SCALING COMPLEXITY COMPARISON OF AN ACO-BASED ROUTING ALGORITHM USED AS AN IOT NETWORK CORE

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Contribution to the State of the Art

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Abstract: This paper proposes a routing method that is based on an Ant Colony Algorithm (ACO) for minimizing energy consumption in Wireless Sensor Networks (WSNs). The routing method is used as the backbone of the Internet of Things (IoT) platform. It also considers the critical design issues of a WSN, such as the energy constraint of sensor nodes, network load balancing, and sensor density in the field. Special attention is paid to the impact of network scaling on the performance of the ACO-based routing algorithm.

Keywords: ant colony algorithm (ACO), energy consumption, internet of things (IoT), network lifetime, optimal path, wireless sensor network (WSN).

INTRODUCTION

In the last decades, the development of wireless sensor networks (WSNs) has completely changed the way various data are collected from the field and sent to the appropriate destination where these are further processed. The flexibility, low cost, and efficiency of WSNs have contributed to their rapid expansion into many sectors. As a result, WSNs became integral parts of some information technologies, significantly improving their characteristics but also opened space for the development of hybrid new technologies. The application of WSNs in many sectors such as medicine, ecology, meteorology, agriculture, army, energy, etc. has eliminated a whole range of sensor cable networking problems, ranging from the high cost of cabling and network inflexibility to the inaccessibility of sensors in the field.

From another perspective, the Internet of Things (IoT) is a set of connected technologies that enable smart management of various devices over the Internet. IoT has found significant application in the so-called 'smart home' area, where it is necessary to network smart devices in the household and make the data obtained from them to be available anywhere in the world. Figure 1 shows the functional architecture of the IoT platform. The core of the IoT is a wireless sensor network that consists of the required number of sensors that represent nodes in the wireless network. Each of the sensors captures (senses) a physical quantity, and then forwards the sensed data (information) using the WSN to the place where they are processed. Then, the data are passed on to the end-user where it is a human or a specific application. The sensors are powered autonomously via small built-in batteries whose replacement is not cost-effective or feasible. After a battery depletes, the sensor shuts down, and the data it needs to deliver becomes unavailable. In the case of IoT heterogeneous sensors, each sensor usually performs specific capturing so the other sensors (located in the immediate vicinity) can not take over this function of the switched-off sensor. Therefore, it is necessary to organize the WSN in a way that will ensure minimum energy consumption and thus maximizing the network lifetime. To send data, the sensor consumes far more energy than it takes to just listen to the terrain and process the data inside the sensor. Energy consumption increases with the square distance of the path along which the communication takes place. Therefore, the choice of the optimal data transmission path is an extremely important factor in reducing the power consumption of nodes, and thus to extend the network lifetime. These are the aspects that have the greatest impact on the stability of the IoT system.

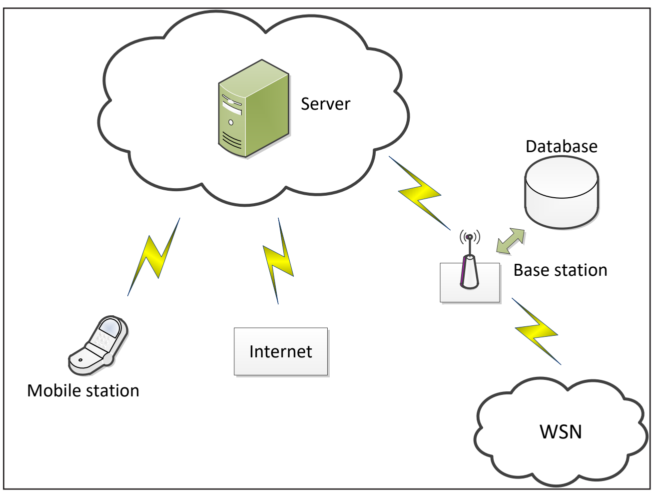

Figure 1. *IoT system architecture*

Depending on the type of networks and their application, different routing techniques (forwarding data from source to destination) are used [12-14]. The choice of routing technique depends on the goals set and expectations of the network behavior. Routing in wireless sensor networks differs greatly from the routing in traditional networks. AWSN has not a permanent infrastructure, links are not always available, and nodes in the network do lose energy over time. Also, the network can be organized in different ways: direct, hierarchical, and radio-relay. For a specific deployment, optimal routing can be realized based on various criteria such as minimum hop, residual node energy, minimum broadcast price, etc.

