Traffic Parameterized ACO for Ad-Hoc Routing

[1]P. Visu and [2]E. Kannan

[1]Research Scholar, Department of Computer Science and Engineering,
Vel Tech Dr.RR & Dr.SR Technical University, Chennai, Tamilnadu, India.
[2]Professor and Dean, Department of Computer Science and Engineering,
Vel Tech Dr.RR & Dr.SR Technical University, Chennai, Tamilnadu, India.
E-Mail:- pvisu_it@yahoo.co.in, pandu.visu@gmail.com

Abstract: Networking becomes most important resources in the modern world. The networking explored as wired networking, wireless networking, vehicular networking and sensor networking. The wireless networking becomes mandatory resources of our day to day life. Most of the modern engineering applications require wireless networking. Therefore, the research in the wireless networking is one of the major researches in the field of computer science. The existing routing protocols are optimized in any of the system parameters based on shortest time, hop count. These routing protocols are suitable in one particular environment and not always optimal. Especially, in the recent world, there are clumsy of nodes and interconnections, which lead to heavy congestion in the communication media. Therefore, the congestion free routing is a major requirement of the wireless world. This paper proposes, the improved version of ACO for congestion free routing in the adhoc network. The proposed routing optimizes the parameters of ACO for traffic free routing. The proposed method also verified using three test cases and various performance analyses in terms of round trip time and packet loss.

[Visu. P, Kannan. E. **Traffic Parameterized ACO for Ad-Hoc Routing**. *Life Sci J* 2013;10(2): 1391-1396] (ISSN:1097-8135). http://www.lifesciencesite.com.

Keyword: Adhoc Network, Routing Protocol, Ant Colony Optimization, Traffic Free Routing.

1. INTRODUCTION

For discrete optimization, a new field of study is emerged recently, called Swarm intelligence (SI). The SI contains relatively optimal approach than the traditional approach for problem solving, which applied almost all engineering domain. SI is developed from the simulations learned from the social behaviours of animals and insects. There are many SI algorithms are developed, for example: Ant Colony Optimization (ACO), Artificial Honey Bee(ABC), Honey Bot and Fire Flies. In which, ACO is learned from the behavioural observation of real ant colonies.

ACO algorithms are used for the design of novel algorithms for the solution of optimization problems like travelling salesman and distributed control problems like scheduling. In ant colony, many behavioural aspects are learned, such as foraging behaviour, division of labour, brood sorting, and co-operative transport. These behaviours of ant colonies have inspired from the real ants working model. Based on these inspiration different kinds of ant algorithms are proposed and redefined in the recent years. In which, the ACO is inspired by the foraging behaviour of ant colonies, and targets the discrete optimization problems.

Ant colonies using a chemical substance called pheromone for identifying optimal path to the food source as well as returning from food to nest. This chemical substance is deposited on the ground when ants walk to and fro of a food source. This layer of chemical substance are used by other ants for following the routes. If there are more number of paths having various level of pheromones, then the higher pheromone concentration path is selected as optimal path. Through this optimization algorithm, ant colonies are able to identify their food source and used to return from food source to their nest in a remarkably effective and easy way.

The working model of ACO is designed initially by Pasteels et al. (1987). The authors thoroughly investigated the pheromone laying behaviour of the real ants in the experiment called "double bridge experiment''. This double bridge experiment is used for fundamental study of ACO. In this double bridge model, the nest is connected to a food source by two bridges of equal lengths. Initially, the term argentine ants is used for the ants which identifies the route. Simply says these ants are the predictor or scout of their colony. In such a setting, ants start to explore the surroundings of the nest and eventually reach the food source. Along their route between food source and nest, Argentine ants deposit pheromone. Initially, each ant randomly chooses one of the two bridges.

In the later stages due to random fluctuations, one of the two bridges presents a higher concentration of pheromone than the other bridge and therefore attracts more ants. This behaviour increases a further amount of pheromone on that bridge which makes more attractive. Therefore, after some time the whole colony converges towards the use of higher concentrated bridge for their transport.

