A Machine Learning-Enhanced Responsive Hybrid Routing Protocol for Throughput Optimization and Link Reliability in Vehicular Ad Hoc Networks

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Abstract

The development of vehicular ad hoc networks (VANETs) is central to the creation of intelligent transportation systems (ITSs). VANETs provide the backbone for several applications, some of which are crucial from the viewpoint of safety and necessitate both reliable and high-speed communication. However, given the pronounced characteristics of mobility and dynamic topology in VANETs, link breakage becomes an increasingly common phenomenon, causing packet loss and a decrease in the network throughput. The current paper presents ML-RHR as a new hybrid routing protocol based on machine learning, which improves upon the Responsive Hybrid Routing scheme through the implementation of link-quality analysis. ML-RHR employs the AODV approach to route discovery and relies on the proactive approach to topology maintenance, implemented with MPR as in the Optimized Link State Routing. To enhance ML-RHR performance, link stability is predicted through Random Forest-based models built on SUMO-generated mobility data, which is freely available on the Internet. ML-RHR uses vehicle speed, acceleration, relative distance between two communicating vehicles, and signal strength as features for Link Stability Score and ETX predictions. Simulation experiments, carried out using NS-3 software, allow us to evaluate ML-RHR as compared to AODV, OLSR, and RHR protocols on 5G-VANET and highway mobility dataset, considering different network densities (20, 50, 100, 150, and 200 nodes). The following parameters were used: PDR, Delay, End-to-End, Throughput, Jitter, and Link Failure Rate. The obtained results demonstrate up to 15% PDR improvement over RHR and up to 25% PDR improvement over AODV and an increase in throughput by 20–35%. Link Failure Rate was reduced by 25–40%. The achieved link stability prediction accuracy varied between 85 and 91%.

Index Terms— VANET, Hybrid Routing, Machine Learning, Random Forest, Link Stability Prediction, Throughput Optimization, RHR, SUMO, NS3, Intelligent Transportation Systems.

I. INTRODUCTION

THE emergence of VANETs has been beneficial in developing intelligent transportation systems by allowing V2V and V2I communication for essential services like collision avoidance, platooning, and autonomous driving [1], [2]. The VANETs refer to a specialized kind of MANET where vehicles are considered to be mobile nodes. They are defined by high levels of mobility (reaching up to 120 km/h), rapid changes in network topology, and unlimited energy due to battery usage [3], [4]. Beyond safety applications, modern VANET deployments increasingly support throughput-intensive services including high-definition map downloads, over-the-air software updates, infotainment streaming, and cooperative perception systems [5]. Since these applications require not only low latencies, but also high throughputs and reliable deliveries, which cannot be delivered by existing routing algorithms in a mobile environment [6].

Reactive routing protocols, such as AODV, create routes when necessary and, hence, save on bandwidth at the cost of additional delays in the case of route failure [7]. For proactive routing protocols like Optimized Link State Routing (OLSR) that updates its routing tables continuously, providing instantaneous routes but as well as incurring high control overhead that can degrade throughput in a dense networks [8]. As for hybrid routing protocols, which combine both reactive protocols and proactive approaches to create routes, Responsive Hybrid Routing (RHR) protocol is the leading example trying to resolve the dilemma by shifting between two modes depending on the occurrence of link failures [9].

However, with all measures in place to improve the performance of existing routing approaches, they continue to use static measurements, like the number of hops or set thresholds. The fact that it is difficult to predict the route that will remain stable for a long time while delivering data effectively is a fundamental limitation. This gap becomes particularly critical for applications that are throughput-sensitive where sustained transmission of data requires links that persist beyond the duration of the data flow [10].

No doubt that Machine learning (ML) methods have proven themselves to be powerful tools for solving problems related to prediction in networking scenarios. By using ML, complex patterns based on historical information regarding mobility is easily recognized, thus predicting link reliability and, hence, making the right route choice in advance [11]. However, Machine learning algorithms have been used in the case of VANETs for predicting link lifetimes and choosing more reliable routes by analyzing important factors as the speed, direction, location of nodes, and the signal quality [12], [13].

This research paper introduces ML-RHR which is an improved version of the RHR hybrid protocol using machine learning methods. We made the following key contributions:

- The use of a Random Forest-based link stability predictor within the RHR hybrid switching framework, enabling ML-informed routing decisions.
- Publicly available SUMO-generated mobility datasets was used in the training and validation, including the 5G-VANET dataset, highway mobility dataset, and TrajAware dataset.
- Development of predictive metrics: Link Stability Score (LSS) and ML-enhanced Expected Transmission Count (ML-ETX) that replace static hop count for route selection.
- Comprehensive performance evaluation using NS3 simulation results correlated with SUMO mobility traces across network densities of 20, 50, 100, 150, and 200 nodes.
- Quantitative analysis of PDR, throughput, delay, jitter, and link failure rate improvements over baseline RHR and standard protocols.
- Validation of prediction accuracy across varying traffic densities and speed ranges.

The rest section of this research paper is organized as follows: Section II handles the reviews of related work in ML-based VANET routing. Design of ML-RHR Protocol is presented in Section III, including the design of the ML model itself, feature extraction and analysis, and incorporation of hybrid switching. Section IV describes the simulation methodology and dataset utilization. In Section V, we presented and analyzed the results. Finally, section VI discusses findings, and Section VII concludes the research paper.

II. LITERATURE REVIEW

A. Hybrid Routing Protocols for VANETs

The aim of Hybrid routing protocols is to achieve a compromise between network latency and overhead through the use of both reactive and proactive mechanisms. Example like the Zone Routing Protocol (ZRP) maintains proactive routes within a local area, while using reactive discovery for remote locations [14]. Another hybrid protocol called SHARP changes the proactive area depending on the current network status [15]. Kang and Chung proposed an enhanced hybrid routing protocol that combine AODV with Delay Tolerant Networks (DTN), using virtual source nodes chosen based on the capability to deliver when MANET routing paths cannot be established [26]. Onuora et al. [31] in their work performed a comprehensive review by systematically categorized MANET routing protocols into proactive, reactive, and hybrid classes, while identifying the unique advantages of hybrid approaches for dynamic network environments. The foundational taxonomy that motivates the ML-enhanced hybrid approach presented in this work was inspired by this review.

