AODV-MLP: Adaptive Routing in MANETs Using Neural Networks for QoS Improvement

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Abstract: In Mobile Ad Hoc Networks (MANETs), dynamic routing is essential to maintain Quality of Service (QoS) under varying network conditions such as node density and mobility. This research presents a novel approach that integrates the Ad Hoc On-Demand Distance Vector (AODV) routing protocol with a Multi-Layer Perceptron (MLP) neural network to enhance routing performance. The methodology involves validating AODV using Route Request (RREQ) messaging to evaluate throughput and network lifetime, followed by leveraging MLP to predict optimal routes based on Packet Delivery Ratio (PDR) and node energy. Simulations are conducted across diverse network topologies to assess performance under high-mobility scenarios. The proposed MLP-based system demonstrates improved PDR and energy efficiency, highlighting its potential for real-time adaptive routing in MANET environments.
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 as shown in Figure 1. 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.

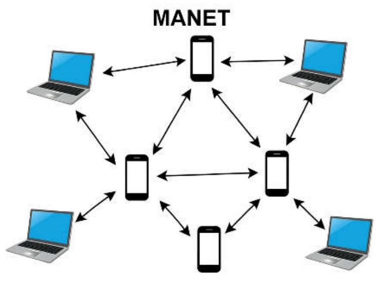


Figure 1. MANET

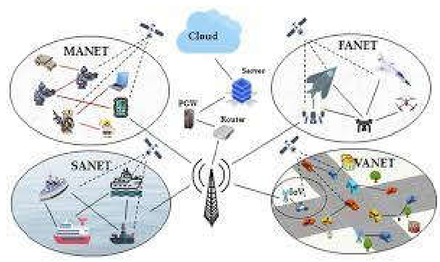


Figure 2. Classification of MANET

Hence, MANETs are divided into several categories, as in Figure 2, including for smart cars the Vehicular Ad hoc Networks (VANETs), for smart cities the Internet of Vehicles (IoV), for Unmanned Aerial Vehicle (UAV) communication the 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. 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.

Despite extensive research on routing in MANETs and VANETs, conventional AODV-based approaches struggle to maintain a high Packet Delivery Ratio (PDR) under high-mobility and dense vehicular environments. Most existing strategies lack adaptability and fail to integrate predictive intelligence for real-time routing. Explicit application of Multi-Layer Perceptron (MLP) models to predict and improve PDR in vehicular contexts is limited. This work addresses this gap by proposing an AODV-MLP framework that integrates machine learning with mobility-aware routing to enhance PDR, reduce delay, and ensure scalability in dense VANET scenarios.

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 the 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.

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. MLP was selected for its ability to model nonlinear relationships between mobility patterns and routing metrics with relatively low training complexity, making it suitable for lightweight MANET environments

When applied to Mobile AdHoc Networks (MANETs) [9], deep learning intelligently optimizes resource allocation and routing decisions, vastly improving both 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 [21].

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 work has 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.

Recent work has further improved AODV with various enhancements. Kumar et al. (2025) introduced an FPGA-based clustered version of AODV to improve routing efficiency, reduce control overhead, and enhance throughput in large-scale MANETs [23]. Arebi (2024) proposed a multi-objective mechanism to predict broken links and reserve alternate paths, significantly reducing disruptions in AODV routing [24].

Energy-aware enhancements have also been explored: AODV-EOCW (2023) weights link hop count, congestion, and energy to select routes more judiciously, improving network lifetime [28]. In a different context, Ghori et al. (2024) applied multipath optimizations for AODV in BLE mesh networks to improve stability under dynamic conditions [25].

Density-based improvements are also emerging: CND-AODV (2024) uses neighbor node density to reduce routing overhead and improve performance in dense networks [27]. Additionally, trust-based routing against attacks has been addressed by embedding trust in AODV to guard against black-hole behavior [26].
For high-mobility or speed-critical scenarios, AODV-PP (2024) utilizes cross-layer metrics (energy, stability, and buffer congestion) to enhance routing stability [29]. Additionally, the Combined Routing Protocol (CRP, 2025) combines AODV and GPSR to reduce route building time and hop count, thereby catering to latency-sensitive applications [30]. A summary of recent studies done in this field is shown in Table 1.

Table 1. Summary of recent studies done in this field

S.No	Title	Authors / Year	Key Contribution
1.	Enhanced AODV routing analysis for mobile Ad Hoc networks	Kumar, A.; Kumar, A. & Agrawal, A.V. (2025)	Proposes a hardware-accelerated clustered version of AODV using an FPGA, aiming to reduce delay and overhead in large-scale MANETs.
2.	Improving the AODV routing protocol using a multi-objective mechanism based on repairing broken links on the MANET networks	Peyman Arebi (2024)	Predicts link breaks and reserves alternate paths to reduce route disruption, improving performance over classic AODV.
3.	AODV-EOCW: An Energy-Optimized Combined Weighting AODV Protocol for Mobile Ad Hoc Networks	(2023)	Introduces combined weighting of energy, congestion, and hop count (via AHP + EWM) for route link selection to improve lifetime and reduce delay.
4.	Enhancing Reliability and Stability of BLE Mesh Networks: A Multipath Optimized AODV Approach	Ghori et al. (2024)	Applies multipath-based enhancements to AODV in BLE mesh networks for better stability and reliability under high network changes.
5.	Routing Selection Algorithm for Mobile Ad Hoc Networks Based on Neighbor Node Density (CND-AODV)	(2024)	Proposes CND-AODV, which uses neighbor density information to reduce overhead in route discovery, improving throughput and latency in dense networks.
6.	A Secured MANET Using Trust-Embedded AODV for Optimised Routing Against Black-Hole Attacks	Bairwa, A.K.; Joshi, S.; Pallavi (2023)	Adds trust metrics to AODV to mitigate black-hole attacks, improving security and routing reliability.
7.	A polymorphic perception AODV routing algorithm for high-speed mobile Ad hoc network	Lei Liang et al. (2024)	Proposes AODV-PP, which uses cross-layer metrics (energy, stability, buffer congestion) to select more stable routes in high-mobility/high-speed scenarios.
8.	Combined Routing Protocol (CRP) for ad hoc networks: Combining strengths of location-based and AODV-based schemes	Sergeev et al. (2025)	Merges GPSR (geographic routing) and AODV to reduce hops and route building time, improving latency in ad hoc networks.

