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Ant Colony-Based Reinforcement Learning Algorithm for Routing in Wireless Sensor Networks

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Abstract – *The field of routing and sensor networking is an important and challenging research area of network computing today. Advancements in sensor networks enable a wide range of environmental monitoring and object tracking applications. Routing in sensor networks is a difficult problem: as the size of the network increases, routing becomes more complex. Therefore, biologically-inspired intelligent algorithms are used to tackle this problem. Ant routing has shown excellent performance for sensor networks. In this paper, we present a biologically-inspired swarm intelligence-based routing algorithm, which is suitable for sensor networks. Our proposed ant routing algorithm also meet the enhanced sensor network requirements, including energy consumption, success rate, and time delay. The paper concludes with the measurement data we have found.*

Keywords – *ant routing, sensor network.*

I. INTRODUCTION

Recently, advances in minimization, low-power, low-cost, efficient and multi-functional wireless communication equipment, and improved small-scale energy supplies make a new hi-tech dream achievable: wireless sensor networks [1], [2]. Since the 1970s, wireless networks have been showing huge interest to the computing industry and the research community [3]. Wireless sensor networks contain a large number of nodes with sensing capabilities such as vibration, temperature, radiation, light, sound etc. and have simple wireless communication capabilities. Many routing protocols have been specifically designed for the wireless sensor networks where several factors such as energy efficiency, low latency, and success rate are necessary to take into account [2], [4], [5]. Among the above factors, energy consumption is one of the important concerns in a sensor network because each sensor node has to be in active mode during routing, communicating and monitoring the environment [6], [7].

Routing is elementary in all wireless sensor networks. The main task of such a routing algorithm is to maintain data flow from the source to destination sensor nodes, maximize network performance, and build routing tables - one for each sensor node in the network, which helps incoming data packets to choose any efficient outgoing link to continue their travel towards the destination node [8]. Existing routing protocols that are not designed for wireless sensor networks show poor performance when implemented in sensor networks. Ant inspired intelligent algorithms show promising results in solving routing problems in sensor network [8]. By using ants, bees and other social swarms as models, we can create software agents that can solve complex problems, such as rerouting of traffic in a busy telecommunication network [9]. Swarm intelligence, which is revealed by such natural biological swarms, has various great properties popular in many engineering systems, for instance in network routing [10]. Swarm intelligence systems refer to complex behaviors, typically invented from some simple agents cooperating with one another and with their environment [11], [12]. One of the most successful swarm intelligence techniques is called Ant Colony Optimization (ACO) [13]. ACO is an optimization algorithm that can be used to find approximate solutions to difficult combinatorial optimization problems. In ACO artificial ants find solutions by moving on the problem graph and imitating real ants. They leave artificial pheromones on the graph in such a way that future artificial ants can find better solutions. ACO has been successfully applied to a remarkable number of optimization problems. Ants use reinforcement learning to discover the best way. In reinforcement learning, the intelligent system is just given a goal to reach. The system then adopts the goal by a trial and error interaction with the environment. For the interactions that take the system close to the target, a positive reward is received while going away from the target, a negative reward is assigned. Computer scientists have addressed the reinforcement learning of an artificial system by introducing a concept called pheromone decay. When the chemical evaporates rapidly, longer paths will have trouble maintaining stable pheromone trails. This has been used for telecommunication networks [9]. Artificial ants continuously explore different paths, and pheromone trails to provide backup plans. Thus, if one link breaks down, a pool of alternatives already exists [14], [15].

