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Adaptive ant-based routing in wireless sensor networks using Energy*Delay metrics*

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Abstract: To find the optimal routing is always an important topic in wireless sensor networks (WSNs). Considering a WSN where the nodes have limited energy, we propose a novel Energy*Delay model based on ant algorithms ("E&D ANTS" for short) to minimize the time delay in transferring a fixed number of data packets in an energy-constrained manner in one round. Our goal is not only to maximize the lifetime of the network but also to provide real-time data transmission services. However, because of the tradeoff of energy and delay in wireless network systems, the reinforcement learning (RL) algorithm is introduced to train the model. In this survey, the paradigm of E&D ANTS is explicated and compared to other ant-based routing algorithms like AntNet and AntChain about the issues of routing information, routing overhead and adaptation. Simulation results show that our method performs about seven times better than AntNet and also outperforms AntChain by more than 150% in terms of energy cost and delay per round.

Key words: Ant colony optimization (ACO), Pheromones, Power consumption, Wireless sensor networks (WSNs)
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INTRODUCTION

The wireless sensor networks (WSNs) technology is widely used in many fields, including environmental monitoring (Arici and Altunbasak, 2004), military surveillance (Nemeroff *et al*., 2001) and health monitoring (Golmie *et al*., 2005), etc. 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 delay if all the other conditions are the same. In this paper, we propose two routing strategies. First of all, we select the most power-efficient path which performs well in real time. Secondly, we avoid the heavy load links and preserve the load balancing of the distribution.

Although an ant itself is a simple creature, collectively a colony of ants perform useful tasks such as finding the shortest path to a food source and sharing the information with another ant through stigmergy (Dorigo and Di Caro, 1999; Bonabeau *et al*., 2000). Ants achieve stigmergic communication by laying a chemical substance called "pheromone" that induces changes in the environment which can be sensed by other ants. In recent years, many researchers have successfully transformed the models of collective intelligence of ants into effective optimization and control algorithms. In the emerging field of ant colony optimization (ACO), a colony of biological ants are typically modeled as a society of artificial ants (Dorigo *et al*., 2000). ACO takes inspiration from ants' behavior in finding the best path. It has recently been successfully applied into different fields including network routing.

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The AntNet algorithm, introduced into normal communication networks by (Di Caro and Dorigo, 1997; Dorigo *et al.*, 1999) for routing in wired networks, outperforms all conventional algorithms on several packet-switched networks such as telecom SDH network. However, routing in the AntNet algorithm was implemented by only pursuing low average delay for data packets and high throughput path metrics. Moreover, using both forward and backward ants generally doubles the routing overhead. And its convergence speed and routing results seem to be unsatisfying in WSNs.

Ding *et al.*(2005) proposed a chain-based protocol, called AntChain which was a centralized approach to energy-efficiently gather data and communicate in WSNs. In the algorithm, the base station uses ACO to form a near-optimal chain and then the chain information is broadcasted to sensor nodes as their routing information, where the base station has unlimited resource (storage and power supply) availability and capacity and is located within or near the sensing area. Therefore, the base station should be burdened with heavy communication and computation cost. However, AntChain was formed by only using the energy metric but neglecting the average end-to-end delays. When an emergent event produced by the chain tail needs to be delivered to the base station, it will have to be relayed one by one. That is unacceptable for long time waiting in the queue of mediate nodes, especially for high real-time civilian applications such as healthcare or emergencies monitoring. The waiting time in the buffer queues accounts for the main end-to-end delay when relaying data packets to the base station. Moreover, when some nodes near the chain head have less energy left, the ant chain should be reorganized to improve the whole network lifetime and not part of the nodes'.

In this paper, for WSNs, we propose a dynamic adaptive ant algorithm, i.e., the E&D ANTS based on Energy*Delay metrics for routing operations. The main goal of our study is to maintain network lifetime in maximum and propagation delay in minimum by using a novel variation of reinforcement learning (RL). Compared to the AntNet and AntChain schemes for different cases, the simulation results show that E&D ANTS performs better than AntNet and AntChain in energy efficiency, real-time characteristic, convergence and robustness.

