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Adaptive Neuro-Fuzzy Congestion Control Algorithm for Real-Time Multimedia Networking in Cloud-Based E-Learning Platforms

Hanadi Hakami[1], Mohammad Kamrul Hasan[2*], Ahmad Alshamayleh[3], Dr. Ali Q. Saeed[4], Dr. Saed Adnan Mustafa[5], and Dr. Taher M. Ghazal[6]

[1]Department of Software Engineering, College of Engineering, University of Business and Technology, Jeddah, Saudi Arabia. h.hakami@ubt.edu.sa, https://orcid.org/0000-0001-5627-6805

[2*]Center for Cyber Security, Faculty of Information Science and Technology, Universiti, Kebangsaan Malaysia (UKM), Bangi, Selangor, Malaysia. hasnakamrul@ieee.org, https://orcid.org/0000-0001-5511-0205

[3]Department of Data Science and Artificial Intelligence, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. a.alshamayleh@ammanu.edu.jo, https://orcid.org/0000-0002-7222-2433

[4]Technical Engineering College for Computer and AI–Mosul, Northern Technical University, Mosul, Iraq. ali.qasim@ntu.edu.iq, https://orcid.org/0000-0002-2276-3776

[5]College of Business, The American University of Kurdistan, Iraq. said_es@yahoo.com, https://orcid.org/0000-0002-3099-7230

[6]Faculty of Computing and IT, Sohar University, Oman; Department of Networks and Cybersecurity, Al-Ahliyya Amman University, Amman, Jordan; Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor, Malaysia. taher.ghazal@ieee.org, https://orcid.org/0000-0003-0672-7924

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Abstract

Innovations in cloud-based platforms for e-learning have been accompanied by an increased demand for real-time multimedia components, such as video lectures, collaboration tools, and interactive quizzes. Multichannel multimedia e-learning platforms face the challenge of maintaining quality of service (QoS) requirements while the network circumstances vary and cause delays, packet dropping, or jitter. Existing congestion control techniques like TCP and AQM fall short for multimedia traffic. In this paper, the Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) is introduced, which uses neural networks and fuzzy logic to make congestion control decisions in real time. We implement the proposed algorithm in the context of cloud-based e-learning, where users access the content under varying network conditions. Performance results demonstrate considerable improvements in traditional techniques in real-time multimedia networking for e-learning, with significant gains in throughput, packet delivery ratio (PDR), and end-to-end delay.

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*Corresponding author: Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor, Malaysia.

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1 Introduction

As cloud-based e-learning systems are centered around virtual classrooms, live tutoring sessions, and collaborative training with multiple users, they require live social interaction, real-time video and interactive audio elements, and more than passive participation from users. With fluctuating network conditions, the task of stabilizing a network connection can become increasingly daunting and unpredictable with the number of users and types of multimedia content available (Ramya et al., 2022). The greater the number of users and multimedia content used, the more vital the challenge to the cloud-based learning system (Berglund & Aalto, 2021).

1.1 Background

Cloud computing has fundamentally altered the dynamics of how educational materials are shared and consumed. Services such as e-learning, Google Classroom, Zoom, and Microsoft Teams have all ushered in the virtual classroom, using live multimedia streaming (video/audio). With technological advancements, the delivery of education has more flexibility and more scalable since the content can be consumed and collaborated upon remotely (Gao, 2024). This offers flexibility; however, the challenge remains preserving network performance in bad situations that have high latencies, packet loss, and jitter, which is typical during conventional streaming of real-time multimedia delivery (Bao et al., 2021).

When streaming is done in the cloud, the network means things could change rapidly, meaning the content could be consumed unpredictably. However, the situation has worsened with interactive multimedia content as well. In these situations, traditional congestion control such as transmission control protocol (TP) and active queue management (AQM) will not give us the expected quality of service (QoS) parameters needed for real-time multimedia applications due to unyielding and inflexibility with fluctuating bandwidth. In this paper, we propose a novel method of controlling network congestion with the use of the Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) (Rao, 2019). It employs neural network capabilities for learning alongside fuzzy logic system synopses for decision-making (Chehreh, 2016). This enables a fully autonomous real-time (self-) adaptation to network conditions while addressing the challenges typical of multimedia streaming in real-time (Walia et al., 2015).

1.2 Statement of the Problem

Ensuring streaming media, such as videos and audio clips, of high quality and stability has become very vital with the popularization of cloud-based e-learning platforms (Zade et al., 2021). Nevertheless, different forms of network congestion continue to have a major impact on the user's quality of experience by causing delays, packet loss, and jitter. These problems occur due to the ever-changing cloud network infrastructure, including, but not limited to, network bandwidth, latency, and packet loss, which is dependent on the load on cloud servers, the distance between the client and the server, and the state of the internet (Polepally & Shahu Chatrapati, 2019).

Maintaining quality with multimedia content platforms is very difficult due to the need for real-time interaction with the users. Any form of disruption leads to a strained experience. This problem is further exacerbated by the need to scale cloud-based e-learning platforms to a larger user base as well as different geographic locations (Ahmad et al., 2022). In such a case, guaranteeing quality of service is important by managing changing network conditions on the fly.

Due to the fact that TCP and AQM focus on resolving general data traffic, they are not suitable for multimedia applications (Djahel et al., 2014). In addition, traditional algorithms tend to be static, not responding to varying network conditions (Zamani et al., 2021).

1.3 Objective of the Study

This research seeks to formulate and assess the Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) proposed for real-time multimedia streaming for cloud-based e-learning systems. This study focuses on the following objectives:

- To formulate a real-time responsive adaptive congestion control mechanism for heterogeneous networks.
- To combine fuzzy logic with neural networks for real-time traffic-responsive decision-making.
- To assess the algorithm performance effectiveness as measured by throughput, packet loss, end-to-end delay, and QoS improvements against existing comparable traditional techniques such as TCP.

