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# Ant Colony Optimization: A Modified Version

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**Abstract**

***Antnet is an agent based routing algorithm based on real ants' behavior. In real life, ants drop some kind of chemical substances to mark the path that they used. Then on their way back they choose the path with the highest pheromones which becomes the shortest path. Ants in antnet algorithm are used to collect traffic condition and are used to update probabilistic routing tables based on the collected information. But Antnet Algorithms may cause the network congestion and stagnation. Here, some special type of ants called clone ants is proposed which is able to produce multiple mutually exclusive optimal paths as compared to single optimal path in original antnet routing by introducing a little overhead. This proposed modified algorithm optimizes the antnet routing by a better throughput.***

**Keywords**: *antnet agent, swarm intelligence, adaptive routing.*

## 1 Introduction

Today with the fast growth of Internet everybody wants to get connected to the internet. Millions of people use the Internet for daily business all over the world. Today the Internet has become very large, complex and dynamic. Failures and challenges occur at every step because of traffic flow from one part of network to another part. Routing is the process of selecting paths in a network to send traffic. Routing is an important aspect of network communication which affects the performance of any network, since other characteristics of the network like throughput; reliability and congestion depend directly on it. In packet switching networks when a packet travels from a source to destination, it has to pass through a number of networks with varying characteristics. So an ideal routing algorithm is one which is able to deliver the packet to its destination with minimum amount of delay. It must be adaptive and intelligent enough to make the decisions. The growing size and increasing demands of Internet impelled the study of more powerful routing algorithms which can optimize the flow of traffic.

The routing algorithms currently in use (e.g. OSPF, RIP, and BGP) are not sufficient to tackle the increasing complexity of such networks. They are not adaptive, intelligent and fault intolerant. The routing tables in them are updated by exchanging routing information between the routers. Different routing protocols use different approaches to exchange the routing information. There are mainly two approaches for routing algorithms, distance-vector algorithms and link-state algorithms. Distance vector algorithms use the Bellman algorithm. This approach assigns a number, the cost, to each of the links between each node in the network. Nodes will send information from one point to another point via the path that result in the lowest total cost. In link-state algorithms for example, Open Shortest Path First (OSPF), the routers exchange link-state information by flooding the link state packets. The link state updates are generated only when the link status changes. Once a node has obtained topology information of the entire network, Dijkstra's algorithm is generally used to compute the shortest path. The two main performance metrics that are affected by the routing algorithm are throughput and average packet delay. Coordination is needed between nodes. Nodes and links can fail, and congestion can arise in some areas. Thus, the routing algorithm needs to modify its routes, redirecting traffic and updating databases very quickly and adaptively.

In recent years, a new kind of routing protocols influenced by software agents called Ant Based routing is developed. S. Appleby and S. Steward were the first ones to introduce the concept of software agents used for control in telecommunication networks [1].This approach of software agents was modified for routing problem by R. Schoonderwoerd[2].The research process continued and it was applied to connection oriented networks [3]. Ant based routing was then applied to packet based connection less systems [4].This agent based approach was further researched and was modified for adaptive routing [5].Swarm intelligence provides a promising alternative to traditional routing algorithms by utilizing mobile software agents for network management.

Although, an ant [1],[2] is a simple and unsophisticated creature, collectively a colony of ants can perform useful tasks such as building nests, and foraging (searching for food)[1],[2],[3].What is interesting is that ants are able to discover the shortest path to a food source and to share that information with other ants through stigmergy [1]-[5]. Stigmergy is a form of indirect communication used by ants in nature to coordinate their problem-solving activities. Ants achieve stigmergic communication by laying a chemical substance called pheromone.

Ant Colony Optimization (ACO) [5]-[9] is a family of optimization algorithms based on real ants' behavior. ACO is inspired by the foraging behavior of ant colonies, where in they are able to find shortest path to food source. It has been observed that of available routes, ants find shortest route to food source. In real life, ants deposit some kind of chemical substances to mark the path that they used. Then on their way back they choose the path with the highest pheromones which becomes the shortest path. AntNet is an Ant Colony Optimization (ACO) meta heuristic for data network routing proposed by Gianni Di Caro and Marco Dorigo [6]-[9]. In this network routing algorithm, a group of mobile agents (or artificial ants) build paths between pair of nodes, exploring the network concurrently and exchanging obtained information to update the routing tables. This information is also used to direct the data packets towards their destination.

