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INTELLIGENT TRAFFIC AND CONGESTION CONTROL SYSTEM FOR 5.4GHZ ENTERPRISE DATA NETWORK USING DYNAMIC ARTIFICIAL NEURAL NETWORK

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Abstract - In modern enterprise data networks, the rapid proliferation of connected devices and the continuous surge in high-volume data transmission have created a critical challenge of traffic congestion. This congestion leads to increased latency, packet loss, reduced throughput, and a significant decline in Quality of Service (QoS). Traditional traffic control mechanisms, often rule-based and static, lack the adaptability required to manage these dynamic and unpredictable network conditions effectively. To address this challenge, this paper presents an intelligent traffic and congestion control system based on a Dynamic Artificial Neural Network (ANN). The proposed system is designed to enhance real-time decision-making and optimize traffic flow across enterprise networks, particularly those operating in the 5.4 GHz frequency band. It achieves this by continuously monitoring critical network parameters such as bandwidth utilization, queue length, packet loss, and channel congestion, and learning from ongoing traffic behavior to prevent or mitigate congestion proactively. The ANN model employed in this system uses a multi-layer perceptronarchitecture, featuring dynamic learning rates and online backpropagation, allowing it to adapt in real time to fluctuating network conditions. The training dataset was generated from a simulated 5.4 GHz enterprise network environment using NS-3 and Wireshark, capturing essential metrics such as throughput, latency, packet loss, and channel utilization. Data was split into training (70%), validation (15%), and testing (15%) subsets. The model used the activation function in its hidden layers and a sigmoid activation in the output layer to estimate congestion probability on a scale from 0 to 1. An optimizer with an initial learning rate of 0.001 was used to fine-tune the model during training. Additionally, a dynamic adjustment mechanism enabled continuous weight updates using an online learning strategy, ensuring the system remains responsive to real-time network changes. Simulation results demonstrated the effectiveness of the proposed system. The ANN-based controller achieved a significant reduction in end-to-end latency (87 ms), improved throughput (190 Mbps), and reduced packet loss by 8.7%, compared to traditional congestion control techniques. Furthermore, the system showed improved responsiveness and scalability in handling dense enterprise traffic. In conclusion, the proposed dynamic ANN-based congestion control system offers a robust, adaptive, and scalable solution for enhancing performance, reliability, and QoS in enterprise networks operating in the 5.4 GHz band.

Keywords:Artificial Neural Network, Enterprise Network, Throughput, Latency, Bandwidth

1. Introduction

Considering the rapid evolution of digital technologies and the proliferation of high-bandwidth applications, data traffic flowing through enterprise networks has since increased (Ikenna et al., 2018). The term traffic congestion, in addition to data bottlenecks and mediocre data routing, stands out as a major challenge before enterprise networks, especially under very high data loads and with dynamic traffic patterns (Donaldson et al., 2016). Any such process of congestion control of the traditional sort cannot be adaptable or forward-looking when faced with such scenarios (Asiya et al., 2020). In today's era, great emphasis is laid on seamless, efficient, and secure data transfer in support of important enterprise functions and decision-making, as well as service delivery.Enterprises nowadays need to handle massive and dynamic volumes of data in real-time. Data-Centric Networks (DCNs) arose as a crucial framework to achieve efficient and content-aware data transmission (Benson et al., 2009). In contrast to traditional host-centric networks that route traffic for it is based on the IP address of the source and destination, DCNs consider characteristics such as content, priority, and nature of data to enable more intelligent data delivery mechanisms (Oloyede et al., 2023). Meanwhile, as enterprise networks grow larger and carry more data, an assortment of problems pertaining to traffic congestion, bottlenecks, increased latency, and packet loss will inevitably arise (Emmanuel et al., 2019). In-network congestion leads to service degradation; it can even cause financial implications, security loopholes, and deterioration of user experience.Since old classical congestion-control systems work based on static rules or return reactive measures that may be incapable of adapting to the rapidly changing traffic conditions emerging in modern networks, such classical methods may find it difficult to predict congestion and hence to prevent it proactively, especially if dynamic workloads and unpredictable bursts of data occur. So, nowadays, the need has gained momentum for some intelligent, adaptive, and predictive solution that should control network traffic and congestion happening in real time.

A kind of artificial intelligence (AI) called artificial neural networks (ANNs), which draws inspiration from the way the human brain works, has demonstrated impressive promise in resolving challenging, non-linear issues. ANNs are ideal for dynamic network situations because of their capacity to learn from past data, identify trends, and generate precise predictions. The problems of traffic and congestion control in enterprise DCNs can be potentially resolved by dynamic ANNs, which continuously modify and update their learning models depending on real-time inputs.