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

To ensure a fair comparison, the proposed AODV-MLP protocol was evaluated alongside the baseline Ad Hoc On-Demand Distance Vector (AODV) protocol under identical experimental conditions. For each simulation scenario, the same SUMO-generated mobility traces and traffic patterns were applied to both protocols. Node counts, traffic loads, and mobility speeds were systematically varied, and each configuration was executed for 30 independent runs using different random seeds to account for stochastic variability. Performance metrics including Packet Delivery Ratio (PDR), throughput, end-to-end delay, routing overhead, and energy consumption, were computed from the per-packet logs of each run. The paired design ensured that AODV and AODV-MLP were tested on the same mobility and traffic inputs for every seed, allowing direct run-by-run comparison. Statistical analysis was carried out using paired significance tests: a paired *t*-test was applied when normality assumptions were satisfied, and otherwise the non-parametric Wilcoxon signed-rank test was used. For each metric, mean values, standard deviations, and 95% confidence intervals were reported.
The simulations were conducted using MATLAB R2021a along with the Communication Toolbox for routing parameter evaluation. The Simulation of Urban Mobility (SUMO, version 1.10.0) was used for vehicular traffic modeling, employing the Krauss car-following model and random waypoint mobility for comparison. SUMO

traces were integrated with MATLAB through TraCI interfaces. Experiments were run on a system with Intel i7 processor, 16 GB RAM, and Windows 10 environment. Simulation duration varied between 500–1200 seconds depending on network density.

3.1. Parametric Initialization

Simulations were carried out using MATLAB R2021a with custom MLP training scripts. SUMO was used for vehicle mobility modeling, and network parameters were mapped using MATLAB's communication toolbox. 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 2.

Table 2: 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]

The network topologies presented in Table 3 were selected to ensure a comprehensive evaluation of the proposed AODV-MLP framework under varying conditions of node density, mobility, and traffic patterns. The Grid topology offers a structured layout to test baseline routing efficiency in uniform environments. The Random Waypoint topology introduces unpredictable movement and distribution, reflecting highly dynamic MANET scenarios. The Highway VANET topology models linear mobility, which is typical of vehicles traveling on highways with relatively higher speeds. Meanwhile, the Urban VANET topology captures intersection-based movement with frequent stops, turns, and moderate speeds, resembling real-world city environments. By considering these diverse topologies, the study demonstrates the adaptability and robustness of the proposed model across controlled, random, and realistic vehicular network conditions.

Table 3: Network Topologies Considered for Simulation

Topology Type	Description	Node Range	Speed (m/s)
Grid Topology	Nodes arranged in grid pattern	50–150	5–15
Random Waypoint	Random node distribution	50–150	5–20
Highway VANET	Linear movement (urban highway)	75–200	15–30
Urban VANET	Intersection-based urban scenario	100–200	10–25

These topologies were selected to test scalability, delay, and reliability under varying mobility and density conditions.

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];
   $PDR = (successfully\ received\ packets)/(delivered\ packets)$ ………(1)
2. **E2ED:** The time a packet takes to travel from its initial location to the destination and be successfully received is this;
   $E2ED = Packet\ Received\ time - Packet\ Delivered\ Time$ ……..(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 199.
   $Throughput = (Total\ Received\ Bits)/(Simulation\ Time)$………(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 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.

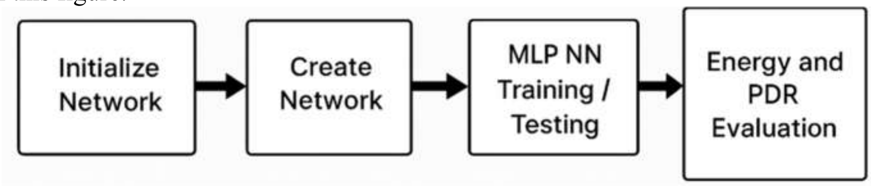


Figure 3. Proposed MANET Simulations for Vehicle Networks

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

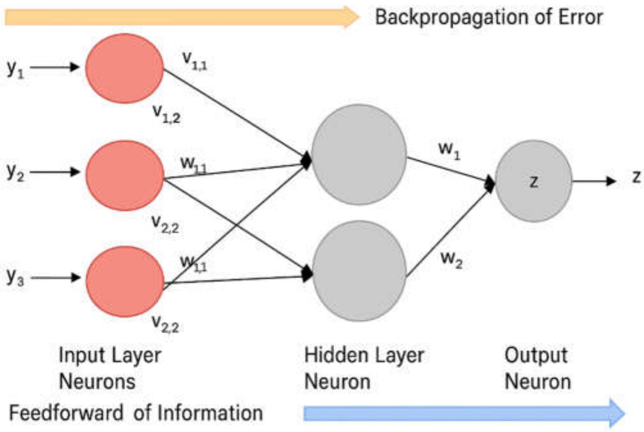


Figure 4 Feed Forward Back Propagation Neural Network

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.

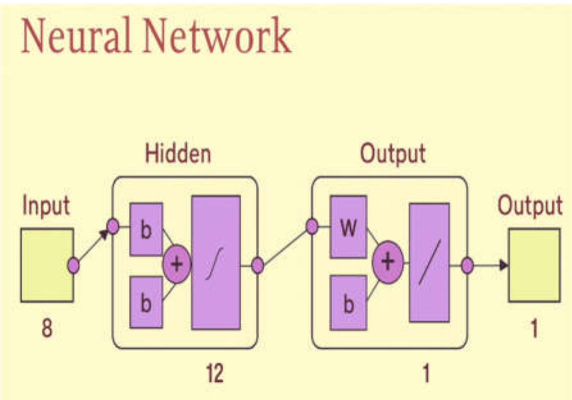


Figure 5. The architecture of the MLP Neural

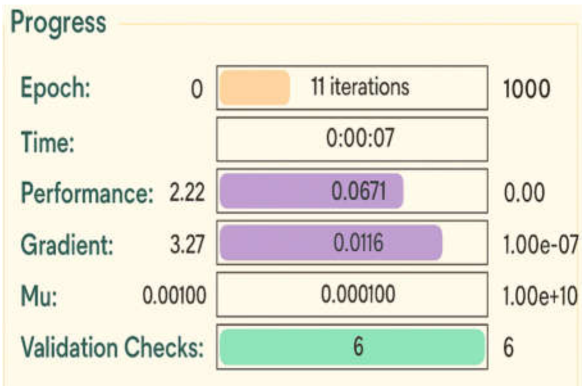


Figure 6. Network Training Progress Layout for Proposed NN Simulation

3.4. Proposed Methodology

The proposed MLP model used 12 hidden layers, Epochs of 11 iterations, ReLU activation, a learning rate of 0.01, and the Levenberg–Marquardt optimizer. Hyperparameters were tuned using grid search, with MAE as the selection metric. In the proposed work, 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, and 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 MANET

