

# Heuristic Approaches with Probabilistic Management for Node Placement in Wireless Sensor Networks

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**Abstract**— In Wireless Sensor Network (WSN), Device placement is a key factor for determining the coverage, connectivity, cost and lifetime. Managing energy of the sensor nodes is not much easy while comparing mobile Ad-Hoc Networks. But the same approach can be implemented to manage the WSN. Addressing the management of the whole network is omitted and energy scheme where only a subset of nodes is managed is provided for light-weight and efficient management. Relay node placement in heterogeneous WSN are formulated using a generalized node placement optimization problem to minimize the network cost with lifetime constraint, and connectivity. Based on the constraints two scenarios are used. In the first scenario relay nodes are not energy constrained, and in the second scenario all nodes are energy limited. As an optimal solution a two-phase approach is proposed. The placement of the first phase relay nodes (FPRN), which are directly connected to Sensor Nodes (SN), is modeled as a minimum set covering problem. To ensure the relaying of the traffic from the FPRN to the base station, three heuristic schemes are proposed to place the second phase relay nodes (SPRN). Some of the heuristic approaches available are Nearest-To-BS-First algorithm (NTBF), Max-Residual-Capacity-First algorithm (MRCF) and Best-Effort-Relaying algorithm (BER). Our contribution is centered on a distributed self-organizing management algorithm at the application layer. We refine a deployment problem in a practical and fundamental scenario. We model this problem with the minimum set covering problem. Furthermore, a lower bound on the minimum number of SPRN required for connectivity is provided.

**Index Terms**— Cost, connectivity, device placement, facility location problem, lifetime, minimum set covering, movable wireless sensor networks, Energy management.

## I. INTRODUCTION

In the recent past, wireless sensor networks have found their way into a wide variety of applications and systems with vastly varying requirements and characteristics. As a consequence, it is becoming increasingly difficult to discuss typical requirements regarding hardware issues and software support. This is particularly problematic in a multidisciplinary research area such as wireless sensor networks, where close collaboration between users, application domain experts, hardware designers, and software developers is needed to implement efficient

systems. Here we discuss the consequences of this fact with regard to the design space of wireless sensor networks by considering its various dimensions. We justify our view by simulation results with various algorithms for movable sensor nodes.

Depending on the actual needs of the application, the form factor of a single sensor node may vary from the size of a shoebox (e.g., a weather station) to a microscopically small particle (e.g., for military applications where sensor nodes should be almost invisible). Similarly, the cost of a single device may vary from hundreds of Euros (for networks of very few but powerful nodes) to a few cents (for large scale networks made up of very simple nodes). Varying size and cost constraints directly result in corresponding varying limits on the energy available (i.e., size, cost, and energy density of batteries or devices for energy scavenging), as well as on computing, storage and communication resources. Hence, the energy and other resources available on a sensor node may also vary greatly from system to system.

## II. SENSOR AND SYSTEM MODELS

### A. Sensor Model

Sensor placement requires accurate yet computationally feasible sensor detection models. In this paper, first assume that the sensor field is made up of grid points. The granularity of the grid (distance between consecutive grid points) is determined by the accuracy with which the sensor placement is desired. Assume that the probability of detection of a target by a sensor varies exponentially with the distance between the target and the sensor. This model is illustrated in Fig. 1. A target at distance  $d$  from a sensor is detected by that sensor with probability  $e^{-\alpha d}$ .

The parameter  $\alpha$  can be used to model the quality of the sensor and the rate at which its detection probability diminishes with distance [1]. Clearly, the detection probability is 1 if the target location and the sensor location coincide. For every two grid points  $i$  and  $j$  in the sensor field, then associate two probability values: (i)  $p_{ij}$ , which denotes the probability that a target at grid point  $j$  is detected by a sensor at grid point  $i$ ; (ii)  $p_{ji}$ , which

denotes the probability that a target at grid point  $i$  is detected by a sensor at grid point  $j$ . In the absence of obstacles, these values are symmetric, i.e.  $p_{ij} = p_{ji}$ . However, we will show later in this section that these values need not be equal in the presence of obstacles. Note that the choice of a sensor detection model does not limit the applicability of the placement algorithm in any way. The detection model is simply an input parameter to the placement algorithm. Alternative detection models can therefore be considered without requiring a major redesign of the placement algorithm.