In [8], the authors show an adaptive distributed, mobile agent-based system, which is inspired from the ant colony metaphor for solving optimization problems and targeted for communication networks. Although their basic ant routing algorithm makes the basic foundation of our work, it is not optimized for routing in wireless sensor networks. Zhang et al. [16] proposed three ant-routing algorithms for sensor networks: the Sensor-driven Cost-aware Ant Routing (SC), the Flooded Forward Ant Routing (FF) algorithm, and the

Flooded Piggybacked Ant Routing (FP) algorithm. The SC algorithm is energy efficient but suffers from a low success rate. The FF algorithm has shorter time delays; however, the algorithm creates a significant amount of traffic. Despite high success rate shown by the FP algorithm, it is not energy efficient. Although the algorithms show significant results, none of them are ideal for routing in wireless sensor networks for the above-mentioned reasons. Moreover, none of the three algorithms take into consideration the concept of reinforcement learning. An Adaptive ant-based Dynamic Routing (ADR) algorithm using a novel variation of reinforcement learning was proposed by Lu et al. [17]. The authors used a delay parameter in the queues to estimate reinforcement learning factor. Although queues are an integral part of communication network, is not an essential part of sensor network. Also, they did not address the suitability of their algorithm for wireless sensor networks.

In this paper, we propose two adaptive routing algorithms based on swarm intelligence: the Adaptive Routing (AR) algorithm and the Improved Adaptive Routing (IAR) algorithm. To check the suitability of ADR algorithm in the case of sensor networks, which was originally intended for packet-switched communication networks [17], we modified the ADR algorithm (removing the queue parameters) and used their reinforcement learning concept with the routing algorithms proposed in [16]. We name it the AR algorithm. However, AR algorithm did not result in optimum solution. Therefore, we propose the IAR algorithm by adding a coefficient, the cost between the neighbor node and the destination node, to further improve the AR algorithm, which is described in details in Section 2. Both algorithms are designed to optimize several criteria such as energy, energy-efficiency, latency and success-rate. The remainder of the paper is organized as follows: in section 2 we introduce our proposed algorithms. In Section 3 we analyze the performance of the proposed algorithms. We finally conclude the paper, in section 4, with a few concluding remarks and possible future research avenues.

II. PROPOSED ALGORITHMS

The proposed AR and IAR uses probability distribution at each sensor node in the network, where a routing table is maintained (see Figure 1). Each routing table contains $|N_k|*N$ entries where $|N_k|$ correspond to the set of neighbors of node k, and N is the number of sensor nodes in the network. Ants use this routing table to choose the next favorable neighbor node.

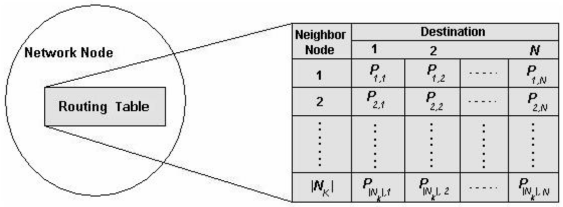

Fig. 1. Routing table structure for node k.

Each row in the table depicted in figure 1 corresponds to a neighbor and each column refers to a destination. We define the probability $P_{i,j}$ of a node k as the probability of desirability of choosing the node i as the neighbor of k to go to the destination node j. Based on this probability distribution, ants explore new and better routes. Once new routes are found, the next-hop probabilities are updated in the routing table, so that the next set of ants can follow this route. The following probability constraint must be satisfied by all routing table entries [8]:

$$\sum P_{i,d} = 1, i \in neighbors(k), d \in [1, N] \tag{1}$$

We initialize all the routing tables with equal probabilities. In our proposed algorithms, we employ two types of ants [8]: (i) forward ant (F_{ant}), which travels from the source node (s) to the destination node (d) and (ii) backward ant (B_{ant}), which is generated by F_{ant}, when F_{ant} reaches the destination d. The B_{ant} will then come back to s by using the information already supplied by F_{ant}. However, the B_{ant} uses a reinforcement learning algorithm [18], [19] in order to get a better and more efficient route than the one chosen by the F_{ant} and at the end it updates the routing tables of the reverse-visited sensor nodes.