# 2 Antnet Routing Algorithm

In antnet [6]-[9] software agents explore the network to find the optimal paths from the randomly selected source destination pairs. Moreover while exploring the network ants update the probabilistic routing tables and build statistical models of the nodes local traffic. Ants use these tables to communicate with each other.

## 2.1 Data Structure maintained at each node

*Routing table* $T_k$ is a local data-base that helps router to decide where to forward data packets. It contains the information which specifies the next (neighbor) node that should be taken by a data packet to get to any possible destination in the network. Each routing table is organized as a set of

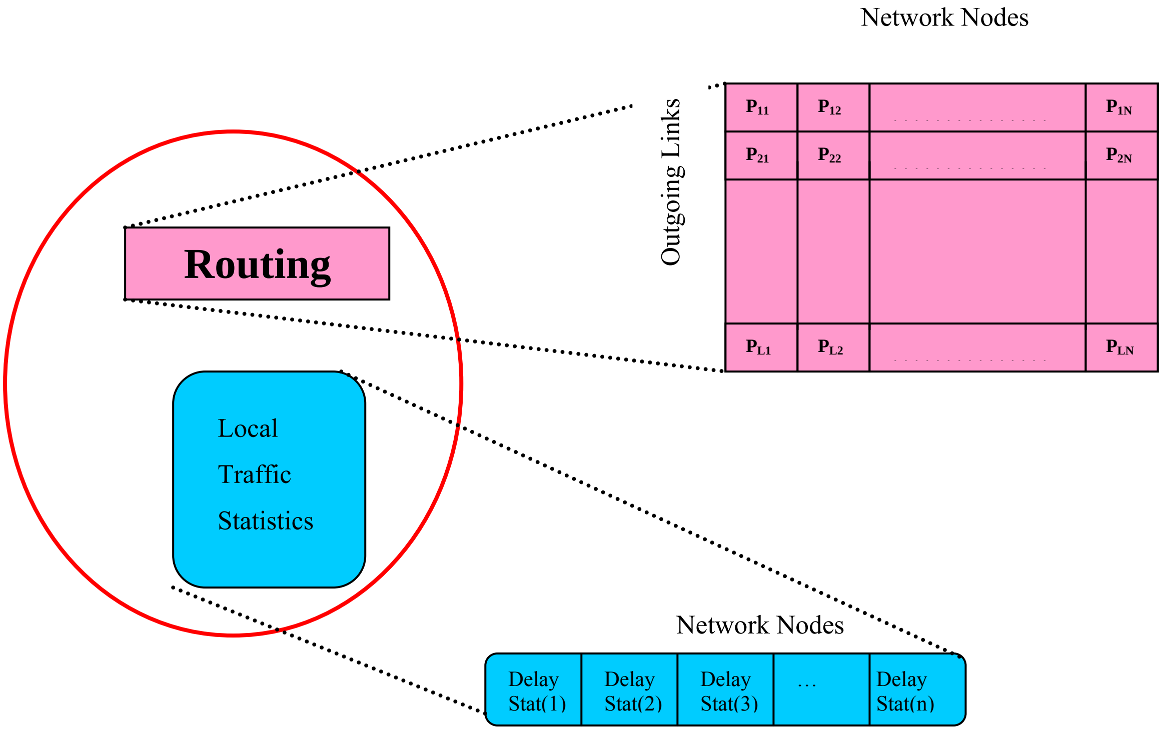
- All the possible destinations (all the nodes in the network).
- The probabilities to reach these destinations through each of the neighbors of the node.

$T_k$ stores a probability value $P_{nd}$ which express the goodness of choosing $n$ as next node when the destination node is $d$

$$\sum_{n \in N_k} P_{nd} = 1,\ d \in [1, N], N_k = neighbors(k)$$

Probability value $P_{nd}$ represents pheromone concentration along the link from node $k$ to neighbor node $n$ for destination node $d$.

**Local traffic statistics** $M_k$ is a second data-structure that each node has. The main task of this structure is to follow the traffic fluctuations as seen by local node $k$. For each destination $d$ in the network, an array $M_k(\mu_d, \sigma_d^2, W_d)$ contains an estimated mean $\mu_d$, an estimated variance $\sigma_d^2$ computed over the times experienced by the artificial ants, and a moving observation window $W_d$. The moving observation window $W_d$, of size $W_{max}$, represents an array containing the trip times of last $W_{max}$ forward ants that travel from the node $k$ to the destination $d$.