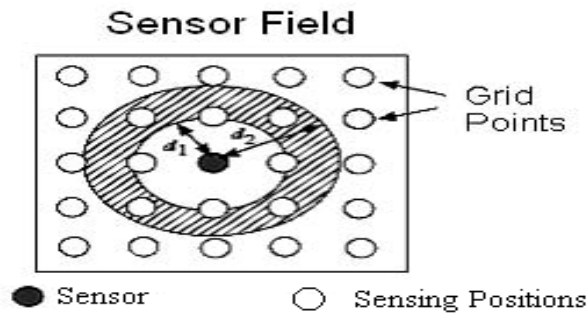


Figure 1. Sensor Model.

A number of sensors, e.g. IR cameras, require a target to lie in their line of sight. Obstacles cause occlusion and render such sensors ineffective for detection. We assume that some knowledge of the terrain is acquired prior to sensor placement, e.g. through satellite imagery. The obstacles are then modeled by altering the detection probabilities for appropriate pairs of grid points.

### B. Network Model and Placement Problems

Depending on the transmission range of RNs, we envision three types of scenarios [2]:

Type I – RNs with adaptive transmission range, where the RNs can adjust their transmission power arbitrarily, so that the transmission from a source RN can reach any destination in the system;

Type II – RNs with fixed transmission range, where the RNs always transmit at a fixed power, thus the transmission from an RN can only reach other RNs that fall in its fixed transmission range; and

Type III – RNs with limited-adaptive transmission range, where the RN can adjust its transmission power within an upper bound.

Note that the energy supply of an RN can be limited or unlimited.

## III. ENERGY MANAGEMENT OF WSN

Radio propagation model is one of the most popular energy modeling scheme available now for sensor networks. A survey on the energy consumption of typical modern sensor nodes illustrates that energy consumption by nodes with two examples,

Rockwell's WINS node and MEDUSA-II, for WINS, turning on the radio receiver increases the power consumption from 383 mW to 752 mW, and using the radio transmitter increases the power consumption to the range of 771 mW to 1081 mW, depending on transmitter

power. For MEDUSA-II, turning on the receiver increases the power consumption from 10 mW to 22 mW, and using the transmitter increases the power consumption to the range of 19 to 27 mW, depending on transmitter power and other factors.

This means that the radio can consume more power than the other parts of the device combined. Thus, when considering battery lifetime, the radio is a key issue. It has been estimated that transmitting one bit of information may consume as much energy as executing more than a thousand processor instructions. Performing significant amounts of data processing and computation in order to decrease the amount of radio communication is thus sensible. It is important to understand that energy resources are a hard constraint, when a node runs out of battery, there is nothing the node can do anymore.

The nodes used in the examples above can adjust their radio transmission power.

We will now consider how much power is needed

### A. Energy Modelling

One important consequence of the physics of radio propagation is that multi-hop routing is often sensible in terms of energy conservation. Multi-hop routing means sending data from one node to another via relay nodes. There are actually two factors which need to be taken into account: the total energy consumption and the energy consumption balance.

Firstly, if transmission costs were a true metric in the sense that the triangle inequality was satisfied, multi-hop routing would have a larger total cost than single-hop routing. However, the squared Euclidean distance does not satisfy the triangle inequality; going from  $a$  to  $c$  via  $b$  may be cheaper than going directly from  $a$  to  $c$ . As we have already seen, energy consumption may be proportional to the radio path loss, which, on the other hand, may be approximately proportional to the squared Euclidean distance. Thus, multi-hop routing may be cheaper in terms of total energy consumption.

Secondly, each node has a limited battery capacity and if one battery is drained, the node will no longer work; no matter how little other batteries have been used. Thus, it may be better to consume a small amount of energy at a large number of nodes than a large amount of energy at one node. Multi-hop routing may help in this respect, too.

### B. Distributed Algorithmic Management Method

The algorithmic method for Network management is based on the spatio-temporal connectivity measure. A network node evaluates its spatio-temporal connectivity with its neighborhood and communicates that information to the other network nodes in order to construct the spatio-temporal connectivity matrix of the wireless sensor network. From this matrix, the node is capable to detect spatio-temporal connected components of the network and to elect its network manager. We assume a minimal cooperation among nodes, where partial control is allowed. If necessary, the cooperation could be stimulated by considering an incentive approach such as [3]. Here in our work we are using a relay node for monitoring process such that a node that can efficiently communicate with all other nodes in a region.

