International Journal of Engineering Applied Sciences and Technology, 2016
Vol. 1, Issue 8, ISSN No. 2455-2143, Pages 153-156
Published Online June - July 2016 in IJEAST (http://www.ijeast.com)

ANTS-BASED ALGORITHMS TO ROUTING PROTOCOLS

Mamta
M.tech Student,
R.N College of Engineering and Management

Ms. Pooja Ahlawat
Assistant Professor, Dept. of CSE
R.N College of Engineering and Management

Abstract— **This paper presents the state-of-the-art studies about Ant Colony Optimization (ACO) algorithm and its application to routing protocols. Many attempts have been done in order to improve overall performance or on a specific problem, as a result several variants of ACO have been developed. ACO algorithms are very good candidates for solving combinatorial problems since the artificial ants build the solution constructively by adding one component at a time. The ACO is also suitable for the problems where the environment may change dynamically, as ACO algorithms can be run continuously and adapted to changes in real time.**

Keywords— **ACO, Routing Protocol**

I. INTRODUCTION

The ACO metaheuristic is a multi-agent framework for combinatorial optimization whose main components are: a set of ant-like agents, the use of memory and of stochastic decisions, and strategies of collective and distributed learning. The networks become nowadays more and more complicated, with moving nodes, varying loads, etc. The users however expect more quality and more services despite the growing complexity of the networks. The paper which will be analyzed in the following study some adaptations of the Ant Colony Optimization to routing protocols, and often compare its efficacy to the current routing algorithms. Most of the papers see in the ACO a great tool for wireless Ad Hoc networks as it has a strong capacity to adapt to changes. However, some new algorithms based on ACO are also analyzed for wired networks and are giving encouraging results. The comparison between ACO and traditional routing algorithms is done with analyzing:

- The routing information;
- The routing overhead;
- The adaptively.

II. ROUTING INFORMATION

The routing information consists of what is exchanged to get to know the architecture of the network, hence forward the data packets to the best path. For RIP, the nodes exchange the distance-vector information, each node giving to the other their neighbours and so on. In OSPF, the nodes tables need on the link-state information of all the links in every path to compute the shortest path. In ACO, the paths from a source to a destination are explored independently and in parallel. The figure.1 shows a simple configuration of 6 nodes.

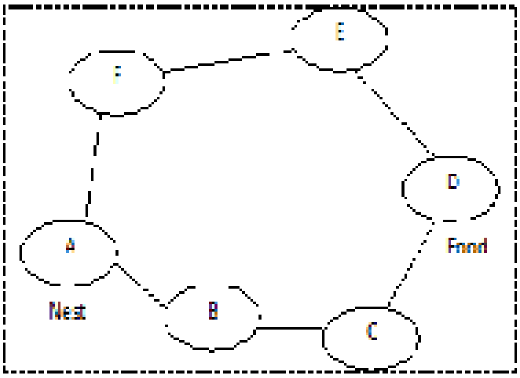

Figure.1

For RIP, the nest A depends on routing tables sent by B and F, as well as the Food depends on C and E’s routing tables. In OSPF, A needs to know all the link-state between itself and the food to find the shortest path. In ACO, the paths from the source to the food are explored by using n number of ants, the ants leaving the nest at the same time and taking a random first path. n/2 ants will go through B while the other half will take the way to F. The ants which reach the first the food indicates which way is the shortest without having to wait for the second half of ants to reach. As soon as an ant arrives at a node, the corresponding pheromones value for a path is updated. Hence, each entry of the pheromone table in a node can be updated independently.

III. INFORMATION OVERHEAD

Routing in RIP involves the transmission of routing tables of each node to every one of its neighbours. For a large network, the routing table of each node, which consists of a list of cost vectors to all other nodes, is large. Since each node needs to transmit its routing table to all of its neighbours, the routing overhead can be very large .In OSPF, routing is achieved by having each node transmit a link-state packet (LSP) to every other node in a network through a flooding processing. Although an LSP, which carries information about the costs to all the neighbours of a node, is generally smaller than a routing table, the flooding process ensures that every node receives a copy of the LSP. Since an LSP from a node can be disseminated via different paths to other nodes, multiple identical copies of the same LSP may be transmitted to the same node. Routing in ACO is achieved by transmitting ants rather than routing tables or by flooding LSPs. Even though it is noted that the size of an ant may vary in different systems/implementations, depending on their functions and applications, in general, the size of ants is relatively small, in the order of 6 bytes[i]. This is because ants are generally very simple agents. The following table summarizes the differences between ACO and traditional routing algorithms.

Table .1 : Differences between ACO and traditional routing algorithms.

