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# Enhancing network Quality of Experience based on Artificial Neural Networks



**Ali Q. Mohammed[a*], Rana F. Ghani[b]**

[a] Informatics Institute for Postgraduate Studies, Iraqi Commission for Computers & Informatics, Baghdad, Iraq.
[b] Computer Science Dept., University of Technology-Iraq, Alsina'a street, 10066 Baghdad, Iraq.
*Corresponding author Email: ms202210710@iips.edu.iq

## HIGHLIGHTS

- Enhancing both Quality of Experience (QoE) and Quality of Service (QoS) is a key focus of the study
- The approach integrates Artificial Neural Networks with multi-level queuing and Weighted Round Robin scheduling
- The method achieves a reduction in average delay to 10.842 ms, jitter to 0.031 ms, and packet loss to 0–1%
- The solution offers operators and providers better methods for managing diverse traffic types

**Keywords:**
Quality of Experience; Quality of Service; Artificial neural; Packet loss reduction, Delay and jitter optimization.

## ABSTRACT

In modern networking, ensuring both Quality of Experience (QoE) and Quality of Service (QoS) is paramount due to the increasing demand for efficient, reliable, and high-performance networks. With the surge in data traffic, traditional network management techniques often struggle to maintain optimal service levels, particularly in addressing challenges such as packet loss, excessive delay, and jitter. This paper presents an approach that integrates an Artificial Neural Network (ANN) into a multi-level queuing system, combined with Weighted Round Robin (WRR) scheduling, to address these persistent issues effectively. The key innovation lies in the dynamic and intelligent adaptation of network resource allocation based on real-time traffic conditions, which significantly outperforms static management methods. The proposed solution optimizes performance across various types of network traffic, enabling efficient handling of voice, video, and other data packets. This enhancement results in measurable improvements in both QoE and QoS, establishing the approach as an invaluable tool for network operators and service providers striving to meet the growing demands of today's dynamic network environments. The system offers an adaptable and forward-looking solution for next-generation networks. Its effectiveness is demonstrated through a substantial reduction in average delay to 10.842 ms, jitter to 0.031 ms, and packet loss to 0–1%.

## 1. Introduction

As digital communication technologies evolve, the demand for high-quality network services continues to increase. This is important to maintain user satisfaction, the efficiency of the network, and the quality of service (QoS). Packet loss, delay, and jitter are common issues that make the availability and quality of network services degenerate and affect users' satisfaction drastically. To overcome these issues, enhanced methods are needed to enhance the usage of network management and resource allocation. Thus, from the perspective of video streaming, important Quality of Service (QoS) factors, such as packet loss ratio (PLR), delay, and jitter, have a close relation to the Quality of Experience (QoE). When the PLR is high, the video quality is drastically affected since frames in a video are mostly relational. Suppose one frame is missing or is received in a very distorted condition. In that case, the subsequent frames that are received may also be affected and, therefore, lead to a generally poor experience when viewing the movie. This is noted specifically in a group of picture structures, whereby frames depend on others for data prediction [1].

Whereas Quality of Service (QoS) describes the technical parameters that underpin the network quality, Quality of Experience (QoE) discusses a range of factors beyond technical specifications to cover those affecting users, perception and satisfaction. Current and comprehensive predictive models, which include network metrics and perceptual audio features, provide the most precise methods for judging audio services' quality and enhancing their quality assurance. Securing the optimal technical solutions in conjunction with the optimal perception of sound means providing users with a better experience [2].

Quality of service controls and measures the configuration of resources to suit the application's needs, taking into consideration parameters such as throughput, latency, jitter, and packet loss. Differentiated Services (DiffServ) classify the traffic



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according to active policies and acts correspondingly, while Integrated Services (IntServ) provide resources reserved for traffic precedence via protocols such as RSVP. At closely located edges, IntServ is used, whereas DiffServ is employed in the central core—it is effective, scalable, and considers guaranteed service levels. This is especially useful in networks that exhibit multi-homing, that is, networks that comprise many interfaces and paths [3]. Queueing theory is a quantitative technique that allows for understanding and establishing the optimum flow of service with reference to or with respect to waiting time. It is broadly used in areas such as operations in telecommunication systems, traffic signals, computer networks, and healthcare activities to enhance competitiveness and deal with congestion [4].

Quality of Experience as a concept concerns the level of perception that the end-user has over several network services that define the quality of throughputs, delay, and packet loss. It is important to measure the likely influence of the quality of service (QoS) mechanisms in guaranteeing quality of experience for end-users in different applications [5]. The proposed method can be applicable to enhance the overall video streaming and IoT video Surveillance [6,7], managing network resources effectively in forest fire detection [8,9], improve network throughput, decrease latency in Vehicle-to-Vehicle (V2V) and Vehicle-to-Everything (V2X) communications [10,11] and in robust character recognition for optical [12]. The DiffServ Code Point (DSCP) is a six-bit field within the internet protocol (IP) header that enables the classification and management of network traffic based on Quality of Service (QoS) criteria. It designates four main Quality of Service (QoS) classes, known as per-hop behaviors, commonly used by network operators: BE is the option that does not provide Quality of Service (QoS) guarantees and corresponding DiffServ Code Point (DSCP) of 0; CS keeps the preservation of older IP precedence fields and ranges from CS1, ranking the lowest level of priority, to CS7, considered as critical network management packets; the AF class is used for delivery assurance at various levels; and the EF class is used for low delay needs in applications, such as voice [13].

