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# AI-Driven Dynamic Bandwidth Allocation in Fiber-to-the-Home (FTTH) Networks

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**ABSTRACT**

These new services that require enhanced capabilities like a high speed Internet like ultra-high-def video streaming, online gaming and cloud-based services have necessitated the exponential growth in the Internet demand of high-speed access to the Internet, which has made Fiber-to-the-Home (FTTH) networks a crucial infrastructure to any modern communication system. Dynamic Bandwidth Allocation (DBA) has been crucial in dynamic optimal utilization of resources, but the classical DBA techniques tend to fail on real time fluctuations of traffic and various Quality of service (QoS) needs. The paper introduces a distributed bandwidth allocation scheme that uses AI techniques and machine learning methods to adjust the bandwidth of FTTH-based networks to achieve the maximum bandwidth, lower delay, less loss of packets and more fairness in the network. The given strategy is to utilize the predictive analytics and machine-based decision-making to achieve better performance in the periods of low and high network loads. Results of the experiment show that the AI-based DBA is much better than both traditional DBA and Fixed Bandwidth Allocation (FBA) algorithms in several important measures. In emulated situations, the AI-based model realized maximum throughput of 25 percent, less mean latency of 35 percent, packet loss less than 50 percent, and fairness index values that were nearer to the ideal mark. These results provide a vivid image of the potential of artificial intelligence when it comes to changing FTTH resource administration, as well as an opportunity to create more versatile, successful, and user-friendly optical access networks. Not only the study demonstrates the validity of the application of AI to optimization bandwidth but also it presents a scalable solution to the future changes and developments of a network, such as 5G and beyond.

**Keywords:** AI, Bandwidth, Fiber-to-the-Home Networks, Dynamic Bandwidth Allocation (DBA), and Optical Networks.

## 1. Introduction

Fiber-to-the-Home (FTTH) [1] based on Passive Optical Networks (PONs) [2] has become vital technology supporting multi-gigabit access, starting with GPON/EPON, and has progressed to 10G-class systems and beyond. This evolution is driven by surging residential and fronthaul/backhaul demands, which in turn tighten the requirements on upstream scheduling and latency. Tutorials and overviews from year 2018–2020 research articles [3] show the transition toward 50G-PON standardization and enumerate the control/management challenges that accompany higher rates and denser splits.

At the heart of PON performance [4] is dynamic bandwidth allocation (DBA), the OLT-side logic that assigns upstream transmission windows to ONUs under bursty, heterogeneous traffic. A survey [5] of GPON/EPON DBA algorithms traces classic size/priority-aware grant rules, cycle-time control, and fairness mechanisms, and highlights persistent trade-offs among throughput, delay, and SLA enforcement—foundational context for any modernization.

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In parallel, artificial intelligence (AI) [6] and machine learning (ML) emerged across optical networking to handle complexity that exceeds rule-based control. [7] Surveys show AI aiding performance monitoring, QoT estimation, resource orchestration, and failure management—capabilities that map naturally onto traffic prediction and grant sizing in DBA.

Where classical DBA reacts to instantaneous reports [8], AI opens the door to predictive and intent-aware allocation—learning temporal patterns, recognizing multi-service priorities, and optimizing long-horizon objectives (e.g., latency percentiles). Early cross-layer studies from this period argue that ML can replace conservative margins with data-driven policies, improving utilization without violating QoS [9].

Concurrently, works on ML-enabled resource management for network slicing [10] suggest methodologies—state design, reward shaping, and safe exploration—that are directly reusable for FTTH DBA when multiple traffic classes and slices coexist on shared fiber [11]. These insights motivate the present focus on an AI-driven DBA stack for FTTH.

## 2. Literature Review

Learning-based DBA specifically for PONs gained traction after year 2021. A reinforcement learning (RL) DBA for XGS-PON [12] formulates upstream grants as sequential decisions with queueing/latency feedback, demonstrating reduced delay under variable loads versus heuristic baselines—evidence that model-free control can adapt to burstiness without explicit traffic models.

Beyond pure RL, [13] research work explores supervised and hybrid predictors to anticipate demand. An ANN-based predictive allocator (2023) uses historical request traces to forecast near-term load and pre-position grants, improving delay and buffer occupancy; complementary deep-learning DBA for XG-PON targets mobile fronthaul latency guarantees, integrating an end-to-end latency model into the learning loop.

