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USING AN EFFICIENT GENETIC ALGORITHM TO IMPROVE THE QUALITY OF SERVICE FOR VARIOUS DATA TYPES TRANSMISSION IN MANET

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Abstract: In contrast to a wired network, ad hoc networks are popular today because they are formed by wireless mobile nodes forming a temporary network without any existing infrastructure or a centralized manager. This type of network can be used for any purpose that requires successful end-to-end data packet delivery with no delay or loss. Because each mobile host has a limited range and acts as a router in the network, it must enlist the assistance of other hosts to forward packets to the destination. The primary goal of deploying a MANET is to relay packets from source node to destination node. Normal data transmission such as text does not impose high Quality of Service constraints. This issue arises when dealing with multimedia data such as image, photo, audio, and video because they necessitate different robust MANET's routing techniques such as multicast techniques for fast and efficient route discovery processes and multimedia data transmission applications that assist us in achieving successful delivery of any types of packets whether ordinary or multimedia data. Because these protocols are complex in nature and require high Quality of Services (QoS), various robust protocols have been proposed in the literature by various researchers; the goal of such mechanisms was to maximize QoS by taking into account multiple QoS-constraints, particularly for multimedia data transmission, but few of them provide an efficient mechanism for this achievement at a moderate rate. The genetic algorithm has been shown to be a reliable mechanism for providing high QoS for multimedia applications. Various scientific researchers attempted to solve issues that arose while transmitting this type of data in Mobile Ad Hoc Networks using this type of algorithm, but problems were not fully resolved because many of them did not use this featured technique appropriately. To address all of these issues, we propose a new protocol in this research study: EGAQM (Efficient Genetic Algorithm for Providing High QoS in MANETs), a very efficient and robust algorithm that is an energy-efficient mechanism that primarily aims at finding an optimal path that is selected by considering multiple QoS-constraints. The proposed protocol is effective in dealing with various types of multimedia data. We compare the efficacy of this routing protocol to the prominent existing QoS-oriented Genetic Algorithms currently available in the literature, namely NSGA-II, NCGA, and AMGA, using NS-2 simulations. We vary the number of network and receiving nodes for better evaluation results, and the evaluation is carried out using popular routing evaluation metrics such as packet delivery ratio, end-to-end latency, packet loss, and residual energy. The simulation results demonstrated that the proposed scheme outperformed the existing ones by increasing the packet delivery ratio and energy on average by more than 10% and significantly reducing packet loss on average by 6% and end-to-end latency on average by 9% for all studied cases.
Keywords: Genetic Algorithm, MANET, Multicast, Multimedia applications, Quality of Service.

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1. Introduction

A mobile ad hoc network is a type of wireless network with an infrastructureless topology, which means there is no central manager, such as a router or server to manage the entire network's topology or data dissemination from one end to the other. This type of wireless network is self-contained, self-deploying, and self-organizing (Ze & Shen, 2014.)

The topology of a MANET is dynamic as nodes freely join and leave the network at any time. This makes the network difficult to manage, but it is typically used in emergency situations such as fire, military battlefield, flood, and so on.

It is also an excellent wireless network for collaborative businesses, private, and special-purpose instant networks such as classroom and conference hall connections where Personal Area Network and local access are required.

The main goal of deploying a MANET is to distribute information from one end to the other, but due to its infrastructureless nature, some of its fundamental characteristics such as wireless medium, dynamic topology, collision and interference events, and distributed cooperation between nodes always influence its overall performance as various problems such as Quality of Service provision's degradation, higher error rates, and various constraints related to bandwidth (Swati et al., 2014).

The aforementioned issues have an impact on Quality of Service which is a prominent measurement metric for the level of Quality of services provided by the network to its users. The QoS gradually degrades as the aforementioned issues arise particularly during the multimedia data transmission process as such data impose stringent constraints on the network because transmitting them requires higher QoS than ordinary data transfer such as text.

MANET performance rises in direct proportion to QoS provisioning. Genetic algorithms have been shown to be effective in providing high Quality of Service in MANETs which is an extremely important factor to consider when designing a robust routing protocol (Priti Gaur, 2013).

A number of parameter metrics can be used to evaluate the efficacy of these types of algorithms for the purpose of achieving high QoS in MANETs; the most important ones are the packet delivery ratio, packet loss ratio, end-to-end latency, and Nodes' residual energy (Haghighat, 2012).

Genetic algorithms are a great tool that is commonly used to solve complex network issues such as the NP-complete problem in various networking fields. The steps in the solving process are as follows: input selection, fitness function calculation, mutation, crossover technique, and output.

After completing the preceding steps, even in the presence of various network issues, an optimal path to pass packets through between source and destination nodes can be selected; this path is the one that achieves both a high packet delivery ratio and energy level as well as a reduced end-to-end latency and packet loss ratio; the effectiveness of the genetic algorithms is provided even in the network with fast nodes during ordinary and multimedia data transmission (Ting, 2013).

In this study, we take the same approach and propose EGAQM (Efficient Genetic Algorithm for providing high Quality of Service in MANETs), a new robust and efficient genetic which combines various techniques and algorithms that have been demonstrated to be effective in dealing with those transmission problems that successfully disseminate multimedia data from one end to another by avoiding packet loss, delivery latency with a maximized packet delivery ratio, and node Residual Energy level.

The rest of this paper is structured as follows: Section 2 discusses related work, Section 3 describes the problem, and Section 4 presents our proposed routing mechanism. Section 5 discusses the results of the experiments, Section 6 concludes our work, and Section 7 is devoted to References.

2. Related Works

Taking into account multiple network constraints, Baolin et al. (2018) proposed the efficient algorithm MQMGA. This protocol was effective at maximizing network utilization by selecting long-life links, employing a multicast tree, and calculating both maximum and end-to-end delays. The protocol provided the network with additional features such as very promising multicast performance, particularly for traffic engineering technologies, and ensuring route stability in highly dynamic MANETs.

