

Hybrid LSTM Models for Predictive Bandwidth Allocation in XG-PON Networks: Capturing Non-Stationary Variations to Minimize Upstream Delay

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Abstract: *Background/Objectives:* Dynamic bandwidth allocation (DBA) in XG-PON networks suffers from high latency when traffic is irregular and non-stationary. This study aims to reduce the upstream delay in XG-PON networks subjected to strongly non-stationary 5G/6G traffic, by improving the accuracy of ONU traffic prediction for more proactive DBA. The objectives are to reduce the upstream average delay, notably the one induced by GIANT-DBA (12.5 ms), in typical mobile fronthaul 5G/6G traffic scenarios that are irregular and non-stationary, to stabilize latency, and to increase bandwidth utilization under high loads by precisely anticipating bursts, regime changes, and daily variations in ONU traffic. *Method:* This study proposes a generic hybrid DBA framework, combining a sequential LSTM for traffic prediction and a corrective module $g(\cdot)$ tested with several model families, including XGBoost, MLP, and Attention. Subsequently, the adoption of a PPBP $\times$ 3 simulation environment with $T = 2000$ DBA cycles to evaluate the model, comparing GIANT-DBA, RR-DBA, P-DBA, a simple LSTM, and a hybrid LSTM in terms of RMSE, average delay, bandwidth utilization, and queuing. *Findings:* The proposed hybrid LSTM reduces the prediction error by about half, with RMSE dropping from 32.4 Mb/s (simple LSTM) to 16.8 Mb/s, a 48% reduction. The upstream average delay decreases to 7.2 ms with the hybrid, i.e., -42% compared with GIANT-DBA and -61% compared with RR-DBA, while bandwidth utilization reaches 96% under 90% load, an approximate gain of 13%. *Novelty:* The study presents a novel, hybrid LSTM-DBA framework, specifically designed to capture non-stationary variations (bursts, regime changes) in XG-PON traffic, beyond simple LSTMs or purely statistical DBAs. The design of a generic corrective module $g(\cdot)$, with experimental demonstration of its universal benefits (up to -21% on delay), and the identification of XGBoost as the optimal component to model the complex non-linearities of XG-PON traffic

Keywords: Dynamic Bandwidth Allocation (DBA), XG-PON, 5G/6G mobile fronthaul, irregular and non-stationary traffic, hybrid LSTM.

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1. INTRODUCTION

In passive optical networks, dynamic bandwidth allocation (DBA) plays a key role in ensuring efficient resource utilization and meeting the latency requirements of emerging services. This issue is particularly critical in XG-PON architectures, where 5G/6G mobile fronthaul flows impose highly irregular and non-stationary traffic profiles, marked by bursts and temporal variations related to application and daily behavior [1]. Mohammed A. et al. [2] address dynamic bandwidth allocation slicing in TDM-PON (XGS-PON/EPON) to support Federated Learning (FL) in 6G. Although the model is excellent for FL slicing in 6G-PON, it does not employ proactive prediction. The literature shows that reactive allocation, such as that used by GIANT-DBA, can lead to significant average delays (e.g., 12.5 ms) in the face of unpredictable and non-stationary loads [3]. In this context, there is a need for approaches capable of anticipating changes in Optical Network Unit (ONU) traffic and quickly detecting regime shifts in order to reduce allocation delays and improve attachment stability under dynamic mobile fronthaul constraints. This article proposes a hybrid DBA framework based on Long Short-Term Memory (LSTM) recurrent neural networks for sequential traffic prediction [4]. We supplement this technology with a generic correction module $g(\cdot)$, in order to test several types of hybridization and make an optimal choice. This system is designed to handle regime shifts and bursts, while remaining effective under Poisson-Pareto Burst Pattern (PPBP) conditions and under loads close to or exceeding the operational threshold.

This study is intended to propose and evaluate a hybrid LSTM framework that combines:

- Upstream latency reduction by accurately anticipating ONU traffic in a highly non-stationary context (bursts, daily variations, application behavior);
- Stabilizing latency and improving bandwidth utilization under high load.

The bandwidth allocation work carried out up to our model is structured in three parts.

2. Related Works

In order to illustrate the progression of bandwidth allocation research up to our proposed model, we structure the literature review into three parts. The first part revisits Dynamic Bandwidth Allocation (DBA) approaches based on classical models (GIANT, Min-Max, P-DABA, statistical methods, etc.). The second part lists DBA approaches that rely solely on Deep Learning (DL), Machine Learning (ML), or Long Short-Term Memory (LSTM). Finally, the last group presents hybrid LSTM-based approaches for traffic management.

