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New Routing Algorithm Based on ACO Approach for Lifetime Optimization in Wireless Sensor Networks

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ABSTRACT

Recently, wireless sensor networks have become an active research topic. Developing solution for the routing problem in this kind of network is one of the main topics considered by researchers in order to maximize the network life time. In this paper we present a novel routing approach using an Ant Colony Optimization (ACO) algorithm for Wireless Sensor Networks. Comparative performance test results of the proposed approach are included. Simulation results show that proposed algorithm provides promising solutions allowing node designers to efficiently operate routing tasks for maximizing the network lifetime.

Keywords : Wireless Sensor Networks (WSN), Network Lifetime, Ant Colony Optimization

1. INTRODUCTION

Due to the advances in low-power wireless communications, the development of low power wireless sensors has received recently an important attention. Wireless sensors have the ability to perform simple calculations and communicate in a small area.

Wireless sensor networks have critical applications in the scientific, medical, commercial, and military domains. Examples of these applications include environmental monitoring, smart homes and offices, surveillance, and intelligent transportation systems. It also has significant usages in biomedical field. Although sensor networks are used in many applications, they have several limitations, including limited energy supply and limited computing capabilities. These limitations should be considered when designing protocols for sensor networks.

In sensor networks, the minimization of energy consumption is considered as a criterion important to provide the maximum lifetime of the network. Routing protocols must be designed to support energy savings and achieve fault tolerance in communications.

The optimization of network parameters for WSN routing process to provide maximum service life of the network can be regarded as a combinatorial optimization problem. Many researchers have recently studied the collective behavior of biological species such as ants as an analogy providing a natural model for combinatorial optimization problems [7-10]. Ant colony optimization (ACO) algorithms are simulating the behavior of ant colonies; they were successfully applied in many optimization problems.

In this paper, we compared the performance results of our ACO approach to the results of the algorithm AODV and LEACH[5] . Different networks of different sizes are considered, and our approach gives better results than AODV algorithm in terms of energy consumption.

2. OVERVIEW OF ROUTING BASED ANT ALGORITHM FOR WSN

2.1 Ant Colony Optimization

Ant Colony Optimization (ACO) is a flavor of Swarm Intelligence based approaches applied for optimization problems. ACO meta-heuristic approach models the real ants. In ACO, a number of artificial ants uild solutions to an optimization problem. In ACO, the exchange of information is done by pheromone value like real ants. The path optimization between nest and food is achieved by ant colonies by exploiting the pheromone quantity dropped by the ants. There are some representative application areas of ACO, meta-heuristic algorithmic approaches [1], i.e. NP-hard problems, telecommunication networks, industrial problems, Dynamic optimization problems, stochastic optimization problems, Multi-objective optimization, Parallel implementations and Continuous optimization.

2.2 GPSAL

These authors [2] were among the first to propose an ACO algorithm for MANETs. GPS/Ant-Like algorithm (GPSAL) is a location-based algorithm. Ants are used for collection and dissemination of information among the nodes. Second feature of GPSAL is the use of fixed hosts as well as possible to route packets. By using the local information routing overhead is decreased as compared to other algorithms.

The GPSAL algorithm assumes the presence of an onboard GPS device. The locally and globally routing information is exchanged sending forward ants to destination geographically. This study shows, GPSAL algorithm is better in performance with less routing overhead as compared to LAR that is also a location based algorithm.

2.3 NNNA

In [3], authors proposed an Node Neighbor Number Algorithm (NNNA) based on swarm intelligence algorithms and Ant Colony Optimization (ACO), particularly. The NNNA hybrid algorithm was introduced by Mohammad Golshali et al (2008) having reactive as well as proactive behavior. This algorithm takes advantage of the neighbor nodes for the selection of next hop. The stated algorithm operation is divided into three stages i.e.

- Reactive Path installation
- Proactive Path maintain
- Contrasting with Link failure

The node's neighbor intensity is considered for the next hop selection. The node having greater number of neighbors provides more information than the others. The simulation results (in NS2) of NNNA are more premise than AODV for packet delivery rate and end-to-end delay.

2.4 Ant-AODV

Uniform ants are used to update the routing table using Ant-AODV technique. By using this technique a route from the source to destination is increased by using its neighbors. The simulation results shows that the Ant-AODV has better performance than the Ant based and the AODV algorithms.

2.5 AntHoeNet

In [4] for mobile and adhoc nature inspired framework ACO is used. Ant Agents for Hybrid Multipath Routing in Mobile Adhoc networks (AntHocNet) technique is sed for the typical path sampling. To efficiently learn the table of pheromone the ACO behavoiur is incorporated in the pheromone bootstrapping mechanism.

3. THE ACO APPROACH

In the ACO based approach, each ant tries to find a path in the network, providing minimum cost.

