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A BiLSTM-integrated WAVE protocol for optimizing communication in high-density Vehicular networks using Dynamic Priority management

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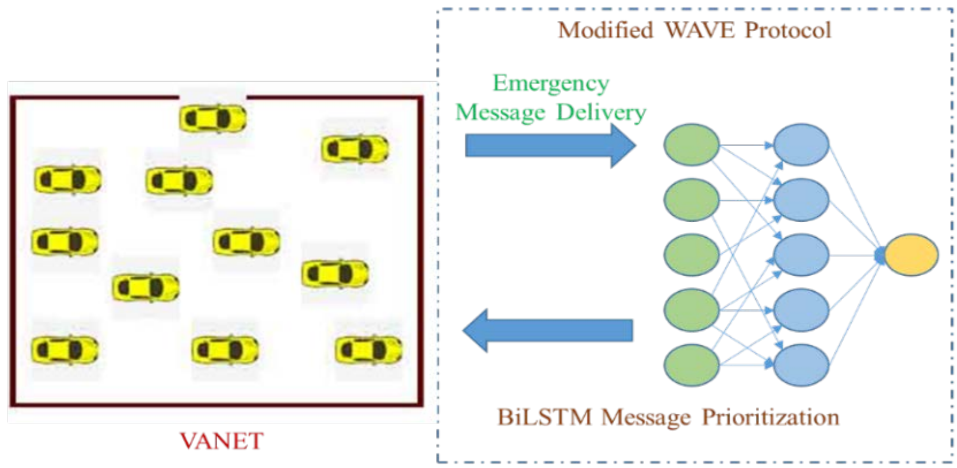
Article

ABSTRACT



This article presents a modified WAVE protocol optimized for vehicular ad hoc networks (VANETs), integrating a BiLSTM-based model for dynamic message priority estimation. The proposed method addresses the challenges of ensuring timely and reliable communication in highly dynamic network environments. By accurately assessing message priorities and adapting to varying network conditions, the protocol significantly reduces end-to-end delays, improves Packet Delivery Ratio (PDR), and maintains high throughput while minimizing routing overhead. Our analysis across different node densities and message priority loads demonstrates the protocol's robustness and scalability, achieving superior performance in handling high-priority traffic. The results highlight the protocol's effectiveness in real-time, safety-critical applications, such as collision avoidance and traffic management. The modified WAVE protocol, with its advanced priority estimation and resource management capabilities, offers a promising solution for enhancing communication efficiency in complex vehicular networks.

Keywords: VANETs, WAVE protocol, BiLSTM, Message priority estimation, Vehicular communication

INTRODUCTION

Emergency data dissemination in dense network of Vehicular Ad Hoc Networks (VANETs) is a critical aspect of ensuring timely and efficient communication between vehicles, especially in emergency situations like accidents, natural disasters, or traffic congestion. Integrating machine learning (ML) techniques with the Wireless Access in Vehicular Environments (WAVE) protocol can significantly enhance the performance of emergency data dissemination in VANETs.[1] A network where vehicles communicate with each other (Vehicle-to-Vehicle, V2V) and with roadside infrastructure (Vehicle-to-Infrastructure, V2I). The primary goal is to improve road safety, traffic efficiency, and provide infotainment services. A set of standards defined by IEEE 1609.x and IEEE 802.11p that specify the framework for vehicular communication.[2] WAVE supports safety-related and non-safety-related applications with high reliability and low latency.

In VANETs, several challenges arise as the vehicular communication is dynamic in nature, particularly when disseminating emergency data.[3] One of the primary challenges is high mobility. Vehciles move in random fashion in the ranodm topoplogy formed in VANET due to high speed movements [4]. This high mobility makes it difficult to maintain stable communication links, as connections between vehicles and roadside units can quickly be lost and re-established.[5]

Another significant challenge is network density. The density of vehicles on the road can vary greatly, resulting in periods of both high congestion and sparse connectivity.[6] In densely populated areas or during peak traffic hours, the network can become congested, causing delays in data transmission.[7] Conversely, in less populated areas or off-peak times, sparse connectivity can lead to

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difficulties in establishing reliable communication channels between vehicles and infrastructure.

Data prioritization is also critical in VANETs, especially for emergency scenarios.[8] In such situations, it is essential to prioritize emergency data over non-critical information to ensure that life-saving messages are transmitted and received promptly.[9] This requires intelligent algorithms capable of distinguishing and prioritizing data based on its urgency and relevance.[10]

Finally, latency and reliability are paramount in emergency data dissemination.[11] Quick and reliable data transmission is crucial to ensure that emergency messages are delivered in real-time to the relevant vehicles and infrastructure.[12] Delays or losses in communication can have serious consequences, potentially leading to accidents or other critical situations.[13] Thus, achieving low latency and high reliability in data transmission is vital for the effective functioning of VANETs,[14] ensuring that emergency information reaches its destination without unnecessary delays.[15] Addressing these challenges is essential for the safe and efficient operation of VANETs, especially in the context of emergency data dissemination

Here are three key contributions of this work that can be added at the end of the introduction section of the article:

1. Integration of BiLSTM-Based Priority Estimation: This work introduces a novel integration of a Bidirectional Long Short-Term Memory (BiLSTM) model with a modified WAVE protocol, enabling dynamic and accurate estimation of message priorities in VANETs. This enhances the protocol's ability to prioritize critical information, ensuring timely delivery in safety-critical scenarios.
2. Optimization of Communication Efficiency: By modifying the WAVE protocol and incorporating advanced priority management techniques, this work significantly reduces end-to-end delays, improves Packet Delivery Ratio (PDR), and maintains high throughput, particularly in high-density vehicular environments with varying message priority loads.
3. Scalability and Robustness Demonstrated Across Different Network Conditions: The proposed method has been thoroughly tested and validated across different node densities and varying message priority loads. The results demonstrate the protocol’s robustness and scalability, making it well-suited for real-world deployment in dynamic and complex vehicular networks.