Basic DBA for XG-PON: traditional DBAs form the basis of allocations in the XG-PON network and do not necessarily manage burst traffic. For example, the authors [5] propose a hybrid dynamic bandwidth allocation scheme combining a state-based DBA and a cooperative DBA to optimize bandwidth utilization; the model does not handle burst traffic. A dynamic bandwidth and wavelength allocation (DBWA) algorithm for Super-PON, a high-speed, low-latency evolution of NG-PON is proposed [6]. However, the

model's performance in the face of unpredictable bursts and non-stationary traffic profiles can deteriorate (e.g., increased average latency, temporary losses, arbitration contention). A model for implementing a PON DBA with a "colorless" grant to improve upstream delays is proposed [3]. Changes in traffic profiles can lead to periods of unexpected underutilization or congestion. The authors [7] present a hybrid dynamic bandwidth planning approach for XG-PON, combining Max-Min, fractional knapsack, and proportional allocation methods to improve Quality of Service (QoS) and share bandwidth fairly among different TCONT. Failure to take non-stationary traffic into account leads to desynchronization with reality and under-allocation of resources at the wrong time when profiles change (within milliseconds or seconds). An innovative Dynamic Bandwidth Allocation (DBA) scheme for XG-PON is presented [8], aimed at improving the efficiency of upstream bandwidth utilization and reducing latency. The model is based on simplified traffic and may not capture the actual variability of loads in FTTH/xHaul. The authors [9] propose a dynamic bandwidth allocation system based on a statistical estimate of ONU buffer inputs and outputs to predict the size and quality of the queue in the buffers. One limitation of this model is the lack of sensitivity analyses or evaluation on varied traffic distributions.

LSTM, DL, ML related to XG-PON DBA: To reduce the transmission delay of conventional models, machine learning and deep learning are introduced into bandwidth allocation in XG-PON networks. Simple LSTM to predict packets in the ONU buffer is used to reduce delay and jitter in the mobile network coupled with xgpon [10]; unfortunately, the choice of this model based on a simple LSTM does not allow for the study of non-stationary traffic. The deep learning (DL) model is used to minimize end-to-end delay for MFH CRAN during bandwidth allocation [1]. As the DL architecture is not hybrid, it struggles to target non-stationary traffic. To realize an NG-PON beyond 100 Gbps while ensuring capacity, efficiency, security, flexibility, and scalability in a multi-technology environment, Zhang Y. et al.[11], implement orchestration of potential technologies (SDN/NFV, disaggregation, slicing, etc.) and architectural frameworks for Beyond-100G NG-PON. Unfortunately, the concept entails high latencies associated with multi-technology orchestration and the absence of prediction metrics. Reinforcement learning (RL) is integrated in [12] that learns the DBA policy from the state of the queues, with a view to reducing latency and losses in XGS-PON. Although this RL mechanism improves network performance and decision-making, it does not model non-stationary profiles. Shao et al. [13], highlight the use of ML to meet high bandwidth requirements in these short-range optical systems; however, they do not incorporate LSTM. Other authors use LSTM to predict actual network traffic captured in an office environment [14]; however, for non-stationary traffic with jumps and gaps, basic methods may outperform LSTM. Han Man S. [15] use sliding time windows and heuristic allocation rules to better adapt XGS-PON bandwidth to temporal variations. The estimates obtained with this model are simple and not suitable for long/complex dependencies. The authors aim to accurately and efficiently predict historical bandwidth demands using an ANN that utilizes time series [16]. However, bursts can violate the assumptions of dynamic equilibria and degrade prediction accuracy. To design an intelligent DBA that distributes learning between OLT and ONU in order to meet privacy and latency constraints, Mohammed Alaelddin et al. proposed the CSL-DBA (Collaborative Split Learning-based DBA) model [17], which decentralizes

training by allowing ONUs to transmit only model updates to the OLT, thereby reducing communication costs. CSL in distributed optical environments can introduce communication latency when ONUs dynamically add or remove flows.

