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Energy efficient multiconstrained optimization using hybrid ACO and GA in MANET routing

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Abstract: Nodes in mobile ad hoc networks (MANET) suffer from limited battery power and bandwidth. Particularly for real time multimedia communications through MANET, metrics like residual node energy, bandwidth, and end-to-end delay have major impacts. In MANET, designing a dynamic routing algorithm to satisfy quality of service (QoS) requirements is a challenging task. Additionally, multiconstrained QoS routing aims to optimize multiple QoS metrics while providing 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 metaheuristic methods like ant colony optimization (ACO) and the genetic algorithm (GA). The proposed energy-efficient ACO GA hybrid metaheuristic approach aims to utilize the benefits of both as a combined approach in order to reduce the routing complexities in the dynamic environment. After due investigation, it has been shown that the proposed hybrid approach improves the performance of MANET routing with satisfied QoS requirements.

Key words: Quality of service routing, multiobjective optimization, ant colony optimization, genetic algorithm, hybrid metaheuristic, mobile ad hoc network, energy-efficient routing

1. Introduction

Because of the dynamic nature of mobile ad hoc networks (MANETs) static routing protocols are not suitable. Hence, there is a need for a dynamic routing protocol. The dynamic routing protocol should be able to provide a certain level of quality of service (QoS) as demanded by the application. Provisioning of QoS is an important task, particularly for real time audio/video/multimedia streaming applications where there is a need for adequate resource requirements. 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.

Since a MANET comprises mobile nodes, the nodes participating in the network are powered by limited battery resources. Battery depletion can instigate network failure. Efficient utilization of battery resources is an important issue. Energy awareness needs to be adopted by the protocols at all layers in the protocol stack, and it has to be considered as one of the important design objectives for such protocols. QoS metrics could be defined in terms of either any one of the parameters or a set of parameters in varied proportions.

Multiconstrained 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,

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concave, and multiplicative metrics are considered. Hence, this problem can be solved using a stochastic optimization method. In general, stochastic programs work by using probabilistic methods to solve problems as in genetic algorithms (GAs), simulated annealing, stochastic neural networks, and ant colony optimization (ACO).

In this paper, we propose a hybrid approach that combines the advantages of the 2 most popular metaheuristic techniques, namely the GA and ACO, in order to reduce the complexities involved in energy-efficient multiconstrained QoS routing for the dynamic environment of MANETs.

2. Related work and motivation

2.1. QoS enabled routing in MANETs

In the last 2 decades, provisioning of QoS in MANET routing has become an emerging area of research. Various papers [1–5] presented reviews of various QoS routing schemes and design considerations in MANET. As per these reviews, several works targeted a single metric like delay, bandwidth, jitter, loss rate, or energy for route selection and very few considered 2 QoS metrics. In [6] the authors proposed several design challenges for energy-efficient routing. In [7,8] the authors considered energy as an important metric for efficient and reliable routing. Even though an energy metric was considered, for reliable multimedia applications, multiple QoS metrics have to be considered. In all of these works, the authors did not use any optimization techniques. However, considering more than 2 metrics for route selection has proved to be an NP-hard [9] problem that requires an optimization algorithm for solving.

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

2.2. ACO-based QoS routing in MANETs

AntNet [10] was an early initiative among ACO-based algorithms, and it considers delay and congestion status. In [11], the ant routing algorithm considers delay as a metric for route selection and reduces routing overhead. AntHocNet [12] is a hybrid routing model considering delay and congestion. In [13], the algorithm takes the remaining energy of a node, path cost, and hop-count as metrics for routing. Swarm-based distance vector routing [14] considers delay, jitter, and energy as route selection metrics.

HOPNET [15] is a hybrid optimization algorithm based on ACO and zone routing framework to compare a random way point model and random drunken model. In [16], the author reviewed a few ACO-based protocols and compared them with traditional protocols, ad hoc on-demand distance vector and dynamic source routing, 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 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 has satisfied end-to-end delay, hop-count, bandwidth, and node energy together.

2.3. GA-based QoS routing in MANETs

A GA-based routing method for MANET (GAMAN) [17] was proposed to find a feasible path from multiple paths, hence providing robustness, and it is a source-routing protocol. E-GAMAN [18] is an enhanced version of GAMAN with the addition of an effective topology extraction algorithm to reduce the search space of GAMAN. In [19] and [20], the authors used the GA for effective tree construction. One of our previous works [21] proposed route optimization with 3 metrics, namely average end-to-end delay, bandwidth, and hop-count using GA. From this review, it was clear that the GA can be effectively applied for reducing the search space and producing only the fittest solutions.

2.4. Combined ACO and GA-based routing

A hybrid genetic algorithm based on the GA and ACO was proposed in [22] to solve QoS optimization problems, which uses the global search capability of the GA. The result is then given as a pheromone value for ACO and it updates local and global pheromone values to determine the optimal solution.

To minimize the travel distance of the dynamic travelling salesman problem, ACO and the GA are applied [23] to the problem space one by one, and the results obtained in each are compared for finding the optimum shortest path. In [24], the author proposed a hybrid GA-ACO for the travelling salesman problem. In this work, one of the properties of the GA, fitness function evaluation, is applied for all ant agents. Although this work shows insignificant results for small amounts of data, it produces improved results for large amounts of data. However, this work focused only on how to combine the GA and ACO procedurally, leaving the detailed implementation to get better results and performance for the future. Thus, based on the literature, hybrid mechanisms have been proven to provide optimum results in shortest path problems.

