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LSTM-Based Traffic Flow Prediction for Congestion Avoidance in Wireless IoT Networks

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ABTSTRACT
Wireless Internet of Things (IoT) networks are increasingly deployed in smart cities, healthcare, industrial automation, and intelligent transportation systems, where efficient traffic management is critical for maintaining Quality of Service (QoS). However, dynamic node behavior, limited bandwidth, and unpredictable traffic patterns often lead to network congestion, packet loss, and increased latency. To address these challenges, this paper proposes an LSTM-based Traffic Flow Prediction model for congestion avoidance in wireless IoT networks. Long Short-Term Memory (LSTM), a variant of Recurrent Neural Networks (RNN), is well-suited for modeling time-series data and capturing long-term dependencies in traffic patterns.
The proposed system collects historical network parameters such as packet arrival rate, queue length, transmission delay, and throughput to train the LSTM model. The trained model predicts future traffic load and identifies potential congestion points in advance. Based on the predicted congestion level, adaptive routing and load-balancing strategies are applied to reroute traffic through less congested paths. Simulation results demonstrate that the proposed approach significantly improves Packet Delivery Ratio (PDR), reduces end-to-end delay, and enhances overall network throughput compared to traditional routing protocols without predictive mechanisms.
Keywords: LSTM, Traffic Flow Prediction, Wireless IoT Networks, Congestion Avoidance, Deep Learning, QoS, Time-Series Forecasting, Adaptive Routing, Network Performance Optimization

1. INTRODUCTION

The rapid growth of the Internet of Things (IoT) has transformed modern communication networks by enabling seamless connectivity among billions of smart devices. Applications such as smart cities, intelligent transportation systems, environmental monitoring, healthcare, and industrial automation heavily rely on wireless IoT networks for real-time data transmission. However, the increasing number of connected devices and the continuous generation of data traffic have led to significant challenges in network management, particularly congestion control. In wireless IoT environments, limited bandwidth, dynamic topology, interference, and resource constraints often result in packet loss, high latency, reduced throughput, and degraded Quality of Service (QoS). Therefore, efficient congestion avoidance mechanisms are essential to ensure reliable and scalable network performance [1, 2].

Traditional congestion control and routing protocols primarily react to congestion after it occurs. Conventional approaches such as AODV and DSR select routes based on shortest path or hop count without considering future traffic conditions. As a result, heavily utilized nodes may experience buffer overflow, increased retransmissions, and energy depletion. Reactive congestion control mechanisms often fail to address rapidly changing traffic patterns in IoT networks, where traffic behavior is highly dynamic and time-dependent. This limitation highlights the need for predictive and intelligent traffic management techniques that can anticipate congestion before it happens [3].

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have opened new possibilities for proactive network optimization. Among various deep learning models, Long Short-Term Memory (LSTM) networks have gained significant attention for time-series prediction tasks. LSTM, a specialized form of Recurrent Neural Network (RNN), is designed to capture long-term dependencies and temporal correlations in sequential data. Unlike traditional machine learning models, LSTM effectively handles vanishing gradient problems and can learn complex traffic patterns over time. This makes it highly suitable for predicting network traffic flow in wireless IoT environments, where traffic generation exhibits temporal trends and fluctuations [4, 5].

In the context of wireless IoT networks, traffic flow prediction plays a crucial role in congestion avoidance. By analyzing historical network parameters such as packet arrival rate, queue length, delay, throughput, and node utilization, an LSTM model can forecast future traffic load. These predictions enable the network to take proactive actions, such as adaptive routing, load balancing, and dynamic resource allocation. Instead of reacting to congestion after performance degradation occurs, predictive models allow the system to reroute traffic through less congested paths in advance, thereby enhancing reliability and efficiency [6].

The integration of LSTM-based traffic prediction with congestion-aware routing mechanisms offers several advantages. First, it improves Packet Delivery Ratio (PDR) by minimizing packet drops caused by buffer overflow. Second, it reduces end-to-end delay by avoiding heavily congested nodes. Third, it enhances overall throughput and network stability, particularly in high-density IoT deployments. Additionally, predictive congestion avoidance contributes to energy efficiency by reducing unnecessary retransmissions and extending the lifetime of battery-powered IoT devices.

