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Mobile Ad Hoc Networks Routing Using Ant Colony Optimization

Aws Kanan, Taisir Eldos, Mohammed Al-Kahtani
Department Of Computer Engineering
College of Computer Engineering and Sciences
Salman in Abdulaziz University
Al Kharj, 11942-0151 Saudi Arabia

Abstract— Ad-Hoc wireless networks are self-organizing multi-hop wireless networks, where all the nodes take part in the process of forwarding packets. Ad-Hoc networks can quickly and inexpensively be set up as needed since they do not require any fixed infrastructure, such as base stations or routers. Therefore, they are highly applicable in many fields such as emergency deployments and community networking. The function of a routing protocol in Ad-Hoc network is to establish routes between different nodes. Ad-Hoc routing protocols are difficult to design in general, for two main reasons: the highly dynamic nature of these networks due to the high mobility of the nodes, and the need to operate efficiently with limited resources, such as network bandwidth, limited memory and battery power of the individual nodes in the network. Moreover, routing protocols in Ad-Hoc networks, unlike static networks, do not scale well due to frequently changing topology, lack of predefined infrastructure like routers, peer-to-peer mode of communication and limited radio communication range. In this paper, we apply the Ant Colony evolutionary optimization technique to the routing problem, where more of those desirable characteristics can be implied in the guided probabilistic choice of paths. Simulations of a routing based on the biological system referred to as Ant Colony Optimization (ACO) are conducted, taking into account several factors to analyze its adaptive nature.

Keywords- Ant Colony; Optimization Algorithm; Ad-Hoc Networks; Routing Protocols; AntNet.

I. Introduction

With the advances in mobile computing and wireless communications technologies, mobile Ad Hoc networking has a wide range of applications, and plays a significant role in mobile communications. A MANET (Mobile Ad Hoc Network) is a group of mobile nodes equipped with wireless communication capabilities. These nodes can communicate with each other without using any fixed infrastructure. Advances in microelectronics technology have enabled the construction of small and portable mobile devices. These devices can move freely, resulting in dynamic topology. Several ad hoc routing protocols have been designed. These protocols can be categorized as table-driven (proactive), on-demand-driven (reactive), and hybrid.

Ant colony algorithms consider the ability of simple ants to solve complex problems by cooperation. Ants do not need any direct communication to find the solution; they communicate using the principle of stigmergy which refers to the indirect communication of individuals through modifying their environment. Several algorithms which are based on ant colony optimization were introduced to solve different problems such as scheduling problems, assignment problems, data mining, classification, traveling salesman problem, and many others. The authors of [1], [2], [3] have introduced a routing algorithm based on ant colony optimization that explores the network aiming to build routing tables while keeping them adapted to network conditions. The algorithm is called AntNet. It can be applied to both connection-oriented and connectionless networks. Ants collect information that is used to build local parametric models of the network status used to compute reinforcements to change the routing tables. In this paper, we will analyze the performance of an ant-based Ad-Hoc routing algorithm that is based on the AntNet algorithm.

II. Related Work

Several Ad-Hoc protocols that use Ant Colony optimization (ACO) algorithms are proposed in the literature. In [4], the authors Propose a new ACO routing algorithm based on robustness of paths for MANETs with global positioning system (GPS), in which each ant-like agent evaluates robustness of a path using GPS information of visited nodes and decides the amount of pheromone to lay down based on the robustness. Moreover, each node predicts link disconnections from neighbors' GPS information in order to adapt to dynamic network change.

The authors of [5] Introduces a multi path hybrid routing algorithm for mobile Ad-hoc networks. This algorithm is based on swarm intelligence algorithms and Ant Colony Optimization (ACO), particularly. By mapping arithmetic and engineering problems on to biological societies, these methods attempt to solve the problems. In the presented algorithm, the number of neighbors of a node has been used to select the next hop.

In [6], the authors Propose EAQR, a novel routing protocol based on an improved Ant colony optimization (ACO) algorithm. The algorithm concentrates on the provision of QoS and balanced energy-consumption over the whole network. With the introduction of some metrics like the minimum path energy and path hop count and by means of advancing pheromone trail model of the ant colony system, the algorithm innovatively provides two heuristic ways respectively based on the length and the comfort of path to meet the different performance requirements of real time and common traffics.

