ACO FOR OPTIMAL SENSOR LAYOUT

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Abstract: Metaheuristic methods have frequently been applied to telecommunication problems in the last years. One of these problems is Wireless Sensor Network (WSN) layout, which is an NP-hard optimization problem. The sensors sent their sensing results to a special station called the High Energy Communication Node (HECN). The sensing area of the WSN is the union of the individual sensing areas of the nodes. When deploying a WSN, the major objective is to achieve full coverage of the terrain (sensor field). Another objectives are also to use a minimum number of sensor nodes and to keep the connectivity of the network. In this paper we address a WSN layout problem in which full coverage and connectivity are treated as constraints, while objective function is the number of the sensors. To solve it we propose Ant Colony Optimization (ACO) algorithm. The terrain is modeled with 500×500 points grid and both sensing radius and communication radius are set to 30. We compare our results with existing evolutionary algorithms.

1 INTRODUCTION

Telecommunications are an important symbol of our present information society. Telecommunication is a field in which many open research lines are challenging the research community. Nowadays, the trend in telecommunication networks is having highly decentralized, multi-node networks. From small, geographically close, size-limited local area networks the evolution has led to the huge worldwide Internet. This same path is followed by wireless communications, where we can already see wireless telephony reaching virtually any city in the world. In this context WSN have recently become a hot topic in research. A WSN allows an administrator to automatically and remotely monitor almost any phenomenon with a precision unseen to the date. The use of multiple small cooperative devices yields a brand new horizon of possibilities yet offers a great amount of new problems to be solved. WSN have so far been employed in military activities such es reconnaissance, surveillance, and target acquisition (Deb et al., 2000), environmental activities such as forest fire prevention, geophysical activities such as volcano eruptions study (Werner-Allen et al., 2006), biomedical purposes such as health data monitoring (Yuce et al., 2007) or civil engineering (Paek et al., 2004).

When deploying a WSN, the positioning of the sensor nodes becomes one of the major concerns. The coverage obtained with the network and the economic cost of the network depend directly of it. Since many WSN can have large numbers of nodes, the task of selecting the geographical positions of the nodes for an optimally designed network can be very complex. Therefore, metaheuristics seem an interesting option to solve this problem.

In this paper we propose a solution method for the WSN layout problem using ACO. We focus on minimizing the number of nodes, while the full coverage of the network and connectivity are considered as constraints.

Jourdan (Jourdan, 2000) solved an instance of WSN layout using a multiobjective genetic algorithm. In there formulation a fixed number of sensors had to be placed in order to maximize the coverage. In (Molina et al., 2008) are proposed several evolutionary algorithms to solve the problem.

For solving the WSN layout problem, the coverage has to satisfied some restrictions and the biggest possible coverage will be preferred: the number of sensor nodes should be kept low for economical reasons and the network needs to be connected.

The rest of the paper is organized as follows. In Section 2 the WSN is described and the layout problem is formulated. Section 3 presents the ACO algorithm. In Section 4 the experimental results obtained are shown. Finally, several conclusions are drown in Section 5.

2 PROBLEM FORMULATION

A Wireless Sensor Network is a wireless network formed by sensor nodes. Each sensor node sens an area around itself called its sensing area. A parameter called sensing radius determines the sensitivity range of the sensor node and thus the sensing area. The nodes communicate among themselves using wireless communication links. These links are determined by a communication radius. A special node in the WSN called High Energy Communication Node (HECN) is responsible for external access to the network. Therefore, every sensor node in the network must have communication with the HECN. Since the communication radius is often much smaller than the network size, direct links are not possible for peripheral nodes. A multi-hop communication path is then established for those nodes that do not have the HECN within their communication range.

The WSN layout problem amounts to deciding the geographical position of the sensor nodes that form a WSN. In our formulation, a non-fixed amount of sensor nodes has to be placed in a terrain providing full sensitivity coverage. The positions of the nodes have to be chosen in a way that minimizes the total number of sensor nodes, while keeps the connectivity of the network.

The WSN operates by rounds: In a round, every node collects the data from its measurements and sends it to the HECN. Every node transmits the information packets to the neighbor that is closest to the HECN, or the HECN itself if it is within the communication range. The sensing area of the WSN is the union of the individual areas of all nodes. The designer wants the network to cover the complete sensing area. On the other hand, the number of sensor nodes must be kept as low as possible, since using many nodes represents a high cost of the network, possibly influences of the environment and also provokes a probability of detection (when stealth monitoring is designed). The objective of this problem is to minimize the number of sensors deployed while the area is fully covered and connected.

