ACO-GA Hybrid Meta-Heuristic (AGHM) Optimization for Multi-constrained Quality of Service Routing in MANETs

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Abstract— In MANET, designing a dynamic routing algorithm by satisfying QoS requirement is a challenging task. Additionally, multi-constrained QoS routing aims to optimize multiple QoS metrics while provisioning required network resources and is an admittedly complex problem. It has been proved to be NP-complete when a combination of additive, concave and multiplicative metrics are considered. Hence this problem can be solved using stochastic optimization methods like ACO and GA. In Genetic Algorithm (GA), a population of candidate solutions to an optimization problem is evolved towards better solutions. But GA doesn’t confirm with an exhaustive exploration while constructing initial candidate solutions. Ant Colony Optimization (ACO) technique matches the routing requirements of Mobile Ad-hoc Networks because of its motivating properties like foraging and self-organising nature. The proposed ACO GA Hybrid Meta-heuristic (AGHM) approach aims to utilize the benefits of the two meta-heuristic techniques as a combined approach in order to reduce the complexities in the dynamic environment. AGHM uses the foraging quality of ACO to construct the initial candidate solutions which includes all possible paths that satisfies required QoS. Then it employs the evolutionary nature of GA to construct best solutions for multi-path multi-constraint QoS routing. After due investigation, it has been showed that the proposed hybrid approach improves the performance of MANET routing with satisfied QoS requirements.

Index Terms— QoS Routing, Multi-objective optimization, Ant Colony Optimization, Genetic Algorithm, Hybrid meta-heuristic, MANET.

I. INTRODUCTION

MANET is made up of collection of mobile wireless nodes each act as router as there is no central coordinator present in this network to assist in network routing. MANETs are used in many applications like crisis management services, personal area network military battlefields, classrooms, etc. MANETs need to
address unique issues that are not applicable in wired networks. Some of the major issues in MANET are medium access scheme, routing, multicasting, quality of service (QoS) provisioning, self-organization and security. Because of the dynamic nature of the MANETs the static routing protocols are not suitable. Hence there is a need for a dynamic routing protocol. The dynamic routing protocol [1] should be able to provide certain level of Quality of Service (QoS) as demanded by the application.

Provisioning of QoS [2] is an important task particularly for real time audio/video/multimedia streaming applications where there is need for adequate resource requirements. But in reality, the capacity of the network may be insufficient to satisfy particular application requirements. Quality of Service (QoS) is defined as a set of service requirements that require to be met by the network while transporting the data packets from source to destination. Average end-to-end delay, available bandwidth, delay jitter, battery power, processing power, hop count, packet delivery ratio and packet loss ratio are some of the QoS parameters. QoS metrics could be defined in terms of either any one of the parameters or a set of parameters in varied proportions.

Multi-constrained QoS routing aims to optimize multiple QoS metrics while provisioning required network resources and is an admittedly complex problem. QoS routing is NP-complete when a combination of additive, concave and multiplicative metrics are considered. Hence this problem can be solved using a stochastic optimization method. Stochastic optimization methods are optimization methods that generate and use random variables. Random variables are involved in the formulation of stochastic optimization problems that involve random objective functions or random constraints. In general, stochastic programs work by using probabilistic methods to solve problems as in genetic algorithms, simulated annealing, stochastic neural networks and ant colony optimization.

In this paper, we propose a hybrid approach which combines the advantages of the two most popular meta-heuristic techniques namely GA and ACO in order to reduce the complexities involved in multi-constrained QoS routing for the dynamic environment of MANETs.

II. RELATED WORK AND MOTIVATION

Several research works had been proposed in the literature using these stochastic optimization methods. Among all, ACO and GA are the most promising and fascinating methods for researchers. Each has its own advantages and disadvantages that seem complementary to each other. Hence, we drive to combine ACO and GA to obtain results closer to the optimum. Some reviews on ACO and GA methods are presented next along with few initiatives on the combinations.

