Approach to an Intelligent Based IP over MPLS VPLS Network for Packet Scheduling

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Abstract - *Multi-Protocol Label Switching (MPLS) uses a brief bit sequence to denote a conventional Internet Protocol's Forwarding Equivalence Class (FEC), and on a hop-by-hop basis, networks decide on routing depending on header analysis. Additionally, MPLS employs a predefined routing table to manage packets with a specific FEC. type. Non-real time traffic will be used in this study to evaluate how effectively to incorporate the intelligence packet scheduling to an integrated MPLS and VPLS (Virtual Private LAN service) networks. At first, Network Simulator (NS2), a non-real-time application platform for file transfer in order to build the IP/MPLS network model, protocol is needed. The two distinct systems, Neuro-Fuzzy and Fuzzy Systems, were used for packet scheduling. This is followed by routinely put into action at the Label Switched Router (LSR) interface, which enable fast delivery of data in the network. Then, the result obtained from trace file will be used to show the critical performance of MPLS network.*

Key Words: Virtual Private LAN service, Forwarding Equivalence Class, Neuro-Fuzzy Inference System, Internet Protocols/Multi-Protocol Label Switching.

1.I NTRODUCTION

The opportunity for enterprises to meet client demand is growing exponentially because to the internet's accessibility, which has given rise to new methods of conducting virtual commerce. Access to network resources has significantly increased end users in an accelerating globe, which has resulted in substantial network and internet service congestion. Additionally, as noted in [1], it significantly impacts performance, which lowers service availability and quality. Traditional IP-based networks that rely on hop-by-hop header inspection for packet forwarding will not be able to meet the demanding network performance requirements such as short delay, high bandwidth, etc. given all these difficulties and the growing popularity of real-time and multimedia applications, such as voice and video. The quality of services (QoS) required by these applications and will not be able to provide such assurance [2]. Label Switched Paths (LSP) are created throughout the network by MPLS using a combination of protocols and careful traffic engineering. In order to support the fast forwarding of ernet Protocol (IP) packets, the information included in the labels is utilised and added to the packets [3]. In order to get beyond network restrictions such high packet loss and excessive delays, it offers scalable function in addition to congestion control [4, 5].

In our previous work, we proposed service-aware LSP with fuzzy-based Packet Scheduling [6][21]. With further approach, the main objective of this paper is to perform a comparative study of fuzzy and neuro-fuzzy-based Packet Scheduling Algorithms using IP/MPLS technology in the NS2 environment. The process of forwarding the packets is applied, which directed traffic to any route based on explicit route enabled. Then, an output of trace files yielded the results of the simulation.

Our contributions to this paper are mentioned as follows: Firstly, packet scheduling algorithms in an appropriate network model (IP/MPLS) are chosen, defining the routers, hosts, and link characteristics using NS2 code with input parameters of the non-real time traffic such as sending rate, link bandwidth, propagation delay, etc. Secondly, we introduce the fuzzy and neuro-fuzzy rules in the fuzzy inference system using different fuzzy input variables. Thirdly, we analyze training error on the packet processing algorithm with the application of a neuro-fuzzy based packet scheduling algorithm at the interface of core routers. Later, we provide the analysis of Probability Distribution for Fuzzy and Neuro-Fuzzy Inference systems. Fourthly, an AWK script is written to interpret the obtained trace files and trace graphs are used for the illustration of performance metrics.

The remaining parts of this paper commenced in Section 2 with the review of related work on MPLS VPLS. Next, it presents the proposed framework and analytical operations of the fuzzy inference system with a learning algorithm in the MPLS routers. The implementation of the proposed intelligence Packet Scheduling Algorithm is provided and yields the results and their discussions. Finally, conclusions are presented in Section 3.

2. REVIEW OF RELATED WORK

It is envisaged that by 2023, 30% of enterprise locations will use internet-only WAN connectivity, up from less than 10% in 2019, to reduce bandwidth costs for MPLS connection. The traffic engineering (TE) techniques and a variety of protocols to establish pre-determined highly efficient routes in Wide Area Network (WAN) is provided by the MPLS [7]. In MPLS, the allocation of a particular packet to a particular FEC is done just once as the packet enters the network. The FEC to which the packet is assigned and encoded as a short fixed length value known as a "label". When a packet is forwarded to its next hop, the label is sent along with it. At subsequent hops, there is no further analysis of the packet's network layer header. Rather, the label is used as an index into a table, which specifies the next hop and a new label is given. The old label is replaced with the new label, and the packet is forwarded to its next hop [12][13]. It can be observed in the MPLS forwarding paradigm, once a packet is assigned to FEC, subsequent routers do no further header analysis; all forwarding is driven by the labels. There have been different approaches to the concept of packet-switched as shown in Figure 1(a).

