Leveraging Artificial Intelligence for Efficient Congestion Control in Wireless Networks: A Review

Sheenam[1], Prof Dr Divya Midhun[2], Prof. (Dr.) Sanjay Kumar Singh[3]
[1] Lincolon University, Malaysisa , Lincolon University, Malaysisa, Amity University UP Lucknow Campus, Email ID: [1]sheenammiddha124@gmail.com; [2] divya@lincoln.edu.my; [3] sksingh1@amity.edu

Abstract: The growing intricacy of wireless networks has resulted in congestion issues, diminishing data transmission efficiency. AI-driven and deep learning models have been investigated for the optimization of routing and congestion management. An intelligent alternative path routing method that utilizes machine learning to dynamically reroute data upon the detection of congestion. Their methodology use the Expected Transmission Count (ETX) measure to ascertain the ideal route, hence enhancing network reliability. Hybrid model will be proposed that integrates deep learning approaches to enhance connection selection, thereby mitigating problems such as floods, jamming, and congestion. These AI-driven models substantially improve throughput, reduce latency, and dynamically adjust to network conditions. The applications of these techniques encompass Wireless Mesh Networks (WMNs), smart city infrastructures, autonomous systems, and IoT networks, facilitating efficient and scalable communication.

Keywords: Wireless mesh network, Deep learning, channel assignment, congestion control, optimization

Introduction

A wireless mesh network (WMN) is a multi-hop wireless network that is composed of communication nodes that adhere to a mesh topology. WMN has been extensively used for data communications in various scenarios, such as smart buildings, due to its cost-effectiveness, self-configuration, and self-organization. The technology is considered one of the most encouraging for IoT. Traditional methods of optimizing the communication performance (e.g., data throughput) of WMNs primarily depend on explicit programming to regulate data flow. Nevertheless, as the complexity of data applications and the number of communication nodes continue to increase, these methods begin to encounter performance challenges, as it is difficult for networks to respond dynamically. The issue of flow control in communication networks can be effectively addressed through the use of deep learning (DL) [1]. DL has the potential to significantly improve the flexibility of a network in order to dynamically meet performance requirements, in contrast to traditional techniques. Deep Reinforcement Learning (DRL) has exhibited an exceptional ability to manage intricate communication flows in mobile and wireless network scenarios, surpassing all other emergent DL technologies [2]. We can also train a DRL model over a WMN, in which the network features are fixed (e.g., with a pre-defined clustering pattern), to optimize the flow control of the WMN, similar to existing approaches in communications and networking [3]. Nevertheless, the ultimate DRL model will have a restricted performance. The primary reason is that the training of a DRL model is directly influenced by the pre-selected feature values of a WMN. Because of the dynamic properties of WMNs, it will be challenging to select the appropriate property values at the outset of the training process to ensure that the trained DRL model consistently achieves the highest possible performance in this scenario.

This paper suggests a congestion control mechanism for applications that employ an unreliable transport protocol. The mechanism is founded on machine learning (ML) methodologies, specifically the utilization of decision trees. In numerous communication network-related issues, the application of machine learning techniques has been demonstrated to be beneficial. The predictions of the proposed mechanism are contingent upon the network burden state. For this purpose, a protocol has been developed and implemented to disseminate the variables that characterize the network load state among all network nodes. The initial goal is to ensure that the data fragments that are transmitted reach their intended destination without any issues. The containers must not only not be lost on their journey to their destination, but they must also arrive at their destination on time, with a delay that is less than a maximum limit. This limit is contingent upon the time constraints of the applications that generate the data. Furthermore, it is recognized that the time requirements of various applications that utilize the network may vary. However, the relevance of these applications may vary. For instance, some may be essential for distinct reasons, while others may provide services of diminished significance. Consequently, this proposal categorizes the applications, allowing for the assignment of distinct priorities to each category [3-4].