A Genetic Algorithm for Steiner Tree Optimization with Multiple Constraints Using Pruffer Number was proposed by Haghighat et al. (2012). The Prüfer number was used for a variety of purposes in the proposed mechanism, most notably genotype representation. The authors also proposed some new heuristic algorithms that were used for various operations such as mutation, crossover, and the creation of random individuals. Through simulation, the authors finally conducted a performance evaluation of the proposed GA-based algorithm in comparison to both the existing heuristic GA-based algorithms, and the results revealed the efficacy of the proposed GA-based algorithm.

Because nodes are mobile in nature, they consume a large amount of energy in a short period of time, causing frequent link breaks. Keeping the network alive for a long time is a topic of many researchers in the literature; finding a correct path that can hold for a long time is another issue. To find an optimal solution to this problem, Basarkod and Sunilkumar, (2014) proposed an efficient proprotocol that is an extension of the ad hoc on-demand multicast routing protocol (ODMRP) to provide QoS support for real-time applications. Various network parameters, such as bandwidth stability and availability, delays, and link and node stability, were also used. Additional operations included the creation of a neighbor stability and QoS database at each node using estimated parameters. Another important parameter is multicast path construction using route request and route reply packets, as well as QoS and stability information, such as link/node stability factor, bandwidth and delays in node route information cache, and performing route maintenance in case of node mobility and route failures. The results showed that the proposed scheme was able to efficiently reduce both packet overhead and end-to-end delay, as well as increase the Packet Delivery Ratio (PDR) when compared to existing protocols in the literature.

Ourabh et al. (2020) presented a structured and explained view of genetic algorithms. In their paper, the genetic algorithm and its variants were thoroughly discussed, as were applications-specific genetic operators. According to the author, some genetic operators are designed for representation and are not applicable to research domains. They also stated that the role of genetic operators such as crossover, mutation, and selection in preventing premature convergence has been extensively researched in the literature. They also stated that the applicability of GA and its variants in various research domains has been discussed, as well as that multimedia and wireless network applications have been discussed. They then investigated recent advances in genetic algorithms. The genetic algorithms of particular interest to the research community were chosen. They stated that the study discussion will assist new and demanding researchers in providing a broader vision of genetic algorithms. The advantages and disadvantages of well-known algorithms and their implementations were discussed. The genetic operators and their applications were discussed with the goal of assisting new researchers. The various research domains involved in genetic algorithms were also discussed. Finally, they recommended various feature additions to future researchers in the areas of genetic operators, fitness functions, and hybrid algorithms.

As a solution to the above problem, Prabhugoud & Sunil, (2014) proposed a robust genetic algorithm; genetic algorithm-based location-aided routing (GALAR) to enhance the MANET routing protocol efficiency. The proposed algorithm keeps an adaptive update of the node location information by adding the transmitting node location information to the routing packet and selects the transmitting node to carry the packets to their destination. It was built on a genetic optimization scheme that uses criterion function optimization to take into account all contributing factors in delivery behaviour. The simulation results showed that the GALAR algorithm can increase the probability of packet delivery to more than 99% while using less network overhead. Furthermore, when compared to other existing algorithms in terms of various network evaluation measures, the GALAR algorithm significantly outperformed the other algorithms in all of the cases studied.

3. Proposed Work

3.1. Problem Definition

MANET is a type of wireless network that lacks a pre-existing infrastructure and has a dynamic topology, which changes as nodes leave and others join the network at any time. These characteristics of this wireless network result in a variety of challenges, including packet drops due to frequent network link failures, node battery drain, increased end-to-end delay, reduced packet delivery ratio, and bandwidth; all of this has a significant impact on the network's Quality of Service, as these tragic events affect the reliable transmission of data from the source node to the destination (Gatete & Vetrivelan, 2015).

The other issue arises when some mobile nodes occasionally fall outside the radio frequency range; some of them were intermediate nodes through which packets had to pass to reach the destination, resulting in route link breaks; this also results in the previously mentioned problems.

Finding a viable solution to the above-mentioned problems at the same time is somewhat difficult; various researchers attempted to solve such problems using a single algorithm, and while they were able to solve some of the problems, others remained unsolved; thus, these problems related to MANET remain unsolved to this day.

To address these issues, we propose EGAQM (Efficient Genetic Algorithm for Providing High QoS in MANETs), a robust protocol that addresses the aforementioned issues.

We use genetic techniques to accomplish this because they have been shown to be efficient in solving various MANET problems. This results in a high packet delivery ratio and residual energy, as well as lower end-to-end latency and packet loss.

