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Original Article

Optimizing Power Consumption in Converged Networks with Novel Deep Learning

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Abstract - *In the present-day world, high-speed internet demand is increasing day by day. Optical Fiber communication, which can cater to high bandwidth requirements, has a bottleneck for extending till the last mile for mobile User Equipment (UE). Converged networks, which use the combined advantage of Optical Fiber for the backbone network and wireless communication through Passive Optical Networks (PON) for the last mile, are the area of focus in this research paper. For effective utilization of available backbone bandwidth, it is essential to use Dynamic Bandwidth Allocation (DBA) techniques by the Optical Line Terminal (OLT) to allocate bandwidth to Optical Network Units (ONUs) to meet the requirements of UE devices. The growing density of UE devices demands power-saving techniques at the access network level. Significant research literature is available on the use of machine learning techniques for DBA in PON, but integration of spatial and temporal learning mechanisms is not widely explored for reducing power consumption in PON. A Hybrid dynamic bandwidth allocation technique is proposed in this work, which uses the temporal recognition capability of the Long Short-Term Memory (LSTM) algorithm and the spatial recognition capability of the Deep Q Network (DQN) Algorithm. The proposed hybrid model requires a considerably large dataset for training, which is achieved using the Generative Adversarial Network (GAN) method. The results of the proposed hybrid model are compared with the standalone Deep Q Network model, and it is verified that there is an 11% reduction in buffer occupancy at ONUs and a 20 % reduction in the Power consumption of the overall system.*

Keywords - *Converged networks, Dynamic bandwidth allocation, Deep Q Learning, Generative Adversarial Networks, Long Short-Term Memory.*

1. Introduction

In the realm of modern telecommunications, Passive Optical Networks (PONs) have become a cornerstone for high-speed, cost-effective broadband solutions. As networks continue to evolve, there is a growing demand for converged infrastructures that integrate multiple services into a unified platform. Optical fiber communication, with its superior bandwidth and transmission capabilities, plays a crucial role in enabling this transformation. To cater for the bandwidth from wired fiber to mobile end users, it is essential to establish a wireless connection. Here, Passive Optical Networks come into the picture. A PON consists of two major components: an Optical Line Terminal (OLT) and an Optical Network Unit (ONU).

A PON is a fiber-based network architecture that delivers data services using optical fiber while minimizing the need for active electronic components between the provider's central office and end users. Unlike traditional networks that require powered equipment at intermediate points, PONs rely on passive splitters, which efficiently distribute signals to multiple users. This characteristic significantly reduces power consumption and maintenance costs, making PONs an attractive choice for service providers. OLT to multiple ONUS is connected through fiber and passive splitters. ONU to end users are connected through a wireless radio link or sometimes through Local Area Network (LAN) cable or OFC. The bandwidth requirement of the ONU is dependent on the end users connected to it. Based on demand from different ONUs, the OLT must allocate bandwidth. Static bandwidth allocation techniques are not adaptive to the asymmetric bandwidth requirements of end users. Here, dynamic bandwidth allocation techniques play a role in adjusting bandwidths as per traffic demand.

Increasing UE density implies the access network (ONU) has to grow proportionally to cater to the requirement. Power consumption of access networks is a major constraint in scaling up to the bandwidth demand. Integration of spatial and temporal learning mechanisms simultaneously is not widely explored for reducing power consumption in PON in the available literature. A Hybrid dynamic bandwidth allocation technique is proposed in this work, which uses the temporal recognition capability of the Long Short-Term Memory

(LSTM) algorithm and the spatial recognition capability of the Deep Q Network (DQN) Algorithm.

Key types of PON technologies include:

Gigabit Passive Optical Network (GPON) - A widely used standard offering high-speed data transmission suitable for residential and business applications. This research paper is based on 10G GPON standards.

Ethernet Passive Optical Network (EPON) - Known for its compatibility with Ethernet-based systems, facilitating seamless integration with existing infrastructure.

Next-Generation PON (NG-PON) - An advanced version that enhances data rates and supports larger network capacities.

With the rise of converged networks, multiple communication services are integrated -such as voice, video, and data into a single network infrastructure. PONs serve as an ideal foundation for this convergence, thanks to their ability to handle diverse data traffic while maintaining high-speed, low-latency performance. Some advantages of PON in converged environments include Scalability - Easily expandable to accommodate growing bandwidth demands. Enhanced Reliability - The absence of active elements in the distribution network minimizes points of failure. Cost Efficiency - Reduced energy consumption and maintenance costs compared to traditional copper-based networks. Optical Fiber's Impact on PON Performance: The deployment of fiber-optic communication in PONs significantly improves network efficiency. Optical fibers enable long-distance, high-speed data transmission with less signal degradation. This is particularly beneficial in converged networks where consistent performance across multiple services is required. Additionally, fiber optics supports higher data capacities, ensuring future-proof solutions for emerging broadband needs.

In the evolving landscape of telecommunications, PON is important for the convergence of networks by offering a scalable, reliable, and cost-effective approach to broadband delivery. The integration of optical fiber communication further enhances the capabilities of PONs, making them a fundamental component in modern high-speed connectivity solutions. As technology advances, next-generation PON architecture will continue to shape the future of converged networks, meeting the ever-growing demands for seamless, high-performance digital communication. Optical hybrid communication is a communication system that combines several optical transmission methods to enhance performance and capabilities. It frequently involves the integration of numerous optical communication systems, such as fiber optics, both wired and wireless. A communication network that integrates optical and other transmission methods to enhance the exchange of information is commonly referred to as a converged network. This method combines optical communication with wired or wireless technologies, creating a diverse and efficient network infrastructure. Optical fiber serves as the backbone for high-speed, high-capacity data transmission across vast distances.

