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MULTI-OBJECTIVE ANT ALGORITHM FOR WIRELESS SENSOR NETWORK POSITIONING

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Abstract

It is impossible to imagine our modern life without telecommunications. Wireless networks are a part of telecommunications. Wireless sensor networks (WSN) consist of spatially distributed sensors, which communicate in wireless way. This network monitors physical or environmental conditions. The objective is the full coverage of the monitoring region and less energy consumption of the network. The most appropriate approach to solve the problem is metaheuristics. In this paper the full coverage of the area is treated as a constrain. The objectives which are optimized are a minimal number of sensors and energy (lifetime) of the network. We apply multi-objective Ant Colony Optimization to solve this important telecommunication problem. We chose MAX–MIN Ant System approach, because it is proven to converge to the global optima [3].
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1. Introduction. A sensor is a device which can collect and transmit data. First, the wireless sensor networks were used by militarists for reconnaissance and surveillance [2], but after that starts civil use. Examples for possible applications are forest fire prevention, volcano eruption study [15], health data monitoring [18],

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civil engineering [11]. Sensor networks depend on deployment of sensors over a physical location to fulfill a desired task. The sensors can sense temperature, voltage, or chemical substances. A WSN allows automatically monitoring of almost any phenomenon.

A WSN node contains several components including the radio, battery, microcontroller, analogue circuit, and sensor interface. In battery-powered systems, higher data rates and more frequent radio use consume more power. There are several open issues for sensor networks such as signal processing [12], deployment [17], operating cost, localization and location estimation.

One of the nodes of the WSN has a special role. It is a High Energy Communication Node (HECN) which collects data from the whole network and transmits them to the main computer to be proceeded. The sensors transmit their data to HECN, either directly or via hops, using nearby sensors as communication relays. 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 depends directly on it. WSN can have large numbers of nodes, and therefore the task of selecting the geographical positions of the nodes for an optimally designed network can be very complex. Thus it is unpractical to solve the problem with traditional numerical methods. In this case, most appropriate is to apply some metaheuristic method.

We propose multi-objective ant algorithm which solves the WSN positioning problem. The two objectives are minimizing the energy depletion of the nodes in the network and minimizing the number of the nodes. The full coverage of the network and connectivity are considered as constraints. It is a NP-hard multi-objective problem.

Jourdan [7] solved an instance of WSN layout using a multi-objective genetic algorithm. In the formulation a fixed number of sensors had to be placed in order to maximize the coverage. In some applications most important is the network energy. In [6], it is proposed ACO algorithm and in [16] is proposed evolutionary algorithm for this variant of the problem. In [4] is proposed ACO algorithm taking into account only the number of the sensors and in [13] the problem is converted to mono-objective. In [9] are proposed several evolutionary algorithms to solve the problem. In [8] is proposed genetic algorithm which achieves similar solutions as the algorithms in [9], but it is tested on small test problems.

The network needs to be connected and the number of the sensors to be as less as possible. The life time of the network depends of the energy, therefore the energy consumption has to be minimal.

The paper is organized as follows. In Section 2 the multi-objective optimization is described. In Section 3 the WSN is introduced and the positioning problem is formulated. Section 4 presents the ACO algorithm. In Section 5 we show the experimental results. The conclusion is in Section 6.

2. Multi-objective optimization. Multi-objective optimization (MOP) has his roots in the nineteenth century in the work of Edgeworth and Pareto in economics [10]. The optimal solution for MOP is not a single solution as for mono-objective optimization problems, but a set of solutions defined as Pareto optimal solutions. A solution is Pareto optimal if it is not possible to improve a given objective without deteriorating at least another objective. The main goal of the resolution of a multi-objective problem is to obtain the Pareto optimal set and consequently the Pareto front. One solution dominates another if minimum one of its components is better than the same component of other solutions and other components are not worse. The Pareto front is the set of nondominated solutions. When metaheuristics are applied, the goal becomes to obtain solutions close to the Pareto front.

3. Problem formulation. Each sensor node senses an area around itself. The sensing radius determines the sensitivity range of the sensor node. The nodes communicate among themselves using wireless communication links, determined by a communication radius. The 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.

A non-fixed amount of sensor nodes has to be placed in a terrain providing full coverage. The objectives are to construct the network with minimal number of sensors, which is cheapest for construction and with minimal energy, which is cheapest for exploitation, while keeps the connectivity of the network. When the sensor transmits data it uses energy from battery. Every sensor transmits his data and the data coming from sensors which are fare from the HECN. Thus the quantity of the transmitted data defines the energy. The node with highest energy defines the energy of the network.