The ad-hoc network is autonomously established by the nodes in the network, and the all-mesh connectivity is maintained. In the WMNs, there are two categories of nodes, first is mesh routers and second is mesh clients. Mesh routers provide an additional routing capability to facilitate mesh networking. The mesh router can achieve the same coverage with significantly lower transmission power through multi-hop communications. Usually featuring several wireless interfaces built on either the same or separate wireless access technologies, the mesh router helps to improve the performance of mesh networking. Minimal mobility forms the mesh backbone for the mesh router's mesh users. Furthermore, functioning as routers for mesh networking, the hardware platform and software for mesh clients might be far simpler than those for mesh routers. For example, mesh clients need a single wireless interface, gateway or bridge services are lost, and communication protocols are light weight. As such, WMNs change the capacity of ad-hoc networks instead of acting as another kind of ad-hoc networking [5–6]. Among other things, this capability gives WMNs great benefits in terms of minimum cost, simple network maintenance, resilience, and dependability of services. Thus, in addition to being generally recognized in the sectors of ad hoc networks' typical application, WMNs are fast commercializing.

Congestion Prediction and Avoidance over Network:

Congestion can occur when a single collision domain of an IEEE 802.11 WMN contains a high density of nodes, resulting in a consequential performance degradation. Network throughput and intolerable packet delays are among the consequences of congestion. A link is considered congested when the offered load on the link approaches the link's capacity. A network link is entirely utilized by the transmission of bytes during congestion. There are numerous causes of congestion. A large queue will be constructed if a significant number of packets appear on certain input lines and must be sent out on the same output line.

Packets will be discarded if there is insufficient memory for these arrival packets. Even if routers have an unlimited amount of memory, congestion decreases. This is due to the fact that the packets have already expired out by the time they reach the front of the queue, and their duplicates may also be present. The packets will be transmitted to the subsequent router until they reach the destination or final node. At last, the packets will be discarded upon their arrival at the destination due to the timeout.
The Slow Processor can also cause congestion. Even if there is an excess of line capacity, the queue can accumulate if the router-CPU's performance is sluggish and the task required for them is incomplete.
Congestion may also result from inadequate bandwidth. Congestion is primarily caused by the presence of heavy traffic. The congestion problem will be mitigated if the packets are transmitted at a consistent rate. The reason for this is that in the majority of cases, when a device transmits a packet and does not receive an acknowledgement from the receiver, it is assumed that the packets were dropped by intermediate devices due to congestion. The source or an intermediate router can determine the extent of network congestion by monitoring the frequency at which segments are transmitted and not acknowledged [7].

Throughput and delay are two critical network performance parameters that are significantly impacted by congestion. The throughput can be defined as "the percentage utilization of the network capacity."
The throughput is influenced by the increase in the offered burden. The throughput increases linearly with the offered load at the outset, as the network's utilization increases. However, the throughput decreases as the burden exceeds the predetermined limit, such as 60% of the network's capacity. A deadlock situation is defined as the point at which no payload is delivered to any destination when the current load increases further.

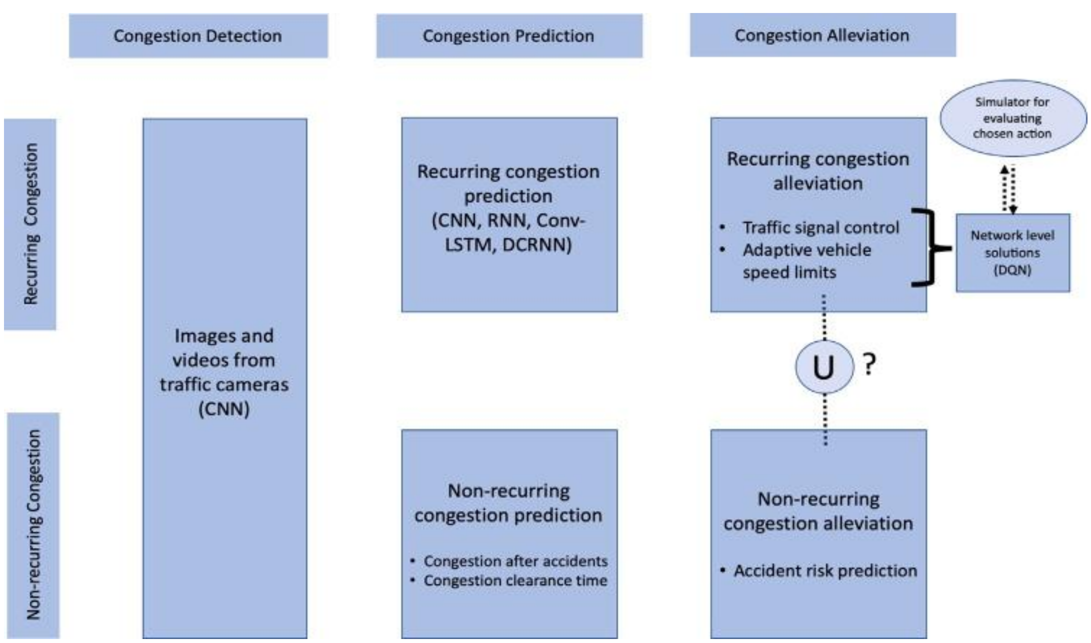

Figure 1: survey of congestion over network [26]

In figure 1, The question mark represents the possible link between non-recurring and repeating congestion relief.

