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Adaptive Routing in MANETs Using Neural Networks for Real-Time QoS Enhancement

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Abstract-- **In Mobile Ad Hoc Networks (MANETs), routing protocols are crucial in ensuring Quality of Service (QoS) and improving network efficiency. Selecting the optimal routing protocol and settings for specific network circumstances, such as mobility and density, significantly influences MANET behavior. This paper presents the proposed methodology for simulating MANET networks to enhance routing efficiency. The research contributes in two phases: in the first phase, MANET for vehicles using the Ad Hoc On-Demand Distance Vector (AODV) routing protocol with RREQ is validated and evaluated based on throughputs and network lifespan. In the second phase, a MANET is simulated for vehicle networks. Multiple routes are provided for each packet delivery, and machine learning is employed to select the best and safest route. Packet Delivery Ratio (PDR) is assessed through simulations across various network topologies. The utilization of a Multi-Layer Perceptron (MLP) neural network yields higher PDR.**

Keywords-- **Quality of Service (QoS), Deep Learning, Routing, Mobile Ad hoc Networks (MANETs), Lifetime maximization, Packet Delivery Ratio (PDR).**

I. INTRODUCTION

1.1. Overview

Multiple mobile gadgets are used to build Mobile Ad hoc Networks (MANETs), interconnected through wireless communication, forming a decentralized network without a central controller. These mobile nodes within MANETs possess routing capabilities, ensuring efficient network operations within the dynamic network topology. An inherent challenge in MANETs [1]–[3] arises from the limited battery life of the devices. As device batteries deplete, connections may break, significantly affecting network stability. Consequently, strategies to conserve energy and maintain network connectivity become imperative [4]–[6]. The military is just one field where MANETs have proven useful, in emergency rescue missions, education, environmental sensing, gaming, and personal area networking. In military operations, where fixed infrastructures are infeasible, MANETs are crucial because they provide constant, instantaneous communication in harsh, shifting environments.

Similarly, during emergency rescue operations, where traditional communication infrastructure may fail due to natural disasters, MANETs prove invaluable in swiftly restoring connectivity.

Figure 1. MANET

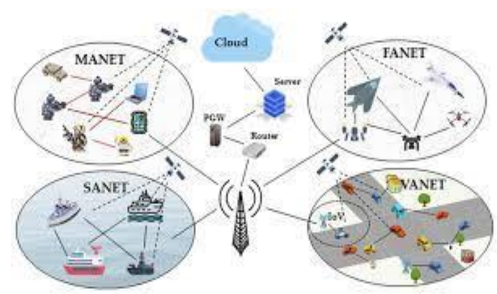

Figure 2. Classification of MANET

Hence, MANETs are divided into several categories, including for smart cars the Vehicular Ad hoc Networks (VANETs), for smart cities the Internet of Vehicles (IoV), for Unmanned Aerial Vehicle (UAV) communicationthe Flying Ad hoc Networks (FANETs), and Autonomous Underwater Vehicles (AUVs), vessels, and boats the Sea Ad hoc Network (SANET) [1].

Data transmission between nodes is made possible by routing, which is one of the most significant issues with networks. Research is now shifting its attention to routing following the discovery of MANET. For a wide range of dynamic network topologies, a variety of MANET routing protocols have been created to provide accurate, fast, dependable, scalable, stable, equitable, robust, and energy-efficient routing.

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These protocols need to handle the common drawbacks of reconfigurable network topologies, which include high error rates, low bandwidth, and high power consumption. Numerous routing systems have been proposed up to this point for mobile ad hoc networks. Effective routing protocols are required to build a communication path between nodes. In MANETs, a variety of routing protocols are currently available.

1.2. Objectives and Contributions

- The primary contribution of this research is to ensure Quality of Service (QoS) and enhance network efficiency for future MANETs. The main objective is to evaluate QoS parameters like Packet Delivery Ratio (PDR) and total network energy considering high network density.
- The number of nodes is increased, and as a worst-case scenario, the velocity is also heightened to evaluate performance in such conditions. Furthermore, assessing throughput and the lifespan of the MANET for various packet sizes is proposed.
- Additionally, different packet densities are considered for QoS evaluation, where an increase in the number of packets is implemented, and PDR is evaluated.
- This research involves emulating a vehicular MANET network by offering multiple paths for each packet delivery, utilizing machine learning to select the optimal and safest route.
- Various simulations with diverse network topologies are conducted to assess PDR. The application of a Multi-Layer Perceptron (MLP) neural network results in higher PDR

1.3. Organization of the paper

The paper's organization is as follows: Section 2 discusses the related work. Section 3 discusses the proposed routing algorithm. Section 4 includes result analysis and discussion, and section 5 concludes the proposed work.

II. Related Work

Based on their operation, Some MANET routing systems are proactive (table-driven), while others are reactive (on-demand), and still others are a hybrid of the two. Proactive protocols maintain up-to-date routing information on all network nodes by periodically exchanging control messages. This makes the route instantly available when needed. It keeps track of the most recent path information to every destination in a routing database (DSDV).

Routes are changed regularly or in response to changes. Optimized Link State Routing (OLSR) pre-computes routes depending on the current network topology as a preventive strategy [1,8].Reactive protocols minimize the number of control messages transmitted and improve the network's ability to adapt to changing circumstances by only creating routes when necessary. A node must determine a path to reach a given location when it needs to communicate with it. For example, the acronym AODV (Ad hoc On-Demand Distance Vector) only establishes and maintains a route as long as it is necessary. It makes use of methods for route discovery and upkeep [7].