ACO-AOMDV is presented in [7]. The authors presents an ant colony optimization and ad-hoc on-demand multipath distance vector (AOMDV) based routing protocol (ACO-AOMDV) for ad hoc networks. In ACO-AOMDV, ant packets deposit simulated pheromone as a function of multiple parameters corresponding to the information collected each path visited, such as average link count of path, average load of path, hop count and the current pheromone the nodes possess and so on, and provide the information to the visiting nodes to update their pheromone tables by endowing the above different parameters corresponding to different information with different weight values.

In [8], a hybrid QoS routing algorithm which can improve the performance in MANET is proposed. The hybrid quality of the algorithm makes it suitable for all the environments in comparison with reactive and proactive protocols. Ant's pheromone update process approach has inherited advantage of robustness and fast convergence, which makes it an appropriate choice over existing QoS algorithms to improve the performance for MANET.

The authors of [9] Develop an improved routing algorithm for MANETs based on Ant Colony Optimization (ACO) inspired by real ants. The performance of the routing algorithm is evaluated through simulation and is compared to an existing well known MANET routing protocol, Ad hoc On-Demand Distance Vector (AODV). Several performance metrics are considered in different scenarios with varying mobility levels and traffic load.

Mobile Ants Based Routing (MABR) is introduced in [10] as a routing algorithm for MANET's inspired by social insects [10]. The authors extend the approach presented in AntNet to ad hoc networks by abstracting the network into logical links and nodes based on relative node location. Location data is used by positioning devices. Messages are forwarded between nodes by an optimized greedy routing algorithm. In [11], the details of Ant colony based routing Al algorithm (ARA) is presented including route discovery and maintenance mechanisms. Route discovery is achieved by flooding forward ants to the destination. A reverse links to the source is established. Route maintenance is accomplished by data packets as they pass through the network. When a route failure occurs, an attempt is made to send the packet over another link. Otherwise, it is returned to the previous node for similar processing. If the packet is returned to the source, a new route discovery is started.

III. Ant Colony system

In ACO, artificial ants build solutions to the problem by traversing a fully a construction graph, as sets of denoted by cij, towards a set of all possible solution components denoted by C. A pheromone trail value τij is associated with each component cij, to allow the probability distribution of different components of the solution to be modeled. The ants move from vertex to vertex along the edges of the construction graph exploiting information provided by the pheromone values to incrementally build solutions. Ants deposit pheromone on the components, whose amount $\Delta\tau$ of is a function of the iteration and the quality of the solution found.

A set of m artificial ants construct solutions from elements of a finite set of available solution components $C=\{c_{ij}\}$, $i=1,\ldots,n$, $j=1,\ldots,|D_i|$. A solution construction starts with an empty partial solution $s^p=\emptyset$. Then, at each construction step, the current partial solution sp is extended by adding a feasible solution component from the set of feasible neighbors $N(s^p)\subseteq C$. The process of constructing solutions can be regarded as a path on the construction graph.

The choice of a solution component from $N(s^p)$ is done probabilistically at each construction step, and the best known rule is the one of ant system:

$$p\left(c_{ij}\middle|s^p\right) = \frac{\tau_{ij}^{\alpha}\cdot\eta_{ij}^{\beta}}{\sum_{c_{ij}\in N(s^p)}\tau_{il}^{\alpha}\cdot\eta_{il}^{\beta}}, \forall c_{ij}\in N(s^p) \qquad (1)$$

where τij and ηij are respectively the pheromone value and the heuristic value associated with the component cij. Furthermore, α and β are positive real parameters whose values determine the relative importance of pheromone versus heuristic information.

Pheromone update is meant to increase the pheromone values associated with good solutions, and to decrease those that are associated with bad ones. Usually, this is achieved (i) by decreasing all the pheromone values through pheromone evaporation, and (ii) by increasing the pheromone levels associated with a chosen set of good solutions *Supd*:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij} + \rho\cdot\sum_{s\in S_{upd}|c_{ij}\in s} F(s) \qquad (2)$$

where *Supd* is the set of solutions that are used for the update, , $\rho\in(0,1)$ is a parameter called evaporation rate, and $F{:}S\rightarrow R^{+}{}_{0}$ is a function such that;

$$f(s) < f(s') \Rightarrow F(s) \geq F(s'),\ \forall s \neq s' \in S \qquad (3)$$

F is commonly called the fitness function.