2. SURVEY

The well-known double bridge experiment is developed by the Goss et al. (1989), in which one bridge is significantly longer than the other, shown in Figure 1. In double bridge experiment, the nests of a ant colony are connected to a food source by two bridges of equal lengths. The ants are choosing the short bridge randomly will reach the nest as quicker than other bridge. This leads to early onvergence, and the shortest bridge receives more density of pheromones earlier than the long bridge. This fact will increases the probability of choosing the shorter bridge by further ants to select it.

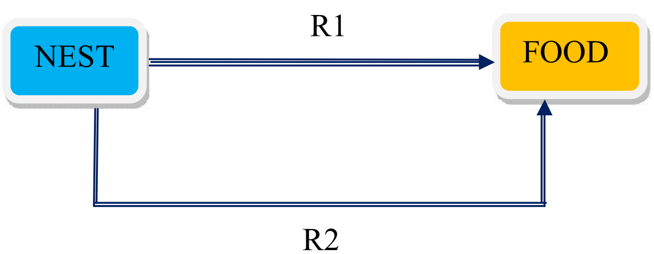

Figure 1. A double bridge method for ACO with varying length routes R1 and R2.

There are various kinds of ACO are proposed, in which, Ant System, Ant Colony System and Ant Net proposed by Dorigoet al (1996), Dorigo and Luca (1997), Dorigo and Stutzle (2004) are the significant implementation of ACO. Dorigo et al (1996) applied the simple probability rule and Dorigo and Luca (1997) applied the state transition rule for the decision model. According to Dorigo et al (1996), Roberto and Moacir (2011), the characteristics of Ant Model is defined.

ACO is appled to the computer science field of study, whcih initiated with the Ant-Net developed by Dorigo and Stutzle (2004). The Ant-Net is a networking solution which applied for routing problem. The Ant-Net proved better result in the wired networking. Dorigo and Stutzle (2004) and Frank and Carsten (2010) investigated the variant of the pheromone laying policies and the retun policies. Dorigo and Stutzle (2004) used the term Argentine ants for the ants which identifies the path, simply says the predictor of the path. The Argentine ants always spread the work place, searching other possible routes. In ths working environment, argentine ants are start to explore the surroundings of the nest and eventually reach the food source. Along their path between food source and nest, Argentine ants will deposit pheromones.

Kwang and Weng (2003) reviewed the ACO with existing routing algorithms, and concluded that the ants are relatively small, therefore ants can be piggybacked in data packets. This suggestion leads to more frequent transmission of ants in order to provide updates of routing information for solving link failures, which decreases the convergence time. Hence, using ACO for routing in dynamic network seems to be appropriate. Routing in ACO is achieved by transmitting ants rather than routing tables or by flooding Link Stat Packets. 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 8 bits.

Dorigo and Stutzle (2004) redefined the pheromone update policy of ACO, and the term argentine ant is replaced with forward ant. Furthermore, there are some ACO approaches that adopt the privileged pheromone lying in which ants only deposit pheromones during their return trips. Simple ACO uses two working ant model called forward ant and backward ant, the probabilistic forward ant generated in the nest and flooded towards food source.

The forward ant do not deposit pheromone while moving, this helps in avoiding the formation of loops. Once the forward ant reaches its destination, it is switched to the backward ant and copies the route information from the forward ant. Then the backward ant moves to the nest using the information copied from the forward node.

The ACO is an optimization technique which is widely applied for a variety of optimization problems and in almost all engineering field of studies. The few application of ACO in the recent years are Job Scheduling by Li-Ning Xing et al (2010), Project Scheduling by Wang Chen et al(2010), Production management and maintenance scheduling by Osama et al (2005), Cash Flow Management by Wei-Neng Chen et al (2010), Manpower Scheduling and management Hsin-Yun et al (2010), Travelling Salesman Problem by Manuel and Christina (2010) and Xiao-minget al (2010), Clustering and set partitioning by Ali and Babak (2010), Pattern Recognition by Zhidinget al (2010).

Amilkaret al (2010) analysed the performance of ACO on various case studies in the TSP using a two stage approach and concluded the performance of ACO is optimal than existing for TSP. The two-stage approach will converge quickly for lesser nodes whereas it requires more convergence time, if number of nodes increases. Visu et al (2012 and 2013) involved detailed implementation methodology for swarm intelligence based routing optimisation techniques.