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

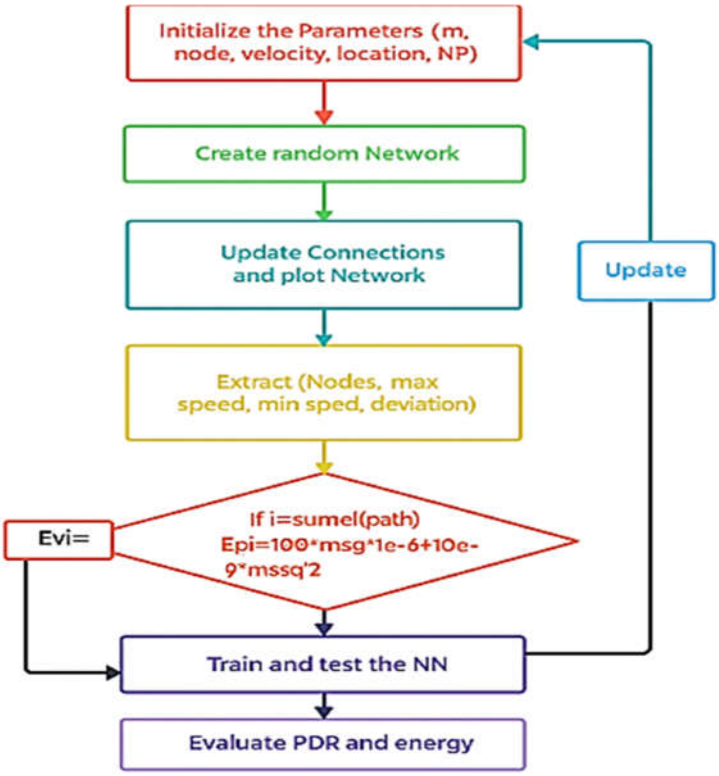


Figure 7. Flow Chart of the Proposed MANET Designs

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

Figures and tables present the comparative performance of AODV-MLP and baseline AODV across all metrics. Each point in the plots represents the mean of 30 independent runs, with error bars indicating 95% confidence intervals. The paired design enabled statistical testing of differences between the two protocols. Significant improvements ($p < 0.05$, Wilcoxon signed-rank test) are highlighted in the figures. Results consistently demonstrate that AODV-MLP improves Packet Delivery Ratio and throughput while reducing end-to-end delay, with moderate increases in control overhead. These findings confirm that the integration of the MLP module provides measurable performance gains over conventional AODV under dense network conditions.

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.

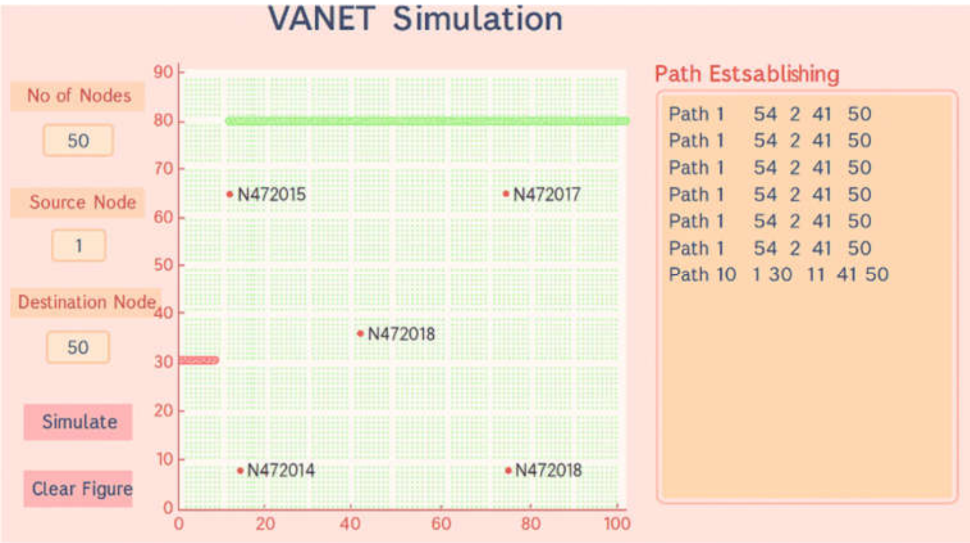


Figure 8. Snapshot of the Experiment for GUI-Based MANET Routing

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.

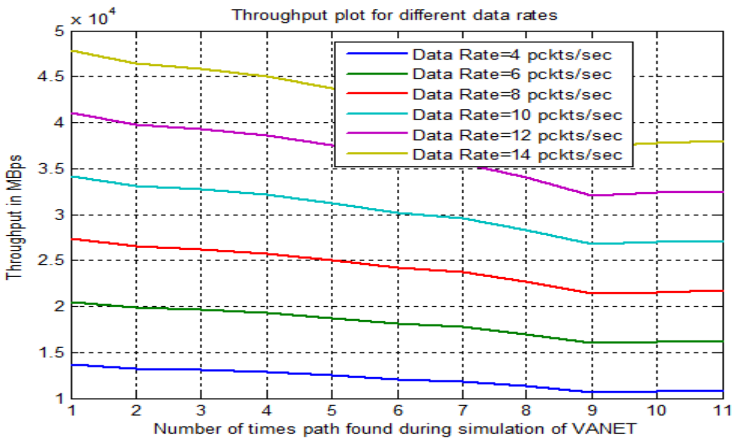
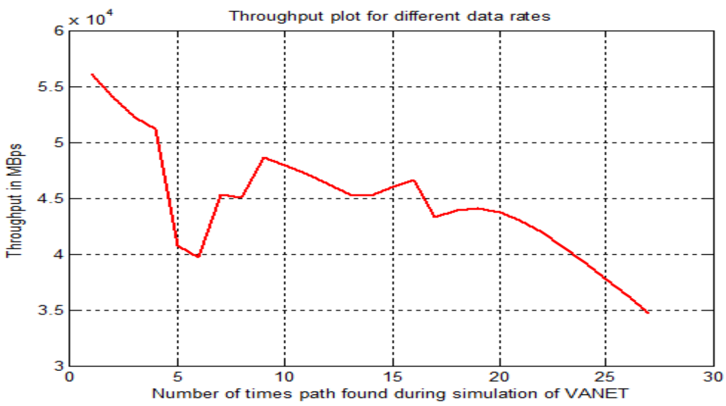