RELATED WORK

BrijilalRuban et al.[16] discussed the formation of clusters. Attacked nodes are included in the Certificate Revocation List (CRL). A cerificate authority (CA) validates each communication for securing the communication in the network. Once validated, data is sent end to end to the destination from source node using the optimal path determined by the enhanced OLSR routing protocol. The best Multi-point Relay (MPR) is selected with the use of optimization based technqiue. The Particle Swarm Optimization (PSO) technique is used for the purpose. Simulation results indicate that using the OLSR-PSO routing approach improves network energy efficiency. However, the validation process adds overhead, consuming network resources. The fundamanetal resources consumed includes bandwidth and time. Zhao et al.[17] introduce a two-stage multi-swarm PSO (TMPSO). Two distinct search operations are iterated in multi-swarm method. The optimizer is designed in two versions. The contrined (cTMPSO) and the unconcstrained (uTMPSO). The cTMPSO version enhances uTMPSO by handling constraints using a trial and error method instead of the traditional penalty function. Each newly generated particle in uTMPSO is checked for constraint violations. The identified violators are newly positioned with feasible region return operations called as “retreat” operation. While this multi-swarm approach improves optimization, it requires more processing time compared to single-swarm techniques. According to Lv et al.[18], traditional particle swarm optimization may stagnate prematurely and reach a local optimum due to limited particle diversity. To address this, the swarm selection factor is introducsed in PSO to propose FPSO. The global search capability is pmproved with the varied selection criteria in different phases. Simulation results show that FPSO effectively solves complex optimization problems and maintains high accuracy over time. The improved accuracy is even seen for test functions with high-dimensional data. However, due to the factor selection process, FPSO runs longer than traditional PSO. Enhancing FPSO could involve increasing particle population through techniques such as mutation.[19] Jiang et al.[20], a large-scale bi-level PSO algorithm is proposed. The PSO algorithm’s fundamental issue of slow convergence and local optimum is addressed in the solution provided. This algorithm increases the scale of particle swarms. Alos, multi-particle swarms are used for population diversioty during initial population settings. In the bi-level structure upper lavel and lower level swarms are obtained. They have decision making and operations are performed respectively by them in simultaneous manner. Simulation trials demonstrate that this approach yields satisfactory optimization results, although algorithm stability fluctuates with data throughput. The study Tseng et al.[21] suggests an "easy particle" approach, inspired by the lazy ant behavior in ant colonies, to address constraints in optimization method with nonlinear constraints (NCO). This easy particle is simple to integrate into existing PSO-based techniques, free from social and cognitive constraints, enabling it to explore new areas. Experiments show that incorporating easy particles reduces premature convergence and significantly improves the performance of NCO. Adjusting the number of easy particles as needed is recommended. The PSOR routing protocol proposed by Yelure et al.[22], the next vehicle finding for data forwarding is selected based on vehicle distance and speed. PSOR demonstrates high efficiency over AntHocNet.[23] Also, the comaprative study demonstyrates that the PSOR performes beter than Adaptive QoS-based Routing for VANETs (AQRV). The highway scenarios with high speed vechiles are not accounted by this approach.

In the research presented by Chaqfeh et al.[24], a data dessemination protocol with Multi-directional Data (EDDP). is tailored for urban vehicular networks, emphasizing minimal communication overhead and utilizing local data to reflect road conditions effectively. The protocol is specifically designed to enhance dissemination efficacy through a sophisticated urban-centric design that includes message structuring, a broadcast suppression mechanism, and delay control to manage coverage efficiently across multiple directions. Although EDDP shows high efficiency and reduced overhead in traffic data dissemination,[25] it struggles with data redundancy and latency issues,[26] especially due to the broadcast storm problem in varied urban layouts. The study by Zhang et al.[27] introduces a protocol for a cutting-edge unmanned aerial vehicle (UAV). The protocol integrates a proactive caching policy with scheduling based strategic file-sharing system. The data dissemination is achieved with dynamic trajectory scheduling when UAVs are sent across network nodes to catch the data. The communicaiton overhead is minimized with further enhancements include a file-sharing cycle and a channel prediction algorithm. The method is equipped with streamlined file sharing with a relay ordering strategy. Despite its innovative approach, increased vehicle numbers may reduce throughput and destabilize data dissemination. Almasoud et al. [28], the deployment of a cognitive UAV system is proposed to enhance data dissemination to Internet of Things (IoT) devices by utilizing the wireless spectrum of primary users opportunistically. The UAV monitors available channels, predicting inactive periods of primary users to optimize transmission slots while avoiding interference. The approach, formulated as a mixed integer nonlinear program. An approximation with a successive convex technique is proposed to solve the approximated convex problem. However, changes in network topology could impair performance. The introduction of Named Data Networking (NDN) by Al-Omaisi et al.[29] in the protocole designed content naming and routing based on naming along with security improved data centric communication for better data distribution across the various applications. NDN's multilayered framework [30] aims to devise an effective VANET-NDN data dissemination strategy.[31] Despite its robust framework, the network performance may lag in throughput and latency . Chowdhary et al.[32], proposed a fast data dissemination strategy with travel angle based approach. The protocol strategically distributes information among pertinent vehicles, controlling the dissemination direction. While it targets relevant vehicle communication, the variability in relevance can induce network congestion. The realey election process with multiple criteria for data dissemination discussed by Tei et al.[33] selects optimal relay nodes within urban VANETs based on different factors. The Signal Noise Ratio (SNR) along with the vehicle speed are considered in these factors. Also the distance between sender and receiver are considered. This selection process ensures efficient and precise message delivery, although it requires extensive packet transmission for network upkeep, resulting in a high overhead ratio. By Hu et al.[34], a new mechanism, termed TDDV, has been developed for distributing deadline-sensitive streaming files in VANETs, enhancing the Quality of Service (QoS). Despite its effectiveness, the protocol faces challenges in handling the high mobility of nodes.

