A Hybrid Optimized VANET Routing Protocol Based on RNN and LPC for Reliable Communication

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Abstract: Vehicular Ad Hoc Networks (VANETs) are characterized by high mobility and the absence of centralized infrastructure, posing significant challenges in maintaining stable and reliable communication. One of the key issues in VANETs is the frequent link breakage due to the dynamic topology, which affects routing stability and network performance. To address this challenge, a Hybrid Optimized VANET Routing Protocol Using RNN-LPC is proposed, leveraging Recurrent Neural Networks (RNNs) and Linear Predictive Coding (LPC) to predict the future distance between a node and its neighbors. By incorporating predictive distance estimation, the proposed protocol selects more stable nodes, thereby enhancing route longevity and communication reliability. The protocol is evaluated against a traditional VANET routing protocol using key performance metrics such as packet delivery ratio, routing overhead and end-to-end delay. The results demonstrate that the proposed approach reduces routing overhead while improving packet delivery ratio, making it a more efficient and scalable solution for highly dynamic VANET environments.

Keywords: VANETs, Routing protocol, Recurrent Neural Network, Linear Predictive Coding, Prediction models, Reliable communication, Performance's analysis.

1. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) emerged as a fundamental concept in wireless networking, enabling self-organizing communication in environments without fixed infrastructure. One of the earliest implementations of MANETs can be traced back to the U.S. Department of Defense (DoD)-sponsored Packet Radio Network (PRNET) in 1972, which later evolved into the Survivable Adaptive Radio Networks (SURAN) program. These initiatives were designed to provide robust, packet-switched networking for military applications, where nodes such as soldiers, tanks, and aircraft operated in highly dynamic and infrastructure-less environments. (Ramanathan and Redi, 2002)

The rapid growth of intelligent transportation systems has made real-time vehicle communication a crucial component of modern road safety and traffic management. As wireless networking technology advanced, MANETs found broader applications beyond military settings, giving rise to specialized forms such as Vehicular Ad Hoc Networks (VANETs). VANETs leverage the core principles of MANETs but are specifically designed for vehicular environments, where vehicles act as mobile nodes communicating with each other (V2V) and with roadside infrastructure (V2I). The primary goal of VANETs is to enhance road safety, traffic efficiency, and Intelligent Transportation Systems (ITS) through real-time data exchange.

With the evolution of wireless technologies, VANETs are increasingly integrating with emerging paradigms such as 5G, edge computing, and artificial intelligence to improve communication efficiency and scalability. Despite these advancements, ensuring seamless and secure vehicular communication remains a critical challenge. However, VANETs present unique challenges distinct from traditional MANETs. Unlike conventional MANET nodes, vehicles in VANETs move at high speeds, leading to rapid topology changes and frequent disconnections. Additionally, VANETs require highly reliable communication to support safety-critical applications such as collision avoidance and emergency braking alerts. As a result, extensive research has been conducted on developing efficient routing protocols, security mechanisms, and data dissemination strategies tailored to vehicular networks (Hartenstein and Laberteaux, 2008; Olariu and Weigle, 2009)

In this context, Recurrent Neural Networks and Linear Predictive Coding emerge as promising tools for predicting future vehicle positions based on historical mobility data. RNNs are well suited for modelling temporal dependencies inherent in sequential data such as vehicle trajectories. Meanwhile, LPC, traditionally employed in signal processing, can be adapted for mobility prediction by analyzing prior movement patterns. By integrating RNN and LPC into the routing process, the protocol anticipates future distances between nodes and their neighbors, enabling the selection of more stable routes and enhancing network reliability.

This paper presents an optimized VANET routing protocol that leverages RNN and LPC for future distance prediction, aiming to improve route stability and communication reliability. The protocol's performance is evaluated against AODV using key metrics, including packet delivery ratio, routing overhead, throughput, and end-to-end delay. Simulations are conducted within an urban environment to reflect realistic vehicular mobility. Results demonstrate that the proposed protocol enhances packet delivery and throughput while reducing routing overhead, offering a scalable and efficient solution for highly dynamic urban VANET scenarios.

To address these challenges, this study seeks to answer the following research questions:

- How can integrating Recurrent Neural Networks and Linear Predictive Coding improve the stability of VANET routing protocols?
- What is the impact of the proposed protocol on key performance metrics such as packet delivery ratio, throughput, routing overhead, and end-to-end delay?
- How does the proposed protocol perform in comparison with the traditional AODV protocol under realistic urban mobility scenarios?

The remainder of this paper is organized as follows. Section 2 reviews the background and related work. Section 3 describes the proposed routing protocol in detail. Section 4 outlines the simulation setup and evaluation metrics. Section 5 presents and analyzes the simulation results, including a partial ablation study. Finally, Section 6 concludes the paper and suggests future research directions.

2. BACKGROUND AND LITERATURE REVIEW

Numerous research studies have focused on various types of ad hoc networks (Asad et al., 2019; Li et al., 2020; Maivizhi and Yogesh, 2022). In the paper of (Gbadebo et al., 2023), an upgraded cluster-based routing model for energy-efficient wireless sensor networks was proposed. Meanwhile, in (Kies et al., 2022), an optimal approach for distributing roadside units was suggested for vehicular ad hoc networks. Additional research papers (Bairwa and Joshi, 2022; Malnar and Jevtic, 2022; Arebi, 2024) have introduced different modified versions of the AODV protocol (Perkins and Royer, 1999) to enhance network performance.

(Arebi, 2024) has proposed a new protocol to address broken links during the routing process. Their solution allows for predicting and repairing routes when links break, achieving an average improvement rate of 45% compared to AODV. (Bairwa and Joshi, 2022) recommended a variant of AODV that targets QoS by reducing routing overheads in MANETs. Simulation results have demonstrated the effectiveness of the proposed technique over the AODV routing protocol.

The Neighbourhood-Density AODV protocol (Malnar and Jevtic, 2022) is an improved version of AODV designed to reduce routing overhead in large dynamic networks. This protocol uses a metric called Power Light Reverse ETX, based on expected transmission count, which significantly enhances reliability. In (Liu et al., 2019), the authors proposed a protocol that uses two channels to transmit data packets and control messages separately. This solution predicts the reception of packets on each link and utilizes the Dijkstra algorithm to select the optimal route. This protocol has shown improvements in the rate of received packets compared to AODV.

