ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 8, August 2014

Simple ACO and ACO with Neural Network for implementing multicast routing in a network: A Comparison based study

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Abstract: This paper introduces a comparative study of implementing simple ACO and ACO using neural network concept for multicast routing in a network.ACO optimizes the path by which ants search for their food by laying a chemical substance named pheromone. Ants on the graph move from a node to other node depending on the corresponding probabilities function, and update the pheromone locally and globally on graph when every iteration is finished. The complexity study, iteration wise shows that merging ACS with neural networks provides features of well performance of cost, fast convergence and stable delay to reach optimal solution as compared to simple ACO.

Keywords: Ant Colony System, Ant colony optimization, pheromone, local pheromone update rule, state transition rule, global pheromone updating rule, synaptic weight.

I. INTRODUCTION

Ant colony algorithm determines optimal solution by simulating the process of ants looking for food. The ants collectively behaviour reflects an information of positive feedback phenomenon [2]. This optimization technique does not rely on mathematical description of the specific issues, but has strong global optimization feature, high performance and flexibility. Three main aspects to determine ACS are:

A. State Transition Rule:

Ants prefer to move to nodes which are connected by short edges with a high amount of pheromone [1, 8]. It can be done by using following rule:

$$PIk(r,s) = \begin{cases} \dfrac{ʈ(r,s).[\eta(r,s)]\beta}{\sum_{u\epsilon Jk(r)} ʈ(r,u)[\eta(r,u)]\beta}, & \text{if } s\ \epsilon Jk(r) \\ 0 & \text{otherwise} \end{cases} \quad \text{.........(1)}$$

B. Local pheromone updating rule

While building a solution , ants visit edges and change their pheromone level by applying this rule:

$$ʈ(r,s) \leftarrow (1-\rho).ʈ(r,s)+\rho.\Delta ʈ(r,s) \quad \text{................................(2)}$$

where $0<\rho<1$ is a pheromone evaporation parameter, and $\Delta ʈ(r,s)=ʈ0$ where ʈ is pheromone.
(r,s)-edge where ant build their path depositing pheromone. We here assume ρ as 0.5.

C. Global pheromone updating rule

Once all ants have build their tours, pheromone is updated on all edges by using the following rule:

$$ʈ(r,s) \leftarrow (1-\alpha)*ʈ(r,s)+\alpha*\Delta ʈ(r,s) \text{.....................(3)}$$

where $0<\alpha<1$ is pheromone decay parameter and we assume $\alpha=0.2$

$$\text{Where } \Delta ʈ(r,s)= \begin{cases} 1/Lgb & \text{if } (r,s)\ \epsilon \text{ global best tour} \\ 0 & \text{otherwise} \end{cases} \quad \text{..............................(4)}$$

where Lgb is length of globally best tour.
Though, ACS has various applications but certain problems are also encountered while implementing it to multicast routing [4].

The 4 C factors:

- Convergence time – more
- Convergence speed – less
- Complexity - more
- Cost - more

Because of these above problems faced with ACS implementation we tried to overcome these problems to some extent, improving the solution by adding the features of neural network [7].

II. LITERATURE REVIEW

Using simple ACO approach, an algorithm MACA[6] was developed ,convergence rate was slower and also there was problem of stagnation. New ACA with orientation factor accelerated the convergence speed, and enabled the ant to get rid of blindness but the problem of stagnation still remained. In ACO for multicast routing [7],the performance of the algorithm developed would improve with decrease of evaporation rate of pheromone but at the same time the speed of the algorithm is lowered ,the edges

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which have been used by the ants will lower to zero with adaptive change in the value of pheromone trail. Marco Dorigo in his paper[2] also focused on the pheromone processing i.e, pheromone control, pheromone-heuristic control and privileged pheromone laying it also introduced the effect of various network parameter to mitigate stagnation to a certain extent[5].Neural Network approach came into picture, as Evolutionary Neural network[6],which is combination of evolutionary algorithm and traditional neural network. A comparative analysis was done based on traditional NN based on genetic algorithm and evolutionary NN based on evolutionary programming [9]. However, computation precision and efficiency can be enhanced even more. Random neural network approach provides an empirical comparison and finds that the heuristics which are modified using NN yield significantly better results [3]. In our algorithm, both the approaches for optimization are combined to develop an algorithm which reduces the complexity and speeds up the convergence rate to reach an optimal solution [6, 10].