Although many research works have been done for QoS routing optimization problems, they either optimize 1 or 2 of the QoS parameters. However, real time communication through ad hoc networks requires lowest delay, shortest distance, energy efficiency, and bandwidth efficient routing. This work aims to suggest a single approach to achieve all 4 using a hybrid metaheuristic that has been already initiated for other problems and has proven to be a useful method for achieving optimum results.

3. Problem formulation

3.1. Defining the network

The problem space is considered as a graph G = (V, E), where each vertex represents a node and V is the set of all nodes in the network, and each edge represents a link between 2 nodes and E is a set of all links. For each node, ‘r’ is the range of transmission and ‘d’ is the distance between 2 adjacent nodes. If d $\leq$ r then there exists a 2-way link e(e ϵ E) between them. P is the set of all paths from source s(s ϵ V) to destination t(t ϵ V). E(p) and N(p) represent the set of all edges and set of all nodes of a path p(p ϵ P), respectively. Figure 1 shows a sample graph with 15 nodes where 1 is the source node and 7 is the destination. Each radio link is represented with its cost such as [delay, distance]. Delay is varied from [0–30] and distance is uniformly distributed as [1–50].

3.2. Defining the QoS parameters

A path P must be chosen when the bandwidth is greater than the minimum, the delay is less than the maximum, the hop-count is kept as minimum as possible, and node energy is greater than the threshold. The average end-to-end delay, available bandwidth, hop-count, and average node residual energy are the routing metrics considered. Packet delivery ratio (PDR) and routing overhead are the performance metrics considered. They are defined as follows:

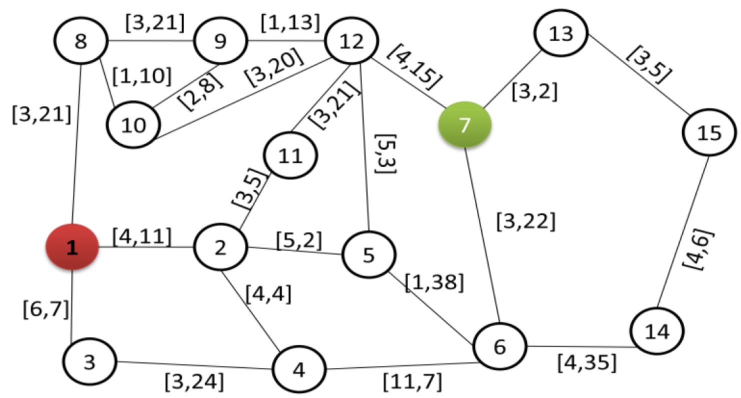

Figure 1. Sample scenario with 15 nodes.

End-to-end delay (additive metric): the amount of time needed to successfully deliver a packet from the source to the destination. In Eq. (1), the value of Delay(p), which represents the delay of a path p(pϵP), is calculated by adding the summation of delay that occurred at all edges/links in path p and the summation of delay that occurred at all intermediate nodes of path p. D is the maximum delay tolerable and is fixed for a particular run as 150 ms. If Delay(p_i) is 120 ms, then this path satisfies the quality requirement.

$$\text{Delay}\,(p) = \sum_{e\in E(p)} \text{Delay}\,(e) + \sum_{n\in N(p)} Delay(n), \text{Delay}\,(p) \leq D \tag{1}$$

Bandwidth (concave metric): the amount of data that can be carried from one point to another in a given time period. The bandwidth of a path is determined by the link with the minimum available bandwidth. For example, if a path p_i contains 3 hops with 1 Mbps, 0.5 Mbps, and 2 Mbps as the available bandwidth, respectively, then Bandwidth(p_i) is 0.5 Mbps. B is the minimum bandwidth required for a particular application. If B = 1 Mbps, then p_i does not satisfy the quality requirement.

$$\text{Bandwidth}\ \ (p) = \min\{\text{Bandwidth}\,(e)\,, e \in E\,(p)\},\ \text{Bandwidth}\,(p) \geq B \tag{2}$$

Hop-count (additive metric): the number of intermediate nodes between the source and destination. Hop-count(p) is always kept as minimum as possible.

$$\text{Hopcount}\,(p) = |E\,(p)| \tag{3}$$

Residual node energy (concave metric): the remaining energy/battery power of a node after a data transmission. R_i is the residual battery charge at node i. Using this value, the energy lifetime of a link (L_{ij}) between nodes i and j can be captured. En_{ij} is the energy required to transmit a data packet of any specified size over the link between node i and j.

$$L_{ij} = \frac{R_i}{En_{ij}} \tag{4}$$

$$En_{ij} = \frac{T_{ij}}{(1-P_{ij})^H} \tag{5}$$

Here, T_{ij} is the energy required for a packet transmission attempt, which is set as 1.5 W, and P_{ij} is the packet error probability of the link between node i and j, which is the expectation value of packet error rate (ratio between incorrect number of packets received and total number of received packets) retrieved from the link layer protocol. The value of H will be 1 as it follows a hop by hop routing.

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

$$PDR\,(s,t) = \frac{X_A}{X_I} \tag{6}$$

Here, X_A is the number of data packets received successfully and X_I is the number of data packets sent in total.

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.

$$RO\,(s,t) = \frac{X_C}{X_Z} \tag{7}$$

Here, X_Z is the number of packets sent in total and X_C is the number of control packets sent.