A. Ant Colony Optimization

The ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which then can be reduced to find good paths through graphs. ACO routing algorithms [10] model the behaviour of insect swarms to solve the dynamic routing problem and demonstrate several motivating properties in contrast with traditional routing algorithms. Firstly, they are adaptive by means of continuous path sampling and probabilistic ant forwarding which leads to an uninterrupted exploration of the routing capabilities. Additionally, they are robust as they acquire routing information from the results of the repeated sampling of paths. Furthermore they enhance reliability as the use of sampling implies that routing information is based on direct measurements of the real network situation. Thus, ACO technique matches the routing requirements of Mobile Ad-hoc Networks because of its foraging and self-organising nature.


Wang et al proposed Hybrid ACO routing algorithm for MANET (HOPNET) [7] which is based on ACO and Zone Routing framework to compare random way point model and random drunken model and the results show the efficiency and inefficiency of border-casting. In [11], the author reviewed a few ACO based protocols, namely Antnet, AntHocNet, ARA, PACONET, Ant-AODV and Ant-DSR. These are compared with the conventional protocols, AODV and DSR, against the QoS parameters such as end-to-end delay and
packet delivery ratio based on the random waypoint mobility model. Based on the simulation studies, the author concluded that the biological inspiration such as ACO in MANET routing helps in improving QoS. Although many routing algorithms were proposed in the literature based on ACO, until now no algorithm satisfies end-to-end delay, hop count and bandwidth together.

B. Genetic Algorithm

Genetic algorithm is a stochastic search technique and an evolutionary approach inspired by the Darwinian principles of natural selection and natural genetics which have revealed a number of characteristics particularly useful for routing exploration in MANETs. GA with its evolving nature, optimizes the shortest path problem by producing better results with the given candidate solutions. Although several approaches based on nature-inspired techniques have been proposed, multi-objective optimization with genetic algorithms has received comparatively little attention in the literature.

Barolli et al proposed a Genetic Algorithm (GA) based routing method for MANETs (GAMAN) [12] to find a feasible path from multiple paths hence providing robustness and is source-routing protocol. Ohba et al enhance the GAMAN algorithm and named it as E-GAMAN [14] by adding an effective topology extraction algorithm to reduce the search space of GAMAN. E-GAMAN has two algorithms, Search Space Reduction Algorithm (SSRA) and GAMAN. SSRA reduce the search space for the GAMAN so the GAMAN can find a feasible wireless path very fast. In [17] and [13], the authors applied GA in MANETs for achieving security and robustness respectively.

Tseng et al [15] proposed a novel genetic algorithm (NGA) to construct a Delay and Degree Constrained Minimum Spanning Tree (DDCMST) for multimedia broadcasting on overlay networks. Ting Lu et al [20] et al proposed an energy efficient genetic algorithm to find the delay-constrained multicast tree and reduce the total energy consumption of the tree. From this review, it has been clear that GA can be effectively applied for reducing the search space and producing only the fittest solutions.

C. Combined ACO and GA

Zhang et al proposed hybrid genetic algorithm [16] that provides the advantages of GA and ACO to solve QoS optimization problem. It first uses the global search capability of GA then it will be given as initial parameter for ACO. The result is then given as pheromone value for ACO and updates local and global pheromone values to determine the optimal solution.

Farhad et al, proposed a hybrid algorithm [18] based on GA and ACO to minimize the travel distance of Dynamic Travelling Salesman Problem (DTSP). ACO and GA are applied to the problem space one by one and the results obtained in each are compared for finding the optimum shortest path. In this work, chromosomes are represented as a string of natural numbers that are related to a special parameter in the problem space unlike traditional method which uses binary encoding. This work also avoids converging into local optimum.

