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DYNAMIC BANDWIDTH ALLOCATION IN OPTICAL NETWORKS USING MACHINE LEARNING

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Abstract

This review paper reflects the benefits of Dynamic Bandwidth Allocation (DBA), which explains bandwidth allocation in the PON (Passive optical network) network. By raising the percentage of appropriate oversubscription, a service provider can greatly increase network efficiency, which gives a way of flexibly tailoring responsiveness networks and produces more profits from their networks (FTTH) without increasing raw bandwidth. Optical networks are an ideal nominee for future-generation broadband access over the last decade. Meanwhile, machine learning has been described as a game-changer in the field of classification and prediction of bandwidth. Machine techniques can be used to improve the efficiency of Next-Generation Ethernet PONs (NG-EPONs) due to the recent developments in hardware and cloud technologies. Controlled messages are swapped between the ONU and the OLT in every cycle in NG-EPON systems to allow DBA in the upstream direction. In the upcoming years, the access network space will be dominated by the ONUs. Ethernet passive optical networks that take advantage of Ethernet's widespread availability at customer locations seem to be destined for success in the optical access network. This paper provides an overview of dynamic bandwidth allocation. This study presents a structure for categorizing DBA schemes and provides a detailed overview of the current DBA methods. The research concludes with a side-by-side analysis of the schemes based on their most salient features, as well as an overview of possible dynamic bandwidth allocation scheme improvements.

Keywords: Dynamic Bandwidth Allocation (DBA), Optical Networks (ON), Machine Learning (ML), Optical Network Units (ONU), Optical line networks (OLT), Passive Optical Networks (PON).

1. INTRODUCTION

The backbone of the telecommunication traffic has increased dramatically in recent decades. Service providers must offer additional bandwidth to their subscribers for evolving technologies like as High-Definition Television (HDTV), IP telephony, Video-on-Demand, and HD audio transmission as the Internet has grown in popularity. Despite the dramatic rise in bandwidth demands for telecommunication backbone networks, the availability of access networks has remained relatively unchanged due to the limitations of the current dominant broadband [1]. PONs (Passive Optical Networks) is appealing and promising options for providing ample bandwidth for the bottleneck in the broadband access network.

Passive optical networks (PONs) are widely used in today's operational access networks. PONs are popular because of their long lifespan, low operating costs, and large bandwidth. PONs are ATM-based systems that come in three types: ATM - asynchronous transfer mode, PON (APON), and broadband PON (BPON) [2]. Ethernet PONs (EPONs), which are regulated by the Institute of Electrical and

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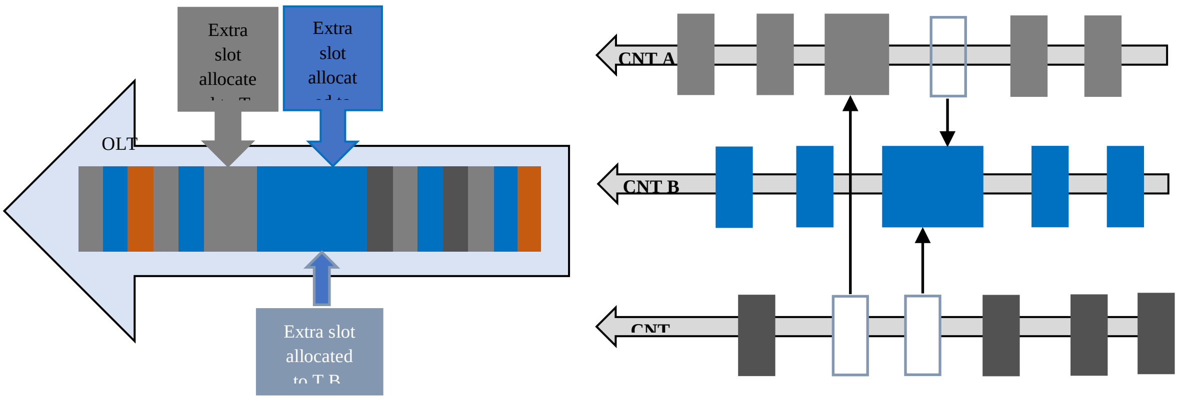
Electronics Engineers.802.3ah Ethernet in the First Mile Task Force have newly drawn a lot of attention from industry and academia. EPONs seek to merge Ethernet's low-cost equipment and simplicity with PONs' low-cost fiber infrastructure. EPONs are a promising option for providing enough bandwidth for new services like distributed gaming conferencing, video on demand, and IP telephony [3].