PROPOSED NETWORK MODEL ON ACO

In nature, biological ants have the power of finding the shortest path from ant nests to foods (Di Caro and Dorigo, 1997). They use ant algorithms 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. Therefore, the amount of 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. Based on the research, we propose the E&D ANTS model especially for the application of WSNs. The key idea of our E&D ANTS scheme is taking advantages of the conjunction of energy and delay in wireless communication in order to update the nodes' pheromones.

The wireless network in consideration is modeled as a directed graph $G(N, A)$, where $N=\{1, 2, ..., n\}$ is the set of all the nodes which can queue and transfer packets and A is the set of all directed links (i, j) $(i, j\in N)$. Let $L=\{1, 2, ..., l\}$ be the set of all nodes that can be reached by node i with a certain power level in its dynamic range. We assume that link (i, j) exists if and only if $j\in L$. Each node i has the residual energy e_i (with its initial value being E_0). Assume that the transmission energy required for node i to transmit an information unit to its neighboring node j is e_{ij}, and that the ant routing tables of node i are denoted as follows:

$$\boldsymbol{A}_i=[a_{jd}^i(t)]=\begin{bmatrix} a_{11}^i(t) & a_{12}^i(t) & ... & a_{1n}^i(t) \\ a_{21}^i(t) & a_{22}^i(t) & ... & a_{2n}^i(t) \\ \vdots & \vdots & ... & \vdots \\ a_{l1}^i(t) & a_{l2}^i(t) & ... & a_{ln}^i(t) \end{bmatrix}, \quad (1)$$

$$\text{s.t.} \quad \sum_{j\in L} a_{jd}^i=1, \quad (2)$$

where a_{jd}^i $(i, d\in N; j\in L)$ represents the probability of selecting the path from the current node i to the destination node d via node j.

DESCRIPTION OF ADAPTIVE DYNAMIC ACO ALGORITHM

Basic ACO algorithm

In the past, researchers presented many ant network models (Dorigo *et al*., 1999; 2000), where the ant routing tables $\boldsymbol{A}_i$ of node i were obtained by integrating partial pheromone trail values $\tau_{jd}(t)$ and heuristic values η_j, which is shown as follows:

$$a_{jd}^{i}=\frac{\omega\tau_{jd}(t)+(1-\omega)\eta_j}{\omega+(1-\omega)(|L|-1)},\quad \omega\in[0,1], \tag{3}$$

where L is the neighbor set and $j\in L$, d represents the destination node, ω is a weighting factor and the denominator is a normalization term. When ants exploit the path from node i to node d, the strategy to make a decision of routing depends on the probability a_{jd}^{i}.

An artificial ant reaches its destination node and returns to the source node by the same path, which is called a round trip. On its way to the source, the pheromone trail values along the path are calculated by

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

where $1-\rho$ represents the pheromone trail decay coefficient, $\rho\in[0, 1]$. $\Delta\tau_{ij}^{\text{best}}$ is the best solution of pheromones updating, $\Delta\tau_{ij}^{\text{best}}=f^{\text{best}}(t)$. The function $f^{\text{best}}(t)$ is the best solution of iteration. In the following subsections, this function is our crucial object which needs further research on many metrics such as power consumption and delay in WSNs.

Although the path with the least power consumption and the shortest delay could be chosen for routing, the residual energy of hop nodes is another factor to work on routing. The heuristic values are set as

$$\eta_j=\frac{e_j}{\sum_{m\in L}e_m}\in[0,1]. \tag{5}$$

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

Implementation of ACO

In ACO algorithms, all the ants are identified into two types of artificial ants, a forward F_k and a backward B_k by their functions, which are shown in Fig.1. An artificial ant F_k represents an ant agent that moves from a source node s to a destination node d by hopping from one node to the next till node d is reached. In its exploration, F_k will collect all the information of the paths passed by. An artificial ant B_k represents another ant agent that moves backward from a destination node d to a source node s. During its moving back, B_k will update the routing tables of all the nodes along the path according to the information collected by the corresponding F_k.