1.4 Contribution to the Field

This paper provides a novel contribution by proposing an adaptive congestion control algorithm based on neuro-fuzzy systems, which is specific to the context of cloud-based e-learning systems. In particular, ANFCCA:

- Supports real-time dynamic adjustments to congestion windows and transmission rates to counteract network congestion.
- Enhances the delivery of multimedia applications in cloud environments to enable seamless streaming of video and audio during lectures and discussions.
- Expedites network-sensitive multimedia applications by improving the cloud’s environment adaptive capabilities to the network’s present conditions.
- The implementation of this algorithm is anticipated to enhance the performance of cloud-based e-learning systems by improving the delivery of multimedia content during poorer network conditions, thus enhancing the overall learning experience for the users (Pecheranskyi et al., 2024).

1.5 Scope of the Study

This research investigates the use of the Adaptive Neuro-Fuzzy Congestion Control Algorithm within the scope of cloud-based e-learning systems. The focus will be on assessing the algorithm's capability to:

- Enhance network throughput for the real-time transmission of multimedia.
- Reduce the loss of packets and jitter to maintain consistent audio and video quality.
- Minimize latency and keep a low end-to-end delay essential for live sessions.

Comparison will be made to the conventional congestion control methods, mainly TCP and AQM, to showcase the adaptability and unique features of ANFCCA in a real-time e-learning context.

2 Literature Survey

Effective management of network congestion is critical in multimedia networking. For cloud-based e-learning platforms, managing congestion is of the utmost importance. Reliably transmitting real-time data using congestion control methods such as TCP, which is widely used for data transmission, is ineffective in real-time applications because of concerns such as Buffer Bloat and high latency (Singh et al., 2022). These issues are detrimental to applications requiring consistent low latency and high reliability (e.g., educational video conferencing and streaming). The TCP data transmission methodology used for content delivery is adverse to real-time applications that need guaranteed delivery (Qu et al., 2016). Active Queue Management offers a solution for latency control and queue management in multimedia applications (Çakmak, 2024). One of the most used active/queue management methods, Random Early Detection (RED), works to keep a queue from exceeding a desirable length and prevent congestion by detecting potential congestion in advance (AlZyoud et al., 2024). Although implementations of AQM, notably RED, are more successful in mitigating congestion than TCP, RED and other active queue management methods still lack sufficient flexibility for real-time applications like cloud-based eLearning platforms (Mishra & Majhi, 2020). Plenty of approaches, in particular, are not capable of adapting to changes in network traffic (Do et al., 2019). This ultimately leads to issues with jitter, packet loss, and variable delays for time-sensitive applications - live video and audio calls. To circumvent the earlier-mentioned challenges with conventional congestion control approaches, Neuro-fuzzy systems have surfaced, especially as an Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is flexible like a neural network, and can make decisions like fuzzy logic can. This dual model will allow for dynamic responses to real-time changes and modify network settings; therefore, it can be viewed as suitable to provide real-time congestion control. ANFIS has one of the greatest differentiating strengths, the ability to respond to dynamic network changes, especially under conditions where the network has high variable network inflows, such as live-streaming, cloud gaming, or cloud-based e-learning situations (Kowalski, 2024).

2.1 Applications in Real-Life Scenarios

Applications in real life, like YouTube Live or Twitch, offer good examples of the need for dynamic bandwidth adjustment and bitrate scaling for handling congestion in the network during a live stream. These services make use of the possibility for dynamic bitrate shifting due to the high dependence on network congestion to offer services reliably. Regardless of the existence of adaptive bitrate streaming, buffering issues and delay persist during changing network loads. Here, ANFIS can help by monitoring network traffic and changing the congestion control parameters elastically to provide real-time adjustments and buffering or video lag, thereby improving the Quality of Service (QoS) (Kumar et al., 2013). ANFIS has also been effectively used to control real-time data streams from distributed devices in IoT (Internet of Things) networks. These networks exhibit the same kind of behavior as other multimedia applications, where constant changes in bandwidth and network congestion are fundamental challenges. With the use of ANFIS, real-time network parameters such as data stream, throughput, packet loss, and stream delay can be dynamically tuned, improving guaranteed reliable transmission and overall enhanced network performance (Fu et al., 2016). This idea applies to cloud-based e-learning systems like Google Classroom, Zoom, and Microsoft Teams, where students and instructors expect audio and video communication to be uninterrupted and of superior quality (Andrade-Zambrano et al., 2024).

2.2 Adapting to Cloud-Based E-Learning Platforms

In the context of the cloud-enabled e-learning platforms, the ANFIS-based adaptive congestion control algorithm may be able to control and manage bandwidth and interruptions to provide a better overall user experience (Narang & Kulkarni, 2023). E-learning platforms leverage real-time video and audio together for lectures, discussions, and group work, but network issues and congestion can negatively impact the overall learning experience, especially by freezing video and delaying audio or making it sound distorted. ANFIS can implement functions and make predictions and dynamically apply parameters in real-time, easing the user experience and helping to ensure that multimedia can be transmitted using ANFIS and still ensure that quality multimedia can continue to be distributed even in poor network conditions (Ancillotti et al., 2018). Furthermore, ANFIS should also most likely improve and provide a better performance to the overall network, in that it can provide sufficient bandwidth more efficiently by prioritizing audio and video streams when there is congestion. The algorithm can predict network conditions and, therefore, can adjust the buffer sizes and the rate of transmission along with congestion parameters to prevent packet loss, eliminate jitter, and maintain low latency. This greatly improves the learning experience, which is critical during periods of peak usage, and significantly enhances the responsiveness and fluidity of the learning experience.

