

Load Balanced Ant Based Routing Algorithms for Mobile Ad Hoc Network

Abstract

Mobile ad-hoc networks are infrastructure-less networks consisting of wireless, possibly mobile nodes which are organized in peer-to-peer and autonomous fashion. Each node in such a network is more than a data receiver/sender, it is also a router that forwards data packets to its proper destination. The main characteristics of ad hoc network highly dynamic topology, limited bandwidth availability and energy constraints make the routing problem a challenging one. Recently a new family of algorithms emerged inspired by Swarm Intelligence, which provides a novel approach to distributed optimization problems. Initial studies have unveiled a great deal of matching properties between the routing requirements of ad-hoc networks and certain features of SI, such as the ability of ant colony to find a nearly optimal route between elements. Several algorithms which are based on ant colony optimization were introduced in recent years to solve the routing problem in ad-hoc networks. In this paper we present implementation of load balanced Ants based routing algorithm for mobile ad hoc network for improving scalability and load balancing of network. This algorithm is based upon AODV and ACO Metaheuristics.

Keyword: Ant Colony Optimization, Ant Routing, Metaheuristics, Mobile Ad Hoc Network, Swann Intelligence.

Introduction

Mobile Ad Hoc Networks are communication networks built up of a collection of mobile devices which can communicate through wireless connections. Routing is the task of directing data packets from a source node to a given destination. This task is particularly hard in Mobile Ad Hoc Networks, due to the mobility of the network elements. In this paper, we describe an algorithm which draws inspiration from Swarm Intelligence to obtain these characteristics. More especially, we consider ideas from ant colonies and the Ant Colony Optimization framework. The networks are becoming more and more complex and are desirable that they can self-organize and self-configured, adaptive to new situations in terms of traffic, services, network connectivity, etc. To support new paradigm network, algorithms should be robust and work in a distributed way. The robustness and effectiveness of such collective behaviors with respect to variations of environment conditions are key aspects of the algorithm success. [1]-[5].

Swarm intelligence is a relatively new approach to problem solving that takes inspiration from the social behavior of insects and of other animals. In particular, ants have inspired a numbers of methods and techniques among which the most studied and the most successful is the general purpose optimization technique known as ant colony optimization. Ant colony optimization (ACO) takes inspiration from the foraging behavior of some ant species. These ants deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony. Ant colony optimization exploits a similar mechanism for solving optimization problems.

In the forties and fifties of the twentieth century, the French entomologist Pierre-Paul Grass'e [1] observed that some species of termites react to what he called "significant stimuli". He observed that the effects of these reactions can act as new significant stimuli for both the insect that produced them and for the other insects in the colony. Grass'e used the term stigmergy to describe this particular type of communication in which the "workers are stimulated by the performance they have achieved". The two main characteristics of stigmergy that differentiate it from other forms of communication are the following.



Archana Chhikara
Assistant Professor,
Deptt. of Computer Science,
Hibdu College,
Sonapat

1. Stigmergy is an indirect, non-symbolic form of communication mediated by the environment insects exchange information by modifying their environment and
2. Stigmergic information is local: it can only be accessed by those insects that visit the locus in which it was released (or its immediate neighborhood).

Examples of stigmergy can be observed in colonies of ants. In many ant species, ants walking to and from a food source deposit on the ground a substance called *pheromone*. Other ants perceive the presence of pheromone and tend to follow paths where pheromone concentration is higher. Through this mechanism, ants are able to transport food to their nest in a remarkably effective way.

Deneubourg et al. [2] thoroughly investigated the pheromone laying and following behavior of ants. In an experiment known as the "double bridge experiment", the nest of a colony of Argentine ants was connected to a food source by two bridges of equal lengths. In such a setting, ants start to explore the surrounding of the nest and eventually reach the food source. Along their path between food source and nest, Argentine ants deposit pheromone. Initially, each ant randomly chooses one of the two bridges. However, due to random fluctuations, after some time one of the two bridges presents a higher concentration of pheromone than the other and, therefore, attracts more ants. This brings a further amount of pheromone on that bridge making it more attractive with the result that after some time the whole colony converges toward the use of the same bridge. This colony-level behavior, based on autocatalysis, that is, on the exploitation of positive feedback, can be exploited by ants to find the shortest path between a

bridge are the first to reach the nest. The short bridge receives, therefore, pheromone earlier than the long one and this fact increases the probability that further ants select it rather than the long one. The model proposed by Goss and co-workers for explaining the foraging behavior of ants was the main source of inspiration for the development of ant colony optimization. In ACO, a number of artificial ants build solutions to an optimization problem at hand and exchange information on the quality of these solutions via a communication scheme that is reminiscent of the one adopted by real ants.