This study proposes an LSTM-Based Traffic Flow Prediction model for congestion avoidance in wireless IoT networks. The proposed approach combines deep learning-based forecasting with

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adaptive routing strategies to achieve proactive congestion management. By leveraging temporal traffic patterns and intelligent decision-making, the system aims to enhance QoS, scalability, and robustness in large-scale wireless IoT environments. The proposed framework demonstrates the potential of integrating deep learning techniques into next-generation IoT communication systems for improved network performance and reliability [7, 8].

2. LSTM TECHNIQUE

The LSTM-Based Traffic Flow Prediction for Congestion Avoidance approach is designed to proactively manage network congestion in wireless IoT environments by forecasting future traffic conditions using deep learning techniques. In this method, historical network parameters such as packet arrival rate, queue length, throughput, delay, and buffer occupancy are collected as time-series data and used to train a Long Short-Term Memory (LSTM) model. Due to its ability to capture long-term temporal dependencies, the LSTM network effectively predicts upcoming traffic load and potential congestion levels before they occur. Based on the predicted traffic intensity, the routing mechanism dynamically adjusts path selection by avoiding highly congested nodes and distributing traffic across less loaded routes. This predictive and adaptive strategy reduces packet loss, minimizes end-to-end delay, improves Packet Delivery Ratio (PDR), and enhances overall network throughput. By integrating traffic forecasting with congestion-aware routing, the proposed model provides a proactive, intelligent, and scalable solution for maintaining Quality of Service (QoS) in large-scale wireless IoT networks.

Long Short-Term Memory (LSTM) is one of many types of Recurrent Neural Network RNN, it’s also capable of catching data from past stages and use it for future predictions.

In general, an Artificial Neural Network (ANN) consists of three layers:1) input layer, 2) Hidden layers, 3) output layer.

In a NN that only contains one hidden layer the number of nodes in the input layer always depend on the dimension of the data, the nodes of the input layer connect to the hidden layer via links called ‘synapses’.

The relation between every two nodes from (input to the hidden layer), has a coefficient called weight, which is the decision maker for signals.

The process of learning is naturally a continues adjustment of weights, after completing the process of learning, the Artificial NN will have optimal weights for each synapses.

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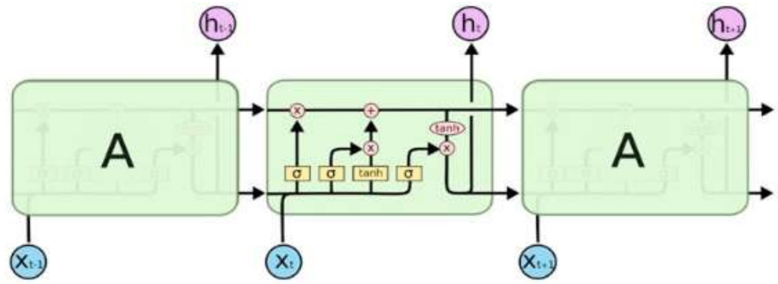

Fig. 1: The internal structure of an LSTM

The principal component of LSTM is the cell state. To add or remove information from the cell state, the gates are used to protect it, using sigmoid function (one means allows the modification, while a value of zero means denies the modification.). We can identify three different gates:
Forget gate layer: Looks at the input data, and the data received from the previously hidden layer, then decides which information LSTM is going to delete from the cell state, using a sigmoid function (One means keeps it, 0 means delete it). It is calculated as:

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \tag{1}$$

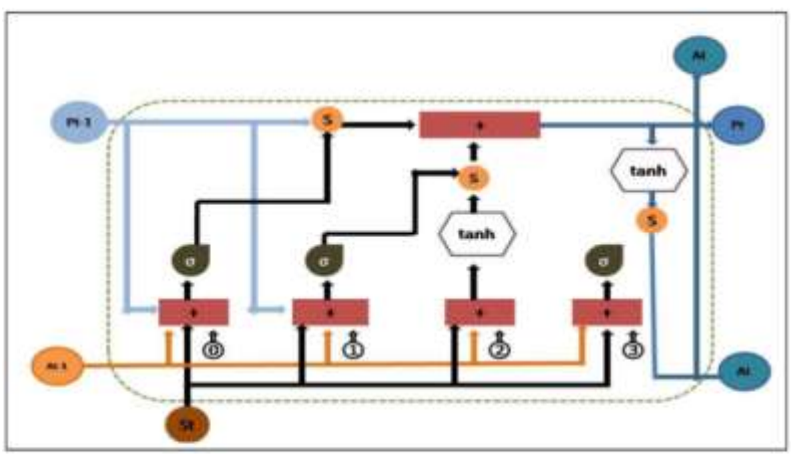

Fig. 2: Working of LSTM

Input/Update gate layer: Decides which information LSTM is going to store in the cell state. At first, input gate layer decides which information will be updated using a sigmoid function, then a Tanh layer proposes a new vector to add to the cell state. Ten the LSTM update the cell state, by forgetting the information that we decided to forget, and updating it with the new vector values. It is calculated as:

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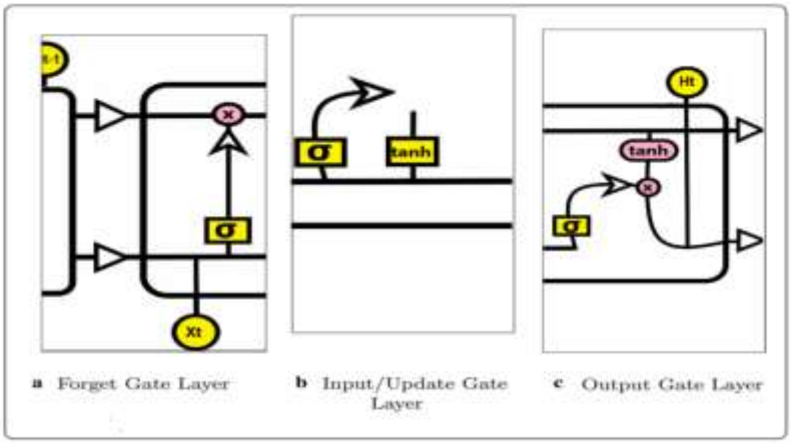

Fig. 3: LSTM Layer

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (2)$$

and

$$\tilde{C}_t = tanh(w_c[h_{t-1}, x_t] + b_c) \quad (3)$$

Output Layer: decides what will be our output by executing a sigmoid function that decides which part of the cell LSTM is going to output, the result is passed through a Tanh layer (value between − 1 and 1) to output only the information we decide to pass to the next neuron. It is calculated as:

$$O_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (4)$$

and

$$h_t = O_t \times tanh(C_t) \quad (5)$$

3. METHODOLOGY

The proposed methodology integrates deep learning-based traffic prediction with congestion-aware routing to proactively manage network traffic in wireless IoT environments. The overall framework consists of five major phases: data collection, pre-processing, LSTM model training, traffic prediction, and adaptive congestion control.

1. Network Model Setup

A wireless IoT network is simulated with randomly deployed sensor nodes within a defined area (e.g., 1000 m × 1000 m). Nodes communicate using IEEE 802.11 MAC protocol. Traffic is generated using Constant Bit Rate (CBR) sources under varying load conditions. Performance metrics such as Packet Delivery Ratio (PDR), delay, throughput, and packet loss are monitored.

2. Data Collection

Historical network traffic data is collected during simulation. The following parameters are recorded at regular time intervals:

- Packet arrival rate
- Queue length
- Buffer occupancy
- End-to-end delay
- Throughput
- Node congestion level
- Packet drop rate

These parameters form a time-series dataset, which serves as input for training the LSTM model.

