

An Ant-based approach to Power-Efficient Algorithm for Wireless Sensor Networks

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Abstract—We present an adaptive approach for improving the performance in randomly distributed Wireless Sensor Networks (WSNs). The goal is to find the optimal routing not only to maximize the lifetime of the network but also to provide real-time data transmission services. Considering a wireless sensor network where the nodes have limited energy, we propose a novel model Energy * Delay based on Ant Colony Optimization (ACO) algorithm (E&D ANTS) to minimize the time delay in transferring a fixed number of data from the source nodes to the destination nodes in an energy-constrained manner. In the algorithm, an amount of artificial ants randomly explored the network and exchanged collected network information to periodically update ant routing-tables which were obtained by having integrated partial pheromones and heuristic values. Our study is focused on influence functions of pheromones. Because of the tradeoff of energy and delay in wireless network systems, we propose the Reinforcement Learning (RL) algorithm to train our model. The simulation results show that our method boasts undoubtedly a number of attractive features, including adaptation, robustness and stability.

Index Terms— ACO, Pheromones, Power consumption, Wireless sensor networks

I. INTRODUCTION

The wireless sensor networks (WSNs) technology is widely used in many fields, including environmental monitoring, health monitoring, military surveillance and earthquake observation. In the wireless systems, a lot of nodes operate on limited batteries while satisfying given throughput and delay requirements. So the development of low-cost and low-power sensor network system has received increasing attentions. Low power research is concentrated in the RF, Baseband, network, and application layers of wireless devices. A high performance routing algorithm is often a crucial part in network system, because good routing can contribute either greater throughput or lower average delays if all the other conditions being the same. In the paper, we propose two routing strategies. First of

all, we select the most power-efficient path and perform well in real time. Secondly, we avoid the heavy load links and preserve the load balancing of the distribution.

Algorithms which take inspiration from ants' behavior in finding the best paths have recently been successfully applied into different fields including WSNs. Reference [1] Shows that some researchers introduced the ACO algorithm into WSNs and implemented it on the hardware. However, how to adjust the pheromone of each node by total energy level, throughput and delay of wireless networks is typically ignored. Reference [2] introduced the AntNet Algorithm into normal communications networks. However it seems to be unsatisfactory in WSNs. In this paper, in order to enhance the capability and network lifetime, we employ an adaptive dynamic algorithm based on ACO for routing operations. The ant routing-tables of each node are regularly updated by a back round ant holding network load and delay information.

The rest of the paper is organized as follows: in Section II, we propose a practical ACO model for WSNs. In Section III, The scheme of routing algorithm are implemented, Section IV presents the simulation results. Finally in section V, some concluding remarks are made.

II. THE PROPOSED NETWORK MODEL ON ACO

In DI CARO G's paper [2], ants have the power of finding the shortest path from ant nests to foods. They use AntNet routing algorithm to select intermediate nodes to relay data packets on the overall energy efficiency of the network and the capability of ants is achieved by their releasing one kind of volatility pheromones along the path. Supposing a certain path is selected by more ants than other paths, more pheromones increments will be saved to the path, and as a result, more ants will select the path at the next time. Thus, the amount of the pheromones in the specific path will grow gradually because of accumulated positive feedback. In the end, ants will find the shortest path on a stable state. However, the key idea of our E&D ANTS scheme is taking advantages of the conjunction of energy and delay in wireless networks in order to update nodes' pheromones.

The wireless network in consideration is modeled as a directed graph $G(N, A)$, where N is the set of all the nodes which can queue and transfer packets and A is the set of all directed links (i, j) where $i, j \in N$. Let L_i be the set of all nodes that can be reached by node i with a certain power level in its dynamic

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range. We assume that link (i, j) exists if and only if $j \in L_i$. Each node i has the residual energy e_i (its initial value E_0). Assume that the transmission energy required for node i to transmit an information unit to its neighboring node j is e_{ij} . Assume the ant routing-tables of node i are denoted as follows:

$$A_i = [a_{jd}^i(t)] = \begin{bmatrix} a_{11}^i(t) & a_{12}^i(t) & \dots & a_{1N}^i(t) \\ a_{21}^i(t) & a_{22}^i(t) & \dots & a_{2N}^i(t) \\ \vdots & \vdots & \ddots & \vdots \\ a_{L1}^i(t) & a_{L2}^i(t) & \dots & a_{LN}^i(t) \end{bmatrix} \quad (1)$$

$i \in N, j \in L, d \in N$

Where each row in the upper matrix must meet the following constrained equation:

$$\text{s. t.} \quad \sum_{j \in L_i} a_{jd}^i = 1; d \in [1, N] \quad (2)$$

Where a_{jd}^i represents the probability of selecting from the current node i to destination node d via the node j [3].