The Metaheuristic

A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems. In other words, a metaheuristic is a general-purpose algorithmic framework that can be applied to different optimization problems with relatively few modifications. Examples of metaheuristics include simulated annealing [7], taboo search [8], iterated local search [9], evolutionary computation [1], and ant colony optimization [4]- [6].

A combinatorial optimization problem

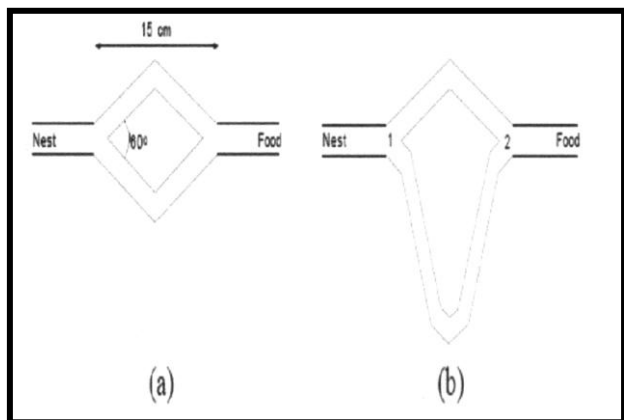
An instance of a combinatorial optimization problem is a triple (S, f, Ω) , where S is a set of candidate solutions, f is the objective function which assigns an objective function value of $f(s)$ to each candidate solutions $s \in S$, and Ω is a set of constraints. The solutions belonging to the set S of candidate solutions that satisfy the constraints Ω are called feasible solutions. The goal is to find a globally optimal feasible solution s^* .

The Ant Colony Optimization Metaheuristic

Ant colony optimization (ACO) has been formalized into a metaheuristic for combinatorial optimization problems by Dorigo and coworkers [5], [6]. The model of a combinatorial optimization problem is used to define the pheromone model of ACO. A pheromone value is associated with each possible solution *component*; that is, with each possible assignment of a value to a variable. The set of all possible solution components is denoted by C . In ACO, an artificial ant builds a solution by traversing the fully connected *construction graph* $G_c(V,E)$, where V is a set of vertices and E is a set of edges. This graph can be obtained from the set of solution components C in two ways: components may be represented either by vertices or by edges. Artificial ants move from vertex to vertex along the edges of the graph, incrementally building a *partial solution*. Additionally, ants deposit a certain amount of pheromone on the components; that is, either on the vertices or on the edges that they traverse. The amount Δt of pheromone deposited may depend on the quality of the solution found. Subsequent ants use the pheromone information as a guide toward promising regions of the search space.

Algorithm 1: The Ant Colony Optimization Metaheuristic

- Set parameters, initialize pheromone trails
- While termination condition not met do
- Construct Ant Solutions
- Apply Local Search (optional)
- Update Pheromones



food source and their nest.

Goss et al. [3] considered a variant of the double bridge experiment in which one bridge is significantly longer than the other. In this case,

Fig. 1 Experimental setup for the double bridge experiment. (a) Branches have equal lengths. (b) Branches have different lengths

the stochastic fluctuations in the initial choice of a bridge are much reduced and a second mechanism plays an important role: the ants choosing by chance the short

End while

The ACO metaheuristic is shown in Algorithm 1. After initialization, the metaheuristic iterates over three phases: at each iteration, a number of solutions are constructed by the ants; these solutions are then improved through a local search (this step is optional), and finally the pheromone is updated.

Applications of ACO

In recent years, the interest of the scientific community in ACO has risen sharply. Because of its robustness, and adaptive nature, ACO can find its applications in routing, assignment, scheduling, subset and classification rules problem [1], [5].

ACO for Routing: general principles

ACO routing algorithms [1], [10] take inspiration from the behavior of ants in nature and from the related field of ACO to solve the problem of routing in communication networks. ACO routing algorithms boast a number of interesting properties compared to traditional routing algorithms.

1. They are adaptive by means of continuous path sampling and probabilistic ant forwarding which leads to an uninterrupted exploration of the routing capabilities.
2. They are robust. This is because routing Information is the result of the repeated sampling of paths. The use of sampling implies that routing information is based on direct measurements of the real network situation, which enhances its reliability.

The rest of the paper is organized as follows Design space by analyzing the problem and the related work done by researchers till now .in Section II.System description model in Section III,The proposed algorithm in Section IV, Simulation result and discussion in Section V, Finally, conclusions and future work are described in Section VI.