## 2.2 The AntNet algorithm

The operation of AntNet as proposed by Di Caro and Dorigo is based on two types of agents:

- Forward Ants who gather information about the state of the network, and
- Backward Ants who use the collected information to update the routing tables of routers on their path

The AntNet algorithm is described as follows

1. At regular time intervals $\Delta t$ from every node s, forward ant $F_{s\to d}$ is launched toward a destination node $d$ to discover a possible, low-cost path to that node and to explore the load status of the network. The forward ants make use of the same priority queues as used by data packets. Destinations are locally selected according to the data traffic patterns generated by the local workload: if $f_{sd}$ is a measure (in bits or in number of packets) of the data flow $s\to d$, then the probability of creating at node $s$ a forward ant with node $d$ as destination is

$$p_{sd} = \frac{f_{sd}}{\sum_{i=1}^{N} f_{si}}$$

.

2. The forward agents create a stack where they store memory of their paths and of the traffic conditions found. The identifier of every visited node $i$ and the time elapsed since the launching time to arrive at this i-th node is pushed onto the memory stack.

3. At each node $i$, each forward ant moving towards its destination $d$ chooses the next node $j$ to move to as follows:

- If all the neighboring nodes have not been visited, then the next neighbor is chosen among the nodes that have not been visited as:

$$P_{ijd} = \frac{\tau_{ijd} + \alpha\eta_{ij}}{1+\alpha(|N_i|-1)}$$

Here, $N_i$ represents the set of neighbors of the current node $i$ and $|N_i|$ the cardinality of that set, i.e., the number of neighbors, while the heuristic correction $\eta_{ij}$ is a normalized value [0,1] such that $1 - \eta_{ij}$ is proportional to the length $q_{ij}$ (in bits waiting to be sent) of the queue of the link connecting the node $i$ with its neighbor $j$:

$$\eta_{ij} = 1 - \frac{q_{ij}}{\sum_{l=1}^{|N_i|} q_{il}}$$

The value of $\alpha$ weighs the importance of the instantaneous state of the node's queue with respect to the probability values stored in the routing table. $\eta_{ij}$ reflects the instantaneous state of the node's queues, and assuming that the queue's consuming process is almost stationary or slowly varying, $\eta_{ij}$ gives a quantitative measure associated with the queue waiting time.

- If all the neighboring nodes have been visited previously, then the next node is chosen uniformly among all the neighbors. In this case, since all the neighbors have been visited previously the forward ant is forced to return to a previously visited node. Thus, irrespective of which neighbor is chosen as the next node, the forward ant is in a loop (cycle).

4. If a cycle is detected, that is, if an ant is forced to return to an already visited node, the cycle's nodes are popped from the ant's stack and all the memory about them is destroyed. If the cycle lasted longer than the lifetime of the ant before entering the cycle, (that is, if the cycle is greater than half the ant's age) the ant is destroyed.

5. When the destination node d is reached, the agent $F_{s \to d}$ generates backward agent $B_{d \to s}$, transfers to it all of its memory, and dies.

6. The backward ant takes the same path as that of its corresponding forward ant, but in the opposite direction. At each node *i* along the path it pops its stack to know the next hop node. Backward ants don't share the same link queues as data packets; they use higher priority queues, because their task is to quickly propagate to the routing tables the information accumulated by the forward ants.

7. Arriving at a node *i* coming from a neighbor node *f*, the backward ant updates the two main data structures of the node, the local model of the traffic $M_i$ and the routing table $T_i$, for all the entries corresponding to the (forward ant) destination node *d*.

## 2.3 Update traffic model $M_i$

$M_i$ is updated with the values stored in the stack memory. The time elapsed to arrive (for the forward ant) to the destination node *d* starting from the current node *i* is used to update the mean $\mu_d$, variance estimates $\sigma^2_d$ and the best value over the observation window $W_d$. The moving observation window $W_d$, of size $W_{max}$ represents an array containing the trip times of last $W_{max}$ forward ants that travel from the node *i* to the destination *d*. The moving observation window $W_d$ is used to compute the best trip time $t_{bestd}$ i.e., the best trip time experienced by a forward ant travelling from the node *i* to the destination *d* among the last $W_{max}$ forward ants that travel from the node *i* to the destination *d*.