Ants are launched from a source node s and move through neighbor repeater nodes ri, and reach a final destination node (sink) d. Whenever, a node has data to be transferred to the destination which is described as a base or base station, launching of the ants is performed. After launching, the choice of the next node r is made according to a probabilistic decision rule (1):

$$p^k(r,s) = \begin{cases} \dfrac{[\tau(r,s)]^{\alpha}[\eta(r,s)\ ]^{\beta}}{\sum_{k\in R_S}[\tau(r,s)]^{\alpha}[\eta(r,s)]^{\beta}} & \text{if } j \notin tabu_r \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

where $\tau(r,s)$ is the pheromone value, $\eta(r,s)$ is the value of the heuristic related to energy, Rs is the receiver nodes. For node r, $tabu^r$ is the list of identities of received data packages previously. α and β are two parameters that control the relative weight of the pheromone trail and heuristic value.

Pheromone trails are connected to arcs. Each arc(r,s) has a trail value $\tau(r,s)$ in [0,1]. Since the destination d is a stable base station, the last node of the path is the same for each ant travel. The heuristic value of the node r is expressed by equation (2):

$$\eta(r,s) = \frac{(I-e_r)^{-1}}{\sum_{k\in R_S}(I-e_n)^{-1}} \qquad (2)$$

where I is the initial energy, and e_r is the current energy level of receiver node r. This enables decision making according to neighbor nodes' energy levels, meaning that if a node has a lower energy source then it has lower probability to be chosen. Nodes inform their neighbors about their energy levels when they sense any change in their energy levels.

In traditional ACO, a special memory named M_k is held in the memory of an ant to retain the places visited by that ant (which represent nodes in WSNs). In equation (1), the identities of ants (as sequence numbers) that visited the node previously, are kept in the node's memories, instead of keeping node identities in ant's memories, so there is no need to carry M_k lists in packets during transmission. This approach decreases the size of the data to be transmitted and saves energy. In equation (1) each receiver node decides whether to accept the upcoming packet of ant k or not, by checking its tabu list.

So, the receiver node r has a choice about completing the receiving process by listening and buffering the entire packet. If the receiver node has received the packet earlier, it informs the transmitter node by issuing an ignore message, and switches itself to idle mode until a new packet arrives.

After all ants have completed their tour, each ant k deposits a quantity of pheromone $\Delta\tau^k(t)$ given in equation (3), where $J_w^k(t)$ is the length of tour $w^k(t)$, which is done by ant k at iteration t. The amount of pheromone at each connection (l(r, s)) of the nodes is given in equation (4). In WSNs, $J_w^k(t)$ represents the total number of nodes visited by ant k of tour w at iteration t:

$$\Delta\tau^k(t) = 1/J_w^k(t) \qquad (3)$$

$$\tau(r,s)(t) \leftarrow \tau(r,s)(t) + \Delta\tau(r,s)(t), \quad \forall\ l(r,s) \in w^k(t),\ k = 1,.,m \qquad (4)$$

Pheromone values are stored in a node's memory. Each node has information about the amount of pheromone on the paths to their neighbor nodes. After each tour, an amount of pheromone trail $\Delta \tau^k$ is added to the path visited by ant *k*. This amount is the same for each arc(r, *s*) visited on this path. This task is performed by sending ant *k* back to its source node from the base along the same path, while transferring an acknowledgement signal for the associated data package.

Increasing pheromone amounts on the paths according to lengths of tours, J_w (*t*), would continuously cause an increasing positive feedback. In order to control the operation, a negative feedback, the operation of pheromone evaporation after the tour is also accomplished in equation (5). A control coefficient 0< ρ <1 is used to determine the weight of evaporation for each tour [6]:

$$\tau_{ij}(t) \leftarrow (1-\rho)\tau_{ij}(t) \qquad (5)$$

In simulations, ACO parameter settings are set to values 1 for α 0,5 for β , and 0.5 for ρ , which were experimentally found to be good by Dorigo [7].

The following algorithm describes the proposed approach for discovering the shortest path to destination:

Algorithm:

Initialization ：

Initialization all nodes in the network
Get all sensor nodes'coordinates by the network topology, and calculate distance between nodes.
TC←0 (TC is total cycle times) ;
Set an initial value τij for trail intensity on every path ij as INIT_PHEROMONE
Set Δτij= 0 for every i and j;
Place m ants on n nodes, in common m=n;
dij is the distance between i and j .

Begin:
Step 1:

put the source node in the first row of tabu^r list
（ *r=0,1,…,m-1* ， *m is ant's number* ）
tabu^k list's row denoted by s ,the initial value is 1 and the ant r trail is saved in tabu^k list.

Step 2:
Repeat until tabu^r list is full;
k increases 1 each time ;
Choose the node to move to, with probability p(r,s) given by equation (1);
Insert the chosen node in the tabu^r list of the ant r.

Step 3:
Compute τij (t+n) and Δτij as defined in (3),(4) and (5);

Setp 4:
Set Δτij=0 for every i and j and
TC←TC+1;
Setp 5:
if
TC< preconcerted cycle times and no degenerate action
Memorize the shortest path found up to now and empty all tabu^r lists, go to step 1;

Otherwise print the shortest path while ants travel all the nodes and return the source node.
END.