3.2 Proposed Protocol

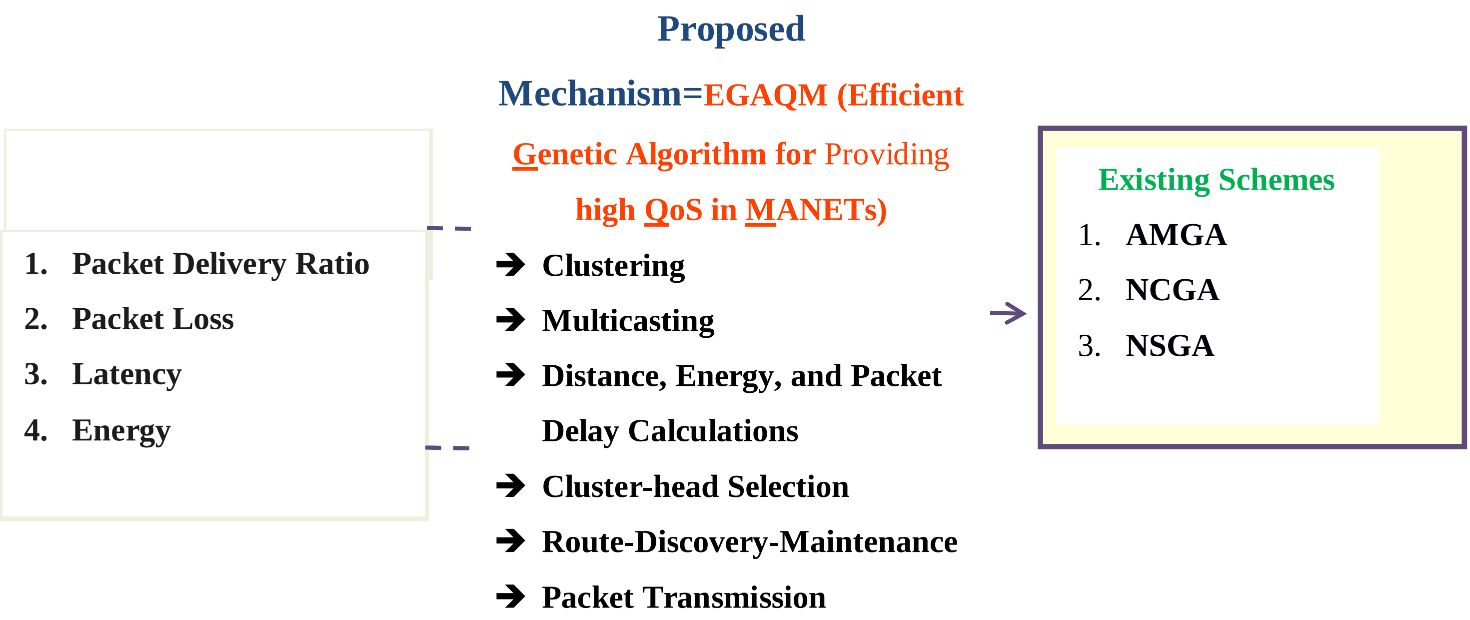

Figure 1: Framework of EGAQM

Figure 1 depicts the framework of the proposed scheme-EGAQM which solely aims to increase packet delivery ratio, minimize packet loss and latency, and reduce energy consumed by mobile nodes. To achieve this goal, we must find a very efficient route from the source node to the destination node, the path must be a shortcut to the destination, i.e. the distance between such node and both the source and destination nodes must be small, and the energy consumed by nodes on that path must be reduced.

Because large networks are difficult to manage, we begin by segmenting the network into small groups of manageable nodes (clusters). The next step is to select a cluster-head node, which will be capable of controlling the network and performing route discovery, routing, and post-routing operations such as route maintenance, acknowledgment management, and so on.

This node will be chosen using the genetic algorithm operations shown in Figure 1: Encoding, initial population, fitness function evaluation, parent selection, mutation, crossover, and convergence analysis will all be performed.

3.2.1 Representation of the Network Model

The network is represented as a weighted digraph G = (N, L), where N denotes the set of nodes and L denotes the network links between nodes. The network's nodes and links are represented by |N| and |L|, respectively. Only where there are connected nodes do we specify digraphs.

3.2.2 Multicasting

Multicast from source node s in the set S={s, a1,a2,a3, …, am} S inclusive in N to multiple destination nodes in G(N,L) namely D={d1,d2,d3, …, dn}

T = (N T , L T), where N T incusive in N, L T # L, if C(T) is the cost of T.

3.2.3 Distance Calculation

The mobile adhoc network can be thought of as a two-dimensional, square-shaped symmetric wireless network.

We always represent this network as a digraph G=(N,L), with the set of mobile nodes represented as a set of vertices as shown below:

A = { a1 , a2 , ..., an }

In the graph G(N, L), the set of edges L consists of all edges l = (i, j) E iff g I reaches g j, i.e. the distance between gi and vj is less than d, where d is the maximum distance between two nodes after which communication ceases to exist, i.e. if the distance between two nodes is greater than d, communication between these two nodes is impossible, implying that these two nodes are not neighbors. The weight w(e)≤d of the edge l =(i,j) between two neighbor nodes gi and gj is defined as the distance between them.

Finally, G is a Euclidean graph in which each mobile node has a coordinate (xi, yi) € R2 in a two-dimensional space. The coordinate (x i,y I represents the location of node i in the given mobile network's area.

3.2.4 Consumption of Energy during packet transmission

To model the consumption of energy during packet transmission across a link between two nodes, namely source node S and destination node d1 at a cost T, we can calculate the energy required to transmit the packet p for that link Ls,d1=E1(rs,d1) β+E2, where rs,d1 is the Euclidean distance for the link Ls,d1 and E1 is a constant dependent on the properties of the antenna, whereas is the path loss exponent depends on the current medium's losses, while E2 is another constant that accounts for the overheads that occur during digital processing.

3.2.5 Estimation of Packet Delay

We employ a two-way approach to estimate the delay incurred during packet transmission, in which the receiver node sends an acknowledgment signal in response to the one sent to the sender, with the goal of measuring the round-trip time for distance estimation between transmitter and receiver [15].

A mobile node a, for example, sends a signal at its local time ta1.

It arrives at the mobile node b at tb1 local time.

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The mobile node b sends the signal back after some delay at its local time tb2.

Node a receives the signal at its local time ta_2.

We have following calculations:

Round-trip time including delay $= t\,a_2 - t\,a_1$

Incured Delay at b$= t\,b_2 - t\,b_1$

Actual roundtrip time $= (t\,a_2 - t\,a_1) - (t\,b_2 - t\,b_1)$

One-way time of flight $= \underline{(t\,a_2 - t\,a_1) - (t\,b_2 - t\,b_1)}/2$

Node a subtracts its local time ta2-ta1 from its round-trip time to save extra hardware costs and energy required for time synchronization. Node b must do the same thing, subtracting its local time tb2-tb1 from the processing delay incurred during packet transmission. Because both mobile nodes must process only their respective local times, no time synchronization is required.

3.2.6 Bandwidth

We have a multicast tree T, and the bandwidth is estimated as the minimum value of the link bandwidth on the path from source node s to various destination nodes; each destination node in the multicast is denoted by d € D.