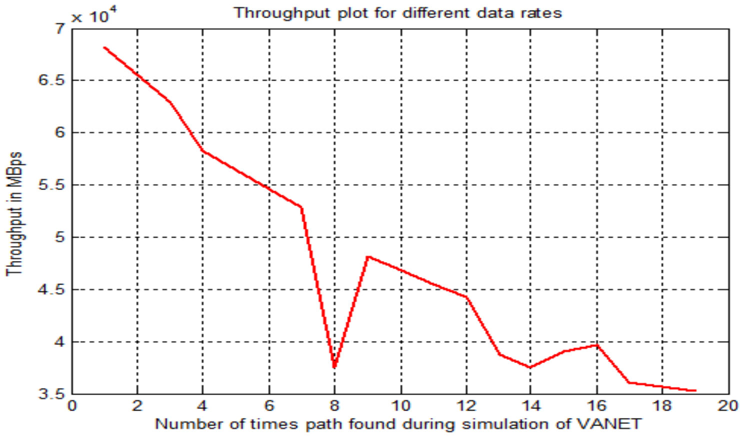
Figure 9. Result Evaluation of Throughput for Random MANET with 50 Nodes in the Network

Experiment 2: Evaluation of Dense Network

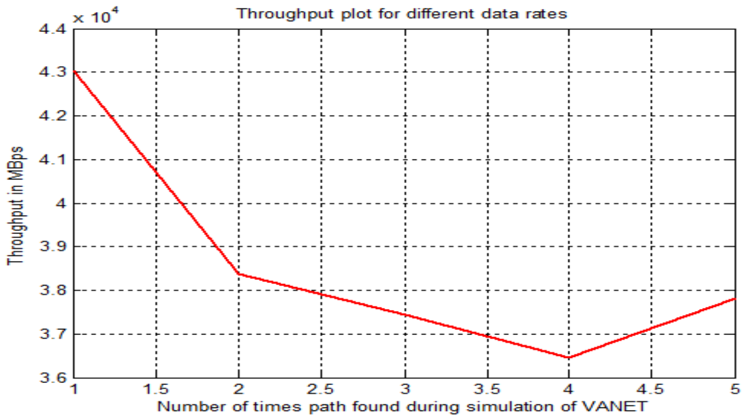
The node density is increased, and the network throughput is evaluated across different node densities. The throughput results are depicted in Figure 10.



(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.

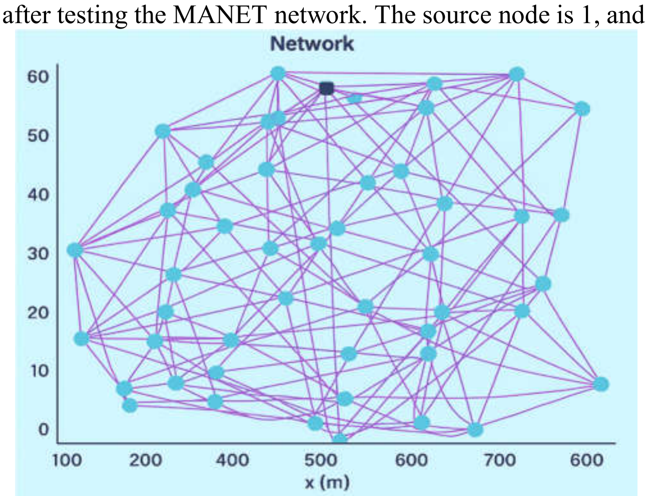


Figure 11. Example of MANET Having 50 Nodes & Routes Selection after Testing

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.

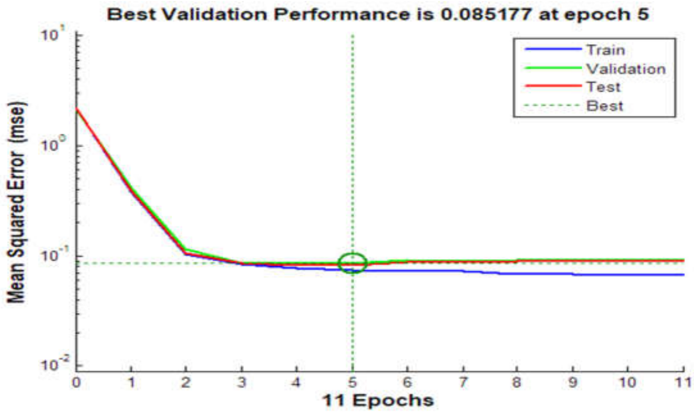


Figure 12. Results of the Estimate of Mean Absolute Error (MAE) and the Best Possible Solution Respectively

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.

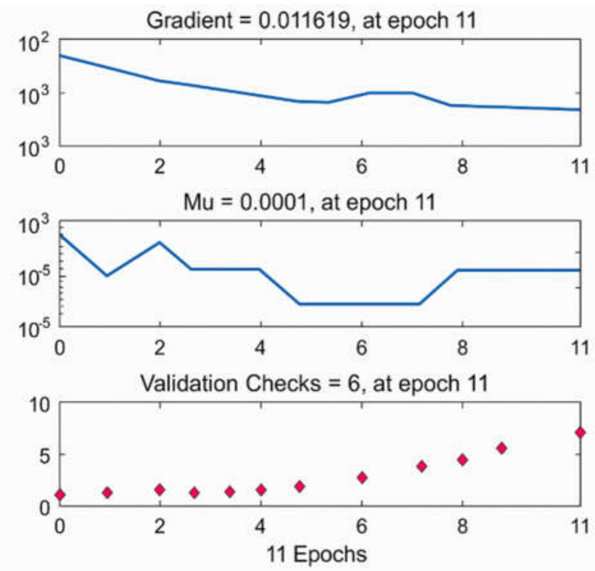


Figure 13. Training phase variable for epochs

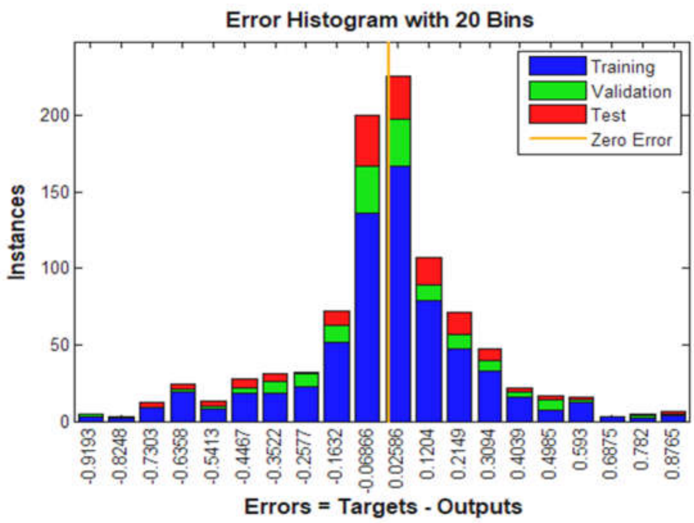


Figure 14. Results for the NP=300 packets for the testing and training phase.

