Multi-objective ACO Algorithm for WSN Layout: InterCriteria Analisys

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Abstract. One of the key objectives during wireless sensor networks deployment is full coverage of the monitoring region with a minimal number of sensors and minimized energy consumption of the network. In this paper we apply multi-objective Ant Colony Optimization (ACO) to solve this hard, from the computational point of view telecommunication problem. The number of ants is one of the key algorithm parameters in the ACO and it is important to find the optimal number of ants needed to achieve good solutions with minimal computational resources. The InterCriteria Analisys is applied in order to study the influence of ants number on the algorithm performance.

1 Introduction

Initial deployments of wireless sensor networks (WSN) were completed by the military, for reconnaissance and surveillance [1]. Examples of other possible applications of WSN's are: forest fire prevention, volcano eruption study [8], health data monitoring [9], civil engineering [7] and others.

The energy for collecting data and its transmission comes from the battery of a node. One of the WSN nodes has special role. It is a High Energy Communication Node (HECN), which collects data from across the network and transmits it to the "main computer" to be processed. The sensors transmit their data to the HECN, either directly or via hops, using closest sensors as communication relays. The WSN can have large numbers of nodes and the problem can be very complex. Thus, one of the best choice is to apply some metaheuristic method.

The problem of designing a WSN is multi-objective, with two objective functions. These are (1) minimize the energy consumption of the nodes in the network, and (2) minimize the number of nodes. The full coverage of the network and connectivity are considered as constraints. In our work we propose a multi-objective ant colony optimization (ACO).

In the past, [15] solved an instance of the WSN layout using a multi-objective genetic algorithm. In their formulation, a fixed number of sensors had to be

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placed in order to maximize the coverage. However, in some applications the most important is the network energy. In this context, in [4] an ACO algorithm was proposed, but it is applicable to a special case when the sensors are antennas and the work concerns only energy minimization. In [20] an evolutionary algorithm was applied to this variant of the problem. In [6] several evolutionary algorithms to solve the problem were proposed. Finally, in [5] a genetic algorithm, which achieves similar solutions as the algorithms in [6] was studied, but tested only on small test problems.

In this paper we study the influence of the number of ants to the algorithm performance and quality of the achieved solutions. The computational resources, which the algorithm needs, are not negligible. The computational resources depends on the size of the solved problem and on the number of ants. Our aim in this work is to find a minimal number of ants which allow the algorithm to find good solution. Moreover, the recently proposed approach InterCriteria Analisys (ICrA) is applied for further investigation of the influence of the ants number on ACO algorithm.

ICrA, proposed by [13], is a recently developed approach for evaluation of multiple objects against multiple criteria and thus discovering existing correlations between the criteria themselves. It is based on the apparatus of the index matrices (IMs) [10], and the intuitionistic fuzzy sets [11] and can be applied to decision making in different areas of knowledge [16–19].

2 Theoretical Background

2.1 Multi-objective ACO for WSN Layout

We apply multi-objective ACO to solve the WSN problem. The ACO algorithm uses a colony of artificial ants that behave as cooperating agents. With the help of the pheromone and the heuristic information they try to construct better solutions and to find the optimal ones. The pheromone corresponds to the global memory of the ants and the heuristic information is a some preliminary knowledge of the problem. The problem is represented by a graph and the solution is represented by a path in the graph or by tree in the graph. Ants start from random nodes and construct feasible solutions. When all ants construct their solution the pheromone is updated. The new, added, pheromone depends to the quality of the solution. The elements of the graph, which belong to better solutions will receive more pheromone and will be more desirable in the next iteration.

In our implementation, we use the MAX-MIN Ant System (MMAS) which is one of the most successful ant approaches originally presented in [2].

In our case, the graph of the problem is represented by a square grid. The nodes of the graph are enumerated. The ants will deposit their pheromone on the nodes of the grid. We will deposit the sensors on the nodes of the grid too. The solution is represented by tree. An ant starts to create a solution starting from random node, which communicates with the HECN. Construction of the heuristic information is a crucial point in the ant algorithms. Our heuristic information is a product of three values (Eq. 1).

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

where s_{ij} is the number of the new points (nodes of the graph) which the new sensor will cover, and which are not covered by other sensors, and

$$l_{ij} = \begin{cases} 1 \text{ if communication exists}\,; \\ 0 \text{ if there is not communication}\,. \end{cases} \tag{2}$$

Here, b_{ij} 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 number of 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. With b_{ij} we guarantee that maximum one sensor will be mapped on the same point. The search stops when transition probability $p_{ij} = 0$ for all values of i and j. It means that there are no more free positions, or that all area is fully covered.