III. DESCRIPTION OF THE NETWORK

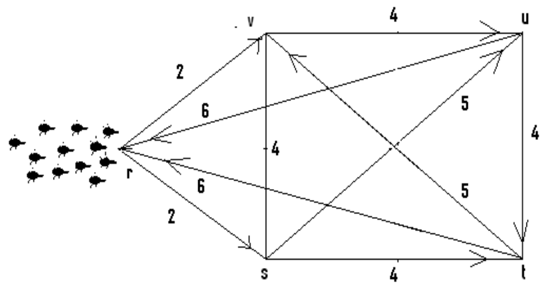

Fig. 1: Sample network

'r','v'and 's' are the source node respectively.
'u' and 't' are the destination nodes.
The cost and pheromone intensity of the paths are:
Cost: (r,v)=(r,u) = 2
Pheromone intensity : 4
Cost:(r,u)=(r,t) = 6
Pheromone intensity : 1.4
Cost:(v,u)=(v,s)=(u,t)=(s,t) =4
Pheromone intensity: 2
Cost:(v,t)=(s,u) = 5
Pheromone intensity: 1.6

IV. IMPLEMENTING SIMPLE ACS IN A DIRECTED GRAPH

The final solution can be tabulated as follows:

TABLE I

Source	Destination	Final path
R	U	6(3)/7(2)
R	T	6(4)/10(3)
V	U	4(6)/9(2)
V	T	8(4)/10(6),13(2)
S	U	5(3)
S	T	4(9)/9(3)

For the said network:
Taking 'r' as the source node, 'u' as destination node. The optimal solution is reached after 4 iterations with minimum path length 6. Taking 'v' as the source node ,'u' as the destination node . The optimal solution is reached after (n-1) iterations with minimum path length 4. Taking 's' as the source node ,'u' as the destination node. The optimal solution is reached after (n-1) iterations with minimum path length 4.

V. IMPLEMENTATION OF ACS USING NEURAL NETWORK CONCEPT

The delta rule is an algorithm for taking a particular set of weights and a particular vector, and yielding weight changes that would take the neural net on the path to minimal error [7].We use this property, considering synaptic weights as cost or pheromone trail laid in the path of traversal to reach final destination with optimal cost of routing [9].

VI. IMPROVED NEURAL HEURISTIC FOR MULTICAST ROUTING

Mapping Approach:

- A single neuron is used to represent each vertex.
- The synaptic weights are represented by the cost of edges of the network [7].
- For each neuron i ,the firing rate of neuron is given

by $r_i = \Sigma_j (w_{ij}^+ + w_{ij}^-)$

- The probability that neuron i is excited is given by

$q_i = \lambda_i^+ / r_i + \lambda_i^-$
where ri=firing rate of neuron
wij=synaptic weights of neurons

VII. ALGORITHM

ACS Implementation

- State transition rule
- Local pheromone update rule
- Global pheromone update rule

NN Implementation

- Finding firing rate and probability of excitation of neuron from a node to another node
- Combining both approaches
- ACS state transition
- ACS Local Update
- ACS Global Update of the optimal (shortest) path
- Neural Global Update of the optimal(shortest) path
- Final solution obtained in less iteration reducing complexity of the algorithm

VI. IMPLEMENTATION

Parameters Considered For Calculating Average Cost of an Undirected Network:

- Bandwidth
- Distance
- Delay
- Hop Count
- Packet Loss

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Taking 'r' as the source ,'u' as the destination :
The optimal solution is reached in single iteration with minimum path length of 6.
Taking 'v' as the source ,'u' as the destination :
The optimal solution is reached after 3 iterations with minimum path length of 4.
Taking 's' as the source ,'u' as the destination :
The optimal solution is reached after 3 iterations with minimum path length of 4.