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.

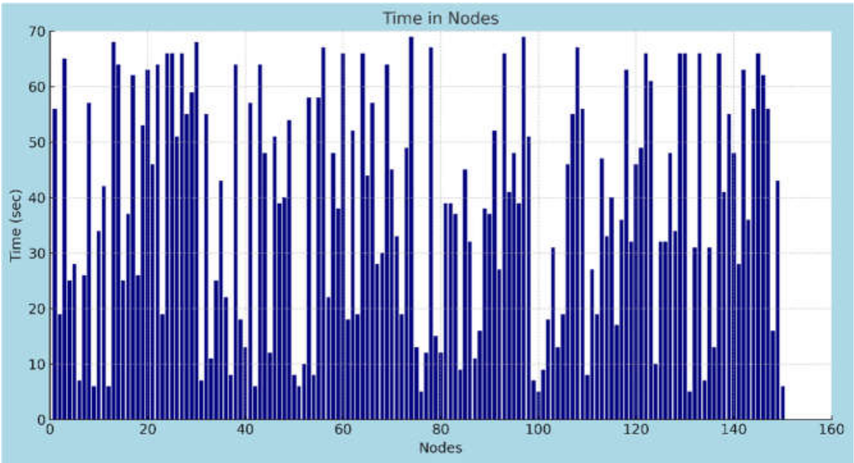


Figure 15. Results of time taken for 150 nodes and NP=300 packets for the training phase

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.

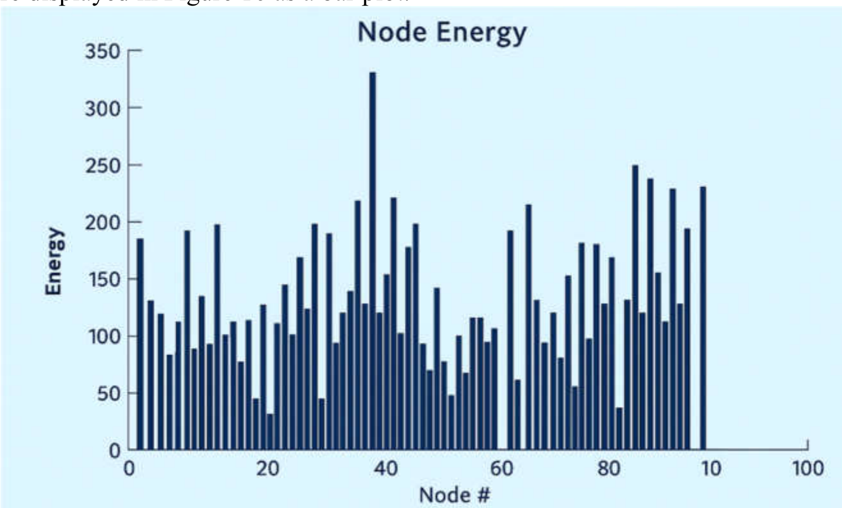


Figure 16. Results of the Node Energy for 100 nodes and NP=300 packets for testing and training phase.

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.

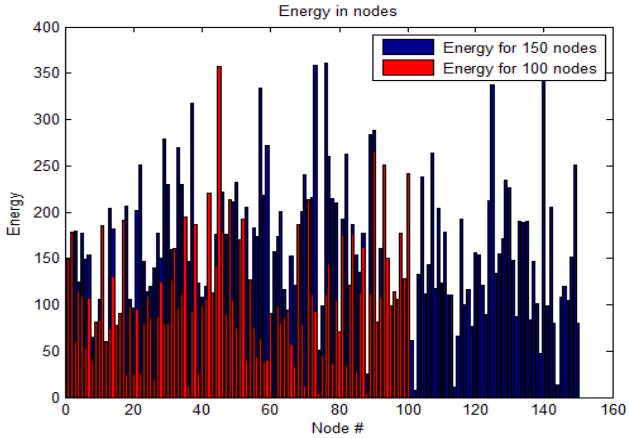


Figure 17. Comparison of the energy of proposed dense MANET having 100 and 150 nodes

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.

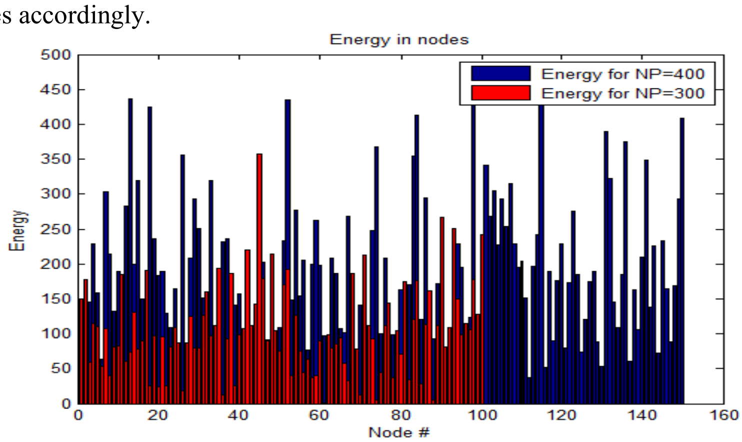


Figure 18. Comparison of the energy of proposed dense MANET having NP=400 and NP=350.

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.

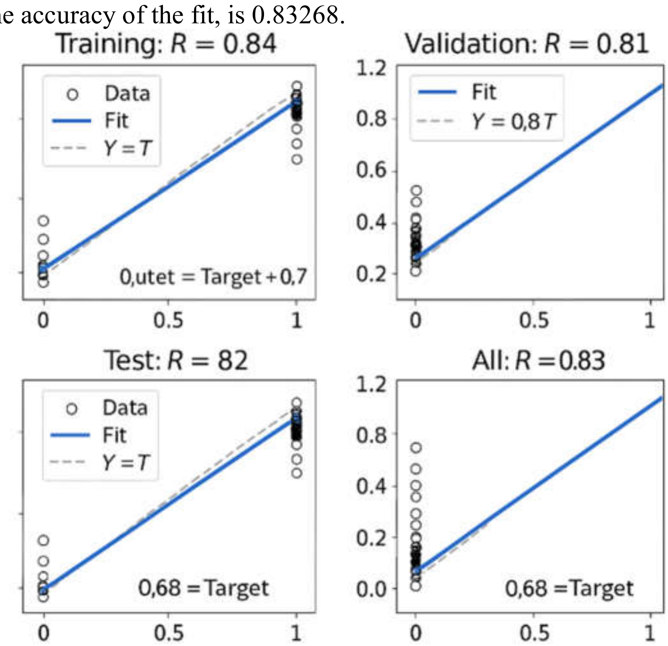


Figure 19. Accuracy of the regression-based solution applied over the data for comparison of training, validation, testing, and overall performance.