Obviously, MPLS and VPLS (Virtual Private LAN Service) are defined using point-to-multipoint topology and transport of IP packets. This can carry various different protocols such as L3VPNs, L2VPLS, EoMPLS, AToMPLS, and FRoMPLS [8][9][10]. VPLS is a protocol for building a virtual multipoint Ethernet network on top of an MPLS network or IP network. It performs the same way as MPLS, but it has the capability to provide more services than MPLS. However, MPLS is still a vital option for many businesses. With VPLS, customer level of achievement increases dramatically from a technical perspective. VPLS is also easier to support, which in turn reduces costs and improves the customer experience for a business. Hybrid deployment of MPLS VPLS technologies and services may be better suitable to meet business-critical needs [10]. The three primary types of MPLS VPNs are shown in Figu -1(b). It is imperative to combine the services of MPLS VPLS to yield level of achievement to the customer Network Simulator (NS) possesses Tool Command Language (Tcl) for creating a simulation scenario file such as Network topology, transmission time, using the protocol, etc. It consists of an event scheduler and IP-based network components. This is written in both Object-oriented Tcl and C++ language. C++ is used for detailed protocol implementation, such as packet action and state information management, while Tcl is used for simulation configuration, such as event scheduling [11]. The following are the steps used to create MPLS network scenarios in NS environment:

Declare simulator;

Set output file;

Set node and link with bandwidth and delay;

Set agents such as Transmission Control Protocol (TCP) and User Datagram Protocol (UDP);

Setting applications (FTP) and Constant Bit Rate CBR);

Setting simulation time and schedules;

Declare finish.

Therefore, Table -1 provides simulation information, while the network information and architecture of the MPLS Network used in NS2 are illustrated in Fig -2(a) and 2(b), respectively. It consists of four nodes as the sources, seven Label Switched Router (LSR), and four nodes as destinations.

Table -1: Simulation Information

Parameters	Non-Realtime Traffic
Simulation length (s)	180
Number of nodes	15
Packet size (bytes)	1000
Sending rate (kbps)	500
Interval (s)	0.005
Link bandwidth (MB)	2, 5
Propagation delay (ms)	10
Transmission delay (ms)	4
Processing delay (μs)	10-20
Queuing delay (ms)	Variable
Type of source	FTP traffic

2.1 Forward Equivalence Class

The incoming packets are allotted with a label by a Label Edge Router (LER)according to their Forwarding Equivalence Class (FEC) in MPLS [14]. Packets are forwarded alongside an LSP where each LSR (label switch router) makes forwarding decision entirely based on the content of the label, in this way eliminating the need for the IP address so that the transitional router does not have to execute routing lookup, which is a very time-consuming process [15].

The MPLS allows an LSR to distribute FEC label binding in response to an explicit request from another LSR. This is known as Downstream on Demand label distribution. It also allows an LSR to distribute label bindings to LSRs that have not explicitly requested them [12][15]. In order for MPLS to operate correctly, label distribution information needs to be transmitted reliably, and the label distribution protocol messages pertaining to a particular FEC need to be transmitted in sequence [16][17][18][19]. The distribution of labels and the construction of LSPs is done by exchanging Label Distribution Protocol (LDP) messages between the LDP agents of LSR nodes.