Pheromone evaporation implements a useful form of forgetting, favoring the exploration of new areas in the search space. Instantiations of the update rule given above are obtained by different specifications of S_{upd}, which in many cases is a subset of $S_{iter}\cup\{s_{bs}\}$, where S_{iter} is the set of solutions that were constructed in the current iteration, and s_{bs} is the *best-*

so-far solution, that is, the best solution found since the first algorithm iteration.

Usually, the update rule is $S_{upd} \leftarrow S_{iter}$, although $S_{upd} \leftarrow \arg\max_{s \in S_{iter}} F(s)$, is more often used in practive

IV. Main ACO algorithms

Several special cases of the ACO metaheuristic have been proposed in the literature.

Ant System (AS)

AS was the first ACO algorithm to be proposed in the literature, its main characteristic is that the pheromone values are updated by all the ants that have completed the tour. Solution components cij are the edges of the graph, and the pheromone update for τij , that is, for the pheromone associated to the edge joining cities i and j , is performed as follows:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij} + \rho\cdot\sum_{k=1}^{m}\Delta\tau_{ij}^{k} \tag{4}$$

where $\rho \in (0,1]$ is the evaporation rate, m is the number of ants, and $\Delta\tau^{k}_{ij}$ is the quantity of pheromone laid on edge (i,j) by the k-th ant:

$$\Delta\tau_{ij}^{k} = \frac{1}{L_k}\ if\ ant\ k\ has\ edge(i,j) in\ tour, else\ 0 \tag{5}$$

where L_k is the tour length of the k-th ant.

When constructing the solutions, the ants in AS traverse the construction graph and make a probabilistic decision at each vertex. The transition probability $p(c_{ij}|s^{p}_{k})$ of the k-th ant moving from city i to city j is given by:

$$p(c_{ij}|s^{p}) = \frac{\tau_{ij}^{\alpha}\cdot\eta_{ij}^{\beta}}{\sum_{c_{ij}\in N(s^{p})}\tau_{il}^{\alpha}\cdot\eta_{il}^{\beta}}, \text{if } j \in N(s_{k}^{p}), \text{else } 0 \tag{6}$$

where $N(s^{p}_{k})$ is the set of components that do not belong yet to the partial solution s^{p}_{k} of ant k , and α and β are parameters that control the relative importance of the pheromone versus the heuristic information $\eta_{ij}=1/d_{ij}$, where dij is the length of component c_{ij} (i.e., of edge (i,j)).

Ant Colony System (ACS)

It is the first major improvement over the original ant system; the first important difference is the form of the decision rule used by the ants during the construction process. Ants here use the so-called pseudorandom proportional rule: the probability for an ant to move from city i to city j depends on a random variable q uniformly distributed over [0,1], and a parameter q0 ; if $q \leq q_0$, then, among the feasible components, the component that maximizes the product $\tau_{il}\eta^{\beta}_{il}$ is chosen; otherwise, the same equation as in AS is used.

This rather greedy rule, which favors exploitation of the pheromone information, is counterbalanced by the introduction of a diversifying component: the local pheromone update. The local pheromone update is performed by all ants after each construction step. Each ant applies it only to the last edge traversed:

$$\tau_{ij}=(1-\varphi)\cdot\tau_{ij}+\varphi\cdot\tau_0 \tag{7}$$

where $\varphi \in (0,1]$ is the pheromone decay coefficient, and τ0 is the initial value of the pheromone.

The main goal of the local update is to diversify the search performed by subsequent ants during one iteration. In fact, decreasing the pheromone concentration on the edges as they are traversed during one iteration encourages subsequent ants to choose other edges and hence to produce different solutions. This makes less likely that several ants produce identical solutions during one iteration. Additionally, because of the local pheromone update in ACS, the minimum values of the pheromone are limited.

At the end the construction process, an offline pheromone update is performed; performed only by the best ant, that is, only edges that were visited by the best ant are updated, according to the equation:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij}+\rho\cdot\Delta\tau^{best}_{ij} \tag{8}$$

where $\Delta\tau^{best}_{ij}=1/L_{best}$ if the best ant used edge (i,j) in its tour, , $\Delta\tau^{best}_{ij}=0$ otherwise (L_{best} can be set to either the length of the best tour found in the current iteration -- iteration-best, L_{ib} -- or the best solution found since the start of the algorithm -- best-so-far, L_{bs}).