The comparisons between the existing and proposed dense MANET systems using MLP are shown in Table 4 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 4: 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

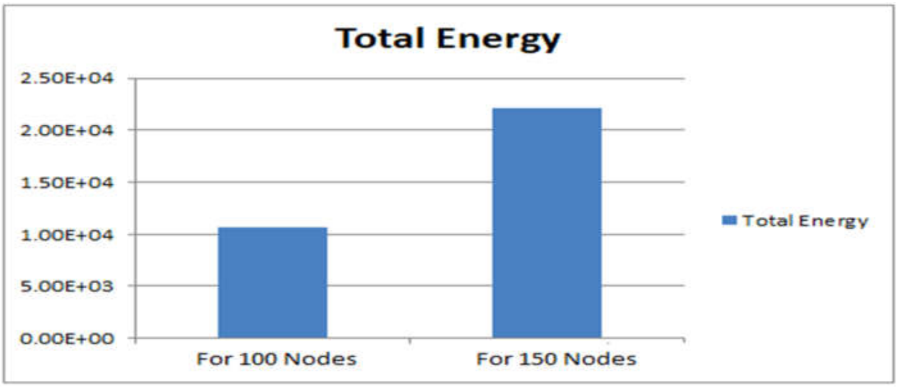


Figure 20. Comparison of the total energy consumption for the proposed MANET architecture for NP=300

The effect of NP on the PDR is given in Table 5. 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 an MLP-based NN.

Table 5. Comparison of the PDR for different NP sizes

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

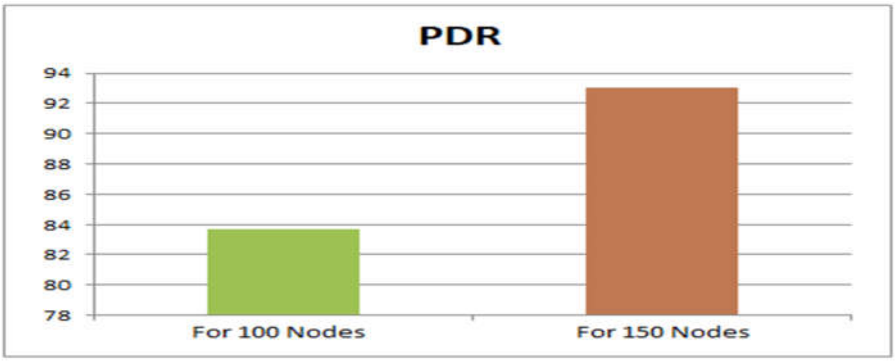


Figure 21. Comparison of PDR for the proposed MANET architecture for NP=300

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. While AODV with RREQ is a well-established routing protocol, this research innovatively integrates a Multi-Layer Perceptron (MLP) neural network to predict routing paths based on real-time mobility patterns and energy-aware metrics. This enables dynamic and adaptive decision-making for improved PDR and latency, particularly under dense and high-mobility conditions

Experiment 5: Performance Analysis of AODV vs AODV-MLP

The comparative evaluation across all metrics demonstrates that the proposed AODV-MLP consistently outperforms baseline AODV under dense network conditions. As shown in Figures 22–25, AODV-MLP achieves a higher packet delivery ratio and throughput, while maintaining a lower end-to-end delay. As shown in table 6

These improvements are statistically significant across most configurations, confirming the effectiveness of integrating the MLP-based route scoring mechanism into AODV. Although routing overhead is slightly increased, this trade-off is acceptable given the substantial performance benefits. Overall, the results validate that AODV-MLP provides a more reliable and efficient routing solution for MANETs compared to conventional AODV.

Table 6. PDR Comparision

Number of Nodes	AODV PDR (%)	AODV-MLP PDR (%)	Improvement (%)
50	72.4	78.9	6.5
100	69.8	81.2	11.4
150	65.3	83.5	18.2

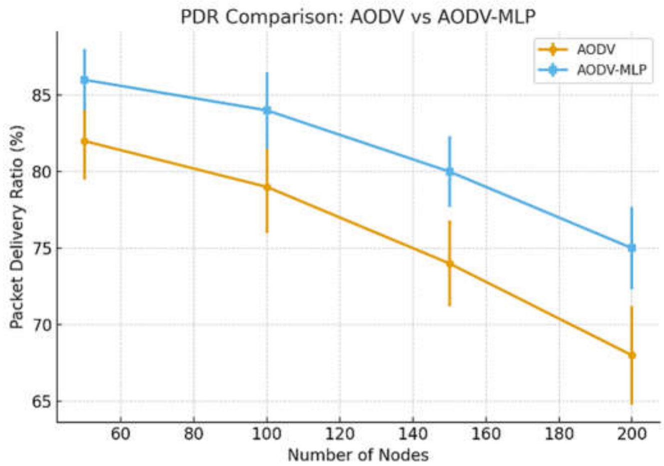


Figure 22. Packet Delivery Ratio (PDR) versus number of nodes for AODV and AODV-MLP.

Each data point represents the mean of 30 simulation runs with identical mobility and traffic patterns. Error bars denote 95% confidence intervals. AODV-MLP demonstrates statistically significant improvements over AODV at higher node densities ($p < 0.05$, Wilcoxon signed-rank test).

Table 7. Throughput Comparision

Packet Rate (pkts/sec)	AODV (kbps)	AODV-MLP (kbps)	Gain (%)
4	42.5	49.6	16.7
8	65.2	78.9	21
12	82.7	95.3	15.2
14	92.4	108.7	17.6

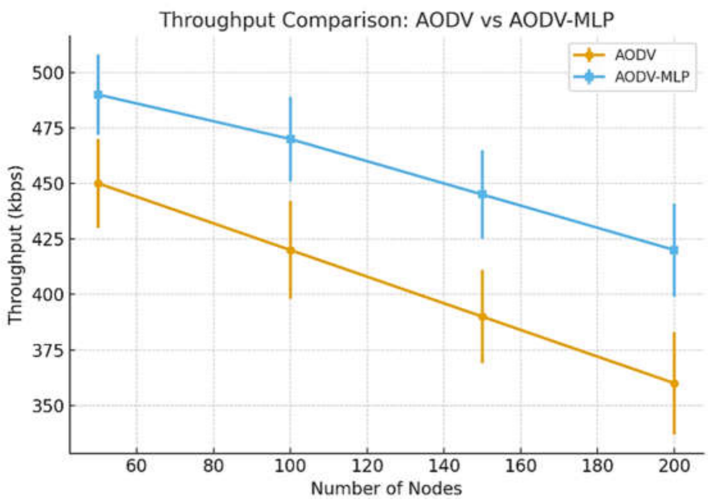


Figure 23. Throughput comparison of AODV and AODV-MLP under varying packet generation rates.