The NACK-based (Bianchiet al., 2015) is a variant of the well-known AODV protocol that aims to improve network topology awareness compared to the original protocol. The results of the comparison of this proposed protocol against AODV show a higher utilization of network topology awareness. Furthermore, in the paper of (Kabir et al., 2015) , researchers have proposed the Pro-AODV (Proactive AODV) protocol, which minimizes congestion in VANET and is based on the size of the routing table of the network nodes. This protocol has demonstrated positive results in terms of average delay and packet delivery ratio.

Traffic prediction plays a crucial role in VANETs for improving routing efficiency and congestion control. (Abdellah and Koucheryavy, 2020) proposed a deep-learning-based approach using Long Short-Term Memory (LSTM), a variant of RNNs, to predict traffic conditions in urban environments, demonstrating significant improvements in accuracy compared to traditional models. Similarly, (He et al., 2024) applied a hybrid RNN model that combined LSTM and Gated Recurrent Units (GRU) for real-time traffic flow prediction, reducing computational overhead while maintaining high accuracy.

3. PROPOSED METHODOLOGY

This section presents the design and operation of the Hybrid Optimizer Ad hoc On-Demand Distance Vector (HO-AODV) protocol, a reactive routing approach aimed at improving route selection and network performance in Vehicular Ad Hoc Networks. Operating on an on-demand basis, the protocol dynamically determines the most optimal routes over a specified period. To enhance routing stability, HO-AODV integrates a predictive mechanism that estimates the future distances between a node and its neighbors. This is achieved through a hybrid approach combining Recurrent Neural Networks and Linear Predictive Coding, ensuring more accurate mobility predictions.

Based on these predictions, the protocol computes a Mobility Index (MI) to quantify the stability of neighboring nodes. The optimal reverse path is then identified, and the RREQ of this path is selectively rebroadcasted. This approach reduces redundant transmissions and enhances communication reliability. By prioritizing stable nodes, HO-AODV minimizes link failures, decreases routing overhead, and improves overall network efficiency.

3.1 Distance capturing process

The proposed HO-AODV protocol integrates a real-time distance capturing mechanism to monitor the relative positions of neighboring nodes before applying predictive techniques. This process is illustrated in Fig 1 and it involves the following steps:

- *Neighbor Discovery*: Each vehicle periodically broadcasts Hello messages containing its unique identifier and current position, allowing neighboring nodes to detect its presence. This process ensures that nodes maintain an updated list of active neighbors.
- *Distance Calculation*: Upon receiving a Hello message from a neighboring node, the recipient calculates the Euclidean distance based on the GPS coordinates of both nodes. The Euclidean distances between the actual node A and each neighbour B_i is expressed as:

$$d_j(A, B_i) = \sqrt{\left(x_A - x_{B_i}\right)^2 + \left(y_A - y_{B_i}\right)^2}, \quad \forall B_i \in \mathcal{N}(A) \tag{1}$$

Where:

- j is the **index of the distance measurement**, representing different observations of the distance between node A and its neighbour B_i
- i is the **index of the** neighbor
- (x_A, y_A) are the coordinates of node A
- (x_{B_i}, y_{B_i}) are the coordinates of neighbour B_i
- $\mathcal{N}(A)$ is the set of all neighbors of A

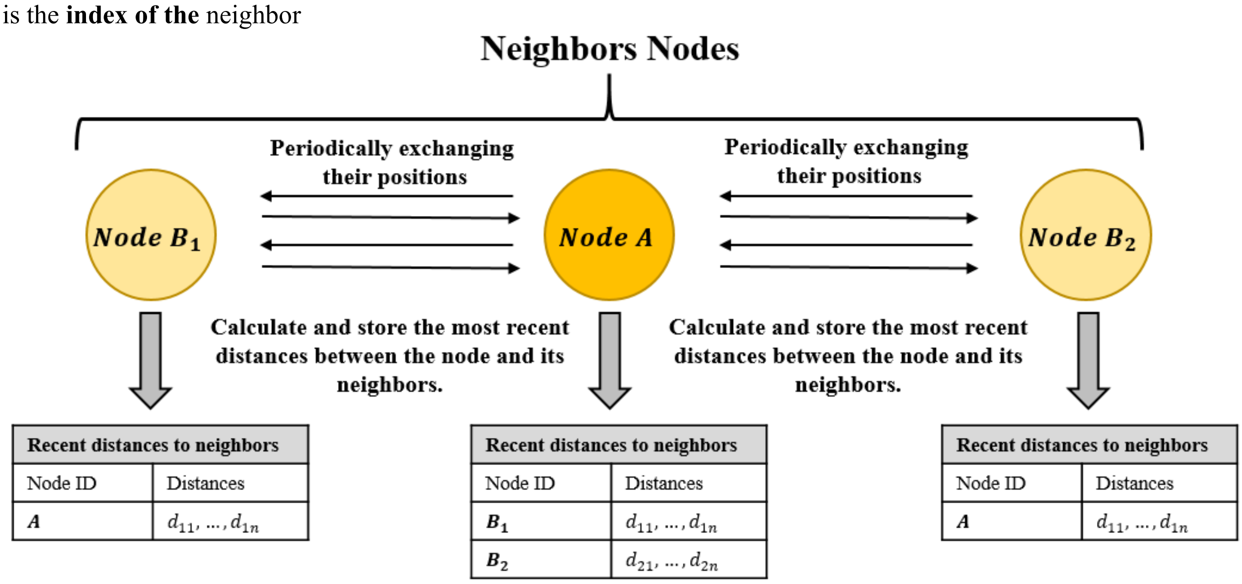

Fig. 1. An overview of the Distance Capturing Process.

3.2 Distance prediction process

Due to the high mobility of vehicles in VANETs, predicting future distances is essential for maintaining stable communication links. Our protocol integrates two prediction techniques, as illustrated in Fig. 2.

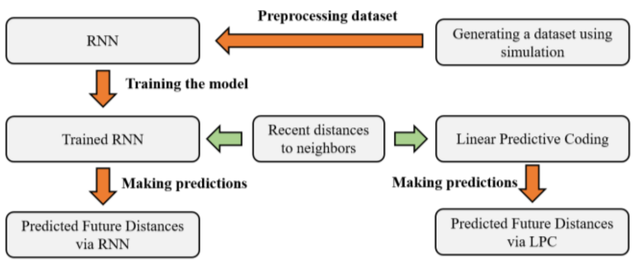

Fig. 2. An overview of the prediction process of the future distances to neighbors.