IV. LOCALIZED HEURISTIC PLACEMENT ALGORITHM

For an arbitrary placement of SNs, the solution space for placing RNs is infinitely large, and finding the optimal one is highly non-trivial. A two-phase topology design framework is proposed, wherein each phase decides the number and locations of RNs in a locally optimal fashion. The placement of first phase relay nodes (FPRNs) aims at ensuring the connectivity and lifetime of SNs with a minimum number of RNs. The placement of FPRNs was formulated as a minimum set cover problem, and an optimal recursive algorithm was proposed [4].

Since RNs are energy limited, in general FPRNs connecting to SNs are not able to transmit data to the BS by themselves. Thus, placement of second phase relay nodes (SPRNs) is needed to satisfy lifetime and connectivity requirements of FPRNs. In [4], two essential design principles, namely, the Far→Near and Max→Min (FNMM) principles have been identified.

A. Localized Heuristic Algorithms

- 1) Nearest-To-BS-First algorithm (NTBF)
- 2) Max-Residual-Capacity-First algorithm (MRCF)
- 3) Best-Effort-Relaying algorithm (BER)

V. PERFORMANCE EVALUATION AND SIMULATION

RESULTS

By implementing the different algorithms stated above with the node energy model, we formed the Table I, tabulated using NS-2 simulator.

Here the initial energy of the node is fixed to 10 and for each algorithm we have different amount of energy depletion with respect to time.

So far, the papers we referred were modeled only the fixed sensor nodes. Here we modeled the given approaches with movable sensor nodes and relay nodes and a fixed base station.

Total numbers of nodes used in our model were 30 and 2 base stations; the relay nodes are inserted/modified on the basis of algorithms

From Fig. 2, we observe the following.

- 1) All algorithms require fewer SPRNs as the RN's

TABLE I.  
SHOWS THE ENERGY LEVEL OF THE THREE ALGORITHMS AT TIME INTERVALS

Time (msec)	NTBF	MRCF	BER
0	10	10	10
1.5	9.32322	9.73425	9.82351
2.2	7.85473	7.97475	8.02365
3.7	6.35456	6.73749	7.24231
4.8	5.25101	5.25305	6.84521
5.2	4.85423	5.25305	5.96482
6.4	3.57705	3.57903	5.11124
7.9	2.21252	2.21409	4.16242
8.2	1.87566	2.18981	3.69842
10	0.75179	2.18981	2.94213

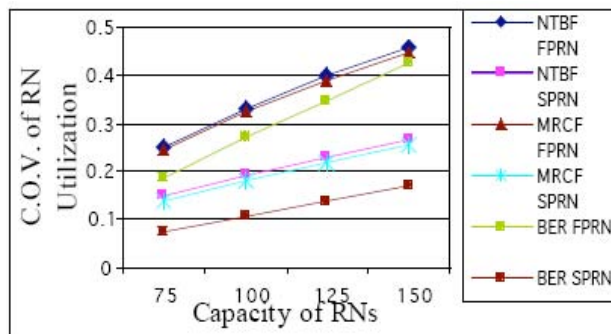


Figure 2. C.O.V. of Node utilization vs. Capacity

capacity increases. This is a desirable property, as nodes with higher capacity should relay more traffic than those with lower capacity.

2) The Best-Effort-Relaying algorithm outperforms the both the Nearest-To-BS-First algorithm and Max-Residual-Capacity-First algorithm in terms of smaller number of SPRNs, higher utilization, and smaller Coefficient of Variance (C.O.V.), though the improvement is moderate.

CONCLUSIONS

Here we have given the common problems of optimal WSN device placement, aiming at minimizing the network cost with constraints on lifetime and connectivity. And hence here the available heuristic approaches were used to construct for movable sensor nodes and their energy utilization were analyzed with each other. In future the Probabilistic management approach which was widely used for ad-hoc networks to monitor the network will be implemented with this network for effective security purpose to keep away the malicious nodes and intruders, is under construction.

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REFERENCES

- [1] H. Abelson et al., "Amorphous Computing," CACM, vol. 43, no. 5, pp. 74–82, Mar. 2000.
- [2] Y. T. Hou, Y. Shi, H. D. Sherali, and S. F. Midkiff, "On energy provisioning and relay node placement for wireless sensor networks," IEEE Trans. Wireless Commun., vol. 4, no. 5, pp. 2579–2590, Sep. 2005.