First of all we elaborate the proposed AR algorithm. From each sensor node k, having $|N_k|$ neighbors, F_{ant} selects the next hop i with a probability of $P'_{i,d}$, which is computed as follows:

$$P'_{i,d} = \frac{P_{i,d} + \beta \times c_i}{1 + \beta \times (|N| - 1)} \tag{2}$$

where $P'_{i,d}$ is the normalized sum of the probabilistic entry $P_{i,d}$ of the routing table with a correction factor c_i and the coefficient β.

c_i is the cost from the current node k to the neighbor node i that is calculated as follows:

$$c_i = 1 - \frac{D_{k,i}}{\sum_{j=1}^{|N_k|} D_{k,j}} \tag{3}$$

where $D_{k,i}$ is the distance between current node k and its neighbor node i.

As shown in equation (3), the heuristic correction c_i is proportional to the distance $D_{k,i}$. The value of β in equation (2) weights the desirability of the correction factor c_i with respect to the probability values ($P_{i,d}$) stored in the routing table. The coefficient β has a value between zero and one. The simulation results found with the AR algorithm was not satisfactory with regards to the requirements of sensor networks, which is shown in Section 3.

Now, we present the modification we made with the AR algorithm, which we call IAR algorithm. Here we propose a modified heuristic correction factor $A_{i,d}$ that is the cost from the neighbor node i to the destination node d to find the following probability $P'_{i,d}$:

$$P'_{i,d} = A_{i,d} \times \frac{P_{i,d} + \beta \times c_i}{1 + \beta \times (|N| - 1)} \tag{4}$$

where the coefficient $A_{i,d}$ is given by:

$$A_{i,d} = \frac{1}{\lambda \times C_{i,d}} \tag{5}$$

In the above equation $C_{i,d}$ is the distance from the neighbor node i to the destination node d and λ is a coefficient, which has a value between zero and one. For example, for geographic routing, we may estimate the node's cost by:

$$\sqrt{(x_d - x_i)^2 + (y_d - y_i)^2} \tag{6}$$

where (x_i, y_i) is the location of the current node and (x_d, y_d) is the location of the destination.

When a F_{ant} moves toward its destination d, it remembers the list of nodes it has visited while updating a global two dimensional matrix. Subsequent forward ants use this list to avoid visiting the same node. Also, if the visited nodes by a F_{ant} are larger than half of the total number of nodes, the F_{ant} dies, which indicates that the path it was following was not efficient.

The B_{ant} works similarly except that during the backward travel, every intermediate node is treated like a destination and its associated probabilities are changed. The function 'change of probability' is a negative exponential, with the exponent proportional to the cost between the current node k and the destination node d through the neighbor node i:

$$\Delta P = e^{-\gamma * d^k_{i,d}} \tag{7}$$

where γ is a coefficient and has a value between zero and one.

$d^k_{i,d}$ in the AR algorithm is $C_{k,i}$, which is the cost between the current node k and the neighbor node i, and $d^k_{i,d}$ in IAR algorithm is $C_{k,i} + C_{i,d}$, that is the cost between the current node k and the neighbor node i plus the cost between the neighbor node i and the destination node d. When a B_{ant} arrives at node i, the entry in the routing table corresponding to the node i from which the ant has just come is increased by ΔP as following [8], [17]:

$$P_{i,d} = \frac{P_{i,d} + \Delta P}{1 + \Delta P} \tag{8}$$

Similar to [8] and [17], the other entries in the routing table of that node are decreased as following:

$$P_{i',d} = \frac{P_{i',d}}{1 + \Delta P}, \quad i' \in neighbors(k), i' \neq i \tag{9}$$

Figure 2 shows the pseudo-code of the proposed IAR algorithm.

III. PERFORMANCE EVALUATION

We used Java-based simulation to evaluate the proposed AR and the IAR algorithms as depicted in Figure 3. Because ADR [17] is not suitable for sensor networks, we only compare our proposed AR and IAR algorithms with the following four routing algorithms: Basic Ant Routing [8], Sensor-driven Cost-aware Ant Routing, Flooded Piggybacked Ant Routing, and Flooded Piggybacked Ant Routing [16], all presented with detailed explanations and results.