3 ANT COLONY OPTIMIZATION FRAMEWORK

Many of the existing solutions to this problem come from the field of Evolutionary Computation (Alba and Molina, 2008; Molina et al., 2008). After analyzing them, we noticed that these interesting developments are quite similar to ACO algorithms. The relation between ACO algorithms and evolutionary algorithms provides a structural way of handling constrained problems. They have in common the use of a probabilistic mechanisms for recombination of individuals. This leads to algorithms where the population statistics are kept in a probability vector. In each iteration of the algorithm, these probabilities are used to generate new solutions. The new solutions are then used to adapt the probability vector.

Real ants foraging for food lay down quantities of pheromone (chemical cues) marking the path that they follow. An isolated ant moves essentially guided by an heuristic function and an ant encountering a previously laid pheromone will detect and decide to follow it with high probability thus taking more informed actions based on the experience of previous ants (and thereby reinforce it with a further quantity of pheromone). The repetition of the above mechanism represents the auto-catalytic behavior of real ant colony where the more the ants follow a trail, the more attractive that trail becomes.

The ACO algorithm uses a colony of artificial ants that behave as cooperative agents in a mathematic space were they are allowed to search and reinforce pathways (solutions) in order to find the optimal ones. The problem is represented by graph and the ants walk on the graph to construct solutions. The solution is represented by a path in the graph. After initialization of the pheromone trails, ants construct feasible solutions, starting from random nodes, then the pheromone trails are updated. At each step ants compute a set of feasible moves and select the best one (according to some probabilistic rules based on a heuristic guided function) to carry out the rest of the tour. The structure of ACO algorithm is shown in Figure 1. The transition probability p_{ij}, to chose the node j when the current node is i, is based on the heuristic information η_{ij} and on the pheromone trail level τ_{ij} of the move, where $i, j = 1, \ldots, n$.

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{k \in allowed} \tau_{ik}^{\alpha}\eta_{ik}^{\beta}} \qquad (1)$$

The higher value of the pheromone and the heuristic information, the more profitable is to select this move. In the beginning, the initial pheromone level is set to a small positive constant value τ_0 and then ants update this value after completing the construction stage (Bonabeau et al., 1999). ACO algorithms adopt different criteria to update the pheromone level.

Ant Colony Optimization.

Initialize number of ants;
Initialize the ACO parameters;
while not end-condition **do**
  for k=0 **to** number of ants
    ant k starts from a random node;
    while solution is not constructed **do**
      ant k selects higher probability node;
    end while
  end for
  Local search procedure;
  Update-pheromone-trails;
end while

Figure 1: Pseudocode for ACO.

In our implementation we use MAX-MIN Ant System (MMAS) (Stutzle and Hoos, 2000), which is one of the more popular ant approaches. The main feature of MMAS is using a fixed upper bound τ_{max} and a lower bound τ_{min} of the pheromone trails. Thus the accumulation of big amounts of pheromone by part of the possible movements and repetition of same solutions is partially prevented. The main features of MMAS are:

- Strong exploration to the space search of the best found solution. This can be achieved by only allowing one single ant to add pheromone after each iteration (the best one).
- Wide exploration of the best solution. After the first iteration, the pheromone trails are reinitialized to τ_{max}. In the next iteration, only the movements that belong to the best solution receive a pheromone, while the rest pheromone values are only evaporated.

The aim of using only one solution is to make the solution components, which frequently occur in the best found solutions, get a larger reinforcement. The pheromone trail update rule is given by:

$$\tau_{ij} \leftarrow \rho\tau_{ij} + \Delta\tau_{ij}, \tag{2}$$

$$\Delta\tau_{ij} = \begin{cases} 1/C(V_{best}) & \text{if } (i,j) \in \text{best solution} \\ 0 & \text{otherwise} \end{cases},$$

Where V_{best} is the iteration best solution and $i, j = 1, \dots, n$, $\rho \in [0,1]$ models evaporation in the nature. To avoid stagnation of the search, the range of possible pheromone values on each movement is limited to an interval $[\tau_{min}, \tau_{max}]$. τ_{max} is an asymptotic maximum of τ_{ij} and $\tau_{max} = 1/(1-\rho)C(V^*)$, while $\tau_{min} = 0.087\tau_{max}$. Where V^* is the optimal solution, but it is unknown, therefore we use V_{best} instead of V^*.