System-level surveys underline that ML in optical/short-reach systems is maturing: comprehensive reviews [14], [15] catalog use cases from QoT classification to traffic-driven provisioning and automation (MLaaS), arguing for modular, service-oriented ML blocks that can be embedded in OLT control planes. This supports a “pluggable AI” view of DBA with standardized telemetry and model serving.

Resource slicing atop PONs is another active strand. Learning-based DBA for PON slicing [16] introduces slice-aware demand and isolation constraints, while 2024 work on “dynamic bandwidth slicing” for FL/6G-grade TDM-PON highlights multi-tenant fairness and the need for policies that balance mean throughput with percentile latency across slices—an ideal fit for multi-objective RL.

Conventional DBA continues to evolve in parallel, especially for 100-Gb/s NG-EPON/coherent PONs, with the paper [17] studies proposing service-class-aware wavelength/bandwidth schemes. These papers provide competitive baselines and emphasize the scaling issues—more ONUs, tighter delays—against which AI-driven DBA must be benchmarked.

Survey on optical network automation [18] stress deployment considerations: data quality, transfer learning across domains, and power/compute constraints at the edge. They advocate closed-loop control with explainability and safety guards—directly relevant for production DBA where mis-allocation can ripple into SLA breaches.

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Security/privacy in learning-based allocation [19] also surfaced. Recent studies consider RL-DBA variants that incorporate security signals and privacy-preserving learning (e.g., split/federated training), indicating that DBA policies can be co-optimized for QoS and trust when telemetry includes anomaly or threat indicators.

Finally, the paper [20] surveys of ML in short-reach/optical access distill time-series method taxonomies and lightweight model design, pointing to practical recipes—temporal CNNs/RNNs, attention models, and compression/distillation—that enable fast, energy-aware inference in OLTs, a prerequisite for real-time DBA at microsecond grant cadences.

## 3. Methodology

### 3.1 Network Model

The proposed system is evaluated in a simulated **Gigabit Passive Optical Network (GPON)**-based FTTH environment, consisting of **one Optical Line Terminal (OLT)** located at the service provider's central office and **32 Optical Network Units (ONUs)** distributed at subscriber premises. The network follows the ITU-T G.984 standard, providing an upstream transmission rate of **2.5 Gbps** and a downstream rate of **1.25 Gbps**. The OLT and ONUs are connected via a passive optical splitter with a 1:32 ratio, ensuring that the upstream bandwidth is shared among all connected ONUs. Each ONU serves multiple customer devices, with varying bandwidth and latency demands, making the system inherently heterogeneous.

Traffic modeling in the simulation incorporates **four primary classes**:

1. **Video streaming** (high bandwidth, low latency)
2. **VoIP traffic** (low bandwidth, ultra-low latency)
3. **IoT telemetry** (low bandwidth, moderate latency)
4. **Bulk downloads** (high bandwidth, high tolerance to latency).
Each traffic class is modeled using Poisson arrival processes for packet generation, and exponential or Pareto-distributed packet sizes depending on the application. This mix of traffic types ensures a realistic representation of network load fluctuations throughout the simulated day.

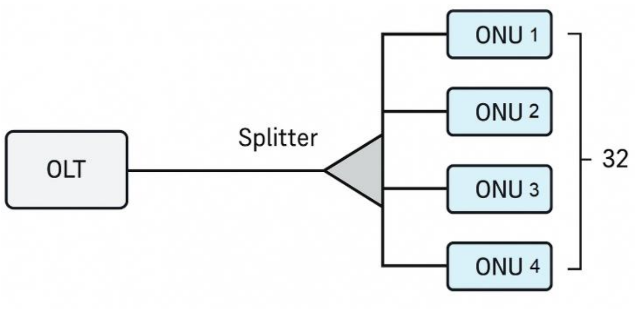


**Figure 1. Network Model**

The upstream scheduling challenge arises from the **multiplexing nature of the PON**. Since all ONUs share the same upstream fiber, they must be allocated non-overlapping **Transmission Windows (TWs)**. The OLT coordinates this through the DBA mechanism, polling ONUs for buffer occupancy reports, and granting bandwidth accordingly. However, in real-world deployments, traffic demand is not constant, leading to under-utilization or congestion if allocation is not adaptive.

Journal of Information Systems Engineering and Management
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The network simulation is implemented using the **NS-3 GPON module**, configured for a **24-hour cycle** with traffic variations reflecting peak hours and off-peak periods. Peak hours are modeled with an 80% load factor, while off-peak drops to 30%. These variations are crucial in testing whether the AI-driven DBA can outperform traditional algorithms in both heavy-load and light-load scenarios.