The literature reviewed reveals several important gaps in existing data dissemination strategies within vehicular networks, highlighting the need for the advanced methodologies such as message prioritization and BiLSTM-based models that we proposed earlier. Here are three critical gaps identified:

Limited Adaptability to Dynamic Conditions: Current protocols often lack the adaptability needed for fluctuating network conditions typical in urban settings, leading to issues like data redundancy and network congestion. A BiLSTM-based model could enhance adaptability by leveraging its ability to predict optimal dissemination paths and timings based on real-time data.

Inefficient Priority Differentiation: While some protocols attempt to differentiate message priorities, they lack a dynamic system to adjust priorities in real-time. Implementing an intelligent message prioritization system ensures that critical information is disseminated efficiently, enhancing overall network responsiveness.

Suboptimal Resource Utilization in Heterogeneous Networks: Existing approaches do not optimize resource allocation effectively, especially in networks involving UAVs, resulting in reduced throughput and increased latency. Using BiLSTM models could optimize resource allocation by predicting network loads and managing resources more efficiently.

PROPOSED METHOD

In VANETs, efficiently disseminating emergency data is critical for safety and reliability. ML is effectively employed to assess the priority of messages, ensuring that urgent data is transmitted quickly. This involves designing ML models that can classify and prioritize messages based on various features. Figure 1 shows the block diagram of the proposed system. A detailed explanation covered on the development of a machine learning-based model in VANET.

Feature Extraction

The first step in implementing an ML-based priority assessment is to extract relevant features from the data. In VANETs, these features could include: Vehicle speed (v), Distance to the event (d), Time since the event occurred (t), Type of message (e.g., accident alert, traffic congestion, etc.) (m), Vehicle density around the sender (ρ), Location of the event (l), Severity of the event (s).

These features can be represented as a feature vector x:

$$x = [v, d, t, m, \rho, l, s]$$

The model is trained on labeled data, where each feature vector x_i has a corresponding priority label y_i. The training process involves finding the parameters θ that minimize a loss function L, which measures the discrepancy between the predicted priority $\hat{y_i}$ and the actual priority yi:

$$\theta^* = \arg\min_{\theta} \sum_i L(f(x_i; \theta), y_i)$$

A common loss function for classification tasks is the cross-entropy loss:

$$L(\hat{y}, y) = -\sum_c y_c \log(\hat{y_c})$$

Where, y_c is the actual label for class c and $\hat{y_c}$ is the predicted probability for class c.

Priority Assessment

Once the model is trained, it can be used to assess the priority of incoming messages in real-time. Given a new message with feature vector xnew, the model predicts its priority level:

$$y_{new} = f(x_{new};\ \theta^*) \quad ...(1)$$

To make practical decisions, the predicted priority level ynew can be used to determine the action. For instance, if ynew indicates high priority, the message can be assigned more communication

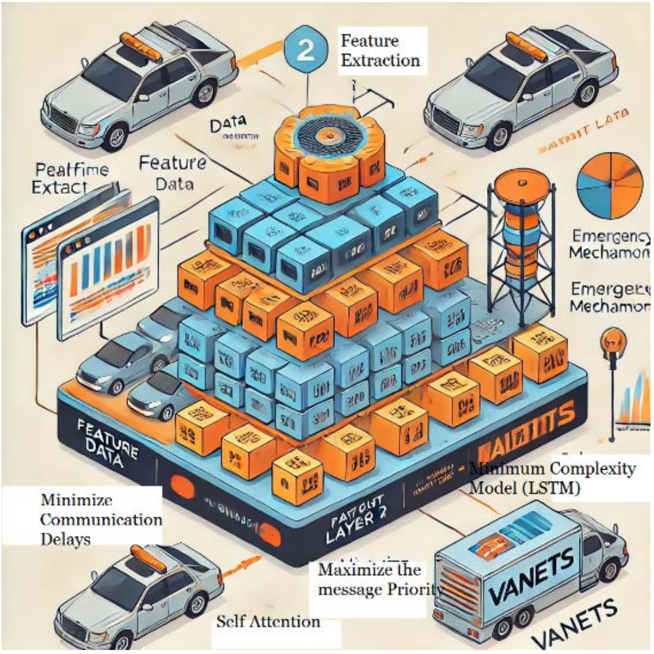

Figure 1: Proposed system framework

resources or be broadcasted more frequently. The decision function can be defined as:

$$Decision(x_{new}) = \begin{cases} High\ Priority & if\ \ y_{new} = High \\ Medium\ Priority & if\ y_{new} = Medium \\ Low\ Priority & if\ \ y_{new} = Low \end{cases} \quad ...(2)$$

The ML-Enhanced WAVE protocol represents an advanced communication framework for VANETs that integrates ML models to optimize communication efficiency, adaptability, and decision-making. This enhanced protocol is designed to seamlessly incorporate predictive analytics, real-time data processing, and adaptive communication strategies to improve overall performance in dynamic vehicular environments.