3 Proposed Methodology

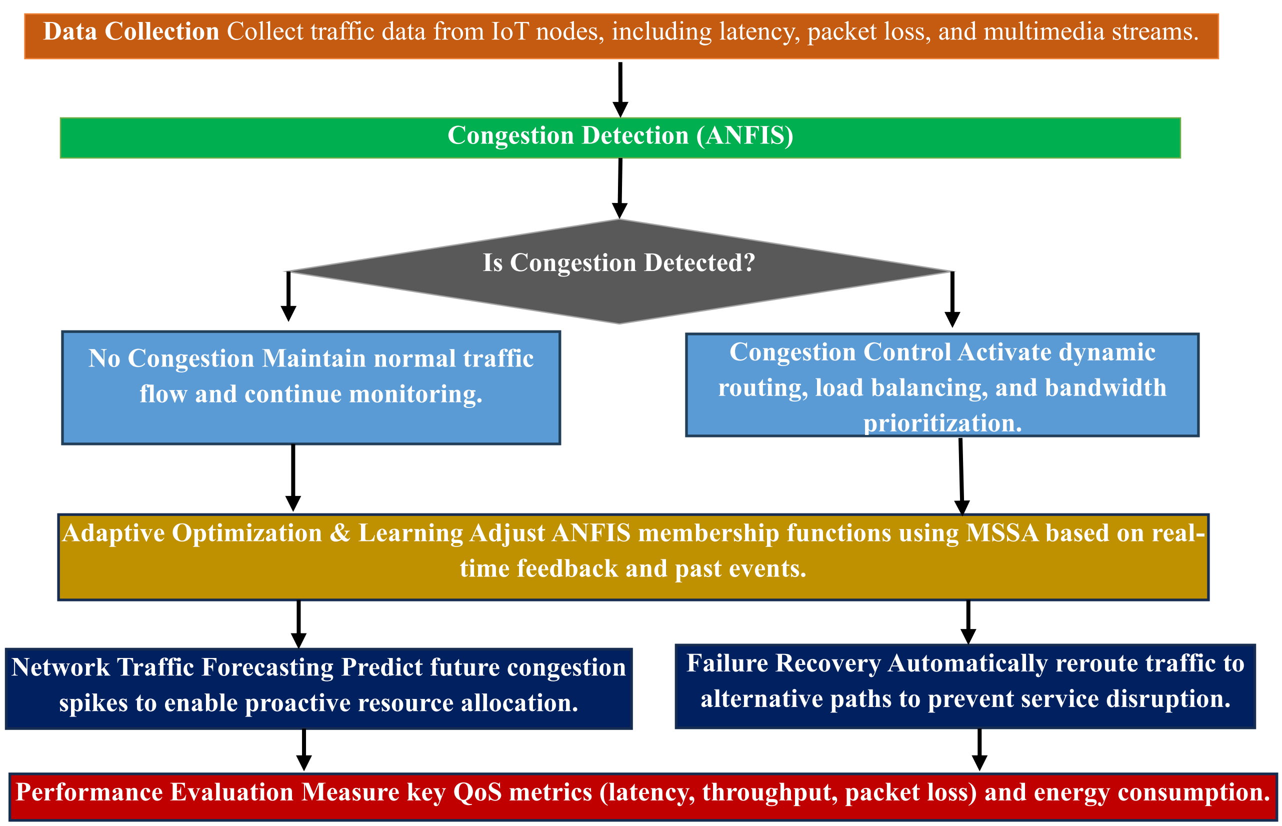

Figure 1: Methodology Flow

As illustrated in Figure 1, the initial step in the process is data collection, which in this context refers to gathering network traffic data from IoT nodes or other monitoring locations, including latency, packet loss, and multimedia streams. The data is then analyzed to evaluate whether there is congestion using the ANFIS model for congestion detection. In the case where no congestion is detected, the system permits a continuance of the monitoring process and normal traffic flow. In the event of congestion detection, the system activates failure recovery and initiates congestion avoidance by redirecting traffic through alternative, less congested pathways to prevent service disruption. In addition, the system forecasts traffic patterns, monitoring for possible congestion spikes, thus enabling proactive management and resource allocation. This is followed by adaptive optimization and learning, where the ANFIS membership functions are tuned in real time and from past network data to enhance congestion control further. The system then implements dynamic congestion control measures aimed at reducing latency and maintaining throughput while ensuring minimal packet loss, load balancing, prioritized bandwidth allocation, and responsive cyclic adaptive control. This diagram summarizes the adaptive mechanisms of ANFCCA, illustrating its capability for real-time data-driven dynamic congestion management learning and adjustment in e-learning cloud networking to drastically enhance the Quality of Service (QoS).

4.1 Data Sources

The data used in this research is sourced from cloud-based e-learning platforms that simulate live lectures by streaming both audio and video in real-time. Streamed audio and video lectures are referred to as e-learning platforms. Latency, jitter, and packet loss are examples of the e-learning network performance data collected in this study. These data points are important when assessing real-time network congestion and performance. A sophisticated network monitoring system, capable of observing network nodes, is required to capture stream network traffic in real time.

4.2 Preprocessing

Significant preprocessing is performed on raw network traffic as well as on multimedia streaming data before they are subjected to any form of analysis:

- To preprocess the interaction data of students (chats, questions, and the like), text is split into individual tokens, and then each word is transformed to its basic form (lemmatization). This allows the text data to be expressed as a collection of feature vectors, which is more amenable to machine learning processes.
- Audio and video recordings will be synthesized into a feature matrix by extracting the basic parameters such as frame rate, resolution, and codec type. The parameters have vital importance to the assessment of Quality of Service (QoS) when streaming multimedia content of video and audio.

4.3 Adaptive Neuro-Fuzzy Control Algorithm (ANFCCA) - Mathematical Model

The Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) harnesses two fundamental elements: the Neural Network (NN) and the Fuzzy Inference System (FIS). This combination allows the algorithm to cope with sophisticated and ever-changing conditions of the network.