An intelligent system that can monitor real-time traffic conditions, anticipate future congestion scenarios, and make proactive adjustments to data flow can be implemented by incorporating dynamic ANN models into enterprise network infrastructure (Oloyede et al., 2023). Such a system can forecast and reduce congestion before it affects network performance by analysing a variety of network metrics, such as traffic volume, packet delay, error rates, and capacity utilisation.

Numerous advantages, such as improved network resource utilisation, decreased packet loss, fewer delays, and increased overall network efficiency, might result from the deployment of an intelligent traffic and congestion control system using dynamic artificial neural networks (ANNs). Additionally, the system can handle scalability, maintain high QoS, and adjust to changing traffic patterns—all of which are essential for enterprise operations.

This research uses dynamic artificial neural networks (ANNs) to offer an intelligent traffic and congestion control system for enterprise data-centric networks. By using machine learning approaches for real-time traffic management and congestion prevention, the system seeks to improve enterprise networks' performance and dependability.

2. 1 Network Traffic Parameters

The key performance network traffic parameters are shown in Table 1 (Donaldson et al., 2016):

Table 1: Network Traffic Parameters

Parameters	Formula	Threshold
Bandwidth	$\frac{\text{Data Transmitted (bits)}}{\text{Time (seconds)}}$	<80%
Utilization ($\boldsymbol{\rho}$)	$\rho = \frac{\lambda}{\mu}(2)$	<0.8
Latency	$\text{Dtr} + \text{Dpr} + \text{Dq} + \text{Dp}$	<150ms
Propagation Delay	$\frac{d}{s}$	<80%
Throughput	$\text{Tx. Rate}\,(1 - \text{Packet Loss Rate})$	<0.5 Mbps
Packet Loss Rate	Sent 100	<0.05
Dqueue	$\frac{\rho}{\mu(1-\rho)}$	ρ <0.8
Buffer Occupancy	$\left(\frac{\text{Packets in Buffer}}{\text{Buffer Capacity}}\right) \times 100\%$	<0.8

2.2 Proposed System

Figure 1 depicts the block design of a traditional data network, whereas Figure 2 shows the block diagram of the suggested system. Conventional congestion control systems, as shown in Figure 1, rely on static rules or measures that are unable to effectively adjust to the quickly shifting traffic conditions in contemporary networks.