3.2.1 Prediction using recurrent neural networks

RNN is a deep learning technique well suited for capturing temporal dependencies in node movement. It learns from past mobility patterns to make future distance predictions between a node and its neighbors. After performing extensive hyperparameter tuning, we selected the configuration that achieved the best performance.

A summary of the tuned hyperparameters and their selected values is provided in Table 1. Based on this tuning process, we finalized the RNN model architecture, which is detailed in Table 2. This architecture enables the network to effectively capture temporal dependencies and learn complex patterns from sequential data.

Table 1. Summary of Hyperparameter Tuning and Selected Values.

Experiment No.	Learning Rate	Number of Layers	Dropout Rate	Balanced Accuracy(%)
1.	0.001	2	0.0	50
2.	0.001	3	0.0	50
3.	0.001	4	0.0	50
4.	0.01	2	0.0	95.56
5.	0.01	3	0.0	91.19
6.	0.01	4	0.0	63.55
7.	0.1	2	0.0	50
8.	0.1	3	0.0	50
9.	0.1	4	0.0	50
10.	0.001	2	0.3	50
11.	0.001	3	0.3	50
12.	0.001	4	0.3	50
13.	0.01	2	0.3	95.53

14.	**0.01**	**3**	**0.3**	**95.94**
15.	0.01	4	0.3	59
16.	0.1	2	0.3	50
17.	0.1	3	0.3	50
18.	0.1	4	0.3	50

Table 2. Summary of the RNN Model Architecture.

Layer	Type	Units	Activation Function	Output Shape
1	Input Sequence	-	-	(10000, 9, 1)
2	RNN (Hidden Layer 1)	32	Tanh	(10000, 9, 32)
3	RNN (Hidden Layer 2)	32	Tanh	(10000, 9, 32)
4	RNN (Hidden Layer 3)	32	Tanh	(10000, 32)
5	Dense (Output Layer)	1	Linear	(10000, 1)

The RNN receives as input a sequence of nine consecutive recent distance observations, which are used to predict the future distance. This sequence-based approach effectively captures the time-series characteristics of the vehicular data. The dataset used for training and testing consists of 10000 entries collected from vehicle movement simulation scenarios. Repeated K-Fold Cross-Validation was applied on 80% of the data (training-development set), with k = 5 and 3 repetitions. The remaining 20% was held out as an untouched test set to assess generalization performance. Within each fold, the RNN model was trained for 2,500 epochs to ensure convergence and effective learning of temporal dependencies.

After training, the RNN model achieved a balanced accuracy of 95.57% on the test dataset, demonstrating its ability to predict future distances with good reliability. The accuracy of the RNN model is calculated based on the correct prediction of link status. Specifically, a prediction is considered correct if it accurately determines whether the predicted distance value indicates a link failure or a maintained connection between vehicles. Given the imbalance in the dataset—with significantly more samples representing one link status over the other—balanced accuracy (García et al., 2009) was chosen as a more appropriate evaluation metric than standard accuracy. This ensures that the performance reflects the model's ability to handle both classes fairly, providing a more robust assessment of its predictive capability in a realistic VANET scenario.

3.2.2 Prediction using linear predictive coding

LPC is applied to model linear motion trends, offering a lightweight and efficient approach for short-term mobility prediction. An LPC order of three was used, estimating the next value based on the three most recent observations. This balances accuracy and computational cost, making it suitable for real-time vehicular scenarios. The LPC prediction is computed using the following formula:

$$\hat{x}(n) = -\sum_{i=1}^{3} a_i \cdot x(n-i) \tag{2}$$

Where

- $\hat{x}(n)$ is the predicted value at time step n
- a_i are the LPC coefficients, and $x(n-i)$ are the previous observations.

3.3 Mobility index computation

Once the future distances between a node and its neighbors are predicted, the protocol computes a Mobility Index (MI) to quantify the stability of each neighbor. The MI is derived from the variation between previously recorded distances and predicted future distances over a given time window. A lower variation indicates a more stable neighbor. The MI for previously recorded distances and predicted future distances using RNN is computed as follows:

$$MI_{B_i}^{RNN} = \alpha * \sigma_{B_i}^2 + \beta * \mu_{B_i} \tag{3}$$

$$D_{A\to B_i}^{RNN} = \{d_1(A,B_i), d_2(A,B_i), \dots, d_m(A,B_i), \hat{d}^{RNN}{}_{m+1}(A,B_i), \hat{d}^{RNN}{}_{m+2}(A,B_i), \dots, \hat{d}^{RNN}{}_{m+f}(A,B_i)\} \tag{4}$$

Where:

- $D_{A\to B_i}^{RNN}$ is the set of previously recorded distances and predicted future distances using RNN to $Node\ B_i$.
- $d_j(A,B_i)$ is the Euclidean distance between node A and neighbor B_i at time instance j.
- $\hat{d}^{RNN}{}_{j+1}(A,B_i)$ is the predicted distance using RNN for the next time steps f.
- m is the number of recorded distances over time.
- f is the number of future predicted distances.
- α and β are weighting coefficients.
- μ_{B_i} is the mean distance to neighbor B_i :

$$\mu_{B_i} = \frac{1}{m+f}\sum_{j=1}^{m+f} d_j(A,B_i) \tag{5}$$

- $\sigma_{B_i}^2$ is the variance of distances for neighbor B_i :

$$\sigma_{B_i}^2 = \frac{1}{m+f}\sum_{j=1}^{m+f}\left(d_j(A,B_i) - \mu_{B_i}\right)^2 \tag{6}$$

The MI for distances predicted using LPC is computed as follows:

$$MI_{B_i}^{LPC} = \alpha * \sigma_{B_i}^2 + \beta * \mu_{B_i} \tag{7}$$

This is computed in the same manner as $\boldsymbol{MI_{B_i}^{RNN}}$ except that it is based on the following extended distance set**:**

$$D_{A\to B_i}^{LPC} = \{d_1(A,B_i), d_2(A,B_i), \ldots, d_m(A,B_i), \hat{d}^{LPC}{}_{m+1}(A,B_i), \hat{d}^{LPC}{}_{m+2}(A,B_i), \ldots, \hat{d}^{LPC}{}_{m+f}(A,B_i)\} \quad (8)$$

The computed mobility indexes are subsequently combined using the following formula:

$$MI_{B_i}^{combined} = \alpha \cdot MI_{B_i}^{RNN} + \beta \cdot MI_{B_i}^{LPC} \quad (9)$$

Where

- α and β are weighting coefficients,
- $\alpha + \beta = 1$ to ensure proper weighting.