We constructed an event driven simulator to evaluate the performance of the algorithms such as success rates, latency, energy consumption and energy efficiency as performance metrics. We can select the sensor networks both orderly and randomly. To better compare the results with respect to [16], we run the simulation for 200 seconds having total number of 7 X 7 sensor node grid.

In each evaluation, we choose a value for β, γ and λ between 0 and 1. We chose the increment factor of 0.1 for each of the variables and conducted the simulation. Among all the combinations of the three variables, β=0.1, γ=0.5 and λ=0.7 resulted in optimum results that are shown in Figure 4, 5, 6 and 7. Figure 4 shows the success rate comparison among the algorithms.

Algorithm 1: The Proposed IAR Algorithm for Forward-Ant

Forward-Ant(source-node, current-node, destination-node)
begin
  if *destination is reached* **then**
    Create a new Backward-ant and Copy forward-list to backward-list
  else
    Add current-node to forward-list
  if *Less than half of the sensor nodes visited* **then**
    Choose the next neighbor according to the following probability
    $P'_{i,d} = A_{i,d} \times \frac{P_{i,d}+\beta\times c_i}{1+\beta\times(|N|-1)}$
    if *selected neighbor visited* **then**
      choose another neighbor node
  else
    Die Forward-Ant
end

Algorithm 2: The Proposed IAR Algorithm for Backward-Ant

backward-Ant(source-node, current-node, destination-node)
begin
  if *source is reached* **then**
    Release Backward-Ant
  else
    for *all neighbor nodes* **do**
      if *selected neighbor node visited by Forward-Ant* **then**
        $P_{i,d} = \frac{P_{i,d}+\Delta P}{1+\Delta P}$
      else
        $P_{i,d} = \frac{P_{i,d}}{1+\Delta P}$
      Remove first item of Backward-list
    Send Backward-Ant to selected neighbor node
end