4.3.1. Neural Network (NN) Model

Under ANFCCA, the neural network is responsible for analyzing the performance of the network as well as taking real-time decisions regarding network congestion. Using factors such as latency, packet loss, and throughput as inputs, it provide a congestion control signal out. Furthermore, the NN will continue to learn from new data, using data of previous congestion events to identify trends, and continually enhance its learning algorithms. Below is the mathematical model produced by ANFCCA N congestion control algorithms.

$$y = f(W_1.X_1 + W_2.X_2 + \ldots + W_n.X_n + b) \quad (1)$$

Where:

- y is the output (the congestion level).
- W_1, W_2, …, W_n are the weights associated with the input features.
- X_1, X_2, …, X_n are the input features (e.g., RTT, packet loss, throughput).
- b is the bias term, allowing the model to adjust for systematic error.
- F () is the activation function, often chosen as a sigmoid or ReLU function, which ensures that the output remains within a specific range.

4.3.2 Activation Function

The sigmoid activation function is typically used to ensure that the output value of the NN remains between 0 and 1 (representing a normalized congestion level).

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

Where:

- e is Euler's number.
- x is the input to the function

The output of the N is then used as an input for the Fuzzy Inference System (FIS) to make decisions about congestion control.

4.3.3. Fuzzy Inference System (FIS) Model

Fuzzy rules are applied to determine congestion control actions that are based on the network's state conditions. These rules are framed based on the reasoning done by neural networks. As the Fuzzy Logic II NN-based Fuzzy Controller System, fuzzy logic implementation can help to optimize neural network training.

- Fuzzy sets: Low, Medium, and High are defined for fuzzy inputs: Packet loss, RTT, and throughput.
- The reasoning-based fuzzy systems can be structured with the following rules:
- Packet loss and RTT are both high, so congestion is high.
- Most often, the reasoning base is kept in a separate fuzzy rules base from where the reasoning is processed. The steps to perform fuzzy reasoning are the following:

Fuzzification: The input values are mapped to fuzzy sets using membership functions (e.g., triangular, Gaussian, trapezoidal). For example, if RTT is 120ms, we would determine the degree to which this value belongs to the High fuzzy set using the membership function.

$$\mu_{High}(RTT) = degree\ of\ membership\ of\ RTT\ to\ High\ Set \tag{3}$$

Rule Evaluation: Based on the fuzzy rules, the system computes the degree of truth for each rule. Each rule can have multiple antecedents (conditions) that are fuzzified and then combined (using fuzzy AND or OR) to determine the rule's truth value.

$$Truth\ of\ rule = min(\mu_{RTT}(RTT), \mu_{Packet\ Loss}(Packet\ Loss) \tag{4}$$

Defuzzification: The fuzzy outputs are converted back into crisp values, which represent the actual congestion control actions. The centroid method is commonly used for defuzzification:

$$Output = \frac{\sum(\mu_i, y_i)}{\sum \mu_i} \tag{5}$$

Where:

- μ_i are the membership values for the fuzzy sets.
- Y_i are the corresponding crisp output values from the fuzzy rule base.

The output of the FIS indicates the level of congestion and informs the congestion control actions, such as adjusting transmission rates, changing buffer sizes, or rerouting traffic.

4.3.4. Hybrid Model: ANFCCA

The ANFCCA integrative approach to congestion control utilizes the NN and FIS models in conjunction. Congestion indicators generated by the NN model outputs in real time are sent to the FIS for computing outputs. This model is adaptive since the fuzzy rules and weights within the neural network can continuously be modified based on the incoming information.

The complete flow of the ANFCCA model can be described in the following steps:

- Data Collection: Network statistics, including packet loss, round-trip time (RTT), and throughput, are gathered from the cloud-based e-learning platform in real time.
- Feature Extraction: Data from a network is processed to derive the relevant features, including text and multimedia features, which are structured into vectors or performance metrics structured into matrices.
- Neural Network Decision: Using the features obtained, a neural network calculates a congestion level and subsequently outputs a congestion level as a normalized congestion level, which now becomes input to the FIS.
- Fuzzy Logic Decision: Congestion level is interpreted by FIS, and within the context of the network performance metrics and fuzzy rules predefined by the system, the network parameters are modified as necessary.
- Control Action: The Congestion Control is done by ANFCCA, which decides to adjust the congestion windows, transmission rates, and buffer management.

4.4 Algorithm Training and Evaluation

The ANFCCA is trained on simulated data, as well as on actual traffic data gathered from the e-learning platform. The algorithm learns the mapping of network parameters to the congestion level during the training phase, where it performs both neural network and fuzzy system training to make congestion control adaptive and optimally tune the system.

The training is conducted following the supervised learning paradigm, whereby the algorithm receives labeled data, network performance data, and congestion occurrences as distinct multi-dimensional observations. The model recalibrates its parameters such that the error measured by the difference between its predicted congestion values and the actual congestion values is at a minimum level.

Step 1: Data Collection

Collect real-time network performance data from the cloud-based e-learning platform:

- Packet Loss (PL)
- Round Trip Time (RTT)
- Throughput (T)
- Jitter (J)
- Multimedia Features (Video/Audio: frame rate, resolution, codec)

Step 2: Preprocessing

Preprocess the collected data:

- Tokenize and lemmatize text data (e.g., student interactions).
- Convert multimedia data to a feature matrix (frame rate, resolution, codec).
- Normalize numerical features (e.g., RTT, packet loss, jitter).