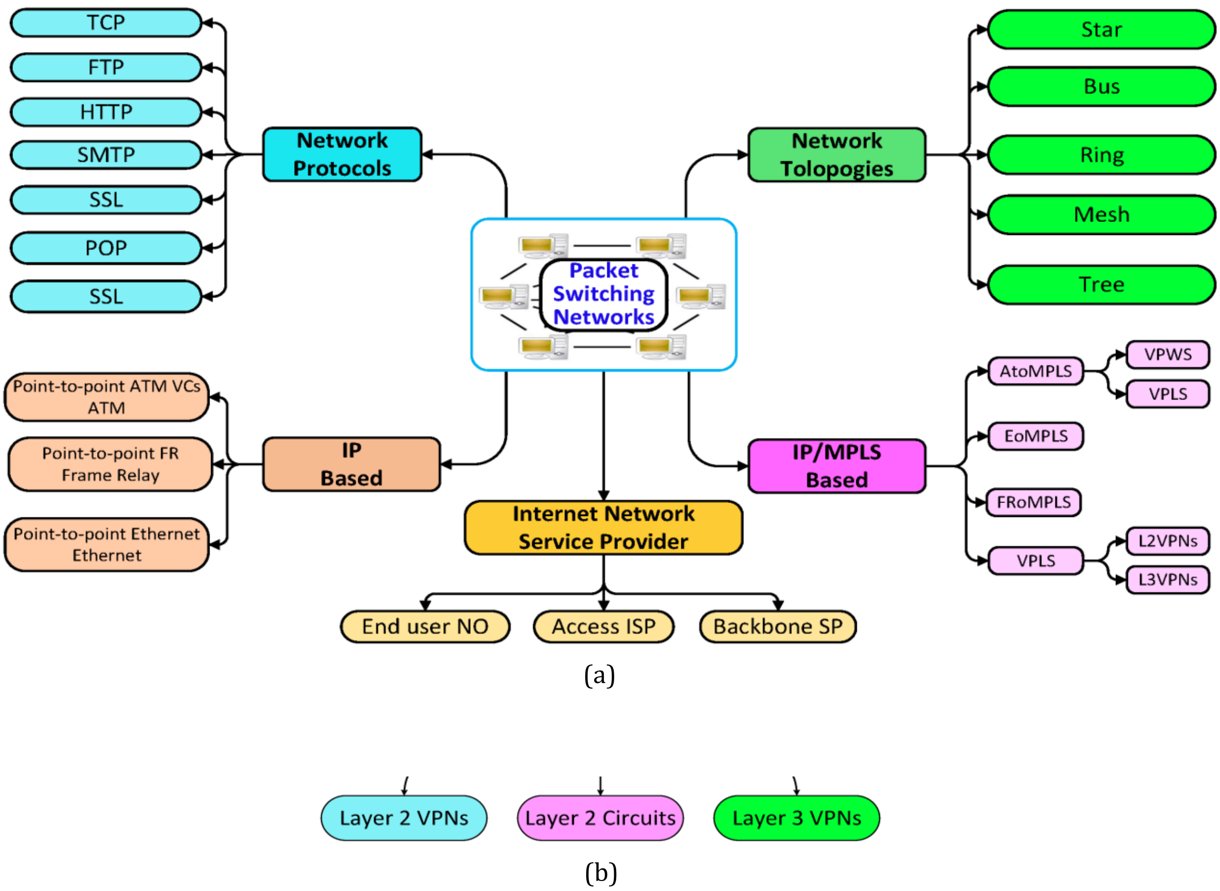

Fig -1: (a) Conceptual of Packet Switching Networks (b) Types of MPLS VPNs

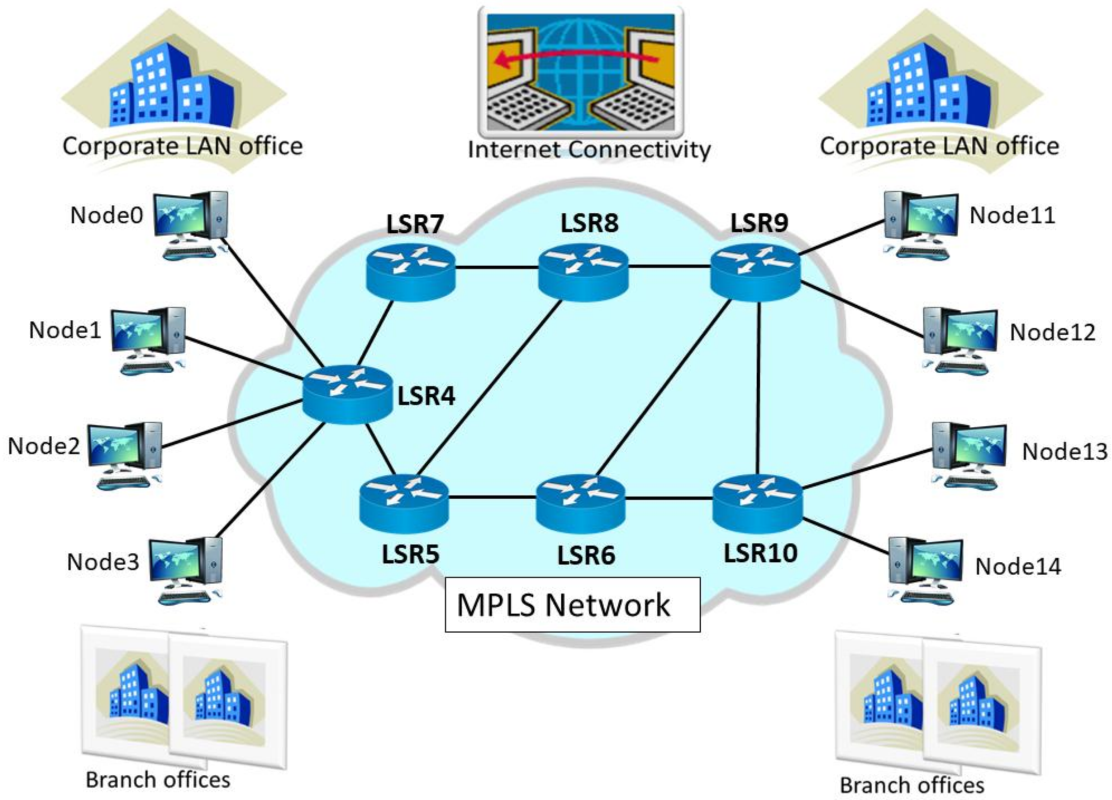

Fig -2(b): Architecture of MPLS Network

2.2 Analytical Operation of Fuzzy Inference System with Neuro-Fuzzy Algorithm

The first layer and the fourth layer of the Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture contain parameters that can be changed over time. It has non-linear premises parameters in the first layer and linear consequent parameters in the fourth layer [26]. Both of these factors need to be trained and able to adapt to their surroundings in order to be updated. In this research, these parameters will be trained using a hybrid approach that Jang (1993) presented. The backpropagation technique, which was used to train the parameters in adaptive networks, was found to be problematic, especially when it had a sluggish convergence rate and tended to become stuck in local minima. This led to the usage of this algorithm. An adaptive network using supervised learning that functions similarly to the Takagi-Sugeno fuzzy inference system model is known as the ANFIS architecture. Let's assume for the sake of simplicity that there are two inputs (x and y) and one output (f). The "If-Then" technique for the Takagi-Sugeno model employed the following two principles [20]:

Rule 1: If ($X_a = A_1$)and ($Y_b = B_1$) Then $f_1 = u_1x+v_1x+r_1$
Rule 2: If ($X_a = A_2$)and (Y_b is B_2) Then $f_2 = u_2y+v_2y+r_2$
Rule 3: If ($X_a = A_3$)and (Y_b is B_3) Then $f_3 = u_3y+v_3y+r_3$
Rule 4: If ($Xa = A_4$)and (Y_b is B_4) Then $f_4 = u_4y+v_4y+r_4$