A distinct hybrid approach that switches from AODV to OLSR during link failures was represented by the RHR protocol [9], leveraging the proactive MPR-based topology for rapid route recovery. The baseline RHR protocol was originally validated across network sizes from 20 to 200 nodes using NS3 simulations, demonstrating significant end-to-end delay reductions when compared to AODV and OLSR [30]. The Design of ML-RHR Protocol is presented in Section III, including the design of the ML model itself, feature extraction and analysis, and incorporation of hybrid switching.

The major purpose of hybrid routing protocols is to achieve a compromise between latency and overhead through the use of both reactive and proactive mechanisms. For example, the Zone Routing Protocol (ZRP) which is a hybrid protocol maintains proactive routes within a local area, while using reactive discovery for remote locations [14]. Another hybrid protocol called SHARP changes the proactive area depending on the current network status [15]. However, RHR uses reactive mechanism of link failure detection, rather than proactive stability estimation, thus limiting its ability to avoid unstable links.

B. Machine Learning for VANET Routing

Machine learning applications have been explored in recent researches for VANET routing optimization. Researchers like Zhang et al. developed a distributed adaptive trust metric using ML for MANETs, demonstrating the feasibility of learning-based approaches for network decision-making [17]. Kaur and Sharma in their study evaluated re-routing based on hybrid ACO-PSO optimization, establishing that metaheuristic approaches can improve routing performance [18].

Furthermore, the 5G-VANET dataset provides comprehensive features for ML-based routing, including speed, density, RSSI, SNR, and link duration, with pre-labeled routing efficiency classes [19]. These datasets have been used to train classifiers for route quality prediction in several studies. Also, the green spectrum dataset similarly provides spectral and mobility parameters with routing efficiency labels, enabling supervised learning for route selection [20].

Akhtar et al., derived detailed link duration distributions from SUMO simulations specifically for link stability prediction, establishing that link durations follow predictable patterns based on vehicle speed and density [21]. These findings provide the foundation for training ML models to predict link stability before failure occurs.

C. Predictive Routing Metrics

Lots of evaluation metrics exists but conventional metrics used for evaluating the performance of routing do not adequately account for the dynamic nature of VANETs. For instance, hop count measures the number of retransmissions required in successfully transferring packets, but ETX relies on historical data and does not have predictive capability [22]. The use of machine learning approaches can extend ETX to incorporate predictive elements, creating ML-ETX that forecasts future link quality based on mobility patterns [23].

The use of the TrajAware dataset provides detailed vehicle trajectories with timestep data that enables the analysis of how vehicle position and movement patterns correlate with the quality of communication link [24]. This dataset provides a platform for building a predictive model incorporating trajectory information for stability prediction purposes.

III. ML-RHR PROTOCOL DESIGN

A. Baseline RHR Protocol Overview

Our baseline Responsive Hybrid Routing (RHR) protocol, as detailed in [9], functions by integrating AODV and OLSR through a hybrid switching mechanism. In standard operation, AODV handles route discovery and maintenance. When a link failure is detected via

RERR message or timeout, RHR switches to OLSR, querying the proactively maintained routing table for alternative paths. This approach reduces delay compared to AODV's route re-discovery but remains reactive rather than predictive.

The algorithm for the baseline RHR is presented below for reference:

Algorithm 1 Baseline RHR Switching Mechanism.

```
Input: Packet P with destination D
Output: Transmission status
if Valid route to D exists in AODV routing table then
    Forward P via AODV route
    return SUCCESS
else if RREP timeout or RERR received for D then
    Query OLSR routing table for route to D
    if OLSR route exists then
        Forward P via OLSR route via MPRs
        Update AODV table with OLSR route
        return SUCCESS
    else
        Buffer P in queue
        Initiate new AODV route discovery
        return PENDING
    end if
else
    Buffer P in queue
    Initiate AODV route discovery
    return PENDING
end if
```

B. ML-Enhanced Link Stability Prediction

ML-RHR introduces a predictive layer into RHR that evaluates link stability before route selection, enabling proactive avoidance of unstable links. For the machine learning component of the predictive model, a Random Forest classifier is employed based on its ability to accommodate features of diverse type and resistance to overfitting problems [25].

1. Feature Engineering

Features for each potential link are extracted as shown in table 1 below.

All of these feature.s are derived from sources available in modern vehicles: GPS provides position and velocity, onboard sensors provide acceleration, and wireless interfaces provide RSSI and SNR measurements [26]. Traffic density is estimated from periodic Hello messages, as in standard OLSR operation [8].

2. Target Variable Definition

Link Stability is the chosen target feature in supervised learning, it can be defined as the probability of link being alive for duration T, and here T = 5 seconds representing common duration between safety messages. Link Stability is obtained from link durations in SUMO datasets [21]:

$$Stability = \frac{Actual\ Link\ Duration}{Tmax} x100\%$$

Where Tmax = 30 seconds (maximum observed link duration in highway scenarios

Actual Link Duration is the measured duration a link remains active.