The bandwidth of multicast tree T is the smallest value of the link bandwidth in the path from source node s to each destination node d, d € D. i.e. BS=Min{B(p(s,d)}.

3.3 Genetic Optimization Mechanism

The terminology used in genetic algorithms is borrowed from biology, but the entities in such terminology in genetic algorithms are simple.

Genetic algorithms are well-known for their ability to search through large amounts of data. Iterative calculations are used, and fitness answers provided by bio-informatics knowledge are required.

The genetic algorithm works as follows:

1. It uses natural evolution principles such as reproduction, natural selection, and species diversity.

2. It operates on a group of people, each of whom represents a potential solution.

3. A criterion is typically used to apply the selection principle, which results in an evaluation of the individual based on the desired solution.

4. The best of the chosen individuals are designated as the next generation members.

The following are the basic components shared by almost all genetic algorithms:

- A fitness function for optimization
- A chromosome population
- Chromosome selection
- Crossover to produce the next generation of chromosomes
- Random chromosome mutations in the next generation.

Terminologies

1. Population

Population is a subset of all possible solutions available in current generation operations.

It's a collection of chromosomes.

We have two options for population initialization: random initialization and sequential initialization.

- Random Initialization: Completely Random Initialization
- Heuristic initialization Instead, a heuristic algorithm is used.

2. Fitness Function

The fitness function is commonly used to predict how chromosomes will change over time. It is used to represent the process of programming. We have a defined problem, and our goal is to provide solutions to it. The role of the fitness function problem-solving process is to take a candidate solution to the problem as input and output how "fit" or "good" the solution is with respect to the problem under consideration.

3. Crossover

Crossover is a genetic operator that is commonly used in genetic operations to vary chromosome programming across generations. According to the encoding method, it is a sexual reproduction, which means that two strings can be selected from the mating pool, resulting in superior offspring production.

In a network, crossover is an efficient technique for determining the best path for packets to take from send to destination.

4. Mutation

A mutation is a random change in the chromosome that must be minor in order to aid in the discovery of a new solution.

The primary goal of a mutation is to increase population diversity.

We can use a low probability pm, and if it is very high, the GA will perform a random search.

It is concerned with the exploration of search space; the difference between mutation and crossover is that the former provides genetic algorithm convergence while the latter does not.

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Mutation ensures that it is still possible to reach the extreme through random changes in some of the genes, even if none of the individuals have the required gene value for the extreme.

5. Survivor Selection

The survivor selection process addresses the issue of selecting the best individual, keeping them, and making them a member of the next generation while removing the undesirable one.

A precaution is required because it can weed out the fittest members of the population while also preserving diversity.

Most genetic algorithms employ elitism, a process in which current fittest members are immediately promoted to the next generation and are never replaced.

The Termination Condition

At this stage, we will decide when the GA will end.

GA advances quickly at first, providing better solutions at each stage, but saturating later on due to small improvements.

We can stop when there is no more improvement in the population, when we reach an absolute number, or when the objective function value reaches a certain predefined value.

Algorithm 1: Genetic Algorithm

```
BEGIN
   Input:
 initialize population
 find fitness of population
  do until best node found
    parent selection
    crossover with probability cp
    mutation with probability
    decode and fitness calculation
    survivor selection
    find best
  end do
```

Output:

return best

END

3.4. The proposed Sub-Algorithms:

Algorithm 2: Proposed-EGAQM-ClusterHead Selection

Genetic Algorithm(G, s, D)