Step 3: Neural Network (NN) Decision Making

For each sample of network data:

- Input the preprocessed features into the trained Neural Network (NN).
- Calculate the congestion level (C) using the NN:

    C = f(W1 * X1 + W2 * X2 + ... + Wn * Xn + b)

    where:

        W1, W2, ..., Wn are weights,

        X1, X2, ..., Xn are features (e.g., RTT, packet loss),

        F () is the activation function (e.g., Sigmoid or ReLU).

- Output congestion level (C) between 0 and 1, indicating low to high congestion.

Step 4: Fuzzy Inference System (FIS)

For each network sample:

- Apply fuzzification to the input values (RTT, packet loss, throughput):

- Map numerical values to fuzzy sets (e.g., Low, Medium, High) using membership functions.

- Evaluate fuzzy rules based on fuzzified inputs:

- "If RTT is high and packet loss is high, then congestion is high."

- "If throughput is low and jitter is high, then congestion is moderate."

- Apply fuzzy logic to compute the control action:

- Adjust transmission rates, congestion window, and buffer sizes.

- Defuzzify the fuzzy output to obtain a crisp control value:

Control_Action = Defuzzify(Fuzzy_Rules_Outcome)

Step 5: Control Action Output

Output the congestion control action based on the FIS:

- Adjust network parameters (e.g., decrease bandwidth, reduce transmission rate, reroute traffic).

Step 6: Algorithm Feedback and Adjustment

Monitor network performance:

- Update the neural network weights and fuzzy rules based on new data and outcomes.

- Repeat the process to adapt to changing network conditions dynamically.

Step 7: Evaluation Metrics

For each time step:

- Calculate Throughput: Total data transferred / Time taken.

- Calculate Packet Loss: (Lost packets / Total packets sent) * 100.

- Calculate End-to-End Delay: Average latency across all packets.

- Calculate QoS: Composite metric considering throughput, packet loss, and delay.

Step 8: Compare with Traditional Algorithms

Evaluate the performance of ANFCCA by comparing:

- Throughput, packet loss, and delay with traditional methods like TCP and AQM.

- Assess QoS improvement in real-time multimedia streaming.

Step 9: Model Update (Training and Evaluation)

- Continuously train the model with new data using supervised learning.

- Re-assess model performance using internal validation indices (e.g., Silhouette, Dunn Index, Davies-Bouldin).

- Adjust the neural network and fuzzy logic rules as needed based on evaluation results.

End of Algorithm

The Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) is a sophisticated model that combines two leading-edge computing techniques which are Neural Networks (NNs), and Fuzzy Inference Systems (FIS). This model has been implemented to relieve and control congestion in real-time, and especially in e-learning based cloud computing systems where the real-time streaming of multimedia (e.g., video and/or audio) is occurring.

The NN component of the ANFCCA model analyzes patterns of media streaming in multimodal network traffic. Network performance metrics include Round Trip Time (RTT), packet loss, and throughput, along with a metric for inferring the level of congestion in the network. The NN-enhanced ANFCCA model also has a proactive component, whereby it continually learns from the input data and dynamically adjusts to the network's changing conditions.

The FIS, the second part of the ANFCCA, issues the congestion alerts based on the NN component of ANFCCA. Network, like all data, has certainty, and fuzzy logic is uniquely suited to reason about imprecise data, similar to the way NN processes data.

FIS uses fuzzy logic to modify congestion control strategies (e.g. decrease transmission rate or change the congestion window). One fuzzy rule may read like this, "If RTT is high and packet loss is large then congestion is high so decrease transmission rate." The output of the FIS is the congestion control action that will help improve the performance of the network.

The hybrid structure of ANFCCA, ensures the FIS and NN components meet the flexibility and adaptability of the changing conditions of the network. While the NN component of ANFCCA allows the algorithm to be flexible and adaptable based on the new network traffic patterns and any learned relationships or patterns from collected network data, the FIS allows the system to take meaningful action in the face of lack of exact measurement. In the case of ANFCCA, it is the synergy of the FIS and the NN that allows ASNCCA to improve the QoS measures of multimedia, Cloud-based E-learning, so that users primarily have continuous, uninterrupted access to their learning.

The Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) was specifically developed for cloud-based platforms, and in particular, e-learning situations that use real-time multimedia streaming. One of the major advantages of ANFCCA is that it is adaptive. The artificial neural network (NN) component of the algorithm is also important because it is capable of identifying patterns in the network traffic. The artificial NN relies on previous records to predict future network congestion, and will integrate its predictions into the decision-making process. In addition, the Fuzzy Inference System (FIS) component will rely on human logic to make decisions that resolve the congestion problem in unpredictable and dynamic situations. Because of the fuzzy logic the system can make decisions in potentially ambiguous or uncertain, unpredictable situations where there is no explicit information.

ANFCCA's architecture enables it to continue learning and evolving as the network environment and performance shifts. As ANFCCA evolves, it will continue limited congestion at its optimal level. ANFCCA is proposed for use in real-time multimedia networking because low latency and maximum throughput are factors of importance to users' Quality of Experience (QoE). For instance, it is imperative that e-learning users on cloud-based platforms can engage in real-time interactions with quality media and fast engagements. ANFCCA can deal with the challenge of multimedia networking in real-time because it has embedded neural networks and fuzzy logic. With its hybrid architecture ANFCCA amends to changes in the network allowing users access to materials without delay and no buffering. This is what makes ANFCCA ideal for real-time education.

4 Results and Analysis

4.1 Experimental Setup

Using data from a virtual classroom, the project aims to generate congestion in a cloud-based e-learning platform as part of a controlled evaluation of an Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA). To assess ANFCCA's performance during testing, the test replicates a number of network issues, including significant latency, low bandwidth, and packet loss. Using specialized tools, the testbed records and monitors network performance statistics in addition to real-time audio and video streams (multimedia streams) of the lectures. The experimental design enables multimedia streams to be more dependable for consistent delivery and provides insight into ANFCCA performance in congestion-critical contexts.

