ENERGY-AWARE NODE PLACEMENT IN WIRELESS SENSOR NETWORK USING ACO

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ABSTRACT

The recent popularity of applications based on wireless sensor networks (WSN) provides a strong motivation for pursuing research in different dimension of WSN. Node placement is an important task in wireless sensor network and is a multi-objective combinatorial problem. A multi-objective ACO (Ant Colony 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, ACO.*

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. 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. A wireless sensor network (WSN) is a computer network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different locations. The development of wireless sensor networks was originally motivated by military applications such as battlefield surveillance. However, wireless sensor networks are now used in many civilian application areas, including environment and habitat monitoring, healthcare applications, home automation, and traffic control.

In addition to one or more sensors, each node in a sensor network is typically equipped with a radio transceiver or other wireless communications device, a small microcontroller, and an energy source, usually a battery. The size a single sensor node can vary from shoebox-sized nodes down to devices the size of grain of dust.[1] The cost of sensor nodes is similarly variable, ranging from hundreds of dollars to a few cents, depending on the size of the sensor network and the complexity required of individual sensor nodes [1]. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and bandwidth [1].

The Wireless Sensor Networks (WSN) is intended for monitoring an environment. The main task of a wireless sensor node is to sense and collect data from a certain domain, process them and transmit it to the sink where the application lies. The main characteristics of a WSN include power consumption constrains for nodes using batteries or energy harvesting, ability to cope with node failures, mobility of nodes, dynamic network topology, communication failures, heterogeneity of nodes, scalability to large scale of deployment, ability to withstand harsh environmental conditions, ease of use, unattended operation. However, ensuring the direct communication between a sensor and the sink may force nodes to emit their messages

with such a high power that their resources could be quickly depleted. Therefore, the collaboration of nodes to ensure that distant nodes communicate with the sink is a requirement. In this way, messages are propagated by intermediate nodes so that a route with multiple links or hops to the sink is established. This paper focuses on these applications, for which it proposes a multi-objective ACO based placement node placement methodology. There are number of reasons that ACO algorithms are a good fit for WSN placement problem.ACO algorithms are decentralized just as WSNs are similarly decentralized. WSNs are more dynamic network, where. nodes can break, run out of energy, have the radio propagation characteristics change. But ACO algorithms have been shown to react quickly to changes in the network.

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 ACO. 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 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. Ant Colony Optimization 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 [10-13], 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. This 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).
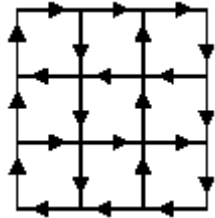

Figure 1. A Grid (Mesh) Based Wireless Sensor Network Layout.

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 [14-16], 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

$$\textbf{\textit{Min}} f(\text{FC, OCE, SOE, SPC}, E) \qquad (1)$$

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

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

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

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.

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

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 $\bar{u} = (u_1, u_2 ...., u_m)$ is said to dominate $\bar{v} = (v_1, v_2 ...., v_m)$ (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, . . .,m}, $u_i \leqslant v_i \land \exists_i \in$ {1, . . ., m} : $u_i < v_i$

A solution α is said to be non-dominated regarding a set $X^l \subseteq X$ if and only if, there is no solution in X^l, 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 ACO Framework

In many real-life optimization problems there are several objectives to optimize. For such multi-objective problems, there is not usually a single best solution but a set of solutions that are superior to others when considering all objectives. This set is called the *Pareto set or non dominated solutions*. This multiplicity of solutions is explained by the fact that objectives are generally conflicting ones. Recently, different researchers have introduced ACO algorithms for multi-objective problems. These algorithms mainly differ with respect to the three following points. Pheromone trails. The quantity of pheromone laying on a component represents the past experience of the colony with respect to choosing this component. When there is only one objective function, this past experience is defined with respect to this objective. However, when there are several objectives, one may consider two different strategies. A first strategy is to consider a single pheromone structure, as proposed in [18,19]. In this case, the quantity of pheromone laid by ants is defined with respect to an aggregation of the different objectives. A second strategy is to consider several pheromone structures, as proposed in [20,21]. In this case, one usually associates a different colony of ants with each different objective, each colony having its own pheromone structure.

In this section, we present m-ACO a generic ACO framework for multi-objective problems developed by Ines Alay et al [22]. m-ACO is parameterized by the number of pheromone structures $\#\tau$ Figure 1 describes the generic framework of m-ACO($\#\tau$). Basically, the algorithm follows the MAX-MIN Ant System scheme [23]. First, pheromone trails are initialized to a given upper bound τ_{max}. Then, at each cycle every ant constructs a solution, and pheromone trails are updated. To prevent premature convergence, pheromone trails are bounded within two given bounds τ_{min} and τ_{max} such that $0 < \tau_{min} < \tau_{max}$. The algorithm stops iterating when a maximum number of cycles have been performed.

