Multi-Objective Node Placement Methodology for Wireless Sensor Network

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ABSTRACT

Node placement is an important task in wireless sensor network. Node placement in wireless sensor network is a multi-objective combinatorial problem. A multi-objective evolutionary algorithm based framework has been proposed in this paper. Design parameters such as network density, connectivity and energy consumption have been taken into account for developing the framework. The framework optimizes the operational modes of the sensor nodes along with clustering schemes and transmission signal strengths.

Keywords: Network Configuration, Sensor Placement, Wireless Sensor Networks.

1. INTRODUCTION

Smart environments represent one of the key future development steps in building, utilities, industrial, home, shipboard, and transportation systems automation. The smart environment basically relies first and foremost on sensory data from the real world. Sensory data comes from multiple sensors of different modalities in distributed locations. The smart environment needs information about its surroundings as well as about its internal workings. On the other hand the challenges in the smart environment lies in detecting the relevant quantities, monitoring and collecting the data, assessing and evaluating the information, formulating meaningful user displays, and performing decision-making and alarm functions. The information needed by smart environments is provided by Distributed Wireless Sensor Networks (DWSN), which are responsible for sensing as well as for the first stages of the information processing. The importance of wireless sensor networks is highlighted by the number of recent funding initiatives, including the DARPA SENSIT program, military programs, and NSF Program Announcements. But the rapid progress of wireless communications and micro-sensing MEMS technologies has enabled the development of low-cost, low-power sensor nodes, each capable of sensing, processing, and communicating with neighboring nodes via wireless links. Wireless sensor networks [1] are composed of a great number of sensor nodes densely deployed in a fashion that may revolutionize information collecting, which makes it a very promising technique for surveillance in military, environmental monitoring, target tracking in hostile circumstances, and traffic monitoring.

The rest of this paper is structured as follows. The review of the literature is followed in Section 2, The proposed methodology is formulated in Section 3. Section 4 discusses the multi-objective optimization using evolutionary algorithm. Section 5 discusses the experimental results of the proposed methodology. Finally, conclusions are given in Section 6.

2. RELATED WORK

Extensive research has focused on almost every layer of the network protocol, including network performance study [2], energy-efficient media access control (MAC) [3], topology control [4] and min-energy routing [5], enhanced TCP [6], and domain-specific application design [7]. Sensor networks are different from other networks due to the limitations on battery power, node densities, and the significant amount of desired data information. Sensor nodes tend to use energy-constrained small batteries for energy supply. Therefore, power consumption is a vital concern in prolonging the lifetime of a network operation. Many applications, such as seismic activity tracking and traffic monitoring, expect the network to operate for a long period of time, e.g., on the order of a few years. The lifetime of a wireless sensor network could be affected by many factors, such as topology management, energy efficient MAC design, power-aware routing, and energy-favored flow control and error control schemes. Different methods for reducing energy consumption in wireless sensor networks have been explored in the literature. Some approaches [8] were suggested, such as increasing the density of sensor nodes to reduce transmission range, reducing standby power consumption via suitable protocol design, and advanced hardware implementation methodology. Algorithms for finding minimum energy disjoint paths in an all-wireless network were developed [5]. SEAD [9] was proposed to minimize energy consumption in both building the dissemination tree and disseminating data to sink nodes. Few researches have, however, studied how the placement of sensor/aggregation nodes can affect the performance of wireless sensor networks.

On the other hand several interesting approaches like Neural Networks, Artificial Intelligence, Swarm Optimization, and Ant Colony Optimization have been implemented to tackle such problems. Genetic Algorithm (GA) is one of the most powerful heuristics for solving optimization problems that is based on natural selection, the process that drives biological evolution. Several researchers have successfully implemented GAs in a sensor network design [10]-[17], this led to the development of several other GA-based application-specific approaches in WSN design, mostly by the construction of a single fitness function. However, these approaches either cover limited network characteristics or fail to incorporate several application specific requirements into the performance measure of the heuristic. In this work, I tried to integrate network characteristics and application specific requirements in the performance measure of the proposed optimization algorithm based methodology. The algorithm primarily finds the operational modes of the nodes in order to meet the application specific requirements along with minimization of energy consumption by the network. More specifically, network design is investigated in terms of active sensors placement, clustering and communication 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. PROPOSED METHODOLOGY