$$a_{jd}^i = \frac{\omega \tau_{jd}(t) + (1-\omega) \eta_j}{\omega + (1-\omega)(|N_i| - 1)} \quad (3)$$

Where $\omega \in [0, 1]$ is a weighting factor and the denominator is a normalization term. The ant routing-tables A_i are obtained by integrating partial pheromone trail values $\tau_{jd}(t)$ and heuristic values η_j . The pheromone trail values are calculated by (3):

$$\tau_{ij}(t+1) = \rho \tau_{ij}(t) + \Delta \tau_{ij}^{best} \quad (4)$$

Where $\rho \in [0, 1]$ and $\Delta \tau_{ij}^{best} = f^{best}(t)$.

The function $f^{best}(t)$ is the best solution of iteration. In the following subsections, this function is our crucial object which needs further research on the tradeoff between power consumption and delay in wireless sensor networks. In [1], the heuristic values are set as the following equation:

$$\eta_i = \frac{e_i}{\sum_{n \in N_i} e_n} \in [0, 1] \quad (5)$$

This enables an ant to make a decision according to neighbor nodes' energy levels. A node will have less opportunity to be selected when it has a lower energy source.

III. DESCRIPTION OF ADAPTIVE DYNAMIC ACO ALGORITHM

A. The implementation of ACO

In this ACO algorithm, all the ants are identified into two types of artificial ants, a forward F and a backward B by their functions. An artificial ant F represents an ant agent moves from a source node s to a destination node d hopping from one node to the next till node d is reached. An artificial ant B represents an ant agent moves backward from a destination node d to a source node s . Each ant researches for a minimum cost path between a pair of nodes of the network. All the ants are equally allocated from each network node

towards destination nodes randomly selected to match the traffic load. Each ant has a memory tab_k which contains the already visited nodes. The memory $L_i - \{tab_k\}$ is used to define, for each ant k , the set of nodes that an ant started from node i still has to visit. By exploiting $\{tab_k\}$ an ant k can build feasible solutions. That is to say, ant can try to avoid visit a node twice which is shown as follows:

$$p_{jd}^i(t) = \begin{cases} a_{jd}^i(t) & \text{if } j \notin tab_k \\ 0 & \text{if } j \in tab_k \end{cases} \quad (6)$$

Where $p_{jd}^i(t)$ is the probability of selecting the next node j .

The ant routing-tables of node i are denoted by $P_i = [p_{jd}^i(t)]$.

Also, memory allows the ant to compute time delays and power consumption of the tour generated and to cover the same path backward to deposit pheromones on the visited nodes. When an F ant arrives at its destination node d , the node d will produce one B ant to go back to the source node s along the same path $\{tab_k\}$. At the same time, the B ant will update pheromones of each node in $\{tab_k\}$ based on information of the F ant's collecting delays and power levels. The following two paragraphs describe the expressions of delay model and energy model.

Each node in network will send packets by a certain speed. A split packet from each source is called and F_k ant whose destination node is selected by random probability. The intermediate nodes memorize and transfer F_k ants according to the FIFO principle. The strategy of transferring F_k ants depends on the ant routing-tables A_i in node i . The tables are applied to all the nodes unvisited by ant k . In forming the path from the source node to the destination node, ants F_k use the same queue with numbers of packets to transfer. By this way, ants or data packets are totally delayed. So we record the delay time D_d^s that it costs when moving from the node s to the node d as one important factor of evaluating the quality of the traffic of the path. Let D be the set of time delay of each nodes which are denoted as the following matrix:

$$D = \begin{bmatrix} d_{11}^i & d_{12}^i & \dots & d_{1N}^i \\ d_{21}^i & d_{22}^i & \dots & d_{2N}^i \\ \vdots & \vdots & \ddots & \vdots \\ d_{L1}^i & d_{L2}^i & \dots & d_{LN}^i \end{bmatrix}, j \in L; d \in N \quad (7)$$

Where d_{jd}^i represent the delay from the node i to the destination d via the node j . In this paper D is regarded as one factor of evaluating the model $f^{best}(t)$. That is because the factor of delay can show the quantities when an ant passes by, the capability of transferring packets and the performance of the link. Another reason is that it shows the status of congestion when artificial ants pass by the stagnated nodes.