In [19], the author proposed a hybrid GA-ACO for Travelling Salesman Problem. In this work, one of the properties of GA such as fitness function evaluation is applied for all ant agents in each cycle in every generation and only the unvisited cities will be assessed by ACO. Although this work shows insignificant results for small data, produces improved results for big data. However, GACO focused only on how to combine GA and ACO procedurally, leaving the detailed implementation to get better result and performance in the future. Thus, based on the literature, hybrid mechanisms have been proved to provide optimum results in shortest path problem.

Although many research works are done for QoS routing optimization problem, they either optimize one or two of the QoS parameters. But, real-time communication through ad hoc networks requires lowest delay, shortest distance and bandwidth efficient routing. This work aims to suggest a single approach to achieve all the three using a hybrid meta-heuristic which has been already initiated for other problems and proved to be a useful method for achieving optimum results.

The rest of the report is organized as follows. The next section showcases problem formulation and the following section describes the ACO GA Hybrid Meta Heuristic (AGHM) method that can be used to improve the performance of existing QoS routing approach. This is followed by the results and discussions of the proposed work.
III. PROBLEM FORMULATION

A. Defining the network

The problem space is considered as a graph $G = (V, E)$, where each vertex represents a node, $V$ is set of all nodes in the network. Each edge represents a link between two nodes, $E$ is set of all links. For each node, ‘$r$’ is the range of transmission and ‘$d$’ is the distance between two adjacent nodes. If $d \leq r$ then there exists a two-way link $e (e \in E)$ between them. $P$ is the set of all paths from source $s (s \in V)$ to destination $t (t \in V)$. $E(p)$ and $N(p)$ are representing the set of all edges and set of all nodes of a path $p (p \in P)$ respectively. The following figure shows a sample graph with 15 nodes where 1 is the source node and 7 is the destination. Each wireless link is represented with its cost-delay.

![Sample scenario with 15 nodes](image)

B. Defining the QoS parameters

A path $P$ must be chosen when the bandwidth is greater than the minimum, the delay is lesser than the maximum, the hop count is kept as minimum as possible. The average end-to-end delay, available bandwidth and hop count are the routing metrics considered. Packet Delivery Ratio (PDR) and throughput are the performance metrics considered. They are defined as follows:

**End-to-end delay (additive metric):** The amount of time needed to successfully deliver a packet from the source to the destination. $D$ is the maximum delay tolerable.

$$\text{Delay}(p) = \sum_{e \in E(p)} \text{Delay}(e) + \sum_{n \in N(p)} \text{Delay}(n), \quad \text{Delay}(p) \leq D$$

**Bandwidth (concave metric):** The amount of data that can be carried from one point to another in a given time period. $B$ is the minimum bandwidth required.

$$\text{Bandwidth}(p) = \min \{ \text{Bandwidth}(e), e \in E(p) \}, \quad \text{Bandwidth}(p) \geq B$$

**Hop count (additive metric):** The number of intermediate nodes through which data must pass between source and destination. Hopcount$(p)$ is always kept as minimum as possible.

$$\text{Hopcount}(p) = |E(p)|$$

**Packet delivery ratio (PDR):** The ratio of successfully delivered data packets to the total data packets sent from the source to the destination.

$$\text{PDR}(s,t) = \frac{X_A}{X_I}$$

where $X_A$ is the number of data packets received successfully, $X_I$ is the number of data packets sent in total. **Throughput:** The ratio between the number of packets sent and the number of packets received.
Throughput\((s,t)\) = \(\frac{X_B}{X_Z}\)

where \(X_Z\) is the number of packets sent in total, \(X_B\) is the number of packets received.

**Routing overhead (RO):** The ratio of routing packets transmitted to the total data packets delivered. Routing packets include control packets used for route discovery, route maintenance, and pheromone updates.

\[\text{RO}(s,t) = \frac{X_C}{X_Z}\]

where \(X_Z\) is the number of packets sent in total, \(X_C\) is the number of control packets sent.