On the other hand, Dynamic source routing (DSR) is a form of routing in which the complete path is encoded in the packet header (thus the name "source routing") and routes are determined on demand. These hybrid methods combine the best features of proactive and reactive approaches. Using the Zone Routing Protocol (ZRP), the network is divided into several sections. Within each sector, a proactive protocol is implemented, while a reactive strategy is used between them. On the other hand, ToRA stands for Temporally Ordered Routing Algorithm: Uses a reactive approach for route discovery but may use proactive techniques for route maintenance [8].

The Optimized Link State Routing Protocol (OLSR) was created for use in MANETs, but it can be implemented in other kinds of wireless ad hoc networks as well. To relay information about the state of a connection, OLSR uses messages like hello and topological control (TC), enabling each node to determine an effective path to the next hop destinations.

Artificial neural networks, or ANNs, are sophisticated models with numerous configuration options fine-tuned for specific regression or classification tasks. Configuring these settings involves a laborious learning process and multiple trial-and-error assessments. The feed-forward ANN (FFANN) sometimes referred to simply as a multi-layer perceptron (MLP), is the ANN model used for our data. It consists primarily of three layers: the input layer, the hidden layer, and the output layer. This approach draws an analogy from natural brain networks, where approximations are performed by layering neurons, the building blocks.

When applied to Mobile AdHoc Networks (MANETs) [9], deep learning intelligently optimizes resource allocation and routing decisions, vastly improving both

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performance and Quality of Service (QoS). Utilizing neural networks, the system analyzes network traffic, device mobility, and link quality to forecast the most efficient routes, reducing delays and packet loss.

Additionally, deep learning algorithms optimize routing considering energy constraints, effectively extending device battery life while maintaining network connectivity. This dynamic resource allocation based on QoS requirements vastly improves network efficiency, reliability, and overall user experience in MANETs [9].

Moreover, energy-aware QoS-based routing methods are critical for real-time applications in MANETs, addressing challenges by prioritizing QoS, minimizing power consumption, and optimizing node longevity. Employing Deep Learning-based Lifetime Maximization with artificial neural networks offers superior routing decisions adaptable to evolving network conditions. Conducting real-time trials in a MANET scenario using SUMO in the specific context of Gwalior-area networking further validates the proposed approach. Comparative analysis of two widely used routing protocols, AODV and OLSR, deepens the understanding of their respective advantages and limitations. The outcomes of this research hold promise for enhancing MANETs across various applications like mobile communications, disaster relief, and military networks.

The workhas been developed to facilitate routing in networks [10]. Proactive protocols, reactive protocols, and hybrid protocols are the three main types of protocols. This work has explored the CART method, a classification technique from machine learning that predicts the pattern or the choice a node acting as an individual rational entity would make.

The work has been employed in the ongoing effort to enhance the network's capacity for data handling and efficiency in energy consumption [11]. DRC design's primary goals are cluster head selection and maintaining cluster stability. To ensure effective, non-congested data sharing, LR chooses distinctive neighbors. To improve the network's performance when dealing with differential network traffic, the two incompatible approaches have been combined. The suggested method is evaluated using simulations and compares results to measure output.

The author of the paper has severe computing, communication, memory, and energy resource limitations. These two traits cause selfish nodes to exist in MANETs [12]. This has several adverse implications for the efficiency of the network. Here, the authors have performed a quantitative study of how energy scarcity-induced node selfishness impacts the packet loss rate, round-trip duration, and overall throughput of MANETs.

In this work, the authors described the difficulties in managing time-slotted TDMA-based MANETs with varying traffic loads while trying to keep routing delays to a minimum [13]. To reduce the overall weighted end-to-end packet latency, weights are modified based on the priority of the requests, which recognizes the challenges of TDMA power regulation and request scheduling. In addition, this work presents a deep-learning-based delay-minimization network, which is far more effective than other state-of-the-art methods. Using scheduling and power control, this method is one of the first to deal with delay mitigation from beginning to end.

Using lengthy short-term memory, this model predicts how efficient a device will be at finding and fixing defects. Utilizing insights gathered from the uncertainty detection job, the model attempts to provide an uncertainty-free estimate of the petrochemical process's fuel efficiency [14]. To deal with the issue of weight initialization, the transfer method employs a procedure known as partial layer freezing, which is carried out before the extra model component is calibrated.

The effectiveness of the proposed method is assessed across a wide variety of fault variations to precisely establish the maximum contribution of defects that the model can handle. On the 10% and 20% fault variation datasets, TFDI-EEP performed better than other conventional approaches in terms of r-squared and testing errors, according to the evidence. The occurrence of outliers and the potential of the proposed system to identify strong fault-correlated features, as well as to enhance monitoring capabilities and increase the model's resilience & dependability, are further proved by the identification of links between domains. This transfer parameter raises prediction performance based on detection accuracy by 9.86% with just 40% testing fault variance.

III. Proposed Routing Algorithm

3.1. Parametric Initialization

For experimentation purposes, the simulation of MANET routing is conducted to evaluate performance improvements under varying dense node densities and vehicle velocities. The optimal simulation parameters are outlined in Table 1.

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Table 1:
Simulation parameters used for MANET Routing

Parameter	Description	Range
M	Nodes used for modeling Network	[50, 75, and 100]
V	Velocity of mobile nodes	19 m/s
D	Directions	[1=North, 2=South, 3= East, 4= West]
S	Source node in the network	S=1
D	Destination node in the network	d=50
R	Range of the nodes	R=250 m
NP	Number of packets	NP=[200, 300, 400]

3.2. Performance Metrics

The packet-delivery ratio (PDR), end-to-end delay (E2ED), and network throughput are measurement parameters used in the AFB-GPSR protocol's performance evaluation procedure [15, 16] and for comparative analysis [17, 18].