ML is a field of AI that allows computers capable of doing individually intelligent tasks that were previously done by humans by using advanced mathematical and statistical methods. The concept of automating complex tasks has ignited a lot of interest in the networking area, intending to offload many tasks involved in the operation and design of transmission networks to systems. This paper gives an overview of key machine learning method that is used in the rest of the paper [4,5,6]. This paper provides readers with some basic information that will aid in understanding the remainder of the paper. A broad range of problems has been successfully solved using machine learning algorithms. Before researching the various ML approaches, it is worth noting that there has been over a variety of investigate in Machine learning to wireless devices, varying from opportunistic spectrum access [7] to an approximation of channel and event processing in systems of OFDM [8], to Multiple communications in Input-Output [9] besides frequency by dynamic reuse. [10]

1. DYNAMIC BANDWIDTH ALLOCATION (DBA)

The Dynamic bandwidth allocation is divided into 2 subparts. In this paper i.e., Traditional and Machine learning approach. GPON specification offers the tools for implementing DBA, but the bandwidth allocation scheme is left up to various implementations. The Optical line networks can assign bandwidth per-ONT function using GPON methods and based on ONT demands, upstream traffic measurements, or some mixture of the two, all while considering the subscriber SLA (Service Level Agreement). The upstream bandwidth allocation is easily adjusted by a good DBA



algorithm for the Changing traffic situations. At any time of bandwidth will be assigned to unique

ONTs (or certain services). The bandwidth will be assigned to other ONTs or services during other time slots, optimizing PON bandwidth usage [11]. Figure 1

Figure 1: Dynamic Bandwidth Allocation Example

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depicts a situation in which bandwidth that is not used by ONTs A& C is provided to other ONTs that it requests for it.

3. TRADITIONAL APPROACHES FOR DBA

Data Mining

This study proposes rational data mining, Dynamic Bandwidth Allocation scheme called forecasting of data mining to address the issue (DAMA). During the polling process, DAMA includes an improved k-nearest neighbors' algorithm for forecasting the further arrivals in ONUs. During the polling process, DAMA includes an improved k-nearest neighbors' algorithm for forecasting the further arrivals in ONUs. Furthermore, a learning-based tool is developed for determining the acceptable value of neighbors to enhance the process of forecasting.

The proposed scheme appears to be capable of effectively predicting Additional bandwidth demands, as it manages to boost network capacity in terms of jitter and latency [12].

3.1 K-NN Method

K-NN methods are known for their reliability and simplicity. Also, in complex nonlinear settings, these approaches can make an accurate prediction. 'K-nearest neighbors' methods merge the observed data samples, then compare the predicted outcome for the later time frame to find the k for the most comparable time series into a provided time frame. The reason for their versatility stems from the fact that,it may contain the established neighbors'complex nonlinear patterns. This is one of the key reasons why the k-NN approach was chosen for forecasting network traffic that is complex in access networks like systems XG-PON.

1. Network Modeling

In a tree topology access network with N ONUs, XG-PON and optical line termination is considered. The network's traffic conditions are considered unsaturated. it means there is enough (upstream) bandwidth to meet all Allocation-IDs' bandwidth requirements. The number of Alloc-IDs per Optical Network Units is denoted by the set M = M1,M2,..., MN. Downstream frames are used to organize the transmission schedule, with t = 1, 2,... denoting the index of the tth (downstream) frame.

K-NN Forecasting

During the polling process, DAMA includes an improved k-nearest neighbors' algorithm for forecasting the further arrivals in ONUs. Additionally, consider T j(t) = {T j(1), T j(2), . . . , T j(t)} the time series of the consequent appearance times of the downstream form in the j ONU. In the perspective of this work, the estimating obstacle aims at estimation of the forthcoming value Oji (t + 1), 8i, j. The k-nearest neighborslook for k subsequences from Oj I (t) that are nearest to T j. (t). For selecting the neighbours, the distance (Euclidean) is used as the similarity criterion.