4. Proposed hybrid metaheuristic

The proposed algorithm uses ACO to find the possible paths from any source node to the destination node for the given network topology. Once the set of possible routes are found based on the pheromone concentration of delay and hop-count 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 is identified from the initial population for the network for any source-destination pair. A fitness function is designed with minimum required bandwidth in addition to node energy required for the given data traffic. The GA cycle is continued until either the predefined number of generations is reached or there are no unique offspring included in the new population for 3 successive turns. 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.

4.1. Design of ACO algorithm

Ant colony optimization is an iterative algorithm [25] 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 they have 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 towards 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.

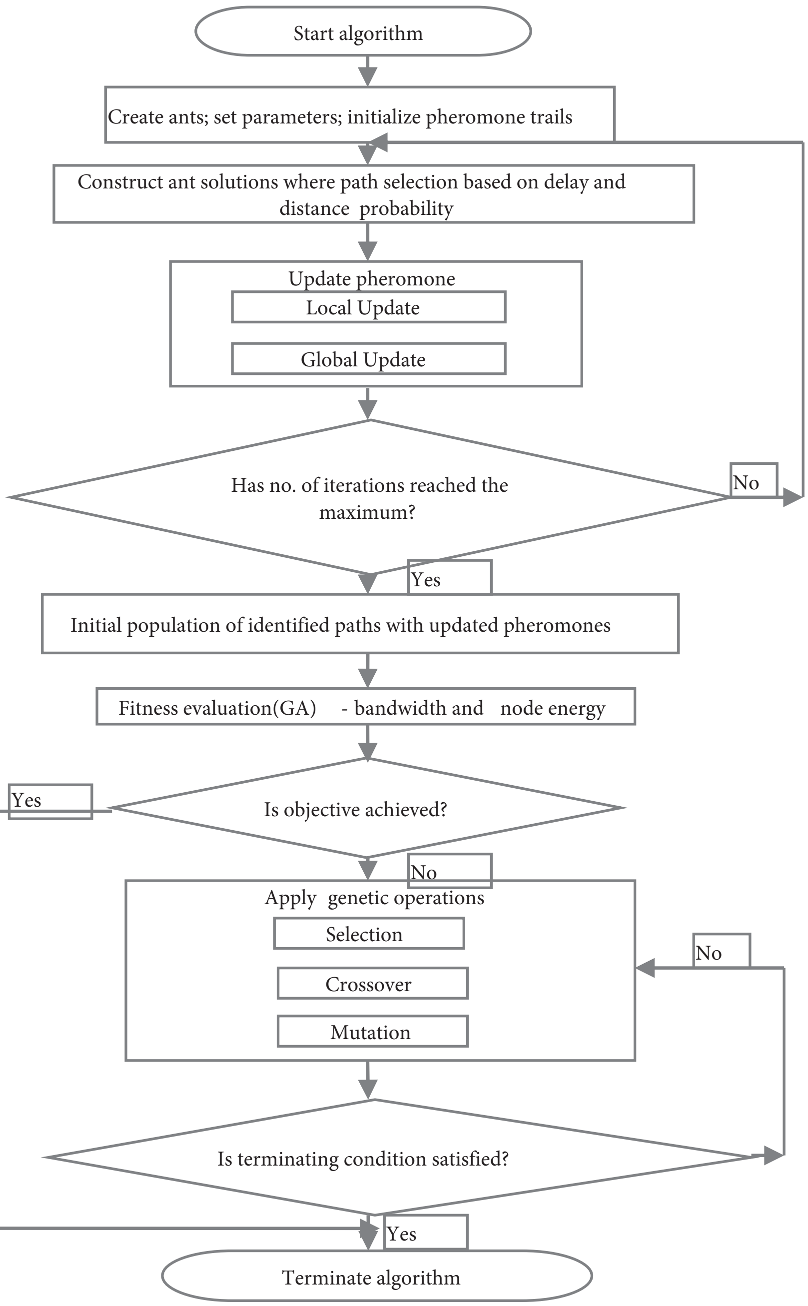

Figure 2. Flowchart for ACO GA hybrid metaheuristic approach.

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 a pheromone, which can be read and modified by ants. The pheromone value τ_{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. For this work, delay and distance (hop-count) are the 2 additive metrics considered for route selection. The maximum value of iterations $I_{max} = 50$.

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

$$O\,(f)=\frac{1}{cost(p)},\ \text{where cost}\,(p)\ \text{considers 2 additive QoS parameters} \tag{8}$$

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^p = ϕ. 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 at node$_i$, the next node node$_j$ should be selected according to the following formula:

$$P_{ij}^{k}=\begin{cases}\dfrac{[\tau_{ij}]^{\propto}\cdot[\eta_{ij}]^{\beta}\cdot[D_{ij}]^{\gamma}}{\sum\limits_{c_{il\in N(S^P)}}[\tau_{ij}]^{\propto}\cdot[\eta_{ij}]^{\beta}\cdot[D_{ij}]^{\gamma}}, & \text{if } c_{il\in N(S^P)}\\ 0, & \text{otherwise}\end{cases} \tag{9}$$

where P_{ij}^{k} is the probability with which ant k selects edge e$_{ij}$, and N(S^p) is the set of feasible components that is edge (i, l), where l is a node unvisited by ant k. $[D_{ij}]^{\gamma}$ is a relative metric for delay from i to j. α and β are control parameters with the relative importance of the pheromone [26] versus the heuristic information η_{ij}, which is given by:

$$\eta_{ij}=\frac{1}{d_{ij}} \tag{10}$$

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

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

$$\tau_{ij}=(1-\rho).\tau_{ij}+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}\qquad 0<\rho<1 \tag{11}$$

where ρ is the residual pheromone coefficient, $(1-\rho)$ is the pheromone evaporation rate, m is the total number of ants, and $\Delta\tau_{ij}^{k}$ is the pheromone value deposited by the kth 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, i.e. ants selecting a path that has minimum delay and less number of hops:

$$\Delta\tau=\begin{cases}\frac{Q}{\text{Delay}_{ij}.\text{Hop-count}_{ij}.}, & \text{where } kth \text{ ant passing by } e_{ij}\\ 0, & \text{otherwise}\end{cases} \tag{12}$$

where Q is a constant, and Delay_{ij} and Hop-count_{ij} are relative metrics for end-to-end delay and number of hops between source to destination.