1. *PDR:* The percentage of successfully received packets by the destination to the total number of packets provided by the source referred to here [19];

   $PDR = (successfullyreceivedpackets)/(deliveredpackets)$ ....(1)

2. *E2ED:* The time a packet takes to travel from its initial location to the destination and be successfully received is this;

   $E2ED = PacketReceivedtime - PacketDeliveredTime$ ....(2)

3. *Throughput (bps):* The correctly received bits by the recipient over a predetermined amount of time is how this is expressed. The total number of beacon packets transmitted is included in the control overhead for the GPSR routing protocol [20] [21].

   $Throughput = (TotalReceivedBits)/(SimulationTime)$.........(3)

4. *MAE:* The mean absolute error (MAE) is employed to estimate the best possible solution. The point or epoch, at which the MAE is minimum, is considered as the optimal solution for the gradient problem.

3.3. Proposed System

The proposed system diagram is shown in Figure 3. The blocks and steps incorporated for the VANET simulation are presented in this figure.

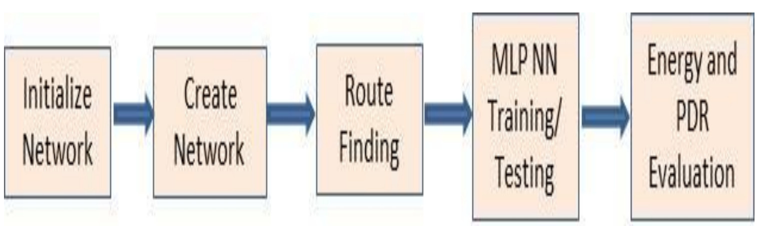

Figure 3. Proposed MANET Simulations for Vehicles Network

The basic routing performance is assessed using the MLP neural network with a feed-forward network as shown in Figure 4.

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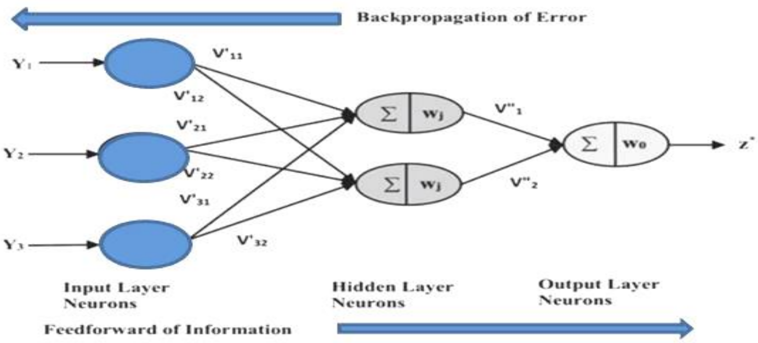


Figure 4 Feed Forward Back Propagation Neural Network

The respective number of hidden layers is set to 12, increased from the earlier 10, as depicted in the architecture diagram in Figure 5. The figure illustrates a neural network's training diagram that takes into consideration the various lighting conditions under which the network was constructed.

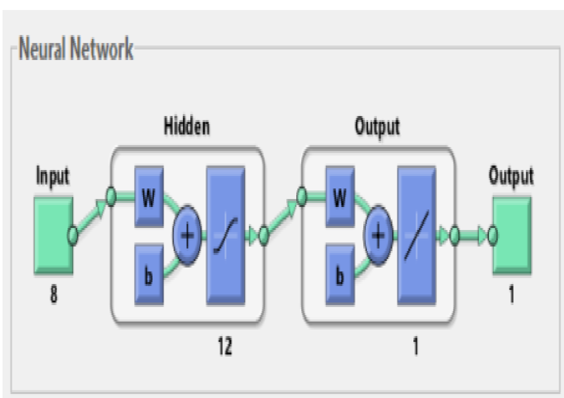


Figure 5. The architecture of the MLP Neural network

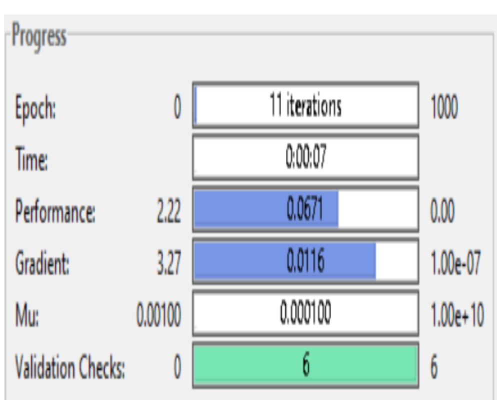


Figure 6. Network Training Progress Layout for Proposed NN Simulation

3.4. Proposed Methodology

In the proposed research, the prime focus is on evaluating the performance of PDR and time concerning the number of nodes, considering a higher mobility ratio in MANET using MLP and NN, as depicted in Figure 6. The analysis incorporates RREQ messaging. The performance will be assessed for highly dense MANETs, and NN parameter selection optimization cases, different MLP architectures may be considered as one objective for evaluation.