where A_1, A_2, B_1, and B_2 are the membership functions of each input x and y (part of the premises), while u_1, v_1, r_1, and u_2, v_2, r_2 are linear parameters in part-Then (consequent part) of Takagi–Sugeno fuzzy inference model. Layer 1: The convolution sum in (2) is equivalent to a neural network, as illustrated in Fig -2, where smf_{ikj} can be regarded as the weight connecting the j^{th} element of the input vector presented to ANFIS to the kth sample point of the ith membership function in the first layer. This insight provides essential guidance in deriving the gradient descent formula for the ANFIS learning algorithm.

$$\text{Conv sum} = \sum_{k=1}^{2n-1} h(k) = \sum_{k=1}^{2n-1} \sum_{i=\max(i,k+1-n)}^{\min(k,n)} f(j)g(k+1-j) \tag{1}$$

This can be written as:

$$\text{Conv sum} = \sum_{j=i}^{n} \left(L_{0,j} \times \sum_{k=1}^{n} smf_{ikj} \right)$$

$$\text{where, } L_{1,i} = \frac{\sum_{j=i}^{n} (L_{0,j} \times \sum_{k=1}^{n} smf_{ikj})}{1 + |\sum_{j=i}^{n} (L_{0,j} \times \sum_{k=1}^{n} smf_{ikj})|}$$

and $i = 1,2,\ldots\ldots |L_1|$

Layer 2: (Firing strength): Each node in layer 2 is a fixed node that outputs the product of its complex inputs as:

$$L_{2,j} = \prod_i L_{1,i,} \text{ where } i=1,2,\ldots\ldots |L_1| \quad (2)$$

Every layer 2 node's output corresponds to the firing power of a fuzzy rule. This may also entail input interaction in the case of multivariate time series [24][25]. According to [22], the algebraic product is a complicated fuzzy intersection, which was also suggested in [23]. The circle node is marked with the letter I and every other node in this layer is fixed or non-adaptive. The signal that enters the node and is sent to the following node is multiplied to create the output node. The firing strength for each rule is represented by each node in this layer. To obtain the output in the second layer, the T-norm operator with general performance, such as AND, is utilized

$$L_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \text{ where } i = 1,2,\ldots\ldots \quad (3)$$