### IV. PROPOSED HYBRID META-HEURISTIC

The proposed algorithm uses ACO to find the possible paths from any source node to destination node for the given network topology. Once the set of possible routes are found based on the pheromone concentration by the artificial ants, the resulting set of routes forms the initial population for the GA phase. Then based on the fitness function and genetic operations, the set of optimal paths are identified from the initial population for the network for any source-destination pair. The GA cycle is continued until either the predefined number of generations reached or there are no unique offspring included in the new population for three successive times. As the algorithm proceeds, the weaker solutions tend to be discarded and hence the resulting population will have the optimal set of paths required for multipath routing. This work is summarized in the flowchart in Figure 2.

#### A. Design of ACO Algorithm

Ant colony optimization [3] is an iterative algorithm where, at each iteration artificial ants are created to build solutions by walking from node to node on the network with the constraint of not visiting any node that it has already visited. Additionally, ants deposit a certain amount of pheromone on the links that they traverse. The amount of pheromone \(\Delta \tau\) deposited may depend on the quality of the path found. Subsequent ants use the pheromone information as a guide toward promising regions of the search space. At each step of the solution construction, an ant selects the next node to be visited according to a stochastic mechanism that is biased by the pheromone. At the end of an iteration, on the basis of the quality of the solutions constructed by the ants, the pheromone values are updated in order to bias ants in future iterations to construct solutions similar to the best ones previously constructed.

**Encoding and setting parameters:** ‘\(M\)’ numbers of artificial ants are created at each iteration. The value of ‘\(M\)’ is chosen based on the size of the network topology. Each link is associated with a special variable called pheromone which can be read and modified by ants. The pheromone value \(\tau_{ij}\) deposited on the link \(e_{ij}\) is associated with the solution component \(c_{ij}\). The set of all possible solution components is denoted by \(C\). The number of pheromone variables is based on the number of quality metrics considered for route selection. The maximum value of iterations \(I_{\text{max}} = 50\).

**Objective function \((O(f))\):** The rule for the stochastic choice of solution components is as follows: a) the cost (enough bandwidth, minimum delay and minimum hops) of selected route should be minimum. b) The selected route must be an existent link. c) The path must meet the transmission constraints.

\[O(f) = \frac{1}{\text{cost}(p)}, \text{ where cost}(p)\text{considers all QoS parameters}\]

When an ant is in node\(_i\), the following node\(_j\) is selected stochastically among the previously unvisited ones. Specifically, the unvisited path is selected with a probability that is proportional to the pheromone associated with the link \(e_{ij}\).

The path construction starts from an empty set \(S^0 = \emptyset\). At each construction step, the path set \(S^p\) is extended by adding a feasible solution component from the set \(N(S^p) \subseteq C\), which is defined as the set of components that can be added to the current partial solution \(S^p\) without violating any of the constraints of the objective function.

**Path selection:** When the ant \(k\) is on the node\(_i\), the next node node\(_j\) should be selected according to the following formula,
Figure 2 Flowchart for ACO GA Hybrid Meta-Heuristic Approach

\[ P^k_{ij} = \begin{cases} \frac{\tau^k_{ij} \cdot \Pi^k_{ij}}{\sum_{c \in N(S^p)} \tau^k_{ij} \cdot \Pi^k_{ij}} \cdot \beta, & \text{if } c_{i \in N(S^p)} \\ 0, & \text{otherwise} \end{cases} \]
where $P_{ik}^*$ is the probability with which the ant $k$ select edge $e_{ij}$, $N(S^p)$ is the set of feasible components that is, edges ($i$, $l$) where $l$ is an unvisited node by the ant $k$. $\alpha$ and $\beta$ are control parameters with the relative importance of the pheromone versus the heuristic information $\Pi_{ij}$, which is given by:

$$\Pi_{ij} = \frac{1}{d_{ij}}$$

where $d_{ij}$ is the distance between the adjacent nodes $i$ and $j$.

**Local update:** In order to avoid that several ants produce identical solutions during single iteration it has been suggested to decrease the pheromone concentration on the traversed edges and encourage subsequent ants to choose other edges, hence, produce different solutions. The pheromone is updated using the following formula when the ant $k$ successfully complete a hop from $i$ to $j$.