Related Work

AntNet [11] is a routing algorithm proposed for wired datagram networks by Gianni Di Caro and Marco Dorigo, based on the principle of ant colony optimization. In AntNet, each node maintains a routing table and an additional table

Containing statistics about the traffic distribution over the network. The routing table maintains for each destination and for each next hop a measure of the goodness of using the next hop to forward data packets to the destination. These goodness measures, called pheromone variables, are normalized to one in order to be used by a stochastic routing policy. AntNet uses two sets of homogeneous mobile agents called forward ants and backward ants to update the routing tables. The forward ants use heuristics based on the routing table to move between a given pair of nodes and are used to collect information about the traffic distribution over the network. The backward ants retrace the paths of forward ants in the opposite direction. At each node, the backward ants update the routing table and the additional table containing statistics about the traffic distribution over the network. AntNet [11] has been shown to perform better than Bellman-Ford, Open Shortest Path Forwarding (OSPF) etc. routing protocols under varying and near saturation traffic loads.

Ant-Based Control (ABC) is an algorithm proposed by Schoonderwoerd et al. [12] for load balancing in circuits switched networks. In ABC, the calls are routed using probabilistic routing tables that consist of next hop probabilities for each destination. The link costs are assumed to be symmetric and hence, only one-directional mobile agents are used for updating and maintaining the routing tables. The mobile agents use heuristics based on the routing tables to move across the network between arbitrary pairs of nodes. At each node along the path, the mobile agents update the routing tables based on their distance from the source node and the current state of the routing table.

Camara and Loureiro [16], [23] described a novel routing protocol called Global Positioning System ANT-Like Routing Algorithm (GPSAL) which uses a Global Positioning System and mobile software agents modeled on ants for routing. Ants are used to collect and disseminate information about the location of nodes in the MANET while the GPS provides the physical location of a destination node. This algorithm focuses on position-based routing and so does not consider the concentration of pheromone on any paths.

Another ant based routing algorithm for wired networks has been proposed by Kuntz et al. [13]. The proposed algorithm differs from AntNet in terms of different loop detection behavior, simpler backward ant and different routing table update procedure.

The authors also proposed another routing protocol called Co-operative Asymmetric Forward (CAP) routing. CAP is similar to ABC but it works for asymmetric networks where the link costs are not identical in opposite directions. CAP has been shown to perform as well as AntNet and is able to cope with changing bandwidth and network topology [21].

Ad hoc Networking with Swarm Intelligence (ANSI) is a reactive routing protocol proposed by Rajagopalan and Shen [22] for mobile ad hoc networks. ANSI protocol uses two sets of mobile agents called forward reactive ants and backward reactive ants. The routing tables in ANSI contain an entry for each reachable node and next best hop while the ant decision tables store the pheromone values. In ANSI, the forward reactive ants are generated only when a node needs to transmit data to another node. The forward reactive ants are broadcast while the backward reactive ants retrace the path of forward reactive ants and update the pheromone values at the nodes. The data packets choose the next hop deterministically i.e., the hop which contains the largest pheromone value is chosen as the next hop. ANSI has been shown to perform either better or comparable with AODV with respect to packet delivery and end-to-end delay [14].

(ARAMA), [20] is a proactive routing algorithm proposed by O. Hossein and T. Saadawi. The main task of the forward ant as in other ACO algorithms for MANETs is to collect path information. However, in ARAMA, the forward ant takes into account not only the hop COWIt factor, as most protocols do, but also the links local heuristic along the route such as the node's battery power and queue delay. ARAMA defines a value called grade. This value is calculated by each backward

ant, which is a function of the path information stored in the forward ant. At each node, the backward ant updates the pheromone amount of the node's routing table, using the grade value. The protocol uses the same grade to update pheromone value of all links. The authors claim that the route discovery and maintenance overheads are reduced by controlling the forward ant's generation rate. However, they do not clarify how to control the generation rate in a dynamic environment.

System Description of Model

Swarm intelligence is a type of artificial intelligence based system on the collective behavior of decentralized self organized systems. Swarm Intelligence appears in biological swarms of certain insect species. It gives rise to complex and often intelligent behavior through complex interaction of thousands of autonomous swarm members. Interaction is based on primitive instincts with no supervision. The end result is accomplishment of very complex forms of social behavior and fulfillment of a number of optimization and other tasks. The main principle behind these interactions is called stigmergy / communication through the environment. An example is pheromone laying on trails followed by ants. Pheromone is a potent form of hormone that can be sensed by ants as they travel along trails. It attracts ants and therefore ants tend to follow trails that have high pheromone concentrations. This causes an autocatalytic reaction, i.e., one that is accelerated by itself. Ants attracted by the pheromone will lay more of the same on the same trail, causing even more ants to be attracted. Swarm intelligence boasts a number of advantages due to the use of mobile agents and stigmergy. They are as follows [19]-[21]

Pheromone Table

Paths are implicitly defined by the pheromone tables which are kept locally at each node. An entry of the pheromone table i at node i contains a value indicating the estimated goodness of going from i over neighbor n to reach destination d . This goodness is a combined measure of path end-to-end delay and number of hops.

