# Efficient Mobile Element Deployment in Tactical Wireless Sensor Networks

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## Abstract

Mobility in Wireless Sensor Networks (WSNs) has quickly become a useful research direction for those looking to minimize the energy usage of sensors and thus maximize the lifetimes of networks. To get a better picture of the events occurring, we may want to deploy a set of robots with more capabilities than a simple sensor and more energy. Even though these robots will have a larger battery capacity, we still want to efficiently distribute them within the system in order to minimize response time and distance traveled. We do this by solving a modified dynamic location-allocation problem. The approaches evaluated for deployment are a random deployment, a deployment based on a genetic algorithm, and a deployment based on a partitioning of the WSN. Evaluation of these approaches is conducted through simulation of a real-world application. All three approaches have their merit, although the last two have much more efficient deployments than the random deployment. This shows three possible approaches to deployments of mobile elements within a tactical WSN.

## Background

The location allocation problem, also known as facility localization, is very similar to our problem and has been studied in various aspects throughout the years. It was first proposed in [1] as the optimal distribution of facilities to satisfy the demands of customers at known locations. The original problem considers a fixed set of demand points, with fixed demand, and a fixed set of shipping costs and attempts to find the optimal number of sources, the location, and capacity of each source. Certain theorems were discovered after the initial definition of this problem, including one which reduces the search space for optimal locations if certain criteria are met [2]. From this problem came a multitude of applications that continue to even be studied today. One extension is to increase the number of objectives and attributes in the problem as shown in [3]. This is an interesting problem, but does not quite lend itself to our problem as there are not multiple different objectives we are considering as much as multiple constraints. One other popular route for research is using the location-allocation problem in order to solve the maximal covering problem in WSNs [4].

Similar problems occur when looking at dynamic location-allocation problems. These are setup usually as multiperiod problems, where at each timestep a new distribution of facilities can be considered. With the ability to relocate facilities, the time period must be defined and split into smaller timesteps which allows the facilities to respond better to changes in demand at certain locations. In [5], they consider the cost of moving a facility in their objective function to associate a cost of removing and relocating a facility. The redeployment of ambulances is considered in[6], where the deployed ambulances must be able to reach certain areas within a certain time constraint with a given reliability. The objective is to minimize the number of ambulances deployed at any given time by separating the call distributions by certain time periods (i.e. rush hour, early morning). They, however, do not have a mechanism to adapt to changing call distributions apart from historical information.

## Problem Formulation

Given a set of $N$ sensors and $M$ robots, $\{s_1, s_2, \ldots, s_N\}$ and $\{r_1, r_2, \ldots, r_M\}$ respectively, we want to find an efficient distribution of the robots. The goal is to minimize the response time to any given sensor of the closest robot.

$$\text{Minimize } \sum_n \sum_m d(n,m) x_{nm} \tag{1}$$

subject to

$$\sum_n x_{nm} \le N \ \forall m \in \{1, \ldots, M\} \tag{2}$$

$$\sum_m x_{nm} = 1 \ \forall n \in \{1, \ldots, N\} \tag{3}$$

where

$$x_{nm} = \begin{cases} 1, & \text{if } d(n,m) \text{ is minimum } \forall m \\ 0, & \text{otherwise} \end{cases}$$

$d(n,m)$ = Euclidean distance from sensor $n$ ($s_n$) to robot $m$ ($r_m$)

## Strategies

The first strategy is a random deployment strategy, which is the simplest strategy of the three. We simply deploy each robot to a random location within the field. The positive aspects of this strategy is its speed and simplicity, as well as its ability to be decentralized rather easily. The drawback is of course its inefficient distribution of the mobile elements, which will lead to a degradation in performance metrics such as distance traveled and average response time.

The second strategy is deployment through a genetic algorithm. We take a population of random deployments and calculate each deployments fitness by adding together all of the distances from each robot to every sensor. Slowly a good solution will evolve out of these initial random deployments. The good thing about this strategy is that the deployment will be a much more efficient deployment than the random strategy and in polynomial time. Genetic Algorithms have been shown to result in near-optimal solutions in an efficient amount of time. The problem is this algorithm requires global information and thus cannot be easily distributed.

The third strategy we used is a partitioning strategy, where we partition the sensor nodes into a set of partitions such that each robot has one partition to serve. This strategy also requires global information and thus will not be easily distributed, but is an extremely efficient algorithm (even more so than the genetic algorithm). We create these partitions by creating a minimum spanning tree and then removing the largest weighted edges which create partitions with the minimum of the maximum edges in a partition.