Fig. 2. The proposed IAR algorithm

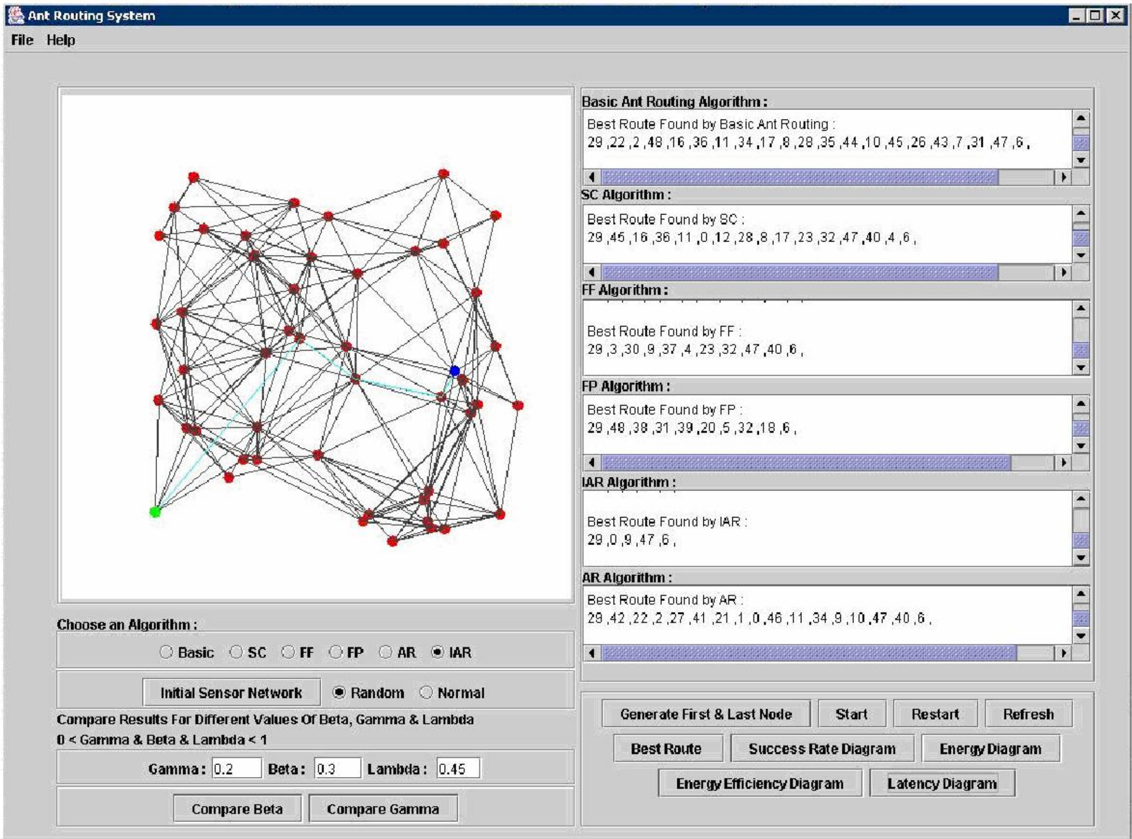

Fig. 3. Randomized sensor network environment.

Success rate is the total number of packets received at the destination vs. the total number of packets sent from the source [16]. As shown in the figure, in the case of IAR, the success rate is almost close to 1, which means least number of packets is lost in the network. After IAR, the AR shows better success rate in comparison with the FF, FP, Basic and the SC algorithms.

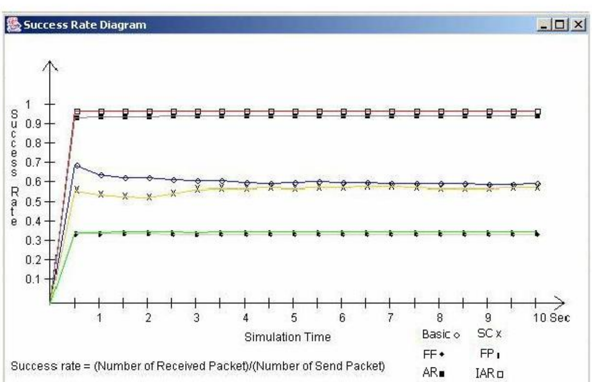

Fig. 4. Evaluation of success rate.

Figure 5 shows the comparison of time delay of a packet between the source and the destination (latency) among the algorithms. We assume that in a wireless sensor network, the

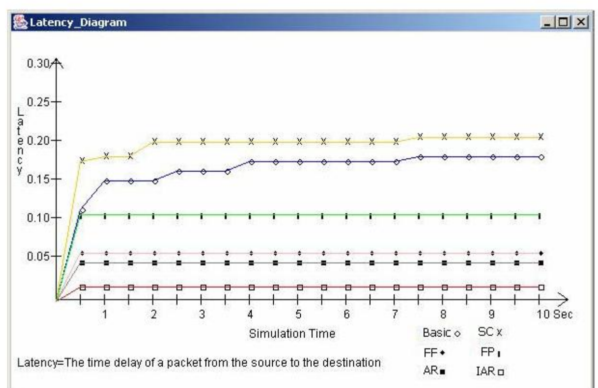

Fig. 5. Evaluation of latency.

sensory data/packet processing time within a sensor node (including receiving and sending) is significantly larger than that of the delay in wireless channel. In other words, visiting more number of nodes in a route by a packet will result in higher latency. We assume that the time taken between any of two neighbour nodes and the processing time of packet in each sensor node are uniform. Therefore, we can ignore the time unit and calculate delay as the division of ‘number of visited nodes’ by the ‘number of routes found’, which results in ‘average number of nodes visited per each route’. As shown in Figure 5, in the case of IAR, the latency is the lowest, followed by the AR, the FF, the FP, the Basic and the SC respectively.