Reactive path setup

When a source node s starts a communication session with a destination node d , it broadcasts a reactive forward ant. At each node, the ant either unicast or broadcast accordingly whether or not the current node has pheromone information for d . If information is available, the ant chooses its next hop n with the probability P which depends on the relative goodness of n as a next hop, expressed in the pheromone variable parameter which controls the exploratory behavior of the ants.

Proactive path maintenance and exploration

During the course of a communication session, source nodes send out proactive forward ants to update the information about currently used paths and try to find better paths. They follow pheromone and update routing tables in the same way as reactive forward ants. Such continuous sampling of paths and pheromone updating by ants is the typical mode of operation in ant inspired routing algorithms.

Stochastic data routing

Nodes in AntHocNet forward data stochastically according to the pheromone values. When a node has multiple next hops for the destination d of the data, it randomly selects one of them, with probability.

Link Failures

Nodes can detect link failures (e.g., a neighbor has moved away) when unicast transmissions fail, or when expected periodic pheromone diffusion messages were not received due to less available Bandwidth at node.

Description of the Proposed Algorithm

Design of proposed load balanced Ant based Routing algorithm is based by ACO routing algorithm for wired networks. It uses ant agents which follow and update pheromone tables in a stigmergic learning process. Data packets are routed stochastically according to the learned tables. It is reactive in the sense that nodes only gather routing information for destinations which they are currently communicating with, while it is proactive because nodes try to maintain and improve routing information as long as communication is going on. We make a distinction between the path setup, which is the reactive mechanism to obtain initial routing information about a destination at the start of a session, and path maintenance and improvement, which is the normal mode of operation during the course of a session to proactively adapt to network changes. Path maintenance and improvement is supported by the pheromone diffusion process. The routing information obtained via stigmergic learning is spread between the nodes of the MANET in an information bootstrapping process to provide secondary guidance for the learning agents. Link failures are dealt with using a Backpressure Technique (Ants messages).[22]

Algorithm

The sequence of actions in proposed algorithm are as follows.

1. Each network node launches forward ants to all destinations in regular time intervals.
2. The ant finds a path to the destination randomly based on the current routing tables.
3. The forward ant creates a stack, pushing in trip times for every node as that node is reached
4. When the destination is reached, the backward ant inherits the stack.
5. The backward ant pops the stack entries and follows the path in reverse.
6. The node tables of each visited node are updated based on the trip times.
7. The message ant is generated as link failure occurs.

Following statements describe the functions of a node for each type of ant for path from source to destination

if (Forward ant)

{ Get the next node based on the value of gene position

if (the link is available and no loop caused) then

{ Update forward ant with network status (stack)

Send forward ant to the next node }

else if (no such link exist)

{ Create backward ant and load contents of forward

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ant to backward ant (queue).
Send backward ant towards source along the same path
as forward ant }
}
if (backward ant)
{ if current node is source node
Store path and kill backward ant
Update routing table }
else
{ Forward backward ant on to link available on queue
Update routing table }
if (next node is not available)
Kill backward ant
Else
{if link failure then
Update forward ant with network status as failure and
stop
sending information (data)
Send message ant to the previous node regarding link
failure update table for alternative path till path is
recovered
or restore}
} // End of proposed algorithm

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Simulation Results

We evaluated the performance of load balanced Ant Based Routing algorithm for Mobile Ad Hoc Networks Using Ns-2 and Several measurement metrics were collected from our propose simulator to evaluate the performance of load balanced Ant based routing algorithm. The data packet delivery ratio is defined as the number of successfully delivered data packets to the number of data packets generated by the source .Algorithm mostly selects the optimal path for transmission of packets from source to destination. The routing overhead, in terms of number of control packets forwarded per successfully delivered data packet. This will lead in the improvement of the QoS.

We investigate performance at various levels of mobility and node density, increasing network sizes, and different data traffic pattern. It observed that the curves decrease when the network density increases.