Fiber optics includes advantages such as reduced signal loss, resilience to electromagnetic interference, and huge bandwidth capacities. This enables consistent and effective communication between network nodes. Wireless technologies, on the other hand, come into play when wired connections are not possible or practicable, such as in mobile or remote areas where wired connections are not feasible. For transmission between network nodes, optical signals are translated into wireless signals. Free-space optics transmits data over the air using lasers or LED-based devices, enabling high-speed wireless optical communication across short to medium distances. RF wireless communication, on the other hand, uses radio waves to wirelessly send data across larger distances. The combination of optical fiber and wireless technologies in an optical hybrid network communication system offers various advantages. It permits the development of high-speed optical links whenever possible, enabling efficient and reliable data transfer. Simultaneously, wireless technologies give flexibility and mobility in regions where physical connections are difficult or impossible to establish, such as in the case of public transport vehicles. This hybrid technique provides a balanced solution that combines the benefits of optical fiber's speed and capacity with the ease and flexibility of wireless communication.

It entails combining the benefits and strengths of fiber optics with wireless communication to build a complete and effective network solution. Light signals sent over tiny strands of glass or plastic fibers allow high-speed, dependable, and secure data transfer across great distances. It has a high bandwidth and low latency, making it excellent for transporting huge volumes of data with little signal deterioration. The combination of fiber optic and wireless communication technologies is referred to as fiber-wireless integration, sometimes known as fiber-wireless convergence or FiWi. This integration allows for the smooth integration and cohabitation of both technologies, exploiting their individual benefits to improve network performance and provide a diverse set of applications. The merging of fiber and wireless can give high-speed broadband access to households, companies, and public areas. Fiber optics can be employed as the network's backbone architecture, giving high-bandwidth connectivity to wireless access points, which then wirelessly disseminate the signal to end-user devices. Fiber-wireless integration is critical for mobile network operators to meet the rising demand for mobile data traffic. To connect cellular base stations, fiber optic lines can be employed, allowing for high-capacity and low-latency backhaul connections. This guarantees that data is sent efficiently between mobile devices and the main network. Fiber-wireless integration is critical to the development of smart cities. Fiber optics is the foundation for a range of smart city applications, like intelligent transportation systems, smart grid networks, environmental monitoring, and public safety. Wireless connection supplements fiber optics by giving IoT devices, sensors, and end-user devices flexible and extensive access.

The convergence of fiber and wireless speeds up the deployment of IoT devices and systems. Fiber optic networks can support the large volumes of generated data by IoT devices, whilst wireless connection provides the mobility and flexibility necessary for IoT applications. This combination enables an extended range of IoT use cases, like industrial automation, asset tracking, smart agriculture, and healthcare monitoring. The merging of fiber with wireless allows for the establishment of resilient and scalable wireless mesh networks. Mesh networks may be used for disaster recovery, outdoor events, and rural connections. By employing fiber optic connections to deliver signals throughout buildings, fiber-wireless integration can increase indoor wireless coverage. Fiber-To-The-distribution-point (FTTdp) designs can provide high-speed connections to a distribution point, from which wireless access points can be placed to guarantee robust and stable wireless coverage throughout the premises. Wireless signal strength decreases as the distance from the transmitter rises. This can be a problem in fiber-wireless integration since it limits the wireless network’s range. In the existing literature, it is identified that DBA techniques are discussed for various applications, but relatively less focus has been placed on PON applications. Delays in data transmission between the two networks (wired and wireless) are challenging. Also, there is a need to enhance power efficiency as multiple PON devices need to be deployed over a wide area. Moreover, we need to improve the extended fiber connectivity and enhance security and scalability. However, strategies are used to improve optical hybrid communication in the enhancement of fiber wireless integration using proposed Machine Learning (ML) techniques.

ONUs smooth the interface between users and the network by changing the optical pulses into electrical signals for Ethernet cables or radio signals for wireless connection to UEs. They are typically placed at the client’s location. OLTs located at the Central Office (CO) manage multiple ONUs. They aggregate and groom traffic to ensure optimal throughput. Traffic requirements in the network keep changing with time, and the same need to be captured temporally with time stamps; this requirement is generally not taken care of while using Reinforced Learning techniques discussed in the majority of the literature. Deep Neural Networks (DNNs) are used in the proposed model. Weights and biases are adjusted such that the amount of influence of a particular neuron is controlled based on feedback from the predicted output of the DNN. In the proposed model, at each stage, two hidden layers are used. The LSTM stage is useful for capturing the temporal aspect of traffic and predicting future long-term traffic with special attention to important short-term traffic demands. The GAN stage will be useful for simulating diverse traffic conditions and patterns. This stage makes the model more robust with an enhanced data set for training the model. Deep Q Network stage makes use of the Q look-up table principle. While a Q table is generally used for a small discrete state space, DQN is used for a large state space. This stage requires extensive training to make the model robust.

Some of the important concepts that are used in the proposed model are discussed below.

1.1. Activation Function

The activation function will determine the output of a neuron; it is a mathematical function that determines whether a specific neuron should be activated based on input. Choosing the right activation function is important to make the learning model effective in neural networks. Activation functions used at different stages of the proposed model are summarized in Table 1.

Table 1. Activation functions used in the proposed model

Component	Layer type	Activation
GAN (Generator)	Hidden	Leaky ReLU
	Output	Sigmoid
GAN (Discriminator)	Hidden	Leaky ReLU
	Output	sigmoid
DQN	Hidden	ReLU
	Output	Linear
LSTM	Hidden	Sigmoid
	Output	ReLU

ReLU activation is particularly chosen to avoid negative bandwidth predictions. The sigmoid activation function is useful for normalizing the range between 0 and 1.

1.2. Buffer Size at ONUs

Buffer at ONUs is used to collect and store packets received from End User (EU) devices. The EU packets are accumulated in the buffer until the window for uplink transmission is opened by the OLT for that ONU. Most of the existing literature is focused on static size ONU buffers, but in this article, variable buffer sizes are considered at ONUs based on the traffic demand at respective ONUs.

The time between a packet (from EU) arriving at the buffer of ONU and the time at which that packet leaves the ONU buffer is considered latency at the ONU. If the buffer size is too large, end-user packets are processed without loss, but latency increases, whereas if the buffer size is too small, end-user packets will be lost. A Buffer size of 2Mb with 20% variation as per traffic requirement is considered at ONUs in the proposed model.