The comparison of energy consumption among the algorithms is shown in Figure 6. Similar to [16], we also assume each transmission consumes one energy unit. Therefore, we define the total energy consumption is equivalent to the total number of packets sent to the network. As shown in the figure, in the case of IAR, the least number of packets are sent in the network, thereby consuming the least energy. AR consumes a bit higher energy than IAR followed by the FF, the Basic and the SC respectively. The FP consumes the highest energy.

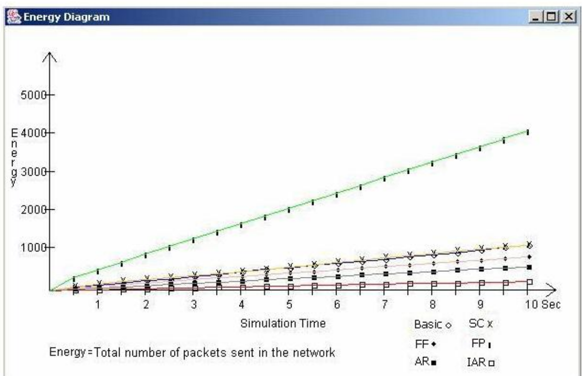

Fig. 6. Energy Evaluation.

The IAR algorithm also exhibits the most energy efficiency in comparison with the others. Energy efficiency is the ratio between the numbers of packets received at the destination vs. the total energy consumption in the network [16]. As shown in the figure, in the case of IAR, the energy efficiency is almost 0.32, the highest among all, which in the case of AR 0.13, for FF 0.8, for Basic 0.44, for SC 0.35 and for FP 0.19.

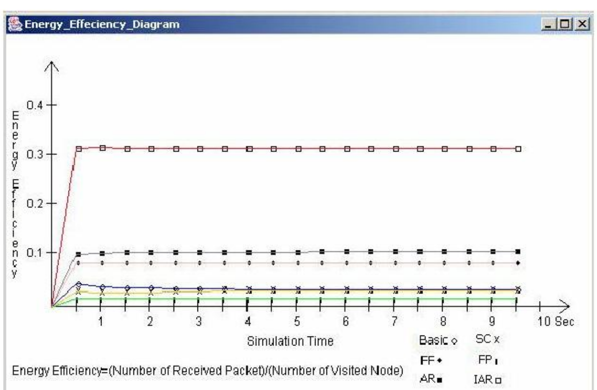

Fig. 7. Evaluation of energy efficiency.

In summary, the IAR algorithm has many advantages similar to the advantages found with the algorithm proposed in [17]. In all the cases, the IAR algorithm exhibits superior result in comparison with that of the AR algorithm. The IAR algorithm also requires the least energy consumption and the highest success rate among rest of the algorithms. It visits the least number of nodes, sends the least packets and finds better paths rapidly. In IAR, we also take into consideration the distance between the neighbor sensor node and the destination sensor node while we calculate heuristic correction factor $A_{i,d}$. Therefore, the packets always tend to go in a route, which is closer to the destination. This ensures that the number of packets sent in the network is less; the latency decreases and the success rate increases.

IV. CONCLUSION

Routing in sensor networks is growing rapidly. In this paper, we have presented a new scheme based on ant algorithm for routing in wireless sensor networks. We have proposed two new algorithms, the Adaptive Routing (AR) algorithm and the Improved Adaptive Routing (IAR) algorithm. Our proposed algorithms are able to deal, react and adapt themselves to changes in the network. We have used reinforcement learning features for the algorithms. For evaluating the performance of the AR and the IAR algorithms, we compared them with the four other routing algorithms- Basic Ant Routing, Sensor-driven Cost-aware Ant Routing, Flooded Piggybacked Ant Routing, and Flooded Piggybacked Ant Routing proposed in [16].

Among the algorithms, the AR shows good performance results, and the IAR shows the best performance results in all the tested conditions. Adopting the AR and the IAR algorithm for routing in wireless sensor network can result in low energy consumption, high-energy efficiency, less latency, and a high success rate.