Quality of Service (QoS) in software-defined networking is significant for controlling the resources of networks and ensuring optimal data flow. Some of the noted methods include control plane strategies on the distributed controllers and some data plane strategies, such as server load balancing. Ideal routing reduces delay and packet loss, while adaptive Quality of Service (QoS) policies prioritize critical applications based on real-time conditions. The combination of statistical and evolutionary algorithms also raises the efficiency of the network, and monitoring tools provide insights for proactive management. This approach addresses network performance complexities and enhances overall functionality [14,15]. Packet queue scheduling theory is the process of placing packets in the right order or prioritizing the packets for the flow of data through switches. Different algorithms, such as Shortest Remaining Processing Time (SRPT) and Start-Time Fair Queueing (STFQ), are used to regulate the ranks of packets, which determine the order of packet processing. The SRPT algorithm focuses on minimizing flow completion times by prioritizing packets with the least remaining processing time. At the same time, STFQ provides weighted utilization by calculating the virtual start time according to flow weight. The programmable scheduling framework includes the Push-In First-Out (PIFO) queue as one of the most important features, which operates with different algorithms based on rank computations. However, the realization of PIFO in hardware, especially in switch application-specific integrated circuits, is not straightforward, mainly due to the requirement that the arrival queues must be kept sorted in the data plane [16].

The proposed mechanism described by the author uses the Software-Defined Network (SDN) architecture to achieve packet scheduling and the Quality of Service (QoS) by predicting the congestion and thus generating an entirely congestion-free routing topology. The mechanism, by employing the queuing model and the theory of Lyapunov optimization, adjusts and channels the packets through the less congestion-prone routes. This approach helps minimize the delay, packet loss, and jitter to allow high-priority data to get to its destination intact [17]. Packet loss, delay, and jitter all affect Quality of Service (QoS) and Quality of Experience (QoE) in video streaming. The above problem affects the quality of the video in the following ways: packet loss impacts the video by interrupting the stream, the delay has the impact of making the audio and video out of sync, and jitter affects the playback of the video by causing it to appear jerky [18].

The issues of latency in Quality of Service (QoS) are well-tacked by the use of machine learning (ML) algorithms to analyze the performance of the network and develop algorithms to predict similar trends. Through the removal of any buffer in the transfer of information, the network operations are made faster and improved through the use of ML algorithms [19]. The methods of machine learning are actively used for the relevant research of the assessment and promotion of Quality of Experience (QoE)in network systems. Thus, by analyzing the relationship between various elements of Quality of Service (QoS) and users' satisfaction with the help of association mechanisms K-Nearest Neighbor (KNN), regression trees, and Artificial Neural Networks (ANNs), it is possible to identify complex dependence interconnections. These models are aimed at predicting Quality of Experience (QoE), depending on a number of degradations, such as packet loss, delay, and jitter, which contributes to the improvement of the service quality in the environment of a network [20].

A new artificial intelligence ML algorithm is intended to enhance the Quality of Service (QoS) in networking. In this case, the algorithm uses Artificial Neural Networks (ANNs) in a manner that attempts to determine the optimal parameters of the communication network to minimize packet loss and delay. In this way, data transmission is made efficient, and the network's capability is increased [21]. Mean Absolute Error (MAE) works out the average angular difference between the actual values and the predicted values. Hence, it is the right measure to decide the effectiveness of the models. The MAE error is less sensitive to large errors, unlike the root mean square error (RMSE), which makes it a good measure of the general prediction performance [22,23]. Improving queue scheduling enhances QoS by efficiently managing how packets are queued and prioritizing packets. Scheduling algorithms ensure that high-priority traffic receives the necessary resources, improving overall network performance and meeting the requirements of different applications [24].

The principal contribution of this study is the use of an Artificial Neural Network (ANN) for the adaptive control of the network Quality of Experience (QoE) and Quality of Service (QoS) through the minimization of packet loss, delay, and jitter rates. Our approach of combining Artificial Neural Network (ANN) with a multi-level queuing system as well as Weighted

Round Robin (WRR) scheduling adapts in real-time to the changing conditions in the network, which results in much better performance characteristics of the designed system. The proposed method improves the network parameters and user satisfaction.