The estimated mean and variance are updated as follows:

$$\mu_{id} \leftarrow \mu_{id} + \square\ (o_{i \to d} - \mu_{id}) \qquad (1)$$

$$\sigma^2_{i\,d} \leftarrow \sigma^2_{\ id} + \square\,(o_{i\rightarrow d} - \mu_{id})^2 - \sigma^2_{id})$$

Where $o_{i\rightarrow d}$ , represents newly observed ant's trip time from node *i* to destination *d*. The factor □ weighs the number of most recent samples that will really affect the mean $\mu_d$ and the variance $\sigma_d^2$ .

$$W_{max} = \frac{5c}{\square} \qquad \text{where c} < 1$$

The best value $t_{bestd}$ of the forward ants trip time from node *i* to the destination *d* stored in the moving observation window $W_d$ is also updated by the backward ant. If the newly observed forward ant's trip time $o_{i\rightarrow d}$ from the node *i* to the destination *d* is less then $t_{bestd}$ then $t_{bestd}$ is replaced by $o_{i\rightarrow d}$.

## 2.4 Update pheromone matrix $T_i$

The reinforcement $r = r(T,M_i)$ is defined to be a function of the goodness of the observed trip time as estimated on the basis of the local traffic model. *r* is a dimensionless value, $r \in (0,1]$ , used by the current node *i* as a positive reinforcement for the node *f* the backward ant $B_{d\rightarrow s}$ comes from. Reinforcement value *r* takes into account some average of the so far observed values and of their dispersion to score the goodness of the trip time *T*, such that the smaller *T* is, the higher *r* is.

The backward ant $B_{d\rightarrow s}$ moving from node *f* to node *i* increases the pheromone value $\tau_{ifd}'$

$$\tau_{ifd}' \leftarrow \tau_{ifd}' + r.(1 \quad - \ \tau_{ifd}')$$

Pheromones $\tau_{ijd}'$ for destination *d'* of the other neighboring nodes $j,\ j \in N_i\ ,\ j \neq f,$ evaporate implicitly by normalization. That is, their values are reduced so that the sum of probabilities will still be 1.

$$\tau_{ijd}' \leftarrow \tau_{ijd}' - r.\ (\tau_{ijd}'),\ j \in N_{i\ ,}\ j \neq f$$

The factor of reinforcement *r* is calculated considering three fundamental aspects: (i) the paths should receive an increment in their probability of selection, proportional to their goodness, (ii) the goodness is a traffic condition dependent measure that can be estimated by $M_i$ and (iii) they should not continue all the traffic fluctuations in order to avoid uncontrolled oscillations. It is very important to establish a commitment between stability and adaptability. Between several tested alternatives was chosen to calculate *r*:

$$r = c_1\left(\frac{W_{best}}{T}\right) + c_2\left(\frac{I_{sup} - I_{inf}}{\left(I_{sup} - I_{inf}\right) + \left(T - I_{inf}\right)}\right)$$

where: $W_{best}$. best trip of an ant to node *d'*, in the last observation window $W_{d'}$,
$I_{inf} = W_{best}$ lower limit of the confidence interval for $\mu$,
$I_{sup} = \mu + z * (\sigma / \sqrt{|W|})$ upper limit of the confidence interval for $\mu$ , with:
$z = 1/(\sqrt{1-\square})$ , $\square$ = confidence level, $\square$ ∈ [0.75, 0.8].
$c_1$ and $c_2$ are weight constants, chosen experimentally as $c_1 = 0.7$ y $c_2 = 0.3$.

## 2.5 Limitations of Antnet Routing

Although Experiments of AntNet have shown very promising results, antnet has outperformed under different experimental conditions with respect to other dynamic routing algorithms e.g. RIP, OSPF. Still there are some problems with this adaptive algorithm. One of the major problems is that the network gets trapped because a node prefers a link with higher probability to a destination when choosing an outgoing link say $n_o$ to send a packet. If link $n_o$ keeps good condition for a long time, its probability to that destination will be very high. Such a condition may cause congestion of $n_o$; it also reduces probability of selecting other paths. Hence the node will stuck to this outgoing link and loose its adaptive ability. This is called the problem of "stagnation". Stagnation is reached when a node reaches its convergence. Stagnation is a very critical problem for any network because
1) $n_o$ may lose its optimality if it gets congested;
2) If the network gets fails at any time then the most preferred path $n_o$ may become unavailable.
3) Other non-optimal paths may become optimal due to changes in network topology.
4) Searching for the shortest path by an ant is a statistical process. If ants choose nom optimal path in the beginning the probability of other ants following them increases.