MAX-MIN Ant System (MMAS)

MMAS is another improvement, it differs from AS in that (i) only the best ant adds pheromone trails, and (ii) the minimum and maximum values of the pheromone are explicitly limited. The pheromone update equation takes the following form:

$$\tau_{ij} \leftarrow (1-\rho)\cdot\tau_{ij}+\Delta\tau^{best}_{ij} \tag{9}$$

where $\Delta\tau^{best}_{ij}=1/L_{best}$ if the best ant used edge (i,j) in its tour, $\Delta\tau^{best}_{ij}=0$ otherwise, where L_{best} is the length of the tour of the best ant. As in ACS, L_{best} may be set (subject to the algorithm designer decision) either to Lib or to L_{bs} ,or to a combination of both.

The pheromone values are constrained between τ_{min} and τ_{max} by verifying, after they have been updated by the ants, that all pheromone values are within the imposed limits.

$$\tau_{ij} \text{ is set to } \tau_{max} \text{ if } \tau_{ij}>\tau_{max} \text{ and to } \tau_{min} \text{ if } \tau_{ij}<\tau_{min} \tag{10}$$

The minimum and maximum values are experimentally or analytically selected.

V. The Routing Algorithm

AntNet algorithm is designed for wired networks. The protocol used in the simulations of this paper is based on AntNet with few modifications to work in mobile Ad-Hoc networks [10].

Three types of packets are used in the network:

- Data packets: that the end-users exchange with each other. They do not maintain any routing information.
- Forward and Backward ants: control packets used to update the routing tables and distribute information about the load in the network.

- Neighbor Control packets: HELLO messages broadcasted periodically from each node to all its neighbors to maintain a list of available nodes to which packets may be forwarded.

Similar to AntNet, there are two types of mobile agents:

- Forward Ants: gather information on a regular time base. Each router sends one Forward Ant with a random destination through the network. It is forwarded by intermediate routers to its final destination. As Forward Ants pass through the network, they save information about the intermediate routers.
- Backward Ants: created out of Forward Ants, once they have reached their final destination. They get the information gathered by Forward Ant. The Backward Ant follows exactly the same path as the Forward Ant, but in the opposite direction. In all the intermediate routers, the information of the Backward Ant is compared to the corresponding entry in the statistical model. This comparison is used to adapt the probabilities in the routing table, as well as the statistical model itself. Once the Backward Ant arrives in the starting router, it is discarded.

VI. Experimental Results

In this section, we will analyze the performance of the routing algorithm described in section 3. The simulation environment [10], provides a control variable called speed factor to control the mobility of nodes in the network. By increasing the value of this number, the speed on moving nodes is increased.

Average delay is calculated dividing the total delay by the number of packets arrived at destination.

Table 1 shows the average end-to-end delay calculated over 4 different values of the speed factor.

TABLE 1: EFFECT OF MOBILITY ON AVERAGE END-TO-END DELAY

Speed Factor	**Mean Data Travel Time**
1	18.8
2	16.7
3	17
4	18

It is clear from the above table that changing the speed of mobile nodes does not have strong impact on the average end-to-end delay values. The values are close to each other. This implies that the protocol is immune to dynamicity and frequent topology changes.

Figure 1 shows how the success rate improves over time, which is defined as the ratio of packets arrived successfully.

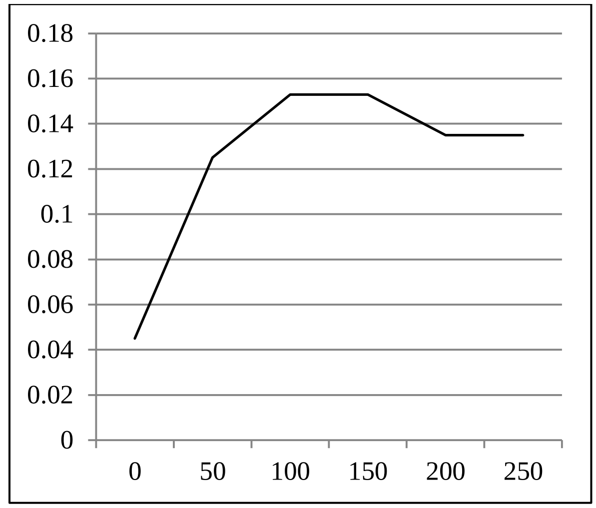

Figure 1: Success rate with time

In Figure 2, it is obvious that the number of dead ants; the ants killed before reaching their final destination, is higher than the number of successful ant. This is an indication that the criteria used to decide when to kill an ant needs, which is typically a TTL value indicate to the maximum number of hops an ant may traverse before being killed, needs more investigation.