At the end of every iteration the quantity of the pheromone is updated. The pheromone trail update rule is given by:

$$\tau_{ij} \leftarrow \rho \tau_{ij} + \Delta\tau_{ij}, \tag{3}$$

$$\Delta\tau_{ij} = \begin{cases} 1/F(k) \text{ if } \ (i,j) \in \{\text{non-dominated solution constructed by ant } k\}, \\ 0 \qquad\quad \text{otherwise}\,. \end{cases}$$

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 on the search process. After that, we add the new pheromone, which is proportional to the value of the fitness function. The fitness function is constructed as follows:

$$F(k) = \frac{f_1(k)}{\max_i f_1(i)} + \frac{f_2(k)}{\max_i f_2(i)} \tag{4}$$

Where $f_1(k)$ is the number of sensors proposed by the k-th ant and $f_2(k)$ is the energy of the solution of the k-th ant. These are also the objective functions of the WSN layout problem. We normalize the values of two objective functions with their maximal achieved values from the first iteration.

2.2 InterCriteria Analysis

InterCriteria analysis, based on the apparatuses of Index Matrices (IM) [10] and Intuitionistic Fuzzy Sets (IFS) [12], is given in details in [13].

In order to find the agreement between two criteria, the vectors of all internal comparisons for each criterion are constructed, which elements fulfill one of the three relations R, $\overline{R}$ and $\tilde{R}$. The nature of the relations is chosen such that for a fixed criterion C and any ordered pair $\langle x, y\rangle \in C^*(O)$:

$$\langle x, y\rangle \in R \Leftrightarrow \langle y, x\rangle \in \overline{R}, \langle x, y\rangle \in \tilde{R} \Leftrightarrow \langle x, y\rangle \notin (R \cup \overline{R}), R \cup \overline{R} \cup \tilde{R} = C^*(O).$$

When comparing two criteria the degree of "agreement" ($\mu_{C,C'}$) is usually determined as the number of matching components of the respective vectors. The degree of "disagreement" ($\nu_{C,C'}$) is usually the number of components of opposing signs in the two vectors. From the way of computation it is obvious that $\mu_{C,C'} = \mu_{C',C}$ and $\nu_{C,C'} = \nu_{C',C}$. Moreover, $\langle \mu_{C,C'}, \nu_{C,C'}\rangle$ is an Intuitionistic Fuzzy Pair.

There may be some pairs $\langle \mu_{C,C'}, \nu_{C,C'}\rangle$, for which the sum $\mu_{C,C'} + \nu_{C,C'}$ is less than 1. The difference

$$\pi_{C,C'} = 1 - \mu_{C,C'} - \nu_{C,C'} \tag{5}$$

is considered as a degree of "uncertainty".

3 Experimental Results

3.1 ACO Application on Various Sizes of Problem

We have implemented software, which realizes our ant algorithm. Our software can solve the problem at any rectangular area, the communication and the coverage radius can be different and can have any positive value. We can have regions in the area. The program was written in C language, and the tests were run on computer with an Intel Pentium 2.8 GHz processor. In our tests we use an example where the area is square. The coverage and communication radii cover 30 points. The HECN is fixed in the centre of the area. For the tests we have used areas with three sizes: 350×350 points, 500×500 points, and 700×700 points.

In our previous work [3], we showed that our ant algorithm outperforms the existing algorithms for this problem. There, after several runs of the algorithm we were able to specify the most appropriate values of its parameters: $\alpha = \beta = 1$, $\rho = 0.5$, $\tau_0 = 0.5$. We study the influence of the number of ants on the quality of the solutions. We fixed the number of the iterations to be 60 (about 3 h per ant) and the number of ants to have following values $\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$.

We run our ACO algorithm 30 times for each number of ants. We extract the Pareto front from the solutions of these 30 runs. In Tables 1, 2, and 3 we show the achieved non dominated solutions (approximate Pareto fronts) for case 350×350, 500×500, and 700×700, respectively.

The left column represents the number of sensors and in other columns we present the energy corresponding to this number of sensors and the number of ants. Analyzing the Table 1 (case 350×350) we observe that the best algorithm performance in the case 350×350 is achieved by 7 ants, more ants leads to more computational time. From Table 2 (case 500×500) we observe that the

Table 1. Approximate Pareto fronts, example 350 × 350

Sensors	Ants									
	1	2	3	4	5	6	7	8	9	10
111	30	36	30	30	30	30	30	30	30	30
112	30	36	30	30	30	30	30	30	30	30
113	28	35	28	30	30	30	28	28	28	28
114	26	26	26	26	26	26	26	26	26	26
115	26	26	26	26	26	26	26	26	26	26
116	26	26	26	26	26	26	25	25	26	25