It is proposed to evaluate the expected outcome of this work, aiming to develop efficient routing schemes that satisfy multiple metrics to achieve reduced delay and increased network lifetime. The routing protocols have been designed to find optimal paths by considering multiple metrics using deep learning, restricting the rebroadcasting of RREQ packets while considering energy and neighbor coverage, and balancing the load across multiple paths. The training progress of the NN is depicted in Figure 6, indicating that the proposed method undergoes six validation checks, hence demonstrating efficiency.

3.5. Flow Chart of Proposed MENET

The systematic step vise flow chart of the proposed MLP-based NN methodology is presented in Figure 7.

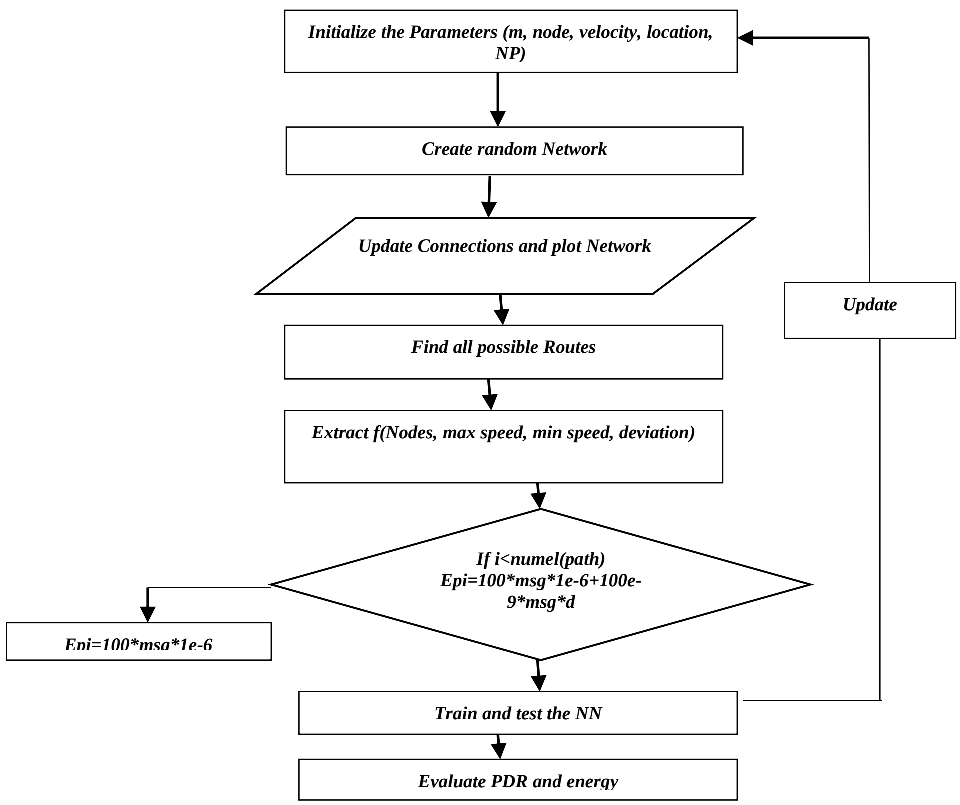


Figure 7. Flow Chart of the Proposed MANET Designs

The MLP-based NN is utilized, and the Levenberg-Marquardt (LM) based NN is trained with data unaffected by outside influences to enhance performance. Especially when the solution is close, the LM algorithm can converge more rapidly than conventional gradient descent techniques, offering a good trade-off between the stability of gradient descent and the speed of the Gauss-Newton method. The optimal routing is attained through NN-based training and testing. The ultimate aim is to achieve the highest possible accuracy.

IV. Results And Discussions

This section presents the results and evaluation of the MANET routing and PDR performance.

The results of the feed-forward neural network, a part of the MLP, are assessed for training and testing the network routes. The initial phase of the research aims to design and evaluate the AODV-based routing using the RREQ messaging concept for the routing fading algorithm. In the subsequent phase, the outcomes of the MLP-based training for PDR optimization are presented.

4.1. Results of VANET Routing

The initial experiment validates the MANET routing using 50 nodes, with s=1 and destination node d=50. The routing table has been generated in every iteration, as depicted in Figure 8. The numbers of nodes, as well as the source and destination locations, are varied in the Figure 8 user interface for evaluation.

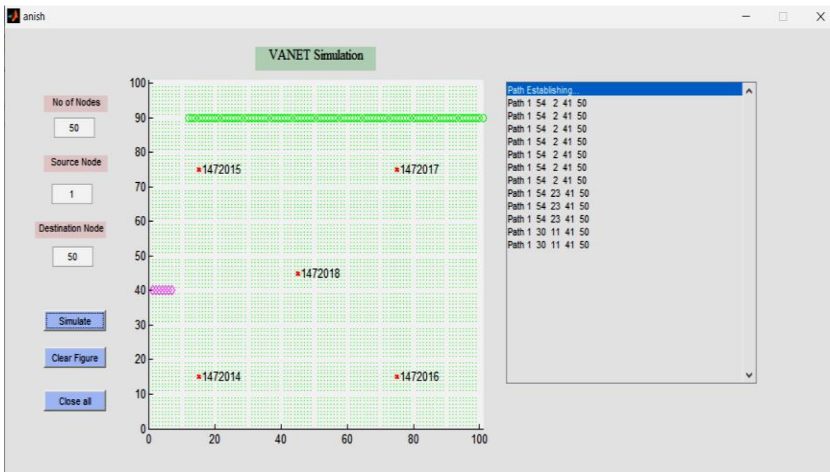


Figure 8.Snapshot of the Experiment for GUI-BasedMANET Routing

Experiment 1: Determining the Throughput and Life of Network

Experimenting, the AODV based on RREQ routing is validated using 50 nodes, with varying packet sizes to evaluate throughput and network lifespan. The results of throughput for different packet sizes are depicted in figure 6.2, where the network is randomly formed. From Figure 6.2, it can be concluded that as the packet size increases, the overall system throughput also increases. The packet rates used were [4, 6, 8, 10, 12, and 14]. Notably, for a packet rate of 14, the maximum throughput of 6.78 x 10-4 is observed on the 1st path. As a result, for further evaluation in the next section, the packet rate is set to 14 packets per second.