In our future work, we would like to implement this algorithm on real sensor networks to see the suitability of our algorithm.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless Sensor Networks: a Survey". *J. Comput. Networks (Elsevier)*, 38, 4, pp. 393-422, 2002.

[2] H. Karl and A. Willig, "A short survey of wireless sensor networks". *TKN Technical Reports*, Technical University Berlin, Berlin, Oct. 2003.

[3] E. M. Royer and C. Toh. "A review of current routing protocols for ad hoc mobile wireless networks". *IEEE Personal Communications*, pp. 46-55, April 1999.

[4] J. N. Al-Karaki and A. E. Kamal, "Routing techniques in wireless sensor networks: a survey". *IEEE Wireless Communications*, pp. 6-28, Dec. 2004.

[5] K. Akkaya and M. Younis, "A survey on routing protocols for wireless sensor networks". *Elsevier Ad Hoc Network Journal*, 3, 3, pp. 325-349, 2005.

[6] R. Muraleedharan and L. A. Osadciw, "A Predictive Sensor Network Using Ant System," *In Proceedings of SPIE*, 2004.

[7] R. Muraleedharan and L. A. Osadciw, "Sensor Communication Network Using Swarm Intelligence," *IEEE Upstate New York Networking Workshop*, Syracuse University, Syracuse, NY, 2003.

[8] G. D. Caro, and M. Dorigo, "AntNet: Distributed Stigmergetic Control for Communications Networks". *J. of Artificial Intelligence Research, vol. 9*, Dec. 1998, pp. 317-365.

[9] Bonabeau, E., and Théraulaz, G., "Swarm Smarts". *Scientific American Inc.*, pp. 72-79, March 2000.

[10] I. Kassabalidis, M. A. El-Sharkawi, R. J. Marks II, P. Arabshahi and A. A. Gray, "Swarm Intelligence for routing in communication networks," *GLOBECOM IEEE*, 2001.

[11] C. Shen and C. Jaikaeo, "Ad Hoc Multicast Routing Algorithm with Swarm Intelligence". *J. of Mobile Networks and Applications*, vol. 10, pp. 47–59, 2005.
[12] T. White, B. Pagurek, and F. Oppacher, "Connection Management using Adaptive Mobile Agents," *In Proceedings of International Conference on Parallel and Distributed Processing Techniques and Applications (PDPTA'98)*, 1998.
[13] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*, Oxford University Press, 1999.
[14] M. Heusse, D. Snyers, S. Gu'erin, and P. Kuntz, "Adaptive agent-driven routing and load balancing in communication networks," D'epartment Intelligence Artificielle et Sciences Cognitives, ENST Bretagne, 1998.
[15] R. Schoonderwoerd, O. Holland, J. Bruten, and L. Rothkrantz, "Ant-Based Load Balancing in Telecommunications Networks". *J. of Adaptive Behavior*, vol. 5, no. 2, pp. 169-207, 1996.
[16] Y. Zhang, L. D. Kuhn, and M. P. J. Fromherz, "Improvements on Ant Routing for Sensor Networks," *International Workshop on Ant Colony Optimization and Swarm Intelligence*, Sep. 2004.
[17] Y. Lu, G. Zhao, and F. Su, "Adaptive Ant-based Dynamic Routing Algorithm," *In Proceedings of the 5th World Congress on Intelligent Control and Automation* (IEEE, Hangzhuo, China, June 2004), 2694-2697.
[18] L. P. Kaelbling, M. L. Littman and A. W. Moore, "Reinforcement Learning: A Survey". *J. of Artificial Intelligence Research*, 4, pp. 237-285, 1996.
[19] D. Subramanian, P. Druschel, and J. Chen, "Ants and reinforcement learning: A case study in routing in dynamic networks," *In Proceedings of IJCAI*, pp. 832-838, 1997.