3. TRAFFIC PARAMETERIZED ACO FOR ADHOC ROUTING

This section explains the improved version of ACO, which is called as traffic parameterized ACO. The adhoc routing is more critical than wired routing due to many limitations of wireless networks like frequent mobility, limited bandwidth and hidden, exposed terminals.

3.1 Design of ACO

The real ants and artificial ants are differed in few assumptions, in the real ant behaviour the pheromone intensity is reduced over time as the pheromone is the chemical substance and so it evaporates over time. However, in the ACO, this can be set to a constant rate, this pheromone evaporation reduces the influence of the pheromones deposited in the early stages of the search, and this property is very useful for adaptive route search in such a situation that frequent path failures. The system design of ant flow is shown in the figure 2.

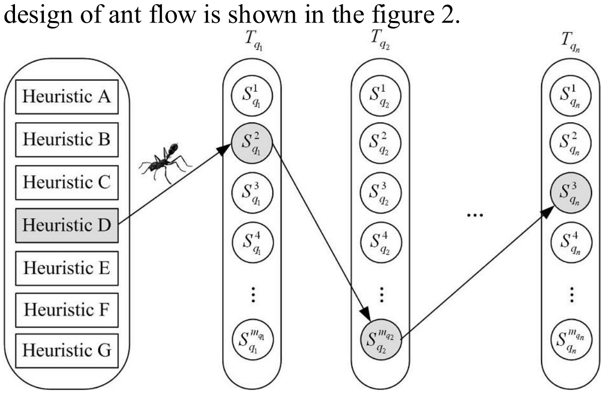

Figure 2 System design of Ant flow

The ACO metaheuristic is based on a multi-agent architecture. The agents of the system, which are called ants, have a double nature. On the one hand, they are an abstraction of those behavioral traits of real ants which are at the heart of the shortest path finding behavior observed in real ant colonies. On the other hand, they have been enriched with capabilities which do not find a natural counterpart, but which are in general necessary to obtain good performance when the system is applied to difficult optimization tasks.

In ACO a colony of autonomous and concurrent agents cooperate in stigmergic way to find good, possibly optimal, solutions to the combinatorial problem under consideration. The choice is to allocate the computational resources to a set of agents that, mimicking the actions of ants, iteratively and concurrently construct multiple solutions in a relatively simple and computationally light way.

Starting from an empty solution, each ant during its forward journey constructs a possibly feasible solution by applying at each construction step a stochastic decision policy to decide the next action, that is, the new solution component to include into the current partial solution. The decision policy depends on two sets of values, in some sense local to each decision step, that are called respectively pheromone variables and heuristic variables. Both these two sets of variables encode the desirability of issuing a specific decision to extend the current partial solution conditionally to the characteristics of the current decision step and of the current partial solution.

Pheromone variables, as in the case of the ants, encode the value of desirability of a local choice (i.e., a solution component given the current partial solution and decision point) as collectively learned from the outcomes of the repeated solution generation processes realized by the ants. On the other hand, heuristic variables assign a value of desirability on the basis of either some a priori knowledge about the problem or as the outcome of a process independent of the ants (e.g., the computation of a lower bound estimate).

Pheromone (and heuristic) variables bias the step-by-step probabilistic decisions of the ants, that at each decision step favor those decisions associated to pheromone variables with higher values. In turn, pheromone variables are repeatedly updated during algorithm execution to reflect the incremental knowledge about the characteristics of the solution set that has been acquired through the iterative generation of multiple solutions.

In particular, after building a solution, the ant metaphorically reports the solution to a pheromone manager, which authorizes or not the ant to update the pheromone variables associated to the built solution. In the positive case, the ant starts its backward journey, retracing its solution and updating pheromone values, usually of an amount proportional to the quality of the solution. In this way, decisions associated to solutions which are either of good quality or are chosen more often, will likely have associated higher levels of pheromone, that is, higher local desirability.