Algorithm m-ACO (#τ)

Initial all pheromone trails to τ_{max}

repeat

   for each ant k in 1….. #Ants

    Construct a solution

     for i in 1….#τ

      update the ith pheromone structure trails

       if a trail is lower than τ_{min} then set it to τ_{min}

       if a trail is greater then τ_{max} then set it to τ_{max}

until maximal number of cycles reached

Here #τ is represents the number of objectives.

Algorithm Solution Construction S

  S ← Θ

Cand ← V

While *Cand ≠ Θ* do

Choose $v_i \epsilon Cand$ with probability $p_S(v_i)$

Add v_i at the end of S

Remove from *Cand* vertices that violate constraints

end while

the algorithm used by ants to construct solutions in a construction graph G = (V, E) the definition of which depends on the problem to solve. At each iteration, a vertex of G is chosen within a set of candidate vertices *Cand*; it is added to the solution S and the set of candidate vertices is updated by removing vertices that violate constraints of C. The vertex v_i to be added to the solution S by ants of the colony c is randomly chosen with the probability $p_S^C(v_i)$ defined as follows:

$$p_S^C(v_i) = \frac{[\tau_S^C(v_i)]^\alpha \cdot [\eta_S^C(v_i)]^\beta}{\sum_{v_j \epsilon Cand} [\tau_S^C(v_i)]^\alpha \cdot [\eta_S^C(v_i)]^\beta} \qquad (7)$$

where $\tau_S^C(v_i)$ and $\eta_S^C(v_i)$ respectively are the pheromone and the heuristic factors of the candidate vertex v_i. α and β are two parameters that determine their relative importance. The definition of these two factors depends on the problem to be solved and on the parameter #τ.

The important factors in the above algorithm m-ACO are discussed below:

Pheromone factor: At each step of a solution construction, ants randomly choose an objective r ϵ {1, ...,m} to optimize. The pheromone factor $\tau_S(v_j)$ is defined as the pheromone factor associated with the randomly chosen objective r.

Heuristic factor: The heuristic factor $\eta_S(v_j)$ considered by the single colony is the sum of heuristic information associated with all objectives,

Pheromone update: Once the colony has computed a set of solutions, the m best solutions with respect to the m different objectives are used to reward them pheromone structures. Let S^i be the solution of the colony that minimizes the ith objective f_i for the current cycle, and let S_{best}^i be the solution that minimizes f_i over all solutions built by ants since the beginning of the run (including the current cycle). The quantity of pheromone deposited on a solution component c for the ith pheromone structure is defined by

$$\Delta\tau^i(c) = \begin{cases} 1/(1 + f_i(S^i) - f_i(S_{best}^i)), & \text{if } c \text{ is a component of } S^i \\ 0, & \text{otherwise} \end{cases}$$

$$(9)$$

5. EXPERIMENTAL RESULTS

ACO involves exploration and tuning of a number of problem specific parameters for optimizing its performance, namely $\alpha, \beta, \rho, \#Ants$ and number of cycles(#cycles) etc. The Table-1 summarized the parameter values considered for the experiment.

Table-1: Parameter Values

α	β	ρ	#Ants	#Cycles
1	4	0.01	100	3000

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-3 also shows the variation of the result with respect to the generations of our algorithm (m ACO).
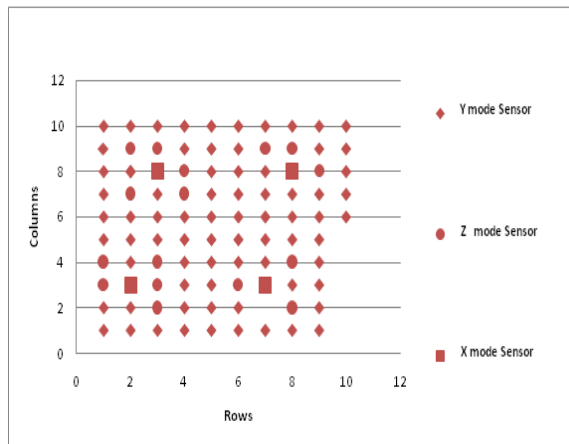
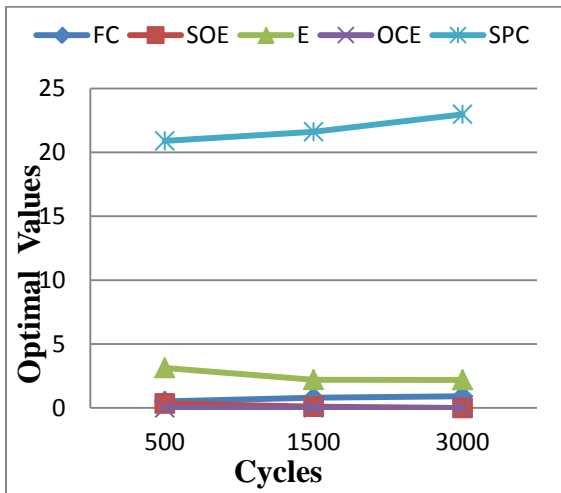*Figure 2: Final Placement Of Nodes Obtained By M-ACO Algorithm*

Figure 3: Performance Of M-Aco Algorithm

6. CONCLUSION

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

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