3.4 Mobility index-based RREQ forwarding

During the route discovery phase, a node receives multiple Route Request (RREQ) messages from its neighbors; the RREQ message format is illustrated in Fig. 3, where the additional fields introduced in our approach are highlighted in grey. Instead of rebroadcasting all received RREQs, the protocol follows a selective rebroadcasting approach based on the computed mobility index:

- Receiving RREQs: A node receives multiple RREQs from its neighbors, each containing information about the sender (neighbor node).
- Evaluating Stability: The node computes the mobility index for each neighbor using the predicted distances.
- The combined mobility index (CMI), denoted as $MI_{B_i}^{combined}$, is added to the existing cost value of the received RREQs to refine the route selection process.

$$RREQ_{cost}^{B_i} = RREQ_{cost}^{B_i} + MI_{B_i}^{combined} \quad (10)$$

Where:

- $RREQ_{cost}^{B_i}$ is the cost of RREQ received from neighbour B_i
- The RREQ with the lowest cost value is selected as the optimal one.
- Suppressing Redundant RREQs: RREQs from less stable routes are discarded, reducing routing overhead and unnecessary retransmissions.

Formula for selecting the optimal RREQ:

$$RREQ_{\text{optimal}} = \underset{RREQ^{B_i} \in RREQs}{\arg min} \; RREQ_{cost}^{B_i} \quad (11)$$

Where:

- $RREQs$ is the set of RREQ messages received during a predefined waiting period t_w
- $RREQ^{B_i}$ is the RREQ received from neighbor B_i
- $RREQ_{cost}^{B_i}$ is the cost of the RREQ received from neighbor B_i

By forwarding RREQ that comes from the optimal reverse path, the protocol increases the chances of establishing long-lasting routes, thereby reducing frequent route breaks and re-discovery processes. The process is illustrated in Figs. 4 and 5. When “Node SRC” initiates a route discovery process to “Node DST”, the intermediate “Node A” maintains the optimal reverse path and rebroadcasts only the optimal RREQ.

TYPE	FLAGS	RESERVED	HOP COUNT
BROADCAST ID			
ACKNOWLEDGMENT NUMBER			
DESTINATION IP ADDRESS			
DESTINATION SEQUENCE NUMBER			
ORIGINATOR IP ADDRESS			
ORIGINATOR SEQUENCE NUMBER			
COST			

Fig. 3. The RREQ format of HO-AODV.

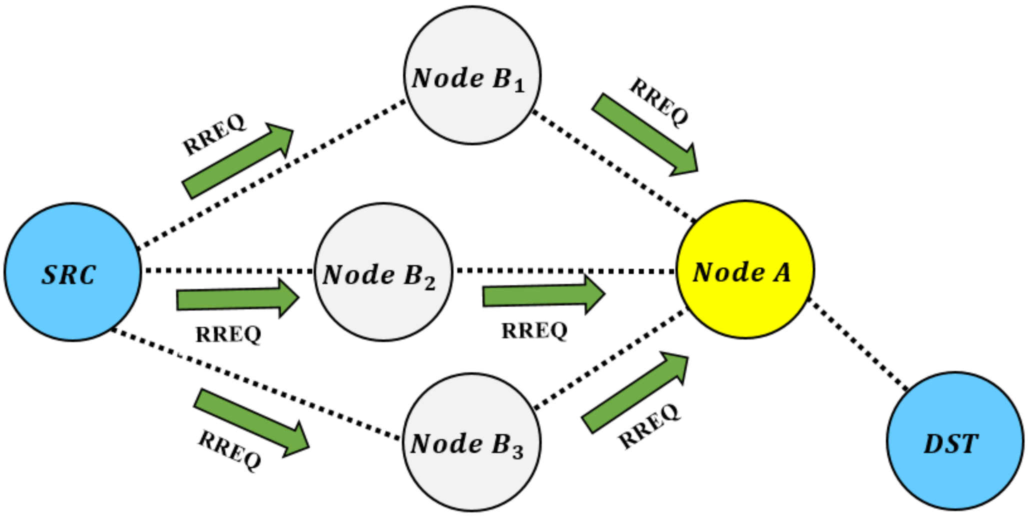

Fig. 4. An example of the route discovery process.