In [5] [6], the studies show that single hop routing is almost

always more power efficient compared to multi-hop under realistic environments when thinking of the basic consumption such as RF circuit, channel fading and path efficiency. Also it is pointed out that multi-hop network schemes will result in significant overhead when we assume a larger number of short hops replace a smaller number of long hops. In our optimization we minimize the network power consumption across all the nodes. So this optimization criterion maximizes average node lifetime in a long run if we assume that the data rate generated at each node is randomly changing to the same distribution, where the path length is a vector whose elements are the link costs given by

$$c_{ij} = e_{ij}^x \tag{8}$$

Where x is nonnegative weighting factors for power consumption of the link, Assume C is the set of c_{ij} . Therefore, we formulate the power consumption problem with the objective of maximizing the system lifetime given the sets of source and destination nodes.

B. Pheromones and E&D ANTS Model

As having been discussed above, energy and delay are two crucial factors in the update of pheromones which contribute on the best solution of the path. The best solution is to minimize the Energy * Delay model. The mathematical expression is shown as follows:

$$g(t) = \text{Min}(\text{Energy} * \text{Delay}), \tag{9}$$

However, generally increasing energy saving comes with a penalty of increased delay. Therefore there is a tradeoff between energy consumption spent and delay cost. Assume ant F passes along the path from the source s to the destination d denoted as the set $P: \{s, i_1, \dots, i_k, d\}$. When ant B moves backward from the destination node d to the source node s , we can calculate energy consumption and time delay of each stage in each agent. Further Integrating (7), (8) and (9), we determine the E&D ANTS module as follows:

$$g(t) = |C \times D| = \sum_{i \in P} \sum_{j \in L_i} (c_{ij} * d_{jd}^s) \tag{10}$$

Where k is the number of solutions repeatedly constructed by all ants, their moving average \bar{z} is computed and each new solution z_{new} is compared with \bar{z} . We can determine the increment of pheromones of the model as follows:

$$\Delta \tau_{ij}(t) = f(t) = \tau_0 \left(1 - \frac{z_{new} - g(t)}{z - g(t)} \right) \tag{11}$$

Where \bar{z} is the average of the last k solutions, in order to achieve the optimal solution cost, we minimize the $g(t)$ value to a low bound as much as possible. So in (10), we use RL algorithm to find the lowest value $g^{best}(t)$ which are shown as follows:

$$g(t) = (1 - \rho)g(t-1) + \rho e_{ij}^x d_{jd}^i \tag{12}$$

Where ρ is the learning rate, $\rho \in [0,1)$, obviously, while the smaller the energy consumption is, the shorter delay time is on

the path $i \rightarrow j$ and the bigger the residual energy of node i has, the $g(t)$ value will become smaller. That is to say, the model estimating value will approach to the best solution. As a result, the increment of pheromones on the path grows bigger and bigger. When the node j is the best choice and ants have less chance to select other paths, the result of repeatedly searching is absolutely $p_{jd}^i(t) \rightarrow 1$. It conforms to the constrained (2).

IV. SIMULATION

To evaluate the above analysis, we use network simulator OPNET to construct the network topology graph which is shown in Fig. 1. For the ACO implementation, program is written in C++. Besides, we also implement AntNet [2] algorithm in OPNET. The network is constructed by twelve nodes and eighteen links.

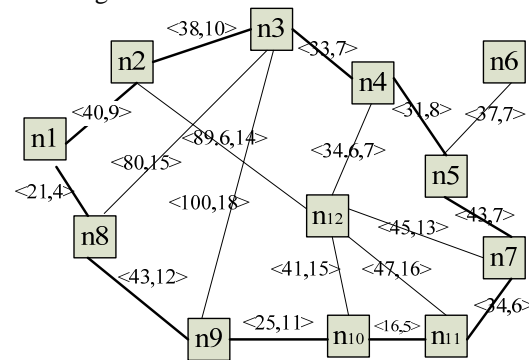


Fig 1: A Topology Graph of Wireless Network

In Fig.1, the numbers within panes indicate node identifiers. Each line in the graph represents a bidirectional link and the original weights each link are indicated as $\langle \text{power consumption, propagation delay} \rangle$, in which power consumption is measured in nJ/bit/message and propagation delay in millisecond (ms).