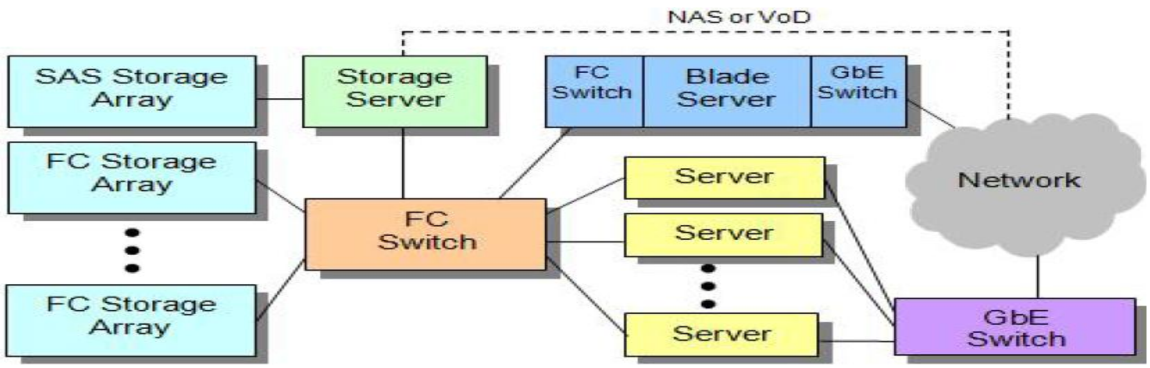

Figure 1: ABlock Diagram of a TraditionalData Network

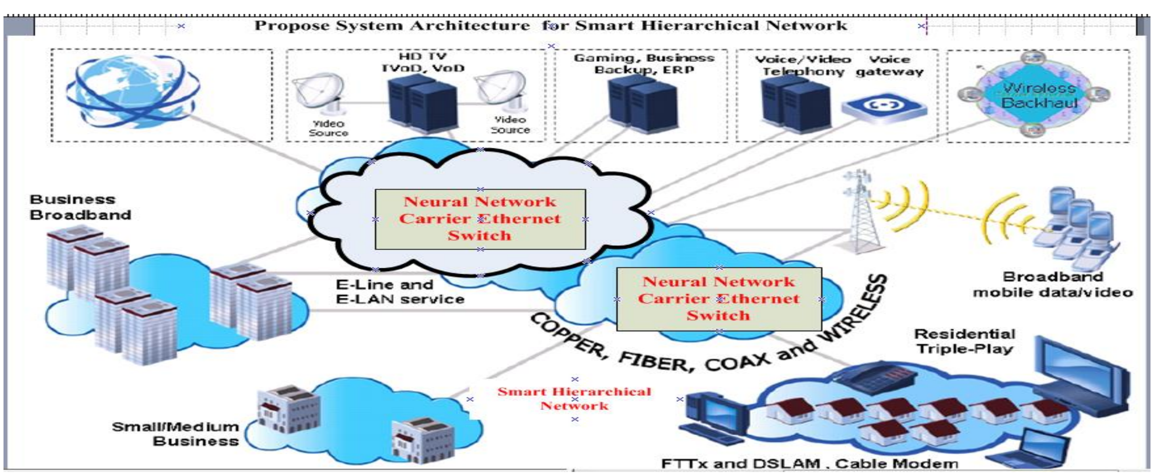

Figure 2: The Proposed System Framework/Architecture.

3. Materials and Methods

3.1 Materials

The materials used for the work are summarized in Table 2

Table 2: Materials, quantities, and functions

S/N	Materials	Quantity	Function
1	Servers/workstation	4	For training and testing the ANN models
2	Routers	1	To simulate or implement network traffic control policies dynamically
3	Switches	1	To simulate or implement network traffic control policies dynamically
4	Switch ports	24	Effective transmission of data between nodes
5	Terminal nodes	4	For connectivity
6	Network Interface Cards (NICs):	4	For communication and data capture across nodes in the simulated or real network.
7	Packet Sniffers (e.g., Wireshark)	1	For monitoring network traffic patterns.
8	Software and Tools -TensorFlow / Keras / PyTorch: -MATLAB: Network Simulation Tools: NS-3 (Network Simulator 3)	1	For building and training the Artificial Neural Network (ANN) models. Used for simulating ANN behaviour and evaluating control algorithms (can also be used for Simulink-based simulations).
9	5.4m VSAT	1	For connectivity through satellite
10	5.4 GHz frequency	1	Transmission of a wireless signal
11	Fibre cables	1	Connectivity
12	Network Architecture	3-Tier	Simulation Testbed

3.2 Description of The Test Bed

The data enterprise network served as the testbed and is a corporate data centre network situated at Latitude**:** 6.61377° N and Longitude**:** 3.35512° E in Lagos State, Nigeria. It is a Nigerian ICT service company.It was discovered that the 5.4GHz radio in the field testbed produced flawless signal quality on the fixed 5.4GHz frequencyband by rebroadcasting wireless signals to improve coverage range (Ubomand Ukommi, 2022). A 24-port gigabit switch is located in the server room, and desktop computers running Windows Server 2008 and Active Directory are linked to it. One is a primary server, and the others are backup servers based on their connection to the primary data-centric switch. While the second server serves as a billing system and the third server as a monitoring system, the primary server manages and distributes bandwidth. On a switch with N+1 ports, all of these servers are referred to as active servers. Different bandwidth sizes are distributed to end users by the network's bandwidth server.

The LAN is home to the gigabit switch that connects the terminal servers and other devices. When it comes to bandwidth control, allocation, blocking, passing, and timing, the Mikrotik router is intelligent. To offer internet access, four fibre patch panels were used to connect fibre edges. It uses a media converter and fibre cable. It might have two modes or just one. A 5.4-meter Sky Vision dish via a VSAT link's KU band was utilised on the outside device. The 5.4-meter outdoor VSAT dish is depicted in Figure 3, and the traditional Ethernet switch used to link the servers is shown in Figure 4.

Figure 5 shows a prototype model of the field testbed setup used in analysing network throughput, latency, and network load stability as measurable parameters. It includesa very small aperture terminal (VSAT) that sends data information from one network to another through a satellite link.