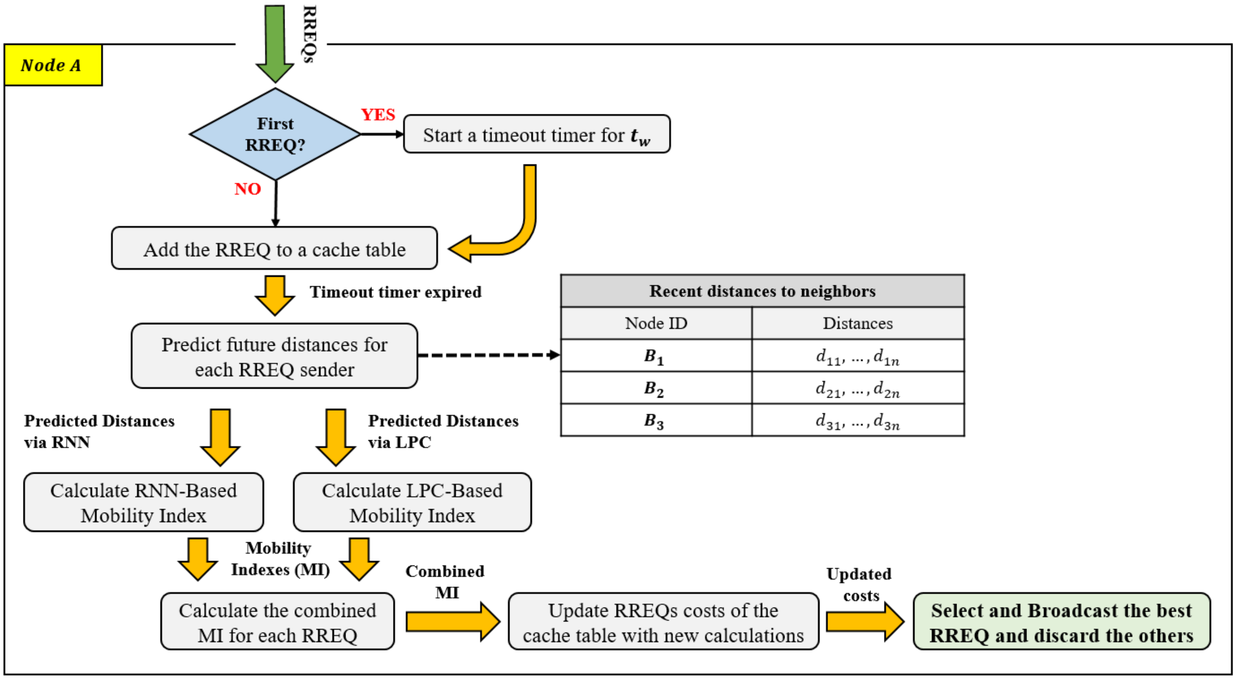

Fig. 5. The proposed process flow when node A receives RREQs in the considered example (Fig. 4).

3.5 Mobility index-based RREQ forwarding

Upon receiving the first Route Request (RREQ), the destination node initiates a timeout timer denoted as (t_w). This waiting period allows the destination to collect multiple RREQs arriving through different paths, thereby increasing the chances of selecting a more efficient or reliable route. Once the timer expires, the destination evaluates each of the received reverse routes by computing a cost metric associated with each path, based on predefined performance criteria. The route with the lowest cost is selected as the optimal path. A RREP is then sent back to the source via the best reverse route. The RREP format is shown in Fig. 6, where the "COST" field indicates the selected route's cost.

TYPE	FLAGS	RESERVED	HOP COUNT
DESTINATION IP ADDRESS			
DESTINATION SEQUENCE NUMBER			
ORIGINATOR IP ADDRESS			
ORIGINATOR SEQUENCE NUMBER			
TTL			
COST			

Fig. 6. The RREP format of HO-AODV.

4. SIMULATION AND PERFORMANCE EVALUATION

To understand the behavior of the newly designed protocol and evaluate its performance, the protocol was implemented and simulated using the Network Simulator v3.44. The protocol was integrated as a module within the NS-3 simulator, and extensive simulations were conducted. The primary objective was to compare the performance of the two protocols, AODV and HO-AODV, using different performance key metrics. Simulations were carried out under various network configurations to ensure a comprehensive evaluation.

4.1 Mobility model selection and configuration

The mobility model defines the movement of mobile entities over time, including direction, location, velocity, and acceleration. It critically affects protocol performance by influencing link stability and connectivity, and must accurately reflect real-world movement behavior.

The Manhattan Mobility Model, first introduced by (Baiet al., 2003), is widely used to simulate urban environments with structured road layouts. In the simulations, this model is adopted as it closely reflects the grid-like street patterns typical of city environments, making it well suited for VANET scenarios. Moreover, the Manhattan model offers ease of implementation and good scalability, enabling realistic and efficient evaluation of our protocol in urban vehicular settings. The configuration parameters of the Manhattan Mobility Model used in our simulations are summarized in Table 3.

Table 3. Simulation parameters of the Manhattan model.

Parameter	Value
Speed update distance	50
Speed change probability	0.4
Speed standard deviation	4
Pause probability	0.3
Turn probability	0.3

4.2 Key performance metrics

To evaluate the performance of HO-AODV against AODV, the following key performance metrics are considered:

- *PDR (Packet Delivery Ratio):* PDR is a key performance metric used to evaluate the efficiency of a routing protocol. It is defined as the ratio of the total number of packets successfully delivered to the destination to the total number of packets sent by the source node.

- *Routing Overhead*: The total number of control bytes generated by the routing protocol to establish and maintain routes.
- *Throughput:* is defined as the average rate of successful data delivery over the network, typically measured in bits per second (bps) or packets per second.
- *End-to-End Delay (e2e delay):* represents the average time taken for data packets to travel from the source to the destination across the network.

4.3 Simulation scenarios

The simulation is conducted based on two main scenarios. For each scenario, multiple simulation runs are performed with several replications while keeping the remaining parameters constant. In the first scenario, the number of nodes is varied, and the corresponding simulation parameters are presented in Table 4. In the second scenario, the average node speed is varied, with the simulation parameters detailed in Table 5.

Table 4. Simulation parameters of Scenario 1.

Parameter	Value
Simulation area	1000m*1000m
Number of nodes	50 | 70 | 90 | 110 | 130
Number of Source-Destination Pairs	%20 of the number of nodes
Simulation duration	500s
Average speed	35 km/h
Application traffic	UDP Client-Server Application
Evaluated protocols	HO-AODV | AODV
Replication number	15

Table 5. Simulation parameters of Scenario 2.

Parameter	Value
Simulation area	1000m*1000m
Number of nodes	110
Number of Source-Destination Pairs	%20 of the number of nodes
Simulation duration	500s
Average speed	5 km/h | 15 km/h | 25 km/h | 35 km/h |45 km/h
Application traffic	UDP Client-Server Application
Evaluated protocols	HO-AODV | AODV
Replication number	15

5. RESULTS AND DISCUSSION

In this section, the simulation results of the two considered scenarios are presented. The results are illustrated in the form of charts for each key performance metric. Each data point represents the average value obtained from multiple simulation replications. In addition to the main performance results, a partial ablation study was conducted to evaluate the individual contributions of the LPC and RNN components. The addition of LPC slightly improved performance compared to using RNN alone in a limited number of simulation scenarios. This improvement is attributed to LPC's ability to predict future distances, while the RNN primarily focuses on determining whether the communication link is broken—implicitly modeled through distance prediction. These tasks are complementary, as distance prediction helps anticipate link failures more effectively. However, the evaluation was constrained by increased simulation complexity and extended processing time.