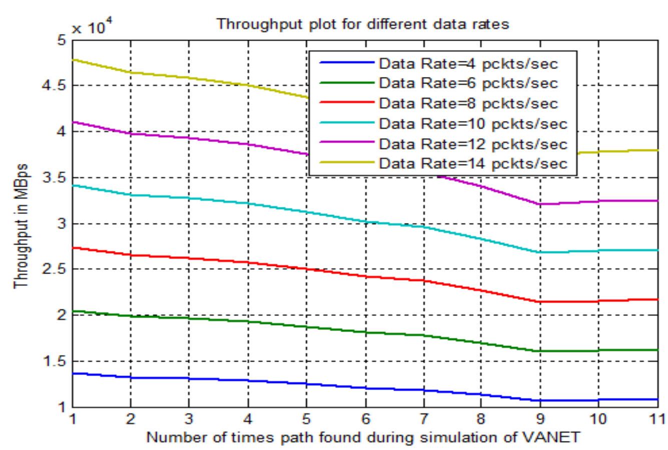
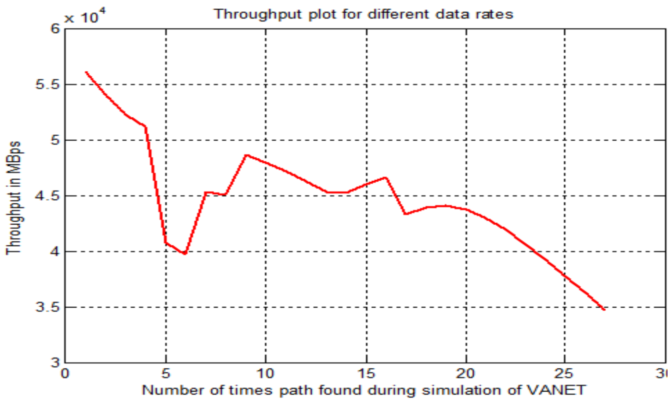


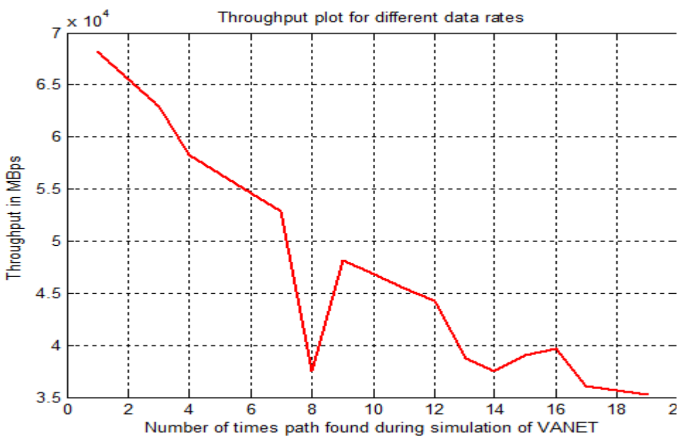
Figure 9.Result Evaluation of Throughput for Random MANET with 50 Nodes in the Network

Experiment 2: Evaluation of Dense Network

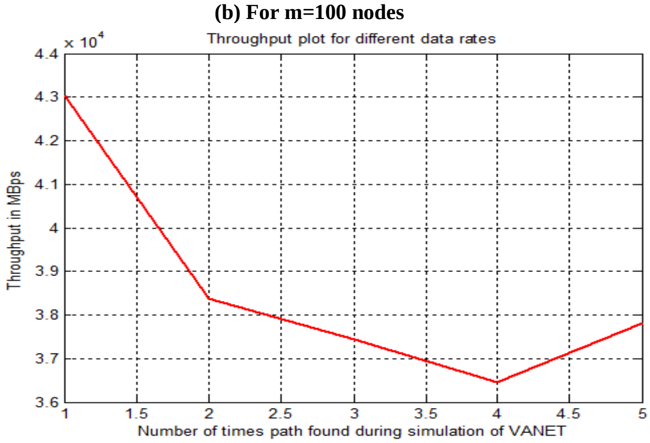
The node density is increased, and the network throughput is evaluated across different node densities. The throughput results are depicted in Figure 10.



(a) For m=50 nodes



(b) For m=100 nodes



(c) For m=150 nodes

Figure 10. Results of the evaluated throughput for different dense networks plotted for a packet rate of 14 pct/sec

Experiment 3: MLP based NN Training Results

The network is trained and tested for optimum routing, and the final connected routes are displayed as a mesh network in Figure 11. All nodes in the **800x800 m** area are mesh-connected. This specific example involves 50 nodes for representation. The use of MLP efficiently discovers paths for all possible routes. The overlapping paths are depicted in Figure 6.4 after testing the MANET network. The source node is 1, and the destination node is 50.

