2012 International Conference on Computer Technology and Science (ICCTS 2012)
IPCSIT vol. 47 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V47.11

Node Placement for Wireless Sensor Network Using Multi-objective PSO

R K Jena[1+] and P K Mahanti[2]

[1] Institute of Management Technology, Nagpur, INDIA

[2] University of New Brunswick, CANADA

Abstract. Node placement is an important task in wireless sensor network and is a multi-objective combinatorial problem. A multi-objective PSO (particle swam optimization) algorithm based framework has been proposed in this paper. 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, PSO.

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. 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 PSO. Section 5 discusses the experimental results of the proposed methodology. Finally, conclusions are given in Section 6.

2. Related Work

Extensive wireless sensor network 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

[+] R K Jena
E-mail address: rkjena@imtnag.ac.in

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. Particle swarm optimization (PSO) 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 evolutionary algorithm based techniques i.e Gas, EA, GP etc in a sensor network design [10]-[12], this led to the development of several other evolutionary 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. Tthis work 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. 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).

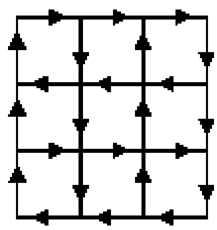

Fig.1: A grid (mesh) based wireless sensor network layout.

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 [13-15], 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 [16]. 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

$$\boldsymbol{Min}\, f(\text{FC, OCE, SOE, SPC}, E) \tag{1}$$

Where

FC is a field coverage and defined as

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

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:

$$OCE = \frac{No\_of\_Overlaps}{n_x} \tag{3}$$

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

$$SoE = \frac{n_{OR}}{n_{tot}-n_{intv}} \tag{4}$$

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

$$SPC = \frac{n_y+n_z-n_{OR}}{n_C} \tag{5}$$

n_C *is the number cluster* incharge

E is the energy consumption and is defined as

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

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

$$min\, y = f(\bar{x}) = \min\,(f_1(\bar{x}), f_2(\bar{x}), \ldots., f_m(\bar{x})) \tag{7}$$

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, ..., m} either ∀i∈I, $f_i(\bar{x}) = f_i(\bar{x}^*)$ or, there is at least one i ∈ I such that $f_i(\bar{x}) > f_i(\bar{x}^*)$

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., ∀i ∈ {1, . . .,m}, $u_i \lesseqgtr v_i \wedge \exists_i \in \{1, \ldots, m\} : u_i < v_i$

A solution α is said to be non-dominated regarding a set $X' \subseteq X$ if and only if, there is no solution in X', 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 PSO in our framework.

4.1. PSO Approach

Problems with multiple objectives are present in a great variety of real-life optimization problems. In these problems there are several conicting objectives to be optimized and it is difficult to identify what the best solution is. Despite the considerable diversity of techniques developed in the Operations Research field to tackle these problems, their intrinsic complexity calls for alternative approaches. Over the last decades, heuristics that find approximate solutions have attracted great interest. From these heuristics the Multi-Objective Evolutionary Algorithms (MOEAs) have been found to be very successful to solve multi-objective optimization problems.Another technique that has been adopted in the last years for dealing with multi-objective optimization problems is Particle Swarm Optimization (PSO) [17-18], which is precisely the approach adopted in the work reported in this paper. The PSO algorithm was first proposed by J. Kennedy and R. Eberhart in 1995 [19-20] and it was successfully used in several single-objective optimization problems. PSO is based on the behavior of communities that have both social and individual conducts, similar to birds searching for food. PSO is a population-based algorithm. Each individual (particle) represents a solution in a n-dimensional space. Each particle also has knowledge of its previous best experience and knows the global best experience (solution) found by the entire swarm. Particles update their exploration directions using the following equations:

$$v_{i,j} = w \times v_{i,j} + c_1 \times r_1 \times (p_{i,,j} - x_{i,j}) + c_2 \times r_2 \times (p_{g,j} - x_{i,j}) \quad (8)$$

$$x_{i,j} = x_{i,j} + v_{i,j} \quad (9)$$

where w is the inertia factor influencing the local and global abilities of the algorithm, $x_{i,j}$ is the velocity of the particle i in the j^{th} dimension, c_1 and c_2 are weights affecting the cognitive and social factors, respectively. r_1 and r_2 ~υ (0,1), p_i stands for the best value found by particle i (pbest) and p_g denotes the global best found by the entire swarm (gbest). After the velocity is updated, the new position i in its j^{th} dimension is calculated. This process is repeated for every dimension and for all the particles in the swarm.