## 2. Related works

This section provides an overview of relevant literature published in high-impact journals, highlighting key studies that explore the application of Artificial Intelligence (AI) to enhance Quality of Service (QoS) and Quality of Experience (QoE). We will review and compare several significant works, with a focus on advancements in AI-driven approaches designed to improve network performance and user experience. Ahmed et al. [25], highlight the issues of Quality of Service (QoS), particularly for the transmission of voice packets, where delay and jitter need to be minimized. In real-time applications, such as voice-over IP, minimal delay and jitter are desirable for proper user experience. Quality of Service (QoS) mechanisms are established to dedicate higher importance to voice packets and minimize the problems of packet drops, thus facilitating clear and interruption-free voice conversation. The clarifies the traffic classification, the policy of prioritization, and scheduling policies in the networks to demonstrate how the networks can enhance voice services. This, in turn, also implies that the latency and the jitter are also significantly reduced in this case, and this, in the long run, improves the quality of the voice transmission. Queue length poses a significant challenge to maintaining Quality of Service (QoS) in virtualized networks. As outlined by the author, excessive queue lengths, combined with limited buffer memory and variable service intensity, lead to increased packet delays and losses, which severely impact Quality of Service (QoS). The problem arises from the load on virtual routers, where the ratio of incoming traffic to packet transmission capacity results in the formation of queues. This queue buildup creates unpredictable delays in packet buffering, making it difficult to maintain the required Quality of Service (QoS) levels. Under heavy traffic conditions, static resource allocation exacerbates the issue, failing to control queue lengths effectively and causing delays that exceed acceptable thresholds [26].

Shah et al. [27], proposed a new adaptive Quality of Service (QoS) model developed for real-time applications in a WN SDN environment. The proposed model constantly assigns queues to traffic flows, taking into account the real-time flow analysis, preventing bandwidth hoarding to certain flows while at the same time preventing other flows from capturing all bandwidth. In contrast to rigid Quality of Service (QoS) models, this will map and reallocate flows to another queue if the first queue associated with a flow is full, thus reducing the drop rate and enhancing the throughput. Based on the study, the adaptive Quality of Service (QoS) model enacted herein was significantly more efficient than the conventional models of Quality of Service (QoS) because it enjoyed better throughput and lower communication packet drop as a result of adaptability. Tomer et al., [28] the authors provide an algorithm to enhance the overall quality of services by reducing the number of packet losses. The strategy relies on the management of the flow of data packets in such a way that the packet loss is the least. This strategy reduces the total load carried to the server and, in the process, brings a positive influence and packet loss. In the case of the application of this specific method, it was possible to define the overall tendency towards the lack of growth in the level of packet losses, as they decreased by 3%–6%. In addition, it described other quality of service (QoS) parameters of the system, such as throughput and latency. Besides solving the problem of packet loss, this approach is targeted at the enhancement of the general efficiency and stability of a network due to better optimization of the data transmission.

Ghani and Al-Jobouri [29], proposed a Particle Swarm Optimization (PSO)-based Weighted Round Robin (psoWRR) algorithm, which aims to enhance the Quality of Service (QoS) by dynamically adjusting the weights of packet queues in a multilevel queue system within routers. Traditional round-robin scheduling uses static weights, which can lead to packet loss and starvation under variable traffic conditions. Thus, by optimizing these weights using a PSO algorithm, psoWRR minimizes packet loss and enhances scheduling efficiency. The results of the experiment reveal that the proposed algorithm psoWRR lowers the PLR and outperforms weight deficit round robin and LLQ, achieving a PLR of 7% for all types of packets. This makes the dynamic weighting of queues better at handling the traffic density optimization, thus minimizing the starvation of low-priority packets and providing real-time applications with a good Quality of Service (QoS). Peñaherrera et al., [30] proposed an ML-based framework to enhance QoE, especially 360-video, using network data. Their approach applies algorithms such as Random Forest, Ridge Regression, Support Vector Machines, K-Nearest Neighbors, and AdaBoost, with Gaussian Naive Bayes for classification-specific tasks. Optimized using feature engineering to support real-time, adaptive network management for improved QoE.

Cristobo et al. [31], showed that machine learning methodologies can dynamically enhance Quality of Experience (QoE) by correlating Quality of Service (QoS) indicators with user experiences. using supervised machine learning algorithms such as linear regression and feedforward neural networks are implemented in order to predict QoE based on various QoS parameters. The feedforward neural network model is particularly effective in handling non-linear relationships within the data, capturing the complexity of the user satisfaction metrics like the Mean Opinion Score (MOS). Applying these machine learning models, the framework aims to anticipate and adapt to network demands in real-time, thus aligning QoS and QoE metrics to user expectations more precisely.