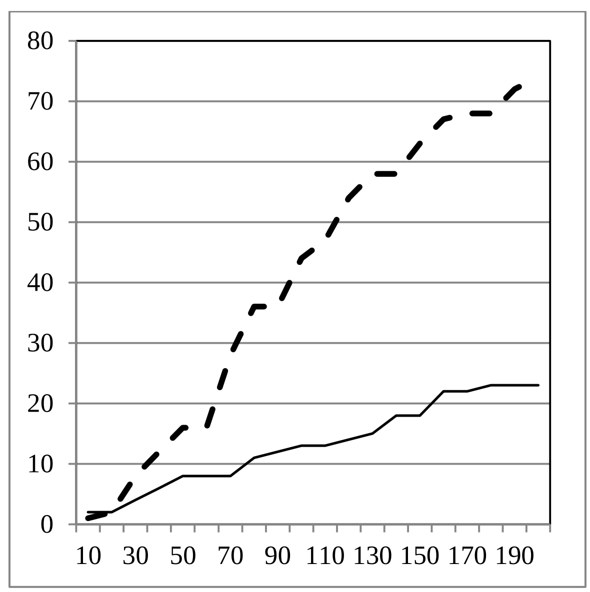

Figure 2: Ants Statistics over Time (Ticks) (successful is dashed, dead is solid)

Table 2 shows the impact of increasing the number of ants per agent on the average end-to-end delay and the algorithm's success rate, respectively. The last column represent and index that divides the success rate by the average end-to-end delay. The higher the index the better the choice, this indicates that 2 or 3 antes per agent is best.

TABLE 2: EFFECT OF NUMBER OF ANTS PER AGENT ON AVERAGE DELAY AND SUCCESS RATE

Ants / Agent	Average Delay	Success Rate	S/D Index
1	16.7	21 %	0.01258
2	7.1	24 %	0.03380
3	8.4	27 %	0.03214
4	7.8	13 %	0.01667
5	9.7	18 %	0.01856

VII. CONCLUSION

Mobile ad-hoc networks are flexible networks that do not require any pre-installed infrastructure. One of the main important challenges in mobile ad-hoc networks is the routing problem, which is highly affected by the node mobility. Several algorithms were introduced in the literature trying to handle the routing problem in this kind of dynamic networks. In this paper, a routing algorithm based on Ant Colony Optimization (ACO) for mobile ad-hoc networks is discussed and analyzed by conducting several simulation experiments. Simulation experiments show that the considered algorithm is able to cope with this type of dynamic networks. Scenarios with high degrees of node mobility show that the performance of the algorithm in terms of average end-to-end delay and success rate is not degraded.

VIII. FUTURE WORK

The next step in our work is to investigate the value of TTL in more details and try to find optimal TTL values for different network conditions. Also, we plan to compare the performance of studied algorithm with other well-known ad-hoc routing algorithms including others that are based on Ant colony Optimization (ACO).

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AUTHORS PROFILE

Aws Kanan

Born in Kufranjah, Jordan 1980. He received BS and MS in Computer Engineering from Jordan University of Science and Technology, Jordan in 2003 and 2006 respectively. Lecturer, department of computer engineering at University of Jordan, King Saud University, and Salman bin Abdulaziz University. Research interest include reconfigurable computing, computer networks, and optimizations algorithms.

Taisir Eldos

Born in Karak, Jordan 1958. He received BS in Electronic Engineering from Menofia University, Egypt 1981, MS and PhD in Computer Engineering from University of Alabama in Huntsville, Alabama USA in 1992 and 1996 respectively. Associate professor and Chair, department of computer engineering at Jordan University of Science and Technology (1996 till now), King Saud University (2008-2010), and Salman bin Abdulaziz University (2010-2013). Research interest include parallel processing/computing, optimizations algorithms and soft computing.

Mohd Alkahtani

Born in Riyadh, Saudi Arabia 1971. He received BS Electrical Engineering from Kind Saud University 1994, MS Electrical Engineering from Colorado State University, USA 2001, and PhD Electrical Engineering from University of Ottawa, Canada 2005. Assistant Professor and Dean of Information Technology and Distant Learning at Salman bin Abdulaziz University. Research interest include mobile networks and distance learning.