In order to use PSO for multi-objective optimization problems, the PSO algorithm is hybridized with some concepts taken from the EAs field such as a mutation operator, and with concepts commonly used in MOEAs, such as a selection based on Pareto dominance and mechanisms to produce a good spread of solutions. The multi-objective PSO (MOPSO) used in this paper is presented below:

```
Algorithm MOPSO{
    Initialize Population ( );
    Initialize Velocity ( );
    Evaluate Population( );
    Update Fbest( );
    Update Pbest( );
    Insert to nondom File( );
    Gbestpos=rnd(0, nondom_filesize);
    for (i=1 to MAXCYCLE){
       for (j=0 to MAXPARTICLE) {
          Update Velocity( );
          Update particle( );
           }
          Keep best solution( );
```

```
            Evaluate Population( );
            Update Fbest( );
            Update Pbest( );
            Insert to nondom File( );
           Gbestpos=rnd(0, nondom_filesize);
           }
    Generate Output File( );
    }
```

5. Experimental Results

PSO involves exploration and tuning of a number of problem specific parameters for optimizing its performance, namely iteration, External File size, mutation probability etc. The Table-1 summarized the parameter values considered for the experiment.

Table-1: Parameter values

Iterations	External File size	Mutation operator	Particles	Divisions	C1=C2	W
5000	600	0.5	30	6	1.5	0.5

Due to the stochasticity of PSO during optimization, the quality of the randomly generated initial population plays an important role in the final performance. 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-2 shows the final placement of nodes in the 10 x 10 mesh grid. The Figure-3 shows the optimal values of the different variables. The Figure-35 also shows the variation of the result with respect to the generations of our algorithm (MOPSO).

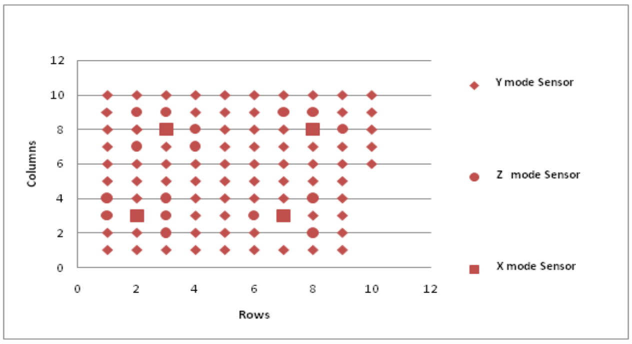

Fig. 2: Final placement of nodes obtained by MOPSO algorithm

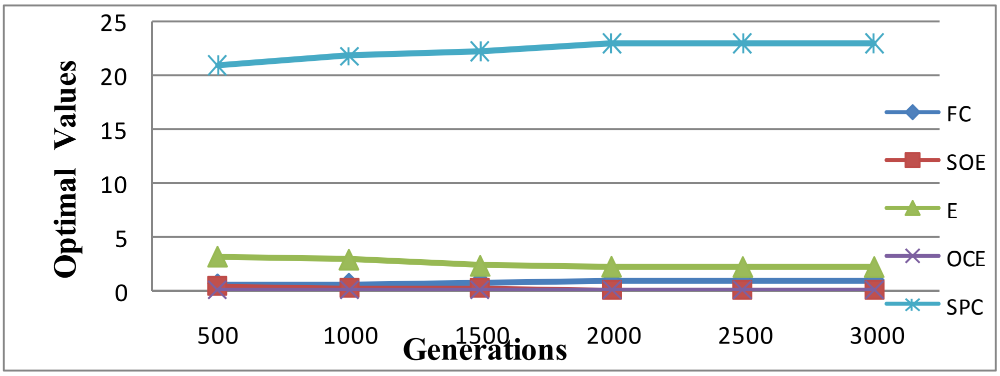

Fig. 3: Performance of MOPSO algorithm

6. Conclusion

In this paper the node placement methodology for a wireless sensor network using PSO based methodology is demonstrated. A fixed wireless network of sensors of different operating modes was considered for a 2D grid based deployment. MOPSO 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.