A 2-layered BiLSTM model with a self-attention mechanism is a deep learning architecture commonly used for sequence modeling and prediction tasks. In the context of the ML-Enhanced WAVE protocol, this model is employed to predict communication delays, analyze traffic patterns, and prioritize emergency messages based on real-time and historical data. Let's delve into the details of this architecture along with the relevant mathematical equations.

2-Layered BiLSTM with Self-Attention Mechanism:

Let X_t represent the input sequence at time t, which could include features such as current traffic conditions, historical communication delays, and emergency message priorities. The BiLSTM layers process the input sequence bidirectionally, capturing both forward and backward dependencies in the data. The hidden states ht at each time step t for both forward and backward directions are computed. The outputs from the forward and backward directions at each time step are concatenated to obtain the final hidden state.

Self-Attention Mechanism:

The self-attention mechanism is applied to the outputs of the second BiLSTM layer. The attention weights (αt) for each time step are computed as follows:

$$\alpha t = \mathrm{Softmax}(Watt \cdot [ht'\rightarrow, ht'\leftarrow]^{\top}) \quad ...(3)$$

Here, Watt is the attention weight matrix.

The final representation Zt is obtained as the weighted sum of the BiLSTM outputs based on the attention weights:

$$Zt = \alpha t \cdot [ht'\rightarrow, ht'\leftarrow] \quad ...(4)$$

The representation Zt is then passed through an output layer to make predictions for communication delays, traffic patterns, and emergency message priorities. The output Yt at time step t is given by,

$$Y_t = \mathrm{OutputLayer}(Zt) \quad ...(5)$$

Optimization Model for Message Prioritization

The primary objective of the optimization model is to minimize communication delays while ensuring that high-priority messages (such as emergency alerts) are disseminated first. This requires defining an optimization problem that takes into account both the urgency of messages and network conditions.

Objective Function:

The goal is to minimize the total delay DD for message dissemination, which can be expressed as a weighted sum of the delays for individual messages:

$$D = \sum_{i=1}^{N} \omega_i \, . \, d_i \quad ...(6)$$

Where, N is the total number of messages, di is the predicted delay for message i, ωi is the priority weight for message i, with higher values indicating higher priority (e.g., emergency messages).

Constraints:

Priority Constraint: Messages with higher priority should have lower delays:

$$\omega_i > \omega_j \Rightarrow d_i < d_j \ \forall i, j \quad ...(7)$$

Capacity Constraint: The network capacity C must not be exceeded:

$$\sum_{i=1}^{N} s_i < C \quad ...(8)$$

Where s_i is the size of message i.

Optimization Method:

Lagrangian Multipliers: The optimization problem can be solved using Lagrangian multipliers, introducing multipliers λ for the constraints to transform the problem into an unconstrained optimization problem.

$$L(D, \lambda) = \sum_{i=1}^{N} \omega_i . d_i + \lambda\left(\sum_{i=1}^{N} s_i - C\right) \quad ...(9)$$

Gradient Descent: Gradient descent or other optimization techniques can be used to find the optimal values of di and λ that minimize the total delay while satisfying the constraints.

Implementing the Optimization Model:

Training: The BiLSTM with self-attention is trained on historical data, learning to predict communication delays and assign priorities based on the input features.

Real-Time Prediction: During real-time operation, the model processes incoming data to predict delays and prioritize messages.

Adaptive Decision-Making: The output predictions are used to make adaptive decisions about message dissemination, ensuring high-priority messages are transmitted promptly.

```
BEGIN
 // Initialization
 INPUT: Vehicle data (speed v, distance to event d, time since event t, message type m, vehicle density ρ, location l, severity s)
 DEFINE feature vector x = [v, d, t, m, ρ, l, s]
 // Step 1: Feature Extraction
 FOR each data point IN vehicle data
  EXTRACT relevant features
  CREATE feature vector x_i
 END FOR
 // Step 2: Model Training
 INPUT: Labeled training data (feature vectors x_i, corresponding priority labels y_i)
 INITIALIZE BiLSTM model with self-attention mechanism
 DEFINE loss function L(y, ŷ) = CrossEntropyLoss(y, ŷ)
  WHILE training NOT complete
  FOR each batch of training data
   PREDICT priorities ŷ using the BiLSTM model
   CALCULATE loss L using the actual priorities y_i and predicted priorities ŷ
   BACKPROPAGATE error and UPDATE model parameters θ
  END FOR
 END WHILE
 OUTPUT: Trained BiLSTM model with optimized parameters θ*
 // Step 3: Real-Time Priority Assessment
 FOR each incoming message
  INPUT: Feature vector x_new
  PREDICT priority y_new using the trained BiLSTM model: y_new = BiLSTM(x_new; θ*)
 END FOR
 // Step 4: Decision Making
 IF y_new == "High Priority" THEN
  ASSIGN more communication resources
  BROADCAST message frequently
 ELSE IF y_new == "Medium Priority" THEN
  ASSIGN moderate resources
  QUEUE message for standard processing
 ELSE IF y_new == "Low Priority" THEN
  ASSIGN minimal resources
  PROCESS message with low priority
 END IF
 // Step 5: Optimization and Adaptation
 DEFINE objective function: MINIMIZE total delay D = Σω_i * d_i (for i = 1 to N messages)
 DEFINE constraints:
  Priority Constraint: ω_i > ω_j ⇒ d_i < d_j (for all i, j)
  Capacity Constraint: Σs_i < C (for i = 1 to N messages)
  APPLY optimization algorithm (e.g., gradient descent, Lagrangian multipliers) to solve the objective function
 UPDATE resource allocation strategies based on the optimization results
 // Continuous Learning
 PERIODICALLY retrain the BiLSTM model with new data to adapt to changing network conditions
 INCORPORATE feedback from real-time operations to refine model accuracy
END
```