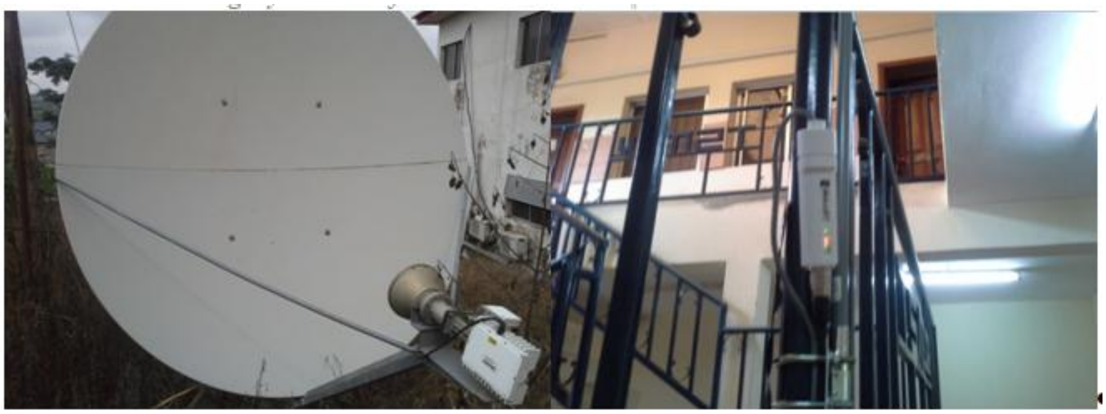

Figure 3: Outdoor5.4m VSAT dish from GILAT running through a KU band

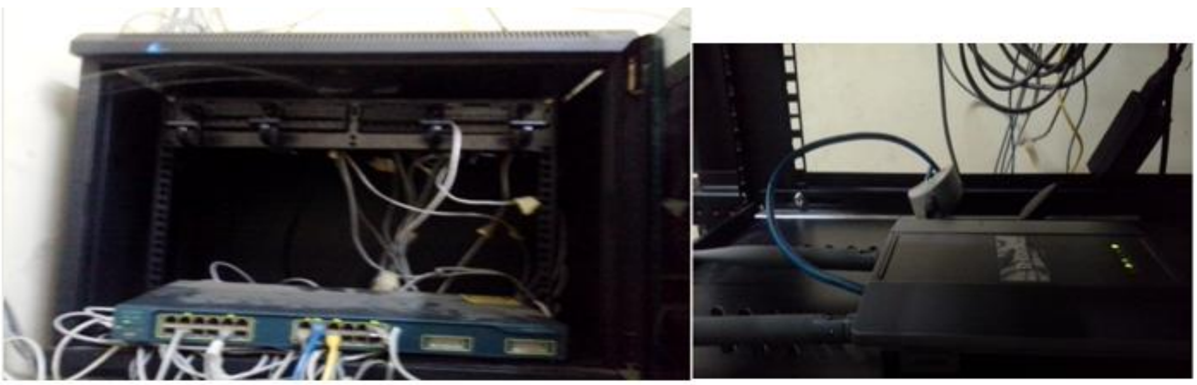

Figure 4: The Gilat Data Network backbone Indoor.

3.2.1: Simulation's Network Topology for System Analysis.

Figure 5 depicts the simulation's network topology. It consists of client nodes that are connected to Gilat'sdata-centric network server via a gateway. The model is connected to distant servers and the internet. The client is the end-user device (e.g., smart phone, laptop, or IoT device) that initiates requests for services or data. It sends requests to the server and receives responses. Clients may use applications that depend on reliable and efficient network service. Gateway acts as a bridge between different networks, often between a private network and the internet or between different segments of the network. Handles protocol translation, routing, and security enforcement, such as firewall operations or traffic filtering. Load balance distributes incoming network traffic across multiple servers to ensure no single server becomes a bottleneck. It improves reliability, optimizes resource use, and ensures high availability by dynamically routing client requests to the healthiest, least-loaded servers. A switch is a hardware component within the network that connects devices and routes data at the data link layer (Layer 2). The forwardingof data packets between devices within the same local network ensures efficient intra-network communication. The application server hosts and runs specific applications and services that respond to client requests. It processes application logic, handles business rules, manages user sessions, and interacts with databases or other backend components. This may include real-time data processing and AI services. The billing server tracks and manages usage data, session times, and service charges to ensure accurate billing for services. It interfaces with the application and network layers to collect data on service usage and generate bills, manage subscriptions, or enforce quotas.