We assume the bandwidth B of each link is divided into two parts for bidirectional communications, and the links are constructed according to the Drop-Tail model (a finite FIFO queue). After source nodes produce a quantity of artificial ants or packets conforming to Poisson distribution, the destination nodes are randomly chosen by average probability. Each packet with an initial energy of 1 joule has a sequence number increased step by step. When one packet passes through a node by a certain speed, the node takes the first step to put all the ant agents into buffer storage and then selects the optimal path from its routing table to transfer packets. In this way all the ants disperse in as much paths as possible to achieve the balance of the load. The different sizes of one packet are considered in our simulations. So some of the experimental parameters used in the simulations are listed in Table I. In order to avoid cycles and

TABLE I
PARAMETERS IN NETWORK THROUGHPUT MODEL

Network traffic model	Parameters description
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Poisson	Initial energy e_0 : 1 Joule per node
	Packet Size (S) : 1 k, 2 k, 4 k, 8 k, 32 k or 64 k bits
	Bandwidth (B) : 1Mbit/s
	Traffic load ($Load$) : 15 packets/s

routing table's freezing, we need initialize τ_0 to $\frac{1}{L_i}$. In this

case, ant agents can adjust to the more efficient path when network traffic loads have changed and congestion fades away. Reference [4] introduced some simulation methods to find the best parameters x in (8). Considering (11) and (12), we assume the parameters of ρ is 0.1.

In this paper, the performance metrics are used as follows:

Energy: Power that all the nodes have consumed on sending a quantity of packets. We use the total energy consumed by sending messages as the indicator of the lifetime of network.

Average delay time: It consists of waiting time in queues and transferring time, which is namely the average time delay of all the ants' arriving at the destination node. We repeated experiments for more than ten times and calculated the average of those experimental data.

In Fig.2, comparing our simulation results with AntNet's, we can see that our improved algorithm has better convergence properties. Otherwise, when we change the structure of network topology (to shut down the node n_{12}) or decrease the bandwidth of nodes to 0.5Mbit/s when t goes to 210, it is shown in Fig.2 that our model undergoes a short time fluctuation and approaches very fast back to the balance status. It has a wonderful robustness. Whereas, AntNet can not adapt to these changes, and the whole curve went up straightly.

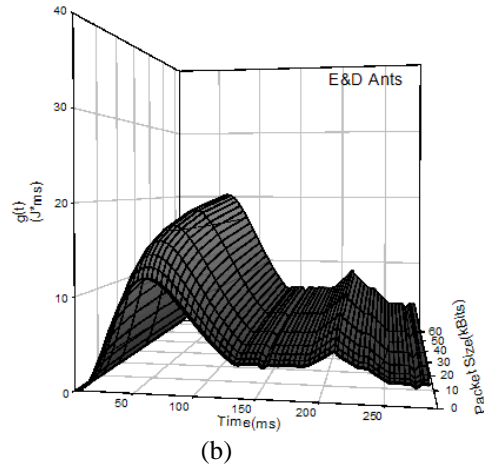
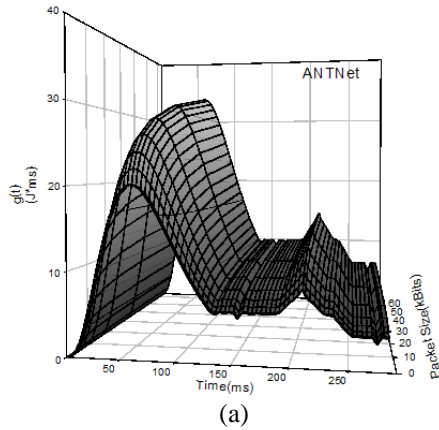


Fig.2 The comparison of E&D ANTS and AntNet

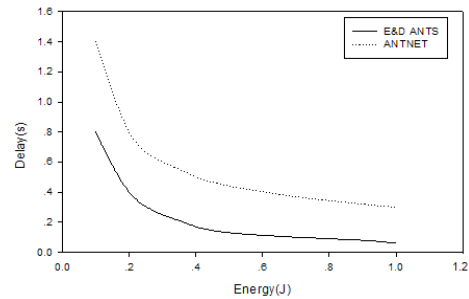


Fig.3 Delay and Energy tradeoff each packet

The tradeoff curve of delay and energy is shown in Fig3, where we conclude that E&D ANTS behaves better than AntNet in WSNs. In our experiments, we also found that the tradeoff curve is influenced by the topology graphs of networks and network load. Reference [7] proposed the tradeoff for different source rates and different network topologies in TDMA-based sensors networks.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a new algorithm model, E&D ANTS, which introduces a great energy-effective solution to communicate information from source nodes to destination nodes and significantly simplifies the topology of network at the same time. From the above research and simulation results, we obtained an amazing effect on determining the increment of pheromones by minimizing the model Energy * Delay. Without founding an enormous model, we optimize it by using the RL algorithm. Our study shows that E&D ANTS achieves up to 127% higher communication throughput while consuming 80% less per packet energy than AntNet. However, in wireless sensor devices, the memory of each node is limited. So when network traffic load is heavy, retransmissions will consume a lot of energy because of high packet loss rate. So the next step is to develop a mechanism which allows a node to accurately estimate the traffic and adjust its wakeup rate accordingly.

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