## 3. Dataset

In the proposed method, two separate datasets are used to accomplish the study goals. The first dataset we generated includes such features as the packet type, which corresponds to the value of DiffServ Code Point (DSCP), the queue length, and the expected number of lost packets. The purpose of this dataset was to create an Artificial Neural Network (ANN) model so as to facilitate the changing of the router's queue length. It has the function of aiding in the training stage and further tuning the model in terms of traffic densities. The second dataset is the real-world trace of the MAWI collection from Japan. It is aimed at the transit of various types of packets through the router queues with real traffic scenes. It includes fields such as Time To Live

(TTL), Type of Service (ToS), and DiffServ Code Point (DSCP) as a means of encompassing a comprehensive and true representation of the study method.

In Figure 1 the ability to explain the Queue Length, Number of Packets, and Packet loss was demonstrated using a sample of 5000 instances. The blue line is for the queue length, and the green is the number of packets in the network at intervals (1-11). The red line represents packet loss, which mainly rises when the queue length is less than the number of packets processing the system. For example, at intervals like 5, the number of packets rises significantly while the queue length fails to match, hence high packet loss. This enables the control that packets may be lost in the network, especially when the packet flow rate is beyond the loaded queue. In the above chart, the relationship between queues and packet rates and how they influence the issue of packet loss is well illustrated, demonstrating the need to monitor queue limits, especially in an instance of high traffic. The second dataset is the MAWI (Measurement and Analysis on the WIDE Internet) working group traffic archive, which contains the traffic traces on the Internet and their usage. It lets one learn the performance and some behaviors of the network. These traces were collected in a real backbone network, which constitutes one of the key parts of the network infrastructure and is mainly associated with the links between Japan and other countries. This dataset is popular in the building of traffic models and assessing protocols, as well as the sample set for assessing networks. It carries very much refined data, which are stated at the packet level. It, therefore, provides a lot of information to the researchers that they can utilize in analyzing the traffic, the bandwidth, and the effects of various protocols in the enhancement of the networks [32].

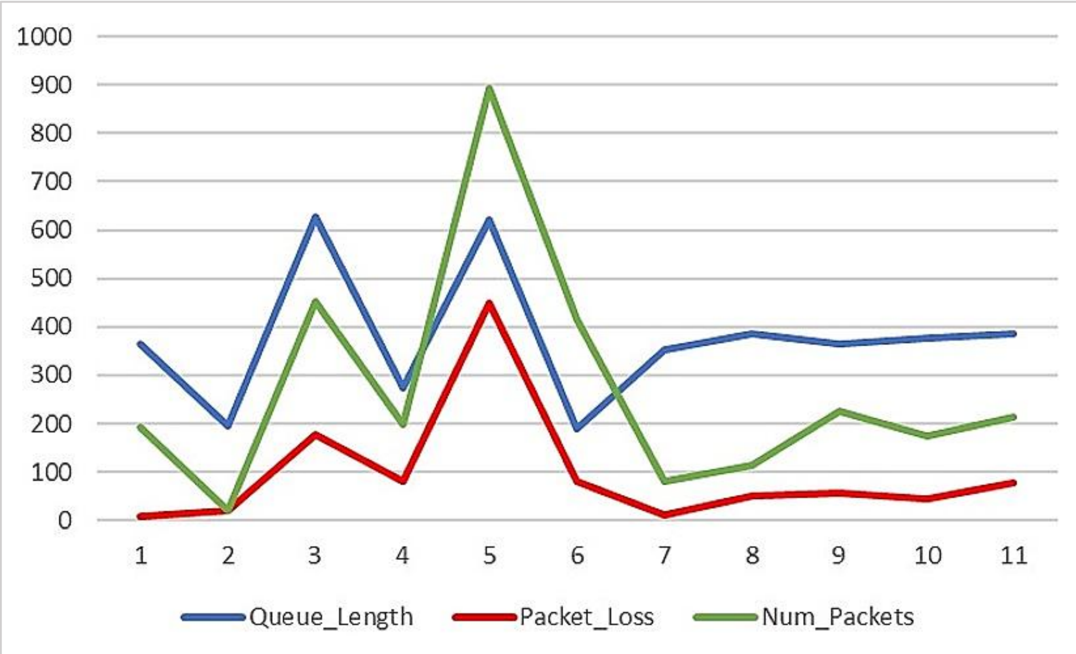


**Figure 1:** Dataset Sample, queue length vs packet flow and their effect on packet loss

## 4. Methodology and proposed system

This section outlines the methodology and proposed system designed to optimize packet handling in backbone routers. The solution combines a multi-level queue structure with Weighted Round Robin (WRR) scheduling and also uses an Artificial Neural Network (ANN) system to control queue lengths. Since the proposed system is based on the actual packet traffic obtained from the MAWI dataset, which represents the real working environment of a Japanese backbone router, the suggested solution becomes both realistic and efficient in terms of network optimization. The subsequent subordinate sections explain each part of the procedure and the introduced system. The dataset downloaded from the MAWI's official website (https://mawi.wide.ad.jp/mawi/) file name (202311121400. cap) and file size of 10.9 GB collected from a backbone router in Japan, which contains different types of packets for voice and video and all other types of packets. Taking a sample from the dataset to deal with as a traffic burst of packets, the sample contained 10,000 packets, including 1818 voice packets, 584 video packets, and 7598 other packets used for other purposes such as file transfer, text messages and mailing.