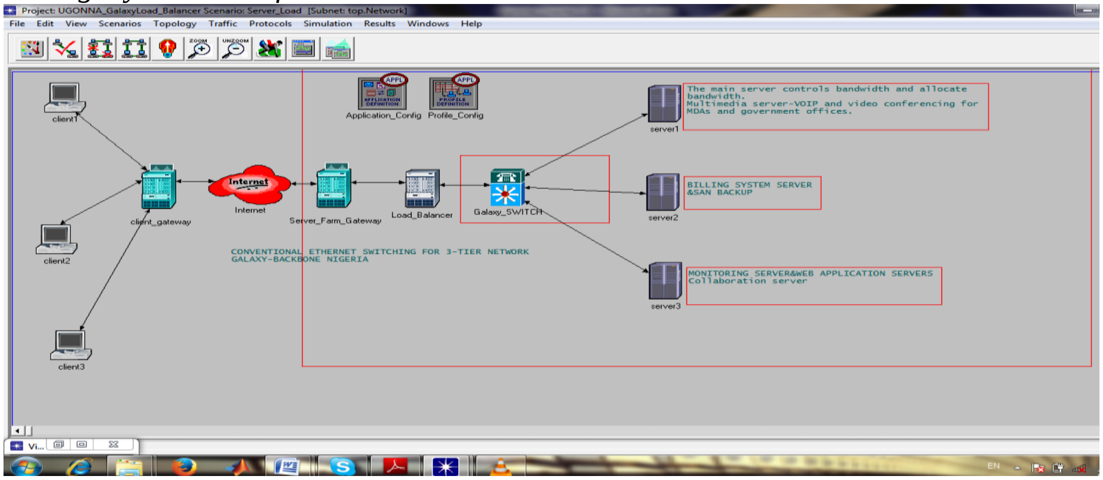

Figure 5: Simulation Model.

3.2.2. Block diagram of the Artificial Neural Network ArchitectureSimulation Testbed.

The block diagram of the simulation testbed is shown in Figure 6, while Figure 7 shows the ANN simulation testbed.

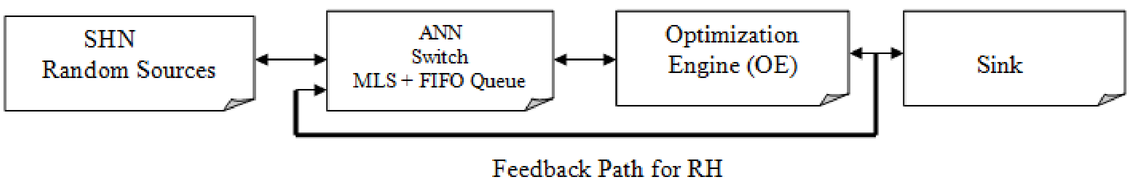

Figure 6: Block diagram of the Neural System Architecture Simulation Network Topology.

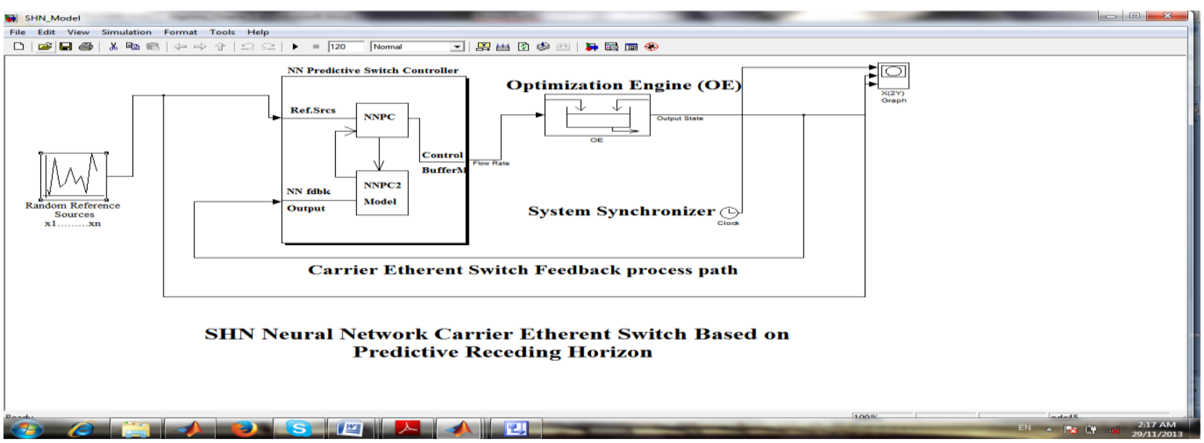

Figure 7: Neural Network Architecture Simulation Topology

4. Results and Discussion

4.1 Results

Thefield data bandwidth utilization is measured from the investigativedata-centric network.is shown in Figure 8.Figures 9 and 10 showa plot of Network throughput on the data centre Network Performance Monitor 9.1 SP4 GB Ethernet switch-1, in July and August 2024, respectively. Table 2 shows simulation results of throughput and delay. Figure 11shows**the** neural network throughput response from the MATLAB workspace on the receding horizon. Figure 12shows**the** Neural network delay response from the MATLAB workspace on the receding horizon. Figure 13 shows server utilization in percentage.Figure 14 shows an end-to-end latency result. Figures 15 and 16 show the network stability responses of the data-centric network. It shows the network load traffic values of 56.0 and 99,000,0000, respectively.