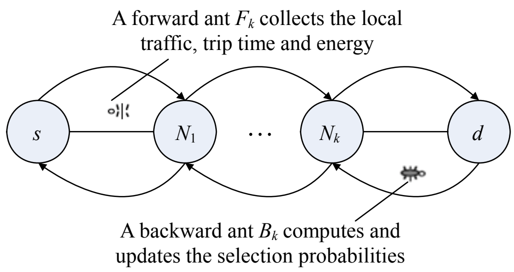

Fig.1 Pheromone updating policy of E&D ANTS

All the ants F_k are equally produced from each node in the wireless network and explore destination nodes randomly selected to match the traffic load. They search for a minimum cost path from the source to the destination. Each ant has a memory tab_k which contains the already visited nodes. The memory L-$\{tab_k\}$ is used to define, for each ant k, the set of nodes that an ant starts from node i and still has to visit. By exploiting $\{tab_k\}$ an ant k can build feasible solutions. That is to say, an ant can try to avoid visiting a node twice, which is shown as

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

where $p_{jd}^{i}(t)$ is the probability of selecting the next node j. The ant routing tables of node i are denoted by $\boldsymbol{p}_i=\left[p_{jd}^{i}(t)\right]$.

Also, processing ability and memory size of one node allow the ant F_k to calculate the cost such as time delay and power consumption that its tour generated. When an ant F_k arrives at its destination node d, the node d will produce one ant B_k to move back to the source node s along the same path $\{tab_k\}$ by higher priority than the data agent. At the same time, the ant B_k will update pheromones of each node in $\{tab_k\}$ based on the ant F_k's collecting some information such as delay and energy, which will influence routing choices when other ants and data agents pass by.

Analysis of routing strategies depending on different metrics

In WSN routing algorithms, many performance metrics including network's lifetime, average end-to-end delay for data packets, throughput and traffic overhead could be defined depending on the type of services delivered on the network and on their associated costs. To evaluate the performance of different metrics in WSNs, the characteristics of the above metrics have been analyzed as follows.

1. Energy metric

Energy metric is regarded as the measurement of the lifetime of a network. Two sides need to be considered. First of all, when transferring data packets between two d-distance neighbors, the total cost of energy in the communication is divided into two parts: the transmitter power and the receiver power, which are presented as

$$P_{\text{total}}(d) = P_{\text{T0}} + \varepsilon \cdot d^{\lambda} / \xi + P_{\text{R0}}, \tag{7}$$

where $P_{\text{total}}(d)$ is the total cost of energy to transfer an agent between two nodes, P_{T0} and P_{R0} represent the power consumption of the transmitter and receiver circuits respectively, ξ is the energy efficiency of the power amplifier in the RF circuit. In this theme, ε is calculated when meeting the signal-interference and noise-ratio (SINR) requirement and reliably communicating by the minimum required received power. Therefore, the total cost of energy is positively proportional to the distance d. The average power consumption is improved by selecting the total shortest path in the routing table. So this optimization criterion maximizes the average lifetime of network by making the best routing choices. The energy cost of the path (i, j) is denoted as

$$E_{ij} = e_{ij}^{x}, \tag{8}$$

where x is the nonnegative weighting factor for power consumption. Assume E is the set of E_{ij} on all the links.

Secondly, as described in the INTRODUCTION, wireless sensor nodes are devices with a very limited energy capacity. This means that the quality of a given path between a sensor node and the sink node should be determined in terms of not only the energy that all the nodes along the path have consumed on sending a quantity of packets, but also every node's power level of that path. So it would be preferable to choose a longer path with high power level than a shorter path with very low power level. As discussed in the previous section, the heuristic values are decided by the nodes' power levels. Eq.(5) indicates that the power level e_j of node j works on the probability to be chosen for routing.