Table 2. Approximate Pareto fronts, example 500 × 500

Sensors	Ants									
	1	2	3	4	5	6	7	8	9	10
223	90	96	90	90	89	81	90	90	90	90
224	61	96	89	89	88	65	61	59	57	71
225	61	96	74	58	60	58	57	58	57	57
226	59	95	73	57	59	57	56	58	57	57
227	60	57	57	57	57	56	56	57	57	57
228	60	57	57	57	57	56	56	57	54	57
229	58	57	57	55	57	56	56	56	54	56
230	57	57	57	55	57	52	56	54	54	56
231	57	55	57	55	55	52	56	54	54	56
232	57	55	55	51	54	50	52	51	54	48
233	57	55	55	51	54	50	51	51	54	48
234	57	55	55	51	53	50	51	48	53	48
235	57	55	54	51	53	50	51	48	50	48
236	57	55	54	51	53	50	51	48	50	48
237	57	55	54	51	53	50	51	48	50	48
238	57	55	53	51	53	50	51	48	50	48
239	56	55	53	50	53	50	51	48	50	48
240	53	53	53	50	53	50	51	48	50	48
241	53	53	53	50	53	50	51	48	50	48
242	53	53	53	50	53	50	51	48	50	48
243	53	53	53	50	53	50	51	48	50	48
244	53	53	53	50	52	50	51	48	50	48

approximate Pareto front achieved by 6 ants dominates others. Analyzing the Table 3 (case 700 × 700) we observe that the approximate Pareto front achieved by 6 ants again dominates others. In all discussed cases the approximate Pareto fronts achieved by 6 and 7 ants outperform others. Thus it is the best number of ants for our sensor layout problem.

3.2 ICrA Results

In case of size 350 × 350, in order to apply the ICrA the IM based on the results presented in Table 1 is constructed. The cross-platform software for ICrA approach, ICrAData, is used [14]. After the application of ICrA the following IM of values of degrees of "agreement" $\mu_{C,C'}$ are obtained (Table 4). In the table, as well as in the Tables 5 and 6, in bold are the estimations that show high correlation between the considered ACO algorithms.

In case of size 500 × 500 again IM based on the results presented in Table 2 is constructed. The obtained degrees of "agreement" are as presented in Table 5.

In case of size 700 × 700 the IM based on the results presented in Table 3 is constructed. The obtained degrees of "agreement" are as presented in Table 6.

Table 3. Approximate Pareto fronts, example 700 × 700

Sensors	Ants									
	1	2	3	4	5	6	7	8	9	10
437	173	173	173	173	173	118	168	172	261	172
438	173	173	173	173	173	118	112	117	260	172
439	172	173	173	173	140	93	110	115	131	172
440	172	173	173	173	115	93	110	114	111	162
441	172	173	173	122	111	93	110	114	111	110
442	172	173	173	114	111	93	110	112	111	110
443	172	150	123	114	111	93	110	112	111	110
444	124	112	112	106	107	93	110	102	111	105
445	117	112	112	106	107	93	110	102	108	105
446	117	112	105	105	105	93	107	102	104	105
447	117	112	105	105	105	93	105	102	102	105
448	115	111	105	105	105	93	105	102	102	105
449	115	111	105	105	105	93	102	99	102	105
450	113	111	105	105	105	93	102	99	102	105
451	113	109	105	105	105	93	102	99	97	105
452	113	109	105	105	105	93	99	99	97	104
453	113	109	105	105	105	93	99	99	97	104
454	113	109	105	105	96	93	96	96	96	104
455	106	106	105	105	96	93	96	96	96	97

Table 4. Obtained degrees of "agreement" $\mu_{C,C'}$ - problem size 350 × 350

$\mu_{C,C'}$	ACO_1	ACO_2	ACO_3	ACO_4	ACO_5	ACO_6	ACO_7	ACO_8	ACO_9	ACO_{10}
ACO_1		**1**	**1**	0.87	0.87	0.87	0.87	0.87	**1**	0.87
ACO_2	**1**		**1**	0.87	0.87	0.87	0.87	0.87	**1**	0.87
ACO_3	**1**	**1**		0.87	0.87	0.87	0.87	0.87	**1**	0.87
ACO_4	0.87	0.87	0.87		**1**	**1**	0.73	0.73	0.87	0.73
ACO_5	0.87	0.87	0.87	**1**		**1**	0.73	0.73	0.87	0.73
ACO_6	0.87	0.87	0.87	**1**	**1**		0.73	0.73	0.87	0.73
ACO_7	0.87	0.87	0.87	0.73	0.73	0.73		**1**	0.87	**1**
ACO_8	0.87	0.87	0.87	0.73	0.73	0.73	**1**		0.87	**1**
ACO_9	**1**	**1**	**1**	0.87	0.87	0.87	0.87	0.87		0.87
ACO_{10}	0.87	0.87	0.87	0.73	0.73	0.73	**1**	**1**	0.87	

