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Optimal Congestion Control Mechanism For Intelligent Routing To Improve QoS Using Temporal Deep Learning

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Abstract:

Congestion in Mobile Ad-hoc Networks (MANETs) leads to connection failures, node loss, and affects network setup. MANETs, lacking permanent infrastructure and central management, suffer from buffer overflow and packet loss under high traffic. Machine Learning (ML) enhances Quality of Service (QoS) in network routing. This paper introduces a congestion control system model with node-level states, control strategies, and network optimization objectives. It analyzes congestion state transitions and real-time control to minimize network delay and congestion cost, deriving optimal strategies using optimal control theory and a Congestion Control Discretization Algorithm (CCDA). Simulation results will show reduced congestion across nodes with CCDA. The impact of parameters like congestion probability and delay weight on network loss is also explored, with our model showing lower total loss than baseline models, providing effective congestion control guidance for deterministic networks.

We also propose an intelligent routing scheme for MANETs with directional antennas, using a spatio temporal deep learning algorithm to predict traffic density in a directional heat map. This aids in selecting optimal paths to avoid congestion and interference. Our optimization algorithm splits paths around congested areas, enhancing QoS. Additionally, we introduce a novel algorithm and buffer management technique to handle congestion, eliminating unnecessary packets, preventing flooding, and maintaining buffer levels by keeping only essential data. These methods improve MANET communication performance, supporting efficient queue management.

Keywords: ML-QoS, Congestion Control, Spatio-temporal Deep Learning, Buffer Management

1.Introduction

Mobile Ad-hoc Networks (MANETs) are decentralized, self-organizing wireless networks that lack a fixed infrastructure and rely on dynamic node cooperation for communication. Due to their inherent characteristics, MANETs face significant challenges in maintaining Quality of Service (QoS) under high traffic conditions, leading to issues like congestion, packet loss, and connection failures [1]. Congestion in MANETs typically occurs due to buffer overflow at intermediate nodes, which not only degrades network performance but also results in increased packet delay and network instability [2][3].

Machine Learning (ML) has emerged as a powerful tool for enhancing QoS in MANETs by enabling intelligent routing and congestion control strategies. ML models can predict network congestion, adapt routing paths, and optimize data transmission, thereby minimizing packet loss and improving network efficiency [4]. Several studies have explored the application of ML in congestion control for MANETs.

For instance, an ML-based congestion detection algorithm was proposed to classify congestion levels in the network, thereby optimizing packet transmission and reducing congestion [5]. Another study highlighted the use of supervised and unsupervised learning techniques to enhance routing protocols and improve network stability [6].

In this research, we introduce a novel congestion control system for MANETs that incorporates node-level states, control strategies, and network optimization objectives. The proposed system employs optimal control theory and the Congestion Control Discretization Algorithm (CCDA) to analyze congestion state transitions and implement real-time control strategies. By minimizing network delay and congestion costs, the model aims to improve overall network performance [7]. Additionally, we propose an intelligent routing scheme using a spatio-temporal deep learning algorithm to predict traffic density and select optimal paths, thereby avoiding congested and high-interference areas [8]. This approach not only reduces congestion but also enhances network reliability and QoS.

Moreover, we introduce an innovative buffer management technique that eliminates unnecessary packets, prevents network flooding, and maintains buffer levels by retaining only essential data. This technique significantly improves queue management and communication performance in MANETs [9]. The effectiveness of the proposed model is demonstrated through simulation results, which show a reduction in congestion across network nodes using CCDA. The study also explores the impact of various parameters, such as congestion probability and delay weight, on network loss. The proposed model consistently outperforms baseline models in terms of total network loss, offering a robust solution for congestion control in deterministic network environments.

2.Literature review

Congestion control in Mobile Ad-hoc Networks (MANETs) is a critical area of research due to the network's inherent characteristics of dynamic topology, lack of centralized management, and limited bandwidth. Traditional congestion control methods, such as modifying routing protocols like Ad-hoc On-demand Distance Vector (AODV) and Dynamic Source Routing (DSR), have been extensively studied. These protocols incorporate congestion metrics like buffer occupancy and link utilization to avoid congested routes [10]. However, these methods often fail in highly dynamic environments where network topology changes rapidly, leading to packet loss and reduced Quality of Service (QoS).