2. Average end-to-end delay metric

As described in the AntNet algorithm, the link cost is designed to the sum of the mean delay of a packet in the link queue and the transmission delay, where the mean of the transmission time over the link T_v and the mean delay in the nodes' queue $T_{q(v)}$ are calculated over the last time window. These two variables are used to evaluate the link cost in the following way: $(1-T_v/T_{q(v)}, T_v+T_{q(v)})$. When an ant F_k explores different paths in wireless networks by the routing tables, all the relay nodes must use the same queue which follows the FIFO (first in first out) principle to buffer all the ant agents and data agents which directly result in time delay. During F_k's exploration from node s to node d, it records the delay value of each link passed by. The value will be regarded as an important factor of evaluating the cost of the path. When F_k arrives at node d, the matrix $\boldsymbol{D}$ presents the set of time delay of each node, denoted as

$$\boldsymbol{D} = \begin{bmatrix} t_{11}^{i} & t_{12}^{i} & \cdots & t_{1n}^{i} \\ t_{21}^{i} & t_{22}^{i} & \cdots & t_{2n}^{i} \\ \vdots & \vdots & \cdots & \vdots \\ t_{l1}^{i} & t_{l2}^{i} & \cdots & t_{ln}^{i} \end{bmatrix}, \tag{9}$$

where t_{jd}^{i} (i, $d \in N$; $j \in L$) represents the time delay from node i to node d via node j.

3. Throughput metric

The throughput of a link is the predicted number of data transmissions required to send a packet over that link, including retransmissions. The metric's overall goal (De Couto *et al*., 2003) was to choose routes with high end-to-end throughput calculated by using the forward delivery ratio t_f, which was the probability that a data packet successfully arrives at the recipient, and the reverse delivery ratio t_r, which was the probability that the ACK packet is successfully answered, over the link. The probability that a transmission is successfully received and acknowledged is $t_f \times t_r$. Those packets not successfully acknowledged will be retransmitted. Each attempt to transmit a packet can be considered a Bernoulli trial. So the expected number of transmissions is $1/(t_f \times t_r)$. The delivery ratios t_f and t_r were measured using dedicated link probe packets. The impacts of varying in throughput include (1) packet size, (2) link loss ratios, and (3) interference between successive hops of multi-hop paths. High throughput is a crucial metric to evaluate the performance of routing algorithms in ad-hoc wireless network. However, in WSNs, the many nodes assumption is conservative most of the time and the traffic load of wireless networks is light. With a few nodes in use, the bandwidth of each link is enough for light-weighted transmissions. Thus, in this paper, two assumptions are made about the link: (1) the link quality is good enough; (2) the network traffic load is light.

4. Traffic overhead metric

The routing traffic overhead is the ratio between the generated routing and the total available bandwidth. In AntNet, using both forward and backward ants generally doubles the routing overhead. The traffic overhead metric of restricting the number of ants inside a network, which should not exceed four times of the number of network nodes, was proposed in (Baran and Sosa, 2000). The simulation results showed that the computing load was diminished a lot. But it was unclear whether the optimal number was appropriate. Although restricting the number of ants may decrease the routing overhead and the possible congestion is controlled, it also leads to possible reduction in the performance of the routing algorithm. And in the AntChain algorithm, the base station periodically broadcasts the control messages and manages the status of the whole network. The main aim of the ants is to sample the paths, assign a quality to them, and apply this information to updating the routing tables in the nodes they passed. Therefore, in the AntNet and AntChain algorithms, where the overhead is independent of the traffic, even if there is no communication, the ants would still be traversing the network and update the routing tables. However, in E&D ANTS, nodes in WSNs stay in sleep status most of the time. The overhead depends on the traffic and if there is no communication no control messages will be produced in the networks. Nodes gather routing information on demand—only when the data for a certain destination are obtained they construct a path, and only when the path becomes infeasible they search a new path. Moreover, most of routing maintenance is performed through data packets, and the expected overhead is very small.

To sum up, considering the characteristics of WSNs, the network's lifetime and the real-time communication are the key topics. And the sets D and E are regarded as two critical measurement parameters to evaluate the updating artificial ants' pheromone values. The reasons are shown as follows: first, energy consumption can prolong the lifetime of the network; secondly, time delay can indicate congestions and hops during artificial ants' exploration. Therefore, the sets D and E are formulated to evaluate the best routing scheme $f^{\text{best}}(t)$ in Eq.(4), which will be further discussed in the next section.