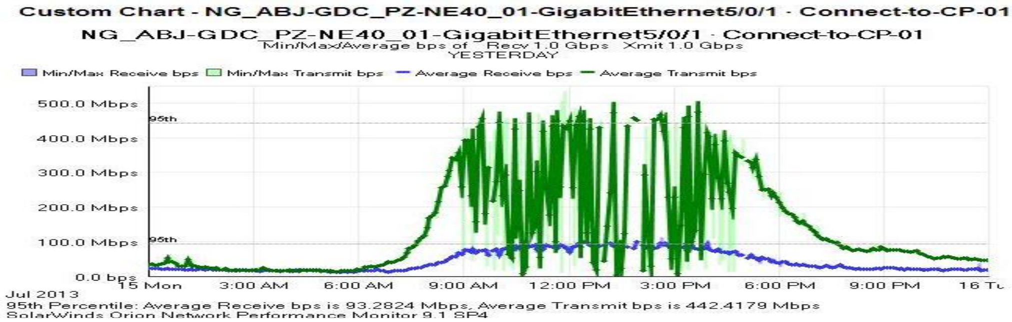

Figure 8: A graphof Networkbandwidthusage onthe investigative DataCentric Network Performance Monitor 9.1 SP4 GB Ethernet switch-1 (July2024).

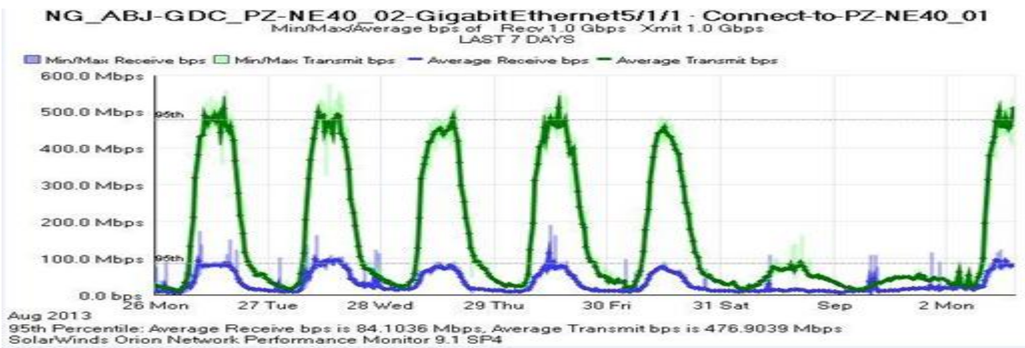

Figure 9: A graph of Network throughput on data centre Network Performance Monitor 9.1 SP4 GB Ethernet switch-1, (July2024)

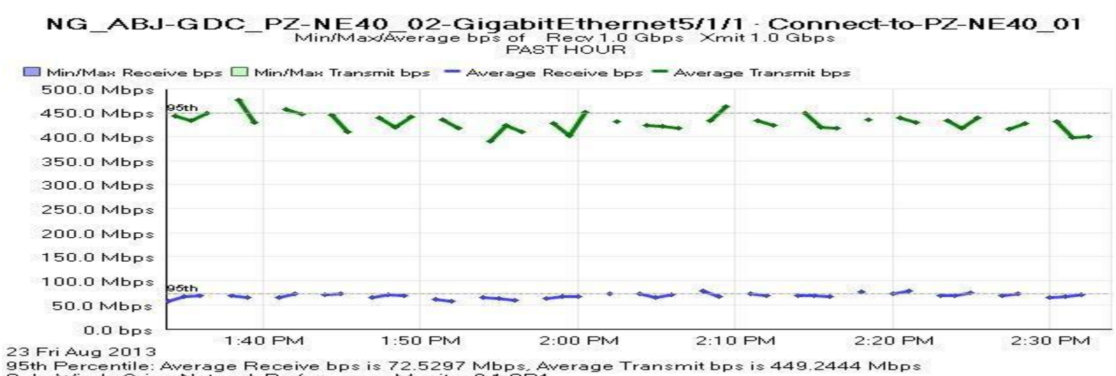

Figure 10: A Plot of Network throughput on data centre Network Performance Monitor 9.1 SP4 GB Ethernet switch-1, (August, 2024)