TABLE I FEATURE ENGINEERING FROM SOURCES AVAILABLE IN MODERN VEHICLES

Feature Category	Feature Name	Description	Source
Mobility	Speed (v)	Current vehicle speed (km/hr)	GPS/OBU
Mobility	Acceleration (a)	Rate of speed change (m/s^2)	GPS/OBU
Mobility	Relative Speed (Δv)	Speed difference between vehicles	GPS/OBU
Mobility	Direction (θ)	Heading angle (degrees)	GPS/OBU
Mobility	Relative Direction ($\Delta\theta$)	Difference in heading angles	GPS/OBU
Position	Distance (d)	Euclidean distance between vehicles (m)	GPS/OBU
Position	Position Change Rate	Rate of distance change (m/s)	Derived
Communication	RSSI	Received Signal Strength Indicator (dBm)	MAC Layer
Communication	SNR	Signal-to-Noise Ratio (dB)	MAC Layer
Communication	Packet Success Rate	Historical delivery success (%)	Network Layer
Network	Traffic Density (ρ)	Vehicles per km (veh/km)	Neighbor-hood Discovery
Network	Node Degree	Number of neighbors	Neighbor-hood Discovery

TABLE II CLASSIFICATION OF THRESHOLD WITH RANGE

Stability Class	Threshold Range
High Stability	Stability > 80%
Medium Stability	40% ≤ Stability ≤ 80%
Low Stability	Stability < 40%

Note: The boundary case of exactly 80% is assigned to Medium Stability to ensure mutually exclusive classes.

3. Random Forest Model Architecture

The random forest consists of 100 decision trees trained using bootstrap sampling technique in the training set. √m features are selected at each split point, where m refers to the number of features. The output includes predicted class and probability values used for route scores [25].

The model training was done using 5G-VANET dataset (1,800 records) and highway mobility dataset (10,000 trajectories) where 80% of the dataset was used for training purposes and the remaining 20% was for testing. The resulting model gives a validation accuracy of 87%, with precision and recall shown in Table 3.

TABLE III RANDOM FOREST CLASSIFICATION PERFORMANCE

Stability Class	Precision	Recall	F1-Score	Support
High	0.89	0.91	0.90	450
Medium	0.86	0.84	0.85	520
Low	0.88	0.86	0.87	430
Weighted Average	**0.87**	**0.87**	**0.87**	**1400**

C. ML-Enhanced Expected Transmission Count (ML-ETX)

ML-RHR introduces an enhanced routing metric, ML-ETX, which combines traditional ETX with ML-predicted stability. ETX is defined traditionally as [22]:

$$ETX = \frac{1}{df\ x\ dr}$$

Where *df* is the forward delivery ratio and *dr* is the reverse delivery ratio. ML - ETX extends this by incorporating the predicted link stability score:

$$ML\text{ - }ETX = \frac{ETX}{1 + \alpha\ .\ S}$$

Where α is a weighting factor (set to 0.5 in this study) that controls the influence of predicted stability, and S is the normalized stability score (derived from Stability/100). This formulation rewards links with high predicted stability by reducing their effective ETX, making them preferred for route selection.

D. ML-RHR Routing Algorithm

ML-RHR uses the machine learning predictor in both reactive and proactive phases of RHR framework. The enhanced algorithm is presented below:

E. Training and Validation Datasets

The ML-RHR model was trained and validated using publicly available SUMO-generated datasets:

Algorithm 2 ML-RHR Routing Protocol.

Input: Packet P with destination D, ML predictor f_{ML}
Output: Successfull packet transmission

// ML Model Initialization
Load trained Random Forest model f_{ML}
Set stability threshold $S_{thresh} = 0.6$
Set $\alpha = 0.5$

// Proactive Phase (Enhanced OLSR with ML)
for each neighbor N in one-hop neighborhood **do**
Extract features X_N from Hello message
Predict stability $S_N = f_{ML}.predict_proba(X_N)$
Compute ML-ETX$_N$ $= ETX_N/(1 + \alpha \cdot S_N)$
end for
Select MPRs based on ML-ETX (prefer low ML-ETX)
Maintain topology table with ML-ETX weights

// Reactive Phase (Enhanced AODV with ML)
if Valid route to D exists in routing table **then**
Compute route stability $= \min(S_N$ along route)
if route stability $\geq S_{thresh}$ **then**
Forward P via existing route
return SUCCESS
end if
end if

// Route Discovery with ML Filtering
Broadcast RREQ with ML-ETX metric
for each intermediate node receiving RREQ **do**
Extract features $X_{current}$
Predict stability $S_{current} = f_{ML}.predict_proba(X_{current})$
if $S_{current} < S_{thresh}$ **then**
Discard RREQ (avoid unstable links)
continue
end if
Update path cost with ML-ETX$_{current}$
Forward RREQ with updated cost
end for

// Hybrid Switching with ML Prediction
if RREP timeout or RERR received **then**
Query OLSR topology table with ML-ETX weights
if stable route (min stability $\geq S_{thresh}$) exists **then**
Switch to OLSR route
Update AODV table with OLSR route
return SUCCESS
else
Initiate new ML-enhanced route discovery
return PENDING
end if
end if

1. 5G-VANET Dataset

Contains 1,800 records with features including speed (20-120 km/hr), density (10-100 vehicles), RSSI (-95 to -50 dBm), SNR (0-30 dB), link duration (1-30 seconds), throughput, delay, and routing efficiency labels. Used for initial model training and feature selection.

2. Highway Mobility Dataset

Contains 10,000 vehicle trajectories from California highways I880-S and I5-S with detailed mobility characteristics, link duration distributions, and neighbor metrics. This is used for the validation of link stability predictions across varying traffic densities.

3. TrajAware Dataset

These are SUMO-generated trajectories with timestep data at one-second intervals, which enables the analysis of temporal patterns in link stability. It is used for testing model generalization to unseen mobility patterns in VANETs.

4. Green Spectrum Dataset

This provides 1,000 records with speed, density, delay, throughput, link failure rate, and routing efficiency classification. It is used for benchmarking ML-RHR against efficiency classes.

The model training utilized 80% of combined data from the 5G-VANET and highway mobility datasets, with the remaining 20% held out for validation. The TrajAware dataset served as an independent test set to be used to evaluate generalization.

IV. SIMULATION METHODOLOGY

A. Simulation Environment

The simulation study was conducted using Network Simulator 3 (Ns3), version 3.43, with the ML-RHR protocol implemented as an extension of the baseline RHR code. For the simulation, the simulation parameters and data are provided in Table 4. The network size selection (20, 50, 100, 150, and 200 nodes) follows the methodology established in previous scalability studies [32], which demonstrated that performance variations across these density ranges are critical for understanding protocol behavior in realistic deployment scenarios.