	RIP / OSPF	ACO algorithm
Routing preference	Based on transmission time / delay	Based on pheromones concentration
Exchange of routing information	Routing information and data packet transmitted separately	Can be attached to data packets
Adapting to topology change	Transmit routing table / Flood LSPs at regular interval	Frequent transmission of ants
Routing overhead	High	Low
Routing update	Update entire routing table	Update an entry in a pheromone table independently

IV. ADAPTIVITY

In dynamic networks, transmitting large routing table (in RIP) or flooding multiple copies of LSPs (in OSPF) in short or regular intervals may incur large routing overhead. However, flooding LSPs and transmitting routing table in longer intervals may result in slower responses to changes in network topology. Since ants are relatively small they can be piggybacked in data packets, more frequent transmission of ants to provide updates of routing information may be possible. Hence, using ACO for routing in dynamic network seems to be appropriate.

Related to the issue of adaptivity is stagnation. Stagnation occurs when a network reaches its convergence; an optimal path ρ is chosen by all ants and this recursively increases an ant's preference for ρ. This may lead to: 1) congestion of ρ, 2) dramatic reduction of the probability of selecting other paths. The two are undesirable for a dynamic network since:

1) ρ may become nonoptimal if it is congested;
2) ρ may be disconnected due to network failure;
3) other nonoptimal paths may become optimal due to changes in network topology, and iv) new or better paths may be discovered.

Furthermore, Bonabeau et al.[ii] have pointed out that the success of ants in collectively locating the shortest path is only statistical. If by chance, many of the ants initially choose a non-optimal, other ants are more likely to select leading to further reinforcement of the pheromone concentration along ρ.This is undesirable for static networks since it is inefficient ants always choose a stagnant path that is non-optimal.

V. LIST OF ANTS-BASED ROUTING ALGORITHM

All the previous papers present new routing algorithm based on ACO. Here is a list of these algorithms and their field of application.

1. *Previous MANET routing protocols*

- DSDV, Destination-Sequenced Distance Vector algorithm
- OLSR, Optimized Link State Routing algorithm
- AODV, Ad Hoc On Demand Distant Vector
- DSR, Dynamic Source routing
- ZRP, Zone Routing Protocol
- GPSR, Greedy Perimeter Stateless Routing
- TRP, Terminode Routing Protocol

VI. RESULTS

ACO algorithms are complex systems whose behavior is determined by the interaction of many components such as parameters, macroscopic algorithm components (e.g., the form of the probabilistic rule used by ants to build solutions, or the type of pheromone update rule used), and problem characteristics. Because of this, it is very difficult to predict their performance when they are applied to the solution of a novel problem. Recently, researchers have started to try to understand ACO algorithm behavior by two typical approaches of science:

1. The study of the complex system under consideration in controlled and simplified experimental conditions, and

2. The study of the conditions under which the performance of the studied system degrades. Contributions along these two lines of research are briefly discussed in the following.

- Study of ACO in Controlled and Simplified Experimental Conditions

- The analysis of ACO algorithm behavior on simple problems is interesting because the behavior of the algorithm is not obscured by factors due to the complexity of the problem itself.