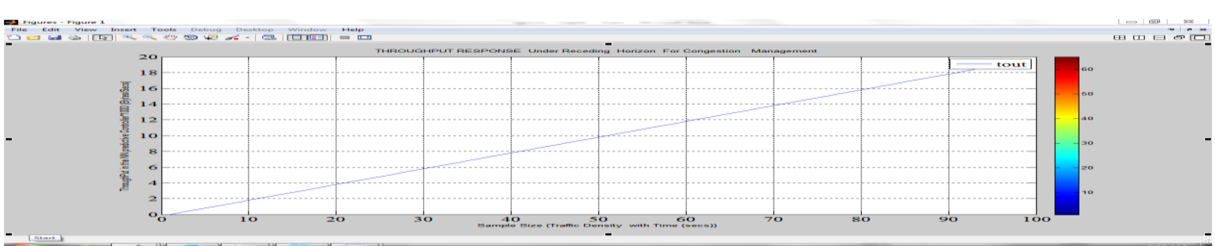

Figure 11: Neural network throughput response from MATLAB workspace on receding horizon.

Figure 12: Neural network delay response from MATLAB workspace on receding horizon.

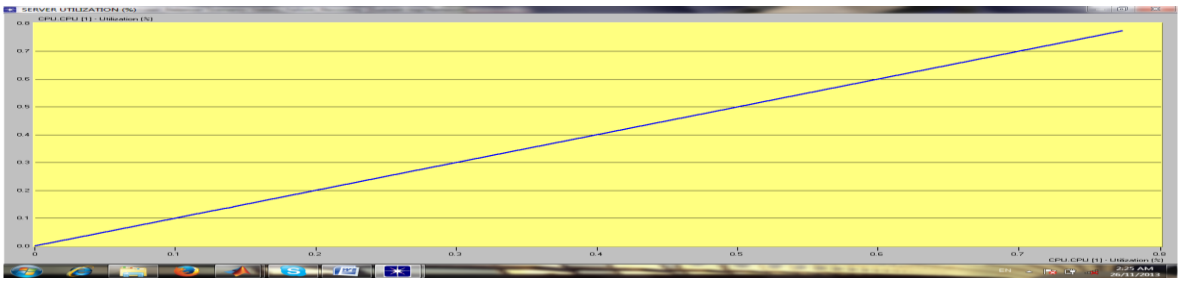

Figure 13: Server Utilization in %

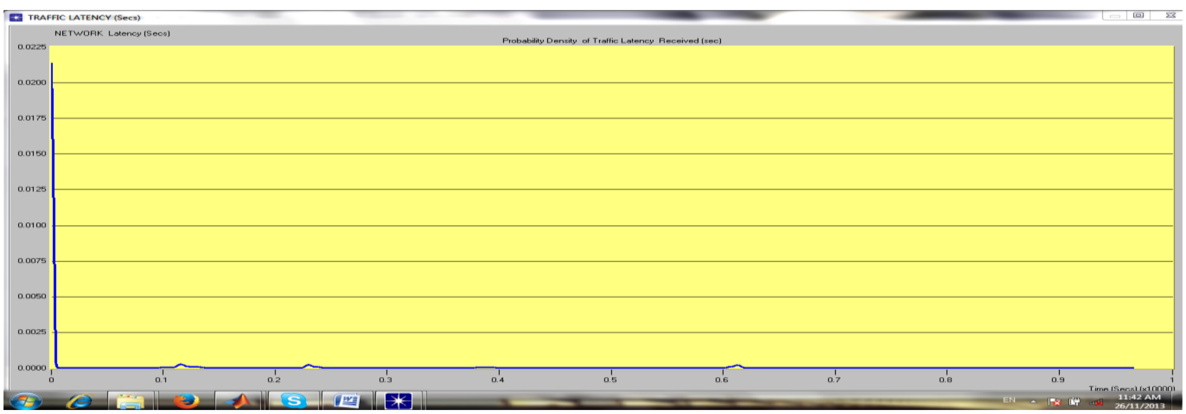

Figure 14: Latency

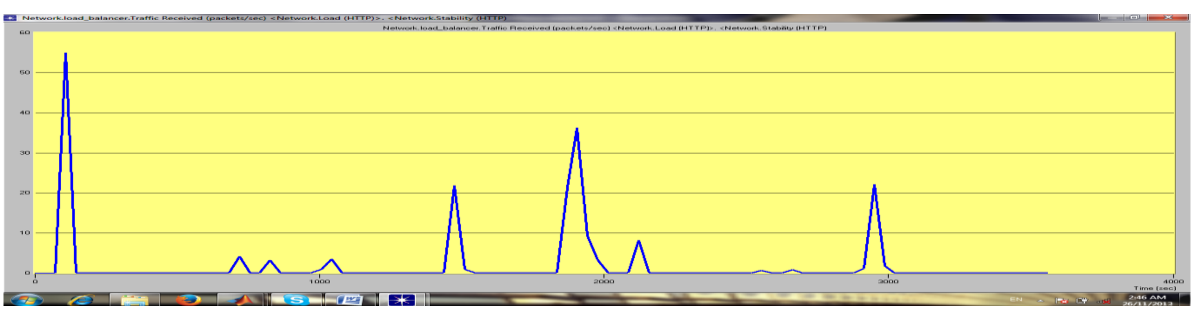

Figure 15: Network load stability (low traffic).