In this work a hypothetical application which involves deployment of three types of sensors (say X, Y and Z) on a two dimensional field is considered. The sensing nodes are identical and assumed to have features like; power control, sensing mode selection and transmission power control. For monitoring of hypothetical parameters, it is assumed that spatial variability $x\rho \in X$, $y\rho \in Y$, $z\rho \in Z$ are such that $x\rho << y\rho << z\rho$. It means that the variation of X in the 2D field is much less than Y and the variation Y is much less than Z. i.e. the density of sensor nodes monitoring Z has to be more than Y and density of sensor nodes monitoring Y has to be more than X in order to optimally monitor the field. The methodology not only takes the general network characteristics into account, but also the above described application specific characteristics.

3.1. Network Architecture Model

Consider a square field of N x N Euclidian units subdivided into grids separated by a predefined Euclidian distance. The sensing nodes are placed at the intersections of these grids so that the entire area of interest is covered (See Figure 1).

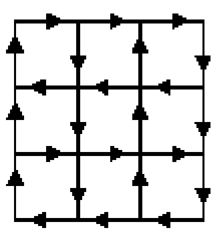

Figure 1. A grid (mesh) based wireless sensor network layout.

The nodes are capable of selecting one of the three operating modes i.e. X sense, Y sense and Z sense provided they are active. The nodes operating in X sensing mode has the highest transmission range whereas nodes in Y and Z sensing modes have medium and low transmission ranges respectively. Although several cluster based sophisticated methodologies have been proposed [18-20], we have adopted simple mesh architecture, wherein the nodes operating in X sense mode act as cluster-in-charge and are able to communicate with the base station (sink) via multi-hop communication and the clusters are formed based on the vicinity of sensors to the cluster-in-charge. The cluster-in-charge performs tasks such as data collection and aggregation at periodic intervals including some computations. So, X sense node will consume more power than the other two modes.

3.2. Problem Formulation

Here we explore a multi-objective algorithm for WSN design space exploration. The algorithm mainly optimizes application specific parameters, connectivity parameters and energy parameters. This fitness function gives the quality measure of each WSN topology and further optimizes it to best topology. WSN design parameters can be broadly classified into three categories [17]. The first category colligates parameters regarding sensor deployment specifically, uniformity and coverage of sensing and measuring points respectively. The second category colligates the connectivity parameters such as number of cluster-in-charge and the guarantee that no node remains unconnected. The third category colligates the energy related parameters such as the operational energy consumption depending on the types of active sensors. The design optimization is achieved by minimizing constraints such as, operational energy, number of unconnected sensors and number of overlapping cluster- in-charge ranges. Whereas the parameters such as, field coverage and number of sensors per cluster-in-charge are to be maximized. i.e

$$\mathbf{Min}\ f(\mathrm{FC},\ \mathrm{OCE},\ \mathrm{SOE},\ \mathrm{SPC},\ E) \qquad (1)$$

Where

FC is a field coverage and defined as

$$FC = \frac{(n_x+n_y+n_z)-(n_{OR}+n_{intv})}{n_{tot}} \qquad (2)$$

n_x , n_y *and* n_z are number of sensors in the cluster , where n_x is the cluster in charge.

n_{OR} is the number of out range sensors, n_{intv} is the inactive sensors and n_{tot} is the total sensing point.