An Ant Colony Algorithm (ACO) is a nature-inspired algorithm based on the behavior of ants when finding food sources, in a way that represents a benefit to the whole community. This paper proposes an ACO-based routing algorithm that is used as an IoT network core. In our framework, we consider the specificity of the application of WSN as the backbone of the network in the IoT infrastructure. ACO was originally proposed by Dorigo [4]. This algorithm belongs to the metaheuristic methods for solving combinatorial optimization problems [1]. Such algorithms generate partial searches to obtain a sufficiently good solution to the optimization problem in cases of insufficient or imperfect information or limited computing power. A globally optimal solution is not guaranteed as only a sample of all possible outcomes is taken.

Using the originally developed MATLAB simulation, we compared the complexity of the proposed algorithm for different network configurations. Therefore, we analyzed the possibilities of applying this ACO-based routing algorithm in different situations.

RELATED WORKS

In previous years, extensive research has been conducted on variants of the application of the ACO algorithms in WSNs. Hereafter, we present those ACO realizations that aim to save energy in the network and thus extend the lifespan of WSN. We outline some important research works which inspired our ACO-based routing algorithm.

Ming-Hua et al. [9] proposed a variant of the ACO algorithm that is based on the fuzzy system FACOA (Fuzzing Ant Colony Optimization Algorithm). FACOA computes the pheromone and residual energy through three different steps: (1) fuzzing; (2) inference; and (3) de-fuzzing. The ants select the next hop according to the result of fuzzy selection.

Luo and Li proposed [8] a modification of the ACO algorithm in part of searching neighbor nodes. They proposed a search angle to limit the neighbor area during the node selection activities. By using the search angle approach, the nodes only broadcast their packets to their neighbor in this search angle area to reduce the energy consumption of the sensor node. This approach can also increase the search speed of ants and reduce the delay in packet transmission.

Sun et al. [15] introduced an improved heuristic function in ACO by considering the distances, transmission direction, and residual energy of the nodes to find the optimal path from the source node to the destination node. Thus, the network energy consumption is reduced and the network lifetime is prolonged.

Okdem and Karaboga [11] presented an ACO-based algorithm for wireless sensor networks consisting of stationary nodes. It provides an effective multi-path data transmission method to achieve reliable communication in the case of node faults while considering the energy levels of the nodes.

Jiang and Zheng [6] proposed a hybrid routing algorithm that integrates ACO and a minimum hop count scheme. The proposed algorithm can find the optimal routing path with minimal total energy consumption and balanced energy consumption on each node.

Chiang SS et al. [3] proposed a routing protocol that chooses hop counts and battery power levels as metrics to conserve as much energy as possible in both computations and data communications. Besides, when some of the nodes fail or run out of battery, the routing protocol could effectively adapt the change and find an alternative path.

Djukanovic and Popovic [5] presented different methods for updating the amount of pheromones in the paths between sensor nodes in wireless sensor networks. The authors [5] concluded that the scaling of the network is one of the problems that emerge in the application of resource conservation algorithms in WSNs. The scaling of the network leads to an increase in the complexity of the proposed algorithms during the growth of the search space. In order to address this issue, we must perform measurements on small and large networks in the simulation. Then, we can compare the measurement results and determine whether the performance of the algorithm changes significantly or not. Although this is an important aspect, it is often neglected in many works Simulation experiments performed would contribute to a more complete understanding of the real performance of the proposed algorithms.