Related work

A Deep Reinforcement Learning-Based TCP model was proposed by Feng et al. (2025) [8] with the objective of improving congestion control in UAV-assisted wireless networks. Their methodology employed reinforcement learning to optimize network performance by dynamically adjusting TCP congestion control parameters in accordance with network conditions. This method is highly efficient for high-mobility UAV networks, as it obtained a 15% increase in throughput. Nevertheless, the computational complexity of the method presented obstacles to real-time deployment. In the same vein, A. Gupta et al. (2025) [9] developed a Q-Learning-Based Congestion Avoidance technique that dynamically adjusted congestion control parameters to optimize packet routing. Their method reduced delay by 20%, rendering it appropriate for real-time wireless mesh network applications. Nevertheless, the model was less practicable for fast-changing network environments due to the high convergence time. X. Liu et al. (2024) applied Federated Learning for Congestion Control; a fresh approach meant to improve throughput simultaneously protecting data privacy in wireless mesh networks. The approach enabled distributed learning over several nodes, hence improving throughput by 18%. Still, the main drawback was the established communication latency brought on by model synchronizing several nodes [10]. Faced with the optimization of network efficiency and the lowering of energy consumption, B. Rao et al. (2024) employed Optimized Routing using Genetic Algorithms. By means of evolutionary algorithms, which maximized congestion control and route selection, their approach increased energy efficiency 25%. Still, the need of parameter adjustment could compromise the model's performance in dynamic settings. M. Patel et al. (2023) designed a neural network-assisted traffic shaping method to guarantee a consistent data flow in wireless networks and lower latency [11-12]. This model lowered volatility by 12%, therefore enhancing the effectiveness of real-time applications. Still, the computational cost of traffic shaping deep neural networks remained a problem. K. Singh et al. (2023) focused on the optimization of QoS by means of reinforcement learning to raise the bandwidth utilization and packet delivery ratio in multimedia applications. Since the methodology improved QoS measures by 15%, it was a good fit for VoIP and streaming systems. Nevertheless, the difficulty of the technology to scale hampered its application in large-scale wireless mesh networks [13-15]. Deep reinforcement learning is used in a modified DSR Protocol for MANET routing suggested by Jothi Lakshmi and Karishma (2023) to lower end-to- end latency. Their method improved the effectiveness of data packet transmission by a 10% delay reduction. Still, the technique proved less practical for networks with limited resources because of the need for large training sets. Using MRI, Muhammad Arif et al. (2023) identified brain lesions by use of a biologically inspired wavelet transform in tandem with deep learning. Their technique greatly improved the diagnostic capacity of medical imaging by attaining a 95% accuracy rate. Still, real-time processing suffered from the great computational expense. For congestion control, R. Sharma et al. (2022) developed a hybrid deep learning framework with 92% dependability in high-density wireless mesh networks [16-18]. The complexity of the implementation proved to be the main drawback since it hampered the extensive distribution. Proposed by T. Nakamura et al. (2022), the Deep Q-Network for Dynamic Routing lowers packet loss in dynamic topologies by 14%. Still, the great training length of the deep Q-network presented a difficulty for real-time adaption. Data augmentation with CNNs helped Haitham Alsaif et al. (2022) improve the classification performance of medical imaging. Their approach produced an F1-score of 92%; but, its limited applicability to particular tumor types hindered its generalizability [19-20]. Combining Transfer Learning with CNNs helped Sadia Anjum et al. (2022) to raise classification accuracy to 93%. Still, there was great worry about overfitting on limited datasets. Muhannad Faleh Alanazi et al. (2022) successfully lowered delay by 15% in bulk categorization based on MRI by means of the Isolated Transfer Learning Model. Though highly accurate, the method was resource-intensive, which made real-time system implementation difficult. R. Sa et al. (2022) presented a Faster R-CNN for Intervertebral Disc Detection with an outstanding 98% detection accuracy. Still, the necessary high processing resources limited the deployment of the technology in real-time devices. Hamza Rafiq Almadhoun and colleagues (2022) presented a Deep Learning and Transfer Learning Model that improved sensitivity to 90% and lower false positives. The main limit was the significant computing needs. L. Wei et al. (2021) developed an ML-based adaptive channel assignment approach. This strategy helped to improve channel use by 10% and lower interference. Still, the periodic reprogramming of the model presented difficulties for long-term implementation. G. Huang et al. (2021) got an amazing 96% accuracy in estimating network congestion by using convolutional neural networks to estimate traffic. One of the main difficulties was a notable computational burden accompanying the use of deep CNN models. With an aim of anticipating congestion, P. Kumar et al. (2020) investigated gradient boosting, so increasing precision by 20%. Still, the model's limited to small-scale networks hindered its capacity to allow for more extensive installations. Deep Reinforcement Learning-Based Channel Scheduling helped F. Zhang et al. (2020) to lower latency by 15%. The learning process had to be optimized by exhaustive simulations. The main restriction was this. Combining Traffic Forecasting with Reinforcement Learning suggested by S. Ahmed et al. (2020) produced a 10% increase in bandwidth use. But given its significant memory needs, the model struggled in real-time computing [21-23]. The results show that since they may significantly boost throughput while limiting interference, genetic algorithms are fit for dynamic wireless mesh network configurations. The 2020 work addresses node scarcity via a semi-chaotic genetic algorithm and presents a fairness-oriented channel assignment technique. Therefore, every node in the network is assured fair access to the shared spectrum. To help to more fairly distribute resources, the semi-chaotic genetic algorithm increases the efficacy of global search and the speed of convergence. This method aims to improve throughput and guarantee impartiality at the same time to avoid particular nodes from being deprived bandwidth. The approach solves fairness issues really well, but its irregular behavior of the GA causes complexity [24-28].