Layer 3: (Normalized firing strength): The output of each node labeled N in layer 3 represents the ith rule's normalized firing strength.

$$L_{3,i} = \overline{w_i} = \frac{w_i}{\sum_{j=1}^{|L_2|} |w_j|} \quad i = 1,2,\ldots\ldots |L_2| \quad (4)$$

$$L_{3,i} = \overline{w_i} = \frac{w_i}{\sum_i w_i}$$

where $|L_2|$ is the number of rules, and $\sum_{j=1}^{|L_2|} |w_j|$ refers to the summation of the magnitude of each weight w_j.

Layer 4 (Dot product): The dot product of each normalized firing strength and the total of all the outputs from the nodes in the layer before is the output of each node with the label "dp" in layer 4. Rule interference is thus implemented at this layer. Keep in mind that layer 4 outputs, all future network signals, and the network output are always real-valued.

$$L_{4,i} = w_i^{dp} = \overline{w_i} \cdot \sum_{i=1}^{|L_3|} \overline{w_i}, \; i=1,2,\ldots\ldots |L_3|$$

$$L_{4,i} = \overline{w_i} f_i = \overline{w_i}(u_i x + v_i y + r_i) \quad (5)$$

where $\overline{w_i}$ is the normalized firing strength from the previous layer (third layer) and $u_i x + v_i y + r_i$ is a parameter in the node. The parameters in this layer are referred to as consequent parameters.

Layer 5: *(Consequent parameters):* Each node i in layer 5 is an adaptive node in the hybrid learning rule. The output of each node *i* is given by (2)

$$L_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{w_i} \quad (6)$$

The equations from (1) to (6) indicate the analytical expressions of fuzzy inference system with a learning algorithm.

2.3 Proposed Framework for Intelligent Packet Scheduling

The algorithm executes the process of deciding which packet to be sent to the outgoing link for transmission. In other words, it is a decision process used to choose which packet to be serviced or dropped. This can influence the delay (and consequently the jitter), bandwidth and loss rate. The most important task of a scheduler is to ensure the satisfaction of QoS requirements for users while efficiently utilizing the available resources. The fuzzy-based packet scheduling algorithm uses logical operations in order to provide a system with improved performance. Therefore, the implementation of the Fuzzy Logic Control System (FLCS) and Neuro-Fuzzy System (NFS) is proposed to select paths and then schedule packets among them since there are many available paths for the same source and destination nodes. The neuro-fuzzy system, with a reduced number of rules, is trained to perform efficiently with the set of rules obtainable [27][28]. This training process of the neuro-fuzzy system adjusts the weights to produce the required output for any input pattern as shown in Figure 3. The neuro-fuzzy system parameters are adequately shown in Table -2. In the fuzzy system, the same process is carried out by tuning the membership functions, which was nearly impossible for the target packet scheduling system with such broad input parameters [29][30] as illustrated in Fig -4. Once the neuro-fuzzy system is trained, a comparison is made between the neuro-fuzzy and the fuzzy inference system with the assistance of 400 input samples for each of the seven input parameters. Each of these inputs is randomly generated and provided to the neuro-fuzzy and the fuzzy inference system. Finally, the obtained decision factors from both neuro-fuzzy and fuzzy inference systems are plotted to compare the output of each system, as shown in both Fig -3 and Fig -4, respectively. The scheduler can be implemented as a fuzzy and neuro–fuzzy controller with inputs such as bandwidth, delay, cost, reliability, packet loss rate, and resource utilization rate. The output defines the LSP that queue from which the next packet will be transmitted Fig -3 and 4 depict the implementations of the Fuzzy logic control system and Neuro-Fuzzy system for packet scheduling using MATLAB, respectively [32].

