An Energy Efficient Routing Based on Swarm Intelligence for Wireless Sensor Networks

Yong Lv
College of Mechanical and Electrical Engineering Jiaxing University, Zhejiang Province, China
Email: lvyongs@sohu.com

Abstract—**Wireless Sensor Networks are characterized by having specific requirements such as limited power, memory and functionality to support communications. In sensor networks, minimization of energy consumption is considered a major performance criterion to provide maximum network lifetime. Traditional routing protocols do not take into account that a node contains only a limited energy supply. In this paper, we describe a novel energy efficient routing approach which combines swarm intelligence, especially the Ant colony based meta heuristic, with a novel variation of Reinforcement learning for Wireless Sensor Networks (ARNet). The main goal of our study was to maintain network lifetime at a maximum, while discovering the shortest paths from the source nodes to the sink node using an improved swarm intelligence based optimization. ARNet balances the energy consumption of nodes in the network and extends the network lifetime. Simulation results show that ARNet can obviously improve adaptability and effectively reduce the average energy consumption compared with the traditional EEABR algorithm.**

Index Terms—**wireless sensor networks, routing, swarm intelligence**

I. Introduction

Wireless sensor networks is a class of wireless ad hoc network which consists of a set of sensor nodes. Such sensor nodes have an ability to sense the environment nearby, perform simple computations and communications in a small region acting as a router. Although these nodes in network may turn on or off during operation due to unexpected failure, battery life, or power management, combining these small nodes in large numbers provides reliable operations in various application areas including traffic controling system, environmental monitoring, health monitoring, object tracking, earthquake observation and military surveillance, etc [1-3].

Although WSNs are used in many applications, they have several restrictions including limited energy supply, computational speed and communication abilities. Because of these considerations specific to WSNs, many routing schemes using end-to-end devices and MANETs are inappropriate for WSNs.

In sensor networks, energy consumption is severely constrained. Therefore, it is important to design sensor networks aiming to maximize their life expectancy. When considering energy conservation, routing protocols should also be designed to achieve fault tolerance in communications. In addition, since channel bandwidth is limited, protocols should have capability of performing local collaboration to reduce bandwidth requirements.

The basic method to transfer information from a sensor node to the base is called flooding. In this method, information is disseminated by all the nodes as well as the base node. The broadcasting operation to all over the network consumes too much energy and bandwidth. Heinzelman et al. proposed a model that disseminates all the information in the network assuming that all nodes are potential base nodes [4]. This model does not consider other important sources of energy consumption, such as transient energy, sensor sensing, sensor logging and actuation. Therefore this model's data advertisement operation does not guarantee data delivery. In this respect multi-path routing protocols promise advantages. The method of multiple paths to transfer data to the base enhances the reliability of WSNs. Directed diffusion [5-6] is a candidate method for multi-path routing. However, directed diffusion may not be suitable for those monitoring applications which require periodic data transfers.

The optimization of network parameters for wireless Sensor Networks routing process to provide maximum network life expectancy might be considered as a combinatorial optimization problem. A promising approach for such a routing algorithm are so-called ant algorithms based on mechanisms inspired by the collective foraging behavior of specific ant species[7-12]. The ant colony algorithm has many distributed merits such as positive feedback, distributed computing and constructive greedy heuristic searching. Ant colony optimization has been a fruitful paradigm for designing effective combinatorial optimization solution algorithm which has been successfully applied in many optimization problems, such as asymmetric traveling salesman(TSP) [13], vehicle routing [14], Job Shop Scheduling Problem(JSP)[15] and WSN routings [16-18].

Singh et al. [19] proposed an algorithm based on ant colony for WSN routings. However, this algorithm does not consider the specifics of WSN structures, including energy limitions. Zhang et al. [20] proposed another algorithm based on ant colony for WSNs. Their study includes three main routing algorithms named SC, FF, and FP. The algorithms are successful with initial

doi:10.4304/jsw.9.10.2758-2763

pheromone settings to have a good system star-up, but the SC and FF algorithms are not very effective in latency, while providing better energy efficiency. Besides, the FP algorithm, while providing high success rates of data delivery, consumes much higher energy than the FF and FC algorithms. The Energy Efficient Ant Based Routing Algorithm for WSNs (EEABR) [21] is another algorithm based on ACO to maximize the lifetime of WSNs. The algorithm uses a good strategy considering energy levels of the nodes and the lengths of routed paths.