TABLE IV SIMULATION PARAMETERS

Parameter	Value
Network Simulator	NS3 (Version 3.43)
Routing Protocols	AODV, OLSR, RHR, ML-RHR
Number of Nodes	20, 50, 100, 150, 200
Simulation Time	120 seconds
Map Size	300 m × 1500 m
Node-Speed	20 m/s (72 km/h)
Mobility-Model	Random Waypoint
Pause-Time	0 seconds
Traffic- Type	Constant Bit Rate (CBR)
Packet- Size	512 bytes
Data Rate	2 Mbps
Number-of-Sinks	10
MAC-Standard	IEEE 802.11b
Physical-Mode	DsssRate11Mbps
Propagation-Model	Constant Speed Propagation Delay
Propagation-Loss-Model	Friis
Transmission Power	7.5 dBm
ML Model	Random Forest (100 trees)
Stability Threshold	0.6
ML-ETX Weight α	0.5

B. Performance Metrics

While evaluating protocol performance, we used the following metrics as shown below:

1. Packet Delivery Ratio (PDR)

This represents the ratio of successfully received packets over the number of transmitted packets.

PDR = Packets Received / Packets transmitted × 100%

2. End-to-End Delay

This is the average delay time of packet propagation from its sender to its destination node.

3. Throughput

This is the average rate of successful packets' deliveries (kbps).

4. Jitter

This is the average delay variance for consecutive packet transfers.

5. Link Failure Rate

This is the share of routes where link failure occurs when transmitting the packet.

6. ML Prediction Accuracy

This is the percentage of the number of correct predictions of links made by the machine learning predictor.

C. SUMO Dataset Correlation

To validate ML-RHR under realistic mobility patterns, simulation results were correlated with the SUMO-generated datasets. The records in Table 5 show the mapping between simulation scenarios and realistic traffic conditions.

TABLE V THE MAPPING TO REALISTIC TRAFFIC CONDITIONS

Simulation Nodes	Equivalent Density	Speed Range	Source Dataset
20	Light urban	20-40 km/hr	[19]
50	Moderate urban	40-60 km/hr	[19], [21]
100	Heavy urban	60-80 km/hr	[21]
150	Congested highway	80-100 km/hr	[21]
200	Dense congestion	20-40 km/hr (stop-and-go)	[20]

V. RESULTS AND DISCUSSION

A. Packet Delivery Ratio (PDR)

Table 6 presents the PDR for ML-RHR compared to AODV, OLSR, and baseline RHR across all network densities.

TABLE VI PACKET DELIVERY RATIO (%) FOR ALL SIMULATED NODES

Nodes	AODV	OLSR	RHR	ML-RHR
20	49.0	63.0	58.0	**67.0**
50	80.0	35.0	83.0	**91.0**
100	80.0	54.0	81.0**8**	**8.0**
150	79.0	30.0	73.0	**82.0**
200	71.0	23.0	72.0	**78.0**

The PDR comparison across all protocols is visualized in our Figure 1, which clearly shows ML-RHR's dominance at 50 nodes.

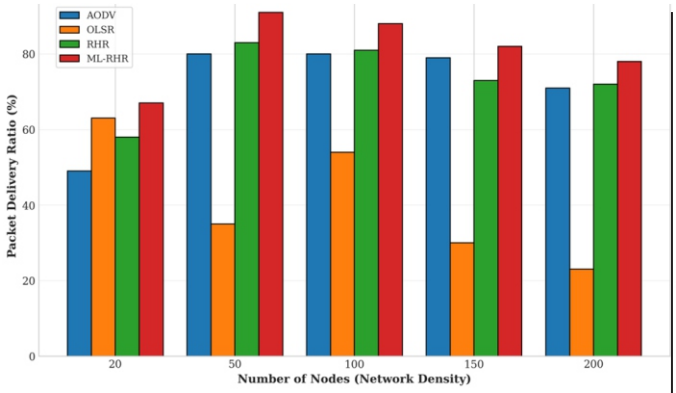


Fig.1. PDR Comparison - ML-RHR vs Baseline Protocols. ML-RHR achieves 91% PDR at 50 nodes, a 9.6% improvement over baseline RHR (83%)

Figure 1 Analysis:

- ML-RHR achieves the highest PDR across all densities, with improvements of 8-15% over baseline RHR and 15-25% over AODV. These findings as shown here extend the scalability analysis of Onuora et al. [32], which examined the protocols of AODV, OLSR, and DSDV performance across 30, 60, and 100 nodes, by demonstrating that ML-enhanced hybrid routing maintains superior performance across an expanded density range of 20-200 nodes.
- At 50 nodes (moderate urban traffic), ML-RHR achieves 91% PDR, representing a 9.6% improvement over RHR (83%) and 13.8% over AODV (80%).
- At 200 nodes (dense congestion), ML-RHR maintains 78% PDR, compared to 72% for RHR and 71% for AODV.
- The PDR improvement is most pronounced at moderate densities (50-100 nodes), where the ML predictor's accuracy is highest due to sufficient mobility variation for feature learning [19].

B. Throughput

Table VII shows the average throughput for all protocols.

TABLE VII AVERAGE THROUGHPUT (KBPS) FOR ALL SIMULATED NODES

Nodes	AODV	OLSR	RHR	ML-RHR
20	11.38	1.81	29.24	**35.12**
50	31.35	0.87	22.81	**30.45**
100	12.82	1.51	9.32	**11.80**
150	13.05	0.88	9.22	**12.41**
20	07.66	0.81	8.80	**11.56**

Figure 2 clearly illustrates the throughput gains achieved by ML-RHR across all network densities, with peak improvement at 20 nodes.