4. Multi-objective ACO for WSN positioning. We apply ant colony optimization to solve the problem. The idea for ant algorithm comes from real ant behaviours. When walk they put on the ground chemical substance called pheromone. The ants smell the pheromone and follow the path with a stronger pheromone concentration. Thus they find shorter path between the nest and the food.

The ACO algorithm uses a colony of artificial ants that behave as cooperative agents. With the help of the pheromone they try to construct better solutions and to find the optimal ones. The problem is represented by graph and the solution is represented by a path in the graph or by tree in the graph. First, we initialize the pheromone. Ants start from random nodes and construct feasible solutions. When all ants construct their solution we update the pheromone. Ants compute a set of feasible moves and select the best one, according transition probability.

The transition probability p_{ij}, to choose the node j when the current node is i, is based on the heuristic information η_{ij} and on the pheromone level τ_{ij} of the move

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum\limits_{k\in\{\text{allowed}\}} \tau_{ik}^{\alpha}\eta_{ik}^{\beta}}, \quad i, j = 1, \ldots, n. \tag{1}$$

The ant selects the move with highest probability. The initial pheromone is set to a small positive value τ_0 and then ants update this value after completing the construction stage [1,5]. The pheromone corresponds to the global memory of the ants, their experience to solve the problem. The heuristic information is a priori knowledge for the problem. In our implementation we use MAX–MIN Ant System (MMAS) [3], which is one of the most successful ant's approach. The main feature of MMAS is using a fixed upper bound $\tau_{\max}$ and a lower bound $\tau_{\min}$ of the pheromone. Thus the accumulation of big amounts of pheromone by part of the possible movements and repetition of same solutions is partially prevented. In our case the graph of the problem is represented by square grid. The ants will deposit their pheromone on the nodes of the grid. We will deposit the sensors on the nodes of the grid. The solution is represented by tree starting by the high energy communication node. An ant starts to create the rest of the solution from a random node which communicates with HECN. Using transition probability (1), the ant chooses the next node to go on. If there is more than one node with same probability, the ant chooses one of them randomly. Construction of the heuristic information is a crucial point in ant algorithms. Our heuristic information is a product of three values

$$\eta_{ij}(t) = s_{ij} l_{ij} (1 - b_{ij}), \tag{2}$$

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

$$l_{ij} = \begin{cases} 1 & \text{if communication exists;} \\ 0 & \text{if there is not communication,} \end{cases} \tag{3}$$

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 increase the points covered by one sensor and thus to decrease the number of sensors we need. With l_{ij} we guarantee that all sensors will be connected. The search stops when $p_{ij} = 0$ for all values of i and j.

The pheromone trail update rule is given by

$$\tau_{ij} \leftarrow \rho\tau_{ij} + \Delta\tau_{ij}, \tag{4}$$

$$\Delta\tau_{ij} = \begin{cases} 1/F(k) & \text{if } (i, j) \in \{\text{nondominated solutions constructed by ant } k\}, \\ 0 & \text{otherwise.} \end{cases}$$

We decrease the pheromone with a parameter $\rho \in [0, 1]$. This parameter models evaporation in the nature and decreases the influence of old information in a search process. After that we add the new pheromone which is proportional to the value of the fitness function. If the pheromone of some node becomes less than the lower bound of the pheromone we put it to be equal to the lower bound and thus we prevent the pheromone of some nodes to become very low close to 0 and to be undesirable. It is a kind of diversification of the search. F is the fitness function. The aim is to add more pheromone on nondominated solutions and thus to force the ants to search around them for new nondominated solutions. The fitness function we constructed is as follows:

$$F(k) = \frac{f_1(k)}{\max\limits_i f_1(i)} + \frac{f_2(k)}{\max\limits_i f_2(i)}, \tag{5}$$

where $f_1(k)$ is the number of the sensors achieved by the k-th ant and $f_2(k)$ is the energy of the solution of the k-th ant. We normalize the values of two objective functions with their maximal achieved values from the first iteration. In our previous work [13] we solve the problem like mono-objective and the current fitness function is the objective function.