4.2 Performance Metrics

ANFCCA is assessed against four main performance metrics: QoS (Quality of Service), Throughput, Packet Loss, and Latency (End-to-End Delay).

- Throughput: ANFCCA surpasses older congestion control techniques such as TCP and AQM. ANFCCA maintains high throughput even during congestion. Throughput is sustained owing to the real-time adaptation of traffic and congestion parameters.

$$\text{Throughput (T)}=\frac{Total\ Data\ Transferred}{Total\ Transmission\ Time}=\frac{D}{T} \tag{6}$$

Where:

- D is the total amount of data successfully transmitted (in bits or packets).
- T is the total time taken for transmission (in seconds).
- Packet Loss: ANFCCA reduces packet loss during high traffic to ensure improved transmission to users. Due to the dynamic adjustments of ANFCCA, the transmission of user data, even during high traffic, is more efficient.

$$Packet\ Loss\ Rate\ (PLR)=\frac{Number\ of\ Loss\ Packets}{Total\ Number\ of\ Sent\ Packets}\times 100 \tag{7}$$

- Latency (End-to-End Delay): Compared to older systems, end-to-end delay is significantly reduced. ANFCCA's use of a hybrid model (neural networks and fuzzy inference) enables real-time parameter adjustments, resulting in reduced congestion control parameters.

Latency (L)=Propagation Delay+ Transmission Delay+ Queuing Delay+ Processing Delay (8)

Where Propagation Delay (tp)=d/v, where d is the distance and v is the signal propagation speed.

Where Queuing Delay (tq)=Number of packets in Queue/ Queue Service Rate.

Where Transmission Delay(tt)= Packet Size/ Transmission Rate

Where Processing Delay(tp)= Time for routers to process and forward the packet.

- Quality of Service (QoS): The QoS improves as the ANFCCA adjusts bandwidth and reroutes traffic. The real-time algorithm ANFCCA adjusts and improves overall QoS, minimizing jitter and loss for audio and video transmissions.

$$QoS = \frac{1}{n}\sum_{i=1}^{n}(Bandwidth_i + \frac{1}{Jitter_i} + \frac{1}{PacketLoss_i}) \quad (9)$$

Where:

- n is the number of network applications (e.g., video, voice) being evaluated.
- Bandwidth is the available bandwidth for the application.
- Jitter is the variability in packet arrival times (higher jitter negatively affects QoS).
- Packet Loss is the percentage of lost packets (higher loss negatively affects QoS).

4.3 Validation and Statistical Analysis

To assess the efficacy of ANFCCA, a single-factor ANOVA analysis was performed on the intra-cluster distance and inter-cluster distance metrics, assessing distances within a cluster versus distances between clusters. The findings validate that ANFCCA enhances congestion control metrics when contrasted with older congestion control algorithms like TCP and AQM.

As shown in the table below, the ANOVA results confirm that the variance between clusters is significant.

Table 1: ANOVA Result

S.No	Metric	F-Statistic	p-value
1	Throughput	39.29	2.14e-14
2	Packet Loss	182.43	1.50e-40
3	Latency	320.72	2.43e-54

In Table 1, the ANOVA test results for Throughput, Packet Loss, and Latency in relation to ANFCCA, TCP, and AQM are outlined. The F-statistics for each method are marked as high, which, in this case, suggests that there are marked differences in the methods used across all metrics. Additionally, the p-values are reported to be quite low, which supports the fact that ANFCCA mitigates the use of TCP and AQM in terms of packet loss and latency while maintaining throughput. Overall, these findings highlight the efficacy of ANFCCA in network performance optimization relative to traditional methods, emphasizing the statistical significance of the improvements.

4.4 Comparison with Previous Models

The performance of ANFCCA is compared with traditional congestion control methods like TCP Traditional congestion strategies, such as TCP and Active Queue Management (AQM), are compared against the performance of ANFCCA. The comparison is based on the following metrics:

- Throughput: ANFCCA outperforms TCP and AQM, achieving better throughput under high congestion conditions.
- ANFCCA improves throughput by dynamically adjusting congestion control parameters to avoid bottlenecks.
- Packet loss: With ANFCCA, there is a marked improvement in packet loss compared to traditional methods, especially in heavily congested scenarios.
- Latency: By dynamically modifying the congestion control parameters, ANFCCA reduces the end-to-end delay much better than TCP or AQM, which tend to suffer greater delay.