Global update: it is called an offline pheromone update when it is performed at the end of the construction process. It is done as per the following formula:

$$\tau_{ij}= (1-\rho).\tau_{ij}+\rho.\Delta\tau \tag{13}$$

In Table 1, the pheromone values calculated for sample paths are shown. The pheromone value lies between the range of 0 to 1. To compute the shortest distance from node 1 to node 7 in addition to minimum delay, data discovery is done, and as a result paths 1-8-9-12-7, 1-8-10-12-7, 1-2-11-12-7, 1-3-4-6-7, 1-2-5-12-7, 1-2-4-6-7, and 1-8-10-9-12-7 are identified, as the probabilities of these paths are best in the dynamic environment. Path-5 has the highest pheromone value with 4 hops but Path-7 has an even higher pheromone value although it has 5 hops. Similarly, paths are discovered for all other nodes for destination node 7 and the best optimal path can then be chosen taking the pheromone value into consideration. The pheromone value is based on indicating the goodness of the outgoing link to various destinations. The paths with the highest pheromone values are considered as the better solutions. These solutions are given as the initial population for the GA phase where the path sequence is encoded as the genome structure.

Table 1. Pheromone values for sample paths.

Paths	Delay	Bandwidth	Hop-count	Pheromone value
Path-1	0.03696	0.76972	4	0.401770
Path-2	0.039296	0.87679	4	0.499231
Path-3	0.04032	0.97523	4	0.540702
Path-4	0.04064	0.70689	4	0.537341
Path-5	0.036608	0.85423	4	0.669612
Path-6	0.04073	0.71341	4	0.542679
Path-7	0.032241	0.70012	5	0.742222

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

4.2. Design of GA algorithm

The resulting path set with good quality pheromone indications calculated by the ants of the ACO phase is now considered as the initial population for the GA phase. The 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 an optimal path set satisfying the required QoS parameters useful for multipath routing.

Encoding rules: in the GA, each node sequence of a path is considered as an individual and coded as a 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:

$$O\left(f\right)=\frac{1}{cost(p)} \tag{14}$$

where cost(p) considers the minimum required bandwidth and node energy for a particular data traffic as QoS parameters. Then the penalty function is defined for each metric considering the set of constraints (Φ) for each. The bandwidth penalty function B(f) is defined as:

$$B\left(f\right)=\Phi_b\left\{B-\text{Bandwidth}\left(p\right)\right\} \qquad \Phi_b^z=\begin{cases} 1, & \&z\leq 0 \\ r_b, & \&z>0(0<r_b<1) \end{cases} \tag{15}$$

where r_b is a constant value that determines the penalty degree for bandwidth. The residual node energy penalty function RE(f) is defined as:

$$RE\left(f\right)=\Phi_{re}\left\{R_i-L_{ij}\right\} \qquad \Phi_h^z=\begin{cases} 1, & \&z\leq 0 \\ r_{re}, & \&z>0(0<r_{re}<2) \end{cases} \tag{16}$$

where r_{re} determines the penalty degree for residual node energy, R_i is the residual energy at node i, and L_{ij} is the energy lifetime of the link between nodes i and j. The residual node energy threshold is set as 2J. If a node's residual energy falls below this threshold, it will not be considered for packet forwarding/it should not forward packets. However, it can receive packets because it may be the receiver for those packets. Based on this, the fitness function for each computed path is defined as follows:

$$F\left(p\right)=O\left(f\right)\left(\mu.B\left(f\right)+\omega.RE(f)\right) \tag{17}$$

where μ and ω are positive real numbers used as normalization coefficients for bandwidth and node energy, 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_{size} is determined based on Eq. (18). It is used to restrict the number of paths from source to destination if many are satisfying the minimum fitness criteria. Based on the fitness evaluation and ranking, only the top ranked paths are retained. However, this equation will be applicable only for atypical situations.

$$P_{size}=\text{ Number of nodes }-15 \tag{18}$$

Selection operation: in general, selection operators are stochastic, probabilistically selecting good solutions [27] and removing bad ones based on the evaluation given to them by the objective function. We applied a 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. A path is selected if c_i becomes greater than a random number r selected a priori.

$$c_i=\sum_{j=1}p_j \tag{19}$$

Crossover operation: it is a 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, paths p_i and p_j are randomly selected and the nodes that appear in both are identified. Among the similar nodes either a gene pattern or a single gene is identified for crossover and then exchanged between the nodes. If it is a single node, then a single point crossover is applied, meaning that from that node onwards the packet follows a different path. If it is a node pattern, then a 2 point crossover is applied, meaning that the data follow a different subset of the path. The crossover pattern is determined based on the chromosome length, i.e. the length of the path. If there are no common nodes identified between the 2 randomly selected paths, then it will choose another set of paths. For example, let T_a and T_b be the selected parents as given in Figure 3 and Figure 4, respectively. The crossover operator generates a child T_c by identifying the same links between T_a and T_b and retains the common links in T_c, which is represented in Figure 5. Retaining these common links may generate separate subtrees. The subtrees are then connected with the least delay path.