1.3. Q Table

The rewards for various actions at different states are updated from time to time in the Q Table. Based on the rewards in the Q Table, the Reinforcement learning model will make the decision.

In this case, the decision is bandwidth allocation to ONUs as per traffic demand. It basically works as a look-up table from which the next step can be taken among a set of available options.

Initially, bandwidth allocated to ONUs is decided randomly and through the Epsilon Greedy strategy, the model keeps learning the best possible decision in each scenario.

1.4. Optimizers

In a Neural network, weights and biases need to be optimized in such a way that the difference between the predicted output of the model and the actual output is minimum. Some of the prominent optimization techniques are presented in Table 2 below, elaborating their advantages and disadvantages. This knowledge is used to select the appropriate optimization technique for the presented model. Optimizers play an important part in defining convergence time to global minima. Optimizers are mathematically defined algorithms that are iteratively adjusted to reduce the loss function to a minimum. Usage of optimizers changes with respect to the nature of the application. The learning rate decides the speed of optimizing the solution.

Table 2. Prominent optimization techniques

Optimization Technique	Advantages	Disadvantages	Suitable Applications
Gradient Descent	Efficient for large data sets. Simple and widely used	Possibility of getting stuck in local minima and not suitable for multiple minima	Small-scale machine learning tasks; Convex optimization problems
Exponentially Weighted Moving Average (EWMA)	Smooths noisy gradients; Helps stabilize updates	Can lag behind actual values; Requires tuning decay factor	Applications to find trends in time series-based data
Momentum	Accelerates convergence; Reduces oscillations in non-convex functions	Can overshoot the optimum due to its velocity	Image and speech recognition
Nesterov Accelerated Gradient (NAG)	More accurate updates than momentum, as the gradient is calculated for the next step	Dampens oscillations, which can limit them to local minima	Applications that enable computers to interpret and understand visual data
Adaptive Gradient (ADAGRAD)	Learning rate is adaptively controlled	Learning rate diminishes over time, leading to slow convergence	Natural Language Processing Applications (NLPs)
Root Mean Square Prop (RMS Prop)	Recent Gradients are given more weight than older ones	Requires hyperparameter tuning	RNNs, LSTMs; Speech and text processing
Adaptive Moment Estimation (ADAM)	Combines the advantages of Momentum and RMSProp; Adaptive learning rates; Works well in practice	Can converge to bad local minima; Sensitive to parameter tuning	General deep learning applications: CNNs, RNNs, reinforcement learning

Through proper usage of dynamic resource allocation during real-time, traffic fluctuations in the network can be captured. Operators can efficiently optimize resource usage while maintaining QoS for critical services. Some parameters of QoS, such as packet loss, jitter, and delay, must be regulated to a certain level to ensure uninterrupted services. Through adaptive traffic control, adaptive bandwidth allocation is accomplished. Future changes in network requirements will rely upon the collaboration between ONUs, OLTs, Adaptive Bandwidth Allocation, QoS, and throughput responsive networks to meet the performance demands of converged networks. With the application of these technologies, network providers can optimize user satisfaction and increase the adoption of services that use high bandwidth.

Advanced data techniques, like predictive analytics, which enable assessment of traffic patterns, area congestion bottlenecks, and resource allocation in advance, can significantly enhance data transfer rates within Optical Network Units (ONUs). The Discount Factor will give an idea of the agent’s consideration for future rewards with respect to immediate rewards. Discount factor, also known as Gamma, often remains between 0.9 and 0.99 and utilize the assessment of value judgment of the weighted future benefits vs rewards. The gamma factor measures the importance of current rewards versus delayed ones. Discounting factors place more importance on future long-term rewards with selections nearer to 0 and short-term rewards with selections nearer to 1. In this work, a discount factor of 0.9 is considered for the DQN stage. This is ideal for faster convergence to global minima.

The type of technology used usually influences measurement metrics. Varying from 1 Gbps to 10 Gbps, higher data speeds may be offered by business-grade ONUs depending on bandwidth and Quality of Service (QoS) requirements. Among the services they support are high-speed internet, VoIP, and video conferencing. The data rate may decrease due to signal attenuation as the distance from the Central office increases. The architecture of the network, with the location of splitters, also has an impact on data rate. Both ONUs and OLTs are necessary to determine the data rate of a passive optical network. While ONU is responsible for providing services to end users, OLT manages and aggregates traffic for multiple ONUs. The data rates of these components depend on the configuration and specific hardware characteristics. To provide faster and more reliable internet access, the data rate is influenced by several factors, such as fibre quality and the distance of the ONU from the OLT, network congestion, and optical signal strength.

2. Discussion on the Available Literature Pertaining to the Research Topic

In the discussion literature, we have covered the earlier works which focused on (i) energy saving in PON networks and Fiber Wireless (FiWi) networks and (ii) Various machine learning techniques used in FiWi networks for improvement of overall PON system efficiency. In this paper, the authors use FiWi networks and converged networks interchangeably. Earlier work by the same authors of this paper studied the bandwidth prediction performance of a Deep Q Network (DQN) based DBA model, which is trained with the help of an enhanced data set generated through the GAN method. It has been identified that there has been a considerable improvement in data rate and a reduction in latency due to the incorporation of GAN. With the help of Forward Error Correction (FEC), the bandwidth prediction of OLT is improved further, which in turn improves throughput, but the variable bandwidth requirements of ONUs lead to inconsistent buffer utilization.

The inconsistent buffer utilization at ONUs leads to an increase in jitter. The present work is focused on reducing the jitters and conserving the energy of the PON network. An extensive study of the evolution of energy conservation in PON was presented by Shah Newaz and the team [1]. Various energy saving approaches in PON are elaborated, which include a) Sleep mode, b) Adaptive link rate control, c) Dynamic ONU buffer size, d) wavelength reuse at ONUs and e) Energy-enabled orchestration & virtualization. The Analyzis suggested that sleep mode-based approaches may face challenges in future requirements of 6G networks, hence suggested researching on the virtualization of PON, especially the OLT network, to improve energy saving. A Unified Dynamic Bandwidth Allocation Scheme (UDBAS) is proposed by Manjur Kolhar et al. It incorporates a Service Level Agreement (SLA) verifier and a decision-making agent to monitor and manage users exceeding bandwidth limits, ensuring SLA compliance. The queue size at respective ONUs is regularly monitored by the SLA verifying agent and proactively allocated bandwidth to privileged users [2]. Various PON standardization efforts made by ITU-T Q2/15 from the early 1990s till recently are elaborated by Jun Shan Wey. Emerging PON standards and the driving factor for such standardization, i.e. bandwidth requirement and Power efficiency, are discussed [3].