OCE is an overlap per cluster in charge error and defined as

$$OCE = \frac{No\_of\_Overlaps}{n_x} \qquad (3)$$

SOE is the sensor out of range error and is defined as

$$SoE = \frac{n_{OR}}{n_{tot}-n_{intv}} \qquad (4)$$

SPC is sensor per cluster in-charge and is defined as

$$SPC = \frac{n_y+n_z-n_{OR}}{n_C} \qquad (5)$$

n_C *is the number cluster incharge*

E is the energy consumption and is defined as

$$E = \frac{4.n_x+2.n_y+n_z}{n_{tot}} \qquad (6)$$

4. MULTI-OBJECTIVE OPTIMIZATION

In multi-objective optimization (MO), there are several objectives to be optimized. Thus, there are several solutions which are not comparable, usually referred to as Pareto-optimal solutions. A multi-objective minimization problem with n variables and m objectives can be formulated, without loss of generality, as

$$min\ y = f(\bar{x}) = \min\left(f_1(\bar{x}), f_2(\bar{x}), \ldots, f_m(\bar{x})\right) \qquad (7)$$

Where $\bar{x} = (x_1, x_2 \ldots, x_n)$ and $y = (y_1 y_2 \ldots, y_m)$

In most cases, the objective functions are in conflicts, so that is not possible to reduce any of the objective functions without increasing at least one of the other objective functions. This is known as the concept of pareto-optimality [21,22].

***Definition 1** (Pareto Optimal)*: A point $\bar{x} \in X$ is **Pareto optimal** if for every $\bar{x}^* \in X$ and

$I = \{1, \ldots, m\}$ either $\forall i \in I$, $f_i(\bar{x}) = f_i(\bar{x}^*)$ or, there is at least one $i \in I$ such that $f_i(\bar{x}) > f_i(\bar{x}^*)$ (8)

In other words, this definition means that $\bar{x}^*$ is Pareto optimal if there exists no feasible vector $\bar{x}$ that decrease some criterion without increment in at least one other criterion.

***Definition 2** (Pareto Dominance)*: A vector $\bar{u} = (u_1, u_2 \ldots, u_m)$ is said to dominate $\bar{v} = (v_1, v_2 \ldots, v_m)$ (denoted by $\bar{u} \preccurlyeq \bar{v}$) if and only if $\bar{u}$ is partially less that $\bar{v}$, i.e., $\forall i \in \{1, \ldots, m\}$, $u_i \leqq v_i \wedge \exists_i \in \{1, \ldots, m\} : u_i < v_i$

A solution α is said to be non-dominated regarding a set $X^1 \subseteq X$ if and only if, there is no solution in X^1, which dominates α. The solution α is Pareto-optimal if and only if α is non-dominated regarding X. The set of all non-dominated solutions constitutes the Pareto optimal set. Therefore, our goal is to find the best Pareto front and near to Pareto optimal.

In order to deal with the multi-objective nature of sensor placement problem we have used multi-objective genetic algorithm in our framework. The algorithm starts with a set of randomly generated solutions (population). The population's size remains constant throughout the GA. Each iteration, solutions are selected, according to their fitness quality (ranking) to form new solutions (offspring). Offspring are generated through a reproduction process. In a multi-objective optimization, we are looking for all the solutions of best compromise, best solutions encountered over generations are fled into a secondary population called the "Pareto Archive". In the selection process, solutions can be selected from this "Pareto Archive"(elitism). A part of the offspring solutions replace their parents according to the replacement strategy. In our study, we used a hybrid algorithm considering both NSGA-II [23] and EA principle called NSEA. The following subsection outlines the working principle of NSGA-II and NSEA.

4.1 NSGA-II

In this section we discuss how the elitist selection occurs in NSGA-II by the classification of the population into different fronts based on non dominated sorting ranks.