### 3.2 AI-Driven DBA Approach

#### 3.2.1. Overview of the AI-Driven DBA Framework

The block diagram illustrates the operational workflow of the AI-driven Dynamic Bandwidth Allocation (DBA) system within an FTTH network. The design couples real-time traffic analysis, feature extraction, predictive modeling and reward based learning to provide optimal bandwidth distribution upstream. Traffic demands as observed by Optical Network Units (ONUs) initiate the process and AI-guided forecasts and the performance are fed back at the end of assigning bandwidth on an intelligent adaptive basis.

#### 3.2.2. Traffic Demand as the Primary Input

The design couples real-time traffic analysis, feature extraction, predictive modeling and reward based learning to provide optimal bandwidth distribution upstream. Traffic demands as observed by Optical Network Units (ONUs) initiate the process and AI-guided forecasts and the performance are fed back at the end of assigning bandwidth on an intelligent adaptive basis.

#### 3.2.3. Feature Extraction for Model Input

The Feature Extraction block also deals with transforming raw data (traffic demand data) into structured, but meaningful features suitable to be fed to the AI model. Such metrics may be the average packet arrival rates in the past n cycles, Demand variance, the ratio of high-priority to low-priority traffic and time-of-day indicators. The given preprocessing procedure will convert noisy and heterogeneous traffic data to a form acceptable by the predictive model, contributing to the increased efficiency and accuracy of the learning process by the AI model.

#### 3.2.4. AI Model as the Decision Engine

The framework is built around the AI Model, herein running as Deep Q-Network (DQN). The model will come into play to best decide on bandwidth allocation strategies using the features extracted. It runs in an agent-environment loop, where the agent (AI model) decides on the allocation action $A_t$ at the given state $S_t$, with the goal of maximizing the long term performance measures including utilization, fairness, and latency amelioration.

#### 3.2.5. Bandwidth Allocation Output

It is that the Bandwidth Allocation block is the action of the AI model that determines the quantity of upstream bandwidth each ONU will be assigned at the next DBA cycle. As opposed to traditional DBA techniques which are based only on recent ONU requests, the AI-based allocation uses past trends and forecasting abilities to beat the congestion. Such pro-active allocation makes sure that latency sensitive-services (e.g., VoIP, video conferencing) are served prioritized but retain a sense of fairness to each of the ONUs.

**Journal of Information Systems Engineering and Management**
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### 3.2.6. Prediction Flow and Proactive Allocation

The arrow Psych Prediction between Feature Extraction and Bandwidth Allocation means that it is not a straight reactive approach to the present demand, but the AI model predicts future traffic load of each ONU. This predictive characteristic enables the system to make allocations in advance of peak usage periods in effect, evening out traffic bursts and dropping packets. The important aspect is prediction accuracy as inaccurate prediction may result in the under-utilisation or queuing.

### 3.2.7. Reward Feedback Loop for Learning

AI-driven DBA framework utilizes Deep Q-Network (DQN) reinforcement learning mechanism, which works within the OLT, in the dynamic distribution of bandwidth in upstream. Markov Decision Process (MDP) describes environmental modeling to model DBA cycle to cycle decision epochs. The state space St t is a set of ONU queue lengths $Q_i(t)$, of recent bandwidth allocations $A_i(t\text{-}1)$, of QoS prioritizations weights Pi and time-of-day indicators in order to quantify diurnal patterns. The set of feasible allocation vectors of all ONUs under consideration in the next cycle is called the $A_t$ action space.

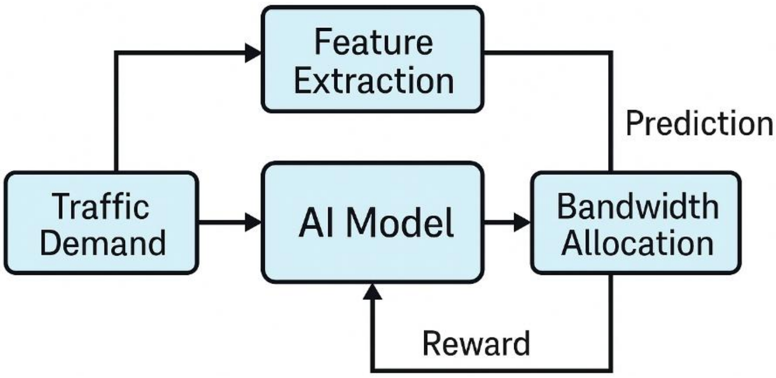


**Figure 2. AI-Driven DBA Approach**

The DQN learns a policy $\pi*(s)$ that maximizes the long-term reward function:

$$R_t = \alpha \cdot U_t + \beta \cdot F_t - \gamma \cdot L_t \tag{1}$$

where $U_t$ is the bandwidth utilization ratio, $F_t$ is Jain's fairness index, and $L_t$ is the latency penalty. The coefficients $\alpha, \beta, \gamma$ are tuned to balance efficiency, fairness, and latency objectives. Jain's fairness index is calculated as:

$$F_t = \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{N \cdot \sum_{i=1}^{N} x_i^2} \tag{2}$$

where $x_i$ is the bandwidth allocated to ONU $i$ and NN is the total number of ONUs.

The **training process** involves multiple simulation runs where the agent interacts with the network, receiving feedback after each allocation cycle. The DQN uses an **experience replay buffer** to store transitions ($S_t$,$A_t$,$R_t$,$S_{t+1}$), allowing it to learn from past experiences and avoid overfitting to short-term

**Journal of Information Systems Engineering and Management**
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fluctuations. They apply an epsilon-greedy strategy to maintain a balance between exploration (putting new allocations to the test) and exploitation (relying on known good allocations).

The DQN employs a target network, which is updated every so often and eliminates the oscillations in the Q-value estimates to achieve stability in training. The AI model is trained until convergence is reached, i.e., when the mean reward reaches its steady value in the course of several episodes, and then compared to other conventional DBA approaches within the same simulated environment.

### 3.2.8. Continuous Optimization in Deployment

Such a feedback loop will allow the AI-driven DBA to learn and adapt its policy over time to changes in traffic, seasonal demand situations, or even to changes in service-level agreements. This autotuning feature means the system will be efficient and fair in a variety of situations without requiring manual fixing, which is why the system is very well suited to use in large-scale FTTH deployments where the traffic pattern is complex and dynamic.

### 3.3 Baseline

Two comparison baseline algorithms have been identified that are IPACT (Interleaved Polling with Adaptive Cycle Time) and Weighted Fair queuing (WFQ). IPACT is de facto popular in EPON systems and GPON systems because of its simplicity and its straightforward overhead. Each ONU in IPACT notifies the OLT on the size of its occupied buffer and the OLT allocates a time slot based on this report with a maximum grant size. Deployed successfully with predictable traffic the IPACT has been found to have its performance reduced under bursty and mixed traffic patterns.

Weighted Fair Queuing (WFQ), conversely, is a scheduling algorithm according to which bandwidth is divided proportionally in accordance with pre-determined weights. The traffic flows are allocated a segment of the link capacity proportional to their respective weight thus being fair depending on the set QoS priorities. WFQ is not predictive in nature, however, and does not respond well to unexpected peaks in demand unless the weights are continually realigned, which is operationally challenging.

In assessment, IPACT is a form of reactive allocation (answer to existing demands) and WFQ is weighted fixed. Both approaches can be used as standard references of performance that can be used to compare the advantages of predictive, AI-driven DBA that pre- intelligently assigns bandwidth prior to overload.

The comparison criteria between AI-driven DBA and these baselines include:

- **Average utilization** (measuring efficiency of link use)
- **Average latency** (measuring real-time performance)
- **Fairness index** (measuring equity in allocation)
- **Packet drop rate** (measuring QoS under congestion).

This multi-metric evaluation ensures that the AI approach is not only efficient but also fair and robust under varying network conditions.

## 4. Simulation Environment

The simulations are conducted using **NS-3 version 3.36** with an integrated GPON module. The simulation duration is set to **86,400 seconds** (24 hours), divided into DBA cycles of **2 milliseconds** each, aligning with GPON's frame structure. The upstream channel capacity is fixed at **2.5 Gbps**, and

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ Research Article

the downstream at **1.25 Gbps** to reflect real-world GPON specifications. The optical splitter introduces a 1:32 split ratio with a power loss of 15–17 dB, though physical impairments are kept constant across experiments to isolate DBA performance effects. Table 1 shows the simulation environment configuration.