Pegcheng Li and colleagues have proposed a Bandwidth Prediction Based Resource Allocation (BPSTA) scheme, where patterns in the traffic based on time stamps are identified, and with the help of such patterns, allocations are made to ONUs for the next cycle. BPTSA also decides the starting time at which ONU can transmit to OLT and vice versa, which helps in extending the available sleeping time of ONUs [4]. Yapeng Xie and colleagues have provided reviews of Machine Learning (ML) applications for optical communication within a distance of 100km. ML techniques useful for Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) and Auto encoders for short-reach optical communication were elaborately discussed [5]. Ganesh and team have identified [6] that the approximate power consumption for a 2MB buffer at ONU is 1.29W. Ways are proposed to run the network at an acceptable performance level even with buffer reduction [6]. Buffer reduction was proposed using three strategies: (i) zero buffers, (ii) node proportional buffers, and (iii) OLT-ONU rate proportional buffers. A proportional buffer strategy was used in the present work as well. Sandra Arnaout and team have transformed the problem of best possible utilization of bandwidth and wavelength into an Integer Linear Programming (ILP) problem.

Transmission Containers (TCONS) were deployed in ONU to optimize bandwidth distribution among ONUs. To solve the optimization problem of ILP, a branch and bound (BB) algorithm is proposed [7]. A method called Gated Recurrent Unit (GRU) was proposed by Shiwen Song et al. This method aggregates PON OLTs into virtual resources. The traffic of the factory network is divided into layers/slices based on bandwidth requirement, and ONU resources are allocated in slices, which is identified to improve data rate and reduce latency [8]. Lihua Ruan and team proposed a Reward Variance Oriented (RVO) exploration strategy where Bandwidth decisions made by the Central Office (CO) are proportional to reward variance. Their work explored how rapidly models can learn an optimal bandwidth decision for minimizing optical access network latency [9]. Alaelddin Mohamm et al introduced a novel Dynamic Bandwidth Allocation system that proactively allocates bandwidth for Federated Learning. It will show the benefits of multiple grants due to improved capacity for implementing PON in implementing FL flows. Unlike the case of traditional DBA, where delay increases with increasing units, the proposed model utilizes the resources effectively by segregating federal traffic and regular traffic by using multiple grants for better Utilization [10]. Garima and team reviewed existing DBA schemes for XG PON systems. They proposed a method with four TCONS that are used to maintain four different queues at ONUs for four categories of services in order of priority. Service Interval (SI) and Allocation Bandwidth (AB) are parameters that are used to characterize TCONs. Scheduling of TCONs is improved using an ML Algorithm [11].

Priyanka Singh and the team discussed the Stochastic Optimization Algorithm for a novel backup Optical Network Unit (ONU) architecture. By reducing the average distance between backup ONU-AP and the end users, the Location of backup ONU-AP is optimized, thereby improved the bandwidth availability for end user devices and reducing the power consumption of the overall system [12]. Huayn Zhu et Al discussed a Deep Reinforcement Learning (DRL) method that will convert scheduling problems with multiple resources into one learning target to learn effective strategies on its own [13]. This work is relevant to the PON traffic data set, where multiple factors such as distance from OLT to ONU, buffer sizes at ONUs, variable traffic at different ONUs are multiple resources based on which a single learning target of bandwidth allocation is to be achieved.

Addallah Shami and team have worked on jitter reduction in PON networks through three proposed strategies, i.e. (a) Expedited Forwarding for high priority traffic, (b) Assured Forwarding for medium priority traffic, and (c) Best effort forwarding for low priority traffic [14]. Also, the general ONU bandwidth allocation strategy of Grant after Report (GAR) is replaced with Grant Before Report (GBR), thereby helping the dynamic allocation of bandwidth. The Authors proposed a vanilla-RNN-based algorithm to predict the unutilized time of RNUs in 25G NGEPON networks [15]. Based on the predicted unutilized time, the ONUs were put into sleep mode, thereby reducing their energy consumption. The [16] Zhiyong Du and team have proposed Reinforcement learning for context-aware network selection in Heterogeneous traffic of LTE, WLAN and VLC using knowledge transfer. Knowledge Transfer here refers to predicting location-based traffic patterns and using that to identify network selection [17].

Shafiqur Rahman et Al discussed Deep reinforcement learning for optimal offloading of computation to the cloud by End-User Devices (EUD). The essential idea of the proposal is to have a DRL controller that autonomously determines if a generated task of computation can be executed on a local device, offloaded to a fog access point, or assigned to a cloud server for processing. This computation offloading will, in turn, offload the power consumption at the end-user device. [18].This analysis can be further explored to find the possibility of offloading computation at ONUs to the cloud to reduce power consumption at ONUs. Gyungmin Kim et Al proposed Deep Reinforcement Learning based routing optimization on Software Defined Network [19], the DRL agent learns interdependency between the traffic load of network switches and network performance. Federico Celi et Al explored a Strategy to directly learn control action without building a system Model in a distributed controller network using Reinforcement Learning [20]. Claudio Savaglio and colleagues discussed about Reinforcement Learning, which is used to identify the sleep and wake-up schedule of nodes communicating through Media Access Control (MAC) address [21]. Mostafa Zaman Chowdhury et al [22] studied the features of Optical Wireless Communication (OWC) and RF and observed that they are complementary; a combination of usage is viewed as a potential method to support LTE, 5G and future generation communication systems.