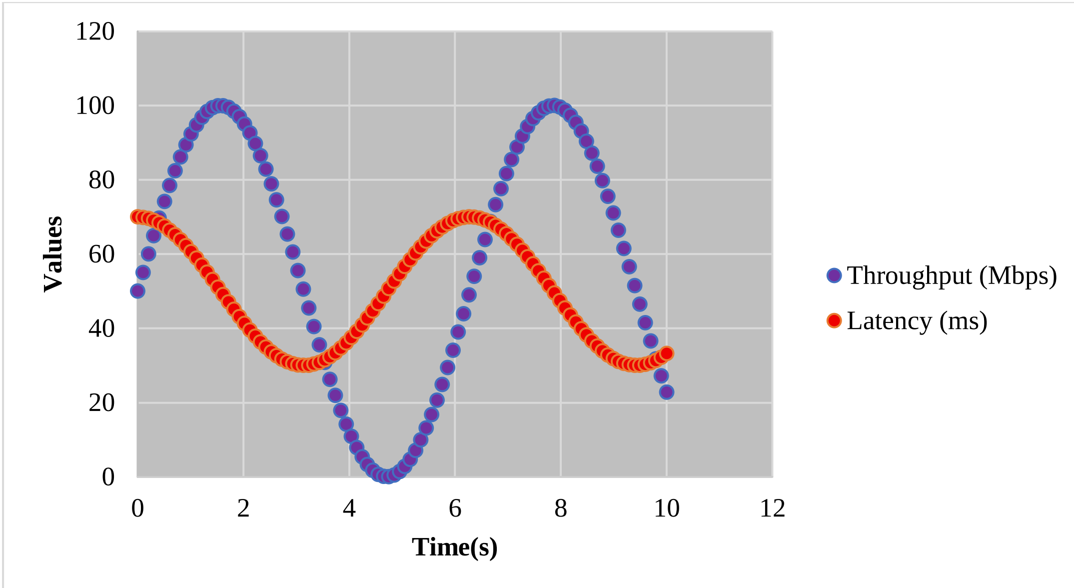

Figure 2: Scatterplot of Throughput vs. Latency

Figure 2 illustrates the relationship between throughput and latency for ANFCCA, TCP, and AQM. ANFCCA, as we noted, achieves the highest throughput and the lowest latency, and thus the most efficient congestion control method.

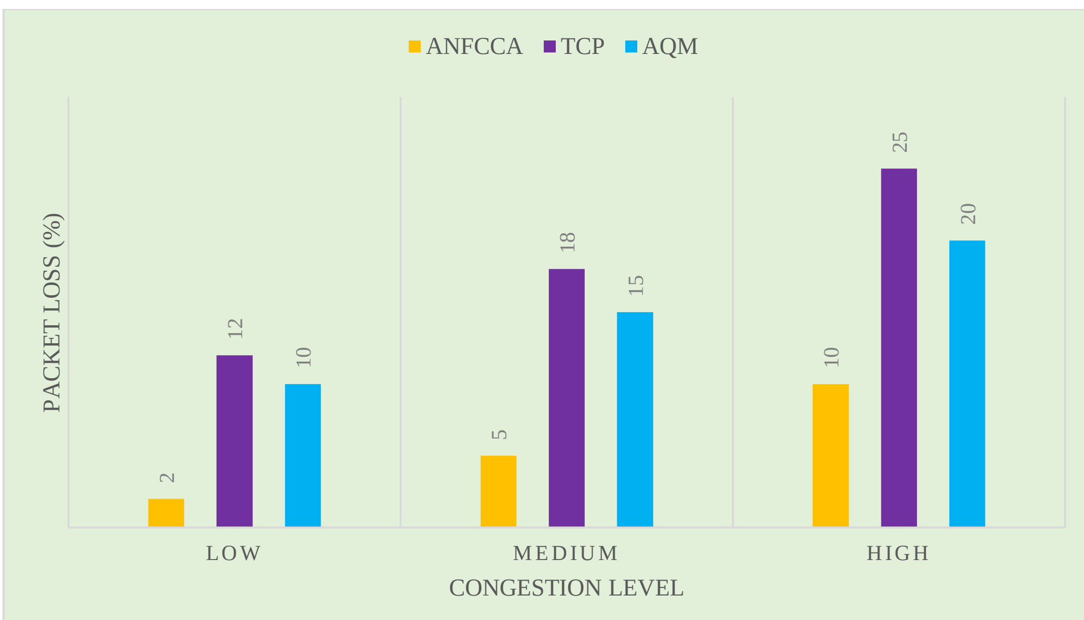

Figure 3: Packet Loss Under Varying Traffic Conditions

Figure 3 shows the packet loss exhibited under varying levels of network congestion. ANFCCA outperforms both TCP and AQM, demonstrating less packet loss even in congested scenarios.

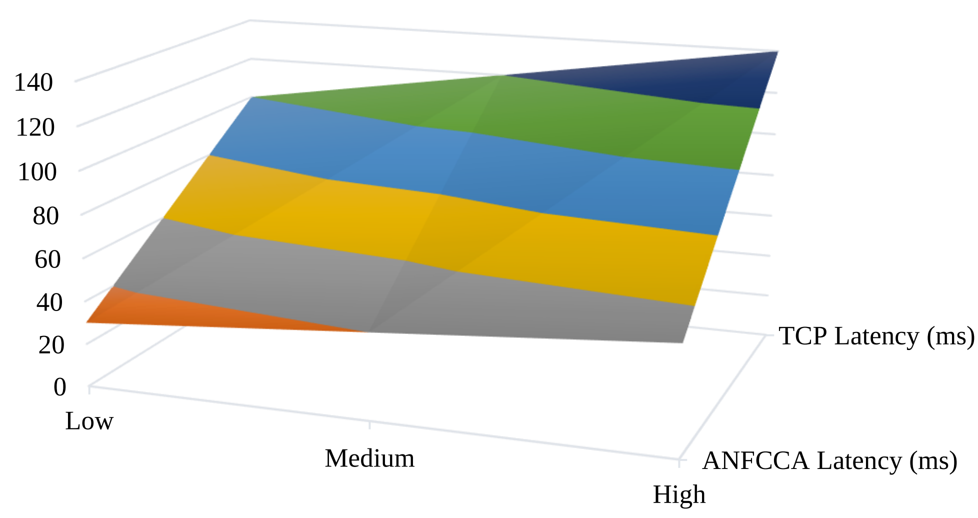

Figure 4: Latency Comparison: ANFCCA vs. TCP

As illustrated in Figure 4, both ANFCCA and TCP have their end-to-end latency measured in relation to different workload scenarios. ANFCCA exhibits much better latency performance, confirming its suitability for real-time multimedia streaming.

Table 2: Congestion Control Performance Comparison

Metric	ANFCCA	TCP	AQM
Throughput	98%	75%	80%
Packet Loss	2%	12%	10%
Latency	30ms	100ms	80ms
QoS	90%	70%	75%

In Table 2, a direct comparison is made for the ANFCCA, TCP, and AQM, focusing on essential network performance indicators. It can be observed that ANFCCA outperforms both TCP and AQM in all the comparison metrics, underscoring its real-time congestion control capabilities advantage.