### 4.1 Multi-level Queue

A multi-level queue structure is employed to simulate packet handling in a backbone router, which is pivotal for maintaining Quality of Service (QoS) across different types of network traffic. This approach allows for differentiated treatment of packets based on their service requirements, ensuring that critical traffic receives higher priority.

The queues fall under the following categories:

1) Queue 1 (Voice Packets): This queue is for voice packets, and its DiffServ Code Point (DSCP) value of 46 is referred to as expedited forwarding [33]. Used for voice, packets need to be characterized by a very small delay and degree of jitter. Packets categorized into this particular queue receive prioritization to minimize delay and packet loss, which are crucial for maintaining call quality.

2) Queue 2 (Video Streaming Packets): This queue accumulates video streaming packets, where the delay issues are not as critical as in voice packets. However, their delivery should still occur promptly to avoid the need to buffer the stream. As a multimedia application, video traffic usually fits into the assured forwarding class, where predictable delivery is crucial for a smooth viewing experience.
3) Queue 3 (Other Packets): This queue includes all other types of packets other than those of expedited-remote and reserved-priority classes, namely the best-effort traffic. These packets do not have delay constraints and can tolerate any extra delay. This queue is used to feed traffic such as file transfers, website browsing, and emails since they are not particularly affected by delay and jitter as compared with voice and video traffic.

Thus, through these three queues, important traffic is certain to get the proper priority, benefiting the total network sphere.

## 4.2 Weighted Round Robin (WRR) scheduling algorithm

The Weighted Round Robin (WRR) scheduling algorithm is employed to manage the dequeuing process from the multi-level queues. Weighted round robin ensures balanced sharing of the bandwidth, with the queues having weights corresponding to their priority levels [34]. This method avoids packets of lower priority being starved out of the network while giving priority to packets of higher priority.

The Weighted Round Robin (WRR) parameters are configured as follows:

1) Queue 1: Dequeue eight packets in one cycle; this shows the priority that has been given to voice traffic to ensure it has a low latency and jitter.
2) Queue 2: Dequeue five packets per cycle; there will not be any issue with video streaming as it will be promptly prevented from buffering and quality degradation.
3) Queue 3: Provide three packets in a cycle to service best-effort traffic without affecting the higher-priority traffic.

## 4.3 Artificial Neural Network (ANN) model for queue length adjustment

An Artificial Neural Network (ANN) model is developed and trained on the generated dataset to adjust the length of each queue dynamically. The Artificial Neural Network (ANN) model leverages ML techniques to make real-time decisions that optimize queue management.

The training process, therefore entails the following steps:

1) Data Preprocessing: The features are scaled to better understand the data, and any outliers in the dataset are dropped. This step helps ensure that the data to be used in training the Artificial Neural Network (ANN) model is appropriate.
2) Model Architecture: The Artificial Neural Network (ANN) model used has more than one layer of neurons, with each layer containing multiple neurons that transform the input features. The architecture is optimized to balance complexity and performance.
3) Training: The pre-processed dataset is used in the training of the model; the objective is to minimize the loss function. The loss function quantifies the disparity between the foresaid and factual queue length to help the training converge and improve accuracy.
4) Validation and Testing: The trained model is then evaluated on similar new data, which helps test its ability and generality. This step is especially important when evaluating the model's ability to be implemented in real life.

Once trained, the Artificial Neural Network (ANN) model works as follows:

1) Input Layer: This layer takes in the input data, where the neuron number is equal to a number of input features, including the one-hot encoded DiffServ Code Point (DSCP) values (Packet_Type).
2) Hidden Layers: Two layers were used for hidden layers: 64 neurons for the first and 32 neurons for the second. Both of them use the activation function ReLU (Rectified Linear Unit). The two layers make the modelling non-linear because the model is capable of capturing the relationship between characteristics like delay, packet loss, and packet type.
3) Output Layer: This layer contains one neuron for the output and has the capability of estimating an approximate queue length, continuous value. In this regression task to minimize the prediction error Mean squared error MSE is used as the loss function.

Algorithm 1 shows how the Artificial Neural Network (ANN) model is trained on the dataset to determine the optimal queue length for the specific number of packets that arrived at the router queue in order to minimize packet loss, delay, and jitter. The dataset is partitioned into training and testing sets, with 80% reserved for training and 20% for testing. This ensures that the model can generalize well, learning from the majority of the data while preserving a portion for evaluating its predictive performance.