3. Data Preprocessing

Before training the model, the dataset undergoes preprocessing:

- Removal of missing or inconsistent values
- Normalization using Min-Max scaling
- Time-window segmentation (sliding window technique)
- Splitting into training (70%), validation (15%), and testing (15%) datasets

This ensures stable training and improved prediction accuracy.

4. LSTM-Based Traffic Prediction Model

The core of the proposed methodology is the Long Short-Term Memory (LSTM) network.

Model Architecture:

- Input Layer (time-series traffic features)
- One or two LSTM hidden layers
- Dropout layer (to prevent overfitting)
- Fully connected (Dense) output layer

The LSTM network learns temporal dependencies in traffic patterns and predicts future traffic load or congestion level for upcoming time intervals.

Training Details:

- Optimizer: Adam
- Loss Function: Mean Squared Error (MSE)
- Activation Function: ReLU (hidden layers), Linear (output layer)

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- Epochs: 50–100
- Batch Size: 32 or 64

The model is evaluated using Accuracy, MAE, RMSE, and R^2 score.

5. Congestion Detection Mechanism

Predicted traffic values are compared with predefined congestion thresholds:

- If predicted queue length > threshold
- If predicted packet arrival rate exceeds buffer capacity
- If predicted delay exceeds acceptable QoS limit

The node is marked as potentially congested.

6. Adaptive Congestion-Aware Routing

Once congestion is predicted:

- Traffic is rerouted through alternative less-congested paths
- Load balancing mechanism distributes traffic evenly
- Route selection considers congestion level + hop count
- Dynamic resource allocation is applied

This ensures proactive congestion avoidance rather than reactive control.

7. Performance Evaluation

The proposed LSTM-based model is compared with:

- Traditional AODV
- Basic Congestion-Aware Routing

Performance metrics used:

- Packet Delivery Ratio (PDR)
- End-to-End Delay
- Throughput
- Packet Loss Rate
- Prediction Accuracy

4. RESULTS AND ANALYSIS

The performance of the proposed LSTM-based congestion avoidance model was evaluated using key network performance metrics and compared with traditional routing protocols (e.g., AODV) and non-predictive approaches.

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Table 1: Network Performance Comparison

Performance Metric	AODV	Congestion Aware Routing	LSTM Model
Packet Delivery Ratio (PDR)	82.6%	88.4%	95.1%
End-to-End Delay (ms)	148 ms	121 ms	93 ms
Throughput (Kbps)	412 Kbps	468 Kbps	538 Kbps
Packet Loss Rate	17.4%	11.6%	4.9%