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If the selected set of neighbours is Oj I (l1), Oj I (l2),...,Oji (lk), the predicted value is Pji (t + 1) is calculated as follows: Pji (t + 1) = k X q=1 Oji (lq)k (1)

1. Optimal K Determination

The k-nearest neighbors' methods is sensitive to environment that is dynamic with frequent changes and is one of their major drawbacks. Input parameters such as the number of nearest neighbors, having a significant impact on forecasting accuracy. Neighbors are frequently found to be biased and those who only uses few of them have a lot of variance. The bias-variance dilemma is the name given to this phenomenon. This problem is addressed in by recommending a learning-based (adaptive) tuning tool that dynamically chooses the approx. numbers of neighbors as shown in equation (i). Let Ej I (t) = |Oj I (t) – Pj I (t)| refer to the predicted value's error rate at the t frame. Furthermore, the error rate is determined based on the expected outcome.

$$\tilde{E}_i^j(k) = \sum_{y=1,k=k_p}^{t} E_i^j\,(y)$$

3.2 Bayesian Estimation And Prediction (BEP)

The proposed BEP-DBA algorithm has three key goals: (a) use Bayesian estimation to accurately approximation of the regular inter-arrival time of packets at the ONUs, (b) use themulti-point control protocol (MPCP) for transition of the ONUs between sleep/doze and active modes just-in-time to receive packets from the OLT, and (c) Sleep and doze operations trigger queuing delays, so try to minimize them. The Bayesian estimation, MPCP control mechanism[13], and packet prediction method will all be addressed in detail in thesubsectionsbelow:

3.2.1 Bayesian Estimation Of Average Inter-Arrival Time

In BEP (probabilistic framework), the undetermined factors to be calculated and displayed as random variables. The benefits of Bayesian philosophy are that we can use prior belief to incorporate our knowledge of undetermined parameters [14]. The interarrival times of packets arrived at ONUs are modelled in our network model by an exponential distribution with parameter λ, and w ƛ e are interested in estimated the average inter-arrival time, 1/λ, using a Bayesian framework named model Random variable. If the Bayesian mean squared error is used to evaluate the estimator's performance, it can be demonstrated as the best estimate is given by the mean of the posterior distribution [15]. The estimate is revised after each amount is collected. Let us start with the estimation procedure when the first measurement, y1, arrives.The posterior p (λ $|y_1$) is proportional to the possibility p ($\lambda|y_1$) and the preceding p(λ) according to Baye's theorem:

$$p(y_1) \propto p(y_1|\lambda)p(\lambda)(1)$$

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A conjugate prior is a delivery that produces a posterior that belongs to the same family as the prior. The computations of the posterior parameters are usually simplified when a conjugate prior distribution is assumed. The likelihood function p (y1 |) for the problem under consideration sees an exponential distribution, and the Gamma distribution (GD) is familiar as the conjugate solution preceding for an exponential likelihood. By swapping a GD with of 0 and 0 parameters into the equation, this can be easily verified (1). G(;,) is a GD with a rating factor and a shape factor.

$$(y_1) \propto \left(\frac{\lambda}{y1}\right) \alpha\, p \left(\frac{y1}{\lambda}\right) G(\lambda; \alpha_0, \beta_0) \quad (2)$$

$$\propto \{\lambda exp(-\lambda_{y1})\} \left\{\frac{\beta_0^{\alpha 0}}{T(\alpha_0)} \lambda^{\alpha_0 - 1}\right\} exp(-\beta_0 \lambda) \quad (3)$$

$$\propto \alpha\lambda(\alpha_0 + 1) - 1\, exp\{-(\beta_0 + y_1)\lambda\} (4)$$

$$\propto \alpha G(\lambda; \alpha_1, \beta_1) \quad (5)$$

$$\text{where,} \alpha_1 = \alpha_0 + 1 \quad (6)$$

$$\beta_1 = \beta_0 + y_1 \quad (7)$$

λafter one measurement is given by the posterior mean, i.e., mean of *G* (*λ*; *α*1*, β*1).

$$\hat{\lambda}_1 = \frac{\alpha_1}{\beta_1} \quad (8)$$

$$= \frac{\alpha_0 + 1}{\beta_0 + y_1} \quad (9)$$

The 2nd measurement, y2, arrives, the precise procedure is followed, except that the G (λ; $\propto_{1,}, \beta_1$ 1) is now the prior distribution. The estimation procedure would easily be generalized to obtain the nth assessment after observing measurements y1, y2,...,yn. The GD's conjugate property to the exponential likelihood ensures.

