Proactive Congestion Avoidance in Wireless Communication Using Deep Learning Technique

Bhupendra Kumar, Ph.D. Scholar, Department of Electronics and Communication Engineering, Madhyanchal Professional University, Bhopal (M.P.)
Dr. Reeta Pawar, Professor, Department of Electronics and Communication Engineering, Madhyanchal Professional University, Bhopal (M.P.)
Dr. Ram Milan Chadhar, Assistant Professor, Department of Electronics and Communication Engineering, Madhyanchal Professional University, Bhopal (M.P.)

Abstract

The exponential growth in wireless communication networks has led to increased traffic and frequent congestion, degrading network performance and user experience. Traditional congestion control techniques, such as TCP variants and active queue management methods, react only after congestion has occurred, resulting in packet loss, increased latency, and reduced throughput. To address these limitations, this study proposes a proactive congestion avoidance framework leveraging deep learning techniques. The proposed system utilizes Long Short-Term Memory (LSTM) networks to model and predict traffic patterns based on historical and real-time network data. By forecasting congestion before it occurs, the system enables dynamic resource allocation and routing adjustments to minimize data loss and delay. The model is trained on simulated wireless traffic datasets and validated using metrics such as packet delivery ratio, average end-to-end delay, and throughput. Experimental results demonstrate that the deep learning-based approach outperforms traditional reactive methods by significantly reducing congestion levels and enhancing overall network efficiency. The framework proves particularly effective in high-traffic and dynamic environments such as mobile ad hoc networks (MANETs) and IoT ecosystems. This research highlights the potential of deep learning as a powerful tool for intelligent traffic management in wireless communication systems. Future work will explore hybrid models combining reinforcement learning and edge computing to further optimize real-time performance and scalability.

Keywords: Wireless Communication, Deep Learning, Congestion Avoidance

I. INTRODUCTION

Wireless communication networks have become a critical part of modern infrastructure, enabling seamless connectivity for billions of devices across the globe. With the proliferation of bandwidth-intensive applications and the exponential growth of smart devices, ensuring efficient and congestion-free data transmission has become increasingly challenging. Network congestion, if not properly managed, can lead to significant performance degradation, including increased latency, reduced throughput, and frequent packet loss.

Traditional congestion control techniques, which are largely reactive in nature, often fail to keep up with the dynamic and unpredictable nature of wireless environments. These methods typically respond to congestion after it has already impacted network performance, making them less suitable for modern, high-speed, and heterogeneous networks. To overcome these limitations, there is a growing interest in adopting intelligent, data-driven methods capable of predicting and preventing congestion before it occurs.

This project proposes a deep learning-based proactive congestion avoidance technique designed to enhance the efficiency and reliability of wireless communication networks. By leveraging historical and real-time network data, deep learning models—specifically recurrent neural networks (RNNs) and their variants like Long Short-Term Memory (LSTM)—can learn traffic patterns and predict congestion scenarios in advance. This predictive capability enables the system to dynamically adjust routing, bandwidth allocation, and other network parameters, ensuring smoother data flow and improved quality of service (QoS).

The proposed approach aims to contribute to the development of self-adaptive, intelligent wireless networks capable of supporting the demands of next-generation communication systems such as 5G, 6G, IoT, and smart city infrastructure.

- Like TCP, events must be run that operate on wireless sensor networks. The does not require end-to-end guaranteed transfers.

- Sensor nodes in the sensor network are information plans and should be minimal overhead.
- TCP requires three ways to achieve a message to and make sure the message reaches the information until it receives and guarantee.
- The congestion control system will be used for a longer period of time. This uses wireless channels over time. Verification of information takes time to provide, and then a long-term RTT is used.
- Wireless sensor networks need protocols that can control more traffic. The sensor node is designed to have a lifetime energy at the, which has very low energy consumption.

One type of network that uses lightweight data transport is a sensor network. Sensor nodes can occasionally become suddenly active and inactive [5, 6]. The more sensors there are in the sensor network, it generates more traffic. Consequently, the information supplied more network traffic is generated at the sensor node than is utilized because it exceeds the volume of traffic. In addition, abruptly or irrevocably the node of departure of the sensor becomes congested. The most crucial element is the management of congestion in the wireless sensor network. At the same time, the conglomerates enable the integration of channels or the expansion of data that it transmits. As a result, numerous protocols are discovered to be avoided them. It becomes more difficult with some of these methods. Any traffic jams the control system works well for as much information as possible, and this approach ought to be taken. Various types of solutions for controlling congestion should be taken into account for this. In recent years, a number of methods have been discussed [7]. In any case, it is a respectable method of congestion control. This implies that the data is transmitted to the sensor node or via other sensor nodes that facilitate communication