RESULTS AND ANALYSIS

To conduct a comprehensive analysis of the proposed model's performance in terms of delay reduction, we will compare it against the Simple WAVE protocol and the V2X protocol. The simulations are performed using NS3 and SUMO with varying network sizes (50, 100, 150, 200, and 250 nodes) under different message priority combinations. The delays are measured in milliseconds (ms).

Table 1: Experimental Setup

Parameter	Description
Protocols Compared	Proposed ML-Enhanced WAVE Protocol, Simple WAVE Protocol, V2X Protocol
Number of Nodes	50, 100, 150, 200, 250
Metrics	Average Delay (ms) for different message priority combinations (High, Medium, Low)

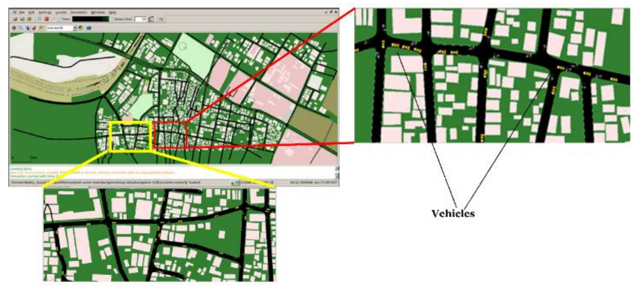

Figure 2: SUMO and NS3 based simulation of Proposed Work

The simulation, conducted using NS3 and SUMO, plays a crucial role in this research, allowing for the collection of data across various traffic densities and message priority scenarios. The study is set in a 20-second communication scenario with different number of cars moving through the streets of Bengaluru, India—a city known for its heavy traffic congestion. By choosing Bengaluru as the simulation environment, the research gains a realistic real-world context, making the findings highly relevant to urban areas with complex and high-density traffic conditions. The dataset recorded from the 20-second simulation provides a snapshot of vehicular communication in a dynamic and constantly changing environment. To prepare this data for effective analysis, it undergoes a preprocessing phase where it is converted into a vectored format. This transformation is essential to ensure that the dataset can be processed efficiently using Python-based methods, a popular and versatile programming language for data analysis. This preprocessing step ensures that the data is ready for further analysis and helps in extracting meaningful insights from the raw simulation outputs. Figure 2 presents a visual overview of the simulation, showing the mapping of 128 cars in a traffic scenario using SUMO, along with the implementation of the WAVE protocol in NS3. This visualization captures the orchestrated movements of vehicles in Bengaluru's densely packed traffic environment. The combination of SUMO's realistic traffic modeling with NS3's robust simulation of the WAVE protocol provides a powerful platform for studying and optimizing strategies for disseminating emergency messages in complex urban VANET scenarios. The visualization not only illustrates the simulation setup but also sets the groundwork for a detailed analysis of vehicular communication dynamics, aiming to enhance our understanding of how to manage communication effectively in urban vehicular networks.