In this paper, we have compared the performance of our ARNet approach using a novel variation of reinforcement learning to the results of the EEABR algorithm. Various differently sized networks are considered, and our approach outperfoms EEABR algorithm in terms of energy consumption.

The main goal of our study was to prolong network life time at a maximum, while discovering the shortest paths from source nodes to base nodes using swarm intelligence based optimization technique called ant colony optimization. A multi-path data transfer is also accomplished to provide reliable network operations, while considering the energy levels of the nodes. The paper is organized as follows. In Section 2, the proposed routing scheme using ARNet is explained. In Section 3, performance results obtained from the simulations are given. Finally, in Section 4 we conclude our study and give our future work plan.

II. Proposed WSN Routing Scheme

To achieve an efficient and robust routing operation, major features of typical WSNs are taken into consideration. First, failures in communication nodes are more probable in WSNs than classical networks, as nodes are often located in unattended places and they use a limited power supply. Therefore the network should not be affected by a node's failure and should be in an adaptive structure to maintain the routing operation. This is performed by sustaining different paths alive in a routing task. A node transfers data packages to the base using different paths. When a failure occurs in a path, the associated data package cannot arrive at the base. To achieve guaranteed delivery, acknowledgement signals are used. In the case of an absent acknowledgement for a data package, the source node resends that package to a different path. By performing acknowledgement-associated data transfers and sustaining different paths alive, routing becomes more robust. It is obvious that some paths in this type of network would be shorter, allowing for lower energy costs. Transmission on these paths should be more frequent so as to reduce the total cost of energy consumed using these paths. In other words, more data packages should be transferred along shorter paths to achieve a lower energy consumption.

Second, the mobility of some node should be allowed in some specific WSN applications. In our approach, nodes are considered to be normally stable. However, probable changes in node locations do not preclude network operation safely. Instead, it causes some setup stage to organize paths well. However, transfer of data packages is still performed in this stage as quality grows over time by exploring new paths.

Third, nodes in WSNs present stringent energy constraints. They consume much more energy when they are in communication. In our proposed approach, the energy levels of the nodes should also be considered as well as the lengths of the paths. This is performed by choosing nodes having more energy in a routing task. Thus, the average network lifetime would be increased.

Fourth, the bandwidth of wireless links in WSNs is limited. It is important not to involve too much information about overhead of the routing task in the communications. This is also a means of preserving more energy. We propose a new communication technique using ant agents in the following.

To summarize the operation of routing scheme, a node having information for the base station initializes the routing task by transferring data packages to different neighbor nodes. Each node then chooses other neighbor nodes and so on. Thus, paths towards the base are formed and each routing operation supplies some information about optimum paths for the consequent routing tasks. While performing this operation, some agents (artificial ants) are used to achieve efficient routing. This operation is explained in the following.

A. ARNet Approach

In the ARNet based approach, each ant tries to find a minimum cost path in the network. Ants are launched from a source node *s*, move through neighbor nodes *j*, and reach a final destination node (sink) *d*. The path length is given by the number of nodes on the path. 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. In order to apply ant colony optimization to networks routing, we replaced the routing tables in the network nodes by tables of probabilities, which we call pheromone tables, see Table 1, as the pheromone strengths are represented by these probabilities. Each row in this table corresponds to a neighbor and each column to a destination.

TABLE I.
PHEROMONE TABLE FOR NODE N

Next node	Destination node			
	1	2	…	*N*
1	P_{11}	P_{12}	…	P_{1N}
2	P_{21}	P_{22}	…	P_{2N}
…	…	…	…	…
L	P_{L1}	P_{L2}	…	P_{LN}

The entries in this table are the probabilities which are used by ants to allow them to randomly explore the network and possibly find new and better routes. Once the routes are discovered, the next-hop probabilities are updated to reflect the new discoveries. All routing table entries conform to the constraint:

$$\sum_{j\in L_i} P_{jd} = 1\,, \quad L_i = \{neighbor(i)\} \qquad (1)$$

Where P_{jd} is the goodness (desirability) of choosing j as next node when the destination node is d, under the current network-wide routing policy.