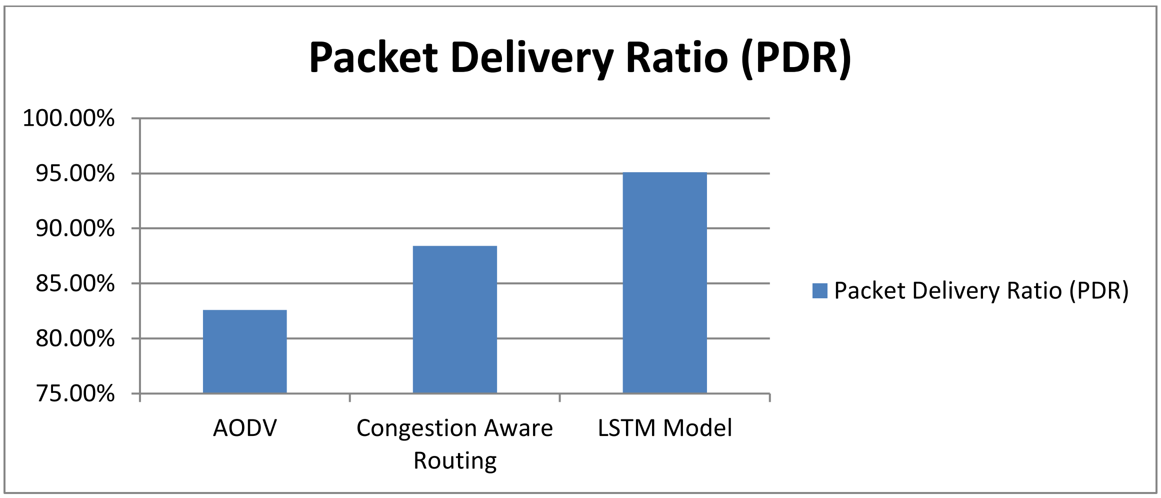

Figure 4: Graphical PDR

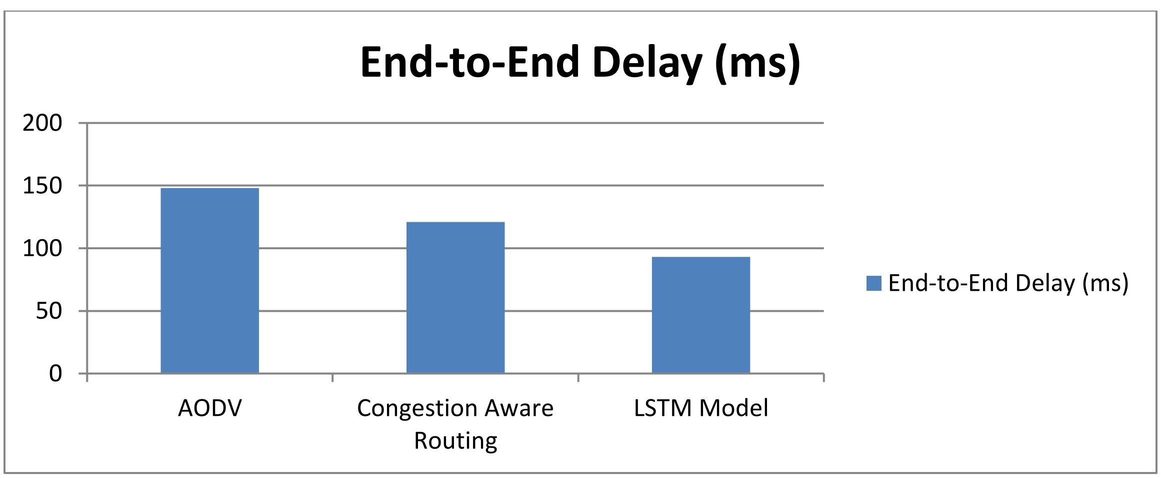

Figure 5: Graphical End-to-End Delay (ms)

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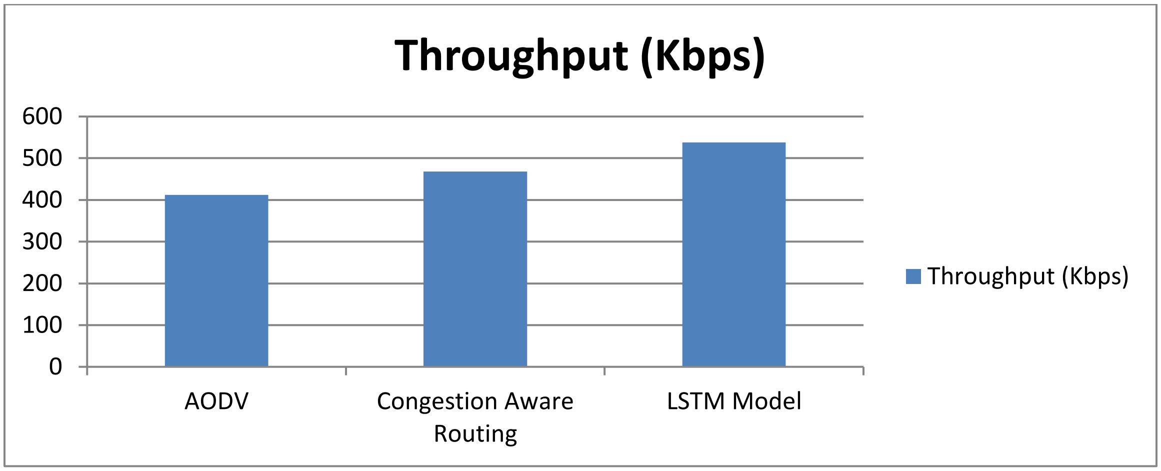