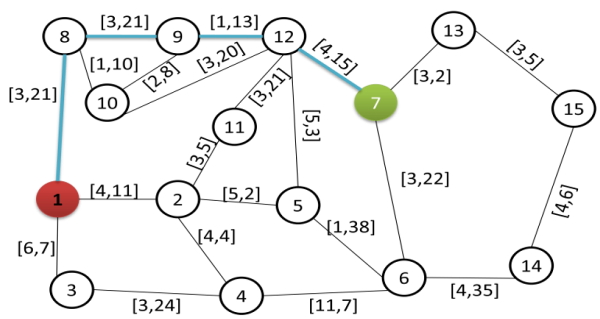

Figure 3. Parent T_a.

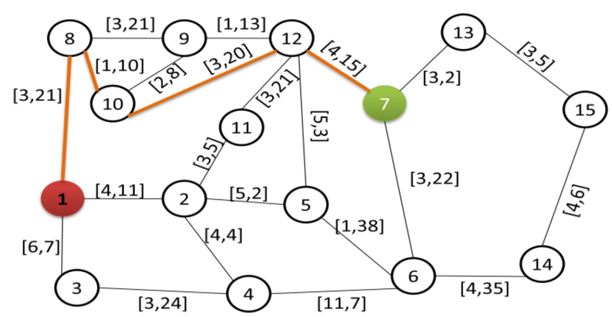

Figure 4. Parent T_b.

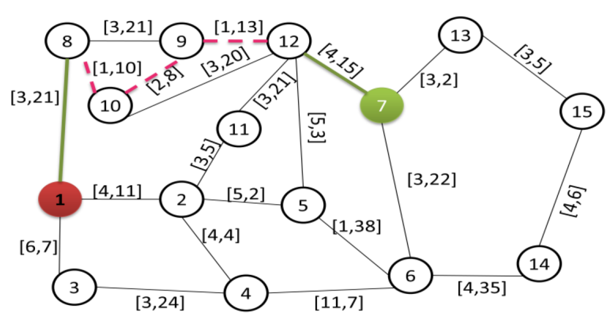

Figure 5. Child T_c.

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 is based on the adjacent node set and avoids introducing an unavailable path. If there is no proper node in the adjacent node set for replacement, this may be omitted.

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_{min}<GN <GN_{max}), where GN_{min}/GN_{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 3 successive times.

5. Results and discussion

5.1. Simulation scenario

In order to analyze the performance of this work, we used the event-driven network simulator NS2 version 2.34. The existing ant algorithm available for MANET routing is extended in order to include the calculations based on fitness function, selection, crossover, and mutation operators of GA. The simulation area is 1500×1500 m^2 with 50 to 100 nodes placed randomly. The channel transmission rate is 2 Mbps whereas the data flow transmission rate is 10 packets/s. Initial node energy for all the nodes is set as 100 J. The transmission power and receiving power of each node is set as 1.5 W and 1.0 W, respectively. The other simulation parameters are shown in Table 2.

Table 2. Parameters for the simulation scenario.

Node communication range	250 m
Node initial placement	Random
Medium access mechanism	IEEE 802.11b
Traffic source model	CBR
Packet size	512 bytes
Mobility model	Random waypoint
Node speed	10 m/s
Pause time	0–480 s
Simulation time	900 s
Number of simulations	15

We considered number of nodes and node pause time as the scenario metrics that define the environment in which an ad hoc network functions. Packet delivery ratio, average end-to-end delay, average residual node energy, hop-count, 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.

5.2. Simulation results

First the simulation results are analyzed under different numbers 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 50 s. The speed was set to 10 m/s. Each simulation result for the proposed energy-efficient ACO GA hybrid metaheuristic (EAGHM) approach was compared to that of an ACO-based algorithm swarm-based hybrid routing protocol (SHRP) [28] and a GA-based algorithm EGHRP [29]. In SHRP, the results were obtained using QualNet. For proper comparison, the same algorithm is simulated using NS 2.34 with similar configurations.

The EAGHM results in 10% less delay than the ACO model and 20% less delay than the GA model. This is shown in Figure 6. The end-to-end delay gradually decreases when the number of nodes increases. This is because during the 50-node scenario the nodes are spread over a 1500×1500 m^2 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.

Figures 7 and 8 show graphs for varying numbers of nodes with packet delivery ratio and bandwidth utilization, respectively. The proposed EAGHM has staged improvements when compared to the other 2 models. The reason for the improved bandwidth utilization may be that the other 2 models were not taking the bandwidth into consideration while computing the route. When the number of nodes is 70 we can see the maximum utilization, and it could slightly reduce after that.

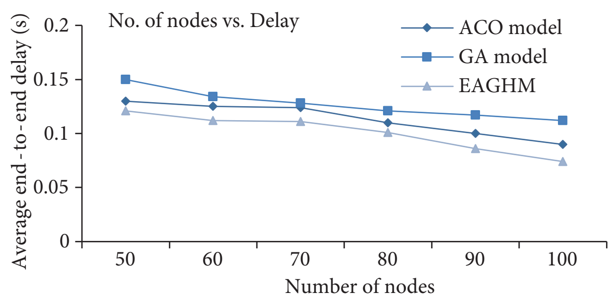

Figure 6. Number of nodes vs. average end-to-end delay (s).