Table -2: Neuro-Fuzzy Parameters

Parameters	Values
Number of Nodes	4426
Number of Fuzzy rules	2187
Number of training data pairs	2187

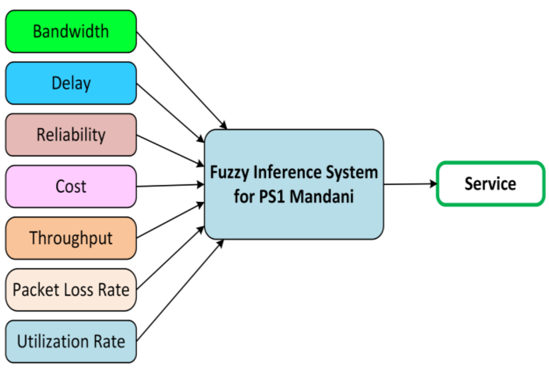

Fig -3: Fuzzy Logic Control System for Packet Scheduling (PS1).

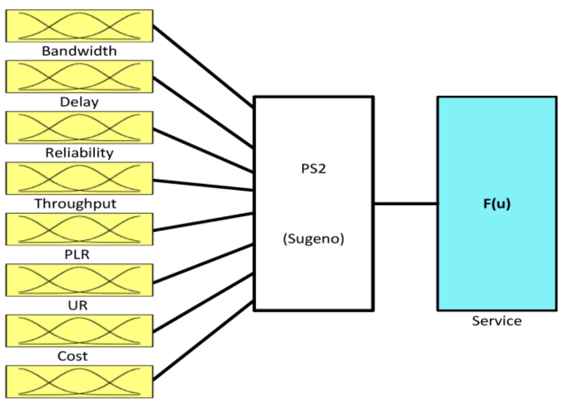

Fig -4: Proposed Neuro-Fuzzy System for Packet Scheduling (PS2)

2.4 Results and Discussions

Network Simulator is used to implement the IP/MPLS VPLS, which includes the components for the creation of a wired network, such as nodes and the link of simplex and duplex types. Each link is configured with the parameters such as bandwidth, propagation delay, and queue type. Data communication between nodes is configured with transport and application layer agents that are required to be attached to both sender and receiver nodes. The results obtained are plotted using a trace graph. In Fig -5 and 6, there is a wide disparity between the cumulative sum of packets generated with that of packets forwarded and dropped in IP/MPLS VPLS networks. This indicates that there are more fast forwarding packets in MPLS than in an IP network. The comparison of average throughput received in IP/MPLS with Weighted Fair Queuing (WFQ) using FTP is shown in Fig -7 and Fig -8. FTP traffic is created on top of a TCP connection between node 0 and node 10. It can be seen that MPLS performed better than IP with the scheduling algorithm as a result of its fast packet forwarding process. Furthermore, it is apparent that this figure gives an improved throughput with WFQ in IP/MPLS networks. Similarly, a further improvement is observed as a result of fuzzy and neuro–fuzzy applied intermittently at the interface of LSR routers. In this scenario of using the decision factor, a peak value of about 69% is obtained with neuro-fuzzy and an approximation of 66% for the fuzzy. An increment of about 3% shows better performance at 220 random input samples. It continues to reiterate at various random input samples. The graphical illustration of 400 samples at the interface with packet scheduling algorithms is shown in Fig -9.