In most of the cases when centralized implementations are possible, the retracing is purely metaphoric, but in the case of fully distributed problems, like routing in communication networks, the ant agent physically retraces backward the network nodes visited during its forward journey. Another peculiar characteristics of network problems consists in the fact that a proper evaluation of the quality of a solution (e.g., a path joining a (source, destination) pair of network nodes) is often rather hard to obtain because of the distributed and dynamic nature of the problem.

For instance, because of the continually changing traffic patterns, the same locally observed value of end-to-end delay can be a good one or a bad one depending on the overall status of network congestion. Unfortunately, a correct and up-to-date view of this status cannot be locally accessed in real-time. On the other hand, in the case of non-dynamic and non-distributed problems, it is usually rather easy to provide a proper solution evaluation.

The complexity of each ant-like agent is such that it can quickly build a feasible solution, but high quality solutions are expected to be the overall result of the accumulation and exchange of information among the agents during the whole execution time of the algorithm. In the same spirit of ants in Nature, the set of capabilities in the repertoire of the single agent is purposely minimal: the agent's complexity is such that according to the allocated time and resources a relatively large number of solutions can be generated.

Moreover, the agent is in general not supposed to be adaptive or to learn during its lifetime (in fact, after generating a solution an ant is usually removed from the colony). On the contrary, learning is expected to happen at a collective level through repeated solution sampling and collective / stigmergic exchange of information about the sampled solutions.

3.2 Probability Rule:

The ACO is applying the following state transition rule for calculating the probability of given path1 over paqth2, which is defined as 'p_1'.

$$p_1 = \frac{(m_1+k)^h}{(m_1+k)^h+(m_2+k)^h} \quad \text{---} \quad (1)$$

In which, 'm_1' and 'm_2' are the pheromone values of available task1 and task2 respectively. The 'k' and 'h' are numeric constants which are used for traffic impact and shortest path impact. Optimization of these parameters may improve the performance of ACO. In this section, the optimization of 'k' and 'h' are explained with various test cases.

For the proposed traffic free routing requires optimal value of path impact and traffic impact constants ('k' and 'h'). Therefore, the following test cases are defined and the performances of each test case are tested. The various six test cases and its 'k' and 'h' values are shown in the table 1. The probability values of each test case on various pheromone values are shown in table 2 to table 6.

Table 1. Test Cases and the values of k, h

	Value of 'k'	Value of 'h'
Test Case 1	1	0
Test Case 2	0.1	0.9
Test Case 3	0.2	0.8
Test Case 4	0.3	0.7
Test Case 5	0.4	0.6

From the above, the various probability values for 'k' and 'h' are computed. The performances of the proposed work on the variety of test cases are shown in table 8. The performance of proposed work is verified on two parameters namely Round Trip Time, Packet Loss. The performance on test case 2 is comparatively so good than other three test cases. Therefore, the proposed work concluded that the optimal values for 'k' and 'h' are 1 and 0 respectively.

Table 2. Probability of Test Case 1

Time	P1	P2	M1	M2	K	h
0	0.33	0.67	2	1	1	0
100	0.33	0.67	4	2	1	0
200	0.33	0.67	6	3	1	0
300	0.33	0.67	8	4	1	0

Table 3. Probability of Test Case 2

Time	P1	P2	M1	M2	K	h
0	0.49	0.51	2	1	0.1	0.9
100	0.49	0.51	4	2	0.1	0.9
200	0.49	0.51	6	3	0.1	0.9
300	0.49	0.51	8	4	0.1	0.9

Table 4. Probability of Test Case 3

Time	P1	P2	M1	M2	K	h
0	0.48	0.52	2	1	0.2	0.8
100	0.47	0.53	4	2	0.2	0.8
200	0.47	0.53	6	3	0.2	0.8
300	0.47	0.53	8	4	0.2	0.8

Table 5. Probability of Test Case 4

Time	P1	P2	M1	M2	K	h
0	0.47	0.53	2	1	0.3	0.7
100	0.46	0.54	4	2	0.3	0.7
200	0.46	0.54	6	3	0.3	0.7
300	0.45	0.55	8	4	0.3	0.7

Table 6. Probability of Test Case 5

Time	P1	P2	M1	M2	K	h
0	0.45	0.55	2	1	0.4	0.6
100	0.44	0.56	4	2	0.4	0.6
200	0.44	0.56	6	3	0.4	0.6
300	0.44	0.56	8	4	0.4	0.6

The performance of proposed and existing routing protocol are compared in the table 7 and 8. In the table 7, the round trip time of proposed and existing routing protocols are recorded.And in the table 8, the packet loss of proposed and existing routing protocols are recorded.