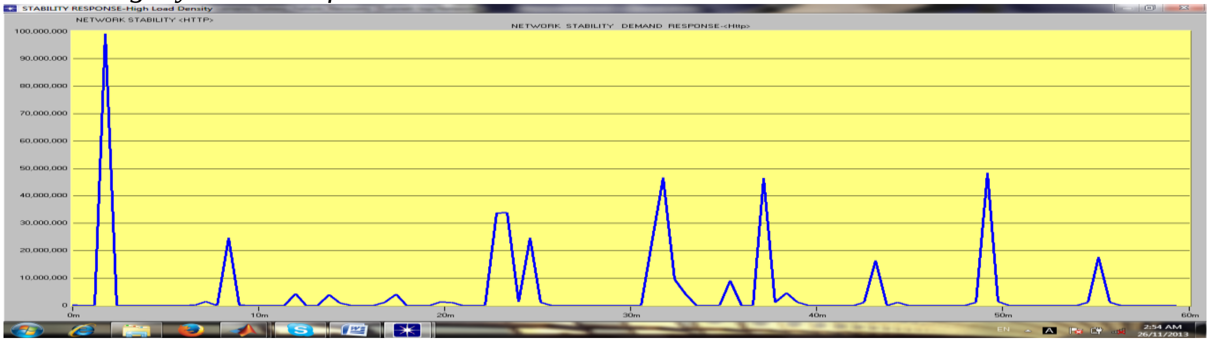

Figure 16: Network load stability (High traffic).

4.2:Discussion

The investigating network's bandwidth usage is displayed in Figure 8. It shows that the transmit bps is 442.4179 Mbps and the received bps is 93.2824 Mbps, which is the 95th percentile average. It implies that network performance is significantly distorted by congestion effects, which should be avoided. The data centre Network Performance Monitor 9.1 SP4 GB Ethernet switch-1's network throughput graphs for July and August of 2024 are displayed in Figures 9 and 10, respectively. Both graphs demonstrate the impact of network congestion and outages. The throughput and latency results of the ANN simulation are displayed in Table 2. Neural network throughput response from the MATLAB workspace on the receding horizon is displayed in Figure 11.

Additionally, it displays the data-centric network backbone's average throughput as determined by simulation. Due to the dynamic ANN congestion algorithm and the influence of the network load balancer, which regulates network traffic, the throughput response was linearly measured. The neural network delay response from the MATLAB workspace on the receding horizon is displayed in Figure 12. As long as the inputs are available via Ethernet NICS, its optimisation algorithm finds the control input that maximises switch performance over a certain period. Multimedia traffic will effectively supply its services without the effects of congestion degradation, thanks to the throughput delay measures in an enterprise workload for NN predictive switches.

Server utilisation as a percentage is displayed in Figure 13. Although the majority of these networks with three-tiered designs have ideal server resource utilisation since average utilisation will have long-term repercussions on the core of the smart network design, resource utilisation in the network areas is fairly high. An end-to-end latency result is displayed in Figure 14. For the majority of networks, the latency response of 106 milliseconds is deemed acceptable. The improved network topology and increased traffic optimisation brought about by the TCP/IP algorithm shorten the transmission time between the access and core layers, even during busy and busy link conditions.

The data-centric network's network stability responses are displayed in Figures 15 and 16. 56.0 and 99,000,0000 are the network load traffic values displayed, respectively. The establishment of a steady user connection on the network took approximately 0.9 seconds.

5. Conclusion

The proposed work demonstrates a transformative approach to network management by incorporating intelligent control mechanisms aligned with modern business requirements. Key features such as rapid service delivery, closer alignment with business objectives, scalability, cost-effectiveness, responsiveness to dynamic demands, and a strong service orientation underscore its suitability for next-generation network environments.

Furthermore, the implementation of the ANN-based controller yields measurable performance improvements over traditional congestion control methods. Specifically, the system achieved a notable reduction in end-to-end latency by 87 ms, enhanced throughput reaching 190 Mbps, and an 8.7% reduction in packet loss. These results confirm the architecture's ability to adapt effectively to network conditions and optimize performance.

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