7. References

[1] G. J. Pottie, "Wireless sensor networks," *Information Theory Workshop* 1998, 139-140.

[2] M. Kodialam, T. Nandagopal, "Characterizing the achievable rates in multihop wireless networks," *Mobicom* 2003.

[3] T. Dam, K. Langendoen, "An adaptive energy-efficient MAC protocol for Wireless Sensor Networks," *Sensys*, 2003

[4] J. Pan, T. Hou, L. Cai, Y. Shi, S. Shen, "Topology control for Wireless Sensor Networks," *Mobicom*, 2003

[5] A. Srinivas, E. Modiano, "Minimum energy disjoint path routing in wireless ad-hoc networks," *Mobicom*, 2003

[6] K. Sundaresan, V. Anantharaman, H. Hsieh, R. Sivakumar, "ATP: a reliable transport protocol for ad-hoc networks," *Mobihoc*, 2003.

[7] W. Heinzelman, "Application-specific protocol architecture for wireless networks," *Ph.D. Thesis*, MIT, 2000.

[8] J. Rabaey, J. Ammer, T. Karalar, S. Li, et al, "Pico-radios for wireless sensor networks: the next challenge in ultra-low power design," *Digest of Technical Papers. ISSCC. IEEE International,* 2002, **2**: 156-445

[9] H. Kim, T. Abdelzaher, W. Kwon, "Minimum-energy asynchronous dissemination to mobile sinks in Wireless Sensor Network," *Sensys* 2003.

[10] R. Min, A. Chandrakasan, "Energy-efficient communication for ad-hoc wireless sensor networks," *Conference Record of the Thirty-Fifth Asilomar Conference on Signals, Systems and Computers*, 2001, **1**: 139-143.

[11] S. Sen, S. Narasimhan, K. Deb, "Sensor network design of linear processes using genetic algorithms", Comput. Chem. Eng. 1998, **22 (3)** :385–390.

[12] S.A. Aldosari, J.M.F. Moura, "Fusion in sensor networks with communication constraints", in: Information Processing in Sensor Networks (IPSN'04), Berkeley, CA, April 2004.

[13] O. Younis, S. Fahmy, "Distributed clustering in ad-hoc sensor networks: a hybrid, energy-efficient approach", in: INFOCOM 2004, Hong Kong,March, 2004.

[14] M. Younis, M. Youssef, K. Arisha, "Energy-aware routing in cluster based sensor networks", in: 10th IEEE/ACM International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS 2002), Fort Worth, TX, October 2002.

[15] S. Bandyopadhyay, E.J. Coyle, "An energy efficient hierarchical clustering algorithm for wireless sensor networks", in: IEEE INFOCOM 2003, San Francisco, CA, April 2003.

[16] Konstantinos P. Ferentinos, Theodore A. Tsiligiridis, "Adaptive design optimization of wireless sensor networks using genetic algorithms", Computer Networks 51 (2007),pp. 1031–1051.

[17] J. Kennedy and R. Eberhart. Swarm Intelligence. Morgan Kaufmann Publishers, California,USA, 2001.

[18] J. Kennedy and R. Mendes. Population structure and particle swarm performance. In Congress on Evolutionary Computation, volume 2, pages 1671-1676, Piscataway, NJ, May 2002. IEEE Sevice Center. pp 849-858. Springer, 2000.

[19] J. Kennedy and R. Eberhart. Particle swarm optimization. In International Conference on Neural Networks, , Piscataway, NJ., 1995. IEEE Sevice Center, pp. 1942-1948.

[20] C. Coello Coello and M. Lechuga. Mopso: A proposal for multiple objective particle swarm optimization. In Congress on Evolutionary Computation,, Piscataway, NJ., 2002. IEEE Service Center, pp.1051-1056.