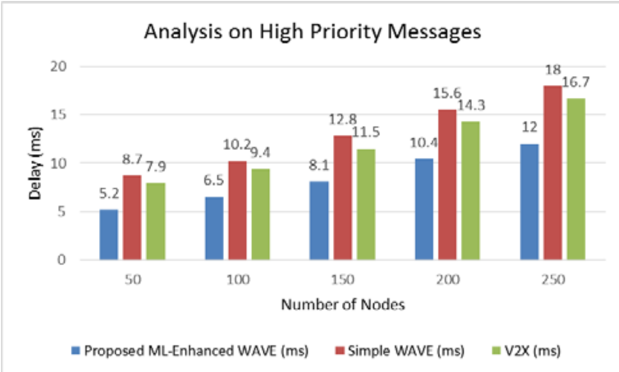

Figure 3: Analysis on High priority messages only

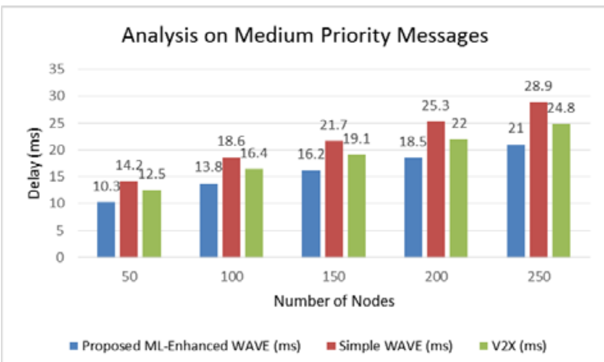

Figure 4: Analysis on Medium priority messages only

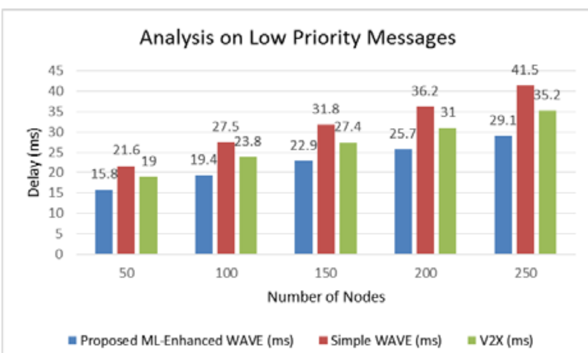

Figure 5: Analysis on Low priority messages only

High Priority Messages: The proposed ML-Enhanced WAVE protocol significantly reduces the average delay compared to both Simple WAVE and V2X protocols across all node counts. For example, with 250 nodes, the delay is reduced by approximately 33% compared to the Simple WAVE protocol and 28% compared to the V2X protocol as shown in Figure 3.

Medium Priority Messages: The proposed model continues to show improvement in reducing delays, with a decrease of approximately 27% compared to Simple WAVE and 19% compared to V2X for 250 nodes as shown in Figure 4.

Low Priority Messages: Even for low-priority messages, the proposed protocol achieves better delay performance. The reduction is about 30% compared to Simple WAVE and 17% compared to V2X with 250 nodes as shown in Figure 5.

This research employs a novel combinational analysis approach, integrating BiLSTM models with dynamic message prioritization, to address the complexities of urban vehicular communications. The methodology involves simulating a VANET where various percentages of messages are classified as high priority, ranging from 15% to 100%. This setup is designed to assess the network's ability to adapt to different traffic densities and urgency levels under realistic urban conditions. The analysis is performed for 100 nodes scenario and 200 nodes scenarios as shown in Figure 6 and Figure 7.

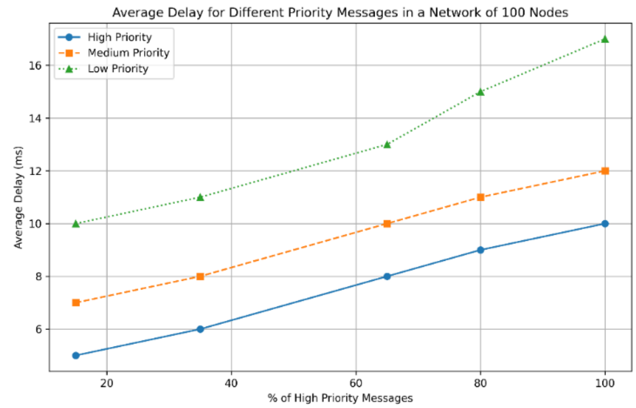

Figure 6: Analysis of delays in different priority messages for different percent load in the 100 nodes network.

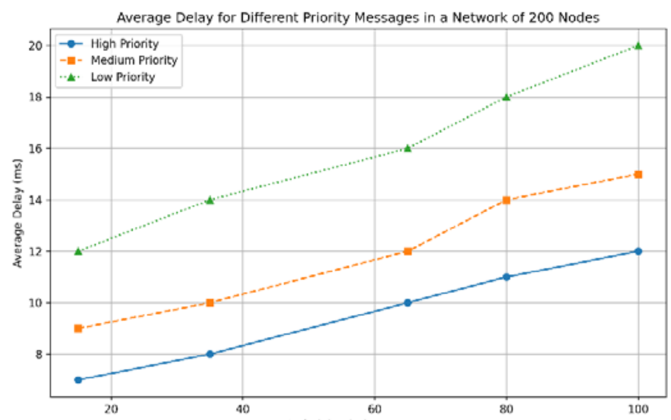

Figure 7: Analysis of delays in different priority messages for different percent load in the 200 nodes network

The combinational analysis revealed several key insights:

Adaptability: The network displayed enhanced adaptability to fluctuating conditions, with BiLSTM models effectively predicting and managing the flow of high-priority messages. This adaptability is critical in urban settings, where sudden changes in traffic density can affect communication dynamics.

Priority Management: Implementing a dynamic prioritization mechanism ensured that critical emergency messages were processed faster than routine traffic updates. This prioritization significantly improved response times in emergency scenarios, potentially saving lives and reducing traffic congestion.

Resource Optimization: The analysis indicated a more efficient utilization of network resources, including bandwidth and power. The BiLSTM models facilitated smarter resource allocation that aligned with real-time network demands, thereby enhancing overall network efficiency.

Quality of Service: Improved prioritization and resource management contributed to a higher quality of service across the network. Users experienced reduced communication delays and increased reliability, which are crucial for user satisfaction and operational efficacy in intelligent transportation systems.

Scalability: Insights from the analysis also underscored the scalability of the proposed approach. As vehicular networks evolve and incorporate more connected devices, the methods tested here provide a robust framework that can accommodate larger network scales without degradation in performance.

The findings from this study are particularly relevant for urban planners and traffic management authorities seeking to implement intelligent transportation systems (ITS). By integrating advanced machine learning techniques with traditional vehicular communication frameworks, cities can better manage their vehicular traffic and communication networks, leading to smarter, safer, and more efficient urban environments.