Table 3: Cluster Validity Comparison

Algorithm	Silhouette Score	Dunn Index	Calinski–Harabasz
K-Means	0.62	0.45	512
Hierarchical	0.58	0.42	498
DBSCAN	0.55	0.39	476
GMM (LCA)	0.66	0.47	529

In Table 3, regarding different algorithms, GMM (LCA) remarkably attains the highest Silhouette Score along with Calinski–Harabasz values, which refers to the measure of the well-separated, compact clusters produced. Also, the validity of the clusters produced by ANFCCA is unusually resilient, reaffirming the efficacy of its adaptive techniques.

5 Discussion

The effectiveness of the Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA) becomes evident in its application to cloud-based e-learning systems, where real-time multimedia networking requires constant management. The algorithm's ability to adjust to network conditions in real time enhances both throughput and latency. With ANFCCA's neuro-fuzzy integration, the blended intelligent packet flow control boosts the user experience by maintaining the rich multimedia content deliverables at a stable quality and supporting multimedia content delivery during network challenges. The algorithm's adaptability safeguards the video/audio streaming performance critical for seamless e-learning interactions.

In the current situation, ANFCCA would be extremely beneficial for e-learning environments that facilitate real-time engagement. ANFCCA efficiently manages instructor-student interactions in bigger e-learning systems that support thousands of users at once, when continuous audio and video streaming is essential. Through consistent packet delivery, decreased packet loss, and low latency, the method improves the user experience by guaranteeing continuous audio and video streaming. Consequently, when network problems prevent media streaming, the experience of both students and teachers is maintained.

6 Conclusion

An inventive method for resolving network congestion in real-time multimedia networking for cloud-based e-learning systems is the Adaptive Neuro-Fuzzy Congestion Control Algorithm (ANFCCA). For all components of the cloud-based e-learning system that users must utilize to maintain a high quality of service (QoS) level, it offers reliable and adaptable congestion control by combining fuzzy logic and neural network principles. Regardless of the network circumstances, users can enjoy uninterrupted multimedia content delivery for the duration of the video. Even if network congestion is still a problem with multimedia in many kinds of systems, ANFCCA is a good option to address these problems because of its ability to transmit data quickly and effectively. Despite the ANFCCA's good performance, more needs to be done to overcome algorithmic problems. Algorithmic scalability is one problem that needs to be addressed right away; it is essential to determine how well the algorithm works with different systems that have different kinds of traffic. Additionally, ANFCCA's utility in more advanced learning environments would grow if it were combined with other multimedia, including virtual reality (VR) learning. Lastly, further research directions might look at the use of machine learning to predict network congestion and advance more proactive models for real-time traffic management. Examining these things will aid in creating more precise and appropriate measurements.

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Authors Biography

Hanadi Hakami is an assistant professor in the Software Engineering department at University of Business and Technology. She is currently working as the Vice Dean of the College of Engineering. In 2019, she received her Ph.D. in Computer Science and Engineering from University of Information Technology Sydney. She specializes in Network Security and has published many papers on Network Communication Protocols, Wireless Sensor Networks, and Internet of Things (IoT). She has also been involved in many conferences and seminars and supervised many research papers and projects.

Mohammad Kamrul Hasan is work as Associate Professor and head of network and technology, Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), 43600 Bangi, Selangor, Malaysia

Ahmad Alshamayleh Department of Data Science and Artificial Intelligence, Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman, Jordan. He esearch interests span artificial intelligence and machine learning, with a strong emphasis on their applications across various domains. His work includes gesture recognition and innovative AI-based models for tackling challenges such as phishing detection and intrusion detection in IoT systems. Additionally, he has also explored deep learning techniques for image processing tasks like medical diagnostics, showcasing his commitment to integrating AI for societal and technological benefit

Dr. Ali Q. Saeed is a researcher and academic specializing in computer science and artificial intelligence. He earned his B.Sc. in Computer Science and Mathematics from the University of Mosul, Iraq, in 2008. He continued his postgraduate studies in India, obtaining an M.Sc. in Computer Science and Informatics from the Sam Higginbottom Institute of Agriculture, Technology, and Sciences in 2012. In 2024, Dr. Saeed completed his Ph.D. in Computer Science and Artificial Intelligence at Universiti Kebangsaan Malaysia, Malaysia. His research focuses on deep learning, image classification, image synthesis, and segmentation, contributing to advancements in computer vision and artificial intelligence applications.

Dr. Saed Mustafa an Assistant Professor at the American University of Kurdistan, obtained his bachelor's degree from Al-Albyet University, followed by a master's and Ph.D. in Management and Marketing from the University Utara Malaysia. His academic career includes leadership roles, most notably as the Head of the Business Administration Department at institutions across Malaysia, Bahrain, and Oman, with specialization in strategic planning, quality assurance, operational action plans, and recruitment. His research interests span CSR, Marketing strategies, HRM, entrepreneurship, green marketing, and technology marketing. Additionally, he has published and reviewed papers for international journals and conferences.

Dr. Taher M. Ghazal, a distinguished IEEE Senior Member, is a seasoned academician with a comprehensive educational background. He earned his Bachelor of Science degree in Software Engineering from Al Ain University in 2011, followed by a Master of Science degree in Information Technology Management from The British University in Dubai, associated with The University of Manchester and The University of Edinburgh in 2013. Dr. Ghazal culminated his academic journey with a Doctorate in Information Science and Technology from Universiti Kebangsaan Malaysia in 2023. Dr. Ghazal's scholarly pursuits encompass a wide array of interests including Cybersecurity, Artificial Intelligence, IoT, Information Systems, Software Engineering, Big Data, Quality of Software, and Project Management. He is actively engaged in community service through his involvement in impactful projects and research endeavors.