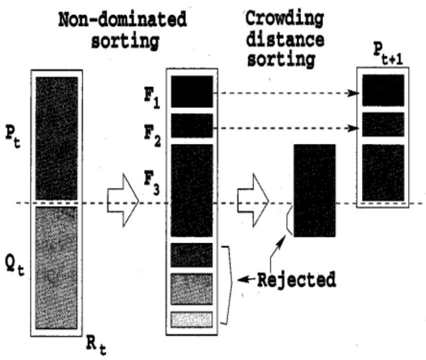

Figure 2: NAGA-II working principle

In NSGA-II, as shown in figure-2 the offspring population Qt is first created by using the parent population Pt. However, instead of finding the non dominated front of Qt only, first the two populations are combined together to form Rt of size 2N. Then a non – dominated sorting is used to classify the entire population Rt. Although this requires more effort compared to performing a non-dominating sorting on Qt alone, it allows a global non-domination check among the offspring and parent solutions. Once the non-dominated sorting is over, the new population is filled by solutions of different non-dominated fronts, one at a time. The filling starts with the best non-dominated front and continues with solutions of the second non-dominated front, followed by the third non-dominated front and so on. Since the overall population size of Rt is 2N, not all fronts may be accommodated in N slots available in the new population. All fronts which could not be accommodated are simply deleted. When the last allowed front is being considered, there may exist more solutions in the last front than the remaining slots in the new population. This scenario is illustrated in Figure-2. Instead of arbitrarily discarding some members of the last front, it would be wise to use a niching strategy to choose the members of the last front, which reside in the least crowded region in that front. But we will not go into too much detail on that.

4.2 NSEA Algorithm

The NSGA-II+ES (NSEA) algorithm is based on the hybridation of Evolution Strategies and NSGA-II. The algorithm uses the standard Evolution Strategies steps [24], replacing the selection process by the NSGA-II [23] selection process.

NSEA Algorithm

```
{ i=0
initialize population
while (i<G) // Number of generation
{
produce new individuals
evaluate population
}
```

This algorithm needs two constants to be defined: the number of generations (G) and the population size (μ). For the initialization, random individuals are spawned. The rest of the steps of the algorithm are explained as follows.

4.2.1 Produce New Individuals

The main difference between Evolution Strategies and Genetic Algorithms is that crossover operators are not used in ES, and each parent produces one offspring only by mutation. Each individual in the population of μ generates an offspring by mutation. The mutation process implemented was the standard (μ + λ) process explained in [25], although in our case, λ = μ. Being x = ($x_1, x_2, \ldots, x_n$, σ) an individual (where x_i are their coordinates, and σ its variance), the mutation procedure that generates an offspring $\bar{x}$ = ($\bar{x}_1$, ..., $\bar{x}_n$, $\bar{\sigma}$) can be mathematically described as:

$$\bar{\sigma} = \sigma e^{N(0,\Delta)} \qquad (9)$$

$$\bar{x}_i = N(x_i, \bar{\sigma}) \qquad (10)$$

Where N(X, Y) represents a normal random variable with mean X and variance Y. Δ is a standard constant. After all this process, the offspring is added to the population, that becomes 2μ size.

4.2.2 Evaluate Population

In this part of the algorithm we need to select the best μ individuals in the 2μ populations in order to be the parents for the next generation. The rest of the individuals will be deleted. In standard Evolution Strategies, the best individuals are selected by its fitness function. Each individual represents a solution of the problem The NSGA-II selection process sorts the solutions in subsets of the population (P) named fronts. These fronts (F_i) can be defined as:

F_1 = Non-dominated individuals of P.
F_2 = Non-dominated individuals of P \ F_1.
F_3 = Non-dominated individuals of P \ ($F_1 \cup F_2$).
Fn = Non-dominated individuals of P \ ($F_1 \cup F_2 \cup \ldots \cup F_{n-1}$).

Solutions in the same front are sorted by a crowding distance (d). After this sorting process, we can define whether an individual is better than another as:

a better than b ⇔ a ∈ F_i, b ∈ F_j

and $\left\{ \begin{array}{c} i < j \\ \text{or} \\ i = j \text{ and } d(i) > d(j) \end{array} \right\}$

Therefore, we can select the μ best individuals in the population as parents for the next generation.

4.2.3 Chromosome representation

As described in previous section a square field of N x N length units is considered which is subdivided into grids of unit lengths. The nodes are assumed to be placed on intersections of these grids. An individual in GA population is represented by a bit-string and is used to encode sensor nodes in a row by row fashion as shown in Figure 3.

00	**01**	**00**	**10**	**11**	**11**	**01**	**10**

Figure 3: Bit string representation of network layout (N=2).

The length of this bit string is $2.N^2$ as two bits are required to encode four types of sensing nodes i.e. X, Y, Z and inactive nodes. In this bit string the sequence of two bits decides the type of node 00 being inactive, 01 being X mode, 10 being Y mode and 11 represents Z mode. In Figure 3, N is 2 and hence the length of bit string is 8.