PHEROMONES AND E&D ANTS MODEL

Generally, increasing energy saving comes with a penalty of longer delay. Therefore, there is a tradeoff between energy consumption and delay. As discussed above, energy cost and delay are two crucial factors of the update of pheromones which contribute to the best solution of the path. The best solution is to minimize the Energy*Delay model. The mathematical expression is shown as follows:

$$g(t) = \min\left(Energy * Delay\right). \tag{10}$$

A very efficient analysis method, the well-known Bellman's principle, of decomposing an optimal link into optimal sub-links is also introduced. Assume an ant F_k passes along the path from the source s to the destination d denoted as the set P:{s, i_1, ..., i_k, d}. When an ant B_k moves backward from the destination node d to the source node s, it can be calculated that the energy and time delay values of each stage are spent in each agent. By further integrating Eqs.(8)~(10), the Energy*Delay model can be determined as

$$g(t)=\min(|E^{\alpha}*D^{\beta}|)=\min\left\{\sum_{i\in\{tab_k\}}\sum_{j\in L}[E_{ij}^{\alpha}*(t_{jd}^{i})^{\beta}]\right\}, \tag{11}$$

where α and β are constant and represent the relative importance of energy cost and delay, respectively when an artificial ant B_k updates the nodes' pheromones along the same path. k is the number of solutions repeatedly constructed by all ants, and their moving average value $\bar{z}$ is computed. When the new (k+1)th solution z_{new} is compared with $\bar{z}$, we can determine the increment of pheromones of the model as

$$f(t)=\Delta\tau_{ij}(t)=\tau_0\left(1-\frac{z_{\text{new}}-g(t)}{\bar{z}-g(t)}\right), \tag{12}$$

where τ_0 is the initial pheromones value and $\bar{z}$ is the average of the last k solutions (and then $\bar{z}$ is used to compute the new moving average value). If z_{new} is lower than $\bar{z}$, the trail level of the last solution's moves increases, otherwise it decreases.

In order to achieve the optimal solution, we minimize the $g(t)$ value to a low bound as much as possible. The homeostasis strategy is introduced to make out the past optimal solutions' great achievements and improve the ability of the new exploration. So in Eq.(13), we use the RL algorithm to find the smallest $g^{\text{best}}(t)$, shown as

$$g(t)=(1-\gamma)g(t-1)+\gamma(e_{ij}^{x})^{\alpha}(t_{jd}^{i})^{\beta}, \tag{13}$$

where γ is the learning rate, $\gamma\in[0, 1]$. Obviously, the smaller the energy consumption, the shorter the delay on the path $i\to j$ and the more the residual energy of node i, the faster the $g(t)$ value will decrease. 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 node j is the best choice and ants have less chance to select other paths, the result of repeatedly searching is absolutely $P_{jd}^{i}(t)\to 1$. It conforms to the constraint of Eq.(2).

PERFORMANCE EVALUATION

System settings

To evaluate the above analysis, we use the network simulator OPNET to construct the network topology graph (Fig.2). The topology is depicted as a randomly deployed 50-node sensor network in a playing field of 100 m×100 m. For the E&D ANTS implementation, the program is written in C++. Besides, we also implement the AntNet and AntChain algorithms in OPNET.

In Fig.2, each link is a bidirectional link and the weighting value of the link depends on the power consumption (nJ/bit) and ant's moving time delay (ms). From Table 1, we assume that the bandwidth B of each link is divided into two parts for bidirectional communications, and that the links are constructed according to the Drop-Tail model (a finite FIFO queue). After the source nodes produce a quantity of artificial ants or packets conforming to the Poisson distribution, the destination nodes are randomly chosen by average probability. Each packet with an initial energy of 1 J has a sequence number increased step by step. When one packet passes through a node

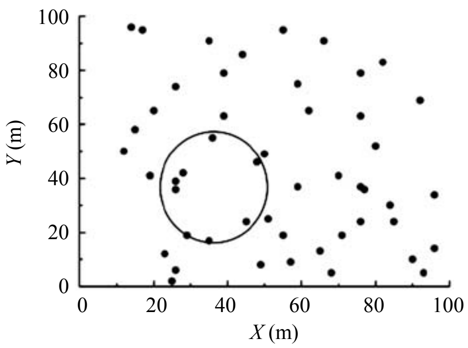

Fig.2 Randomly deployed 50-node topology for a 100 m ×100 m network. Black dots refer to the nodes, and the circle refers to the area to be erased