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

where $\rho$ is residual pheromone coefficient, $(1 - \rho)$ is the pheromone evaporation rate, $m$ is the total number of ants, $\Delta \tau_{ij}^k$ is the pheromone value deposited by the $k$th ant while passing through $e_{ij}$. $\Delta \tau_{ij}^k$ is calculated based on the following formula in order to meet the defined objective function that is ants selecting a path which has enough bandwidth, minimum delay and less number of hops

$$\Delta \tau = \begin{cases} 
Q \cdot e^{\gamma_{ij}} \cdot P_{jb}^{ij}, & \text{where kth ant passing by } e_{ij} \\
\text{Delay}_{ij} \cdot \text{Hopcount}_{ij}, & \text{otherwise}
\end{cases}$$

where $Q$ is a constant, $P_{jb}=B/BL$ is the bandwidth selection probability of choosing the next hop node $j$. B is the bottleneck bandwidth from $j$ to destination node, BL is link bandwidth.

**Global update:** It is called as the offline pheromone update which is performed at the end of the construction process. It is done as per the formula,

$$\tau_{ij} = (1 - \rho) \cdot \tau_{ij} + \rho \cdot \Delta \tau$$

**End conditions:** At the end of global update, the solution set contains the available paths from any source to destination which satisfies minimum QoS requirement. If the number of iterations reaches the $I_{max}$ value, then ACO handover the solution set to GA phase.

**B. Design of GA Algorithm**

The resulting path set with good quality pheromone indications capitulated by the ants of ACO phase are now considered as the initial population for the GA phase. GA will try to eliminate the weaker paths from the set and retain the best fit paths based on the fitness function and based on the applied genetic operations. At the end of this phase, we will have optimal path set satisfying the required QoS parameters useful for multipath routing.

**Encoding rules:** In GA, each node sequence of path is considered as an individual and coded as chromosome. The node in the identified network path is thus coded as a gene. As the number of hops between source and destination can vary, chromosome length can be varied. The following shows the encoded chromosomes between the source destination pair (1, 7) of the sample scenario in Figure 1.

1-2-11-12-7
1-2-5-12-7
1-2-4-6-7
1-3-4-6-7
1-8-9-12-7
1-8-9-10-12-7
1-8-10-12-7
1-8-10-9-12-7

**Fitness function:** Every individual is evaluated based on the fitness function for superiority. The fitness function is composed of the objective function and the penalty function. The objective function $O(f)$ which influences the path cost on the individual is similar to ACO. It is defined as follows,
\[ O(f) = \frac{1}{\text{cost}(p)} \]

where \( \text{cost}(p) \) considers all QoS parameters. Then the penalty function is defined for each metric considering the set of constraints (\( \Phi \)) for each. The delay penalty function \( D(f) \) is defined as,

\[ D(f) = \Phi_d \{ \text{Delay}(p) - D \} \]

where \( \Phi_d \) is defined as:

\[ \Phi_d = \begin{cases} 
1, & \text{if } z \leq 0 \\
r_d, & \text{if } z > 0 (0 < r_d < 1)
\end{cases} \]

where \( r_d \) is the a constant value which determines the penalty degree for delay. The bandwidth penalty function \( B(f) \) is defined as,

\[ B(f) = \Phi_b \{ \text{Bandwidth}(p) - B \} \]

where \( \Phi_b \) is defined as:

\[ \Phi_b = \begin{cases} 
1, & \text{if } z \leq 0 \\
r_b, & \text{if } z > 0 (0 < r_b < 1)
\end{cases} \]

where \( r_b \) is the a constant value which determines the penalty degree for bandwidth. The hop count penalty function \( H(f) \) is defined as,

\[ H(f) = \Phi_h \{ \text{Hopcount}(p) - |E(p)| \} \]

where \( \Phi_h \) is defined as:

\[ \Phi_h = \begin{cases} 
1, & \text{if } z \leq 0 \\
r_h, & \text{if } z > 0 (0 < r_h < 1)
\end{cases} \]

where \( r_h \) determines the penalty degree for hopcount. Based on these the fitness function for each computed path is defined as follows,

\[ F(p) = O(f)(\alpha \cdot D(f) + \beta \cdot B(f) + \gamma H(f)) \]

where \( \alpha \), \( \beta \), \( \gamma \) are positive real numbers used as normalization coefficients for delay, bandwidth and hopcount respectively. As per the above formulas, it is seen that the penalty function value is 1 if the path satisfies the QoS constraints otherwise it is a real number from 0 to 1.

**Initializing population:** The initial population is achieved by encoding the multiple paths searched stochastically through the total network by artificial ants with goodness of pheromones. The optimal population size \( P_{\text{size}} \) is determined based on the number of nodes in the topology.

\[ P_{\text{size}} = \text{Number of nodes} - 15 \]

**Selection operation:** In general, selection operators are stochastic, probabilistically selecting good solutions and removing bad ones based on the evaluation given to them by the objective function. We applied roulette wheel procedure, where each path \( i \) is assigned a probability \( p_i \) to be chosen for reproduction, after which the cumulative probability \( c_i \) is calculated for each.

\[ c_i = \sum_{j=1}^{N} p_j \]

A path is selected if \( c_i \) becomes greater than a random number \( r \) selected a priori.

**Crossover operation:** It is genetic recombination process, in which crossover operators randomly select a set of nodes from each valid path to form a new best path. For example, the path \( p_i \) and \( p_j \) are randomly selected and the nodes which are appearing in both are identified. Among the similar nodes either a gene pattern or single gene is identified for crossover and then exchange the nodes. If it is a single node, then single point crossover is applied meaning that from that node onwards the packet follows different path. If it is a node pattern, then two point crossover is applied meaning that the data follows a different subset of path. The crossover pattern is determined based on the chromosome length that is the length of the path. If there are no common nodes identified between the two randomly selected paths, then it will choose another set of paths. For example, Let \( T_a \) (given in Figure 3) and \( T_b \) (given in Figure 4) are the selected parents. The crossover operator generates a child \( T_c \) (as shown in Figure 5) by identifying the same links between \( T_a \) and \( T_b \) and retains the common links in \( T_c \). Retaining these common links may generate separate sub-trees. The sub-trees are then connected with the least delay path.
Mutation operation: In terms of implementation, mutation consists of randomly changing one or more parts of a chromosome. This is done by changing a randomly chosen node $x$ from a randomly chosen path $p_i$ into another node $y$. $y$ is identified from the adjacent node set $A_y$. This replacement based on the adjacent node set avoids introducing an unavailable path.

Terminal conditions: For each population the GA operators are applied to the chromosomes to lead to a new generation of individuals, ameliorating in the process the best fitness among the individuals of the generation. The process is terminated after a fixed number of generations $GN (GN_{\text{min}} < GN < GN_{\text{max}})$, where $GN_{\text{min}}/GN_{\text{max}}$ represents minimum and maximum genetic iteration, has been reached, or when the best fitness value is no longer ameliorated from one generation to the next and there are no unique offspring included in the new population for three successive times.

V. RESULTS AND DISCUSSION

A. Simulation Scenario

In order to analyze the performance of this work, we used the event-driven network simulator NS2 version 2.34. The simulation area is 1500x1500 square meters with 50 to 100 nodes placed randomly. The channel
Transmission rate is 2 Mbps whereas the data flow transmission rate is 10 packets/s. The other simulation parameters are shown in Table I.