ACO ALGORITHM IN WIRELESS SENSOR NETWORKS

The data routing techniques in WSNs have two goals: (1) to find the optimal path between the source and destination node; and then (2) to transmit data packets along the selected path. Routing techniques significantly affect the energy efficiency of the network. The energy of the sensor nodes is limited, while the longest possible network lifetime is desirable. Depending on the implementation of the IoT system, the number of sensor nodes (inside the network) can vary greatly, with nodes being distributed over different areas. In such conditions, each node has only information about the local topology of the network and knows nothing about the topology of the remote parts of the network except that it knows the exact location of the final destination of the message. Accordingly, routing is performed in steps, where only locally available information is taken into account.

The ACO algorithm mimics the exchange of pheromones between ants in search of food [2,7]. When applied to WSN, ants represent the data packets that are transmitted to a destination (base station) and a pheromone is the data packets that contain the necessary information to select the optimal path between nodes. According to the principle of positive feedback, through iterations in an unlimited number of cycles, the paths between nodes that have a higher pheromone density are more likely to be selected in each of the iterations.

Ants (i.e., data packets) are denoted by k. Each ant autonomously finds the optimal path to its destination. Data can be sent continuously, in response to an event, or at specific, predefined intervals, depending on the application. If the data are sent at regular intervals, the transmission is performed in iterations through the required number of cycles. The iteration begins when everyone (or a predetermined percentage of sensor nodes) starts sending messages at the same time and ends when the last ant returns to its original node. When moving from the source node to a common destination, each of the ants keeps its own list of visited Mk nodes, which ensures that in further routing it will not pass again through the sensor node that it has already visited in the current iteration. This list is carried by each ant and it is deleted at the end of each iteration.

When ant k is found in any node r, this node must perform the calculation of the next step, i.e., to determine the sensor node to which it will forward this message. Only "adjacent nodes" come into consideration, where the term proximity can be defined using different criteria. The next step is determined according to the probability:

$$P_k(r,s) = \begin{cases} \frac{[T(r,s)]^{\mu}[\delta(s)]^{\vartheta}}{\sum_{s \notin M_k}[T(r,s)]^{\mu}[\delta(s)]^{\vartheta}}, s \notin M_k \\ o, else \end{cases} \quad (1)$$

where *Pk(r, s)* is the probability that the ant *k* will move from the node *r* to node *s* in the next step. T is a routing table in each node, which stores data on the amount of pheromones for each of the possible paths *(r, s)* from node *r* to the corresponding adjacent node *s*. Heuristic information, often called the visibility table, is denoted by δ_{rs} and is obtained from expression (2):

$$\delta_{rs} = \frac{E_s}{\sum_{n \in Ni} E_n} \quad (2)$$

where *Es* is the instantaneous residual energy of the node *s*, and is the total energy of the set of adjacent nodes. With the help of weight parameters μ and υ, the relative influence of pheromones in relation to visibility is adjusted, since the probability of path selection is a compromise between the amount of pheromones and the value of heuristic energy.