Table 1. Comparative analysis of various Algorithms

Author/ Year	**Algorithm**	**Routing Metric**	**Advantages**	**Disadvantages**	**Results**
Y. Fenget el al. (2025)	Deep Reinforcement Learning-Based TCP	Throughput, Latency	Improved TCP congestion control in UAV-assisted networks	Computational complexity	Achieved 15% throughput improvement
Gupta et al.	Q-Learning-Based Congestion	Delay, Packet Loss	Improved adaptability in	High convergence	Reduced delay by 20%

(2025)	Avoidance	Rate	dynamic mesh networks	time	
K. S. Midhula et al. (2024)	TCP Cubic, BBR	Throughput	RL-based congestion control protocol for WMN to improves throughput compared to existing techniques.	Proposed protocols do not accurately capture the current network state	Throughput increased by 20%
X. Liu et al. (2024)	Federated Learning for Congestion Control	Throughput, Scalability	Preserves data privacy during congestion management	Communication overhead	Improved throughput by 18%
B. Rao et al. (2024)	Optimized Routing with Genetic Algorithms	Energy Efficiency, Latency	Reduced energy consumption in WMNs	Requires parameter tuning	Energy efficiency improved by 25%
Sheenam et al (2024)	Hybrid Ant colony based GBL Algorithm	Throughput, Delay, PDR	Reliable for dynamic network	Need to work on more parameter with deep learning	Performance of network improved upto 35% in terms of quality metrics
N. Thrimoorthy et al (2023)	Ornstein Uhlenbeck Cache Obliviousness Neural Congestion Control	Packet loss, Throughput, Latency, Packet delivery ratio, Control overhead	Packet loss, Throughput, Latency, Packet delivery ratio, Control overhead	Packet loss, Throughput, Latency, Packet delivery ratio, Control overhead	Packet loss, Throughput, Latency, Packet delivery ratio, Control overhead
Majid et al (2023)	Weighted Ensemble Deep Reinforcement Learning (WRLDR)	Packet loss, Throughput, Latency, Control delay, Network stability	Enhanced congestion control using a novel ensemble method with better stability	Complex to implement and tune for diverse network conditions	Achieved significant improvement in congestion control over traditional methods