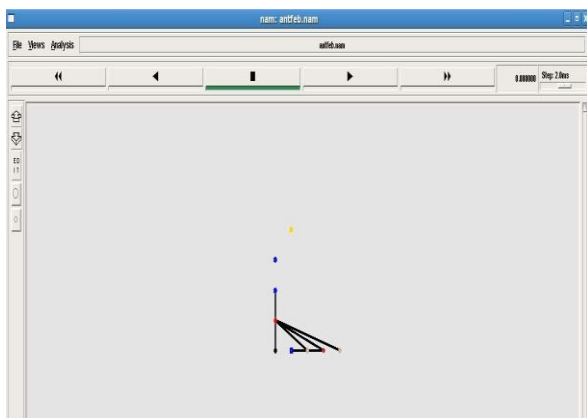


Fig.:2 Simulation

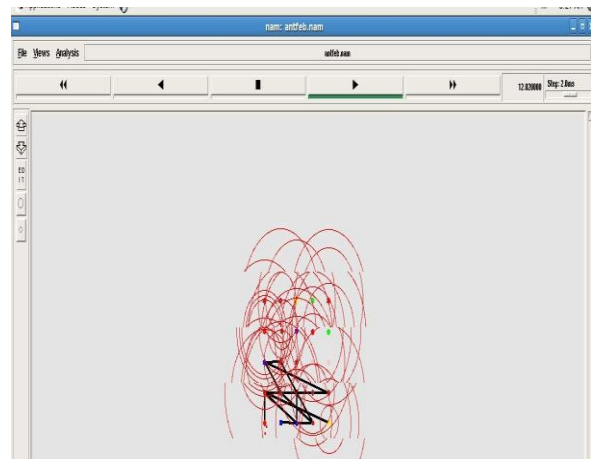


Fig.:3 Simulation

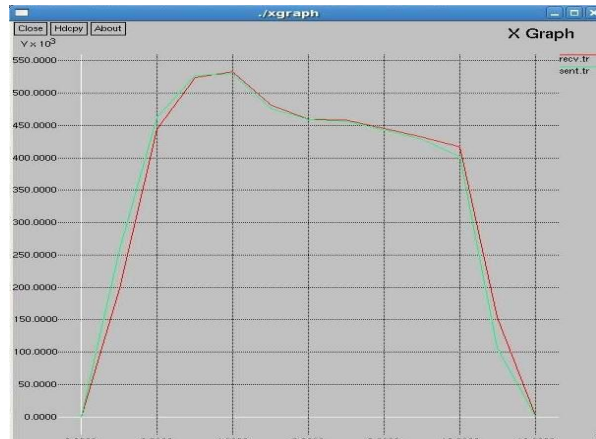


Fig.:4 Graph for send and received Packets

Table I
Simulation Time

Simulation Time	Start Time	Finish Time	Sampling Interval
12 minutes(720 seconds)	0	715	0.5 seconds

To evaluate the performance of protocol, we use different quantitative metrics. They are as following:

Packet Delivery Ratio

The fraction of packets sent by the application that are received by the receivers .

Throughput

The throughput is defined as the total amount of data a receiver receives from the sender divided by the time it takes for the receiver to get the last packet .

Routing Load

Routing Load is the ratio of total number of the routing packets to the total number of received data packets at destination.

Packets Sent	584
Packet Received	276

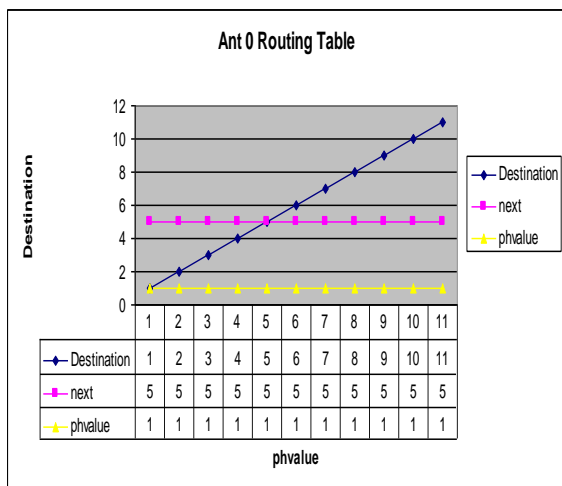


Fig.: 5 Graph for Ant 0

Conclusion

In this paper we proposed an algorithm, Load Balanced Ant Based Routing algorithm for Mobile Ad Hoc. The algorithm mostly selects the optimal paths for transmission of packets from source to destination. The proposed scheme balanced the load of network by using many paths to send packet from source to destination. The simulation shows that the proposed Swarm intelligence based routing protocol achieves the objectives of Path setup, Dynamic path Maintenance, Congestion Control and Bandwidth utilization is better than one Ant scheme for the maintenance overhead and the path reliability. Thus reducing the congestion in network and improving bandwidth utilization. Analytic proof and models of the swarm-based algorithm performance remain topics of future research.

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