Simulated Annealing for Solving the Wireless Sensor Networks Deployment Problem

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1 Introduction

As a fundamental issue in Wireless Sensor Networks (WSNs), deployment is a research topic that has attracted much attention in recent years [3]. Indeed, the number and locations of sensors deployed in a Region of Interest (RoI) determine the topology of the network, which will further influence many of its intrinsic properties, such as its coverage, connectivity, cost, and lifetime. In this paper, we propose a polynomial-time deployment algorithm called Simulated Annealing-based sensor Deployment Algorithm (SADA). SADA is able to determine the minimum number of sensors and their locations to meet the desired user detection requirements.

2 Assumptions and problem formalization

We assume that targets/events appear at a set of known locations referred to as targets points defining the set $T \subseteq RoI$. We constrain the deployment of sensors in the set $D \subseteq RoI$ consisting of deployment points in the RoI. We consider the truncated attenuated disk coverage model [5], and we assume that each target point $p \in T$ is associated with a required minimum event detection probability threshold, denoted by R_p. Thus, the objective of our deployment problem is that $\forall p \in T$, the measured event detection probability of that point, M_p, must be greater than or equal to R_p. More formally, the WSNs deployment problem can be formalized as follows.

$$\begin{aligned} &\min \sum_{p \in D} x_p \\ &\text{s.t. } M_p \geq R_p,\ \forall p \in T \\ &\quad\ x_p = 0 \textit{ or } 1,\ \forall p \in D. \end{aligned}$$

This problem is a Binary Integer Programming problem which is NP-complete [1].

3 Our proposal

We devise a deployment strategy, denoted SADA, based on the Simulated Annealing metaheuristic. In SADA, a solution is a candidate sensor placement that specifies the number and locations of sensors. SADA encodes the solutions as strings of bits with length $L = |D|$ from a binary alphabet. Each bit corresponds to a deployment point $p \in D$ and "1" means that a sensor will be deployed at that point. A mapping algorithm between 2D (or even 3D) and 1D space is required. In our implementation, we consider the Hilbert space-filling curve mapping algorithm.

The fitness function combines the deployment cost and the dissatisfaction of the coverage constraints. The goal of this fitness function (Equation 1) is to obtain a sensor placement which satisfies the user detection requirements with the minimum number of sensors.

$$fitness = \sum_{p \in D} x_p + \sum_{p \in T} 1_{\{R_p > M_p\}} \tag{1}$$

$1_{\{R_p > M_p\}}$ is the indicator function that is equal to 1 if $R_p > M_p$, otherwise it is equal to 0.

In SADA, the cooling process is as follow: we decrease the temperature t continuously, and for each value of t, we iterate the algorithm N times. If the value of the fitness function doesn't change during X iterations, we accept a brusque change of the temperature to attempt to leave this local optimum.

4 Obtained results

We propose here to compare our proposal to three state-of-the-art deployment approaches, namely: Min-Miss [2], BDA [4], and GEBDA [3]. Min-Miss is a greedy heuristic, BDA is based on the Tabu search metaheuristic, and GEBDA is a genetic algorithm. Two scenarios were considered: uniform coverage and preferential coverage.

4.1 Evaluation stage 1: Uniform coverage requirement

The algorithms were tested on three uniform coverage scenarios. In scenarios 1, 2, and 3, an event detection probability equal to 0.2, 0.5, and 0.9, respectively, in the whole RoI (20 $\times$ 20) is required. The obtained results are shown in Table 1.

Table 1. Stage 1 simulations results.

Deployment strategy	**Scenario 1 (0.2)**		**Scenario 2 (0.5)**		**Scenario 3 (0.9)**	
	No. of sensors	Satisfaction rate	No. of sensors	Satisfaction rate	No. of sensors	Satisfaction rate
SADA	13	100%	18	100%	49	100%
Min-Miss	20	100%	23	100%	67	100%
GEBDA	10	100%	25	100%	68	100%
BDA	17	94%	28	93%	75	96%

Obtained results show that Min-Miss, GEBDA, and BDA need more sensors than our proposal SADA to achieve the same performance.

4.2 Evaluation stage 2: Preferential coverage requirement

In this scenario, we assume that the requested geographic distribution for required minimum event-detection probability thresholds is generated according to multivariate normal distribution, as done in [3, 4]. The obtained results are shown in Table 2.

Table 2. Stage 2 simulations results.

Deployment strategy	**Number of sensors**	**Satisfaction rate**
SADA	164	100%
Min-Miss	512	100%
GEBDA	186	100%
BDA	253	94%

Obtained results show that SADA algorithm provides better results than other heuristics proposed in the literature.

References

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