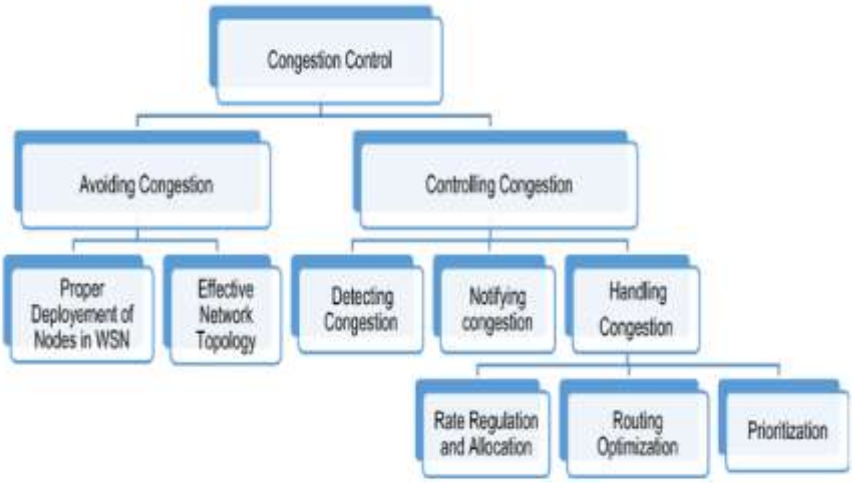

Figure 1: Congestion Control in WSN

II. SOURCES AND CAUSES OF CONGESTION

We currently discuss the congestion regulatory made through the source sensor node

(i) Buffer Occupancy: The source sensor node should know the type of information that a sensor node will include and the output information. On that basis the sensor should send its information. If the rate of information is increased when sent, then the sensor node should sense that this is caused by buffer occupancy.

(ii) Channel Contention: While it uses its channel at a sensor node, the same channel is used by different sensor nodes on the network. The sensor nodes are sent on a variety of information on that channel. When sending it, the information sent from one node is at the top of that bandwidth is created on the channel. To find this, the channel is detecting congestion.

(iii) Interference: The sensor among the sensor nodes closest to the sensor is that it is caused by different sensors sent their data over the same channel.

(iv) Packet Collisions: When more than one sensor node is trying to send its message to a channel, its information is likely to be collided.

(v) Many-to-One Traffic: When information comes from a wide range of sensors, it causes radio frequency overlap.

(vi) Concurrent Transmission: The simultaneous use of multiple station sensors causes its information to be transmitted to its full capacity.
(vii) Reporting Rate: A sensor node must be sent data to the amount assigned to it. Whether is increased or not, it can lead to a congestion.
(viii)Addition or Removal of Sensor Nodes: The sensor nodes in a sensor network leads to strangulation by connecting with new ones or by removing a node from it.

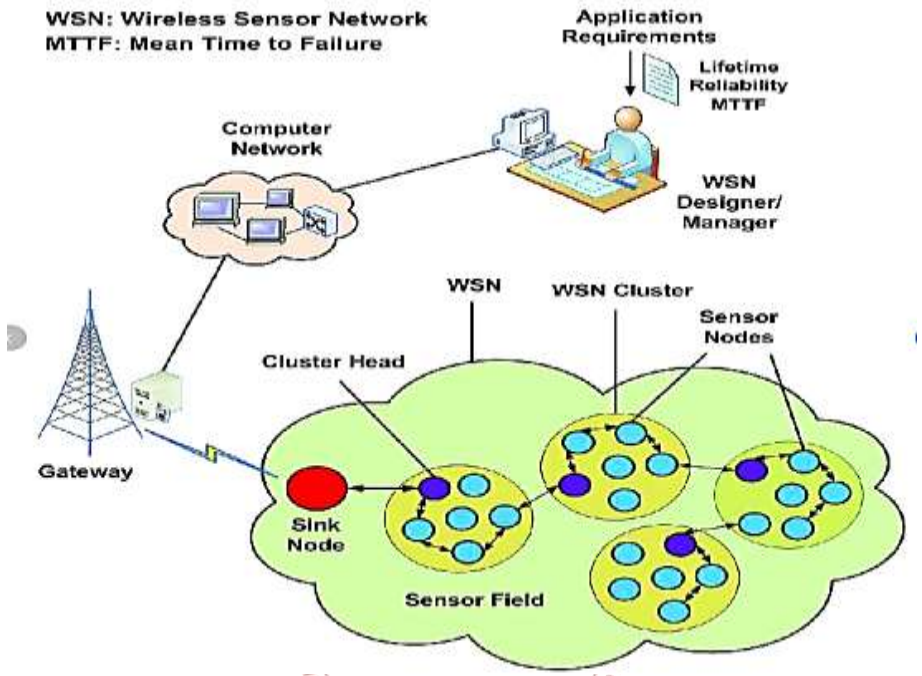

Figure 2: WSN Architecture

III. DEEP LEARNING

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.