Algorithm 2 shows how to employ the dynamic adjustment to the lengths of the three queues, which is accomplished with the help of the generated Artificial Neural Network (ANN) model as presented in Algorithm 1. This trained model then predicts the optimal queue length based on real-time traffic data since the model is trained on diverse traffic conditions data. It is also based on the traffic type and predicted PLR so that the queue management system is dynamic concerning the present traffic in the network. Thus, through the adjustment of the queue lengths, the proposed Artificial Neural Network (ANN) model improves the Quality of Service (QoS) due to the proper handling of packets, low delay, less PLR, and low jitter. When included in the multi-level queue system, the utilization of this model is very useful as an intelligent and adaptive approach to the allocation of obtainable resources, thus enhancing the whole network's performance.

**Algorithm 1: ANN model for queue length adjustment**

**Algorithm 1**: ANN Model for Queue Length Adjustment

**Input**:

- Dataset for training Includes the following:
  - Features X (Delay, Packet Loss, Jitter, Num_Packets).
  - Target variable y (Queue Length).

**Output**: a model to predict the length of queue for a given burst of packets.

**Process:**

1. Normalize X and y using StandardScaler.
2. Split the dataset into training and testing sets.
3. Define an ANN model:
   a. Input layer with size equal to the number of features.
   b. Two hidden layers with 64 and 32 neurons (ReLU activation).
   c. Output layer with 1 neuron (for queue length prediction).
4. Compile the model using Adam optimizer.
5. Train the model for 20 epochs with a 20% validation split.
6. Save the trained model.

**Algorithm 2: Adaptive artificial neural network queue optimization**

**Algorithm 2:** Adaptive ANN queue optimization

**Input:**

Q: List of packet queues [Q1, Q2, Q3]

model: Pre-trained ANN model

**Output:**

Adjusted lengths for each queue

**Process:**

For each queue $Q_i \in$ Q:

1. Initialize variables:

- current_length ← length of $Q_i$.queue

- delay ← $Q_i$.get_total_delay

- packet_loss ← $Q_i$.get_packet_loss

- jitter ← $Q_i$.get_jitter

- num_packets ← $Q_i$.get_num_packets

2. Compute additional metrics:

- average_queue_length ← mean of the lengths of all queues in Q

- packet_arrival_rate ← num_packets

3. Prepare the feature set for the model:

- Initialize hypothetical_features ← [0, 0, 0, 0, 0, 0]

- Formulate features ← array([[current_length, delay, packet_loss, jitter, average_queue_length, packet_arrival_rate, num_packets] + hypothetical_features])

4. Use the model to predict the adjustment factor:

- adjustment_factor ← model.predict(features)[0][0]

5. Adjust the length of the queue:

- $Q_i$. length ← int ($Q_i$. length × (1 + adjustment_factor))

## 5. Results and discussion

The application of an Artificial Neural Network (ANN) model significantly improves the Quality of Service (QoS) in network performance by optimizing key metrics, such as delay, jitter, and packet loss. Traditionally, the Weighted Round Robin (WRR) scheduling algorithm is used to manage packet queues. Still, it has limitations in handling dynamic network conditions, often resulting in higher delay, jitter, and packet loss. In this study, the same number of packet flows with fair bandwidth allocation on each queue were applied, and the performance of Weighted Round Robin (WRR) and the proposed Artificial Neural Network (ANN) model for adjusting router queue length were compared.

The performance of the Artificial Neural Network (ANN) model was evaluated using key regression metrics: MAE, mean square error (MSE), RMSE, and R-squared ($R^2$) score. These metrics provide a comprehensive assessment of the model's predictive accuracy and its ability to generalize to different subsets of the data. Table 1 presents the detailed results, and as all the measures point out, the Artificial Neural Network (ANN) model has a high ability to predict the attribute during the training, validation, and test phases. The high $R^2$ score of the model through phase 1, phase 2, and phase 3 authenticates the ability of the model to capture the variance within the dataset. The above MAE and RMSE results also reflect the high accuracy of the actual queue length estimations of the developed model. The fact that their values are almost stable in all three phases indicates good generalization performances with very little sign of over-training. Altogether, the values in Table 1 confirm that the proposed Artificial Neural Network (ANN) model is both accurate and reliable as far as the estimation of the queue length is concerned.

Figure 2 displays the MAE's learning curve for both training and validation phases across 20 epochs. The MAE drops sharply during the initial epochs, indicating the model's quick learning. At approximately 5 epochs, both curves stabilize, suggesting the model has reached near-optimal performance. The close alignment between the training and validation curves indicates strong generalization with minimal overfitting. To generate the Artificial Neural Network (ANN) model for predicting queue length based on network features, a series of steps involving data preprocessing, model training, and evaluation were employed. Initially, the dataset was loaded, and the features were identified, including delay, packet loss, jitter, packet type, and the number of packets, with queue length as the target variable. Data was split into training and testing sets. Standardization was applied to the features to ensure consistent scaling. The Artificial Neural Network (ANN) model was defined using the TensorFlow Keras library, with an architecture comprising an input layer, two hidden layers with ReLU activation functions, and an output layer to predict the queue length. The model was compiled with the Adam optimizer and MSE as the loss function and MAE as an additional metric. The model was trained for 20 epochs with a batch size of 32, utilizing 20% of the training data for validation.