After launching, the choice of the next node j is made according to a probabilistic decision rule (2) for ant k:

$$P_{jd}^{k} = \begin{cases} \dfrac{P_{jd} + \alpha E_j}{1+\alpha(L_i - 1)} & if\ j \notin tabu^{j} \\ 0 & otherwise \end{cases} \qquad (2)$$

Where P_{jd} expresses the pheromone value. The heuristic correction E_j is proportional to the instantaneous state of receiver node's energy. L_i is the number of neighbor nodes. For node j, $tabu^j$ is the list of identities of received data packages previously. The value of α weights the importance of the heuristic correction with respect to the probability values stored in the routing table, and we set values 0.3 for α. The routing table values, on the other hand, are the outcome of a continual learning process and capture both the current and the past status of the whole network. Hence the ant's decisions are taken on the basis of a combination of a long-term learning process and an instantaneous heuristic prediction.

The heuristic value of node j is expressed by equation (3):

$$E_j = \frac{e_j}{\sum_{i\in Li} e_i} \qquad (3)$$

Where e_j is the current energy level of neighbor node j. 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. Once they sense any change in their energy levels, nodes inform their neighbors about their energy levels.

In classical ACO, a special memory named M_k is held in the memory of an ant to retain the places visited by this ant. In order to decrease the size of the data to be transmitted and save node energy, the identities of ants (as sequence number k) 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. In equation (2), each neighbor node decides whether to accept the upcoming packet of ant k or not, by checking its *tabu* list. So the neighbor node j has a choice about completing the receiving process by listening and buffering the entire packet. If the neighbor 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, pheromone evaporation on all arcs is triggered, and then each ant k deposits a quantity of pheromone Δp on each arc that it has used in the solution:

$$\Delta p = e^{-\beta * h^k(t)/H_d} \qquad (4)$$

Where $\beta$is a dimensionless value. In the current implementation of the algorithm we set β=3. $h^k(t)$ is the length of tour which is done by ant k at iteration t. In WSNs, $h^k(t)$ represents the total number of nodes visited by ant k of tour at iteration t. H_d is a estimated length as follow:

$$H_d(t) = (1-\lambda)H_d(t-1) + \lambda h^k(t) \qquad (5)$$

Where λ is a learning rate parameter. Based on experience with a variety of simulation, we setλ=0.2.

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 Δp is added to the path visited by ant k. This amount is the same for each arc visited on this path. According to the identities of ants kept in the node's memories, 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 (if this is not possible because the next hop is not there, for instance due to unexpected failure, battery life, or power management, the backward ant is discarded). The routing table on the tour is then periodically recalculated at every time step. When an ant arrives at node, the entry in the routing table corresponding to the node j from which the ant has just come is increased as follow:

$$P_{j,d} = \frac{P_{j,d} + \Delta p}{1+\Delta p} \qquad (6)$$

The other entries in the table of this node are decreased according to:

$$P_{j',d} = \frac{P_{j',d}}{1+\Delta p}\ ,\ j' \in neighbor(n)\ ,\ \text{and}\ j' \neq j \qquad (7)$$

Since the new values sum to 1, they can again be interpreted as probabilities. Note that every discovered path receives a positive reinforcement in its selecting probability, and the reinforcement is a non-linear function of the number of nodes visited by ant. In this way, the probability can approach zero if the other entries are increased many times, but will never reach it. For a given value of Δp , the absolute and relative increasing in probability is much greater for initially small probabilities than for those that are larger. This has the effect of giving more weight to nodes that ants come from, but are not on the current preferred route. This method may assist in the rapid solution of the better route.

B. Protocol Operations

1). Disseminating Data

Several nodes become sources having information about an event which takes place nearby. This information is disseminated towards to the base node by the help of neighbor nodes. The data about an event provided by source nodes is named raw data. Associated raw data is split into N pieces called data parts which contain information such as event identification, source node identification, time and data about the event. An integer value N also represents the number of ant agents involving in each routing task.

After splitting the raw data into parts, each part is associated with routing parameters to build a data package ready to transfer. These parameters are code identification *C_ID* (describing the code following as data, acknowledge or error), package number k (also represents the ant agent), next node identification *N_ID* (which the package is transferred to), the sequence number *S_N*, and h^k which contains the number of visited nodes so far. These five parameters are named the data header. When delivery of all data packages is accomplished, the base combines them into raw data.

In Fig. 1, a node participation in a routing is given as an example. In the figure, Node A has just received a data package and makes a decision about the next destination for that package.