$$\hat{T}_1 = \frac{1}{\hat{\lambda}_1} \quad (10)$$

$$= \frac{\beta_0 + y_1}{\alpha_0 + 1} \quad (11)$$

$$\hat{\lambda}_n = \frac{\alpha + n}{\beta + \underline{y}} \quad (12)$$

$$\hat{T}_n = \frac{\beta + \underline{y}}{\alpha + n} \quad (13)$$

where number of measurements is represented by the n, and y is the cumulative of n amounts. When the packet is being detected by an ONU through its subscriber network interface, y and n are updated. If an ordinary packet influx rate to be computed is and are selected so the mean value of the GD, i.e., like Selecting and so that the GD's standard deviation, 2, is high would make sure that the GD can handle a broad range of inter-arrival times in a realistic network. According to equation, the ONU computes the average inter-arrival time of packets Tn using these values y, n, and (13). The first experiment was run in MATLAB to show the efficacy of Bayesian estimation.

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3.3 Machine Technique-Based DBA

3.3.1 System Model

Optical line networks depicting the occupancies of its buffering queues, which represents the end-bandwidth user's demands. Therefore, using GATE messages, the OLT grants time slots to the ONUs in the later cycle; slots are sized these times according to the discipline of DBA. As shown in Figure. 3, this study suggests an ML model to calculate an ONU's bandwidth requirement minimize control messaging overhead. In this case, demands of bandwidth can be gathered in 3 ways:

1) At the end level incoming traffic stream.
2) which depicts bandwidth demands REPORT messagesprovided by the OLT during each polling period.
3) GATE messages delivered by the Optical line networks during each polling cycle, which represent indirectly ONU bandwidth demands. The last two are based on the DBA algorithm used as well as the network design and settings, as these influence the network's actions and, as a result, the bandwidth contained in the GATE and REPORT messages.

The following algorithms are used in the machine learning. techniques: KNN (K-nearest neighbors) is a method that can make accurate predictions even in complex nonlinear environments, and the BEP-DBA algorithm was used to make the predictions. As a result, the collected data is used to train the ML model, which is then again embedded and saved as a module in the predictive bandwidth allocation performed by the predictive bandwidth allocation.

3.3.2 Bandwidth Demand Prediction Using Learning Techniques.

In NG-Ethernet passive optical network, numerous linear prediction methods focused on mathematical learning need to propose the forecast Internet traffic [16].While these techniques can learn the time series' linear correlation structure, but they cannot learn nonlinear patterns. Recently, neural networks have been used to perform non-linear predictions. Neural networks have become common because of their capability to reliably approximate any non-linear or linear pattern, even though the fundamental data relationships are unknown. In comparison to previous approaches like (ARMA) Autoregressive Moving Average, Autoregressive (ARAR), and HoltWinter algorithm, the results showing that in terms of accuracy using a neural network produces better prediction outcomes.

Although Feed-Forward Neural Networks can make accurate predictions and respond quickly, they cannot manage sequence data and are confined to data within a stable-size window. RNNs, on the other hand, use previously seen feedback to

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make forecasts in the present period step, making them an excellent nominee for

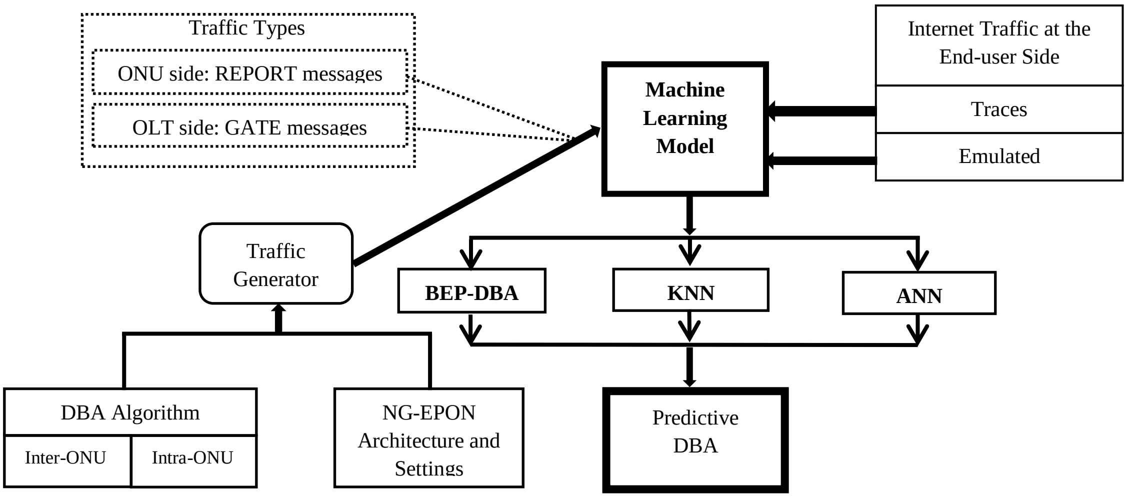

Figure 2: Machine-learning based techniques for DBA.