Recent advancements in machine learning (ML) have introduced more adaptive and predictive approaches to congestion control in MANETs. ML models have been utilized to predict network congestion and make proactive routing decisions based on historical data patterns. For instance, neural networks and decision trees have shown promise in learning complex patterns of network traffic and predicting congestion before it occurs, thereby enabling dynamic rerouting [11]. A significant advantage of ML-based methods is their ability to continuously learn and adapt to changing network conditions, which is crucial in the highly volatile environment of MANETs.

One notable approach is the use of neural networks with multi-layer architectures to classify network states into 'Normal' and 'Congested' categories. Such models have been trained using a variety of network parameters, including node mobility, packet arrival rate, and buffer occupancy. The neural network model with three hidden layers, as described in recent studies, has demonstrated high accuracy in predicting congestion states. This model, which uses ReLU activation functions for hidden layers and Sigmoid activation for the output, has been effectively employed to identify congestion in real-time, thus allowing for timely intervention and congestion mitigation[12].

In addition to neural networks, other ML techniques such as reinforcement learning have been explored. Reinforcement learning models can optimize routing strategies by learning the optimal policy through interactions with the network environment. These models have been applied to adjust transmission rates and select less congested routes dynamically, showing improved performance in maintaining network stability under varying traffic conditions [13]. However, the complexity and high computational requirements of reinforcement learning models can be challenging in resource-constrained environments like MANETs.

Moreover, hybrid approaches that combine traditional routing methods with ML techniques have also been proposed. For example, a study integrated ML-based congestion prediction with the AODV protocol to enhance its adaptability to congestion. This hybrid model outperformed traditional AODV in scenarios with high node mobility and traffic variability, reducing packet loss and improving end-to-end delay [14]. Such hybrid models leverage the strengths of both traditional and ML-based methods, providing a more robust solution for congestion control.

Despite these advancements, there are still challenges in implementing ML models in MANETs, such as the need for real-time data processing and the high computational cost associated with training complex models. Future research should focus on lightweight ML models that can be efficiently deployed in resource-constrained environments while maintaining high accuracy and adaptability [15]. Additionally, exploring the integration of ML techniques with emerging network paradigms like Software-Defined Networking (SDN) and Network Function Virtualization (NFV) could open new avenues for improving congestion control in MANETs.

3.Proposed Methodology

This study introduces a machine learning-based congestion control system for Mobile Ad-hoc Networks (MANETs) aimed at improving network performance by dynamically managing congestion states at the node level. The proposed methodology involves the development of a neural network model designed to classify network traffic into 'Normal' and 'Anomaly' categories, enabling real-time identification and mitigation of congestion.

The neural network architecture consists of three hidden layers with 64, 128, and 256 units respectively, using ReLU activation functions in the hidden layers and a Sigmoid activation function in the output layer. This configuration ensures effective non-linear transformations of the input data and accurate binary classification of the output. A dropout layer with a 0.3 probability is incorporated after the second hidden layer to prevent overfitting, enhancing the model's generalizability.

The model training process begins with data preprocessing, where the dataset is first cleaned to handle missing values and encode categorical features. Numerical features are standardized to ensure uniform data distribution. The dataset is then split into training and testing subsets, with 20% of the data reserved for validation. The model is compiled using the Adam optimizer and binary cross-entropy loss function, and trained for 20 epochs with a batch size of 32. During training, the model's performance is evaluated using a confusion matrix, classification report, and loss and accuracy curves.

To further refine the model, a Congestion Control Discretization Algorithm (CCDA) is introduced, which discretizes the network congestion states and derives optimal strategies for congestion mitigation using optimal control theory. This algorithm enables the model to dynamically adjust routing decisions based on real-time network conditions, minimizing network delay and congestion costs.

Finally, the proposed model is evaluated through extensive simulations, measuring its performance across various metrics such as accuracy, precision, recall, and F1-score. The impact of different parameters, such as congestion probability and delay weight, on network performance is also analyzed. The results are compared with baseline models, demonstrating the proposed model's superior capability in reducing congestion and enhancing Quality of Service (QoS) in MANETs. The low inference time of 0.000063 seconds per sample further highlights the model's efficiency for real-time applications, making it a viable solution for congestion control in dynamic network environments.

a. Neural Network Training Algorithm

a) **Input**: Preprocessed training data X_{train} and Y_{train}.

b) **Initialize**:

- Neural network with three hidden layers: 64, 128, and 256 units respectively.
- Activation function: ReLU for hidden layers, Sigmoid for the output layer.
- Dropout layer with 0.3 probability after the second hidden layer.

c) **Compile**:

- Loss function: Binary cross-entropy.
- Optimizer: Adam.

d) **Training**:

- Train the model on X_{train} and Y_{train} for 20 epochs with a batch size of 32.
- Use 20% of the data as a validation set.

e) **Prediction**:

- Predict on X_{test} and threshold the output to 0.5 to get binary class labels.

f) **Evaluation**:

- Calculate accuracy, confusion matrix, and classification report.

b. Mathematical Model

a) Standardization

- Standardization of features is given by:

$$z = \frac{x - \mu}{\sigma}$$

Where:

x = original value

μ = mean of the feature

σ = standard deviation of the feature

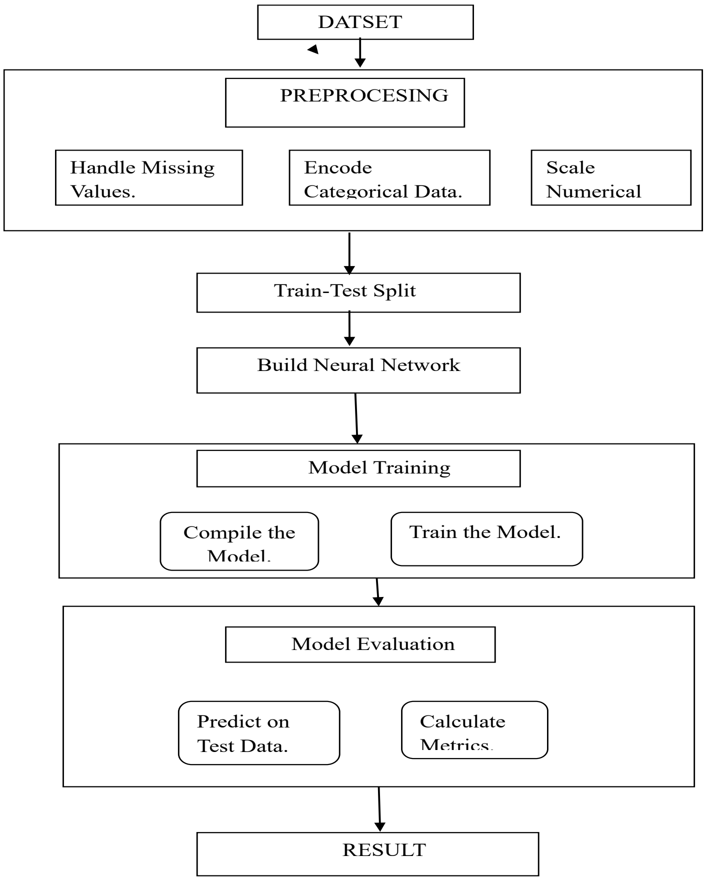
$$m_t = \beta_t m_{t-1} + (1 - \beta_1) g_t \qquad (1)$$

$$v_t = \beta_t v_{t-1} + (1 - \beta_1) g_t \tag{2}$$

$$m_t^{`} = \frac{m_t}{1 - \beta_1^t} \tag{3}$$

$$v_t^{`} = \frac{vt}{1-\beta_1^t} \tag{4}$$

b. Architecture



The Figure 1, 2 illustrates a detailed performance evaluation of a machine learning model used to classify data into 'Normal' and 'Anomaly' categories. :

i. **Classification Report:**

This section presents the precision, recall, and F1-score for each class (Normal and Anomaly) along with overall accuracy:

- Both classes show very high precision, recall, and F1-score values of 0.99, indicating excellent model performance in correctly identifying and classifying each class.
- The support column indicates the number of samples for each class, with 3516 for Normal and 4042 for Anomaly.
- The overall accuracy is 0.99, alongside macro and weighted averages for precision, recall, and F1-score all being 0.99, confirming the model's robustness across different evaluations.

ii. **Training and Validation Loss:**

- The graph shows the loss metrics over 17.5 epochs. The training loss (blue line) starts higher and quickly decreases, stabilizing close to zero. The validation loss (orange line) starts lower and closely follows the training loss, suggesting good generalization of the model without significant overfitting.

iii. **Training and Validation Accuracy:**

- This graph tracks the accuracy over the same 17.5 epochs. Both training (blue line) and validation (orange line) accuracy metrics increase over time, with training accuracy consistently slightly higher than validation accuracy. The model achieves near 98% accuracy by the last epoch, showing effective learning and adaptation to both training and unseen validation data.