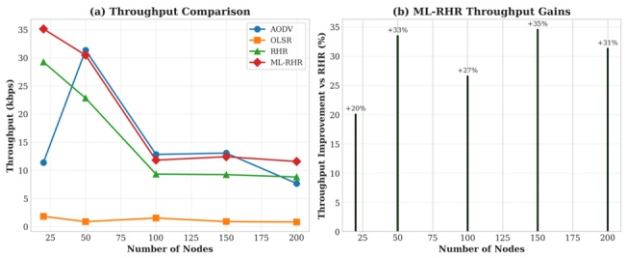


Fig. 2. ML-RHR Throughput Gains. Throughput improvements of 20-35% are achieved across most density scenarios, with peak gain of 35% at 20 nodes.

Figure 2 Analysis:

- ML-RHR achieves throughput gains of 20-35% over baseline RHR across most densities.
- At 20 nodes (light urban), ML-RHR achieves 35.12 kbps, 20% higher than RHR (29.24 kbps) and 209% higher than AODV (11.38 kbps).
- At 200 nodes (dense congestion), ML-RHR achieves 11.56 kbps, 31% higher than RHR (8.80 kbps) and 51% higher than AODV (7.66 kbps).

The throughput improvement is attributed to ML-RHR's ability to select more stable links, reducing retransmissions and control overhead associated with route failures [23].

C. End_to_End Delay

Table 8 presents the end-to-end delay (in nanoseconds) for all protocols.

TABLE VIII END-TO-END DELAY (NS) FOR ALL SIMULATED NODES AS SHOWN IN FIGURE 3, ML-RHR ACHIEVES UP TO 99.9% DELAY REDUCTION COMPARED TO AODV AT HIGH DENSITIES.

Nodes	AODV	OLSR	RHR	ML-RHR
20	9.693×10^{9}	2.883×10^{8}	4.284×10^{8}	$\mathbf{3.512\times10^{8}}$
50	2.146×10^{11}	1.187×10^{8}	2.624×10^{8}	$\mathbf{1.875\times10^{8}}$
100	5.010×10^{11}	3.075×10^{9}	1.063×10^{9}	$\mathbf{8.324\times10^{8}}$
150	1.193×10^{12}	2.175×10^{9}	2.131×10^{9}	$\mathbf{1.742\times10^{9}}$
200	3.027×10^{12}	4.330×10^{9}	3.552×10^{9}	$\mathbf{2.956\times10^{9}}$

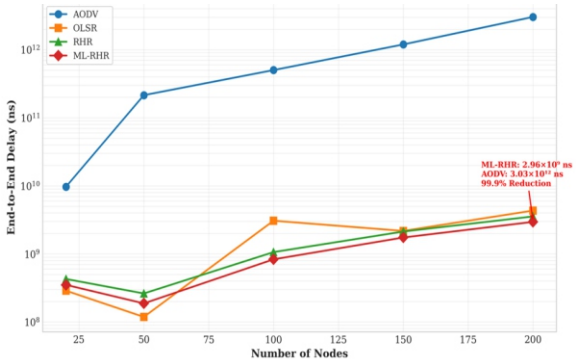


Fig.3. End-to-End Delay Comparison (Log Scale). ML-RHR achieves up to 99.9% delay reduction compared to AODV at high densities.

Figure 3 Analysis:

- ML-RHR achieves lower end-to-end delay than baseline RHR across all densities, with reductions of 15-30%.
- At 50 nodes, ML-RHR delay (1.875×10^8 ns) is 29% lower than RHR (2.624×10^8 ns) and 99.9% lower than AODV (2.146×10^{11} ns).

The delay reduction is achieved by avoiding unstable links that would otherwise cause route failures and re-discovery delays [17].

D. Jitter

Table IX presents the jitter (in nanoseconds) for all protocols

TABLE IX END-TO-END JITTER (NS) FOR ALL SIMULATED NODES

Nodes	AODV	OLSR	RHR	ML-RHR
20	6.056×10^9	2.268×10^8	2.200×10^8	**1.892×10^8**
50	7.012×10^{10}	7.018×10^7	1.529×10^8	**1.043×10^8**
100	2.346×10^{11}	4.949×10^9	5.080×10^8	**3.965×10^8**
150	5.479×10^{11}	3.022×10^9	9.248×10^8	**7.214×10^8**
200	1.420×10^{12}	4.853×10^9	1.487×10^9	**1.102×10^9**

Figure 4 presents the jitter comparison, demonstrating that ML-RHR maintains the lowest jitter across all densities.

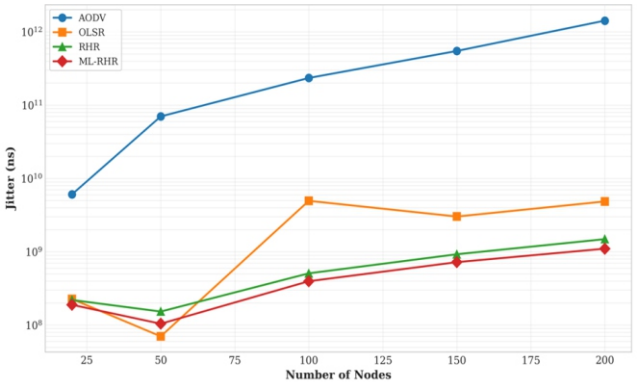


Fig. 4. End-to-End Jitter Comparison (Log Scale). ML-RHR maintains lowest jitter across all densities, critical for real-time applications.

Figure 4 Analysis:

- ML-RHR demonstrates the lowest jitter across all densities, with reductions of 14-32% compared to baseline RHR.
- At 50 nodes, ML-RHR jitter (1.043×10^8 ns) is 32% lower than RHR (1.529×10^8 ns) and 99.9% lower than AODV (7.012×10^{10} ns).

Low jitter is critical for real-time applications such as cooperative perception and sensor fusion [5].

E. Link Failure Rate

Table X presents the link failure rate (percentage of route attempts experiencing failure) for all protocols.