The graphical representation of comparisons in terms of RTT of the proposed and the existing routing protocols are shown in the figure 1. And the comparisons of packet loss of the proposed and the existing routing protocols are shown in the figure 2.

Table 7. Round Trip Time of proposed and existing routing protocols

No of Nodes	AODV	ACO	TP-ACO
10 Nodes	178	169	163
20 Nodes	196	185	171
40 Nodes	213	198	182
100 Nodes	234	212	195

Table 8. Packet Loss of proposed and existing routing protocols

No of Nodes	AODV	ACO	TP-ACO
10 Nodes	6	2	0
20 Nodes	12	4	0
40 Nodes	19	9	2
100 Nodes	29	15	5

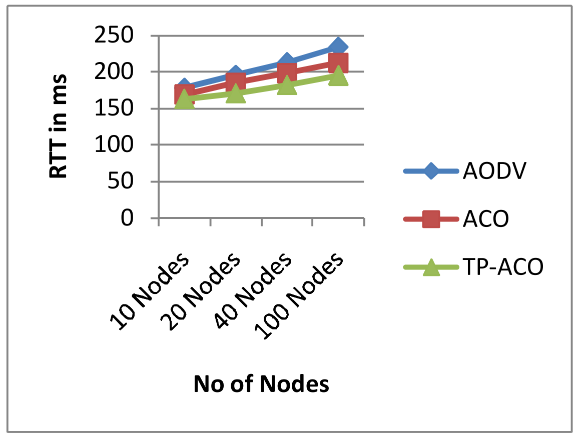

Figure 1. Round Trip Time of proposed and existing routing protocols

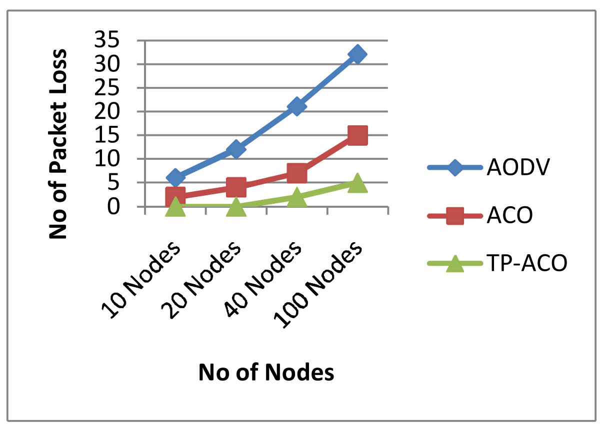

Figure 2. Packet Loss of proposed and existing routing protocols

4. RESULT

The modern computer era, is a combination of wired and wireless networking. In which, the wireless routing becomes unavoidable resource. Therefore, heavy packet loss and long response time are major problems. The proposed routing is designed to provide lesser response time and reduced packet loss. From the performance of the proposed routing shown in the table 5 and 6, figure 1 and 2, it is concluded that the proposed routing offers lesser RTT and lesser packet loss. Hence the proposed routing protocol is provides optimized performance for wireless routing.

Corresponding Author:
P. Visu
Research Scholar,
Department of Computer Science and Engineering,
Vel Tech Dr.RR & Dr.SR Technical University,
Chennai, Tamilnadu, India, 600062.
E-Mail:- pvisu_it@yahoo.co.in,
pandu.visu@gmail.com