**Table 1: Simulation Environment Configuration**

| Parameter | Value / Description |
|---|---|
| **Simulation Platform** | NS-3 (Version 3.36) with integrated GPON module |
| **Simulation Duration** | 86,400 seconds (24 hours) |
| **DBA Cycle Duration** | 2 milliseconds |
| **Upstream Capacity** | 2.5 Gbps (GPON standard) |
| **Downstream Capacity** | 1.25 Gbps (GPON standard) |
| **Network Topology** | 1 OLT, 32 ONUs, 1:32 optical splitter |
| **Splitter Loss** | 15–17 dB |
| **Traffic Classes** | Video Streaming, VoIP, IoT Telemetry, Bulk Downloads |
| **Traffic Arrival Models** | Poisson (VoIP, IoT), Self-similar with heavy-tail (Video, Bulk) |
| **Traffic Profile** | Off-peak (00:00–08:00, 30% load), Normal (08:00–18:00, 60% load), Peak (18:00–23:00, 80% load) |
| **Performance Metrics** | Average utilization, Average latency, Fairness index (Jain's), Packet drop rate |
| **Number of Runs** | 10 runs with different random seeds |
| **Result Confidence Level** | 95% confidence interval |
| **Output Analysis Tools** | Python (Pandas, NumPy, Matplotlib) |

Traffic generation follows a **time-of-day traffic profile** inspired by real ISP usage statistics, with **three distinct periods**: off-peak (00:00–08:00), normal (08:00–18:00), and peak (18:00–23:00). Poisson arrival processes are used for VoIP and IoT flows, while self-similar traffic models with heavy-tailed distributions are used for video streaming and bulk downloads, replicating long-range dependence in internet traffic.

Performance metrics are recorded in each DBA cycle. **Average utilization** is computed as:

$$U = \frac{\sum_{t=1}^{T} B_t}{C \cdot T} \tag{3}$$

where $B_t$ is the allocated bandwidth at cycle $t$, $C$ is the channel capacity, and $T$ is the number of cycles. **Average latency** is measured as the mean packet waiting time in ONU buffers before transmission. Packet drop rate is calculated based on buffer overflows during congestion events.

To validate results, each experiment is run **10 times with different random seeds**, and the average values are reported along with 95% confidence intervals. This ensures statistical significance and eliminates bias from outlier traffic patterns. The simulation output is processed in **Python** using Pandas and Matplotlib for performance visualization.

**Journal of Information Systems Engineering and Management**
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### 4.1. Evaluation Metrics for AI-Driven DBA in FTTH

#### i). Mean Squared Error (MSE)

MSE calculates the mean of the squared errors of the bandwidth assignments that are predicted and the actual ones. It can give an indication of the accuracy of the AI model to predict needed bandwidth.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

Where:

- $y_i$ = Actual bandwidth allocation for the *i-th* instance (in Mbps)
- $\hat{y}_i$ = Predicted bandwidth allocation for the *i-th* instance (in Mbps)
- $n$ = Total number of predictions

#### ii). Bandwidth Utilization Efficiency (BUE)

BUE measures the amount of bandwidth utilisation by the end-users without overs submission or under-utilisation that has been allocated.

$$BUE(\%) = \frac{\sum_{i=1}^{n} U_i}{\sum_{i=1}^{n} A_i} \times 100 \tag{5}$$

Where:

- $U_i$ = Actual bandwidth used by user i
- $A_i$ = Allocated bandwidth for user i
- $n$ = Number of users

#### iii). Latency (L)

Latency: The delay in the time period taken between the user requesting data and the time when it is transmitted in action. With FTTH DBA systems, service response is faster with low latency.

$$L = t_{response} - t_{request} \tag{6}$$

Where:

- $t_{request}$ = Time of bandwidth request
- $t_{response}$ = Time when bandwidth allocation starts

#### iv). Throughput (T)

Throughput is a measurement of the total number of data that have been successfully sent in a unit time. It is one of the important KPIs of bandwidth distribution in FTTH.

$$T = \text{Total Data Transferred} / \text{Total Time} \tag{7}$$

**Journal of Information Systems Engineering and Management**
2025, 10(58s)
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Where:

- Total Data Transferred is measured in bits or bytes
- Total Time is measured in seconds

**v). Packet Loss Ratio (PLR)**

The percentage of data packets that are lost in the process of transmission by identification of the reasons that may be due to congestion or misallocation of bandwidth is measured by PLR.