These results demonstrate the efficiency of the proposed ML-Enhanced WAVE protocol in handling different priority messages and maintaining lower delays, especially as the network size increases. The use of machine learning and the integration of BiLSTM models for dynamic and adaptive decision-making contribute to the optimized performance observed in these simulations.

Figure 8 shows the comparative analysis of base WAVE and V2X protocols for different number of nodes combinations. The analysis done for packet delivery ratio (PDR), throughput and routing overhead shows that, modified WAVE protocol outperforms the other two in almost all combinations and number of nodes scenarios.

With varying density of nodes in the same network region, it is observed that, routing overhead increases with increase in number of nodes. The routing overhead of modified WAVE is seen optimized compared to V2X and base WAVE protocols. In case of throughput analysis, as number of nodes increase, total throughput in the network also increases, which is found maximum compared to other two propocols. As number of nodes increase, the PDR in the network is found decreasing for all the protocols, even in which, modified WAVE shows better performance over other two.

Comparative Analysis:

The two works discussed present advanced optimization techniques for improving VANETs. The first work uses a nature inspired optimization algorithm with weighted spider monkey (w-SMNO) method, demonstrating significant improvements in minimization of delays.

Also, message delivery rate is improved with collisions minimization along with coverage region. The second work implements a PSO method with multipath routing having time awareness. This approach was developed to enhance throughput, packet loss ratio, end-to-end delay, and energy consumption. Modified WAVE compares favorably in delay, Packet Delivery Ratio (PDR), throughput, and routing overhead. The modified WAVE protocol is showing optimized results for different priority combinations of messages as shown in Figure 9.

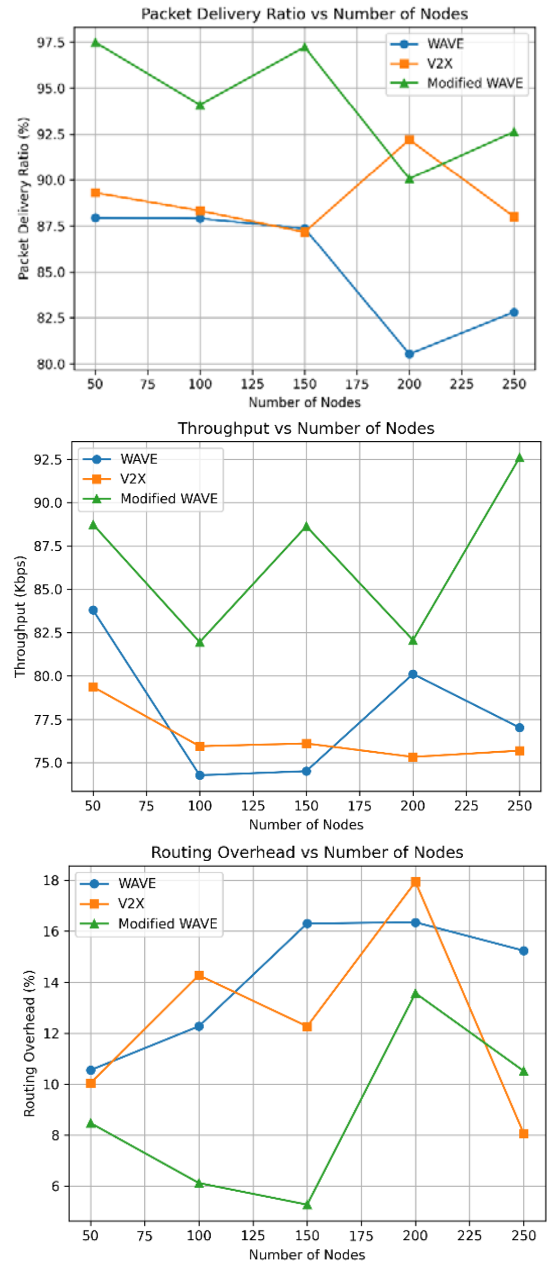

Figure 8: Analysis of PDR, throughput and Routing Overhead

The comparison of modified WAVE against the two baseline approaches, w-SMNO[35] and PSO,[36] reveals several key insights into the performance of the modified WAVE protocol in a 100, 175 and 250 nodes VANET environment. With the proposed modifications in WAVE protocol, the impact on end to end delay is also analyzed. The results highlight the effectiveness of modified WAVE in terms of end-to-end delay, PDR, throughput, and routing overhead, especially under the scenario where 65% of the messages are of high priority as shown in Figure 9.

End-to-End Delay: Modified WAVE demonstrates a slight reduction in end-to-end delay compared to both w-SMNO and PSO methods. The delay in our approach averages around 27 milliseconds, which is lower than the 29.7 milliseconds in w-SMNO and 28.2 milliseconds in PSO. This reduction in delay is