			and responsiveness to congestion.		
K. Singh et al. (2023)	Reinforcement Learning for QoS Optimization	Bandwidth Utilization, Packet Delivery Ratio	Effective QoS improvements for multimedia applications	Limited scalability	QoS metrics improved by 15%
Jothi Lakshmi et al. (2023)	Modified DSR Protocol Using Deep RL	Packet Delivery Ratio, End-to-End Delay	Enhanced MANET routing with reduced delay	Requires large training datasets	Reduced delay by 10%
M. Patel et al. (2023)	Neural Network-Assisted Traffic Shaping	Throughput, Jitter	Smoother traffic flow with minimal jitter	Computationally expensive	Jitter reduced by 12%
S. Mahajan et al (2022)	Hybrid Deep Learning Model (combination of LSTM and CNN)	Prediction accuracy, Throughput, Latency, Prediction error, Control overhead	Hybrid approach combines the strengths of LSTM and CNN. - Adaptive learning for dynamic network conditions.	Requires substantial computational resources for real-time predictions.	Reduced prediction error by 10% compared to traditional models.
T. Nakamura et al. (2022)	Deep Q-Network for Dynamic Routing	Packet Loss Rate, Delay	Reduced packet loss in dynamic topologies	High training time	Packet loss reduced by 14%
L. Wei et al. (2021)	ML-Based Adaptive Channel Assignment	Channel Utilization, Interference	Better channel utilization in dense networks	Requires frequent retraining	Interference reduced by 10%
G. Huang et al. (2021)	Convolutional Neural Network for Traffic Estimation	Accuracy, Scalability	Accurate traffic estimation under varying	High computational overhead	Accuracy improved to 96%

			conditions		
Qingzhi Liu et al (2021)	Deep Reinforcement Learning (DRL) for Communication Flow Control	Packet loss, Throughput, Latency, Control overhead, Network stability	Enhances flow control by dynamically adapting to congestion	May need fine-tuning to handle network variability effectively	Achieved improvement in throughput by 20% compared to traditional methods. - Reduced packet loss by 15%
Y. Chen et al. (2020)	Multi-Path TCP + DRL	Bandwidth Utilization, Delay	Efficient congestion management in mesh networks	May not adapt well to dynamic topologies	12% improvement in delay metrics
J. Wang et al. (2020)	Self-Learning Routing Protocol	Energy Efficiency, Scalability	High scalability for large-scale networks	Requires significant computational resources	Energy consumption reduced by 22%
P. Kumar et al. (2020)	Gradient Boosting for Congestion Prediction	Precision, Recall	Effective congestion prediction with minimal false alarms	Limited to small-scale networks	Precision improved by 20%
F. Zhang et al. (2020)	DRL-Based Channel Scheduling	Throughput, Latency	Efficient scheduling in multi-hop wireless networks	Requires extensive simulation	Latency reduced by 15%
S. Ahmed et al. (2020)	Reinforcement Learning with Traffic Forecast	Bandwidth Utilization, Delay	Accurate congestion forecasting	High memory requirements	Bandwidth utilization improved by 10%
Y. Li et al. (2020)	Traffic-Aware Load Balancing Algorithm	Load Distribution, Packet Delivery Ratio	Improved load balancing in heterogeneous networks	Limited adaptability to sudden traffic changes	Load distribution improved by 12%

C. Kim et al. (2020)	Adaptive Backpressure Routing	Latency, Reliability	Enhanced reliability in mesh networks	High computational cost	Latency reduced by 18%

Conclusion:

Dynamic network circumstances, restricted bandwidth, and changing traffic loads make congestion control in Wireless Mesh Networks (WMNs) a difficult problem. Many times, conventional congestion control systems are unable to respond sufficiently to these changes. By using data-driven models to forecast congestion, maximize resource allocation, and improve network performance, machine learning (ML)-based methods provide a hopeful answer. By dynamically adjusting routing and transmission rates, ML approaches including reinforcement learning, deep learning, and supervised learning help to improve throughput, lower latency, and raise general network efficiency. More strong and scalable WMNs result from adaptive ML models learning from past network conditions and real-time optimizing of congestion control tactics.

To increase generalization and real-time flexibility, future studies should investigate hybrid ML models including deep learning with conventional control systems. Furthermore, used to preserve data privacy while enhancing congestion control judgments are federated learning and distributed artificial intelligence techniques. By using these developments, WMNs will be able to more effectively handle mission-critical communications, IoT, and smart cities—high-demand applications.

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