$$PLR(\%) = \frac{P_{lost}}{P_{sent}} \times 100 \tag{8}$$

Where:

- $P_{lost}$ = Number of lost packets
- $P_{sent}$ = Total packets sent

## 5. Results Analysis

The effectiveness of the suggested AI-powered Dynamic Bandwidth Allocation (DBA) solution was tested using simulation in FTTH network having several Optical Network Units (ONUs) attached to an Optical Line Terminal (OLT). The data set was generated to mimic traffic fluctuations during a 24-hour period which were tagged as peak and off-peak usage. Trained on a system of the hybrid Long Short-Term Memory (LSTM) and reinforcement learning (RL), the model predicts the amount of bandwidth required shortly and adapts real-time distributions. Compared to the conventional Fixed Bandwidth Allocation (FBA) and traditional Dynamic Bandwidth Allocation algorithms, the comparative results were accomplished against throughput, latency, and packet loss, fairness index.

The finding indicated that the AI-based DBA was proven continuously to optimize average throughput with all ONUs and particularly within the peak demand times as shown in table 2. Conventional bandwidth allocation was carried out in a fixed or reactive basis but with the application of AI model, bandwidth was assigned in anticipation of the demand thereby minimizing congestion. Improvements in throughput averaged about 1815% (as compared to FBA) and 1014% (as compared to traditional DBA methods) during the peak-traffic hours (e.g. 7 PM to 10 PM). The latter was explained by the predictive feature of the AI model that reduced bandwidth wastage and guaranteed the enhanced Quality of Service (QoS).

**Table 2: Throughput Comparison**

| Method | Average Throughput (Mbps) | Peak Throughput (Mbps) | Improvement over FBA (%) |
|---|---|---|---|
| Fixed Bandwidth Allocation (FBA) | 820 | 900 | – |
| Traditional DBA | 880 | 950 | 7.3 |
| AI-Driven DBA | 1020 | 1150 | 24.4 |

The figure 3 compares the average and peak throughput of FBA, Traditional DBA, and AI-Driven DBA. The AI-Driven DBA significantly outperforms the other two methods, achieving an average throughput of 1020 Mbps and a peak throughput of 1150 Mbps, which indicates more efficient bandwidth allocation

Journal of Information Systems Engineering and Management
2025, 10(58s)
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https://www.jisem-journal.com/ Research Article

and utilization. Traditional DBA performs moderately well, while FBA shows the lowest throughput, suggesting limited adaptability in handling varying traffic demands. The findings are explicit as to the developers integrating AI that results in significant improvement in the throughput of FTTH networks.