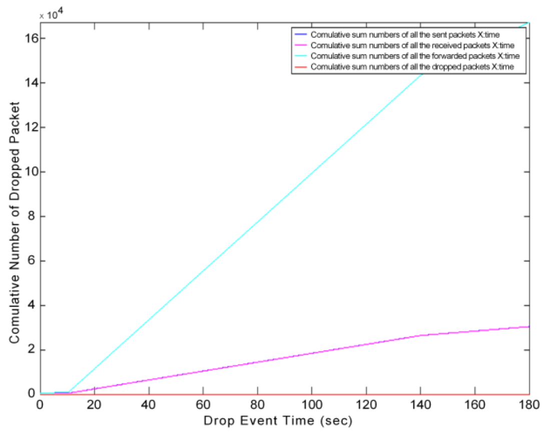

Fig -5: The cumulative sum of packets in the IP network

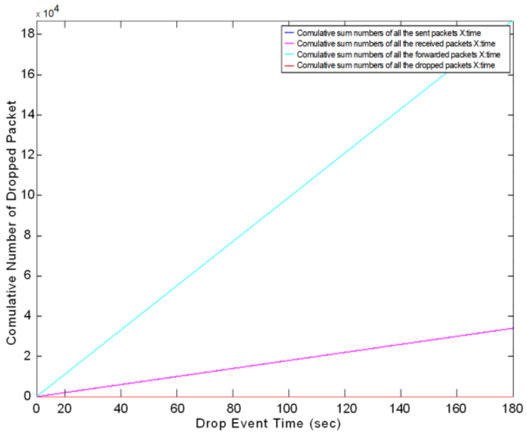

Fig -6: Cumulative sum of packets in MPLS network

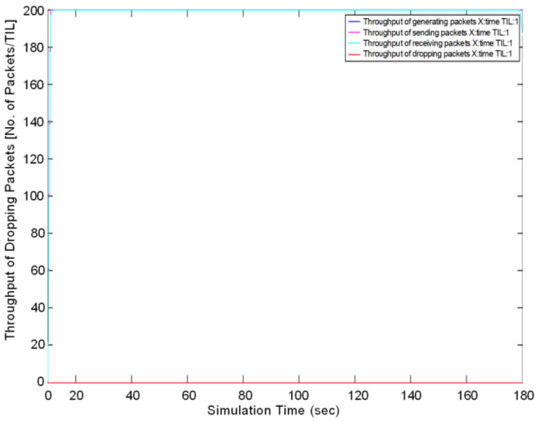

Fig -7: Throughput of Packets in IP network

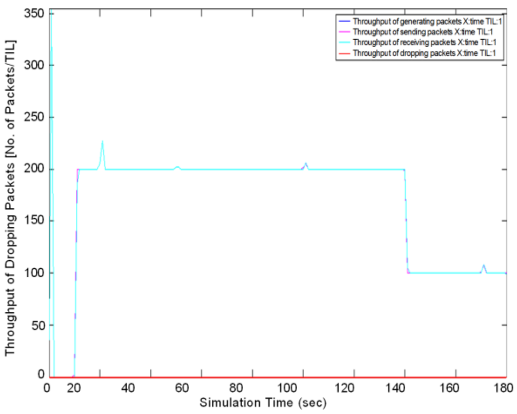

Fig -8: Throughput of Packets in MPLS network

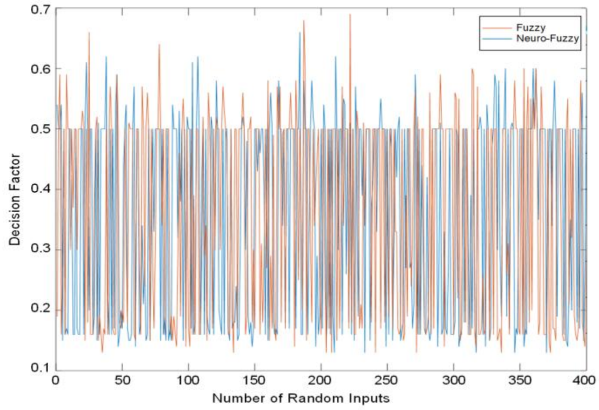

Fig -9: Neuro - Fuzzy and Fuzzy Inference systems with 400 random input samples

Fig -10 shows the impact of subjecting the inputs to the FIS for both algorithms, which later result in some linear FIS outputs while others were scattered based on the random inputs. Fig -11 and Fig -12 show the training errors of the neuro-fuzzy inference system. It is observed that the training errors of the neuro-fuzzy inference system with two different epochs (10 and 200) are decreasing as the number of iterations increases, which indicates that the module is working well in terms of performance. Subsequently, to evaluate further the probability distribution of both decisions is plotted with the peak probability values of 0.995 and 0.999 to ascertain if there will be a remarkable difference between these inference systems. This is as shown in Fig -13 and Fig -14 respectively.