REFERENCES

1. Ali M. and Babak, A. “A new clustering algorithm based on hybrid global optimization based on a dynamical systems approach algorithm”, Expert Systems with Applications (Elsevier), Vol. 37,pp. 5645-5652, 2010
2. Dorigo, M. and Luca, M.G. “Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem,” IEEE Transactions on Evolutionary Computation, Vol. 1, No. 1, pp. 53 – 66, 1997
3. Dorigo, M. and Stutzle, T. “Ant Colony Optimization”, MIT Press, Cambrige MA, 2004
4. Dorigo, M., Maniezzo, V. and Colorni, A., “Ant System: Optimization by a colony of cooperating agents,” IEEE Transactions on Systems, Man, and Cybernetics—Part B, Vol. 26, No. 1, pp. 29 – 41, 1996
5. Frank, N. and Carsten, W. “Ant Colony Optimization and the minimum spanning tree problem”, Theoretical Computer Science (Elsevier), Vol. 411, pp. 2406-2413, 2010
6. Goss, Aron, Deneubourg, and Pasteels, “Self-organized shortcuts in the Argentine ant,” Naturwissenschaften, Vol. 76, pp. 579–581, 1989
7. Hsin-Yun, L., Hao-Hsi, T., Meng-Cong, Z. and Pei-Ying, L. “Decision support for the maintenance management of green areas”, Expert Systems with Applications (Elsevier), Vol. 37, pp. 4479-4487, 2010
8. KwangMongSim and Weng Hong Sun, “Ant Colony Optimization for Routing and Load-Balancing: Survey and New Directions IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems And Humans”, Vol. 33, No. 5, 2003
9. Li-Ning Xing, Ying-Wu Chen, Peng Wang, Qing-Song Zhao, JianXiong, “A Knowledge-Based Ant Colony Optimization for Flexible Job Shop Scheduling Problems”, Applied Soft Computing 10 (2010) 888–896
10. Manuel, L. and Christina, B. “Beam-ACO for the travelling salesman problem with time windows”, Computers and Operations Research (Elsevier), Vol. 37, pp. 1570-1583, 2010
11. Osama, H.H., Tarek, N.S. and Myung, J.L. “Probability Routing Algorithm for Mobile Ad Hoc Networks’ Resources Management”, IEEE Journal on Selected Areas in Communications, Vol. 23, No. 12, pp. 2248-2259, 2005
12. Pasteels, Deneubourg, and Goss, “Self-organization mechanisms in ant societies (i): Trail recruitment to newly discovered food sources,” ExperientiaSupplementum, vol.54, p. 155, 1987
13. Roberto Fernandes Tavares Neto, MoacirGodinhoFilho, “A software model to prototype ant colony optimization algorithms”, Expert Systems with Applications, Vol. 38, pp.249–259, 2011.
14. Visu.P, Janet.J and Koteeswaran.S, “Artificial Bee Colony based Energy Aware and Energy Efficient Routing Protocol”, in the Journal of Computer Science, Volume 8, Issue 2, Page nos: 227-231, Feb 2012.
15. Visu.P, Janet.J, Kannan.E and Koteeswaran.S, “Optimal Energy Management in Wireless Adhoc Network Using Artificial Bee Colony based Routing Protocol”, European Journal of Scientific Research, Vol.74: No.2, pp. 301-307, 2012.
16. Visu.P and Kannan.E, “Combined Swarm Intelligence Routing Protocol for MANET”, Information Technology Journal, Volume 12, Number 4, 791-797, 2013.
17. Wang Chen, Yan-jun Shi, Hong-feiTeng, Xiao-ping Lan, Li-chen Hu, “An efficient hybrid algorithm for resource-constrained project scheduling”, Information Sciences 180, pp.1031–1039, 2010
18. Wei-Neng Chen, Jun Zhang, Henry Shu-Hung Chung, Rui-Zhang Huang, and Ou Liu, “Optimizing Discounted Cash Flows in Project Scheduling—An Ant Colony Optimization Approach”, IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, Vol. 40, No. 1, 2010
19. Xiao-ming, Y., Sheng, L. and Yu-ming, W. “Quantum Dynamic Mechanism-based Parallel Ant Colony Optimization Algorithm”, International Journal of Computational Intelligence Systems, Suppl. 1, pp. 101-113, 2010
20. Zhiding, Y., Oscar, C.A., Ruobing, Z., Weiyu, Y. and Jing, T. “An adaptive unsupervised approach toward pixel clustering and color image segmentation”, Pattern Recognition (Elsevier), Vol. 43, pp.1889-1906, 2010