sequence-to-sequence prediction.

Traditional RNN models, on the other hand, suffers from vanishing and/or explosive gradient issues, restricting the RNN's ability to model enduring dependencies. As a result, LSTM networks were developed to solve the problems, and they have been shown by neural networks and conventional RNNs in several applications [17,18,19].

3.3.3 Operation Of Machine Technique-DBA

Deep-DBA's concept is used to assign bandwidth for the following cycles Q based on forecasts produced by an ML model using the previous P REPORTs, rather than making any additional REPORT messages inside cycles. As a result, a Deep-Dynamic bandwidth allocation loop usually consists of 2 sets of cycles: the cycles (reporting) {p1, p2,.., pP} and the cycles (prediction) {q1, q2..., qQ}. This paper demonstrates the process of the planned Deep-Dynamic bandwidth allocation for P = 2, Q = 8 in Fig. 3 for simplicity and generality. During reporting cycles, each ONU transmits a REPORT message demanding bandwidth based on its range of queue, as shown. Therefore, the OLT executes the DBA algorithm (i.e., TDBA) and sends a GATE messages. containing only a permit for the following cycle, depending on the planning discipline used (i.e., Gated, Limited, etc.). Optical line networks, on the other hand, keep track of past requests to anticipate future requests. As a result, when the OLT gets the message of the Pth REPORT from an ONU during the previous reporting period pP, it utilizes the P collected requests of this ONU as input to the DL model to estimate its sizes for the later Q cycles; thus, the Dynamic Bandwidth Allocation forecast time begins. That is termed as Deep-Dynamic Bandwidth Allocation.

3.4 Artificial Neural Network (Ann) Based Prediction.

3.4.1 Artificial Neural Network

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Vol: 40 Issue: 07-2021
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An ANN is a complex adaptive system that can change its internal structure in view of the information it receives. It is accomplished by adjusting the connection's weight. Each connection carries a certain amount of weight. The signal between two neurons is controlled by a weight, which is a number. To improve the outcome, the weights are adjusted using supervised leaning. This strategy entails the use of a trainer who is more intelligent than the network. A neural network's ability to adjust the network's structure and learn by adjusting the weights makes it useful in the field of AI.

3.4.2Traffic Flow In Predictive Dba

The polling cycle time increases, and the uplink packets latency at such ONU-APs increases, because of wrongly allocating additional bandwidth to them during their OFF intervals. Parameters N and M refer to ONU-APs and the number of total polling cycles, respectively. We build training sets for (16- & 32)-ONU-AP optical access networks using event-driven packet-level models. The optical access network and WLANs have data speeds of 1 Gbps and 100 Mbps, respectively. Every ONU-AP collects traffic features from 2 lakh 50 thousand polling cycles under different network loads, which are then used for supervised learning [22]. In the model, the Hurst parameter is a primary predictor of network traffic dependent on long-range and self-similarity dependence of different applications (LRD). To replicate packet bursts in WLANs, a Hurst factor of 0.8, that is, H = 0.8, was chosen, which is widely used by existing traffic profiles. The sensitivity of the qualified Artificial Neural Network is introduced, which considers a comparison with an exponential traffic model change in the Hurst factor. [23].