Many researchers [11]-[13] have tried to provide the solution for the same. These methods are

- Evaporation
- Aging

- Limiting and Smoothing Pheromone
- Privileged Pheromone Laying
- Pheromone-Heuristic Control

But all the methods are very complex and needed extra overhead. Though Sim and sun[12] tried to give a different approach by applying *MACO*(Multiple ant colony Optimization) but again it required multiple tables at the nodes . Interested reader may get the details in Sim and sun[12].

# 3. Proposed Antnet Modifications

Here, other than forward and backward ants, clone ants are introduced. The clone ants are generated to avoid the frequent generation of forward ants from source node to explore the path. This will be able to reduce the total number of generation of forward ants by introducing a little overhead. The number of clones generated depends upon number of multiple paths identified. Multiple paths are identified according to the probabilities in the pheromone table.

Clones will be generated at every intermediate node also according to multiple paths identified. These ants will reach to the destination according to proposed strategy but instead of one optimal path more than one optimal but mutually exclusive path are explored. In this way we will be able to get multiple optimal paths with one ant only.

The proposed antnet scheme uses the same pseudocode as the original antnet algorithm. However, several modifications are proposed in order to improve the performance of antnet. These modifications are briefly explained below:

## 3.1 Modified Antnet Algorithm

1. At regular time intervals $\Delta t$ from every node $s$, forward ant $F_{s\rightarrow d}$ is launched toward a destination node $d$ to discover a possible, low-cost path to that node and to explore the load status of the network. The forward ants make use of the same priority queues as used by data packets. Destinations are locally selected according to the data traffic patterns generated by the local workload: if $f_{sd}$ is a measure (in bits or in number of packets) of the data flow $s\rightarrow d$, then the probability of creating at node $s$ a forward ant with node $d$ as destination is

$$p_{sd} = \frac{f_{sd}}{\sum_{i=1}^{N} f_{si}}$$

.

2. The forward agents create a stack where they store memory of their paths and of the traffic conditions found. The identifier of every visited node *i* and the time elapsed since the launching time to arrive at this i-th node is pushed onto the memory stack.

3. At each node *i*, each forward ant moving towards its destination *d* chooses the next node *j* to move to as follows:

- If all the neighboring nodes have not been visited, then the next neighbor is chosen among the nodes that have not been visited as:

$$P_{ijd} = \frac{\tau_{ijd} + \alpha\eta_{ij}}{1+\alpha(|N_i|-1)}$$

Here, $N_i$ represents the set of neighbors of the current node *i* and $|N_i|$ the cardinality of that set, i.e., the number of neighbors, while the heuristic correction $\eta_{ij}$ is a normalized value [0,1] such that $1 - \eta_{ij}$ is proportional to the length $q_{ij}$ (in bits waiting to be sent) of the queue of the link connecting the node *i* with its neighbor *j*:

$$\eta_{ij} = 1 - \frac{q_{ij}}{\sum_{l=1}^{|N_i|} q_{il}}$$

The value of $\alpha$ weighs the importance of the instantaneous state of the node's queue with respect to the probability values stored in the routing table. $\eta_{ij}$ reflects the instantaneous state of the node's queues, and assuming that the queue's consuming process is almost stationary or slowly varying, $\eta_{ij}$ gives a quantitative measure associated with the queue waiting time.

- If all the neighboring nodes have been visited previously, then the next node is chosen uniformly among all the neighbors. In this case, since all the neighbors have been visited previously the forward ant is forced to return to a previously visited node. Thus, irrespective of which neighbor is chosen as the next node, the forward ant is in a loop (cycle).

4. If a cycle is detected, that is, if an ant is forced to return to an already visited node, the cycle's nodes are popped from the ant's stack and all the memory about them is destroyed. If the cycle lasted longer than the lifetime of the ant before entering the cycle, (that is, if the cycle is greater than half the ant's age) the ant is destroyed.