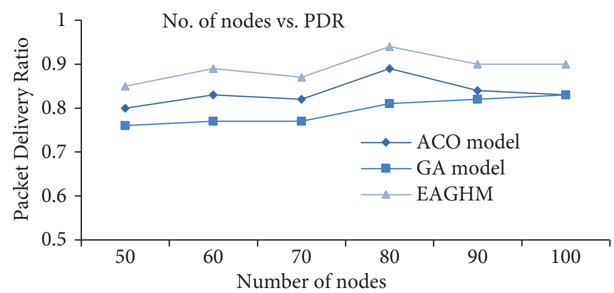

Figure 7. Number of nodes vs. packet delivery ratio.

The 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 the ACO model is better than the GA model but here the GA model outperforms the ACO model. From the graph, we see that the number of hops exploited is minimum in the EAGHM. Figure 10 shows the average residual node energy after the simulation. The involvement of the remaining node energy in route selection helps in avoiding any node losing its battery energy fully, which may lead to network break and thus extended network life. As route selection involves the remaining node energy, this graph illustrates that the energy utilization is effective while using the EAGHM.

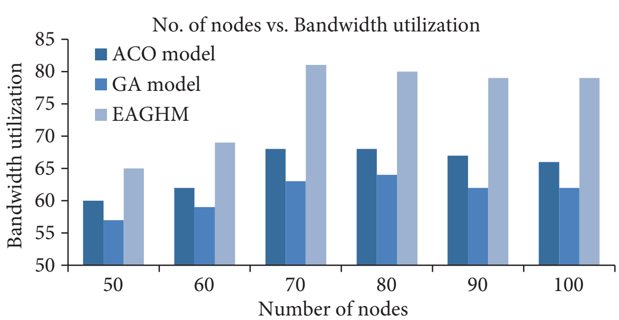

Figure 8. Number of nodes vs. available bandwidth utilization.

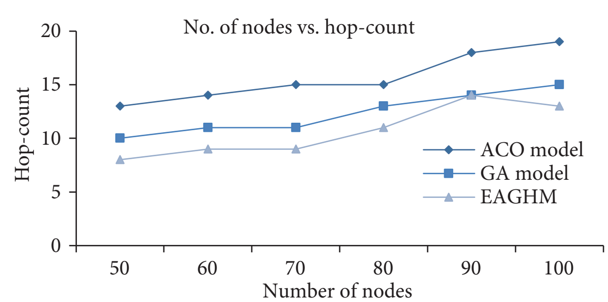

Figure 9. Number of nodes vs. hop-count.

The simulation results are also analyzed under different pause times. Seven different values of pause times from 0 s to 480 s are considered to investigate the effect of the algorithm. The number of nodes was set to 100. The speed was set to 10 m/s. As per the graph shown in Figure 11, when the pause time increases, the delay incurred by the EAGHM algorithm is reduced drastically. This is because when the pause time is more, the topology is static for longer periods and hence the identified path set is effective without more recomputation.

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 a 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 s in Figure 12.

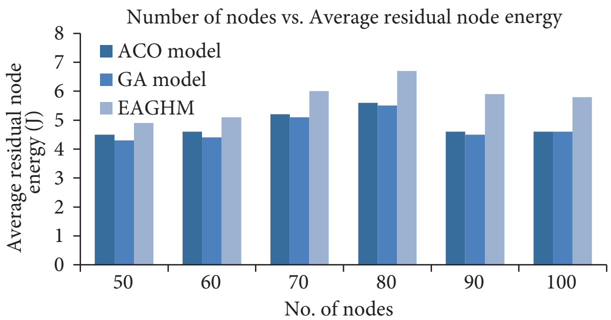

Figure 10. Number of nodes vs. average residual node energy.

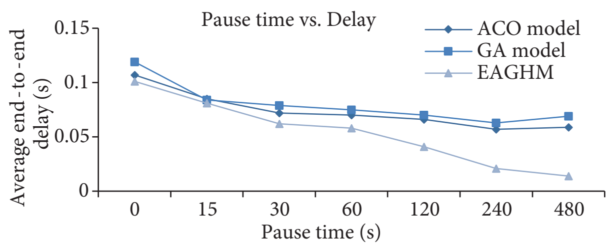

Figure 11. Node pause time (s) vs. delay (s).

The graph for the effective utilization of the available bandwidth is shown in Figure 13. From the graph it has been identified that the EAGHM more effectively utilizes the bandwidth than 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 while varying the node pause time. When pause time increases, number of hops decreases in all the 3 protocols.

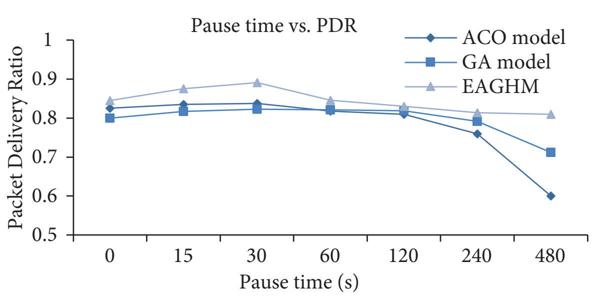

Figure 12. Node pause time (s) vs. packet delivery ratio.