Hybrid RF/optical and optical/optical wireless systems provide an ideal alternative for overcoming the limits of separate systems while still delivering the benefits of each technology. An RF/optical wireless hybrid system is made up of both RF and optical-based wireless technologies, whereas an optical/optical wireless hybrid system is made up of two or more types of OWC technologies. Wireless system co-deployment can increase system performance in terms of throughput, dependability, and energy efficiency of separate networks. Xiang Liu et al [23] proposed an intelligent nonlinear compensation method for an End-To-End (E2E) fiber-wireless integrated system using a Stacked Autoencoder (SAE) model in conjunction with Principal Component Analysis (PCA) technology coupled with an ANN. The nonlinear constellation designed for SAE is used to reduce nonlinearity throughout the optical and electrical conversion processes.

The proposed BiLSTM-ANN equalizer is largely focused on temporal memory and information extraction properties, which compensate for residual nonlinear redundancy. At 92.5 GHz, a low-complexity 50 Gbps E2E-optimized nonlinear 32 QAM signal is successfully delivered via a 20 km Standard Single-Mode Fiber (SSMF) and 6 m wireless connection. BiLSTM analysis in this paper has motivated us to explore the possibility of developing a hybrid DBA model that can capture temporal traffic aspects.

Through the above literature survey, it is identified that a wide focus was not given to using temporal and spatial traffic recognition methods simultaneously. There is scope for improving the efficiency of DBA in PON networks using time-based events and capturing traffic, i.e., through LSTM together with DQN, which captures the spatial traffic pattern. The hybrid model is trained using large datasets developed with the help of a GAN module. Delay due to computational complexity is taken care of using a sliding window section, which will help stabilize the trained model.

3. Methodology Implemented

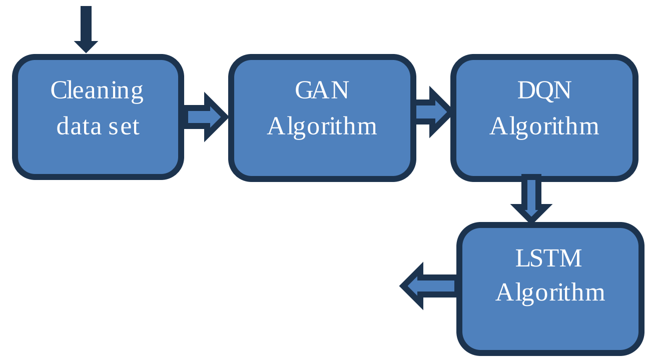

Fig. 1 Block diagram of proposed model

In this research, we propose an intelligent Dynamic Bandwidth Allocation (DBA) scheme for Passive Optical Networks (PONs), leveraging a hybrid GAN-DQN-LSTM model to predict bandwidth demands and optimize resource allocation. Through the proposed model, the prediction of idle time for ONUs is captured. Based on the idle time of ONUs, sleep cycles are allocated, thereby saving power consumption at ONUs. The primary goal is to reduce jitter, buffer occupancy, and power consumption at Optical Network Units (ONUs) and the Optical Line Terminal (OLT), compared to conventional standalone DQN-based DBA methods.

3.1. System Overview

The methodology integrates three key components:

1. Generative Adversarial Network (GAN): Utilized to generate synthetic traffic data that mimics realistic network traffic patterns. This helps in expanding the training dataset for more robust learning and prediction by the model.
2. Deep Q-Network (DQN): Functions as a reinforcement learning agent that makes bandwidth allocation decisions based on the current network state and predicted traffic demands.
3. Long Short-Term Memory (LSTM): A Recurrent Neural Network (RNN) component that processes sequential traffic data to forecast near-future traffic loads accurately.

3.2. Block Diagram Description

Stages of the GAN-DQN-LSTM model are:

1. Traffic Input Layer: A 10G GPON architecture of one OLT and 8 ONUs is considered for simplicity. The traffic data set is generated using the Python sympy library and fine-tuned using a subsequent GAN stage. Generated PON traffic is fed into the input layer.
   The traffic parameters considered for the bandwidth allocation decision of the proposed model:
   i) ONU ID
   ii) Time Stamp
   iii) Packet Arrival rate
   iv) Average packet size
   v) Total data arrival
   vi) Buffer occupancy at ONU
   vii) Service Type (Voice, data, video)
   viii) Grant size from ONU
   ix) Round-trip time
   x) Distance between OLT and ONU (limited to 2km maximum for ease of computation)
2. GAN Module: The Generator works to generate realistic traffic data, which is cross-checked and validated by the discriminator component. Final validated traffic is augmented by this module, which helps in robust training of the proposed model.
3. DQN Decision Engine: Receives the augmented traffic as input and selects the optimal action (e.g., active or sleep state, bandwidth allocation) based on a learned policy.
4. LSTM Predictor: Processes the enriched traffic dataset to predict future bandwidth demands at each ONU. Time-varying characteristics of traffic are captured at this stage and used to predict future traffic requirements for each ONU.
5. Action Execution Layer: Implements the selected action, adjusting ONU/OLT states and bandwidth allocations accordingly.
6. Feedback Loop: Network metrics (e.g., buffer level, delay) are fed back into the system to refine learning over time.

At each stage of GAN, DQN and LSTM, two numbers of hidden layers are considered. Neurons at each stage of the model are defined as in Table 3.

Table 3. Number of neurons at hidden layers

Stage of Model	Hidden Layer 1 Neurons	Hidden Layer 2 Neurons
GAN (Generator)	128	128
GAN (Discriminator)	128	128
DQN	128	64
LSTM	64	32

Optimizers deployed at different stages of the presented model are shown in Table 4.

Table 4. Optimizers employed at three stages of the model

GAN (For Generator & Discriminator)	ADAM
DQN	RMS Prop
LSTM	ADAM

3.3. Sliding Window Section

By making use of three sections, i.e GAN, DQN and LSTM, the accuracy of predicting bandwidth demand of ONUs has increased, which is reflected in the reduction of jitter. Due to the computational complexity involved in the three stages of the proposed model, the convergence time of the model will also increase. The improvement in accuracy achieved in terms of bandwidth prediction will be at the cost of increasing latency due to computational complexity. A sliding window buffer is used to maintain bandwidth prediction accuracy without increasing latency. In the sliding window, the generated traffic is fed as input. The sliding window buffer is programmed such that the generated traffic, which is an epoch behind the live traffic, is considered as input for predicting the bandwidth requirement. As the traffic of the previous epoch is used, the delay of capturing live traffic and using it for model preparation is avoided. After 100 epochs, the system is found to attain convergence. The changes in the trained model after convergence time are minimal, hence the buffer occupancy at ONUs is also improved.