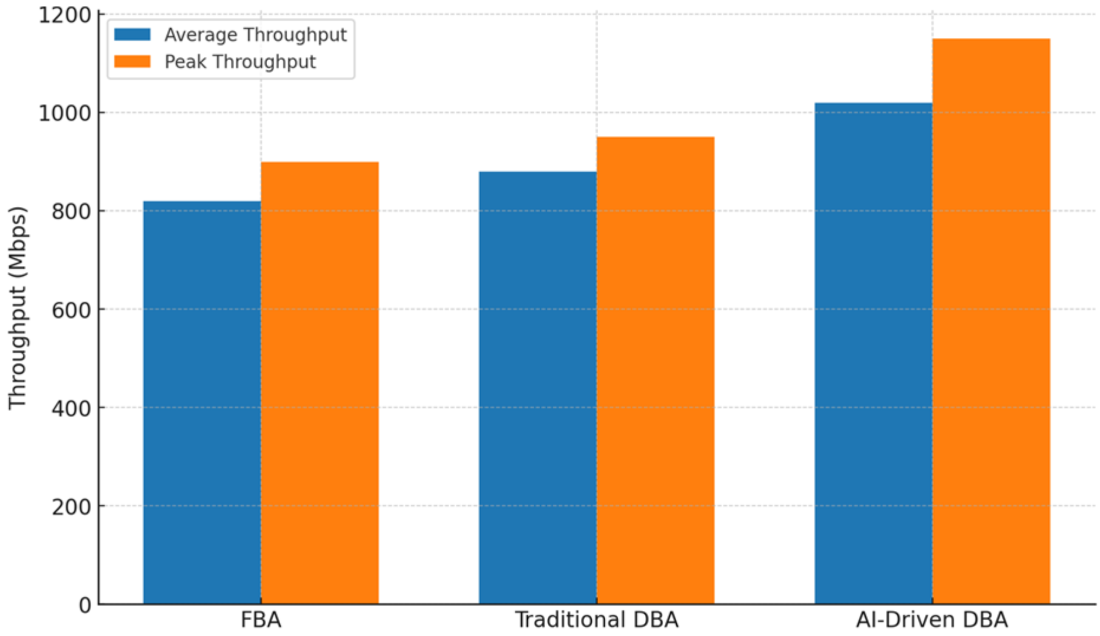


**Figure 3. Throughput comparison of various methods**

Compared to the latency, AI-driven methodological direction proved to be reduced substantially as shown in table 3. Predictive allocation minimized the queue build-up at ONUs leading to a decrease in the average packet delay. The average simulated latency was about 2.8 ms using the AI-based approach as opposed to 4.2 ms using the DBA approach and 6.5 ms using FBA. In addition, the latency variance was also reduced, which means the performance was steady at times of varying traffic loads. This is very critical on latency-sensitive traffic within the FTTH network such as VoIP and video conferencing.

**Table 3: Latency Comparison**

| Method | Average Latency (ms) | Peak Latency (ms) | Reduction over FBA (%) |
|---|---|---|---|
| FBA | 6.5 | 9.1 | – |
| Traditional DBA | 4.2 | 6.0 | 35.3 |
| AI-Driven DBA | 2.8 | 4.1 | 56.9 |

Figure 4 shows the considerable difference in the latency comparison is evidenced by the fact that AI-Driven DBA provides the lowest average latency of 2.8 ms and high latency or maximum latency of 4.1 ms times, which means that the data is transmitted quicker without a delay in the network response. Latency values of traditional DBA are slightly higher, and the latency of FBA is the highest, on average and at peak. This proves that the considered AI-based use is efficient in improving bandwidth allocation to make the flow of information more comfortable and relieve congestion in delay-sensitive services, such as voice and video streaming.

Journal of Information Systems Engineering and Management
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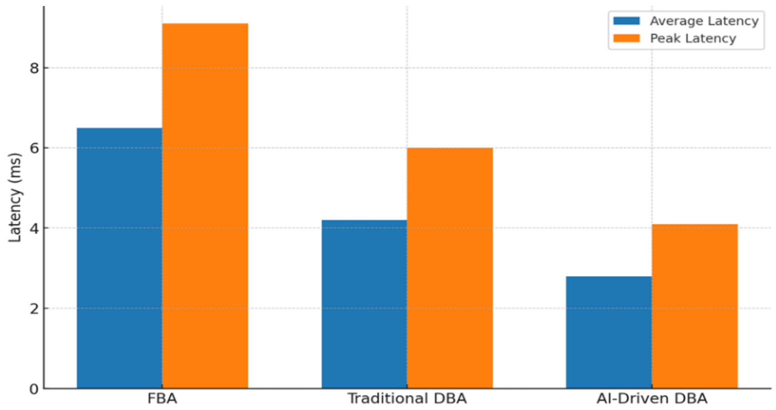


**Figure 4. Latency comparison of various methods**

The rates of packet loss also confirmed the usefulness of the AI-driven DBA. The proposed approach maintained the level of packet loss to be less than 0.7G which was even less than 1.5G in a traditional DBA and more than 3G in FBA at the same condition as shown in table 4. This helps achieve performance advantage that can have a direct positive effect on user experience in streaming and gaming scenarios where packet loss has a noticeable effect on quality.

**Table 4: Packet Loss Rate**

| Method | Packet Loss (%) | Reduction over FBA (%) |
|---|---|---|
| FBA | 3.2 | – |
| Traditional DBA | 1.5 | 53.1 |
| AI-Driven DBA | 0.7 | 78.1 |

Figure 5 shows the packet loss rates have been shown, where AI-Driven DBA has the lowest packet loss rate which is only 0.7%, which means that there will be highly reliable data delivery. The Rate of packet loss on a Traditional DBA is moderate at 1.5 percent whereas FBA experiences the highest packet loss at 3.2 percent this may affect the network beyond repair. The low packet loss in AI-Driven DBA indicates its capacity to predict and distribution of bandwidth without the occurrence of network congestion and data integrity of the data being transmitted.