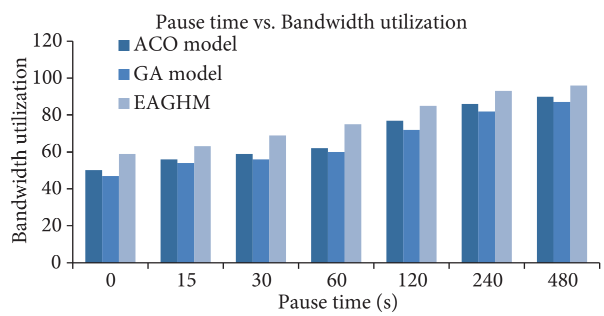

Figure 13. Node pause time (s) vs. available bandwidth utilization (%).

At the end of the simulation, the remaining node energies of all the nodes are noted and the average is calculated. The same is analyzed in Figure 15 for all the protocols. As route selection involves the remaining node energy, this graph illustrates that the energy utilization is effective while using the EAGHM.

The routing overheads computed under varying number of nodes and varying pause times are shown in Figure 16 and Figure 17, respectively. Since more control packets are required at the route discovery of the ACO phase, and periodical update and extra control packets are required for route selection in the GA phase, the routing overhead of the EAGHM is slightly 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 the opposite direction. Because of the periodic updates, the EAGHM requires a certain amount of routing overhead, but when the pause time increases, the overhead is reduced because of the relatively static nature of the topology.

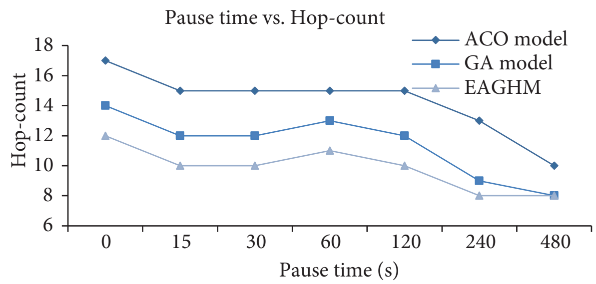

Figure 14. Node pause time(s) vs. hop-count.

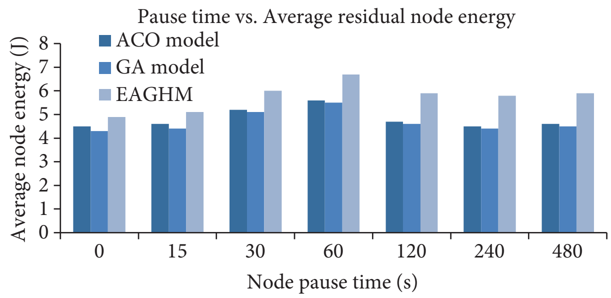

Figure 15. Node pause time (s) vs. average residual node energy.

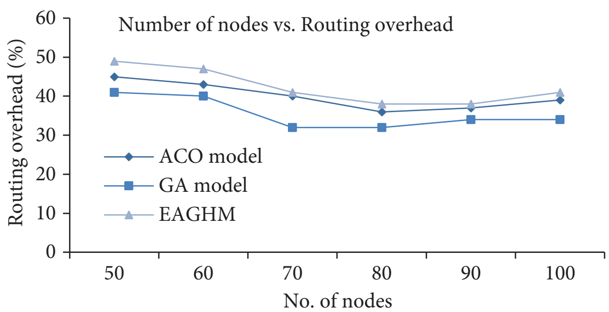

Figure 16. Number of nodes vs. routing overhead.

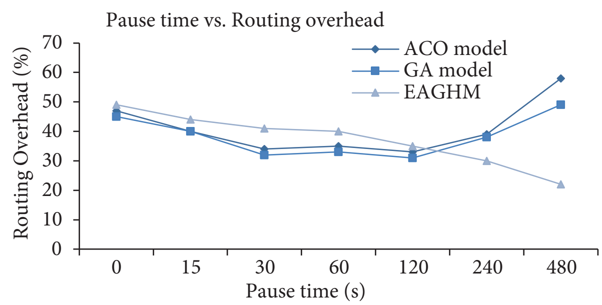

Figure 17. Node pause time (s) vs. routing overhead.

6. Conclusions and future work

In a 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 metaheuristic approaches such as ACO and the GA, which is simulated under varying numbers of nodes and varying node pause times. 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 120 s. The algorithm shows better results when the node pause time is very high. Furthermore, other metaheuristic approaches can also be combined as a new hybrid technology so as to study the performance of optimized QoS routing in MANETs.

References

[1] Chen S. Routing support for providing guaranteed end-to-end quality-of-service. PhD, University of Illinois, Urbana-Champaign, USA, 1999.

[2] Zhang B, Mouftah HT. QoS routing for wireless ad hoc networks: problems, algorithms, and protocols. IEEE Commun Mag 2005; 43: 110-117.

[3] Masip-Bruin X, Yannuzzi M, Domingo-Pascual J, Fonte A, Curado M, Monteiro E, Kuipers F, Mieghem PV, Avallone S, Ventre G et al. Research challenges in QoS routing. Comput Commun 2006; 29: 563-581.

[4] Hanzo L, Tafazolli R. A survey of QoS routing solutions for mobile ad hoc networks. IEEE Commun Surveys Tuts 2007; 9: 50-70.

[5] Conti M, Giordano S. Mobile ad hoc networking: milestones, challenges, and new research directions. IEEE Commun Mag 2014; 52: 85-96.