The ultimate design of the Artificial Neural Network is after supervised learning with the training collection, where there is one hidden state of ten neurons in adding to the layers

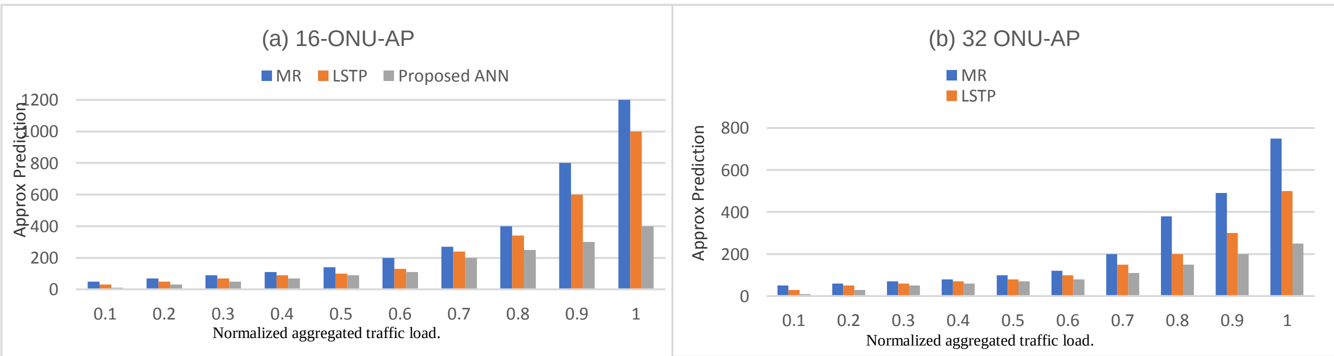

Figure 3(a)and(b): 16 and32-ONU-AP Prediction performance comparison with MR-DBA and LSTP-DBA

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(input/output). Gradient descent is used to calculate the optimal weight matrix by each layer. This structure is used as a final structure in the future investigation because forecast accuracy does not increase with more neurons and layers.

3.4.4Bandwidth Prediction

We calculate the average prediction error using (3), with the qualified Artificial Neural Network forecasting the OFF/ON status of ONU-APs and estimating BW prediction.

$$E_{avg} = \frac{1}{NM}\sum_{j=1}^{M}\sum_{i-1}^{N}\left|BW_{pred}(i.j) - a(i,j)\right|$$

Figures 3 (a), (b) show the Eavg for a 16 and 32-ONU-AP network, separately, & compare the outcomes taken with our planned ANN-based prediction system to those found with the LSTP & MR-DBA. Eavg increases with traffic load as shown in Fig. 3, and our proposed Artificial Neural Network-based prediction has the best results, particularly below hefty traffic loads. The 32-ONU-AP network's Eavg is roughly short that of the 16-ONU-AP network. When compared to the similar combined network load, this is due to the per person less traffic load ONU-AP in the 32-ONU-AP network

This research paper concludes that the ML technique and the adopted algorithm for Dynamic Bandwidth Allocation The network efficiency is increased by extra bandwidth in terms of jitter and latency by using KNN algorithm, provide decreased latency and help for Tactile Resources by using the DBA algorithm, The ONU's estimates the average inter-arrival time of the packets using Bayesian estimation (BE) by using BE and prediction based dynamic bandwidth allocation algorithm. These are some outcomes or the result in this research paper. Researchers are starting to apply the DBA issue to PONs with more than one downstream and/orupstream channel because of their work on single-channel passive optical networks. DBA for multi-wavelength passive optical networks is a large field of potential future work.

4. RESULT AND DISCUSSION

Table 1 discusses the ML technique and the adopted algorithm for Dynamic Bandwidth Allocation in which we have used the technique as algorithms KNN, ANN, BEP-DBA for the predicted Dynamic Bandwidth Allocation, and we got some better allocation after adopting these algorithms.

Table 1: Comparison of Technique and adopted algorithms for DBA allocation.

Traditional Techniques			
Authors	**Technique**	**Adopted algorithm**	**Outcome**

[20]	Data mining/KNN	KNN	• The network efficiency is increased by extra bandwidth in terms of jitter and latency. • Based on the feedback obtained, the number of k is calculated, and the predictions become accurate.
[21]	Bayesian	KNN, ANN	• Decreases both packets drop ratio and average upstream latency. • The packets' typical inter-arrival time. Making use of Bayesian estimation.
Machine Learning Techniques			
[22]	ANN		• Allocate bandwidth to satisfy low latency requirements. • Emphasized the ANN's ability to predict latency using a variety of network features.
[23]	ANN	DBA algorithm	• Provide decreased latency and help for Tactile Resources

This research paper concludes that the ML technique and the adopted algorithm for Dynamic Bandwidth Allocation The network efficiency is increased by extra bandwidth in terms of jitter and latency by using KNN algorithm, provide decreased

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