5. EXPERIMENTAL RESULTS

GAs involves exploration and tuning of a number of problem specific parameters for optimizing its performance, namely the population size, crossover and mutation methodologies. The size of population is fixed at 300 by experiment and nature of the problem. The crossover and mutation probability is taken 0.9 and 0.01 respectively for the experiment. We have taken two-point crossover and a uniform mutation. Δ was set to 0.7. In the ES experiments the number of non-dominated points in the solution never reached the size of the population and was never greater than 300.

Due to the stochasticity of GAs during optimization, the quality of the randomly generated initial population plays an important role in the final performance. So by the nature of the problem I considered a randomly generated initial population. The proposed algorithm is applied in a field of 10 x 10 sensing nodes assuming full battery capacity. The algorithm was started, having available all sensor nodes of the grid at full battery capacities. Figure 4 shows the final placement of nodes in the 10 x 10 mesh grid. The Figure 5 shows the optimal values of the different variables. The Figure 5 also shows the variation of the result with respect to the generations of NSEA algorithm.

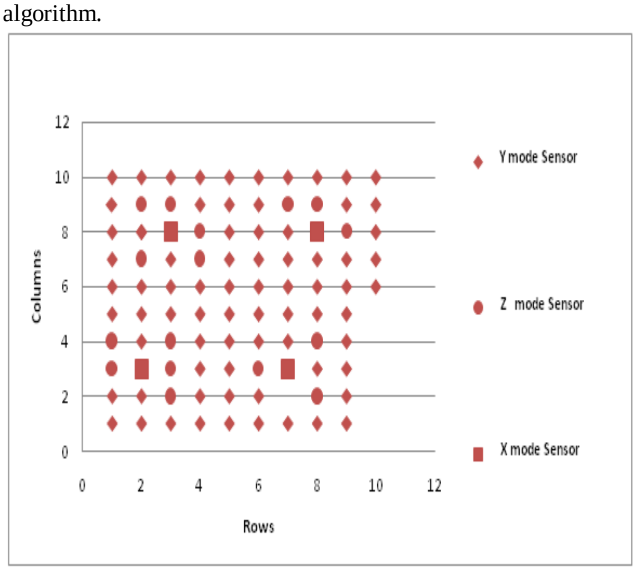

Figure 4: Final placement of nodes obtained by NSEA algorithm

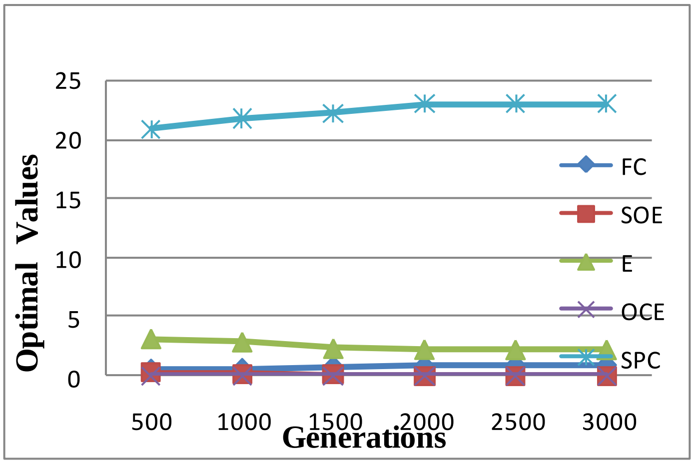

Figure 5: Performance of NSEA algorithm

6. CONCLUSION

In this paper the node placement methodology for a wireless sensor network using evolutionary algorithm based methodology is demonstrated. A fixed wireless network of sensors of different operating modes was considered for a 2D grid based deployment. NSEA algorithm decided which sensors should be active, which ones should operate as cluster-in-charge and whether each of the remaining active normal nodes should have medium or low transmission range. The network layout design was optimized by considering various parameters like application specific parameter, connectivity parameters and energy related parameters. From the evolution of network characteristics during the optimization process, it 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.

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