[6] Goldsmith AJ, Wicker SB. Design challenges for energy-constrained ad hoc wireless networks. IEEE Wireless Commun 2002; 9: 8-27.

[7] Yu C, Lee B, Youn HY. Energy efficient routing protocols for mobile ad hoc networks. Wirel Commun Mob Comput 2003; 3: 959-973.

[8] Garcia JE, Kallel A, Kyamakya K, Jobmann K, Cano JC, Manzoni P. A novel DSR-based energy-efficient routing algorithm for mobile ad-hoc networks. In: IEEE 2003 Vehicular Technology Conference; 6–9 October 2003; Orlando, FL, USA. pp. 2849-2854.

[9] Wang Z, Crowcroft J. QoS routing for supporting resource reservation. IEEE J Sel Area Comm 1996; 14: 1228-1234.

[10] Caro GD, Dorigo M. AntNet: A Mobile Agents Approach to Adaptive Routing. IRIDIA Technical Report. Brussels, Belgium: Université Libre de Bruxelles, 1997.

[11] Gunes M, Sorges U, Bouazizi I. ARA-the ant-colony based routing algorithm for MANETs. In: IEEE 2002 Parallel Processing Workshops; 18–21 August 2002; Vancouver, Canada. pp. 79-85.

[12] Caro GD, Ducatelle F, Gambardella LM. AntHocNet: an adaptive nature-inspired algorithm for routing in mobile ad hoc networks. Eur T Telecommun 2005; 16: 443-455.

[13] Bing S, Yang L, Zhenbo L, Jiapin C. An ant-based on-demand energy routing protocol for ad hoc wireless networks. In: IEEE 2007 Wireless Communications, Networking and Mobile Computing Conference; 21–25 September 2007; Shanghai, China. pp. 1516-1519.

[14] Asokan R, Natarajan AM, Nivetha A. A swarm-based distance vector routing to support multiple quality of service (QoS) metrics in mobile ad hoc networks. J Comp Sci 2007; 3: 700-707.

[15] Wang J, Osagie E, Thulasiraman P, Thulasiram RK. HOPNET: A hybrid ant colony optimization routing algorithm for mobile ad hoc network. Ad Hoc Netw 2009; 7: 690-705.

[16] Godbole V. Performance analysis of bio-inspired routing protocols based on random waypoint mobility model. Defence S & T Technical Bulletin, Science & Research Technology Institute for Defence (STRIDE) 2012; 5: 114-134.

[17] Barolli L, Koyama A, Shiratori N. A QoS routing method for ad-hoc networks based on genetic algorithm. In: IEEE 2003 Database and Expert Systems Applications Workshop; 1–5 September 2003; Prague, Czech Republic. pp. 175-179.

[18] Ohba S, Barolli L, Ikeda M, Marco GD, Durresi A, Iwashige J. An effective topology extraction algorithm for search reduction space of a GA-based QoS routing method in ad-hoc networks. In: IEEE 2005 Parallel Architectures, Algorithms & Networks Symposium; 7–9 December 2005; Las Vegas, NV, USA. pp. 400-405.

[19] Tseng SY, Huang YM, Lin CC. Genetic algorithm for delay-and degree-constrained multimedia broadcasting on overlay networks. Comput Commun 2006; 29: 3625-3632.

[20] Lu T, Zhu J. Genetic algorithm for energy-efficient QoS multicast routing. IEEE Commun Lett 2013; 17: 31-34.

[21] Nivetha SK, Asokan R. GA-based hybrid routing protocol to support multiple quality of service metrics in mobile ad hoc networks. International Journal of Computer Engineering and Applications 2014; 5: 43-50.

[22] Jiang H, Zheng L, Liu Y, Zhang M. Multi-constrained QoS routing optimization of wireless mesh network based on hybrid genetic algorithm. In: IEEE 2010 Intelligent Computing and Integrated Systems Conference; 22–24 October 2010; Guilin, China. pp. 862-865.

[23] Soleimanian F, Maleki I, Farahmandian M. New approach for solving dynamic travelling salesman problem with hybrid genetic algorithms and ant colony optimization. International Journal of Computer Applications 2012; 53: 39-44.

[24] Zukhri Z, Paputungan IV. A hybrid optimization algorithm based on genetic algorithm and ant colony optimization. International Journal of Artificial Intelligence & Applications 2013; 4: 63-75.

[25] Dorigo M, Birattari M, Stützle T, Bruxelles D, Roosevelt AF. Ant colony optimization–artificial ants as a computational intelligence technique. IEEE Comput Intell Mag 2006; 1: 28-39.

[26] Peker M, Sen B, Kumru PY. An efficient solving of the travelling salesman problem: the ant colony system having parameters optimized by the Taguchi method. Turk J Electr Eng Co 2013; 21: 2015-2036.

[27] Mutluer M, Bilgin O. Application of a hybrid evolutionary technique for efficiency determination of a submersible induction motor. Turk J Electr Eng Co 2011; 19: 877-890.

[28] Nivetha SK, Asokan R, Senthilkumaran N. A swarm-based hybrid routing protocol to support multiple quality of service (QoS) metrics in mobile ad hoc networks. In: IEEE 2013 Computing, Communications and Networking Technologies Conference; 4–6 July 2013; Trichengode, India. pp. 32-39.

[29] Brindha CK, Nivetha SK, Asokan R. Energy efficient multi-metric QoS routing using genetic algorithm in MANET. In: IEEE 2014 Electronics and Communication Systems Conference; 13–14 February 2014; Coimbatore, India. pp. 529-534.