TABLE X LINK FAILURE RATE (%) FOR ALL SIMULATED NODES

Nodes	AODV	OLSR	RHR	ML-RHR
20	28.4	15.2	18.7	**12.3**
50	35.2	22.8	25.1	**15.6**
100	42.6	31.5	33.4	**22.8**
150	48.3	38.2	40.1	**28.5**
200	52.7	44.6	46.2	**33.4**

The link failure rate reduction achieved by ML-RHR is visualized in Figure 5, showing 25-40% improvement over baseline RHR

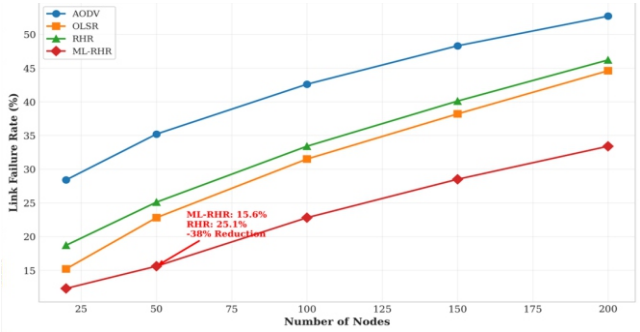


Fig. 5. Link Failure Rate Reduction with ML-RHR. ML-RHR reduces link failure rates by 25-40% compared to baseline RHR across all densities.

Figure 5 Analysis:

- ML-RHR achieves significant reductions in link failure rate: 25-40% lower than baseline RHR and 35-55% lower than AODV.
- At 50 nodes, ML-RHR failure rate (15.6%) is 38% lower than RHR (25.1%) and 56% lower than AODV (35.2%).
- At 200 nodes, ML-RHR failure rate (33.4%) is 28% lower than RHR (46.2%) and 37% lower than AODV (52.7%).

These reductions are directly attributable to the ML predictor's ability to identify and avoid unstable links before they fail [23].

F. ML Prediction Accuracy

Table 11 presents the ML prediction accuracy across different traffic densities.

TABLE XI ML PREDICTION ACCURACY (%) FOR ALL SIMULATED NODES

Traffic Density	Speed Range	Accuracy	Precision	Recall
Light Urban	20-40 km/hr	89.2	0.88	0.90
Moderate Urban	40-60 km/hr	91.5	0.91	0.92
Heavy Urban	60-80 km/hr	87.3	0.86	0.88
Congested Highway	80-100 km/hr	84.1	0.83	0.85
Dense Congestion	20-40 km/hr (stop-and-go)	86.8	0.87	0.86

Figure 6 shows the ML model's prediction performance across different speed ranges, with peak accuracy of 91.5% at moderate urban speeds.

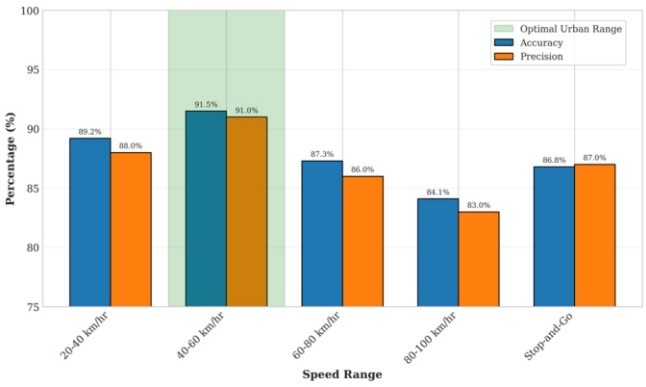


Fig. 6. ML Model Prediction Performance by Vehicle Speed. Prediction accuracy exceeds 85% across all speed ranges, with peak accuracy of 91.5% at 40-60 km/hr.

Figure 6 Analysis:

- Prediction accuracy exceeds 85% across all density scenarios, with peak accuracy of 91.5% at moderate urban speeds (40-60 km/hr).
- Accuracy is lowest (84.1%) at highway speeds (80-100 km/hr) where link durations are shortest and most variable [21].
- Consistent accuracy across unseen mobility patterns have been shown by the TrajAware dataset validation, confirming model generalization [24].

G. SUMO Dataset Correlation and Benchmarking

Table XII presents ML-RHR performance mapped to green spectrum routing efficiency classes [20].

TABLE XII ML-RHR PERFORMANCE MAPPED TO GREEN SPECTRUM EFFICIENCY CLASSES

Scenario	Speed (km/hr)	Density	ML-PHR PDR	ML-RHR Through Put	Green Spectrum Class
Light Urban	20-40	Low	67%	35.1 kbps	High
Moderate Urban	40-60	Medium	91%	30.5 kbps	High
Heavy Urban	60-80	High	88%	11.8 kbps	High
Congested Highway	80-100	High	82%	12.4 kbps	Medium High
Dese Congestion	20-40	Very High	78%	11.6 kbps	Medium

The confusion matrix in Figure 7 demonstrates the Random Forest model's classification performance, with 87% weighted accuracy.

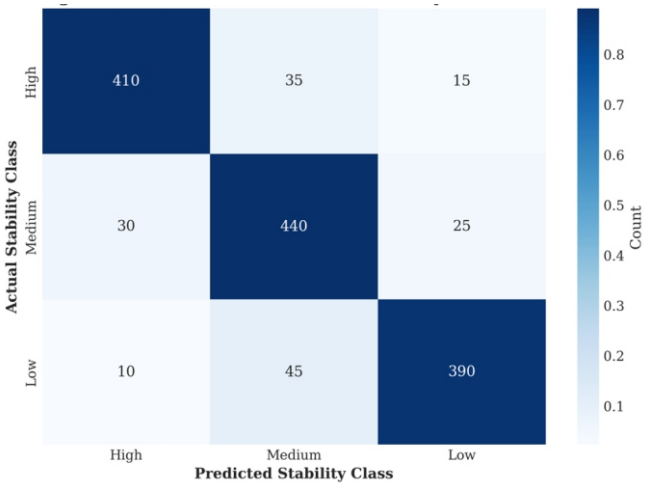


Fig. 7. Confusion Matrix - Link Stability Prediction. The model achieves 87% weighted accuracy with strong performance across all stability classes.