5.1 Scenario 01: evaluation with different node densities

As shown in Fig. 6, HO-AODV consistently achieves higher PDR values than AODV. Although the difference is relatively moderate, it is noticeable and indicates that HO-AODV performs better in maintaining reliable packet delivery as the network size increases. Overall, the proposed protocol achieves an average increase of 3.6% in PDR compared to AODV across all tested node densities. This improvement is due to the prediction mechanism integrated into the route discovery process, which helps reduce packet loss. However, as the network becomes highly dense, the PDR margin between the two protocols becomes moderate, indicating that the benefits of the prediction mechanism diminish slightly under extreme network loads.

Regarding routing overhead (as shown in Fig. 7), the proposed protocol generates less overhead compared to AODV, particularly as the network becomes dense. This improvement is mainly attributed to the efficient route selection process, which reduces unnecessary control packet transmissions due to the longer lifetime of the selected routes. On average, the proposed protocol achieves a 5.9% reduction in routing overhead compared to AODV, demonstrating better efficiency in controlling packet transmissions.

As illustrated in Fig. 8, HO-AODV achieves higher throughput than AODV. This improvement enhances overall data delivery. In terms of end-to-end delay (Fig. 9), AODV performs slightly better than HO-AODV. This is mainly attributed to the waiting time introduced in HO-AODV for collecting additional RREQs to enable the prediction mechanism during route selection.

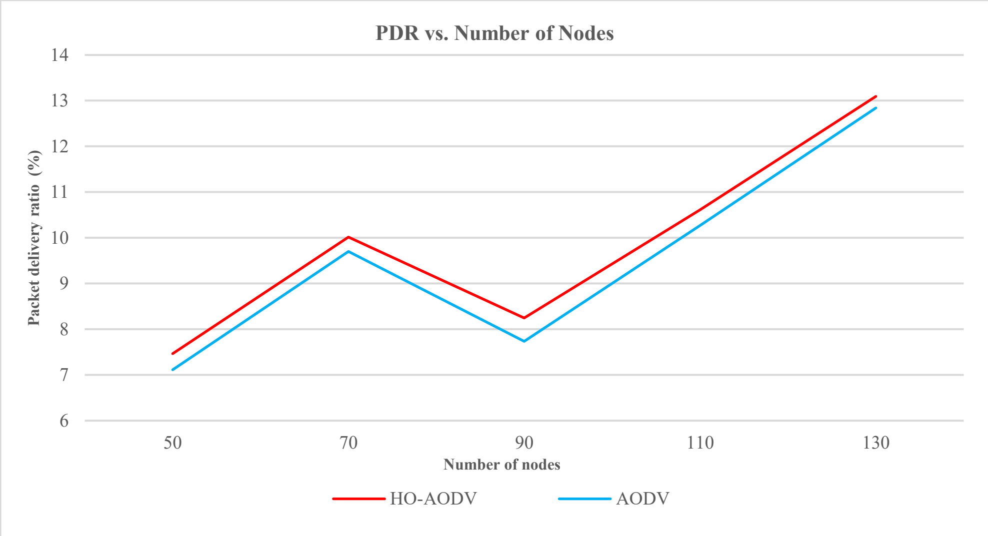

Fig. 6. Packet delivery ratio comparison between the proposed protocol and AODV versus the number of nodes.

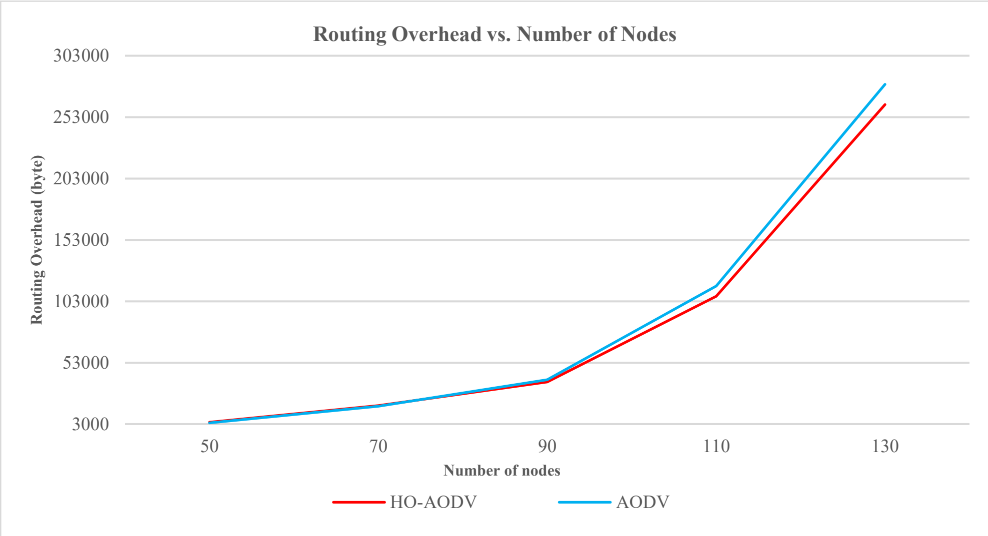

Fig. 7. Routing overhead comparison between the proposed protocol and AODV versus the number of nodes.

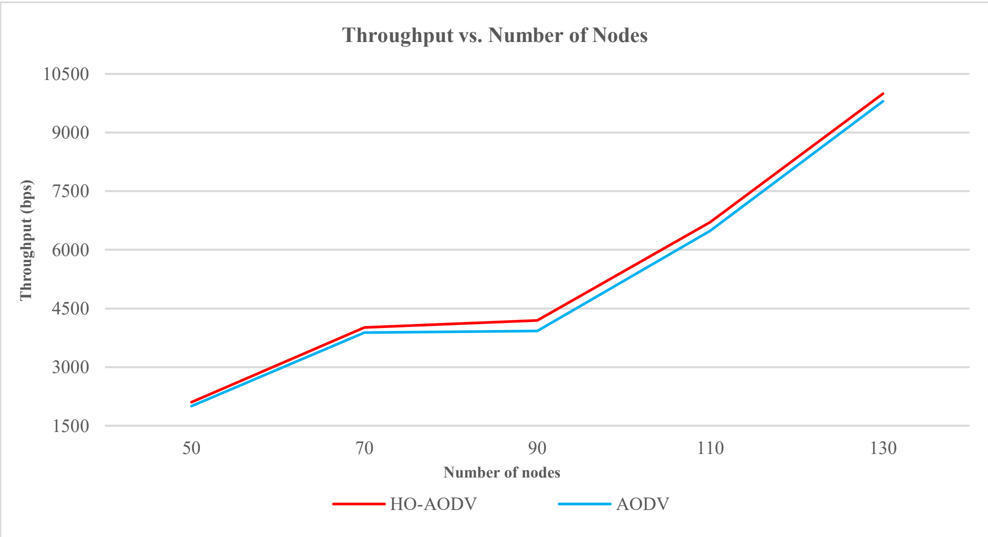

Fig. 8. Throughput comparison between the proposed protocol and AODV versus the number of nodes.