{

For(i=1; i<=N_p; i++) {

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```
  Chromosome(i) = RandomDFS(G, s, D);
 }
 For(j=1;j<=N_g; j++){
 For(k=1;k<=N_p-N_optimal; k++) {
   R_a=MSTSelect(Chromosome);
   R_b=MSTSelect(Chromosome);
   R_c=Crossover(R_a, R_b);
   If(rand()<p_m)
      Mutation(R_c);
   }
}
 Choose the best Nodes to be part of cluster heads and display them.
}
```

3.4.1 Random Depth Search Algorithm

RandomDFS(G, s, D) is a random depth-first search algorithm that builds the tree (the entire network) at random until the network is complete. The maze is represented as a tree here, followed by how the traversal algorithm can be used to generate the network.

In two dimensions, a network is a series of paths separated by walls, and the maze can be thought of as a 2-dimensional grid to simplify generation. The grid has a width and height, and each x/y position in the grid can be represented as a cell.

When viewed in this way, the grid can be thought of as a graph G, with each cell representing a node connected to each of its four neighbors by a wall (the exception to this rule is for edge and corner cells which have 3 and 2 neighbors, respectively). The algorithm then finds a spanning tree - or tree composed of all vertices but only some of the edges - of this graph G based on a random seed.

Selection of Parents

When viewed in this light, the grid can be thought of as a graph G, with each cell representing a node connected to each of its four neighbors by a wall (the exception to this rule is for edge and corner cells which have 3 and 2 neighbors, respectively).

The algorithm then finds a spanning tree - or tree composed of all vertices but only some of the edges - of this graph G based on a random seed.

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3.4.2 Crossover Scheme

The crossover scheme is widely used in genetic engineering. This is particularly useful for determining the best route through networks. A pair of chromosomes is preferred as parents in this scheme, and they are combined to produce new offspring. Consider the case where Ra and Rb are the chosen parents.

To generate a child Rc by analyzing the identical link between two parents Ra and Rb using the roulette wheel selection operator.

According to the definition of fitness function evaluation, the best one is chosen as the parent and has the highest probability value. Based on this, the same connections between two parents have positive characteristics. Furthermore, by retaining that common link, it is possible to construct some sub trees. So, there is a need to connect those sub trees to make multicast tree.

The following procedures are used to connect those sub-trees.

- First, choose any two subtrees at random, and then determine the path with the least delay and highest bandwidth between these subtrees.
- This process is repeated until the entire subtree is connected to form a multicast tree.
- Two nodes are added to the two selected sub trees to select the least delay maximum bandwidth path.
- One node is connected to the entire subtree via a link with zero delay and zero bandwidth.
- Other nodes in the multicast tree can also connect to the entire node with zero delay and zero bandwidth.
- The least delay maximum bandwidth path of two subpaths is chosen from that least delay maximum bandwidth path of two sub trees.

We are not implementing any kind of loop routing method in this connecting mechanism. Figure 4 depicts the cross over operation procedure. This explains the procedure for forming a multicast tree. Two individual subtrees can be combined to form a new multicast tree with the least delay and highest bandwidth link.

3.4.3 Mutation

The results of the crossover operation are then passed on to the mutation stage.

The child node inherits the traits of the parent node during the cross over process.

Mutation is the process of rearranging or revising chromosomal genes in order to extract new specific traits.

Mutation is carried out in our proposed work based on mutation probability pm.

First, it will find or select any two nodes at random from the multicast tree.

After that, the links between the chosen node and the child node on T are severed.

The multicast tree has now been divided into two subtrees.

Following that, it will reconnect all of the nodes in the subtree using the shortest delay maximum bandwidth path.

By connecting two subtrees with the powerful mutation operator, a new multicast tree is created.

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Energy

Algorithm 3: Optimal power consumption

Our algorithm sends the message in equal-length packets to ensure that all nodes along the route consume the same amount of power.

Periodic invigilation is performed to ensure that each node's residual energy does not deviate from the required level.

If the node exceeds the threshold value, it is transformed into a sleep node and an alternate node is selected for transmission.

The key point in the preceding discussion is to reduce power consumption and network lifetime.

The proposed algorithm is as follow:

1. In the source mode, divide the message into packets of equal length and choose a mode M where min(Em>Thm) from all neighbouring nodes.

2. Create a route to the destination where the energy level of all nodes exceeds the threshold value.

3. Repeat the preceding steps at t intervals.

4. Using the equation, calculate the residual energy of each node.

5 Eres=E-Mc(t)

6. where E is the initial energy of a mode

Mc(t) energy consumed in periodical interval t and Eres residual energy of a mode

7. The energy consumption of a mode after time t is calculated using the following equation.