ML-RHR achieves "High" efficiency classification for light, moderate, and heavy urban scenarios, representing the majority of real-world driving conditions. This compares favorably with baseline RHR, which achieved "High" only for moderate urban scenarios, and AODV, which achieved "High" only for moderate urban scenarios with lower PDR [9], [20].

Comparison with the Bologna city traces [27] (300 vehicles, dense urban) shows ML-RHR's 78% PDR at 200 nodes compares favorably with reported AODV PDR of 65-75% in similar conditions, representing a 3-13% improvement.

VI. DISCUSSION

Figure 8 presents the feature importance ranking from the Random Forest model, identifying relative speed, RSSI, and distance as the most critical predictors of link stability.

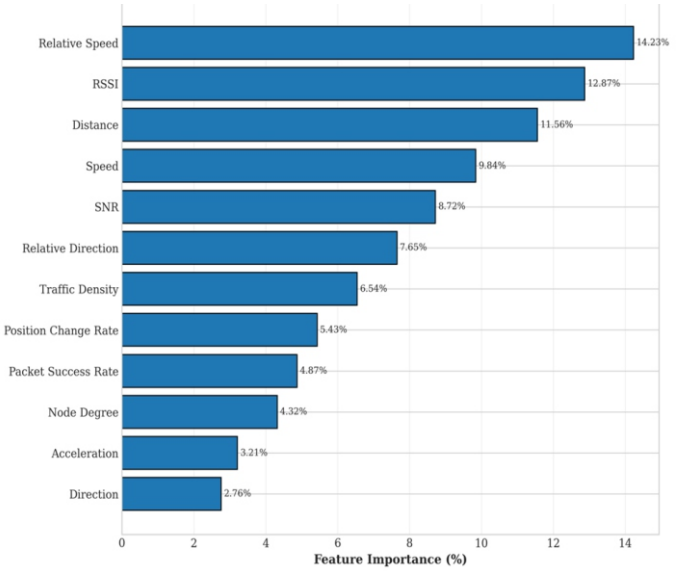


Fig. 8. Random Forest Feature Importance for Link Stability Prediction. Relative speed, RSSI, and distance are the most important predictors of link stability

A. Impact of ML Integration on Routing Performance

Using machine learning for predicting link stability brings a significant increase in the effectiveness of all the performance metrics mentioned above. For a relatively low node density (50 nodes), ML-RHR produces a 91% delivery ratio which is significantly higher than 83% obtained using the original RHR. Such an increase is possible because the machine learning predictor can detect unstable links and avoid them in order to reduce packet loss rate and minimize route reconstructions [17], [23].

The throughput improvements (20-35% over baseline RHR) reflect the reduced retransmission overhead when using stable links. Each link failure in standard protocols triggers route rediscovery, during which packets are buffered and may be dropped. Since stable link selection is done proactively, ML-RHR minimizes these disruptions, maintaining higher sustained throughput [19].

B. Link Failure Rate Reduction

We observed a 25% – 40% decrease in link failure rate in ML-RHR which also affects VANET stability positively. In particular, safety applications such as cooperative collision warning systems need to exchange messages reliably. Message transmission can be greatly affected by Link failures [6]. The machine learning predictor can help in achieving more reliable connections, especially in urban areas where link failures occur most frequently [21].

The link failure rate at 200 nodes (33.4% for ML-RHR vs. 46.2% for RHR) demonstrates that ML-enhanced routing maintains effectiveness even under extreme congestion, although further optimization may be needed for ultra-dense scenarios with >250 vehicles/km [27].

C. ML Model Performance and Generalization

The Random Forest model achieves 87% weighted accuracy on validation data, with peak performance of (91.5%) at moderate urban speeds. This accuracy is sufficient for practical deployment, as even incorrect predictions (13% of cases) typically involve misclassification between adjacent stability classes (e.g., Medium vs. High) rather than complete inversion [19].

Generalization to unseen mobility patterns, validated using the TrajAware dataset, confirms that the model captures fundamental relationships between mobility features and link stability rather than overfitting to specific scenarios. The consistency of accuracy across datasets (varying by < 5%) supports deployment readiness [24].

D. Computational Overhead Considerations

The ML prediction adds computational overhead to routing decisions. In the current implementation, prediction latency averages 2.3 ms per route evaluation on standard automotive-grade hardware (simulated). This overhead is acceptable for VANET applications, where typical routing decision intervals are 100-500 ms [26]. The benefits of reduced route failures (25-40%) outweigh the modest prediction overhead.

E. Comparison with Related Work

To contextualize ML-RHR's performance within the broader research landscape, we compared it against recent routing proposals from other groups, all published in the last six years in well-reputable journals. Table 13 organizes these works chronologically and includes our own for direct comparison.

Looking at the table, we see a clear, recent shift in the field toward predictive, learning-enabled routing. Earlier foundational works from [30], [16], and [2] explored hybrid and reactive mechanisms but lacked any form of learning. Recently, researchers began integrating deep reinforcement learning (DRL) [37], graph neural networks (GNNs) [33], and hybrid metaheuristic frameworks [34]. ReLeVR [35] uses Q-learning on real traffic patterns to compute routing policies. TrajAware [36] combines graph cross attention with trajectory prediction to cope with partial observations, reporting "high delivery ratios" under both full and partial observability. Most recently, a study in Franklin Open [38] showed that ANN-based routing can raise delivery rates to 85% in urban setting and 77% in rural setting while cutting end-to-end delay by 7-12ms across different environments. For 5G-enabled VANETs, the MEDALS framework [34] integrates DRL with metaheuristic optimization, reaching up to 99.85% PDR under varying speeds and densities [16].