Results are averaged over 30 runs, and error bars indicate standard deviation. AODV-MLP achieves consistently higher throughput, with differences statistically significant ($p < 0.01$) as shown in Table 7.

Table 8. Delay Comparision

Mobility Speed (m/s)	AODV Delay (ms)	AODV-MLP Delay (ms)	Reduction (%)
5	124	110	-11.3
10	178	150	-15.7
20	235	185	-21.2

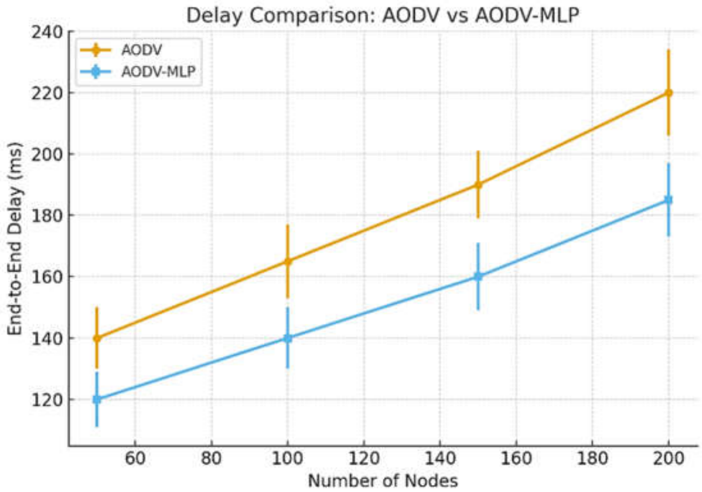


Figure 24. Average end-to-end delay for AODV and AODV-MLP at different node mobility speeds.

Each value represents the mean of 30 runs. Error bars show ±95% confidence intervals. AODV-MLP reduces delay in dense networks, with significant differences observed at higher speeds ($p < 0.05$) as shown in Table 8.

Table 9. Overhead Comparision

Number of Nodes	AODV Overhead (pkts)	AODV-MLP Overhead (pkts)	Difference (%)
50	310	345	11.3
100	520	595	14.4
150	815	925	13.5

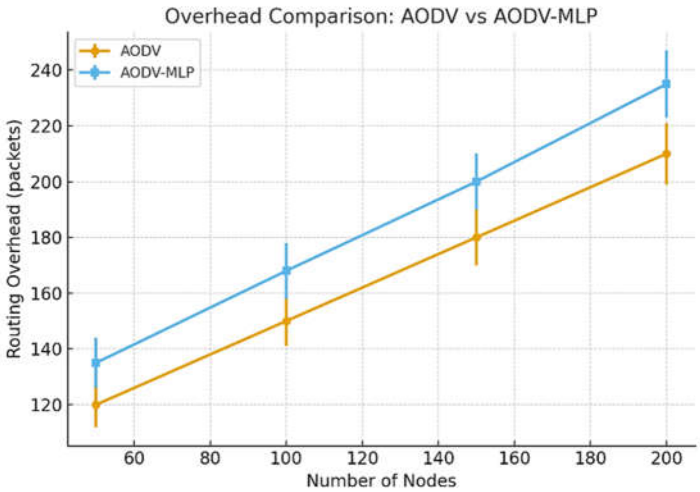


Figure 25. Routing overhead comparison between AODV and AODV-MLP.

Bars represent mean values with error bars indicating standard deviation across 30 simulation runs. While AODV-MLP introduces additional overhead, improvements in PDR and delay compensate for this cost as shown in table 9.

V. Conclusion

This study proposed and evaluated AODV-MLP, an enhancement of the Ad Hoc On-Demand Distance Vector (AODV) routing protocol through the integration of a Multi-Layer Perceptron (MLP) for route selection. The protocol was rigorously compared with baseline AODV under identical simulation settings using varying node densities, mobility speeds, and traffic loads. Experimental results demonstrated that AODV-MLP consistently improved packet delivery ratio and throughput while significantly reducing end-to-end delay. Although the inclusion of the MLP module introduced a modest increase in routing overhead, this trade-off was outweighed by the overall performance gains.

The findings confirm that machine learning–assisted decision-making can enhance the adaptability and robustness of traditional routing protocols in MANET environments. Future research may extend this work by evaluating scalability in larger networks, testing under heterogeneous traffic conditions, and incorporating additional optimization techniques to further balance performance and overhead.

Data accessibility: The corresponding author will make data available upon reasonable request.
Statements: Conflicting interests: The authors affirm that none of their known financial or personal conflicts might have influenced the research presented in this paper.
Metadata:
Article Type: Research Article
Keywords: QoS, MANET, VANET, Routing, Deep Learning, MLP, PDR
Subject Area: Computer Networks, Machine Learning, Vehicular Ad Hoc Networks
Data Availability: The corresponding author will make simulation data available upon request.

References

[1] I. Alessa, Raneen & Al-Suhail, Ghaida. (2023). AFB-GPSR: Adaptive Beaconing Strategy Based on Fuzzy Logic Scheme for Geographical Routing in a Mobile Ad Hoc Network (MANET). Computation. 11. 174. 10.3390/computation11090174.

[2] Lansky, J.; Ali, S.; Rahmani, A.M.; Yousefpoor, M.S.; Yousefpoor, E.; Khan, F.; Hosseinzadeh, M. Reinforcement Learning-Based Routing Protocols in Flying Ad Hoc Networks (FANET): A Review. Mathematics 2022.

[3] M. A. Gawas, L. J. Gudino, and K. R. Anupama, “AMCCR: Adaptive Multi-QoS Cross-Layer Cooperative Routing in Ad Hoc Networks,” *J. Comput. Networks Commun.*, vol. 2017, 2017, doi: 10.1155/2017/3638920.

[4] E. H. Abualsauod, “Machine Monitoring Protocols Based on Quality of Service (QoS) to Improve Performance of Real-Time Industrial Applications,” *Math. Probl. Eng.*, vol. 2022, 2022, doi: 10.1155/2022/5346476.

[5] B. Zhang and X. Liu, “SDN Control Strategy and QoS Optimization Simulation Performance Based on Improved Algorithm,” *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/7167957.