4. SIMULATION PARAMETERS & RESULTS

To simulate ACO algorithm, the simulations are done under the network simulator (NS-2). The implementation was done under the mannasim platform using the version 2.29 of the simulator. This platform supports both AODV and LEACH protocol. The density of network was varied from 20 to 120 static sensor nodes dispatched in area of 500m^2. The link layer is implemented using the ZigBee standard which supports the IEEE802.15 Media Access Control (MAC) protocol. The traffic used is a CBR (Constant Bit Rate) rate is varied with packet's size is fixed as 512bytes. The whole simulation scenario is run for 200 simulated seconds. The energy model is activated, and the initial energy of each sensor node is set to 1000 Joules. For the transmission and reception RtPower is fixed to 0.00075 w and TxPower is fixed to 0.00175 w. The Sleep Energy is about 0.00005j.

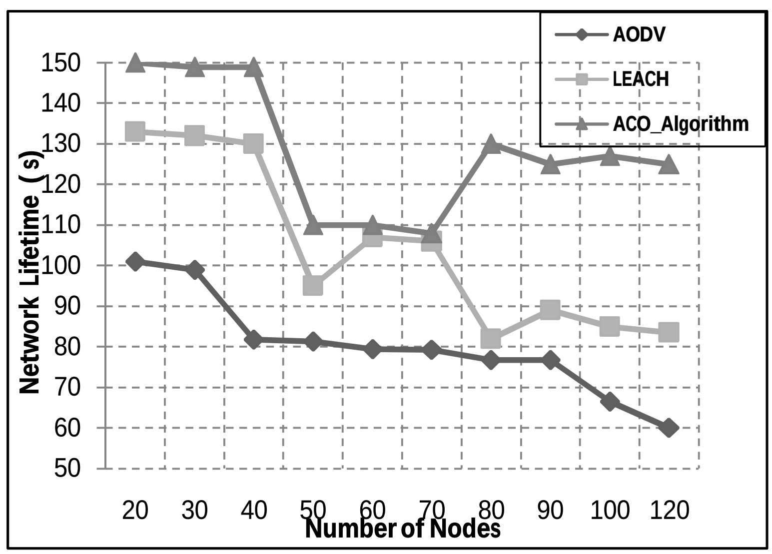

Figure .1: Network lifetime Vs density network varying

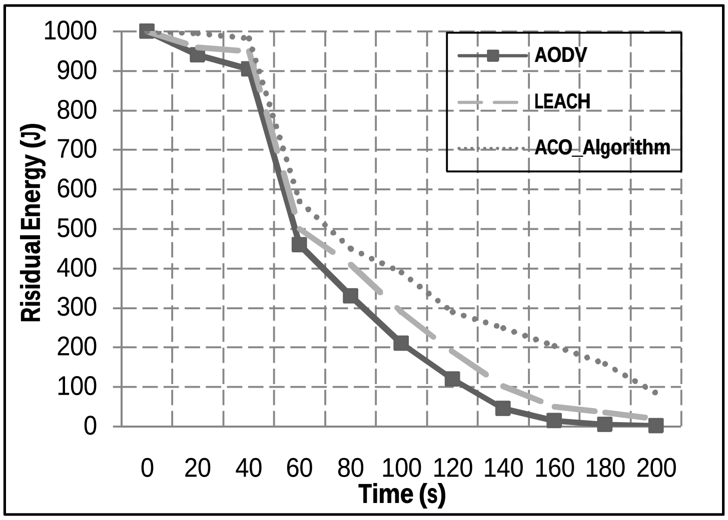

Figure .2: Residual Energy in joules Vs Time for 120 nodes.

In the Figure 1, we study the impact of the density of network by varying the number of nodes to 120 nodes. The results show the performance of network lifetime. ACO algorithm outperforms efficiently and resist for longer time compared to both AODV and LEACH protocols.

Indeed, the three protocols perform similar for low density less than 40 nodes where source reach destination with less energy consumption. The difficulty of discovering destination becomes more and more complex by increasing the density network, that what we can observe for mean density less than 70 nodes where ACO algorithm and LEACH protocols perform in the same way largely better than AODV. More than 70 nodes, the proposed algorithm act with more energy efficiency by prolonging the network lifetime.

Figure 2 shows the performance of residual energy of ACO algorithm. Indeed, the residual energy of the presented algorithm, AODV and LEACH has the same residual energy in the beginning. Gradually, this energy is more consumed versus time when the communication and route discovery start after 40s.

We can remark the premature death of the network using the AODV protocol when reaching 200 s (time of simulation). In spite of the proportionality of the results given, our algorithm performs well when keeping more energy at the end of time of simulation. Generally, the simulation results show the adaptability of ACO algorithm to dense sensor networks.

5. CONCLUSION

In WSN, the life time network is depended essentially to the density and the rate of communications of sensors which affect the battery level and so the network. In this paper, we act on the routing level and present a new routing algorithm, which uses ant colony optimization algorithm for WSNs. This solution improves actively the life time network of the WSN. Indeed, the ACO algorithm outperforms when compared to LEACH and AODV protocols. The effectiveness of the ACO algorithm has been verified by several simulations under NS2 simulator in terms of residual energy and life time network. The next work will be focused on the mobility context of sensors witch considered as a huge challenge in WSN area with energy consumption metric.

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