumed that HSR-sensors cover a circular area with radius equal to 10 length units, while LSR-sensors cover a circular area with radius equal to 5 length units.

Finally, the battery capacities of the sensors were taken into account by the introduction of the battery capacity penalty (*BCP*) parameter (more details can be found in [12]).

Thus, the weighting linear fitness function f of a specific WSN design is given by:

$$f = 1/(\alpha_1 \cdot MRD + \alpha_2 \cdot SDE + \alpha_3 \cdot SCE + \alpha_4 \cdot SORE + ...$$
$$... + \alpha_5 \cdot OE + \alpha_6 \cdot CE + \alpha_7 \cdot BCP) \tag{6}$$

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

TABLE II
WEIGHTING COEFFICIENTS OF GA FITNESS FUNCTION

Weighting coefficient	"Equal importance" values	Final values
α_1	10^2	10^2
α_2	10^4	10^4
α_3	2	10^6
α_4	10^3	10^5
α_5	10	10
α_6	$5\cdot10^{-3}$	10^{-2}

D. *Problem Complexity*

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

The information on the Euclidean distances of the active sensors reduces the problem to a Minimum Weight Spanning Tree (MWST). In the case where all nodes are placed on a two-dimensional plane and the weights of the edges between two nodes correspond to the Euclidean distances, the degree of a MWST is upper-bounded by 6 [16]. However, the other constraints of our optimization problem (e.g., all active nodes other than clusterheads have degree equal to 1, energy requirements, etc.), might not allow the construction of a connected MWST. Therefore, the problem still needs to be solved in the context of the MDST, which as we mentioned above, is NP-hard.

III. DYNAMIC OPTIMAL DESIGN ALGORITHM

The algorithm consisted of two parts: the Optimal Design Algorithm (ODA), which basically consists of the GA scheme and which is applied to a set of sensors with specific battery capacities, and the Dynamic Optimal Design Algorithm (DODA), which updates the battery capacities of the sensors and reapplies the optimal design algorithm accordingly (Fig. 1).

Some of the issues that have to be clarified are the following:

- The measuring cycle is defined as the period of time during which a clusterhead sensor consumes 20% of its full battery capacity.
- The steps of "battery capacities update" and "re-application of the optimal WSN design algorithm" are performed during data collection of the measuring cycle. This is because battery capacities at the end of the cycle can be evaluated based on the developed model, without having to wait until the actual end of the measuring cycle. Thus, at the end of each measuring cycle, the next optimal WSN design has already been formed and it is then used for the next data measuring cycle.

```
Apply GA to find Optimal_WSN_design
while WSN is "alive"
   Initiate new measuring cycle using current
Optimal_WSN_design
   Evaluate battery capacities at the end of current cycle
   Update battery capacities
   Re-apply GA to sensors with updated battery capacities
   Wait until current measuring cycle is completed
end while
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Fig. 1. Pseudocode of the dynamic optimal WSN design algorithm (DODA)

- The life duration of the network, which is referred to as "WSN is alive" in the pseudocode, defines the application time of the dynamic algorithm. The network, i.e. the set of sensors in the field, is considered to be "alive" if the set of sensors with battery capacities above zero is such that some operational WSN can be designed and applied to the next measuring cycle.

The number of iterations performed by the algorithm in a single measuring cycle are in the order of $G\cdot l\cdot M^2$, where G is the number of generations of the GA, l is the bit-string length of the GA and M is the population size. If n is the total number of available sensors in the WSN design, then obviously the computational complexity of the algorithm is O(n), as only the l parameter depends on n ($l=2\cdot n$) [12].

IV. ADAPTIVE CLUSTERING AND DESIGN PERFORMANCE

The adaptation capabilities of the algorithm towards energy conservation but also towards connectivity sustainability and nursing of application-specific requirements were examined, with the dynamic application of the algorithm to a sequence of 15 measuring cycles. Energy conservation results and an analysis on the extension of the life duration of the network can be found in [12].

Table III shows the distribution of operating modes of the sensors at each of the 15 measuring cycles tested, as well as the average number of sensors that each clusterhead coordinates respectively (standard deviations in the parentheses). It can be seen that the number of active sensors remains constant after the first three measuring cycles, and the same holds for the allocation of the active nodes into HSR and LSR operating modes, while there is a slight decrease in the number of CH sensors, which leads to the general increase of the average number of active sensors coordinated by each clusterhead.

It is obvious that the less CH sensors in the WSN, the less operating energy is consumed by the network. At the same time, the average values of sensors per clusterhead shown in Table III are much smaller than the actual capability of clusterhead sensors (15 sensors). Thus, it seems that less clusterheads could be used. These seemingly contradictory facts are justified by the fact that the energy conservation of the operating cost of such designs (with less clusterheads)

TABLE III
DISTRIBUTION OF OPERATING MODES OF SENSORS AND AVERAGE CLUSTERING

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

would have been counterbalanced by the increase in communication energy consumption.

Thus, clustering seems to be managed by the heuristic algorithm in such a way that total communication energy consumption within single-hop transmissions in all clusters is kept as low as possible, while other major issues like optimal sensor usage towards life extension of the entire WSN, are also taken into account.

V. CONCLUSIONS

In this paper, we showed that a heuristic algorithm for optimal design of WSNs can exhibit sophisticated characteristics of adaptive clustering that can lead to energy conservation towards the extension of the life duration of the network. At the same time, application-specific requirements as well as connectivity constraints of the network are met.

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