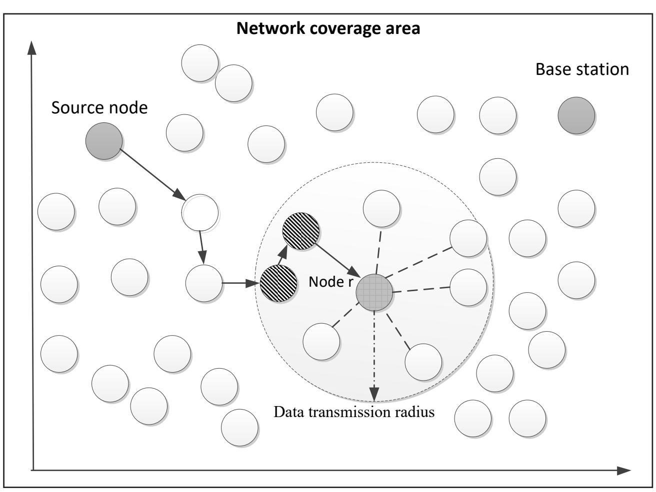

Figure 2. *Area of adjacent nodes*

Figure 2 illustrates the state of the network when selecting the next step for node *r* (calculating expression (1)). The area of adjacent nodes is marked by a dashed circle. Only these nodes are considered for the selection of the next step. The shaded nodes are members of the *Mk* list, so they cannot be selected, regardless of the two located close within the area of adjacent nodes. During one iteration, each ant moves from node to node following expression (1) until it reaches its destination, i.e., the base station. The arrival of the ants to the destination corresponds to the delivery of the data packet to the base station. After the base station receives this data, it sends a return message to the sensor node that sent it. This message is considered as an ant *k* confirming, to the destination node, the receipt of the message in the base station, but its basic mission is related to the optimization of further routing in the network. In return, the ant *k* returns along the identical path along which it reached its destination following the entry in the list of *Mk*. However, on return, the ant secretes a pheromone on the traversed path by analogy with real ants. Of course, the pheromone in this case is not a chemical substance but an update of the members of Table T.

In nature, ants look for food in a group and not individually. In doing so, they use the pheromone as a medium for mutual communication. A pheromone is a chemical that ants release along the entire path they take in search of food. The amount of pheromone released depends on the length of the path. The longer the trajectory, the smaller the amount of pheromone secreted on it and vice versa. Ants are more likely to choose a path with a larger amount of pheromones for their movement. Over time, more and more ants cross the same path, releasing more and more pheromones on it until all the ants choose the same path as the optimal one [10].

In the application of the ACO algorithm to WSN in the first iteration, it is assumed that all elements of the table T are reciprocal values of the distance from node *r* to node *s*, *Trs = Q/drs*, (Q being a constant) so the shortest paths have the highest pheromone density. In all other iterations the table is updated according to expression (3):

$$T_k(r,s) = (1-\rho)T_k(r,s) + \Delta T_k \quad (3)$$

where (*1-ρ*) is the coefficient representing the effect of pheromone evaporation in the previous iteration and is introduced into the formula to avoid the unnecessary accumulation of pheromones on paths chosen with low probabilities, and *ΔTk* is the amount of pheromone that ant *k* secretes on the path between nodes *r* and *s*.

After the ant *k* (feedback from the base station) returns to the node in which it was created, its mission is completed as well as one cycle for this source node. When all the ants return to their destination, the network is ready for a new iteration.

After a few iterations, each of the nodes will find an adjacent node that is best for further sending a message, and over time, more and more ants will pass through the selected routes, secreting more and more pheromones. Since the choice of the shortest paths is desirable, the amount of secreted pheromone on longer paths will be significantly smaller, so the probability of their choice will be relatively small. The paths selected in this way are not globally optimal and over time the energy consumption of the sensor nodes located on these paths will increase unbalanced compared to the other nodes until these sensors are completely turned off. Therefore, it is necessary to carefully choose the way to update the pheromones in the paths and strive for the best possible compromise between energy consumption and the amount of pheromones.

The amount of pheromone secreted depends on the length of the path traveled by the ant during the direct path. In this way, ants search for possible solutions. The amount of pheromones is calculated according to the equation:

$$\Delta T_k = \frac{Q}{L} \tag{4}$$

where Q is a constant, and L is the length of the ant path in particular iteration.

Each time a returning ant arrives at a node *r*, the routing table is updated. During the return of ants, the amount of pheromones in the existing paths between the nodes evaporates, so each time the returning ant enters the node, it is necessary to update the condition, subtract the amount of pheromones that have evaporated in the meantime, and add a new amount of pheromones left by the returning ant.