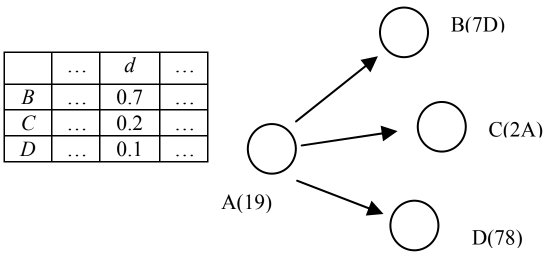

Figure 1. ACO parameters memorized in the nodes.

The next node (the next address of package transfer) is chosen by using equation (2) providing the highest P_{jd}^k. In this example, Node B (identified by 7D) more likely to be chosen as link (A, B) has the highest pheromone value (P_{jd}=0.7). Energy levels of the neighbor nodes B, C, and D play also an important role in the decision rule. If Node B is then chosen, *N_ID* field is updated as "7D" and the package is broadcasted. Nodes C and D also hear this broadcast. They check *N_ID* field and understand that this ID doesn't correspond to them, so they discard the package immediately after only listening to the *N_ID* field. Node B also checks *N_ID* field of the package. With the approval of ID, and ensuring *S_N* isn't in the list of *tabus* of node B, then $h^k(t)$ is updated by incrementing by one. Then, the next node is determined to update the *N_ID* field by performing the same operations as the previous node (Node A) had done. Because the number of ants is equivalent to the number of packages, defining the size of data package is essential. Package size must be defined by the initial system settings according to the average size of event data and hardware specifics.

2). Acknowledgement Method

After the dissemination operation by the source and neighbor nodes is done, the base gets data in parts from several paths. The main idea of using different paths is to provide reliable transfer operations in case of breakdown of the major routes. To prevent package loss in these paths, acknowledgement signals are used. After receiving a package, the base decides the pheromone value to be added on that route by evaluating Δp in equation (4). Then, the base forms an acknowledgement signal and broadcasts it towards to the source, using the same path which has been used for the associated data package.

A node receiving an acknowledgement signal checks the *S_N* value first. If the *S_N* value is found in the node memory (*tabus* list) that has been inserted previously while disseminating associated packages, this signal is broadcasted to other neighbors along the path. The node also updates the pheromone table by using equation (6) and (7), according to Δp specified in the signal. If the node ID is not found in the memory, then this signal is discarded and no further operation is done. Thus, the pheromone table is updated along the routed path. The source node waits for the acknowledgement signal of each data package. In case of an absent acknowledgement signal, caused by errors in the path, that package should be disseminated again.

3). Informing Energy Levels of Neighbor Nodes

Energy levels of neighbor nodes are essential part of decision rule (2), so each node needs to report its energy level to its neighbors. When a change is sensed in the energy level, reporting is carried out by broadcasting. The change is more likely after an active participation of listening or transmitting. So, they could sense their energy status immediately after any participation.

III. SIMULATIONS AND RESULT

In this section, we present the performance results of the simulation experiments. To accomplish the experiments, a parallel discrete event-based platform was developed. In the simulation, a free space radio propagation model is used. In order to verify the success of the proposed approach, an energy-efficient ant-based routing algorithm EEABR [21], a well known ACO based WSN routing algorithm, was used to make comparisons. The simulation is capable of running packet level experiments, specifications of which are given in Table 1. Experimental results are obtained for the two algorithms which are the one proposed in the approach described in Section 2 and the EEABR algorithm in [21]. The ARNet parameters and the specifics of hardware are set to the values specified in Section 2 and Table 2.

TABLE II.
PARAMETER VALUES OF THE HARDWARE USED IN SIMULATION

Parameter Name	Value
Frequency	2.4GHz
Transmit data rate	250Kb/s
Transmit power	-22dBm
Receive Sensivity	-90dBm
Current Draw in Transimit Mode	27mA
Current Draw in Receive Mode	25mA
Battery	2x(1.250Mah,1.5V)
Packet Size	512Kb

The results of the proposed approach and EEABR algorithm were obtained using the same settings for this simulation. Deployment of sensors are made by random distribution over 200 x 200 m^2 (10 nodes), 300 x 300 m^2 (20 nodes), 400 x 400 m^2 (30 nodes), 500 x 500 m^2 (40 nodes) and 600 x 600 m^2 when 50, 60, 70, 80 and 100 nodes are used to monitor a static phenomenon. The locations of the phenomenon and the sink node are not known.