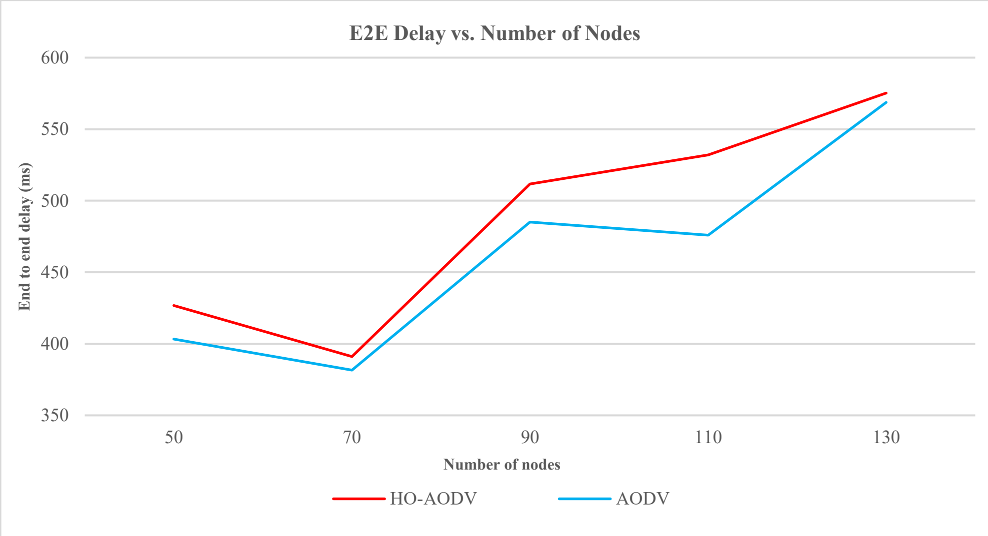

Fig. 9. End to end delay comparison between the proposed protocol and AODV versus the number of nodes.

5.2 Scenario 02: Evaluation under different average speeds

As illustrated in Fig. 10, under varying average speeds, the proposed protocol achieves better PDR than AODV at low and moderate speeds, with an average improvement of 2.82%. This improvement is mainly due to the prediction mechanism integrated into the route discovery process, which allows the protocol to select more stable routes and reduce packet loss when node mobility is moderate. However, at very high speeds, both protocols exhibit comparable performance, although the proposed protocol still maintains a slight advantage over AODV despite the reduced effectiveness of the prediction mechanism due to rapid topology changes.

As shown in Fig. 11, the proposed protocol achieves lower routing overhead than AODV, with an average reduction of 4.83%. Both protocols perform similarly at very low speeds due to network stability. However, as the average speed increases, the HO-AODV demonstrates better performance due to its efficient route selection and the reduction of control packet transmissions.

As illustrated in Fig. 12, throughput decreases for both protocols as the average speed increases due to frequent route breakages. However, the proposed protocol consistently achieves slightly better throughput than AODV across all speed levels, with an average improvement of 2.91%, benefiting from its efficient route selection mechanism. In terms of end-to-end delay (Fig. 13), AODV slightly outperforms HO-AODV under varying speeds due to the additional waiting time required by the prediction mechanism in HO-AODV.

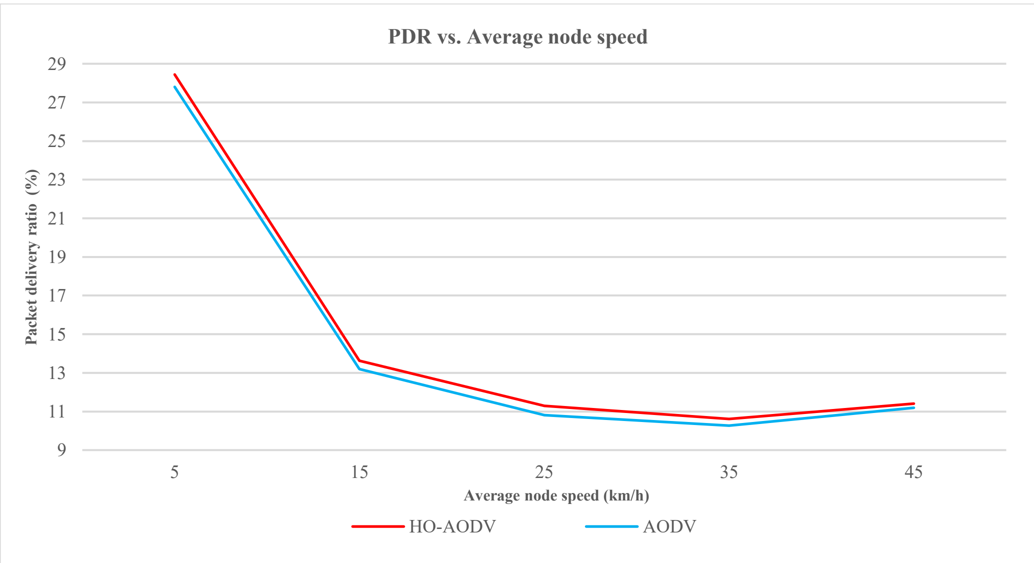

Fig. 10. Packet delivery ratio comparison between the proposed protocol and AODV versus the average node speed.