4. Mathematical Model

4.1. GAN Function

4.1.1. Generator $G(z;\ \theta_G)$

This will generate artificial traffic imitating actual ONU traffic.

$$x_{gen} = G(z;\ \theta_G), z \sim p_z(z) \quad (1)$$

Here z is random noise,

θ_G is the generator parameters, i.e weights and biases.

$p_z(z)$ is a Gaussian probability distribution from which the generator samples noise

4.1.2. Discriminator $D\ (x;\ \theta_D)$:

This will differentiate between original ONU traffic samples and generator samples

$$D(x;\theta_D) = P(x\ is\ real\,|\theta_D) \quad (2)$$

Here

x = input sample (could be real ONU traffic or generated traffic samples)

θ_D is the discriminator parameters, i.e weights and biases

4.1.3. Loss Function for Discriminator (L_D)

$$L_D = -E_{x\sim P_{data}(x)} log\ D(x) - E_{z\sim P_z(Z)} log(1 - D(G(z))) \quad (3)$$

Here $D(x)$ is the probability that the discriminator assigns to a real traffic being real (should be close to 1)

$D(G(z))$ is the probability that the discriminator assigns a fake sample as real (generated samples should be close to 0)

$E_{x\sim P_{data}(x)}$ is the expected value over a real data sample

$E_{z\sim P_z(Z)}$ is the expected value over noise input z, used as input to the generator.

DQN Function

Based on the traffic requirement of the ONU, the DQN agent allocated bandwidth dynamically.

State Space

$$S_t = \{Q_i(t), D_i(t), B_i(t)\}\ i = 1\ to\ 8 \quad (4)$$

Here

$Q_i(t)$ = Queue length for ONU i at time t

$D_i(t)$ = Traffic requirement for ONU i at t

$B_i(t)$ = bandwidth allocated to ONU i at t

Action Space A_t

$$A_t = \{B_i(t+1)|B_i(t+1)\epsilon\{B_{min}, B_{max}\}\} \quad (5)$$

Reward Function R_t:

It works such that delay, jitter and packet loss are minimized

$$R_t = -(\alpha J_t + \beta D_t + \gamma P_t) \quad (6)$$

Here

J_t = jitter at time t

D_t = delay at time t

P_t = Packet loss at time t

Α, β,γ are weights

Bellman equation for Q-value update: $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \eta(R_t + \gamma\ maxQ(S_{t+1}, A') - Q(S_t, A_t))$

Here $\eta = Learning\ rate, \gamma = Discount\ factor$

LSTM Function

Long-term dependencies of ONU traffic are captured by this function, and future bandwidth demands are predicted.

Demands of past traffic for ONU i are given by,

$$X_i = \{D_i(t-3), D_i(t-2), D_i(t-1), D_i(t)\} \quad (7)$$

Based on the above input, the predicted bandwidth at t+1:

$$Ɗ(t+1) = f_{LSTM}(X_i) \quad (8)$$

Loss function of LSTM:

It is given by the mean squared error,

$$L = 1/N\Sigma_{i=1}^{N}\left(D_i(t+1) - Ɗ(t+1)\right)^2 \quad (9)$$

Sliding Window Function

Sliding window predicts bandwidth demand based on past N time steps:

$$Y_t = f(X_t) = f(X_{t-W}, X_{t-W+1}, \ldots, X_{t-1}) \quad (10)$$

Here, f is a learned function of the GAN-DQN-LSTM Model

Sliding Window update:

$$X_{t+1} = (X_{t-W+1}, X_{t-W+2}, \ldots, X_t) \quad (11)$$

Predicted bandwidth will be:

$$Y_{t+1} = f(X_{t+1}) \tag{12}$$

By this, the model will continuously predict future bandwidth requirements without waiting for a live traffic update.

Loss function for convergence:

$$L = 1/N\Sigma_{t=1}^{N}(Y_t - \bar{y}_t)^2 \tag{13}$$

Here
Y_t= bandwidth actually used at time t
$\bar{y}_t$= bandwidth predicted using the model
L= Model minimizes the Mean Square Error (MSE) over time

$$\bar{y}_t = f((X_{t-W}, X_{t-W+1}, \dots, X_{t-1}) + \epsilon \tag{14}$$

Here ϵ represents the error in prediction, which reduces over the convergence of the model.

Algorithmic Steps

1. Initializing parameters:
   - Initialize parameters of GAN, DQN, and LSTM.
   - Learning rate α and discount factor γ are to be set.
2. Training:
   - Use GAN to generate synthetic traffic data.
   - Use predicted traffic as input to DQN to train optimal action policies.
   - Train an LSTM on real and GAN-generated data to predict
     $D(t+1) = f_{LSTM}(X_i)$. now
     $D(t+1)$ is the predicted bandwidth demand at time t+1 for a given ONU.
     f_{LSTM} is a trained LSTM model.
     X_i is the input feature vector.
3. Simulation Execution:
   - At each time step, LSTM predicts traffic.
   - DQN selects action: sleep or active state for ONUs; allocates bandwidth.
   - Update power usage and buffer status.
   - Record metrics: jitter, buffer occupancy, and power.
4. Feedback and Learning:
   - Adjust GAN and DQN parameters (weights and biases) based on performance metrics.
   - Reinforce actions leading to lower jitter and energy consumption.

Simulation & Integration parameters

The methodology was validated using SimPy-based simulations. Eight ONUs and one OLT were modelled, with ONUs generating traffic between 0.5 and 5 Mbps. The baseline standalone DQN model will keep ONUs always active, while the proposed GAN-DQN-LSTM scheme allows ONUs to enter low-power sleep states during low predicted traffic.