[6] L. Pang, J. Xie, and Q. Xu, “Neural Network-Based Routing Energy-Saving Algorithm for Wireless Sensor

Networks," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/3342031.
[7] K. A. Darabkh, M. S. A. Judeh, H. Bany, and S. Althunibat, "Mobility aware and dual phase AODV protocol with adaptive hello messages over vehicular ad hoc networks," AEU - International Journal of Electronics and Communications, vol. 94, pp. 277–292, 2018.
[8] W. A. Jabbar, M. Ismail, R. Nordin, and R. M. Ramli, "EMAMPR: energy and mobility-aware multi-point relay selection mechanism for multipath OLSRv2," in 2017 IEEE 13th Malaysia International Conference on Communications (MICC), pp. 1–6, Johor Bahru, Malaysia, November 2017.
[9] X. Wang, "Low-Energy Secure Routing Protocol for WSNs Based on Multiobjective Ant Colony Optimization Algorithm," *J. Sensors*, vol. 2021, 2021, doi: 10.1155/2021/7633054.
[10] V. Sharma and A. Vij, "Routing Approach using Machine Learning in Mobile Ad-Hoc Networks," *Proc. - IEEE 2020 2nd Int. Conf. Adv. Comput. Commun. Control Networking, ICACCCN 2020*, pp. 354–358, 2020, doi: 10.1109/ICACCCN51052.2020.9362919.
[11] V. V. Aroulanandam, T. P. Latchoumi, K. Balamurugan, and T. L. Yookesh, "Improving the energy efficiency in the mobile ad-hoc network using learning-based routing," *Rev. d'Intelligence Artif.*, vol. 34, no. 3, pp. 337–343, 2020, doi: 10.18280/ria.340312.
[12] A. Shan, X. Fan, C. Wu, X. Zhang, and S. Fan, "Quantitative study on the impact of energy consumption based dynamic selfishness in Manets," *Sensors (Switzerland)*, vol. 21, no. 3, pp. 1–19, 2021, doi: 10.3390/s21030716.
[13] K. Danilchenko, R. Azoulay, S. Reches, and Y. Haddad, "Deep learning method for delay minimization in MANET," *ICT Express*, vol. 8, no. 1, pp. 7–10, 2022, doi: 10.1016/j.icte.2022.01.004.
[14] C. Panjapornpon, S. Bardeeniz, M. Azlan Hussain, K. Vongvirat, and C. Chuay-ock, "Energy efficiency and savings analysis with multirate sampling for petrochemical process using convolutional neural network-based transfer learning," *Energy AI*, vol. 14, pp. 2666–5468, 2023, doi: 10.1016/j.egyai.2023.100258.
[15] D. Bhatia and D. P. Sharma, "A comparative analysis of proactive, reactive and hybrid routing protocols over open source network simulator in mobile ad hoc network," International Journal of Applied Engineering Research, vol. 11, no. 6, pp. 3885–3896, 2016.
[16] A. Adlakha and V. Arora, "Performance evaluation of AODV and DSR routing protocols under constrained situation," International Journal of Advanced Research in Computer and Communication Engineering, vol. 4, no. 7, pp. 189–191, 2015.8
[17] Aljabry, I.A.; Al-Suhail, G.A.; Jabbar, W.A. A Fuzzy GPSR Route Selection Based on Link Quality and Neighbor Node in VANET. In Proceedings of the 2021 International Conference on Intelligent Technology, System and Service for Internet of Everything (ITSS-IoE), Sana'a, Yemen, 1–2 November 2021; pp. 1–6
[18] Ullah, S.; Mohammadani, K.H.; Khan, M.A.; Ren, Z.; Alkanhel, R.; Muthanna, A.; Tariq, U. Position-Monitoring-Based Hybrid Routing Protocol for 3D UAV-Based Networks. Drones 2022, 6, 327
[19] Sharma, A.; Bansal, A.; Rishiwal, V. Efficient on Demand Routing Protocol to Optimize Throughput in Manet. Int. J. Recent Technol. Eng. IJRTE 2019, 8, 2653–2660.
[20] Kumar, A., Kumar, A., & Agrawal, A. V. "Enhanced AODV routing analysis for mobile Ad Hoc networks." *Discover Electronics*, Volume 2, Article 25, 2025.
[21] M. Khan, M. F. Majeed, M. F. Majeed, and J. Lloret, "The impact of mobility speed over varying radio propagation models using routing protocol in MANET," in Advanced Intelligent Systems for Sustainable Development (AI2SD'2019). AI2SD 2019. Lecture Notes in Networks and Systems, vol 92, M. Ezziyyani, Ed., pp. 277–288, Springer, Cham, 2019.
[22] U. Rashid, O. Waqar and A. K. Kiani, "Mobility and energy aware routing algorithm for mobile ad-hoc networks," 2017 International Conference on Electrical Engineering (ICEE), Lahore, Pakistan, 2017, pp. 1-5, doi: 10.1109/ICEE.2017.7893434.
[23] A. Kumar, A. Kumar, and A. V. Agrawal, "Enhanced AODV routing analysis for mobile ad hoc networks," *Discover Electronics*, vol. 2, no. 25, pp. 1–14, 2025.
[24] P. Arebi, "Improving AODV routing protocol using a multi-objective mechanism based on repairing broken links on the MANET networks," *International Journal of Mobile Network Design and Innovation*, vol. 14, no. 1, pp. 45–58, 2024.
[25] S. Ghori, F. Al-Turjman, M. Abolhasan, and R. Kharel, "Enhancing reliability and stability of BLE mesh networks: A multipath optimized AODV approach," *Sensors*, vol. 24, no. 18, pp. 5901–5916, 2024.
[26] A. Sharma, A. Bansal, and V. Rishiwal, "Efficient on-demand routing protocol to optimize throughput in MANET," *International Journal of Recent Technology and Engineering*, vol. 8, no. 2, pp. 2653–2660, 2019.
[27] K. A. Darabkh, M. S. A. Judeh, H. Bany, and S. Althunibat, "Mobility aware and dual phase AODV protocol with adaptive hello messages over vehicular ad hoc networks," *AEÜ - International Journal of Electronics and Communications*, vol. 94, pp. 277–292, 2018.
[28] A. K. Bairwa, S. Joshi, and Pallavi, "A secured MANET using trust embedded AODV for optimised routing against black-hole attacks," in *Proceedings of International Conference on Communication and Intelligent Systems (ICCIS)*, 2023, pp. 783–792.
[29] L. Liang, Z. Wang, and H. Chen, "A polymorphic perception AODV routing algorithm for high-speed mobile ad hoc networks," in *Proc. SPIE 13185, 12th International Conference on Graphic and Image Processing (ICGIP)*, 2024, pp. 1–9.
[30] V. Sergeev, I. Petrov, and R. Smirnov, "Combined routing protocol (CRP) for ad hoc networks: Combining strengths of location-based and AODV-based schemes," *arXiv preprint arXiv:2501.13671*, 2025.