## Results

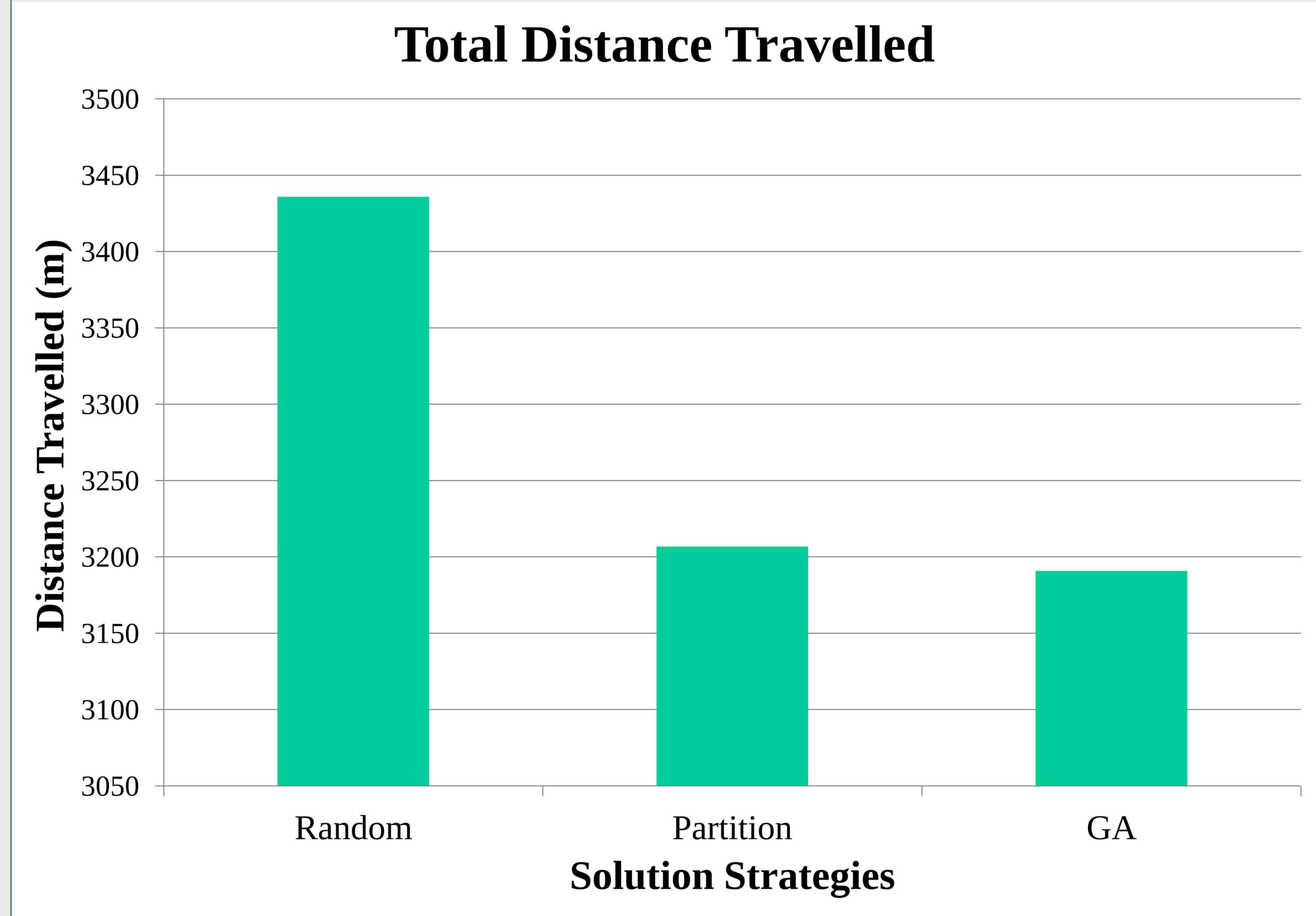


Figure 1. The total distance travelled on average for all of the robots under each deployment strategy. The graph partitioning and genetic algorithm strategies improve by approximately 6% over the random deployment under our simulations.

## Conclusions

- ➢ Mobile elements can enhance WSNs especially for battlefield or environmental monitoring.
- ➢ We study the efficiency of three deployment strategies.
- ➢ We show that a genetic algorithm performs the best, but not significantly better than a graph partitioning strategy.
- ➢ The random deployment is the least efficient even though it is the easiest to convert to a distributed strategy.

## References

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