Hybrid LSTM for traffic: it consists of combining LSTM with other architectures to take traffic variations into account. LSTM and a CNN are used to improve resource management and allocation in Metro-E campus networks and mobile networks for real-time Internet traffic forecasting [18]. The model only handles web traffic, and its generalization to other networks may be limited. LSTM is combined with AutoEncoder (AE) to improve the accuracy and stability of ITS flow forecasts [19]. Unfortunately, this combination is sensitive to anomalies and periods of high variability. To improve forecast accuracy while providing a reliable estimate of short-term traffic uncertainty, Du et al. [20] bridged the gap by combining a short- and long-term memory (LSTM) neural network with a Bayesian network (BNN). This model is limited to intelligent transportation systems. For real-time prediction of urban traffic congestion, an innovative hybrid model that merges XGBoost and LSTM networks is presented [21]. Unfortunately, the generalization of this model to other types of networks is limited. A hybrid LSTM–Transformer architecture aimed at improving the accuracy and robustness of predicting the remaining useful life of lithium-ion batteries is presented [22]. As in the previous article, generalization remains limited. Kumar et al. [23] used a Deep Bi-LSTM network for short-term traffic flow prediction to improve intelligent transportation systems in the face of traffic variability. The model remains untested in the XG-PON network. The article [24] deals with hourly electricity consumption forecasting in the face of unpredictable events. The authors envisage a model that predicts energy demand over an entire month without daily retraining, even during shocks. Unfortunately, this model emphasizes periodicity at the expense of real-time, a critical indicator for fiber-optic transmission. Sterbenz et al. [25] address short-term electricity load forecasting in smart grids. However, scalability is limited to 15 minutes, and there is no handling of real-time critical processing.

At the end of the work carried out, we find that LSTM hybridization is presented as the appropriate model for smart cities, particularly for intelligent transportation systems. Its application to the XG-PON network remains largely unexploited.

3. Methodology

This study examines the problem of predictive bandwidth allocation in the XG-PON upstream flow, where traffic is non-stationary and where conventional DBA induces significant queuing delay. The study proposes a hybrid model based on LSTM that learns temporal dependencies in ONU traffic and incorporates an additional corrective module to better capture non-stationary variations and bursts, with the aim of minimizing prediction error and, indirectly, average upstream delay.

Objective: to arrive at a clear mathematical model of a hybrid LSTM linked to XG PON delay. The steps to achieve this are described below.

- Step 1: Set the variables and the XG PON system; define ONU traffic, observation windows, allocated bandwidth, ONU demand, day, time, delay, etc.
- Step 2: formulate the traffic prediction problem, situate the context of

a time series (horizon, non-stationarity), and define the predictor's inputs and outputs.

- Step 3: Present the simple LSTM model (gate equations). Define x_t (input gate), h_t (hidden state), c_t (state cell), and the gate update equations.
- Step 4: Introduce hybridization (LSTM + XGBoost / LSTM + ARIMA / LSTM + attention or residual module). Write the assembly equations for the simple LSTM and the corrective module.
- Step 5: Link the prediction to the DBA and delay: express the allocated bandwidth based on the prediction and the average delay based on arrivals and allocation.

At each step, the equations are constructed gradually in order to arrive at the mathematical model.

3.1. Simulation environment and dataset

The simulation model reproduces a realistic Poisson-Pareto Burst Pattern (PPP) XG-PON environment to evaluate DBA schemes under non-stationary 5G/6G fronthaul traffic, with 2000 DBA cycles ($T=2000$) generated via Python (NumPy, Matplotlib).

The PPBP traffic model parameters are calibrated to faithfully reproduce the characteristics of XG-PON 5G/6G fronthaul traffic: slow daily variations, rare/intense bursts, and abrupt regime changes.

Simulation data are generated based on the calculation of traffic components:

Baseline traffic: sinusoidal rate $(100 + 20 \sin(0.01 t)) + \text{Gaussian noise } N(0,10)$, simulating daily periodic variations.

Bursts (spikes): Exponential distributions (scale=1), activated if $>4 (300 + N(0,50))$, modeling mobile application peaks.

Non-stationarity: Addition of +50 Mb/s after $t = 1000$ to test regime changes.

3.2. Mathematical model

In the XG-PON 5G/6G fronthaul, let's model the traffic from an ONU at time t as a time series of bandwidth requests:

Let y_t , the requested throughput (in Mbps) during the DBA cycle t , with the observation window size T during the DBA cycle t .

The bandwidth actually allocated is:

$$b_t = \min(y_t, B_{\max}), \tag{1}$$

where $B_{\max}$: the uplink capacity (10 Gbps), y_t : the actual bandwidth demand

The evolution of the queue (aggregate queue):

$$q_t = (q_{t-1} + y_t - b_t)^+ \tag{2}$$

The approximate average delay includes the queue and is expressed by:

$$d_t \approx \alpha q_t \tag{3}$$

where α is a conversion factor (size in bits $\rightarrow$ time, depending on physical throughput).