A. Application based ACO in shortest path searching in RIP (Routing Information Protocol) in Matlab

Tour Path solved by ACO N=48

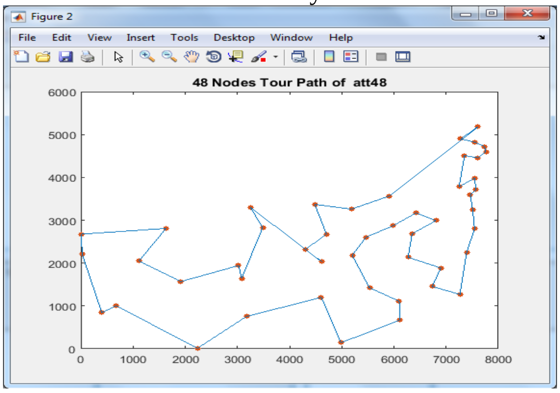

Figure.2: 48 Node tour Path

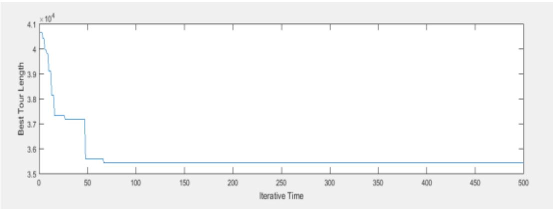

Figure.3: Best Tour Length vs Iteration Time

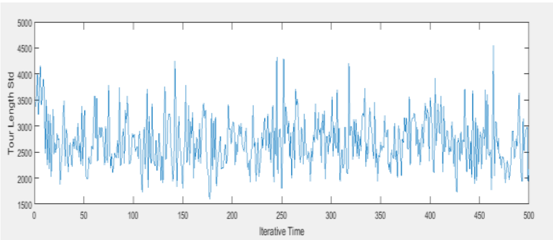

Figure 4 : Tour Length Standard vs Iteration time

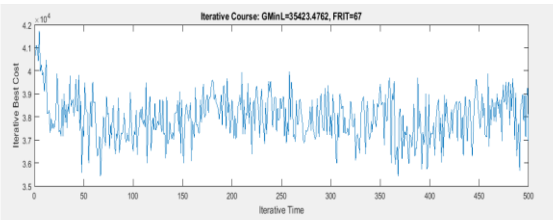

Figure 5 : Iteration Best Cost Vs Iteration Time

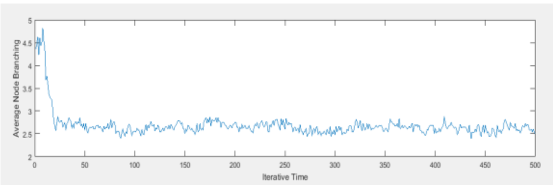

Figure6: Average Node Branching Vs Iteration time

VII. CONCLUSION

This paper tried to cover the state-of-the-art studies about Ant Colony Optimization (ACO) algorithm and its application to routing protocols. It covers recent thesis reports and introduces the latest developed protocols based on ACO. Also, the use of prospect theory could be investigated in the real time application of ACO in the mobile robot path planning where the robot interacts with the environment.

VIII. REFERENCES

1. Grassé P-P, sur la biologie des termites champignonnistes, Ann. Sc. Zool. Animal, 1944.
2. R. Beckers, J.L. Deneubourg, and S. Goss, "Trails and U-turns in the selection of the shortest path by the ant Lasius Niger," Journal of Theoretical Biology, vol. 159, pp. 397–415, 1992.
3. Afshar, M. H., Ketabchi, H., & Rasa, E. (2006). Elitist continuous ant colony optimization algorithm: application to reservoir operation problems. Int J Civil Eng, 4(3), 274-285.
4. Ahmed, H., & Glasgow, J. (2012). Swarm Intelligence: Concepts, Models and Applications. Technical Report, 2012-585: Queen's University, Kingston, Ontario, Canada K7L3N6.
5. Al-Nowaihi, A., & Dhami, S. (2010). Probability weighting functions. Wiley Encyclopedia of Operations Research and Management Science.
6. Andriotti, G. K. (2009). Non-Rational Discrete Choice Based On Q-Learning And The Prospect Theory.
7. Baker, A., Bittner, T., Makrigeorgis, C., Johnson, G., & Haefner, J. (2010). Teaching Prospect Theory with the Deal or No Deal Game Show. Teaching Statistics,, 32(3), 81-87.
8. Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. Econometrica: Journal of the Econometric Society, 23-36.
9. Birattari, M., Pellegrini, P., & Dorigo, M. (2007). On the invariance of ant colony optimization. Evolutionary Computation IEEE Transactions on, 11(6), 732-742.
10. Bonabeau, E., Dorigo, M., & Theraulaz, G. (1999). Swarm intelligence: from natural to artificial systems (No. 1). OUP USA. Brucker, P. (2007). Scheduling Algorithms (Fifth ed.). Springer.
11. Buniyamin, N., Sariff, N., Wan Ngah, W. A., & Mohamad, Z. (2011). Robot global path planning overview and a variation of ant colony system algorithm. International journal of mathematics and computers in simulation, 5(1), 9-16.
12. Grassé P-P, sur la biologie des termites champignonnistes, Ann. Sc. Zool. Animal, 1944.
13. R. Beckers, J.L. Deneubourg, and S. Goss, "Trails and U-turns in the selection of the shortest path by the ant Lasius Niger," Journal of Theoretical Biology, vol. 159, pp. 397–415, 1992.

14. J.-L. Deneubourg, S. Aron, S. Goss, and J.-M. Pasteels, "The selforganizing exploratory pattern of the Argentine ant," Journal of Insect Behavior, vol. 3, p159, 1990

15. Pasteels, J.M., Deneubourg, J.-L., and Goss, S., Self-organization mechanisms in ant societies (i): rail recruitment to newly discovered food sources, ExperientiaSupplementum, 54, 155, 1987

16. T. White, B. Pagurek, and F. Oppacher, "ASGA: Improving the ant system by integration with genetic algorithms," in Proc. 3rd Genetic Programming Conf., July 1998, pp. 610–617