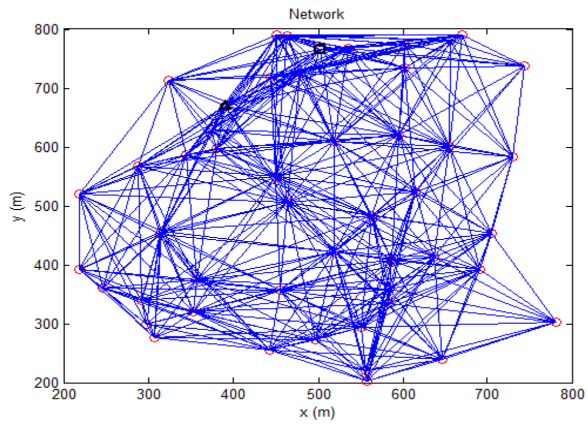


Figure 11. Example of MANETHaving 50 Nodes & Routes Selection after Testing

4.2. Training the NN

In this section, the multi-layer perceptron (MLP) feed-forward NN is utilized to evaluate the PDR. The mean absolute error (MAE) is employed to estimate the best possible solution.

The point or epoch, at which the MAE is minimum, is considered as the optimal solution for the gradient problem [22]. Figure 12 illustrates the results of the Mean Absolute Error (MAE) estimation and the corresponding best possible solution. The minimum MAE error is achieved at the 6th epoch, approximately at the order of 10, as indicated within the circle. There's a 100-fold improvement in the MAE as shown in this figure.

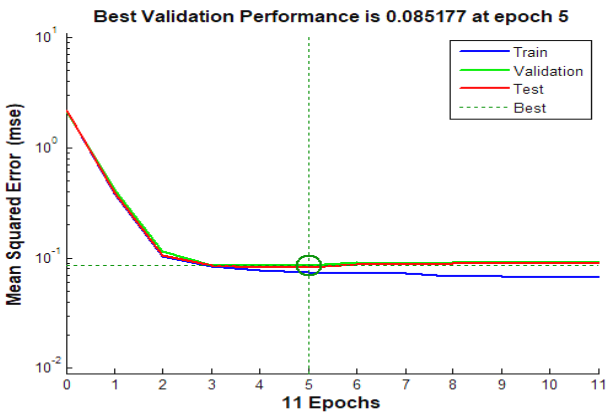


Figure 12. Results of the Estimate of Mean Absolute Error (MAE) and the Best Possible Solution Respectively

The respective training phase variables for epochs are depicted in Figure 13 for the case of 100 nodes. The effectiveness of the proposed training results is evident from the histogram of the error plotted across 20 bins, as shown in Figure 14.

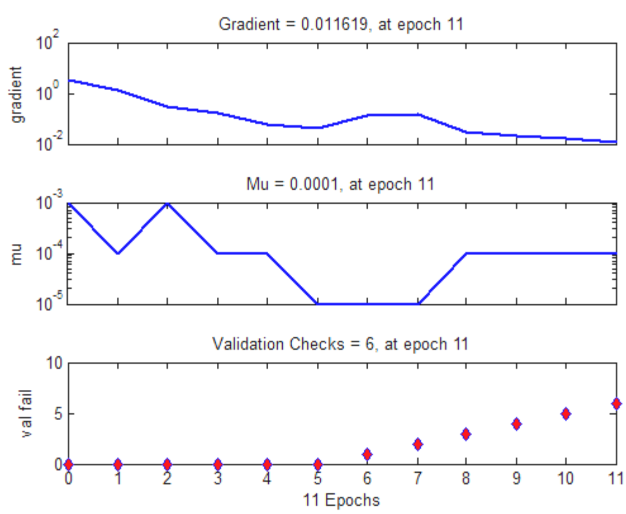


Figure 13. Training phase variable for epochs

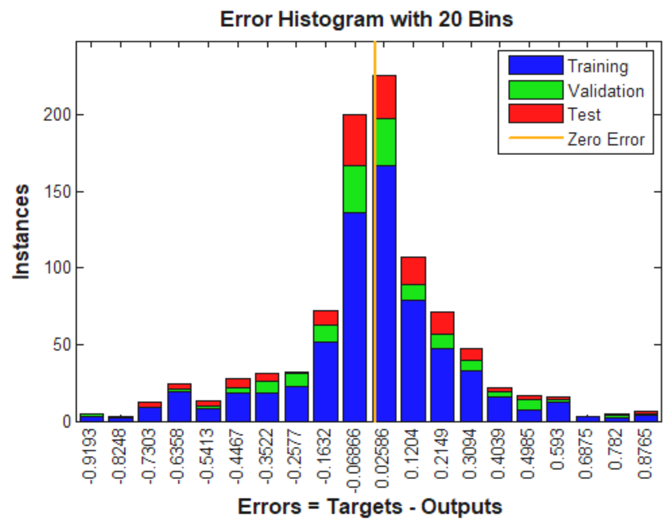


Figure 14. Results for the NP=300 packets for the testing and training phase.

Experiment 4: Energy and PDR Evaluation Results

This section presents the experimental results of node energy and the estimation of the total packet delivery rate (PDR) calculation.