Table 5. Obtained degrees of "agreement" $\mu_{C,C'}$ – problem size 500 × 500

$\mu_{C,C'}$	ACO_1	ACO_2	ACO_3	ACO_4	ACO_5	ACO_6	ACO_7	ACO_8	ACO_9	ACO_{10}
ACO_1		**0.89**	0.78	**0.9**	0.71	0.71	0.68	0.73	0.7	0.7
ACO_2	**0.89**		0.8	**0.87**	0.78	0.76	0.73	0.74	0.71	0.73
ACO_3	0.78	0.8		**0.87**	0.83	0.75	0.79	0.82	0.82	0.73
ACO_4	**0.9**	**0.87**	**0.87**		0.79	0.79	0.78	0.81	0.76	0.81
ACO_5	0.71	0.78	0.83	0.79		0.84	**0.87**	**0.93**	0.84	0.81
ACO_6	0.71	0.76	0.75	0.79	0.84		**0.9**	**0.89**	0.77	**0.96**
ACO_7	0.68	0.73	0.79	0.78	**0.87**	**0.9**		**0.89**	0.81	**0.9**
ACO_8	0.73	0.74	0.82	0.81	**0.93**	**0.89**	**0.89**		**0.87**	**0.88**
ACO_9	0.7	0.71	0.82	0.76	0.84	0.77	0.81	**0.87**		0.79
ACO_{10}	0.7	0.73	0.73	0.81	0.81	**0.96**	**0.9**	**0.88**	0.79	

Table 6. Obtained degrees of "agreement" $\mu_{C,C'}$ – problem size 700 × 700

$\mu_{C,C'}$	ACO_1	ACO_2	ACO_3	ACO_4	ACO_5	ACO_6	ACO_7	ACO_8	ACO_9	ACO_{10}
ACO_1		**0.88**	0.72	0.72	0.8	0.35	0.84	0.85	0.85	0.78
ACO_2	**0.88**		0.77	0.71	0.74	0.28	0.77	0.82	0.81	0.8
ACO_3	0.72	0.77		**0.94**	0.82	0.46	0.64	0.7	0.68	0.7
ACO_4	0.72	0.71	**0.94**		**0.87**	0.46	0.64	0.74	0.7	0.74
ACO_5	0.8	0.74	0.82	**0.87**		0.4	0.76	0.85	0.84	0.83
ACO_6	0.35	0.28	0.46	0.46	0.4		0.36	0.33	0.32	0.39
ACO_7	0.84	0.77	0.64	0.64	0.76	0.36		0.81	**0.89**	0.73
ACO_8	0.85	0.82	0.7	0.74	0.85	0.33	0.81		0.84	0.82
ACO_9	0.85	0.81	0.68	0.7	0.84	0.32	**0.89**	0.84		0.78
ACO_{10}	0.78	0.8	0.7	0.74	0.83	0.39	0.73	0.82	0.78	

Based on the ICrA outcomes it is shown that the ACO algorithms with very close number of ants (e.g. ACO_1 and ACO_2, ACO_3 and ACO_4 or ACO_7 and ACO_8) perform in similar way. The high correlation between such pairs is preserved regardless the problem size. Such relation is obvious. According to the results in Table 4 (case 350×350) very high correlation is observed for the ACO_9 and ACO_1, ACO_2, ACO_3. These relations are not observed in the other two cases. In case of problem size 350×350 the existing many very high correlations are explained with the fact the most of the considered ACO algorithms can solve the problem with good solution quality. Whereas, in the case of size 500×500 or 700×700 only few ACO algorithms perform very well. So, if we considered results in case of larger problem sizes, the ICrA results show that the number of ans has the significant influence on the obtained results.

4 Conclusion

In this paper we have studied the influence of the number of ants on the performance of the ACO algorithm, applied to the wireless sensor network. Smaller number of ants leads to the shorter running time and minimizes memory use, which is important for complex/large cases. We varied the number of ants, while fixing the number of iterations. Furthermore, we included the concept of an Extended front, as an additional tool to compare approximate Pareto fronts that do not dominate each other. The best approximate Pareto front and the best performance were achieved when the number of ants was equal to 6 in the cases 700×700 and 500×500, and 7 in the case 350×350. The results are analysed based on ICrA, too. The analysis confirms considerable influence of the ants number on the quality of the decision, especially in the case of bigger problem sizes.

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