SIMULATION AND RESULTS

In this paper, we present the results of a simulation written and performed using MATLAB. The authors developed an original simulation that implements the idea of an ACO algorithm in a WSN network in the manner described in the previous Sections. Table 1 shows the network parameters used during the simulation.

***Table 1.** The network parameters used during the simulation*

Parameters	Value
Node initial energy	0.2 J
Packet size	2000 bits
Coefficient μ	1
Coefficient θ	1
Pheromone evaporation (1-ρ)	0.8

In order to investigate the influence of the network scaling (i.e., how an increase of search space and an increase of the number of nodes in the network increase the complexity of the algorithm), we simulated three characteristic cases shown in Table 2.

***Table 2.** Parameter values for the three Cases*

Parameters	Case 1	Case 2	Case 3
Number of sensor nodes	20	80	320
Number of ants	5	5	5
Network coverage area	100x100 m2	200x200 m2	400x400 m2
Data transmission radius	50 m	100 m	200 m

These Cases were chosen so that the number of nodes in the network and the network coverage area in each subsequent case increases 4 times. In this way, the density of nodes in the network remains the same, so comparing the complexity makes sense. The radius of adjacent nodes increases 2 times in each subsequent case. The number of ants in each case is the same, i.e., 5. These 5 ants are chosen randomly in each iteration.

After the simulation is finished, we obtained the following graphs (Figure 3, Figure 4, and Figure 5) showing how the total energy of the nodes in the network changes through iterations during the network lifetime.

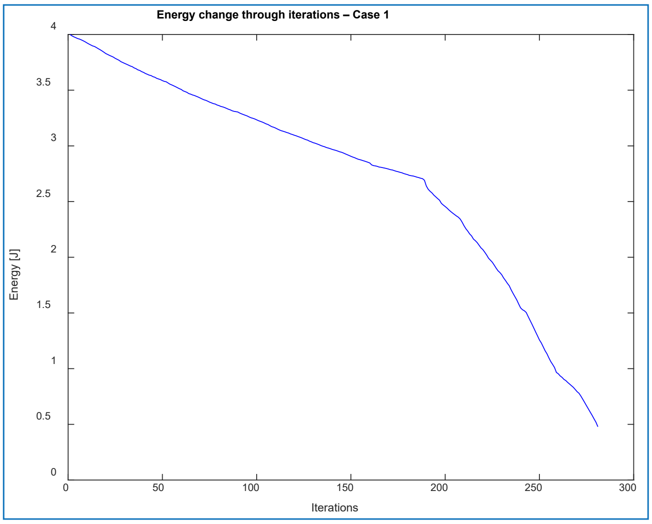

Figure 3. *Energy change through iterations – Case 1*

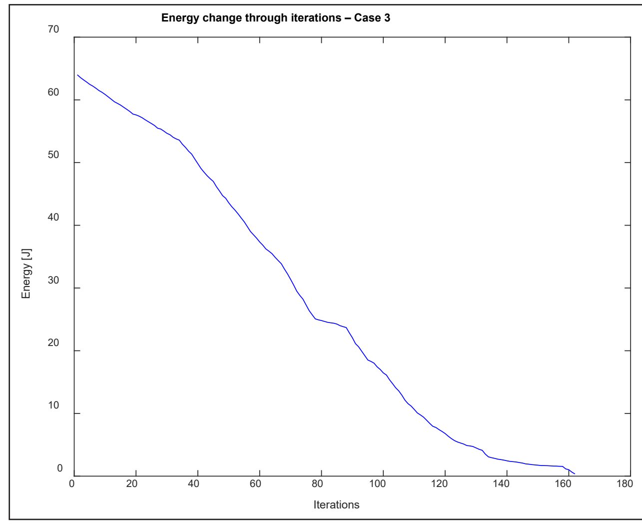

Figure 5. *Energy change through iterations – Case 3*

Figure 3 shows that initial network energy for Case 1 is 4 Joules (20 nodes with 0.2 Joules), and network lifetime is 280 iterations. Initial energy for Case 2 (Figure 2) is 16 Joules (for 80 nodes), and for Case 3 (Figure 3) it is 68 Joules, since 320 nodes with 0.2 Joules are set in field initially.