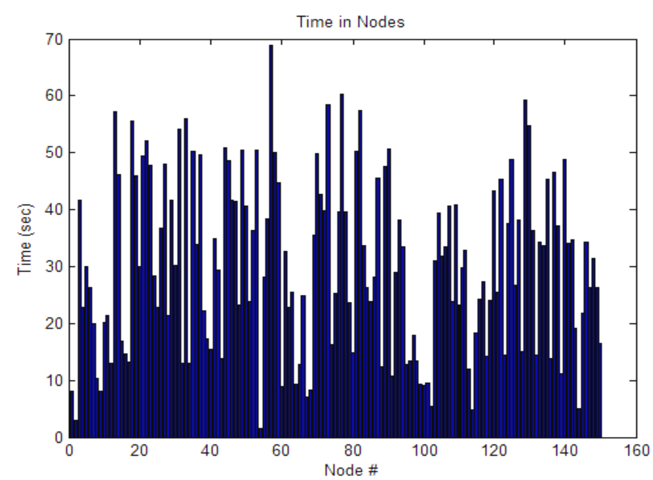


Figure 15. Results of time taken for 150 nodes and NP=300 packets for the training phase

The results of the time taken for 150 nodes and NP=300 packets during the testing and training phases are displayed in Figure 15. The results of the Node Energy for 100 nodes and NP=300 packets during the testing and training phases are displayed in Figure 16 as a bar plot.

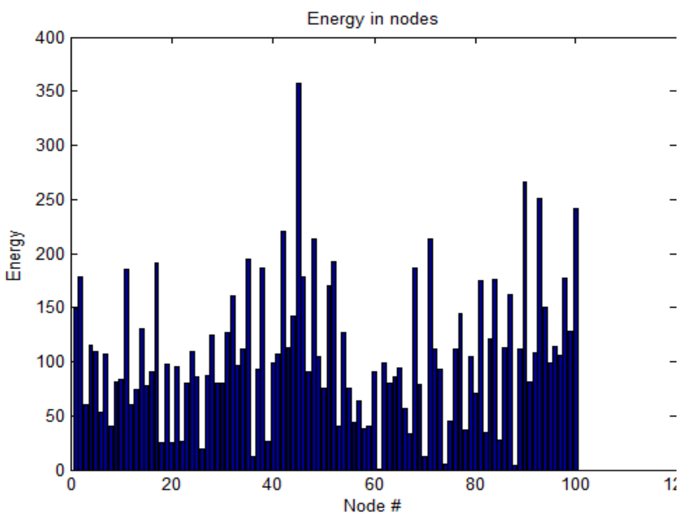


Figure 16. Results of the Node Energy for 100 nodes and NP=300 packets for testing and training phase.

The energy levels notably vary based on the proximity of nodes to the destination node. Figure 17 shows the comparison of the energy of the proposed dense MANET having 100 and 150 nodes. From the figure, it is clear that energy consumption is more in the case of m=150 in comparison to m=100 when the value of NP=300 is fixed.

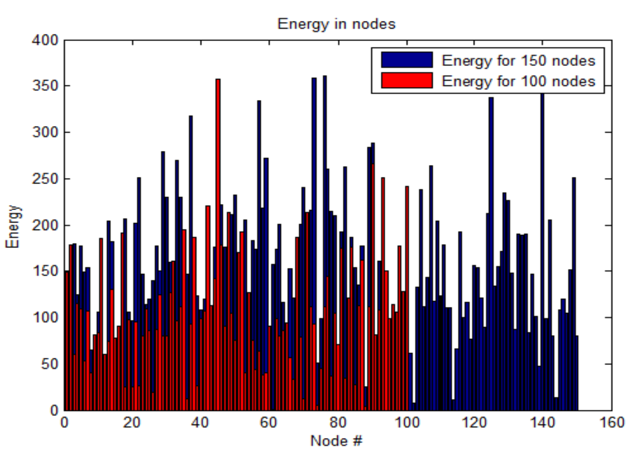


Figure 17. Comparison of the energy of proposed dense MANET having 100 and 150 nodes

Figure 18 shows the comparison of the energy of the proposed dense MANET by varying values of NP from 300 to 400 and the value of m=100. It is clear from the figure that when we increase the value of NP, energy consumption increases accordingly.

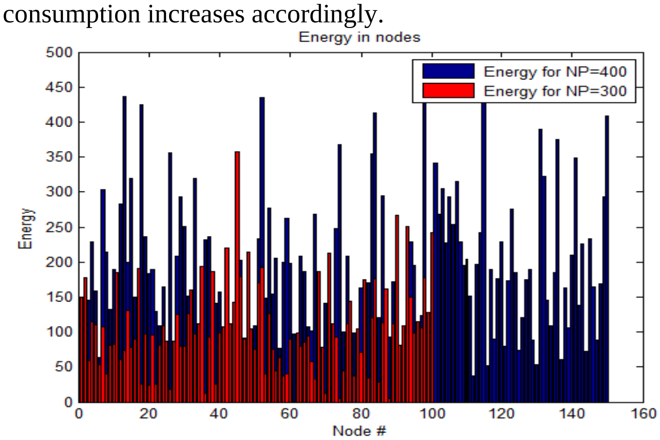


Figure 18. Comparison of the energy of proposed dense MANET having NP=400 and NP=350.

The results depicting the accuracy of the regression-based solution applied to the data for comparison among training, validation, and testing phases, along with the overall performance, are presented in Figure 19. The overall R-value, representing the accuracy of the fit, is 0.83268.