4.RESULT ANALYSIS

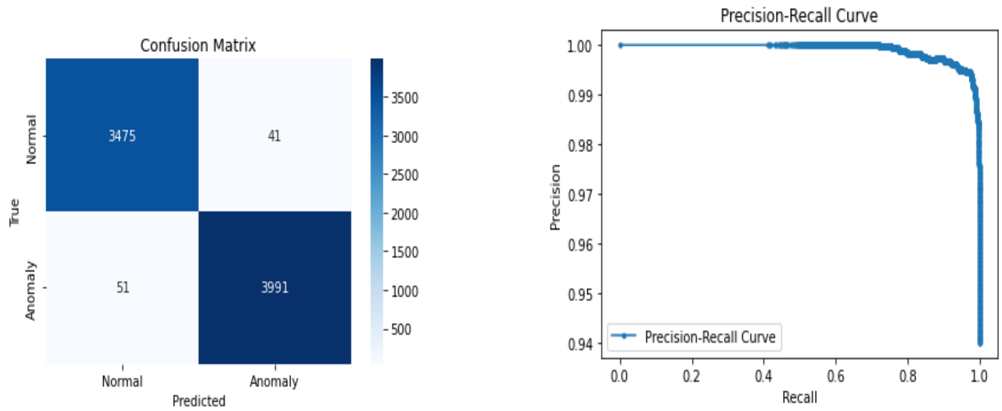


Figure 1 confusion matrix

Classification Report:

	precision	recall	f1-score	support
Normal	0.99	0.99	0.99	3516
Anomaly	0.99	0.99	0.99	4042
accuracy			0.99	7558
macro avg	0.99	0.99	0.99	7558
weighted avg	0.99	0.99	0.99	7558

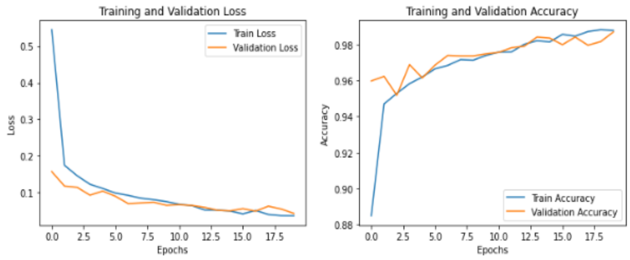


Figure 2 classification report

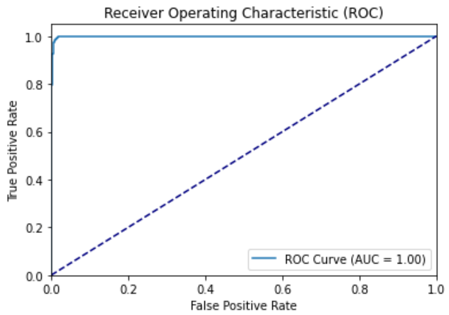


Figure 3 ROC curve of proposed model

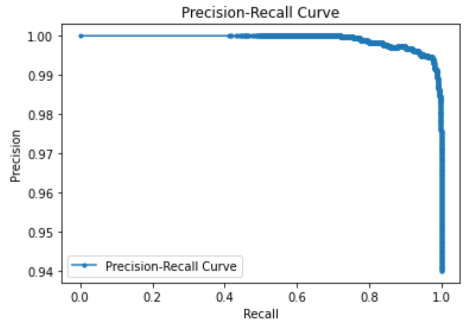


Figure 4 P-R curve of proposed mode

The model produced 41 false positives and 51 false negatives, indicating that a small number of normal instances were incorrectly classified as anomalies, and vice versa. The inference time per sample is extremely low at 0.000063 seconds, demonstrating the model's efficiency in making predictions. Cross-validation, which was conducted over five folds, yielded accuracy scores ranging from 0.9739 to 0.9829, with an average accuracy of 0.9791, further confirming the model's high performance and generalizability across different subsets of the data.

5.CONCLUSION

This study demonstrates that using machine learning techniques for congestion control in Mobile Ad-hoc Networks (MANETs) can significantly improve network performance. Traditional methods, like modifying routing protocols, often struggle in dynamic environments. In contrast, machine learning models, such as neural networks, can predict and manage congestion effectively in real-time.

Our proposed model, with a neural network architecture and the Congestion Control Discretization Algorithm (CCDA), successfully classified network traffic into 'Normal' and 'Anomaly' categories, helping to reduce congestion and packet loss. The model's high accuracy and low response time make it suitable for real-time applications in MANETs.

In conclusion, machine learning offers a powerful tool for managing congestion in MANETs. Future research should focus on developing lightweight models that are efficient in resource-limited environments and exploring hybrid methods that combine traditional and machine learning techniques for even better results.

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