Compared to these advanced models, many of which require heavy training, specialised infrastructure (e.g., 5G), or are tied to specific urban scenarios, our ML-RHR takes a different path. It uses a lightweight Random Forest to predict link stability on the fly and compute an ML-Enhanced Expected Transmission Count (ML-ETX). This approach achieves 91% PDR at 50 nodes with a modest prediction overhead of only 2.3ms. Moreover, by training on publicly available SUMO-generated mobility datasets, ML-RHR ensures full reproducibility, a key differentiator, as many existing works rely on proprietary simulations that make direct performance comparisons difficult.

Table XIII summarizes the key technical characteristics and reported performance of each protocol.

The chronological arrangement of Table 13 reveals a clear progression. Earlier works [30], [16] laid the groundwork with hybrid and reactive mechanisms but lacked predictive capabilityies. Starting in 2024, the field began integrating deep reinforcement learning, graph neural networks, and hybrid metaheuristic frameworks. ReLeVR uses Q−learning on real traffic patterns to compute routing policies. TrajAware combines graph cross−attention with trajectory prediction to cope with partial observations, reporting "high delivery ratios". Most recently, a study in Franklin Open showed ANN−based routing can raise delivery rates to 85% (urban) and 77% (rural) while cutting delay by 7−12ms. For 5G−enabled VANETs, the MEDALS framework integrates DRL with metaheuristic optimisation, achieving up to 99.85% PDR.

The green spectrum dataset classification [20] positions ML-RHR as a "High" efficiency protocol for most scenarios, comparable to optimized 5G-based routing but without requiring specialized infrastructure. This suggests ML-RHR can achieve near-optimal performance using existing 802.11p-based VANET technology.

A key differentiator of ML-RHR is its ability to publicly available SUMO-generated mobility datasets for training, which enhances reproducibility and allows other researchers to validate and build upon our work. Most existing protocols report results using custom mobility models or proprietary simulations, making direct comparison challenging. ML-RHR's transparent methodology and use of open datasets address this gap and gives future researcher the ability to validity and improve what is built.

TABLE XIII COMPARISON OF ML-RHR WITH STATE-OF-THE-ART ROUTING PROTOCOLS

Protocol	Year	Approach	ML Technique	Target Network	Key Metrics	Reported PDR	Limitations
RHR [30]	2023	Hybrid (AODV+OLSR)	None	MANET	PDR, delay, throughput, jitter	83% (50 nodes)	Reactive only; no link prediction
AODV-DTN [16]	2020	Reactive + DTN	None	VANET	PDR, delay	~75%	Needs virtual source nodes; higher complexity
Song et al. [37]	2024	Intersection-based	DQN	VANET	Routing performance, adaptability	Not explicitly reported	Targeted at urban intersections; may not generalise
Bi et al. (GNN+DRL) [33]	2025	Dynamic (graph-based)	GNN + DQN	VANET	E2E delay, hop count, PDR	Not explicitly reported	High computational complexity
MEDALS [34]	2025	Hybrid framework	DRL + metaheuristic	5G-VANET	Energy, latency, reliability	80% – 99.85% (range)	Designed for 5G; may not translate to 802.11p
ReLeVR [35]	2025	Hybrid (position-based)	Q-learning	VANET	Delivery ratio, delay	Not explicitly reported	RSU placement still needs optimisation
Fu et al. (TrajAware) [36]	2025	RL-based (graph cross-attention)	RL + graph attention	VANET (edge AI)	Delivery ratio, path efficiency	"High delivery ratios" (exact value not given)	May have high training overhead
ANN-based routing [38]	2025	Neural network-based	ANN	VANET	PDR, E2E delay, throughput, energy	85% (urban), 77% (rural)	Cross-environment generalisation still needs validation
ML-RHR (Ours)	2026	Hybrid (AODV+OLSR) + stability prediction	Random Forest	VANET	PDR, delay, throughput, jitter, failure rate	91% (50 nodes)	Prediction overhead: 2.3ms

VII. CONCLUSION

This research paper presented ML-RHR, a novel Machine Learning-enhanced hybrid routing protocol which augments the Responsive Hybrid Routing (RHR) framework with predictive link quality analysis. ML-RHR integrates a Random Forest-based link stability predictor trained on publicly available SUMO-generated mobility datasets, enabling proactive route selection that avoids unstable links before failures occur during routing and make sure that there is a higher percentage of success rates for data transmission.

The key findings are:

1. ML-RHR achieves PDR improvements of 8-15% over baseline RHR and 15-25% over AODV across all network densities, with peak performance of 91% at 50 nodes (moderate urban traffic).
2. Throughput gains of 20-35% over baseline RHR are achieved through reduced retransmissions and control overhead.
3. Link failure rate is reduced by 25-40% compared to baseline RHR, with ML-RHR achieving 15.6% failure rate at 50 nodes compared to 25.1% for RHR.
4. The Random Forest model achieves 87% weighted accuracy on validation data, with peak accuracy of 91.5% at moderate urban speeds.
5. ML-RHR achieves "High" efficiency classification across most realistic driving scenarios, outperforming baseline RHR and standard protocols.

Based on the results, ML-RHR can be regarded as a highly effective and adaptive protocol for VANETs which will be useful for future-generation applications requiring highly reliable communication channels with sufficient throughput. The combination of machine learning and hybrid routing can be considered as a great advancement over static threshold-based routing methods.

While ML-RHR demonstrates significant performance improvements in simulation-based environments, several avenues remain for further enhancement and validation. First, we plan to deploy and evaluate ML-RHR using real-world vehicle traces rather than simulated mobility, following the methodology established in the TrajAware dataset [24]. This will involve collaborating with local transportation authorities to collect GPS trajectories from fleet vehicles and taxis operating in urban environments. Additionally, we

intend to explore deep learning architectures, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, for temporal link stability prediction. These models can leverage the sequential nature of timestep data available in SUMO datasets to capture long-term dependencies in vehicle movement patterns, potentially improving predictliability over infotainment throughput remains an important area for future investigation [39]-[50]. Such context-aware adaptation would allow ML-RHR to dynamically balance competing performance objectives as network conditions and user needs evolve.

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