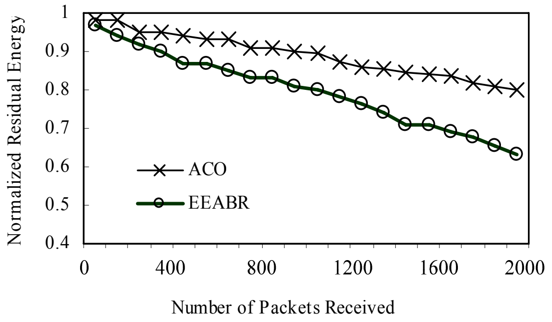

Figure 2. Average residual energy for 80 nodes, density is 222x10^{-6} nodes/m^2

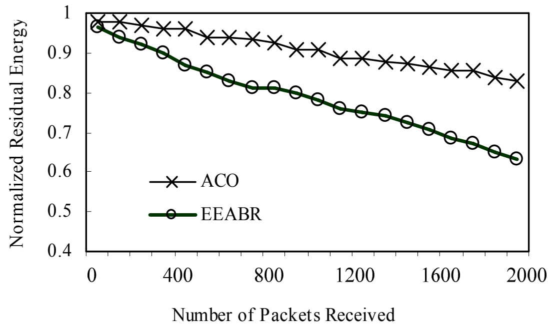

Figure 3. Average residual energy for 80 nodes, density is 222x10^{-6} nodes/m^2.

In Fig. 2 and Fig. 3, network densities are calculated by dividing the number of nodes by the total area. In the scenario, the nodes near the phenomenon send the relevant data through the neighbor nodes to the sink by consuming energy. As the number of packets received by the sink increases, the average residual energy of the nodes decreases as shown in Fig. 2 and Fig. 3. In the

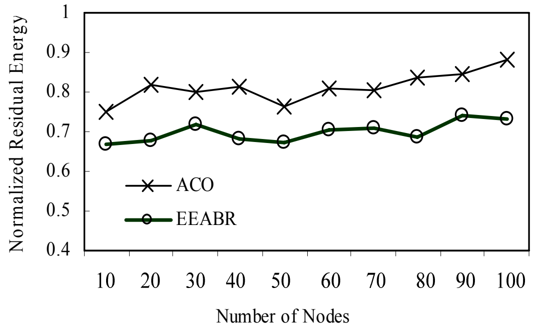

Figure 4. Average residual energy after 1024 packets are received.

simulations, the proposed approach gives better results, providing more network lifetime and consuming less energy, particularly for the networks having high densities.

Fig.4 shows normalized average residual energy after 1024 packets are received by the sink node for different WSNs having various number of nodes. From the figure, it is seen that the difference in energy levels increases as the number of nodes in the network grows.

IV. CONCLUSIONS

Many factors can influence the energy consumption in wireless sensor networks. It is apparent that focusing on any one of these things and ignoring all others may result in consuming energy unnecessarily. In this paper we have presented a new protocol for wireless sensor network routing operations. The protocol is achieved by using an ARNet algorithm to optimize routing paths, and providing an effective multi-path data transmission method to achieve reliable communications in the case of node breakdown. We aimed to maintain maximum network life expectancy, while data transmission is achieved efficiently, so an adaptive approach is developed according to this goal. The proposed approach is compared to a well-known ant based algorithm named EEABR using an event-based simulator. The results show that our approach offers significant reductions of energy consumption which is used as a performance metric for different sized WSNs. The proposed ARNet approach for WSN routings seems to be a promising solution for node designers. As future work, it is planned to improve our routing approach to be effective in proper WSN settings, including nodes having high mobility. The improved approach will also be studied in network types that include multiple sink nodes.

REFERENCES

[1] I. Mohammad, M. Imad, “Handbook of Sensor Networks,” CRC Press: London, 2005; pp. 117-140.

[2] P. Kamat, Y. Zhang, Trappe, W. C. Ozturk, “Enhancing Source-Location Privacy in Sensor Network Routing,” In Proceedings of the 25th IEEE Int. Conference on Distributed Computing Systems (ICDCS05), pp. 599-608, 2005.

[3] J. Z. Sun, “An Essential Technology for Pervasive Computing,” In International Conference on Info-Tech and Info-Net, pp. 316–321, 2001.

[4] W. Heinzelman, C A. handrakasan, H. Balakrishnan, “Energy-efficient Communication Protocol for Wireless Microsensor Networks,” In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, 4-7 pp. 1-10, January 2000.