Ec(t)=Nt*a+Nr*b, where Ec(t) is the energy consumed by a node after time t, Nt is the number of packets transmitted by the node after time t, and Nr is the number of packets received by the node after time t. a and b are constant factors with values ranging from 0 to 1.

8.If Eres>Threshold value, continue transmission through the same node.

9. Otherwise, dynamically find an alternate route for further transmission that satisfies the constraints outlined in our approach.

The above techniques, when combined, are very successful in finding an optimal path to pass packets through and avoiding excessive packet loss ratios during packet transmission processes.

4. Experimental Evaluation

This section demonstrates the unique property of our proposed protocol, EGAQM, that makes it superior to existing approaches such as NSGA-II (Non-Dominated Sorting Genetic Algorithm), AMGA (An archive-based micro genetic algorithm for multi-objective optimization), and NCGA (Neighborhood Cultivation Genetic Algorithm for Multi-Objective Optimization Problems) (Badalló et al., 2013).

A summary of those protocols is provided below:

NSGA-II

Following the creation of the parent population, non-dominance sorting is used. Each solution has a fixed fitness (equivalent to non-domination level). Using the selection, crossover, and mutation operators, the best individuals from this ranking are used to create the new population. It is one of the MoGA techniques for optimizing process parameters in various machining operations. The NSGA-II algorithm is a well-known, fast sorting, elite multi objective genetic algorithm. Process parameters such as cutting speed, feed rate, rotational speed, and so on are important conditions to optimize machining operations in terms of minimizing or maximizing machining performances. Unlike the single objective optimization technique, NSGA-II optimizes each objective simultaneously without being dominated by any other solution.

AMGA

This algorithm employs a small population size and generates an external archive of the best solutions obtained, which is updated after each iteration. AMGA employs the NSGA-II non-dominance ranking concept and generates the parent population from the archive using the SPEA2 method. The mating pool is based on the NSGA-II binary tournament selection method. Using the archive allows you to obtain a large number of non-dominated points at the end of the simulation. AMGA is an NSGA-II-based GA.

NCGA:

A neighborhood crossover mechanism is added to the standard GA mechanisms to improve the crossover operator. The pair of individuals to perform crossover is not chosen at random, but rather individuals who are close to each other in the objective space. NCGA encompasses not only these mechanisms, but also neighborhood crossover. It is a reliable algorithm for locating Pareto-optimal solutions. The effect of neighborhood crossover is demonstrated by comparing the case of using neighborhood crossover to the case of using normal crossover in NCGA. Not only does NCGA have an important mechanism of the other methods, but it also has a mechanism of neighborhood crossover selection. Please be consistent with the language use. The Journal accepts English (UK) as the official language format for its publications, although English (US) is also allowed. Authors should not switch from one format to another, instead, please be consistent with the style that you have selected at the beginning. This can be easily assisted by setting the appropriate language setting for your word processing document or following the style used in this template. Try to avoid common mistakes in research writing; the correct use is “Future work” instead of “Future works”, for an example. Take an extra effort to use *that* and *which* in the appropriate context. It is a pity to reject a research article with a good research outcome, merely because of the poor presentation and language issues. If possible try to improve your article by proofreading before sending it for the review. If you find difficulties with the language use, Editorial Panel might help considering the research value of the article; make sure you inform the Editors of such difficulties at the first instance of your submission.

5. Materials and Methods

5.1.1 Simulation environment

A detailed simulation model based on NS-2 is used to model the comparison of our proposed scheme with existing ones. NS-2 is an object-oriented tool with a C++ back end and an OTCL front end (Object oriented Tool Command Language). Table 1 depicts the scenario and experimental settings. We use 10 to 50 nodes to run the simulation in a 1500mX1500m area, and the simulation takes 100 seconds to complete. We only use the Omani-directional antenna and the IEEE 802.11 MAC layer, and the queue holds 201 packets. Nodes move at random speeds ranging from 1 to 20 m/s. We compare the two models using the Two-Ray Ground radio propagation model and the three metrics listed below.

A Packet delivery ratio

Packet delivery ratio (PDR) is defined as the ratio of total packets delivered to total packets sent from source node to destination node in the network. The maximum number of data packets must be delivered to the destination.

Packet delivery fraction=∑ Number of received packets / ∑ Number of sent packets

Latency

Latency is the time it takes between sending and processing a signal. IT teams typically monitor the latency of data packets transmitted between two sensors. Given that the fastest data transfer speed is the speed of light, it is impossible to completely eliminate latency. As a result, the goal is to reduce latency times to as close to zero as possible. The lower the network latency, the less time spent waiting for data to arrive.

Network latency () is the total of all possible delays encountered by a packet during data transmission. Network latency is commonly expressed as round trip time (RTT) and measured in milliseconds (ms). Processing, queuing, transmission, and propagation delays are all examples of network delays. Consider the following formula for calculating network latency:

- ✓ The acceptable network latency varies by network and application.
- ✓ High network latency can have a negative impact on these applications' performance.
- ✓ On the other hand, some applications, such as email, can tolerate high latency without affecting the application's performance.
- ✓ The round trip time (RTT) is the amount of time it takes a message to travel from its origin to its destination and back.
- ✓ On a network, ping time is very similar to round trip time.
- ✓ Round trip time is related to network latency.
- ✓ Because asymmetric latencies can exist in both directions, it is not exactly double the network latency.
- ✓ Extra processing time at the destination is also included in the round trip time.

$NL=D_p+D_Q+D_t+D_{PR}$

Packet loss

- ✓ Ideally, your network would transmit all data without losing any of it.
- ✓ However, packets are occasionally "lost," which means they do not reach their destination.
- ✓ NPMs detect lost packets for you, so you should investigate how frequently packet loss occurs.
- ✓ Your NPM may also discover what caused the packet loss, allowing you to reduce future data loss.
- ✓ The packet loss rate is the ratio of packets lost in the test to the data group sent.
- ✓ The calculation method is as follows:

PL= [(incoming message - output message)/ incoming message]*100%.

Energy

The amount of energy stored in the battery is referred to as its power capacity. Watt-hours are a common unit of measurement for this power (the symbol Wh). A Watt-hour is the voltage (V) provided by the battery multiplied by the amount of current (Amps) the battery can provide for a given period of time (generally in hours).

If you know the battery voltage V and the battery capacity AH in amp-hours, you can calculate the energy stored by the battery in Joules as E = Voltage * Amps * hours.

5.1.2 Parameter values

Table 1: Network parameters

Simulation metrics	**Values**
Number of nodes	10, 20, 30, 40, and 50
Interface type	Phy/WirelessPhy
Channel	Wireless Channel
Mac type	Mac/802_11
Queue type	Queue/DropTail/PriQueue
Queue length	201 Packets
Antenna type	Omni Antenna
Propagation type	Two-Ray Ground
Size of packets	256-1280
Simulation time	100 seconds
Simulation Area	1500X1500

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A. Performance Evaluation with PDR

Table 2. PDR of EGAQM and existing protocols varying number of nodes

Number of Nodes	Packet Delivery Ratio			
	EGAQM	*NSGA-II*	*AMGA*	*NCGA*
10	0.95	0.93	0.9	0.915
15	0.948	0.929	0.897	0.91
20	0.945	0.925	0.895	0.908
25	0.943	0.923	0.892	0.903
30	0.94	0.909	0.888	0.901

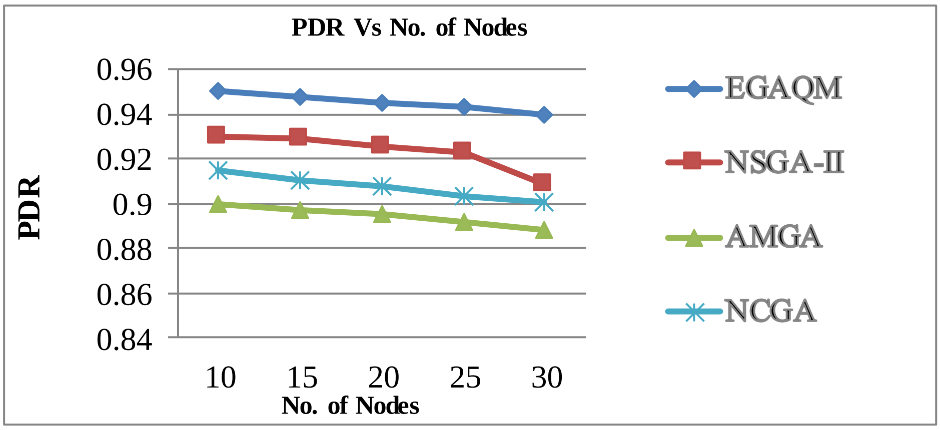

Figure 2: PDR vs. No. of Nodes

Table 2 and Figure 2 show the results of the performance evaluation of PDR with varying node counts. When compared to the other three algorithms, the Packet Delivery Ratio of EGAQM remains high over the entire simulation time; however, it decreases slightly as the number of nodes increases. The same is true for other algorithms due to a lack of capacity to handle highly dense networks.

Table 3: PDR of EGAQM and NSGA-II varying number of receivers

Number of Receivers (Nodes)	Packet Delivery Ratio	
	EGAQM	*NSGA-II*
10	0.95	0.935
15	0.953	0.938
20	0.953	0.94
25	0.953	0.945
30	0.953	0.948

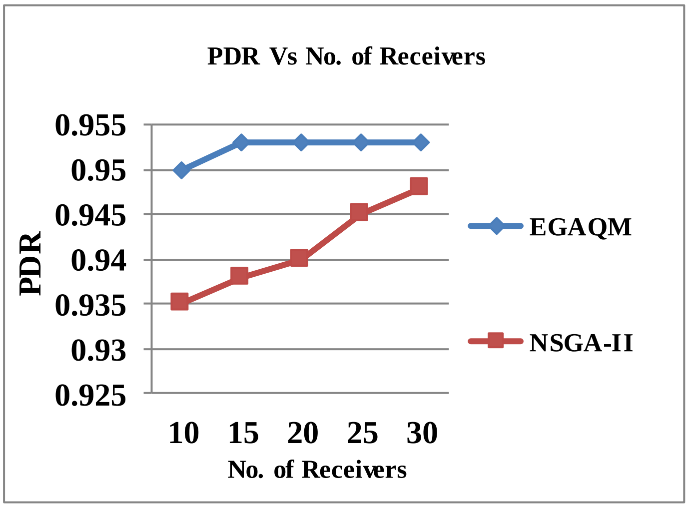

Figure 3: PDR vs. No. of Receiver Nodes

As shown in Table 3 and Figure 3, the PDR of the new algorithm is compared to that of the NSGA-II. The number of receivers is taken into account when evaluating performance. The number of receivers varies between 10 and 30 nodes during the simulation process. EGAQM achieves the best results due to two distinguishing characteristics: the availability of high-quality links and the ability to select a stable path. One interesting finding is that the PDR of both protocols increases in direct proportion to the number of receivers. However, the new algorithm, EGAQM, maintains a high PDR that NSGA-II never achieves, proving EGAQM's superiority.

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B. Performance Evaluation with Latency

As shown in Table 4 and Figure 4, when considering end-to-end latency and varying the number of nodes, EGAQM's latency is maintained at a lower level when compared to existing ones during the overall simulation time, making the EGAQM protocol superior. The best performance behaviour of the EGAQM scheme is achieved by selecting paths with lower distance and reachability values first as optimal paths.

Table 4: End-to-End Latency of EGAQM and existing approaches

Number of Nodes	End-to-end Latency [(secs)]			
	EGA QM	*NSGA-II*	*AMGA*	*NCGA*:
10	0.5	1.2	1.5	1.8
15	3	2.5	4.3	3
20	7	8.8	8.8	9.5
25	9	12	12	13
30	12	15	16	16

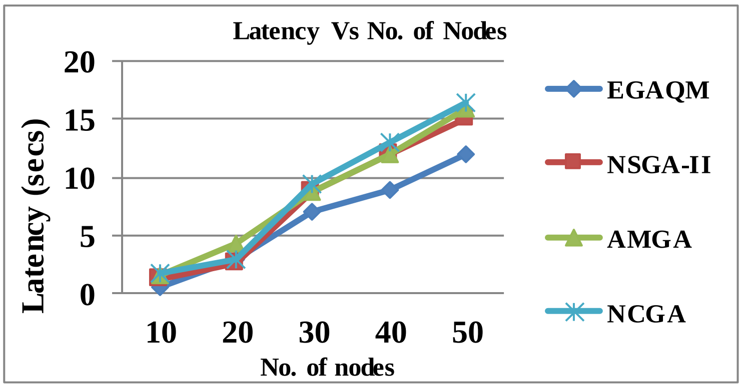

Figure 4: End-to-End Latency vs. No. of Nodes

C. Performance Evaluation with Packet Loss

In Table 4 and Figure 4, the performance of the new algorithm EGAQM in comparison with AMGA is depicted. The results obtained by varying the network size i.e. the number of nodes while considering packet loss as an evaluating parameter metric prove EGAQM attains the minimum ratio of packet loss compared to the existing one.

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Table 4: Packet Loss for EGAQM and AMGA with the varying number of nodes

Number of Receivers (Nodes)	Latency [(secs)]	
	EGAQM	AMGA
10	11	12
15	11.5	12.6
20	11.8	12.9
25	12.2	13.5
30	12.5	14

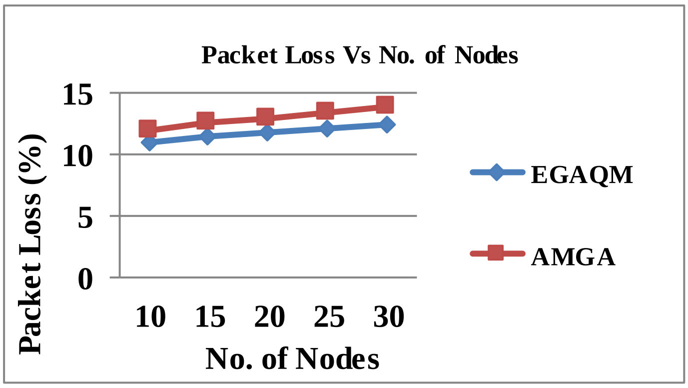

Figure 4: Packet Loss vs No. of Receiver Nodes