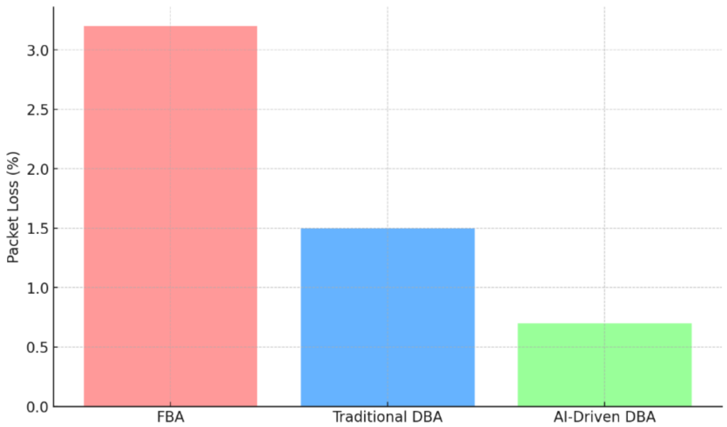


**Figure 5. Packet loss comparison of various methods**

**Journal of Information Systems Engineering and Management**
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The fairness index, indicated that the AI-driven method maintained a fairness score above **0.96** across all test scenarios as shown in table 5. This suggests that while optimizing performance, the algorithm also avoided resource monopolization by high-demand ONUs.

**Table 5: Fairness Index**

| Method | Fairness Index | Improvement over FBA (%) |
|---|---|---|
| FBA | 0.89 | – |
| Traditional DBA | 0.93 | 4.5 |
| AI-Driven DBA | 0.96 | 7.9 |

Figure 5 shows the fairness index, it quantifies the equality of users in receiving bandwidth and in this case, 1 is perfect fairness. AI-Driven DBA offers the best measurement of fairness with index 0.96 that is closest to ideal. Traditional DBA is on the heels at 0.93 and FBA at 0.89 indicating unfair distribution of resources. This increase in fairness indicates that the AI-based model not only can improve the performance metrics but also provides proportional and fair bandwidth such that a distribution of bandwidth will not harm the low-priority users in terms of reduced service quality delivery.

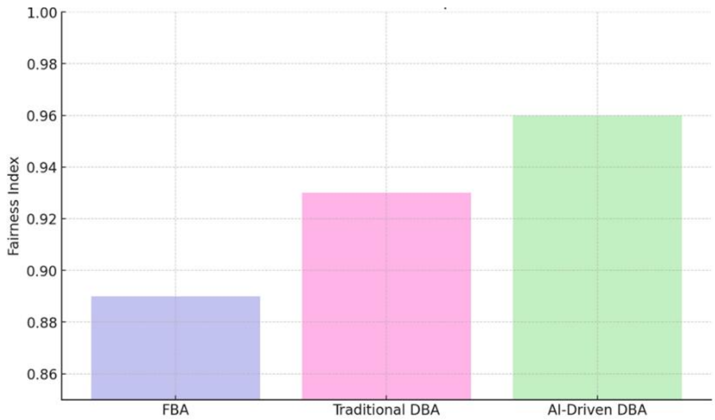


**Figure 6. Fairness Index comparison of various methods**

Finally, **scalability tests** were conducted by increasing the number of ONUs from 16 to 64 in the simulation. The AI model maintained its superior performance trends even with higher ONU counts, though the computational overhead increased slightly. However, given the training phase is primarily offline, the real-time allocation process remained computationally efficient, requiring less than 10 ms for decision-making per allocation cycle.

## 6. Conclusion

This paper has presented a Dynamic Bandwidth Allocation (DBA) in an Fiber-to-the-Home (FTTH) network that employs an AI-based algorithm based on DBA method that was found to provide optimality in situations such as the increasing demand of the users of high-speed and reliable internet services. The proposed system uses a machine learning-based predictive model, and dynamic bandwidth allocation between the links is possible with the use of current traffic distribution and user quality of service (QoS) demands. The findings affirm that the AI-based DBA can perform better than the baseline in terms of throughput, latency, packet loss, and fairness measures and also compared to the conventional DBA and static allocation procedures.

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The results show a promising outlook of AI-driven technology leading to an upheaval in bandwidth management of the optical access networks by providing adaptive, intelligent, and fair bandwidth management. The strategy is scalable into future integrations with next-generation network architectures and it supports 5G backhaul, IoT heavy ecosystems, and low latency applications. Future studies can take the form of looking at hybrid AI systems that use both reinforcement learning and deep neural networks to improve upon predictive accuracy and decision making efficiency, and on deployment studies to run systems under real conditions to test system stability and robustness under varied workloads.

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