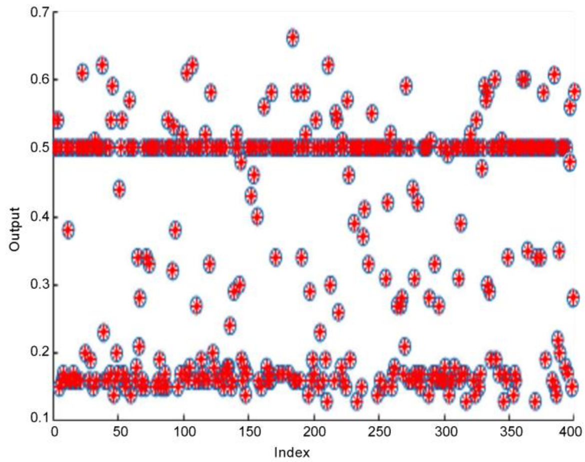

Fig -10: Training data of 400 random input samples with FIS output

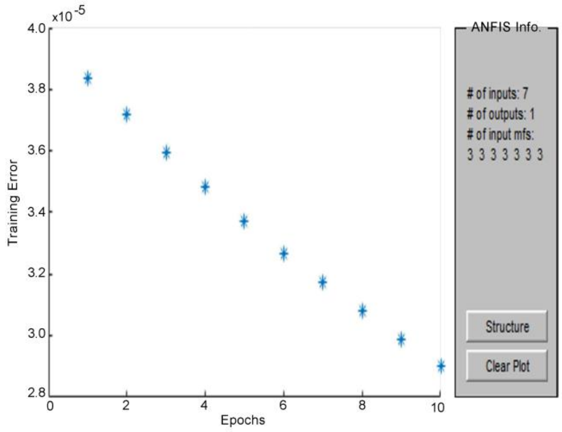

Fig -11: Training Error of Neuro-Fuzzy Inference system for 10 Epochs

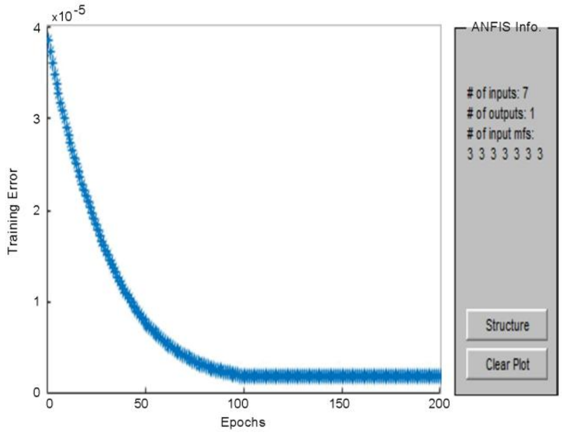

Fig -12: Training Error of Neuro-Fuzzy Inference system for 200 Epochs

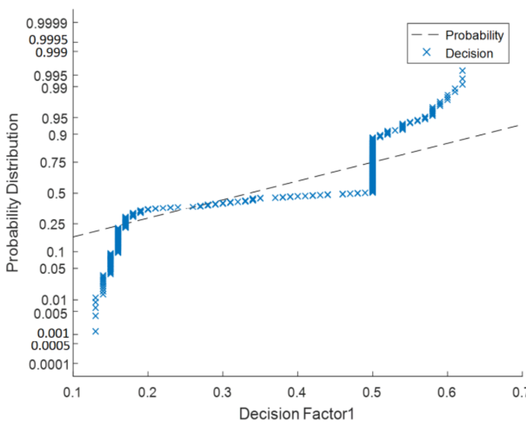

Fig -13: Probability Distribution of Fuzzy Inference system

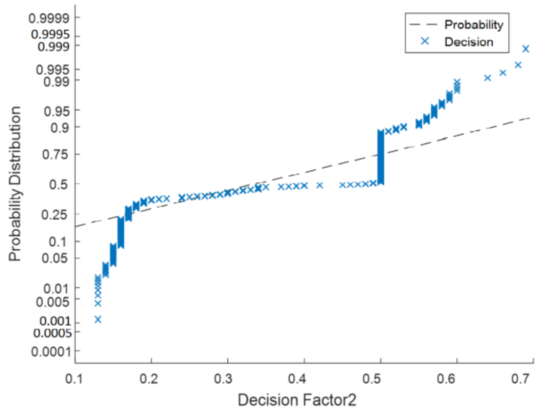

Fig -14: Probability Distribution of Neuro-Fuzzy Inference system

3. CONCLUSIONS

In conclusion, the comparative study of FLCS and NFS was achieved, which shows an improved performance when using a combination of Fuzzy and Artificial neural algorithms in the IP over MPLS VPLS networks. It is observed that the higher the number of epochs, the lower the training error. Furthermore, computed fuzzy and neuro-fuzzy-based service-aware LSPs for forwarding scheduled packets are obtained to avoid the situation of underutilization and overutilization of paths. Therefore, combined FLCS and NFS have a remarkable impact in making the decision for the selection of satisfactory service.

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