The WSN layout problem is represented by graph as follows: the terrain is modeled by grid $G = \{g_{ij}\}_{N\times M}$; the pheromone is related with location sites $Ph = \{ph_{ij}\}_{N\times M}$, the initial pheromone can be a small value, for example $1/n_{ants}$. The central point, where the HECN is located, is included in the solutions like first point (zero point). Every ant starts to create the rest of the solution from a random node which communicates with central one, thus the different start of every ant in every iteration is guaranteed. The ant chooses the next position by the ACO probabilistic rule (equation 1). It choses the point having the higher probability.

The used heuristic information is

$$\eta_{ij}(t) = s_{ij} l_{ij}(1 - b_{ij}), \tag{3}$$

where s_{ij} is the number of points which the new sensor will cover, and

$$l_{ij} = \begin{cases} 1 & \text{if communication exists} \\ 0 & \text{if there is not communication} \end{cases} \tag{4}$$

b is the solution matrix and the matrix element $b_{ij} = 1$ when there is sensor on this position otherwise $b_{ij} = 0$. With s_{ij} we try to locally increase the covered points, with l_{ij} we guarantee that all sensors will be connected; with rule $(1 - b_{ij})$ we guarantee that the position is not chosen yet. When $p_{ij} = 0$ for all values of i and j the search stops. Thus, the construction of the solution stops if no more free positions, or all points are covered or new communication is impossible.

4 EXPERIMENTAL RESULTS

In this work we solve an WSN problem instance where a terrain of 500×500 meters has to be covered using nodes with coverage and communication radii equal to 30 meters. An example of solution that achieves full coverage of the region is a square grid formed by the sensors separated by 30 meters.Thus, the number of sensors is 289 including the HECN. This result is used for comparison. We apply MAX-MIN ant algorithm with the following parameters:

$\alpha = \beta = 1$, $\rho = 0.5$, the number of used ants is 3 and the maximum number of iterations is 10. In Table 1 are reported best found results (minimal number of sensors) achieved by several metaheuristic methods. We compare our ACO algorithm results with results obtained by the evolutionary algorithms in (Molina et al., 2008) and the symmetric solution.

Table 1: Experimental results.

Algorithm	sensors
Symmetric	289
MOEA	260
NSGA-II	262
$IBEA_{HD}$	265
ACO	232

We observe that the ACO algorithm outperforms the symmetric and the evolutionary algorithms. We perform 30 independent runs of the ACO algorithm and the achieved numbers of sensors are in the interval $[232, 247]$. The ACO algorithm outperforms the evolutionary algorithms, because the worst found number of sensors by ACO is less than the best found by the evolutionary algorithms.

The ACO solution is represented on Figure 2. With black dots are represented the sensors and with the rings are represented the coverage and connectivity area by a sensor. We can observe there the coverage of the region, positioning of the sensors and connectivity of the network.

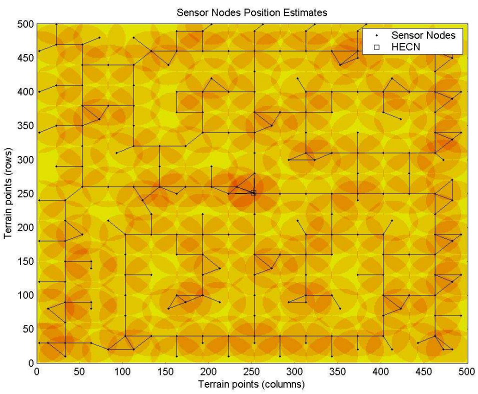

Figure 2: ACO solution.

5 CONCLUSIONS

We have defined a coverage problem for wireless sensor networks with its connectivity constraint. A very large instance consisting of 500×500 square meter area has to be covered using sensors nodes whose sensing and communication radii are 30 meters. We propose ACO algorithm to solve this problem and we compare it with existing evolutionary algorithms. The ACO algorithm outperforms the evolutionary algorithms. The worst found solution by ACO is better than the best found solution by evolutionary algorithms. In a future work we plane to redefine the problem so as to be able to solve more complex WSN layout problem with regions in a sensing area where to put sensors is forbidden and network problem with obstacles. Other interesting direction is to study the robustness of the solutions, to minimize the disturbance in the network when single sensor fail and thus to avid segmentation of the network.

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