TABLE II

Complexity study

ACS WITHOUT USING NN	ACS USING NN	
Slow Convergence	Faster Convergence	
Less complex but time Consuming approach	More complex but less time consuming Approach	
Less dynamic approach	Dynamic approach	
Time complexity more	Time complexity reduced	
Complexity	Simple ACS	ACS with NEURAL Approach
Worst Case	0(n-1)	0(log n)
Average Case	0(n(log n))	0(log n)
Best Case	0(1)	0(1)

VII. RESULT

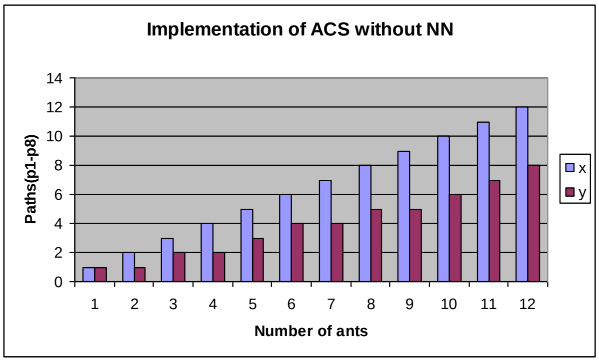

Fig. 2 Convergence rate without NN implementaion

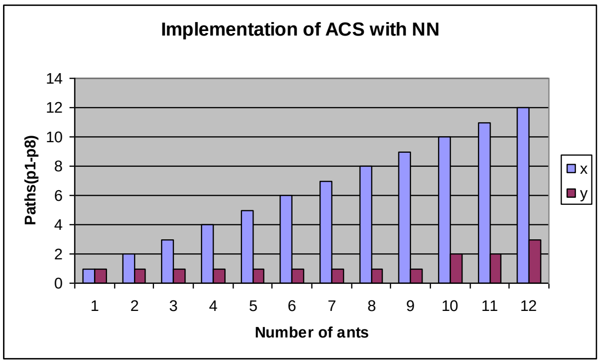

Fig. 3 Convergence rate with NN implementation

VII. CONCLUSION

The aim of our thesis is accomplished by designing a model for our desired objective, analysing it, implementing it in various scenario considering all constraints possible-cost, delay, bandwidth etc and trying to generalize (implementation) through coding, testing manually the concept developed on various networks thoroughly and building the final optimal solution .Apart from what is done, dynamic and parallel implementation can be further concentrated on ,for even better results(with features like faster convergence ,less complexity, cost-effective, more dynamic).The various applications of the model developed can be in various areas like in Traffic management ,scheduling problems etc.

REFERENCES

[1] Mustafa K. Mehmet Ali and Faouzi,"Neural Networks for Shortest path Computation and Routing In Computer Networks" ,IEEE,1993.
[2] M.Dorigo,V.Maniezzo and A.Colorni,"Ant Systems:Optimization by a colony of cooperating agents",IEEE Transaction On Systems,Man,Cybernetics,1996.
[3] Anoop Ghanwani,Vijay Srinivasan,"Improved neural heuristics for multicast routing",IEEE Journal On Selected Areas In Communication,Vol. 15,No. 2,1997.
[4] Ying Wang Jianying Xie,Ant Colony Optimization For Multicast Routing,IEEE,2000.
[5] Yuan Li,Zhengxin Ma,Zhigang Cao,Stata Key Laboratory On Microwave and digital communication,"A Mitigation Stagnation-Based Ant Colony Optimization Routing Algorithm",IEEE,2005.
[6] Hua Wang,Zhao Shi,Jun Ma,"A Modified Ant Colony Algorithm for Multi-Constraint Multicast Routing",IEEE,2006.
[7]Yan-bin Qu,Yang Zhang,"An Application of the combination of Ant Colony Algorithm and Neural Network",Interntional conference on InformationAcquisition,Weihai,Shndong,China,IEEE,2006.
[8]Marco Dorigo,Mauro Biratarri,and Thomas Stutzle,"Ant Colony Optimiztion",IEEE Computational Intelligence Magazine,2006.
[9]Gao Wei,"Evoltionary Neural network Based on New Ant colony Algorithm",International Symposium on Computational Intelligence and Design,2008.
[10]Hua Wang,Zhao Shi,Shuai Li, "Multicast Routing for delay variation bound using a modified ant Colony algorithm",Journal of network and computer Application,2008.

BIOGRAPHIES

Abira Dasgupta, female, was born in Jamshedpur, India on 19th March, 1985.She received her B-tech degree from B.I.E.T, Suiri in 20037 and M-Tech degree from B.I.T Mesra, Ranchi in 2010.Her major field of study is Computer science.

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ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 8, August 2014

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