EGAQM protocol again outperforms other four algorithms as it maintains packet loss lower for the overall simulation time but with a minor difference with the AMGA and NSGA-II. NCGA performs badly as it maintains a very high packet loss. One important observation for EGAQM, AMGA and NSGA-II is that their packet loss ratio almost augments proportionally to the increasing number of nodes, this is possibly due to more hops or queuing available in the network.

D. Performance with Energy

The effects of the total number of packets received by the source from multiple receivers are shown in Table 5 and Figure 5.The experiment results show that the Remaining Energy values of both protocols vary from high to low as the number of receivers increases, which is due to multiple receivers sharing the same channel at the same time. Despite decreasing Remaining Power values, EGAQM outperforms NCGA by maintaining higher Energy levels. Because it is good at selecting an energy-efficient path, the genetic algorithm usually provides an efficient scheme for managing the power consumed by nodes. Nodes use less energy during the multicast process, which primarily aims to find routes to successfully transmit multimedia data. Because of the tree structure coding/decoding mechanisms used in this protocol, incorporating the genetic algorithm in our proposed protocol efficiently reduces the energy consumed by nodes.

Table 5: Energy of EGAQM and NCGA varying number of receivers

Number of Receivers (Nodes)	Energy [Joules]	
	EGAQM	*NCGA*
10	0.97	0.93
15	0.968	0.927
20	0.965	0.925
25	0.963	0.923
30	0.96	0.921

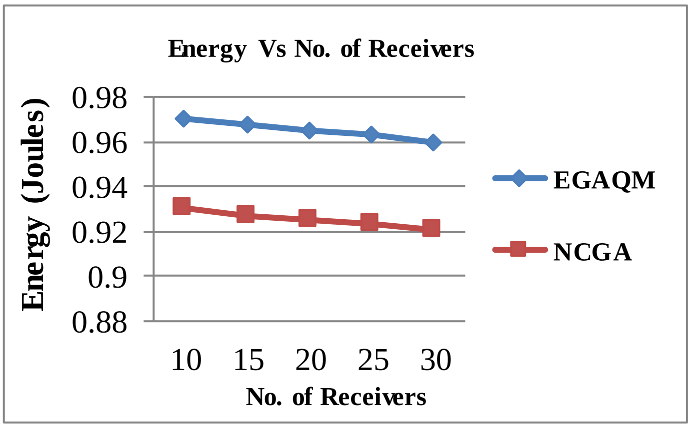

Figure 5: Energy vs. No. of Receiver Nodes

6. Conclusion

We evaluated the performance of our proposed algorithm in this paper; EGAQM, a source-based Genetic Algorithm, was used to find an optimal path between a source and multiple destinations (multicast technique); it achieves a very high QoS because it selects the least-cost, highest-bandwidth, and energy-efficient path. The Genetic Algorithm is capable of transmitting multimedia data successfully. During this evaluation, no coding/decoding processes were used; instead, we invited the tree-structure-based encoding method, efficient crossover, and mutation techniques. After the Genetic Algorithm has completed the route identification process. The EGAQM routing mechanism was tested using the NS-2 simulation tool, with PDR (Packet Delivery Ratio), Latency, Packet Loss, and Energy as evaluating parameter metrics. Our proposed algorithm, EDAQM, outperforms other protocols in all cases studied, regardless of the number of nodes or node speeds. This accomplishment was made possible by the Genetic Algorithm, which was used for route discovery, maintenance, and packet transmission.

References

[1] Ze L., and Haiying S., 2014, A QOS-Oriented Distributed Routing Protocol for Hybrid Wireless Networks", *IEEE Transactions on Mobile Computing*, Vol.13, No.3, PP.693-708.

[2] Swati A., Dr.Nasib S.G., and Jaideep A., (2014), Fuzzy Logic Implementation of Antcolony Based Clusterhead Selection Algorithm", *International Journal of Advanced Research in Computer and Communication Engineering*, Vol.3, PP.6256-6259.

[3] Ting L. and Jie Z.,2013, Genetic Algorithm for Energy-Efficient QoS Multicast Routing", Communications Letters, *IEEE*, Vol.17, Issue: 1, pp.31-34.

[4] Prasanna P., Saravanan D., and Chandrasekaran R.M., 2014, An Energy Efficient Multicast Routing Based On Genetic Algorithm for MANET", *International Journal of Innovative Research in Computer and Communication Engineering* ,Vol.2, Special Issue 1.

[5] Yun-Sheng Y., Yi-Kung C., Han-Chieh C., Jong H.P, 2008, A genetic algorithm for energy-efficient based multicast routing on MANETs, *Computer Communications*, Vol. 31, Issue 10, pp. 2631.

[6] Baolin S., Shangchao P., Chao G., Yue Z., Bing Y., Wenxiang W., Qianqing Q., 2008, Multiple constraints QoS multicast routing optimization algorithm in MANET based on GA, *Progress in Natural Science*, Vol.18, Issue 3, pp. 331–336.

[7] Priti G.,2013, Implementation of Multicast Routing Using Genetic Algorithm", *Proceedings on IJCSMC (International Journal of Computer Science and Mobile Computing)*, Vol.2, Issue.5, pp.226 – 231.

[8] Haghighat A. T, Faez K., Dehghan M., Mowlaei A., and Ghahremani Y., 2012, *A genetic algorithm for Steiner tree optimization with multiple constraints using Pruffer number", Proc. EurAsia-ICT*, pp. 272–280.

[9] Ting L. and Jie Z., 2013, Genetic Algorithm for Energy-Efficient QoS Multicast Routing, *Communications Letters, IEEE*, Vol.17, Issue: 1, pp.31-34.

[10] Haghighat A. T., Faez K., Dehghan M., Mowlaei A., and Ghahremani Y.,2022, A genetic algorithm for Steiner tree optimization with multiple constraints using Pruffer number", *Proc. EurAsia-ICT*, pp. 272–280.

[11] Basarkod P. I. and Sunilkumar S. M, 2014, On-demand QoS and Stability Based Multicast Routing in Mobile Ad Hoc Networks, *Journal of Telecommunications & Information Technology* 2014.3.

[12] Ourabh K. & Sumit S.C. an Vijay K., 2020, A review on genetic algorithm: past, present, and future.

[13] Prabhugoud B. and Sunil M., 2014, On-demand QoS and stability-based multicast routing in mobile ad hoc networks.

[14] GATETE, M. & Vetrivelan, N., 2015, Evaluating the effects of the energy management's issues on the MANET's performance using two native routing protocols against a power-aware routing protocol, *International Journal of Computer Science Trends and Technology (IJCST)*, Vol. 3, Issue 5..

[15] Qi, Y., & Kobayashi, H., 2013, On Relation Among Time Delay and Signal Strength Based Geolocation Methods. I*n Proceedings of IEEE Global Telecommunications Conference 2003, GLOBECOM'03*, pp. 4079-4083.

[16] P. Badalló D. T., Marín L., Mayugo J.A., 2013, A comparative study of genetic algorithms for the multi-objective optimization of composite stringers under compression loads, *Composites Part B: Engineering*, Vol. 47, pp. 130-136.