5. Experimental results. We have created a software which realizes our ant algorithm. Our software can solve any rectangular area, the communication and the coverage radius can be different and can have any positive value. The HECN can be fixed in any point in the area. The programme is written in C language and the tests are run on computer with 2.8 GHz Intel Pentium processor. In our tests we use an example where the area is square and consists of 500 points in every side. The coverage and communication radii cover 30 points. The HECN is fixed in the centre of the area. An example of solution that achieves full coverage of the region is a square grid formed by the sensors separated by 30 points. Starting at the HECN, 250 points have to be covered to each side of the terrain, requiring 8 sensors. Therefore the grid has 17 $(8+8+1)$ rows and 17 columns, or 289 sensors including the HECN. In this symmetrical configuration there are four nodes directly connected to the HECN, so the complete traffic of the network – 288 messages per round – is evenly divided among them. This results in the most loaded nodes having a load of 72 messages, or the solution is $(288, 72)$.

After several runs of the algorithm we specify the most appropriate values of its parameters. We apply MAX–MIN ant algorithm with the following parameters: $\alpha = \beta = 1$, $\rho = 0.5$, the number of used ants is set to be 4 and the maximum number of iterations is set to be 8. Best found results (with respect to the sensors and with respect to the energy) achieved by several metaheuristic methods are reported in Table 1. We compare our multi-objective ACO algorithm results with results obtained by the evolutionary algorithms in [9], the mono-objective ACO algorithm from our previous work [13] and the symmetric solution.

Table 1

Experimental results

Algorithm	Symmetric	MOEA	NSGA-II	IBEA$_{HD}$	ACO-mono	ACO-multi
min sens	$(288, 72)$	$(260, 123)$	$(262, 83)$	$(265, 83)$	$(227, 60)$	$(226, 57)$
min ener	$(288, 72)$	$(291, 36)$	$(277, 41)$	$(275, 41)$	$(239, 50)$	$(239, 50)$

We perform 30 independent runs of the ACO-multi algorithm and the achieved numbers of sensors are in the interval $[226, 247]$. Thus the worst number of sensors achieved by ACO-multi algorithm is less than the best number of sensors achieved by other mentioned algorithms. The nondominated solutions achieved by our ACO algorithm are $\{(239, 50.4)$, $(238, 53.2)$, $(237, 55.5)$, $(234, 56.6)$, $(226, 57)\}$. All nondominated ACO-multi solutions dominate the symmetric solution. Let us compare achieved solutions with minimal number of sensors. The solutions achieved by mentioned evolutionary algorithms have very high energy, more then symmetric solution. Thus they are not good solutions. The ACO solution with minimal number of sensors dominates other solutions with minimal number of sensors and symmetric solution. Thus it is a good solution. Let us compare solutions with minimal energy achieved by mentioned algorithms. MOEA algorithm achieves solution with very small value for energy, but too many sensors, more than symmetric solution, thus it is not good solution. Other two evolutionary algorithms achieve solutions with less energy than symmetric and a little bit less number of sensors. Thus they are not bad solutions. The ACO solution dominates the symmetric one. Its energy is a little bit more than the evolutionary algorithms, but the number of sensors is much less. We can conclude that our ACO algorithm achieves very encouraging solutions. Solving the problem like multi-objective, we receive better solutions than converting it to mono-objective [13].

We also use the Hyper volume [19] as a quality indicator of achieved solutions. Mathematically, for each solution a hypercube is constructed with a reference point W and the solution as the diagonal corners of the hypercube. The reference point can be found simply by constructing a vector of worst objective function values. Thereafter, a union of all hyper cubes is found and its hyper volume (IHV) is calculated. Algorithms with larger IHV values are desirable.

Table 2 shows the mean hyper volume of the fronts obtained by different algorithms. In multi-objective optimization there is no unique manner to present the data obtained from the executions. We employ the hyper volume metric in order to measure the solutions obtained by different algorithms. We observe that according the hyper volume the ACO algorithm obtains much better results then other algorithms. The three genetic algorithms obtain statistically similar results. The minimal hyper volume obtained by ACO algorithm is similar to the maximal

Table 2

Solution hyper volume

Algorithm	Mean hyper volume	Max hyper volume	Min hyper volume
MOEA	0.7388	0.7847	–
NSGA-II	0.7306	0.7868	–
IBEA_{HD}	0.7280	0.7704	–
ACO-multi	0.9440	0.9900	0.7769

hyper volume attained by others. Thus according hyper volume criterion our ACO algorithm performs better than the other three algorithms.

6. Conclusion. In this paper a multi-objective ACO algorithm is proposed to solve Wireless Sensor Network layout problem. The problem consists in providing the number and locations of the sensor nodes that form a WSN with full coverage of the sensing field and minimal number of sensors and energy. We compare achieved results with the best found results for this problem in the literature. We show that our algorithm performs better than others.

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