**Table I. Parameters for the Simulation Scenario**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation Area (Grid Size)</td>
<td>1500 m x 1500 m</td>
</tr>
<tr>
<td>Number of Nodes</td>
<td>50 - 100</td>
</tr>
<tr>
<td>Node Communication Range</td>
<td>250 m</td>
</tr>
<tr>
<td>Node Initial Placement</td>
<td>Random</td>
</tr>
<tr>
<td>Medium Access Mechanism</td>
<td>IEEE 802.11b</td>
</tr>
<tr>
<td>Traffic Source Model</td>
<td>CBR</td>
</tr>
<tr>
<td>Packet Size</td>
<td>512 Bytes</td>
</tr>
<tr>
<td>Traffic Load</td>
<td>10 pkts/s</td>
</tr>
<tr>
<td>Mobility Model</td>
<td>Random Waypoint</td>
</tr>
<tr>
<td>Node speed</td>
<td>10 m/s</td>
</tr>
<tr>
<td>Pause time</td>
<td>0 – 480s</td>
</tr>
<tr>
<td>Simulation Time</td>
<td>900 s</td>
</tr>
<tr>
<td>Number of Simulations</td>
<td>15</td>
</tr>
</tbody>
</table>

Average end-to-end delay, bandwidth and hop count were considered as major QoS parameters for route computation. We considered Number of nodes and Node pause time as the scenario metrics which define the environment in which an ad hoc network functions. Packet delivery ratio, average end-to-end delay, available bandwidth, throughput and routing overhead were used as the performance metrics to compare the performance with the existing system. Each simulation result (each reported point on each curve) represents an average of 15 independent trials.

In Table II, the pheromone values calculated for sample paths are shown. The pheromone value lies between the ranges 0 to 1. The more the pheromone value the more is the possibility of optimal path from source node to destination node. To compute the shortest distance from node 1 to node 34, the data discovery is done, as a result the paths 1-5-35-34, 1-23-31-6-34, 1-29-32-11-34, 1-48-41-24-34 and 1-21-49-8-7-34 are identified, as the probability of these paths are best in the dynamic environment. Similarly paths are discovered for all other nodes for destination node 34 and best optimal path then can be chosen taking the pheromone value into consideration. The pheromone value is based on indicating goodness of outgoing link to various destinations and available bandwidth of outgoing link from that neighbour node. The paths with highest pheromone values are considered as the better solutions. These solutions are given as the initial population for GA phase where the path sequence is encode as the genome structure.

**Table II. Pheromone Values for Sample Paths**

<table>
<thead>
<tr>
<th>Paths</th>
<th>Delay</th>
<th>Bandwidth</th>
<th>Hop count</th>
<th>Pheromone Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path-1</td>
<td>0.03696</td>
<td>0.76972</td>
<td>4</td>
<td>0.601770</td>
</tr>
<tr>
<td>Path-2</td>
<td>0.039296</td>
<td>0.87679</td>
<td>5</td>
<td>0.499231</td>
</tr>
<tr>
<td>Path-3</td>
<td>0.04032</td>
<td>0.97523</td>
<td>5</td>
<td>0.547702</td>
</tr>
<tr>
<td>Path-4</td>
<td>0.04064</td>
<td>0.70689</td>
<td>5</td>
<td>0.587341</td>
</tr>
<tr>
<td>Path-5</td>
<td>0.036608</td>
<td>0.85423</td>
<td>5</td>
<td>0.369612</td>
</tr>
</tbody>
</table>

**B. Simulation Results**

The simulation results are analyzed under different number of nodes. Six different numbers of nodes, from 50 to 100, were modeled to observe the effect of the algorithm. The pause time was set to 50s. The speed was set to 10 m/sec. Each simulation result for AGHM was compared to that of an ACO based algorithm and a GA based algorithm.

AGHM results in 10% lesser delay than the ACO model and 20% lesser delay than the GA model. This graph is shown in Figure 6. The End-to-End delay gradually decreases when the number of nodes increases. This is because during 50 nodes scenario the nodes are spread over 1500x1500 sq.m area and there is a possibility of increase in distance between adjacent nodes. When the network size is scaling high, more adjacent nodes are available to act as intermediate nodes. If the size increases beyond 100, there may be a chance of more packet drops due to collision.