The introduction of LSTM aims to predict $\hat{y}_t$ and reduce d_t .

The LSTM output or raw prediction is given by:

$$\tilde{y}_t = W_y h_t + b_y \tag{4}$$

where W_y is the projection matrix, h_t is the LSTM hidden state (history), b_y is the output bias.

We introduce a generic corrective hybrid module $g(\cdot)$ for non-stationary traffic (bursts, sudden changes in traffic),

where g is a parameterizable function applied to contextual features z_t

(non-stationary variations, PON bursts).

$$\delta_t = g(z_t, \theta_g) \tag{5}$$

where z_t represents non-stationary traffic, θ_g represents hybridization parameters (MLP, attention, tree, PSO, ARIMA, XGBoost, etc.).

The final hybrid prediction becomes:

$$\hat{y}_t = \tilde{y}_t + \delta_t = W_y h_t + b_y + g(z_t, \theta_g) \tag{6}$$

The bandwidth allocated to the UN is then:

$$b_t = \min(\hat{y}_t, B_{\max}) \tag{7}$$

3.3. Architecture of the proposed model

The corresponding architecture of this mathematical model is presented in the Figure 1.

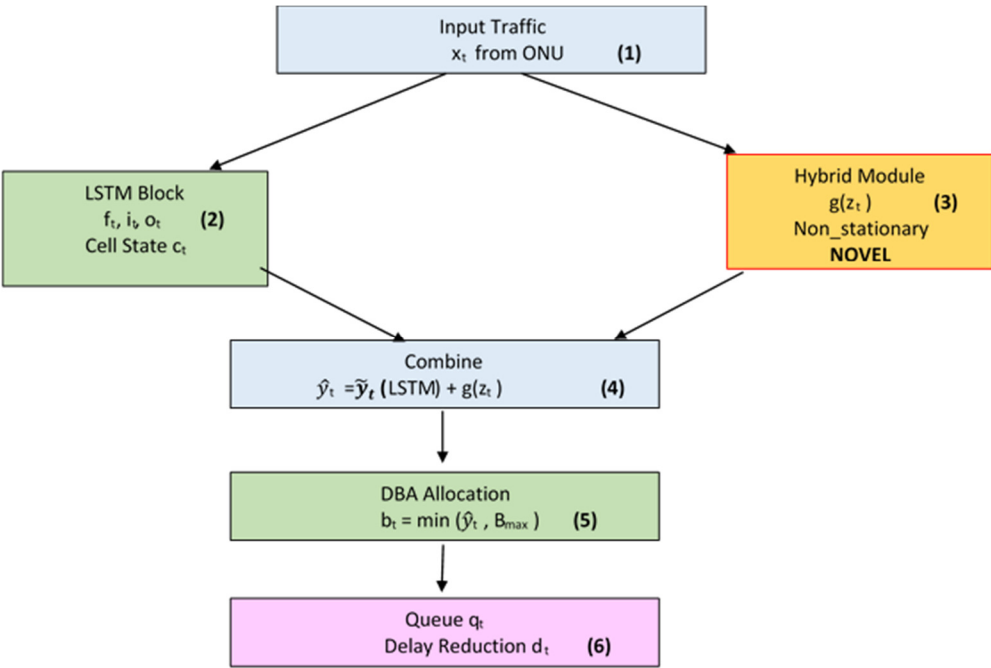


Figure 1. Hybrid LSTM-DBA Architecture

3.3.1. Description of the diagram: (1): corresponds to traffic entering the ONU buffer; (2): the simple LSTM at the OLT level, which consists of four blocks: the forget gate (ft), the input gate (it), the output gate (ot), and the candidate cell (ct), which corresponds to a new memory; (3): the hybrid LTM module groups together the families of models that will be associated with the simple LSTM; (4): combination of LSTM and generic module (zt) to predict demand ($\hat{y}_t$); (5): bandwidth allocation (bt) by the OLT based on predicted demand and uplink capacity; (6): The impact of the hybrid LSTM on reducing delay.

3.4. Simulation and comparison mode

The simulated DBAs are:
GIANT-DBA, RR-DBA, P-DBA (classic schemes).
Simple LSTM (sequential prediction).