Table 1 Parameters in the network traffic model Poisson

Parameter	Value
Initial energy e_0	1 J/node
Packet size S	32 bytes
Bandwidth B	250 kbps
Traffic load	5 packets/s

by a certain speed, the node takes the first step to gather 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 many paths as possible to achieve the balance of the load. A fixed size of one packet is considered in our simulations. Some of the experimental parameters used in the simulations are listed in Table 1. In order to avoid cycles and the routing table's freezing, we need to initialize τ_0 as in (Baran and Sosa, 2000). In this case, ant agents can adjust to the more efficient path when the network traffic loads change and the congestion fades away. Some simulation methods (Chang and Tassiulas, 2000; Wu *et al.*, 2006) are introduced to set up the parameters ($\alpha, \beta, \gamma, x, \rho, \omega$). In our experiment, these parameters are set to (0.8, 0.4, 0.1, 0.2, 0.9, 0.4). Simulation methods for the AntNet were attempted in (Di Caro and Dorigo, 1997) where the parameters (c, a, a', ε, h, t) were set to (2, 10, 9, 0.25, 0.04, 0.5). Considering that AntChain is a centralized approach of energy-efficiently gathering data in WSNs, we assume that data packets are only trained to transfer from the end devices to the sink node in our E&D ANTS module when compared with AntChain.

Evaluation of adaptability, convergence and efficiency using Energy*Delay metrics

Our experiments were repeated more than ten times and the experimental data were averaged. Fig.3 shows the Energy*Delay simulation results which change by time step. Comparing these results in the AntNet, AntChain and E&D ANTS algorithms, we can conclude that the E&D ANTS algorithm has faster convergence than AntNet and AntChain. During the first few periods, the Energy*Delay values went through a huge fluctuation because of the artificial ants' exploration. While the learning was still running, each curve settled down and indicated a stable exploitation and load balance. Otherwise, we changed the structure of the network topology (to shut down some nodes in the circle of Fig.2) or reduced the bandwidth of nodes to 0.5B kbps when the time step arrived at 550. It is shown in Fig.3 that our model underwent a short time fluctuation and approached very fast back to the stable status. It has a wonderful robustness and adaptability. Whereas, the AntNet could not adapt to these changes and the whole curve went up straightly, due to the presence of a large amount of packets saturating the queue buffers after the modification. From the spots, the AntChain performed better than the AntNet because the network status was controlled by the base station that always stayed alive for listening and it had a good self-organization.

Fig.4 shows the routing overhead results for the three algorithms at different time steps, where the routing load is the ratio of the control packets generated to all the data packets received. As expected, the normalized overhead is too high in case of the AntNet scheme, because the actual data packets delivered are too few and the ratio of control overhead to data packets, like forward ants F_k and backward ants B_k, is too high. And the normalized overhead in AntChain (Fig.4) is much less than that in AntNet because of its periodically broadcasting control messages. In case of E&D ANTS, the routing overhead is the least, because the overhead is dependent of the traffic and there are few control messages when the nodes are conservative.