**Table 1:** Evaluation metrics for the artificial neural network model performance

| Metric | Training | Validation | Testing |
|---|---|---|---|
| MAE | 7.7567 | 8.2414 | 7.4843 |
| MSE | 115.3631 | 131.6410 | 109.8653 |
| RMSE | 10.7407 | 11.4735 | 10.4817 |
| $R^2$ Score | 0.9986 | 0.9984 | 0.9985 |

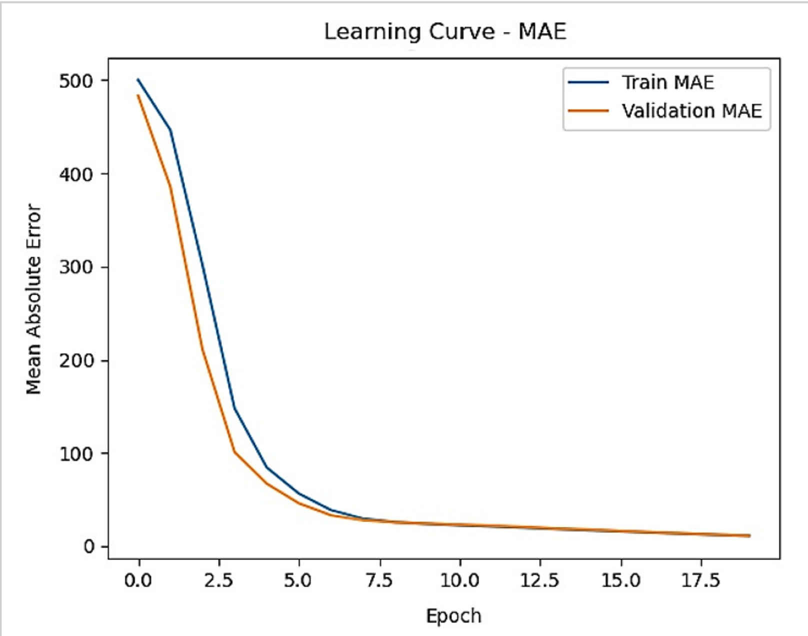


**Figure 2:** Learning curve – mean absolute error (MAE)

The learning curves for both training and validation sets were plotted to visualize the model's performance over the epochs. Specifically, Figure 1 depicts the learning curve for the MAE, showing the MAE for both the training and validation sets across 20 epochs. The curve illustrates how the model's performance improves as the number of epochs increases, eventually stabilizing and indicating successful learning and generalization. This process, from data preparation to model evaluation, demonstrates the effectiveness of the Artificial Neural Network (ANN) model in predicting queue length, supported by the provided MAE learning curve, which highlights the reduction in error over time. The Python programming language is used for simulation, combined with the Scapy library, which facilitates the simulation of network traffic at the packet level, provides tools for sending and receiving network packets, and is utilized to help the flow of packets in the router queue. Unlike traditional simulators that rely on virtual packets, this approach focuses on a real packet from a backbone router dataset. Then, packets are pushed in bursts to simulate traffic from multiple source nodes, providing a realistic representation of the network behavior and the packet flow.

Figure 3 illustrates the relationship between queue size and the number of packets, showing that both metrics rise as traffic intensity increases. Notably, the queue size grows faster, especially in later bursts, highlighting a nonlinear relationship. This demonstrates the robustness of the ANN model in dynamically adjusting queue length to align with increasing packet loads. By effectively scaling the queue capacity, the model ensures efficient traffic handling without excessive packet loss. The direct correlation emphasizes the ANN's adaptability in managing network conditions. Through Artificial Neural Network (ANN), the system can automatically change queue size to reflect the current traffic, making it easier for packets to be processed. As presented in Table 2, the experimental outcome gives significantly low delay, jitter, and packet loss. ANN model was useful in decreasing delay from 19.928 ms to 10.842 ms, jitter from 0.114 ms to 0.031 ms, and packet loss from 26% to 0-1%. These results are supportive of the previous findings approving the fact that the execution of the Artificial Neural Network (ANN) model is efficient for improving the quality of service through offering more responsive and adaptive means for network traffic controlling and thus improving the Quality of Experience (QoE) as well.