Similarly the graph for varying number of nodes with packet delivery ratio is also shown in Figure 7. From the graph it has been shown that AGHM outperforms ACO model and GA model.
The bandwidth utilization graph is shown in Figure 8. The proposed AGHM has staged improvement when compared to the other two models. The reason may be that the other two models were not taking the bandwidth into consideration while computing the route. When number of nodes are 70 we could see the maximum utilization and it is slightly reducing after that.

The following graph in Figure 9 shows the average number of hops exploited for data transfer between a particular source and destination pair. The earlier graphs show that the performance of ACO model is better than the GA model but here the GA model outperforms ACO model. From the graph, we could get that the number of hops exploited is minimum in AGHM.

The simulation results are analyzed also under different pause times. Seven different values of pause times from 0 seconds to 480 seconds are considered to investigate the effect of the algorithm. The number of nodes was set to 100. The speed was set to 10 m/sec. As per the graph shown in Figure 10, when the pause time increases, the delay incurred by the AGHM algorithm was reduced drastically. This is because, when the pause time is more, the topology is static for longer period and hence identified path set is effective without more recomputations.

The PDR tends to increase as the pause time increases. This is manifest since the active path is less likely to break as the network becomes static. However, the PDR first decreases as the pause time increases. Due to mobility, the active path may break. When all paths, including the backup paths, to the destination break, a new path can be discovered only after the change of topology of the network, i.e. a node that can form a path
to the destination should come into the transmission range. Note that the change of topology is proportional to mobility. Hence, as mobility decreases it becomes more difficult to recover from the broken path. This explains the downtime that appears when the pause time is 60 seconds in Figure 11.

The routing overhead is shown in Figure 12. Since more control packets are required at the route discovery ACO phase, periodical update and extra control packets are required for route selection GA phase, the routing overhead of AGHM is higher than that of other protocols. The overhead for path monitoring can be reduced by piggybacking the pheromone information on data packets if appropriate traffic exists in opposite direction.
Because of the periodic updates, AGHM requires certain amount of routing overhead but when the pause time increases the overhead is getting reduced because of the static nature of the topology.

The graph for the effective utilization of the available bandwidth is shown in Figure 13. From the graph it has been identified that the AGHM effectively utilizes the bandwidth than that of the other models.

Figure 14 depicts the reduction in number of hop counts utilized for data transfer between a particular source and destination pair. This has been analyzed under varying the node pause time. When pause time increases, number of hops is decreasing in all the three protocols.

The graph for throughput is shown in Figure 15. From the graph it has been identified that the AGHM outperforms than that of the other models and results in higher throughput.

![Figure 13 Node pause time(s) Vs Available bandwidth utilisation(%)](image1)

![Figure 14 Pause time vs. Hopcount](image2)

![Figure 15 Node pause time(s) Vs Throughput](image3)

**VI. CONCLUSION AND FUTURE WORK**

In MANET, routing and satisfying QoS requirements is a challenging task because of the characteristics of the network. In the proposed work, the performance and the efficiency of the network are enhanced by combining the benefits of the meta-heuristic approaches such as ACO and GA which is implemented using various set of nodes and varying node pause times. At initial stage, the ACO is used to find out the set of feasible paths from source to destination and generate initial population based on the goodness of pheromone values. At later stage, the GA is used to get optimal path set as a new population after applying genetic
operators through various iterations according to the QoS parameters considered. This work results in better performance when compared to the pure ACO model and the pure GA model. But still it incurs some routing overhead when the node pause time for the network is below 120s. The algorithm shows better results especially when the node pause time is very high. Further, evaluation of the proposed algorithm will be extended for incorporating energy model as this is becoming the major issue for battery operated devices nowadays. And other meta-heuristic approaches can also be combined as a new hybrid technology so as to study the performance of optimized QoS routing in MANETs.

REFERENCES