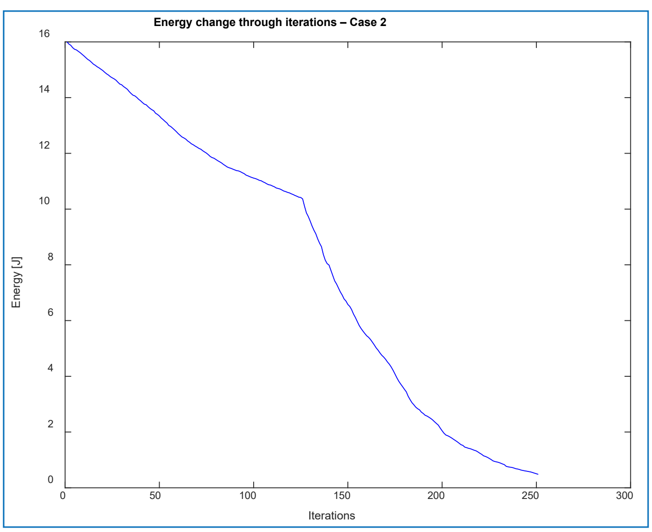

Figure 4. *Energy change through iterations – Case 2*

Table 3 summarizes the simulation results obtained. Every simulation stops when the total energy in the network reaches down to 0.5 J of the initial energy in nodes, or when the network is left with only one node. Both of these cases are considered as the end of the network lifetime.

Table 3. *Results of simulation*

Measured value	Case 1	Case 1	Case 3
Number of iterations	280	250	161
Simulation duration	11.159 s	41.618 s	292.916 s
Average iteration duration	0.0399 s	0.1665 s	1.819 s
Average number of steps per ant	2012	5242	23201

The number of iterations indicates the lifetime of the network. In this case, the data are not delivered in real-time but in stages. When all the ants return to the starting nodes, one can move on to the next cycle. Therefore, reports can be sent periodically according to a predefined rule. The obtained simulation results indicate that the lifespan decreases with the complexity of the network. This occurs although the number of ants in the network, as well as the average density of nodes in the network, are always the same. The duration of the simulation for complex networks increases significantly with increasing complexity. In the third case, the duration of the simulation gets a value that is disproportionately large concerning the scaling of the network. Most of the time is spent on calculating the next step in the network. In the third Case, this calculation becomes extremely complex due to the size of the coverage and the number of nodes. During the lifetime of the network, the average number of steps per ant increases in proportion to the scaling, although the number of ants is always the same and the number of iterations is smaller.

CONCLUSION

This paper evaluates the impact of the network scaling on the performance of an ACO-based routing algorithm. We implemented and simulated this routing algorithm using MATLAB. The ACO algorithm was deployed to the IoT core network in three Cases having different scales. Simulation results are focused on the scaling of the network while keeping the density of the nodes constant. Simulation results show that the simulation time increases significantly for complex networks having increasing complexity while keeping the density and the number of ants the same. The simulation time further increased, it even lasted for tens of minutes or hours. During the lifetime of the network, the average number of total steps per ant increases in proportion to the scaling, and the number of iterations decreases while network complexity increases. Soon, we aim to expand and develop further the developed simulation in MATLAB to investigate and test other cases in WSN network as an IoT network core.

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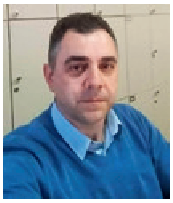

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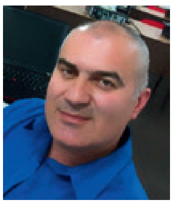

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