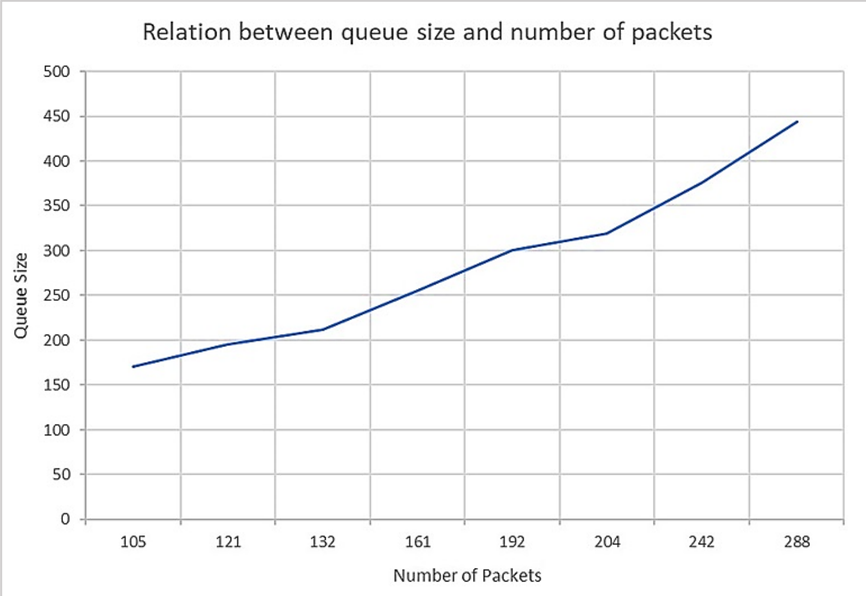


**Figure 3:** Relation between queue size and number of packets

**Table 2:** Enhance quality of service (QoS) parameters

| Methods | Delay (ms) | Jitter (ms) | Packet loss % |
|---|---|---|---|
| Apply only weighted round robin (WRR) | 19.928 ms | 0.114 ms | 26% |
| After applying artificial neural network (ANN) model | 10.842 ms | 0.031 ms | 0-1% |

This section analyses the implication of the marked improvement that has been realized with the use of the Artificial Neural Network (ANN) model in the optimization of the network performance. There are also significant improvements in quality of service (QoS) metrics through the improvement of dynamic adjustments to the routing queues through the application of the Artificial Neural Network (ANN) model. The findings show a significant decrease in means of delay, jitter, and packet loss, which assert the ability of Artificial Neural Networks (ANN) to manage real-time traffic. Table 3 compares previous studies focusing on packet loss enhancement. The proposed method significantly improves by achieving a 0% PLR. In contrast, the PLRs in the other referenced studies range from 3% to 7.07%. This stark reduction in packet loss highlights the effectiveness of the proposed method in optimizing network performance and enhancing the Quality of Service (QoS). The results underscore the broader impact on network operations, highlighting how intelligent, adaptive systems can better meet the increasing demands for high-performance networks. Overall, the application of Artificial Neural Network (ANN) represents a significant advancement in optimizing the Quality of Experience (QoE) and Quality of Service (QoS), demonstrating their value in enhancing user satisfaction and operational efficiency in modern networking environments.

**Table 3:** Comparative with previous packet loss enhancement studies

| Packet loss Ratio % | Work |
|---|---|
| 7.07% | [27] |
| 3-6% | [28] |
| 7% | [29] |
| 0-1% | Proposed Method |

## 6. Conclusion

Given the overload in the networks, Quality of Experience (QoE) and Quality of Service (QoS) optimization became the critical aspect of their functionality. This study demonstrated how Artificial Neural Networks (ANN) could be of immense benefit in addressing some of the most challenging problems affecting networks, including, for instance, packet loss, delay, or jitter. The presented method employs Artificial Neural Network (ANN) to adjust multiple router queue lengths, enhancing network administration. Based on the results, it is identified that this approach of using an Artificial Neural Network (ANN) significantly improves the network performance more than conventional approaches, as indicated by reduced figures in terms of packet loss, delay, and jitter. Further, the employment of an Artificial Neural Network (ANN) is extensible and adaptive to the status of the network, so it provides a high-quality experience to the users of the network. These enhancements stress the possibilities of the usage of Artificial Neural Networks (ANN) to improve greatly both the Quality of Experience (QoE) and Quality of Service (QoS) to offer a viable solution to network operators and service providers who seek better ways of enhancing the quality of the service and dealing with different types of traffic. The results highlight a decrease in delay to 10.842 ms, a reduction in jitter to 0.031 ms, and packet loss to 0-1%. The success of this approach suggests that further exploration and refinement of Artificial Neural Network (ANN) models could lead to even greater advancements in network performance and user satisfaction.

### Author contributions

Conceptualization, **A. Mohammed** and **R. Ghani**; data curation, **A. Mohammed**; formal analysis, **A. Mohammed**; investigation, **A. Mohammed**; methodology, **A. Mohammed**; project administration, **R. Ghani**; resources, **R. Ghani**; software, **A. Mohammed**; supervision, **R. Ghani**; validation, **A. Mohammed** and **R. Ghani**; visualization, **A. Mohammed**; writing—original draft preparation, **A. Mohammed**; writing—review and editing, **R. Ghani**. All authors have read and agreed to the published version of the manuscript.

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### Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

### Conflicts of interest

The authors declare that there is no conflict of interest.

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