5. *Introducing clone ants:* The forward agent produces cloning ants which has the identical structure and properties as the forward agent. The total number of clones generated depends upon number of multiple outgoing paths identified. Multiple paths are identified as explained below. So here, instead of one neighbor node more than one neighbor nodes are selected to navigate the path by the clones.

6. *Identifying multiple optimal Paths*: Multiple paths are identified by using the probabilities calculated in step 3. Probability values in the table are picked up and a sorting algorithm is executed on these values.
   - The table is reshuffled according to the sorting algorithm executed and sorted values ranging from higher to lower are stored in table.
   - The difference p, amongst the adjacent values is calculated and is compared to some threshold value say $p_m$.
   - If the difference p is less than $p_m$ then those values are selected and comparison amongst the adjacent values is continued until difference is greater than $p_m$.
   - Otherwise at the very first occurrence of difference greater than $p_{m,}$ the comparison is stopped and the corresponding value(s) in the table is (are) selected.
7. Every clone ant will parallel travel through the above selected links.

8. At every node it will be checked to see whether it has been visited previously by the clone. This can be checked by fixing a flag bit in every node. A flag bit is set accordingly. The status of flag is checked, if it is "set" then that means the node has been visited previously and the clone is destroyed itself. If flag bit is not "set" then the node is added to the stack of the visiting clone ant. After this, node id is compared with destination id, if this is the destination node then clone ant generates backward ant $B_{d\rightarrow s}$ transfers to it all of its memory, and dies. If this is not the destination node then again go to *step 6*, i.e. again identify the multiple paths and accordingly generate clones.

9. The backward ant takes the same path as that of its corresponding forward ant, but in the opposite direction. At each node $i$ along the path it pops its stack $S_{s\rightarrow d}$ to move to the next node. Backward ants do not share the same queues as data

packets and forward ants; they use high priority queues to quickly propagate to the routing tables the information collected by the forward ants.

10. Arriving at a node *i* coming from a neighbor node *f*, the backward ant updates the two main data structures of the node, the local model of the traffic $M_i$ and the routing table $T_{i,}$ for all the entries corresponding to the (forward ant) destination node *d*.
When the clone reaches the destination node it generates backward ant transfers to it all of its memory, and dies. But here, clones are supposed to explore mutually exclusive paths. So exploration of shortest path by a clone does not end here only. If at destination any other clone of same ant reaches successfully from any other mutually exclusive path then another backward ant is generated by that clone and the process is continued till the life of ant. So ultimately at source mutually exclusive multiple optimal paths if exists are explored.

Traffic model $M_i$ is updated by the estimated mean and variance same as in equation 1.

### 3.2 Update Pheromone matrix $T_i$

The probabilities $\tau_{ifd}'$ associated to the selection of the neighbor nodes $f \in N_{pi,}$ implicitly all receive a positive reinforcement by the forward ant clones (returned by the backward ant).

$\tau_{ifd}' \leftarrow \tau_{ifd}' + (r/n) *( 1 - \sum_{\forall f} \tau_{ifd}')\ , f \in N_{pi}$ , where $N_{pi}$ is the set of neighboring nodes which get positive reinforcement and is subset of $N_{i,}$ , $n$ is the total number of shortest mutually exclusive paths explored by the forward ant clones which get positive reinforcement (returned by the backward ant)

$$\tau_{ijd}' \leftarrow \tau_{ijd}' - r.\ ( \tau_{ijd}'),\ \forall\, j \in Ni\ ,\ j \neq f$$

Pheromones $\tau_{ijd}'$ for destination $d'$ of the other neighboring nodes $j,\ j \in Ni,\ j \neq f,$ evaporate implicitly by normalization. That is, their values are reduced so that the sum of probabilities will still be 1.

Where r is the reinforcement factor as in original antnet algorithm.

## 4. Conclusion

In this paper an improved version of the AntNet algorithm is proposed. In the improved version, more than one optimal outgoing interfaces are identified and clone ants are introduced which will travel through these paths. Hence, multiple paths are explored by a single ant. By this method ,route optimization will not get stranded into local optima and always new and better paths are explored even if the network topologies gets changed very frequently. Hence problem of stagnation is solved. This algorithm was implemented in C language together with AntNet. Simulations results show a better throughput and packet delay for proposed methodology than for other Antnet versions. So, more than one optimal path is successfully identified by using the clone ants with little overhead.

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