Power consumption was calculated using realistic wattage ratings for transmission (4 watts), reception (4 watts), and idle states (1.5 watts). The ONU buffer size is considered to be 2 Mb with a variation of 20% based on traffic demand at the respective ONU.

In the proposed novel model, blocks of Generative Adversarial Network (GAN), Deep Q Learning (DQN) and Long Short-Term Memory (LSTM) are used with specific customizations through layers of neurons, optimization techniques and activation functions as discussed to improve the prediction of bandwidth requirement for ONUs.

5. Results and Discussion

The results show that the proposed novel model of GAN-DQN-LSTM has a combined advantage over Generative Adversarial Networks (GANs) and Long Short-Term Memory (LSTM). GAN helps improve the data set quality and train the model exhaustively.

GANs can model complex traffic patterns and generate realistic future traffic scenarios. The LSTM algorithm can capture the temporal features of traffic. Long Short-Term Memory (LSTM) networks are well-suited for sequential data and can capture long-term dependencies in traffic flows.

This simulation uses SimPy for event-driven simulation and matplotlib for plotting. Based on the results, it is identified that the proposed novel model has better Jitter performance than the traditional RL model. From the results, it is observed that there is an average improvement of 1ms in jitter performance with the proposed DBA scheme. The lower jitter performance indicates consistent packet delivery times, which in turn is essential for latency-sensitive applications like video traffic and gaming.

Hence, the proposed DBA scheme provides better QoS. The improvement in the jitter implied that the scheme proposed is more responsive and adaptive to traffic demands. The proposed scheme reduces traffic delays and re-transmission, which are contributors to jitters.

From Figure 2, it is observed that there is a 1ms reduction in jitters. A 1ms jitter reduction improves the predictability of network performance, which is especially important in multi-user environments or when scaling the network. In terms of percentage, this converts to an improvement of jitter by 21% with the proposed novel model. In real-world deployments, ISPs and network operators could leverage this improvement as a selling point for better Service-Level Agreements (SLAs).

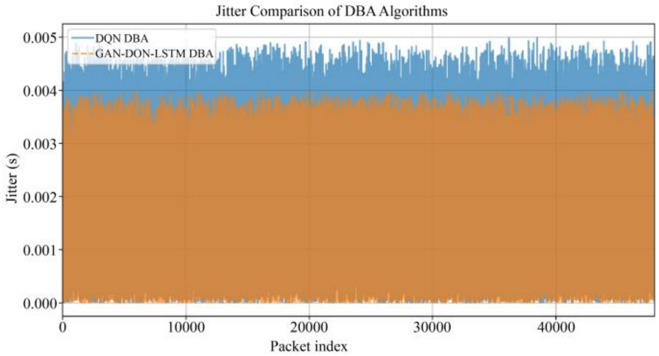

Fig. 2 Jitter comparison graph

OLT buffer occupancy is reduced by 59% using the proposed model in comparison with the traditional DQN model, as evident from Figure 3.

The buffer occupancy at ONUs has been reduced by 500 packets in the case of the proposed model as compared to traditional DQN, as visible in Figure 4. This is evidenced by its 10.98% improvement in buffer occupancy reduction.

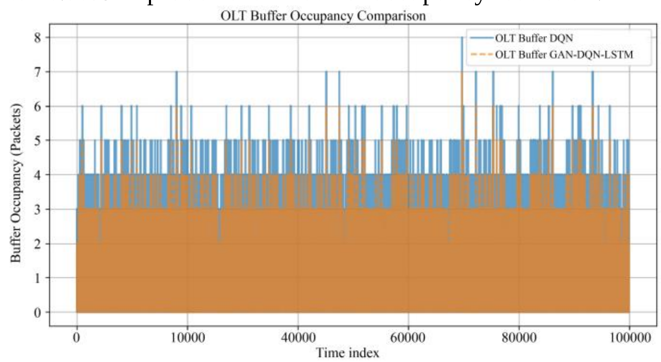

Fig. 3 Comparison of OLT buffer occupancy

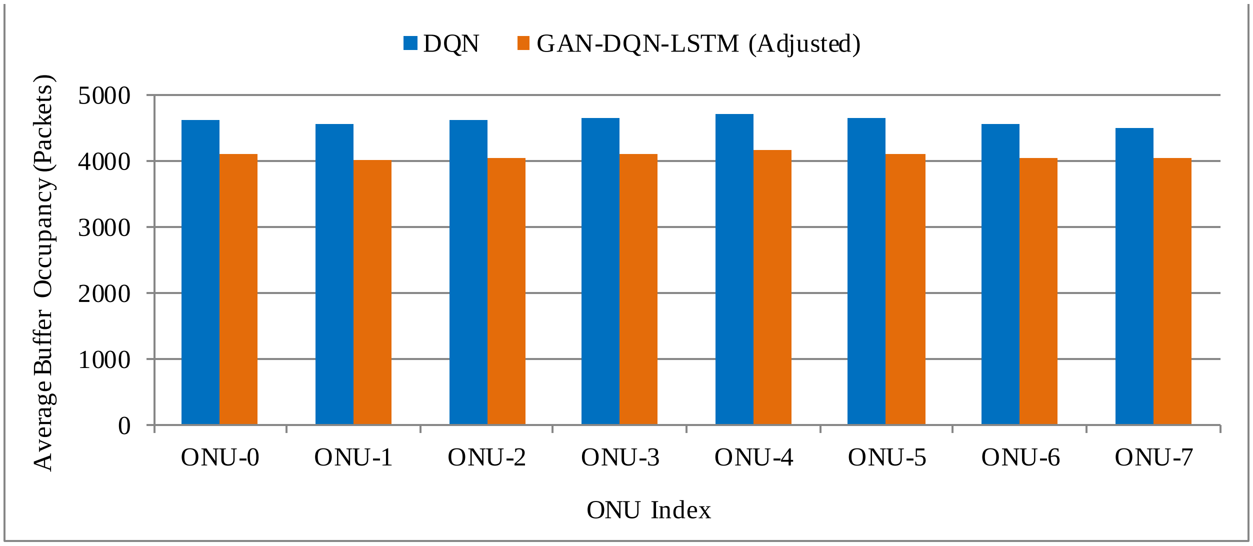

Fig. 4 Comparison of ONU buffer occupancy

Improvement in Power Consumption:

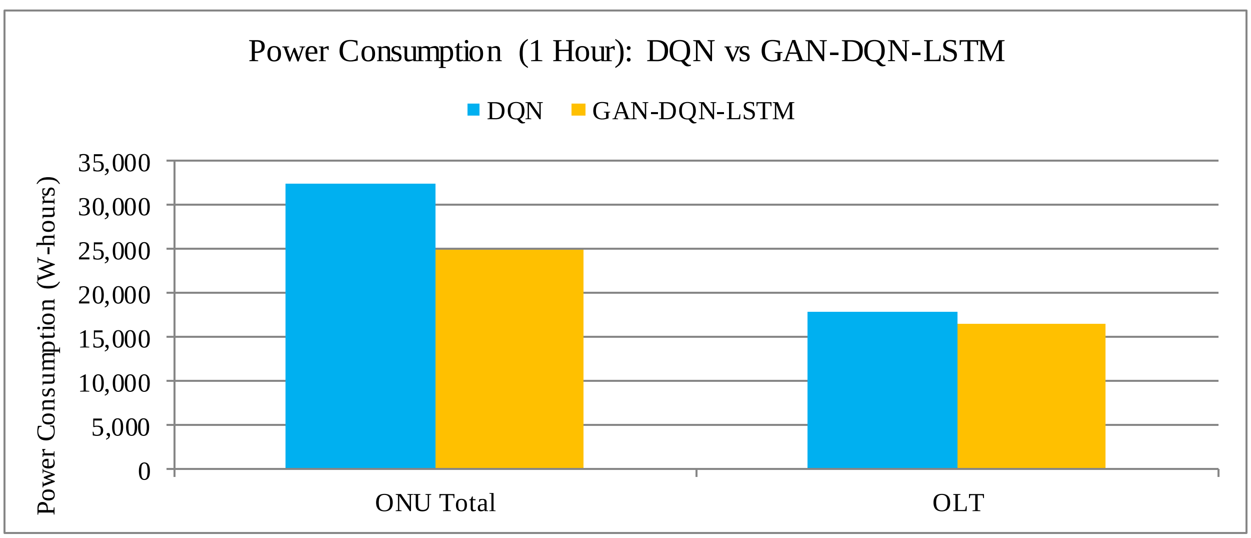

Fig. 5 Comparison of power consumption

Figure 5 illustrates the comparative power consumption between two bandwidth allocation models - the conventional DQN-based approach and the proposed GAN-DQN-LSTM model - over a simulated period of one hour. The measurements account for total power usage by both Optical Network Units (ONUs) and the Optical Line Terminal (OLT), presented in Watt-Hours (Wh).

The results demonstrate a clear energy efficiency advantage of the GAN-DQN-LSTM model. Specifically, the ONUs operating under the DQN scheme consumed approximately 32,000 Wh, while those using the proposed model recorded a reduced consumption of 25,000 Wh, signifying an energy saving of over 20%. This reduction is attributed to the dynamic sleep mechanism in the GAN-DQN-LSTM design, which allows ONUs to enter low-power sleep states during periods of predicted low traffic.

Similarly, at the OLT level, power consumption dropped from approximately 18,000 Wh under the DQN model to around 16,000 Wh using the GAN-DQN-LSTM approach. Although the OLT typically remains active due to its central role in data distribution, the reduced upstream and downstream traffic resulting from efficient ONU activity contributed to lower transmission and reception power demands.

Overall, these findings validate the effectiveness of integrating predictive intelligence into bandwidth allocation strategies, yielding substantial improvements in energy efficiency at both the ONU and OLT levels. The reduction in power usage not only benefits network operators through lower operational costs but also supports sustainability goals by minimizing energy footprints.

5.1. Discussion

The improvement in results compared to the existing state-of-the-art standalone DQN system is possible because the proposed hybrid model captures both temporal and spatial patterns of network traffic. In contrast, the existing standalone DQN models could not capture intricate spatial and temporal traffic patterns simultaneously. Also, the extensive data set required for training a computationally complex hybrid model is achieved using a GAN module.

6. Conclusion

The performance evaluation of the proposed GAN-DQN-LSTM Dynamic Bandwidth Allocation (DBA) framework demonstrates notable enhancements across critical network performance metrics when compared to the traditional DQN-based scheme. Through extensive simulation, three key improvements were observed: jitter minimization, buffer occupancy reduction, and significant power savings.

Firstly, the integration of Generative Adversarial Networks (GANs) and Long Short-Term Memory (LSTM) networks enables highly accurate traffic prediction, allowing the DBA mechanism to anticipate bandwidth demands more effectively. As a result, jitter, characterized by fluctuations in packet delay, was considerably reduced. This stability ensures smoother data transmission and improved Quality of Service (QoS), particularly for latency-sensitive applications such as VoIP and streaming. Secondly, buffer occupancy at both the ONU and OLT levels experienced a marked reduction under the proposed model. By accurately predicting traffic trends and dynamically adjusting transmission patterns, the system minimized the risk of buffer overflow and underutilization. This efficient buffer management not only decreases packet loss but also enhances overall network throughput.

Finally, one of the most impactful outcomes is the observed power consumption reduction. The ability of ONUs to enter sleep modes during predicted low-traffic intervals, guided by the GAN-LSTM traffic forecast, led to significant energy savings. The simulations revealed that ONUs under the GAN-DQN-LSTM scheme consumed over 20% less energy compared to those in the always-active DQN system. Similarly, OLT power usage was reduced, albeit to a lesser extent, owing to decreased transmission load from the energy-efficient ONU behaviour. In summary, the GAN-DQN-LSTM model provides a robust, intelligent solution for next-generation passive optical networks, achieving lower jitter, reduced buffer usage, and enhanced energy efficiency without compromising performance. These improvements contribute to both cost-effective network operation and sustainable energy usage, making the approach highly suitable for modern, large-scale PON deployments.

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