[5] J. N. Al-Karaki, A.E. Kamal, “Routing Techniques in Wireless Sensor Networks: a Survey,” IEEE Wirel. Commun. pp, 6-28, November 2004.

[6] C. Intanagonwiwat, R. Govindan, D. Estrin, “Directed Diffusion: a Salable and Robust Communication Paradigm for Sensor Networks,” In Proceedings of the 6th Annual International Conference on Mobile Computing and Networking, Boston, MA, USA,; pp. 56-67, August 06-11, 2000.

[7] S. Hussain, O. Islam, “Genetic Algorithm for Energy Efficient Trees in Wireless Sensor Networks,” In Advanced Intelligent Environments, Springer: Boston, MA, USA, pp. 1-14, 2008.
[8] S. Iyengar, H.-C. Wu, N. Balakrishnan, S.Y. Chang, “Biologically Inspired Cooperative Routing for Wireless Mobile Sensor Networks,” IEEE Syst. J. pp. 29–37, Janurary, 2007.
[9] E. Bonabeau, M. G. T. Dorigo, “Swarm Intelligence. In Natural to Artificial Systems,” Oxford Univ. Press: London, U.K., pp. 1-278, 1999.
[10] T. White, B. Pagurek, “Toward Multi-Swarm Problem Solving in Networks,” In International Conference on Multi Agent Systems, pp. 333–340, 1998.
[11] Z.B.Liu, L.Zhang, X.S.Meng, “A Novel Hybrid Stochastic Searching Algorithm Based on ACO and PSO: A Case Study of LDR Optimal Design”, Journal of Software, Vol.6, pp.56-63, No.1, 2011.
[12] L. Chen, J. Shen, L. Qin, “An adaptive ant colony algorithm based on equilibrium of distribution”, Journal of Software , Vol.14, No.8, pp.1379-1387, 2003.
[13] Z. Liu, M.Z Kwiatkowska, C. Constantinou, “A Biologically Inspired QOS Routing Algorithm for Mobile Ad Hoc Networks,” In 19th International Conference on Advanced Information Networking and Applications, pp. 426–431, 2005.
[14] R. Schoonderwoerd, O. Holland, J. Bruten, L. Rothkrantz, “Ant-based Load Balancing in Telecommunications Networks,” Adapt. Behavior , pp. 169–207, May 1996.
[15] J.Y.Li, S.D.Sun, Y.Huang. “Adaptive Hybrid Ant Colony Optimization for Solving Dual Resource Constrained Job Shop Scheduling Problem”, Journal of Software, Vol.6, No.4, pp.584-594, 2011
[16] W.-H. Liao, Y. Kao, C.-M. Fan, “An Ant Colony Algorithm for Data Aggregation in Wireless Sensor Networks,” In International Conference on Sensor Technologies and Applications, pp. 101–106, 2007.
[17] D. Niannian, P.X. Liu, H. Chao, “Data Gathering Communication in Wireless Sensor Networks Using Ant Colony Optimization,” In IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 697–702, 2005.
[18] S. Okdem, D. Karaboga, “Routing in Wireless Sensor Networks Using an Ant Colony Optimization (ACO) Router Chip,” Sensors, pp. 909-921, September 2009.
[19] G. Singh, S. Das, S. Gosavi, S. Pujar, “Ant Colony Algorithms for Steiner Trees: An Application to Routing in Sensor Networks,” In Recent Developments in Biologically Inspired Computing, PA, USA, pp. 181-206, 2004.
[20] Y. Zhang, L. Kuhn, M. Fromherz, “Improvements on Ant Routing for Sensor Networks,” In Ants 2004, Workshop on Ant Colony Optimization and Swarm Intelligence, pp. 154-165, 2004.
[21] T. Camilo, C. Carreto, J. Silva, F. Boavida, “An Energy-Efficient Ant Base Routing Algorithm for Wireless Sensor Networks,” In ANTS 2006 - Fifth International Workshop on Ant Colony Optimization and Swarm Intelligence, pp. 49 – 59, 2006.

Yong Lv born in Shandong, China, 1970, has received the PhD degree in Computer Software and Theory from the College of Electrical Engineering, ZheJiang University. He is currently a associate professor at Electrical Engineering College, Jiaxing University. His research work includes recognition, computation intelligence and its application et al.