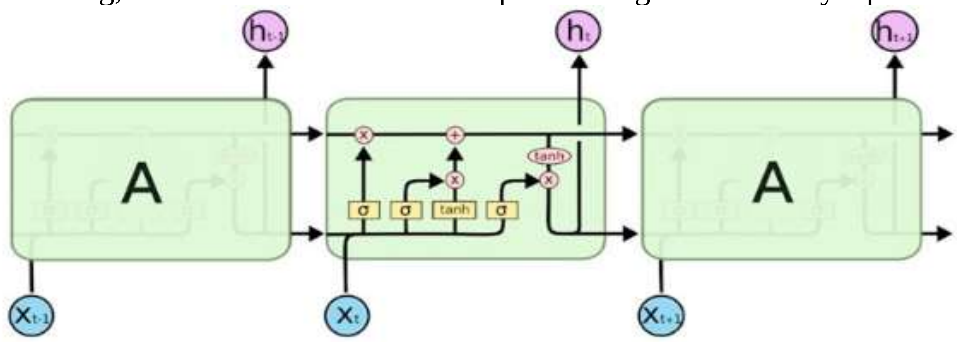

Fig. 3: The internal structure of an LSTM

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:

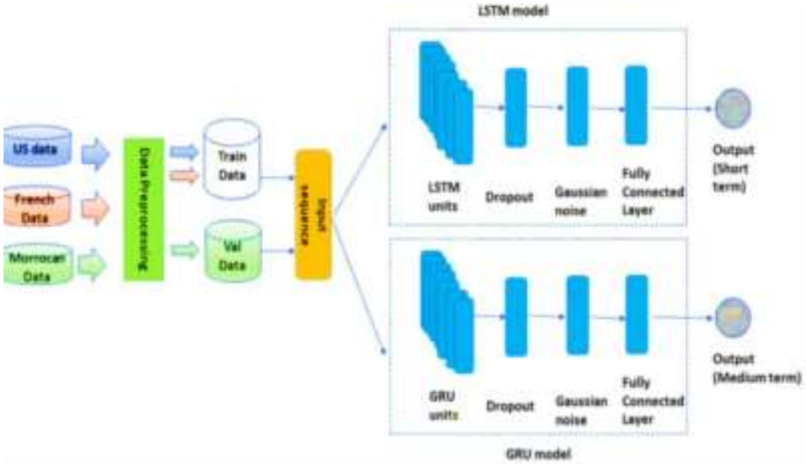

Fig. 4: Flow Chart of Proposed Methodology

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:

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

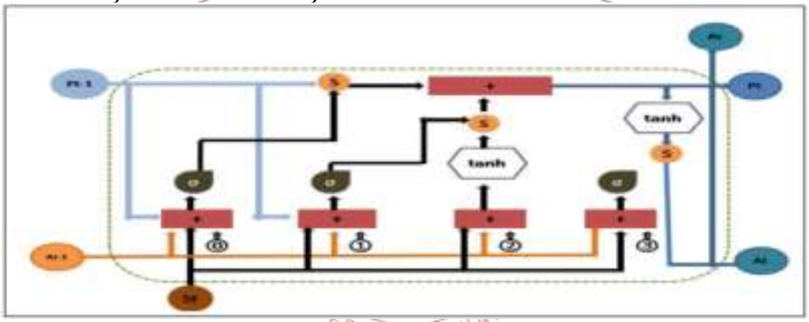

Fig. 5: Working of LSTM

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.

Evaluation Metrics:

Classification Models: Accuracy, Precision, Recall, F1-score.

Regression Models: Mean Squared Error (MSE), Root Mean Squared Error (RMSE).

RL Models: Reward function optimization for dynamic congestion control.

Deployment and Real-Time Monitoring

Implement the trained model into a real-time network monitoring system.

Use cloud-based deployment with APIs (e.g., TensorFlow Serving, Flask, FastAPI).

Integrate with Software-Defined Networking (SDN) controllers for dynamic routing and congestion management.