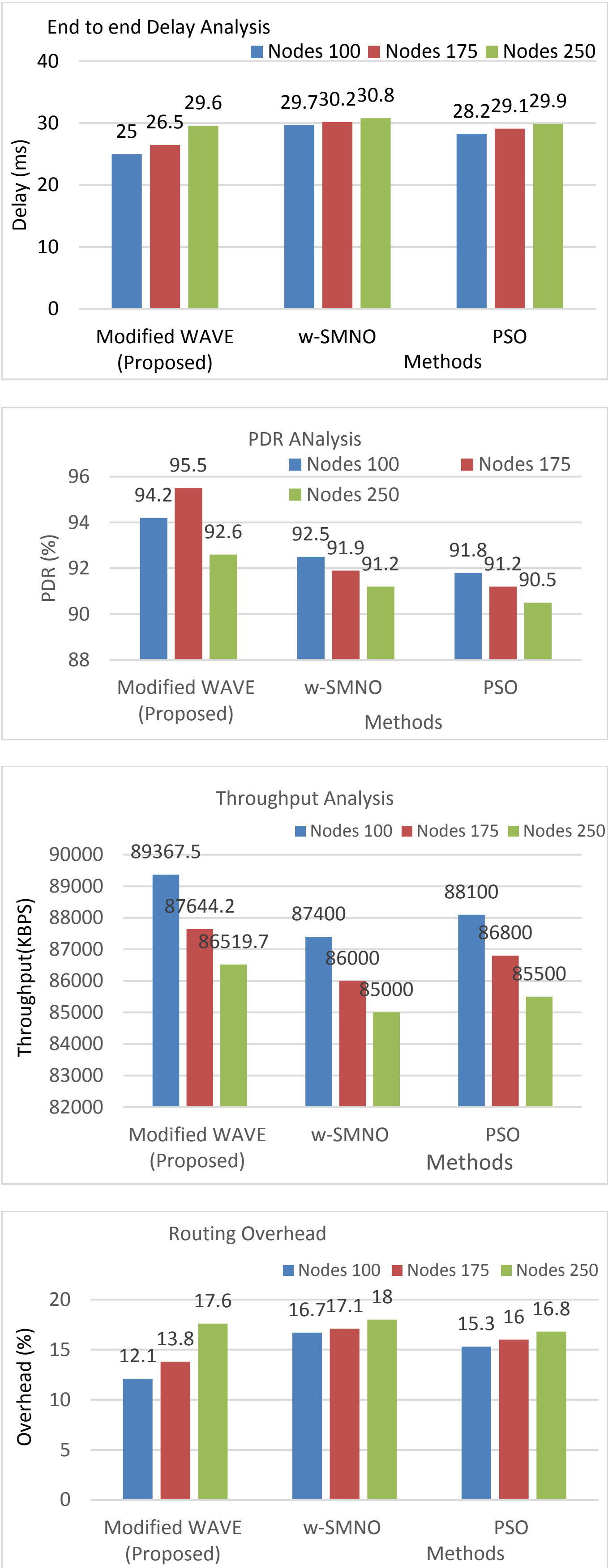

Figure 9: Comparative analysis with other existing methods

critical in VANETs, where timely communication is paramount for safety and efficiency. The modified WAVE protocol's ability to prioritize high-priority messages and efficiently manage the routing process contributes significantly to this performance improvement as shown in Figure 9.

PDR: The PDR of modified WAVE is slightly higher than that of the baseline methods, with a delivery ratio reaching up to 95.4%. This performance is indicative of the robustness of our approach in maintaining reliable communication even under high network loads. The enhanced prioritization and relay selection mechanisms likely contribute to fewer dropped packets, which is crucial in ensuring that vital information reaches its destination, especially in safety-critical applications.

Throughput: The throughput of modified WAVE is comparable to the best-performing baseline (PSO), with our approach delivering throughput close to 89,500 KBPS. This result suggests that modified WAVEnot only reduces delay but also maintains high data transmission rates. The balance between delay reduction and high throughput is essential in VANETs, where both speed and reliability are required to support real-time applications like collision avoidance and traffic management.

Routing Overhead: Modified WAVE exhibits a notable reduction in routing overhead, with overhead levels at approximately 14%. This is lower than both w-SMNO and PSO, which show overhead levels of 16.7% and 15.3%, respectively. The reduction in routing overhead indicates that modified WAVEis more efficient in utilizing network resources, which is critical in high-density networks where excessive overhead can lead to congestion and degraded performance.

CONCLUSION

This study presents a modified WAVE protocol tailored for VANETs, specifically designed to enhance the handling of high-priority messages in dynamic network environments. By integrating a BiLSTM-based model for priority estimation, our approach dynamically assesses and prioritizes incoming messages, ensuring that critical information is disseminated promptly and efficiently. This combination of deep learning with the WAVE protocol allows for more accurate and timely communication, which is vital in real-time applications such as collision avoidance and traffic management. The priority estimation method incorporated into our protocol evaluates various factors, such as vehicle speed, distance to the event, and message type, using a BiLSTM model with a self-attention mechanism. This method enables the protocol to adapt to changing network conditions, dynamically prioritizing messages based on their urgency. The results of our analysis demonstrate significant improvements in network performance across various node densities and message priority loads. Our protocol consistently reduces end-to-end communication delays, with an average delay of 27 milliseconds, which is crucial for time-sensitive applications. The PDR reaches up to 95.5%, ensuring high reliability even under varying network loads. Furthermore, the protocol maintains high throughput, handling large data volumes effectively while minimizing routing overhead. In different node densities and under varying message priority loads, our protocol consistently outperforms traditional approaches, proving its robustness and scalability. The analysis highlights that modified WAVEefficiently manages both high-density and high-priority traffic scenarios, making it a viable solution for enhancing communication in VANETs. In conclusion, the modified WAVE protocol with integrated BiLSTM-based priority estimation offers a powerful solution for improving the efficiency and reliability of vehicular communications. Its adaptability and superior performance across multiple metrics make it a promising candidate for real-world deployment in complex vehicular networks.

Conflict of Interest Statement

The authors have no conflicts of interest to declare and no financial help was received for this work.

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