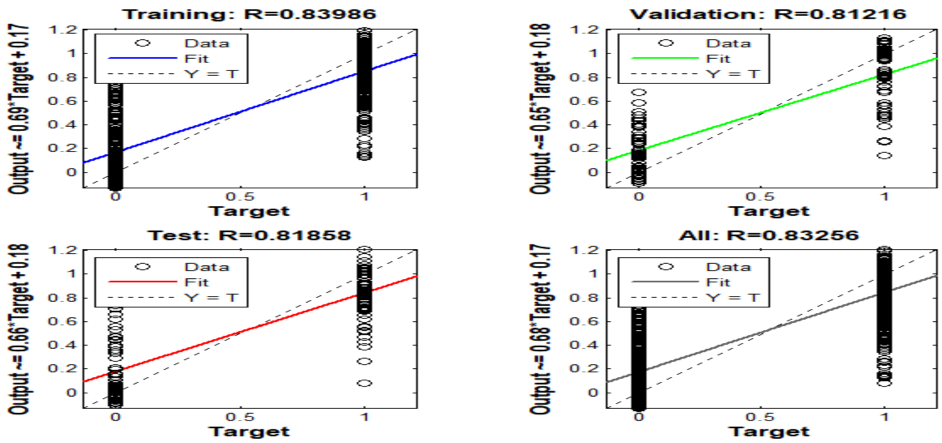


Figure 19.Accuracy of the regression-based solution applied over the data for comparison of training, validation, testing, and overall performance.

The comparisons between the existing and proposed dense MANET systems using MLP are shown in Table 2 and in the corresponding bar chart shown in Figure 20.

From the comparison, it is clear that increasing node density may lead to higher energy consumption.

Table 2.
Comparison of the total energy consumption for different NP sizes

NP	Energy (m=100)	Energy (m=150)
300	1.05 X 10^3	2.20 X 10^3

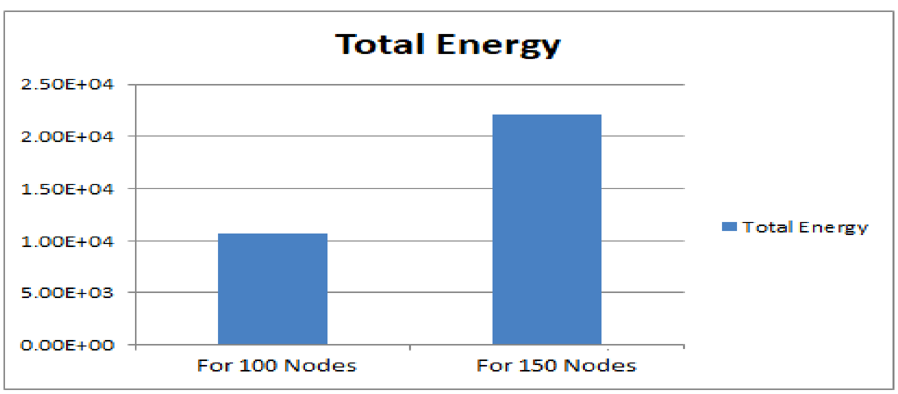


Figure 20. Comparison of the total energy consumption for the proposed MANET architecture for NP=300

The effect of NP on the PDR is given in Table 3. The experimental results of the PDR for dense and normal MANET networks are displayed in Figure 21.

It is concluded that utilizing a dense MANET may yield improvements in the PDR by employing MLP-based NN.

Table 3.
Comparison of the PDR for different NP sizes

NP	PDR (m=100)	PDR (m=150)
300	83.268	93.01
400	---	82.7500

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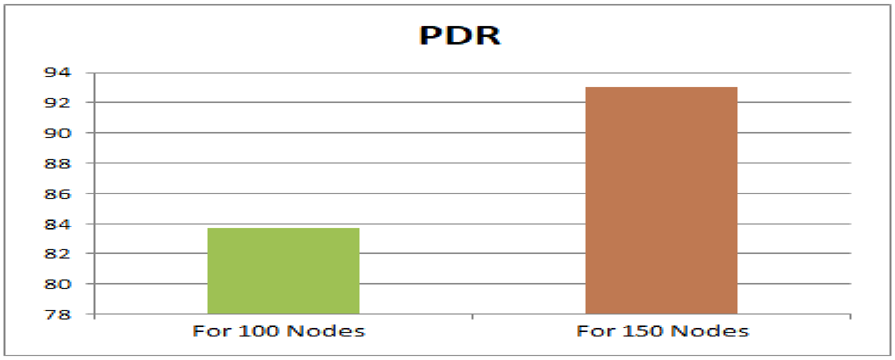

Figure 21. Comparison of PDR for the proposed MANET architecture for NP=300

MANET for vehicles using the Ad Hoc On-Demand Distance Vector (AODV) routing protocol with RREQ is validated and evaluated based on throughputs and network lifespan. Simulation of a MANET for vehicle networks is done in the second phase. Machine learning is employed to select the best and safest route for each packet delivery. Simulations are used to assess the Packet Delivery Ratio (PDR) across different network topologies. The result shows that higher PDR can be achieved by using a Multi-Layer Perceptron (MLP) neural network.

V. CONCLUSION

Ensuring Quality of Service (QoS) and improving network efficiency for future MANETs is the main objective of this research in light of high network density, such as packet delivery ratio (PDR) and total network energy. In addition, an evaluation of the MANET's throughput and lifetime for different packet sizes is suggested. For QoS evaluation, different packet densities are considered, which involve increasing the number of packets and evaluating PDR.

The goal of this research is to emulate a vehicular MANET network by offering multiple paths for packet delivery, using machine learning to select the optimal and safest route. To assess PDR, various simulations with different network topologies are conducted. Using a Multi-Layer Perceptron (MLP) neural network leads to a higher PDR. In the proposed research, the prime focus is on evaluating the performance of PDR and time concerning the number of nodes, considering a higher mobility ratio in MANET using MLP and NN.

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