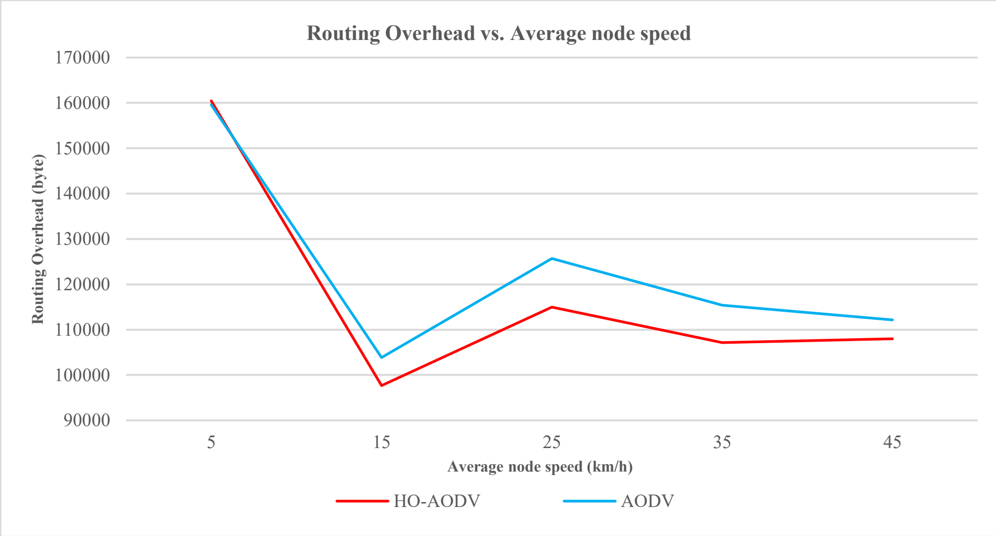

Fig. 11. Routing overhead comparison between the proposed protocol and AODV versus the average node speed.

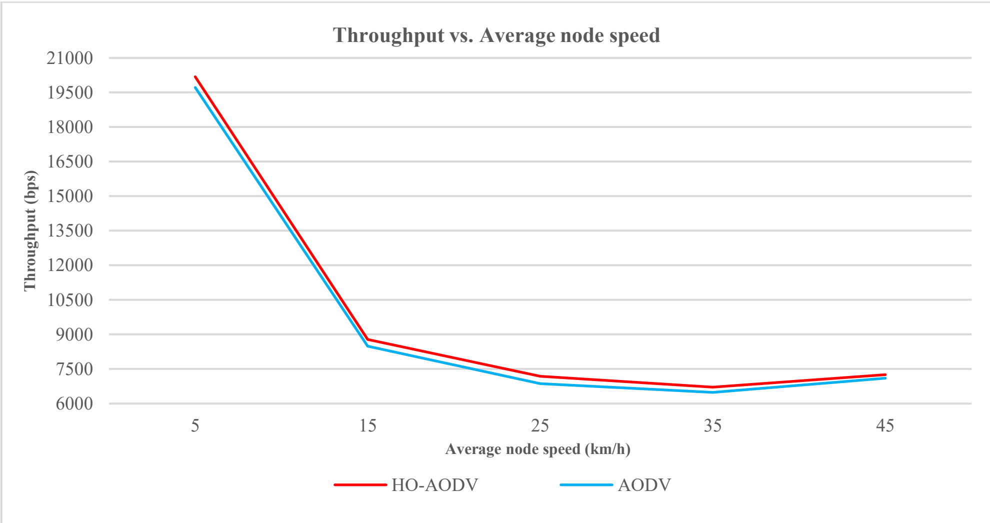

Fig. 12. Throughput comparison between the proposed protocol and AODV versus the average node speed.

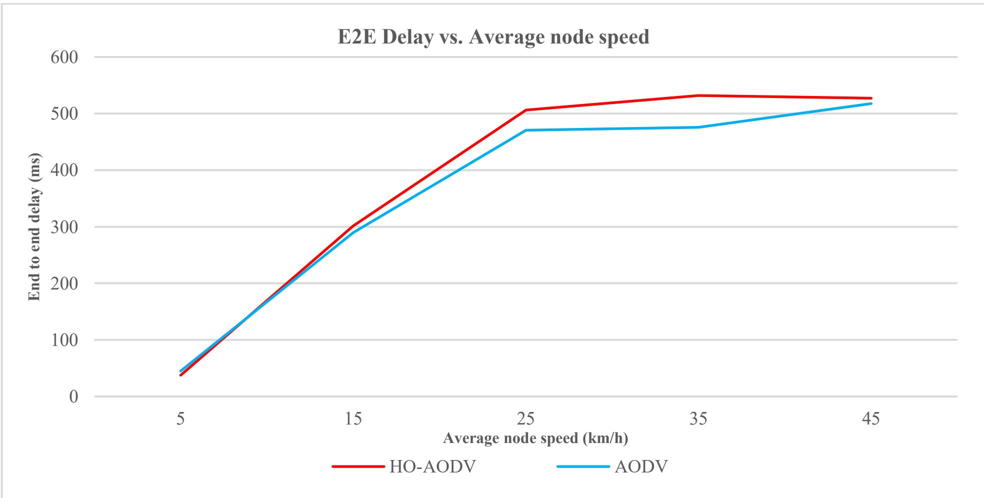

Fig. 13. End to end delay comparison between the proposed protocol and AODV versus the average node speed.

6. CONCLUSIONS AND PERSPECTIVES

In this paper, a Hybrid Optimized VANET Routing Protocol is proposed, integrating Recurrent Neural Networks and Linear Prediction Coding to enhance route reliability and communication efficiency in vehicular ad hoc networks. The proposed protocol leverages the prediction capabilities of

RNN and LPC to anticipate link stability, enabling more accurate route selection and reducing route failures. Simulation results demonstrate that the proposed protocol outperforms the standard AODV in terms of packet delivery ratio, routing overhead, and throughput, particularly in dense network conditions and varying mobility scenarios. Although a slight increase in end-to-end delay is observed due to the waiting time for additional RREQs required by the prediction process, the overall performance gains validate the effectiveness of the proposed hybrid approach in ensuring reliable communication in VANETs. For future work, improving the prediction model to better handle highly dynamic environments will be considered. Additionally, adaptive mechanisms, energy efficiency considerations, and security features will be investigated and integrated. An additional perspective of this research is the dynamic determination of the optimal waiting period to balance rapid route discovery with the selection of more reliable routes. Moreover, while this model does not currently address anomaly detection in time-series data, integrating such capabilities could enhance robustness, and relevant methods (Apostol *et al.*, 2021) will be explored in future extensions.

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