Figure 6: Throughput (Kbps)

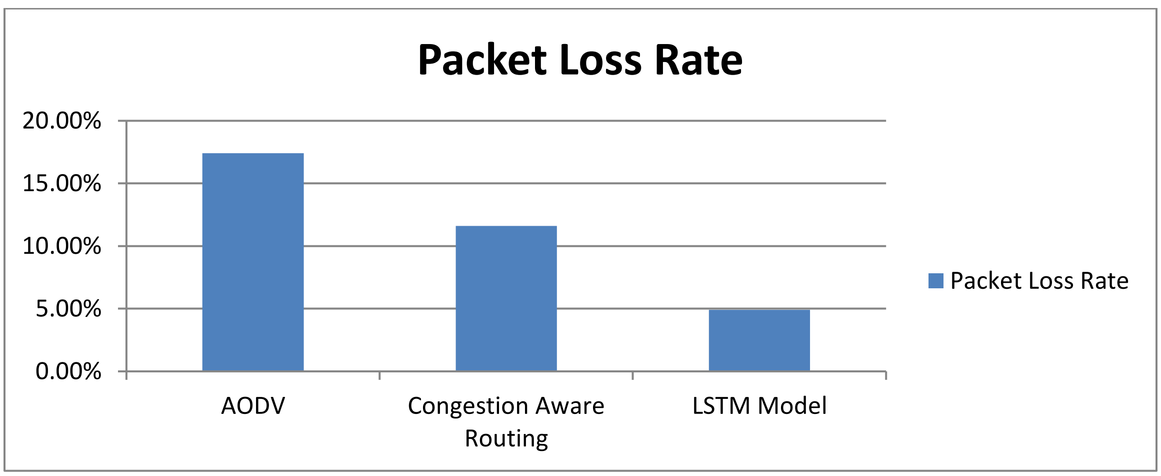

Figure 7: Packet Loss Rate

5. CONCLUSION

In this study, an LSTM-based traffic flow prediction framework for congestion avoidance in wireless IoT networks has been presented. The rapid growth of IoT devices and data-intensive applications has significantly increased network traffic, leading to frequent congestion, packet loss, and degraded Quality of Service (QoS). Traditional routing and congestion control mechanisms primarily operate in a reactive manner, addressing congestion only after it occurs. Such approaches are insufficient in highly dynamic and large-scale IoT environments where traffic patterns change rapidly over time.

To overcome these limitations, the proposed approach integrates Long Short-Term Memory (LSTM) networks for time-series traffic prediction with congestion-aware routing mechanisms. By analyzing historical network parameters such as packet arrival rate, queue length, delay, and throughput, the LSTM model effectively forecasts future traffic load and identifies potential congestion points in advance. This predictive capability enables proactive decision-making, allowing the network to reroute traffic, balance load, and allocate resources before severe congestion occurs.

The integration of deep learning with routing strategies significantly enhances overall network performance. The proposed framework improves Packet Delivery Ratio (PDR), reduces end-to-end delay, minimizes packet loss, and increases throughput compared to conventional routing protocols. Additionally, by avoiding overloaded nodes and reducing unnecessary retransmissions, the system contributes to improved energy efficiency and extended network lifetime—an essential factor in resource-constrained IoT environments.

Overall, the LSTM-based traffic flow prediction model provides an intelligent and scalable solution for congestion avoidance in wireless IoT networks. The proposed approach demonstrates that combining predictive analytics with adaptive routing can substantially improve network stability, reliability, and QoS. Future work may focus on integrating hybrid deep learning models, edge computing-based real-time implementation, and reinforcement learning techniques to further enhance predictive accuracy and dynamic network optimization in next-generation IoT systems.

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