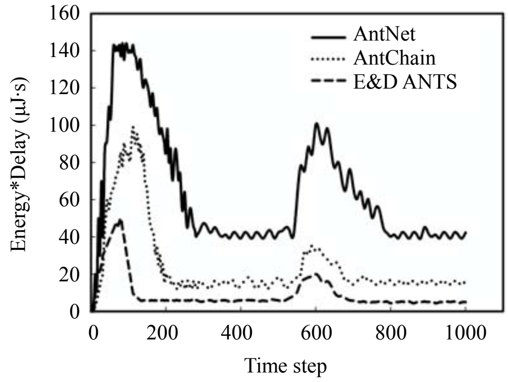

Fig.3 Energy*Delay comparison of E&D ANTS, AntNet and AntChain algorithms

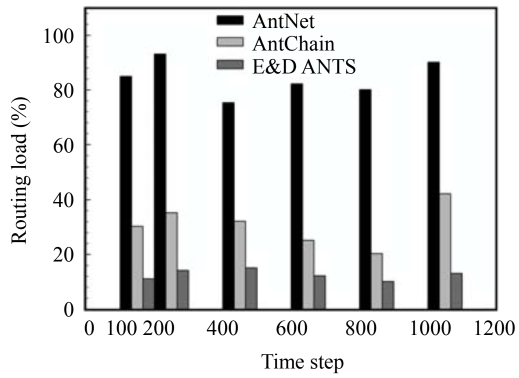

Fig.4 Routing overhead of AntNet, AntChain and E&D ANTS algorithms

CONCLUSION

In this paper, we propose a new algorithm E&D ANTS based on the Energy*Delay model, which introduces a great energy-effective solution to the communication from source nodes to destination nodes and significantly simplifies the topology of networks. From the research and simulation results, an amazing effect on determining the increment of pheromones by minimizing the Energy*Delay model was obtained. We only optimized it by using the reinforcement learning (RL) algorithm without building an enormous model. Experimental results clearly show that the E&D ANTS performs with up to seven times higher communication efficiency than the AntNet and also outperforms the AntChain by more than 150%. Experiments were also done to show that E&D ANTS was able to meet the demands of different applications by adjusting the relative importance of energy cost and delay and the nonnegative weighting factor for power consumption.

References

Arici, T., Altunbasak, Y., 2004. Adaptive Sensing for Environment Monitoring Using Wireless Sensor Networks. Proc. Wireless Communications and Networking Conf., **3**:2347-2352.

Baran, B., Sosa, R., 2000. A New Approach for AntNet Routing. Proc. 9th Int. Conf. Computer Communications Networks, **10**:303-308. [doi:10.1109/ICCCN.2000.885506]

Bonabeau, E., Dorigo, M., Theraulaz, G., 2000. Inspiration for optimization from social insect behavior. *Nature*, **406**(6791):39-42. [doi:10.1038/35017500]

Chang, J.H., Tassiulas, L., 2000. Energy-Conserving Routing in Wireless Ad-hoc Networks. Proc. IEEE INFOCOM, **1**:22-31. [doi:10.1109/INFCOM.2000.832170]

De Couto, D.S.J., Aguayo, D., Bicket, J., Morris, R., 2003. A High-Throughput Path Metric for Multi-Hop Wireless Routing. Proc. 9th Annual Int. Conf. on Mobile Computing and Networking, **9**:134-146. [doi:10.1145/938985.939000]

Di Caro, G., Dorigo, M., 1997. AntNet: A Mobile Agents Approach to Adaptive Routing. Tech. Rep. IRIDIA/97-12, IRIDIA. Free Brussels University, Belgium.

Ding, N., Liu, P.X., Hu, C., 2005. Data Gathering Communication in Wireless Sensor Networks Using Ant Colony Optimization. Proc. Int. Conf. on Intelligent Robots and Systems, **8**:729-734. [doi:10.1109/IROS.2005.1545067]

Dorigo, M., Di Caro, G., 1999. Ant Colony Optimization: A New Meta-Heuristic. Proc. Congress on Evolutionary Computation, **2**:1470-1477. [doi:10.1109/CEC.1999.782657]

Dorigo, M., Di Caro, G., Gambardella, L.M., 1999. Ant algorithms for discrete optimization. *Artificial Life*, **5**(2):137-172. [doi:10.1162/106454699568728]

Dorigo, M., Bonabeau, E., Theraulaz, G., 2000. Ant algorithms and stigmergy. *Future Generation Computer Systems*, **16**:851-871. [doi:10.1016/S0167-739X(00)00042-X]

Golmie, N., Cypher, D., Rebala, O., 2005. Performance analysis of low rate wireless technologies for medical applications. *Computer Commun.*, **28**(10):1266-1275. [doi:10.1016/j.comcom.2004.07.021]

Nemeroff, J., Garcia, L., Hampel, D., Di Pierro, S., 2001. Application of Sensor Network Communications. Proc. Military Communications Conf., **1**:336-341. [doi:10.1109/MILCOM.2001.985815]

Wu, C.M., Chen, Z., Jiang, M., 2006. The research on initialization of ants system and configuration of parameters for different TSP problems in ant algorithm. *Acta Electronica Sinica*, **34**(8):1530-1533 (in Chinese).