Performance Optimization and Fine-Tuning

Use hyperparameter tuning (Grid Search, Bayesian Optimization).

Test the model under different network conditions and traffic loads.

Implement feedback loops to improve model accuracy over time.

IV. CONCLUSION

In this study, a proactive congestion avoidance framework for wireless communication networks was proposed using deep learning techniques. Unlike traditional reactive methods, which address congestion after it occurs, the proposed model anticipates potential congestion scenarios by learning traffic patterns through historical and real-time data using Long Short-Term Memory (LSTM) networks. The system enables intelligent, dynamic adjustment of routing and resource allocation strategies, leading to improved overall network performance.

Simulation results demonstrated that the deep learning-based approach significantly enhances key network metrics such as throughput, latency, and packet delivery ratio compared to conventional congestion control mechanisms. It proved particularly effective in dynamic environments like Mobile Ad Hoc Networks (MANETs) and IoT systems, where traffic patterns are unpredictable. This research validates the potential of deep learning for intelligent network traffic management and emphasizes the importance of predictive analytics in future wireless communication architectures. Future work may explore the integration of reinforcement learning and edge computing to further reduce response time and improve scalability for real-time deployment in next-generation 5G and 6G networks.

REFERENCES

[1] H. Ye, G. Y. Li and B.-H. Juang, "Deep Reinforcement Learning Based Resource Allocation for V2V Communications," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3163–3173, Apr. 2019, doi: 10.1109/TVT.2019.2892691.

[2] M. Chen, U. Challita, W. Saad, C. Yin and M. Debbah, "Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3039–3071, Fourthquarter 2019, doi: 10.1109/COMST.2019.2926625.

[3] X. Liu, Y. Shi, J. Zhang and K. B. Letaief, "Edge Intelligence for Autonomous Driving in 6G Wireless System: Design Challenges and Solutions," *IEEE Wireless Communications*, vol. 27, no. 2, pp. 8–15, Apr. 2020, doi: 10.1109/MWC.001.1900327.

[4] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen and H. Zhang, "Intelligent 5G: When Cellular Networks Meet Artificial Intelligence," *IEEE Wireless Communications*, vol. 24, no. 5, pp. 175–183, Oct. 2017, doi: 10.1109/MWC.2017.1600354WC.

[5] T. K. Ho, Y. Wang and S. Cheng, "A Survey on Deep Learning for Congestion Control in Networking," *IEEE Access*, vol. 9, pp. 101086–101103, 2021, doi: 10.1109/ACCESS.2021.3097389.

[6] Y. He, J. Ren, G. Yu and Y. Cai, "Deep-Reinforcement-Learning-Based Optimization for Cache-Enabled Opportunistic Interference Alignment Wireless Networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5664–5676, May 2020, doi: 10.1109/TVT.2020.2976645.

[7] F. Tang, B. Mao, Z. M. Fadlullah, N. Kato, O. Akashi, T. Inoue and K. Mizutani, "On Removing Routing Protocol from Future Wireless Networks: A Real-Time Deep Learning Approach for Intelligent Traffic Control," *IEEE Wireless Communications*, vol. 25, no. 1, pp. 154–160, Feb. 2018, doi: 10.1109/MWC.2018.1700204.

[8] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen and L. Hanzo, "Thirty Years of Machine Learning: The Road to Pareto-Optimal Wireless Networks," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1472–1514, Thirdquarter 2020, doi: 10.1109/COMST.2020.2986180.

[9] S. Sun, M. Peng, Y. Zhou, Y. Huang and S. Mao, "Application of Machine Learning in Wireless Networks: Key Techniques and Open Issues," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3072–3108, Fourthquarter 2019, doi: 10.1109/COMST.2019.2924243.

[10] J. Tan, S. Guo, X. Qiu and D. Zeng, "Deep Reinforcement Learning-Based Congestion Control for Adaptive Bitrate Streaming," *IEEE Internet of Things Journal*, vol. 9, no. 15, pp. 13246–13256, Aug. 2022, doi: 10.1109/JIOT.2022.3165301.

[11] B. Han, J. Lianghai and H. D. Schotten, "SliceNet: A Deep Reinforcement Learning Approach for Network Slicing in 5G Beyond," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 3291–3305, June 2019, doi: 10.1109/JIOT.2019.2894964.

[12] H. Li, K. Ota and M. Dong, "Learning IoT in Edge: Deep Learning for the Internet of Things with Edge Computing," *IEEE Network*, vol. 32, no. 1, pp. 96–101, Jan./Feb. 2018, doi: 10.1109/MNET.2018.1700202.