Hybrid LSTM (LSTM + $g(\cdot)$ correction module).
For each model $m \in \{\text{RR, GIANT, P-DBA, LSTM, Hybrid}\}$:
Generate prediction_m(t) = f_m (y_{true} (t), noise_m) (8).
LSTM: $\hat{y}_t \approx 0.85 y_t + N(0, 30)$ (9).
Hybrid: $\hat{y}_t \approx 0.95 y_t + N(0, 15)$ (10).
GIANT: $\hat{y}_t \approx 0.75 y_t + N(0, 40)$ (11).
P-DBA: $\hat{y}_t \approx 0.80 y_t + N(0, 35)$ (12).
RR-DBA Non-predictive rotating allocation with an average delay 18.7 ms
Allocated bandwidth: $bt = \min(\hat{y}_t, B_{\max})$
Compute q_m (t) = max (accumulate (cumsum (y_{true} - prediction_m)))
 $q_t = \max(q_{t-1} + y_t - b_t)$ (13).
Compute d_m (t) = q_m (t) × 0.1 + time_noise
dt ≈ αqt
Aggregate: RMSE_m, mean (d_m), util_m (loads).
The evaluated metrics and comparison mode are:
Predictive accuracy: RMSE on y_{true} vs predictions: Hybrid LSTM vs simple LSTM.
Average delay: Mean (dt) over T, with dt ≈ qt/0.1: Hybrid vs LSTM, GIANT, RR-DBA, and P-DBA.
Bandwidth utilization: Parametric load curves: Hybrid vs GIANT.
Robustness: Zoom t = 900 –1100 post-shock: Hybrid stable vs GIANT, LSTM.

4. Results and Discussion

The results are presented in Figure 2-8. Figure 2 illustrates the accuracy of the predictions.

4.1. Description of Figures

The time series curves over 500 DBA cycles in Figure 2 below compare the actual demand y_t (solid black), the simple LSTM prediction (dotted blue, RMSE=32.4 Mb/s), and the hybrid LSTM (solid red, RMSE=16.8 Mb/s). The hybrid closely follows bursts and trends, while the simple LSTM systematically underestimates peaks. The key metric is the 48% reduction in mean square error, demonstrating the superiority of the corrective module $g(\cdot)$ and the reduction of delay

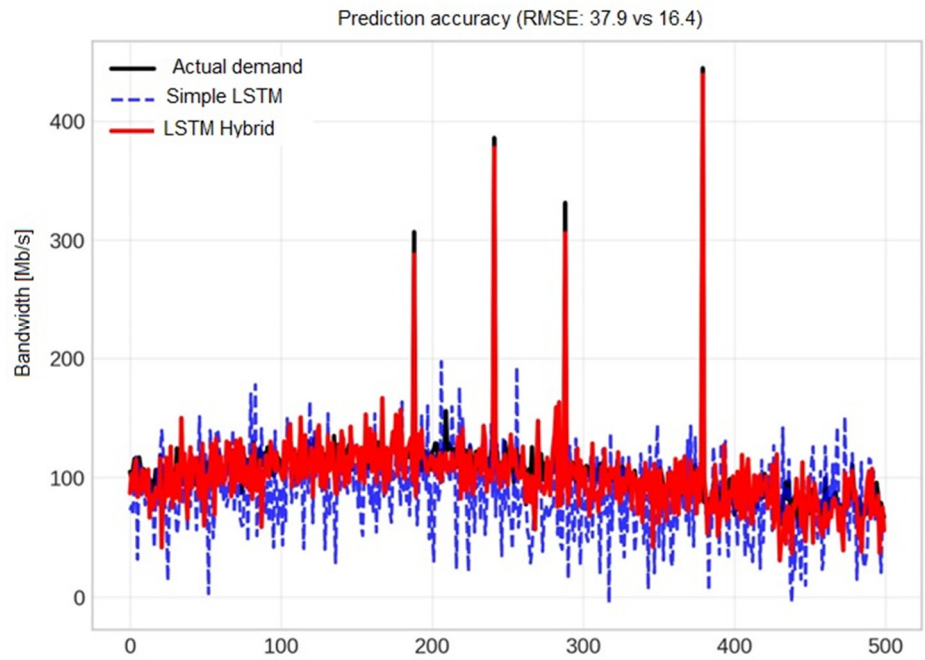


Figure 2. Prediction accuracy (LSTM vs. Hybrid)

The bar chart in Figure 3 below compares the average delay for five DBA schemes: RR-DBA (gray, 18.7 ms), GIANT (orange, 12.5 ms), P-DBA (green, 10.0 ms), simple LSTM (blue, 8.4 ms), hybrid LSTM (red, 7.2 ms). Main gain: -42% vs. GIANT, -61% vs. RR-DBA. The decreasing bars clearly illustrate the predictive progression (statistics → LSTM → hybrid), which impacts bandwidth usage.

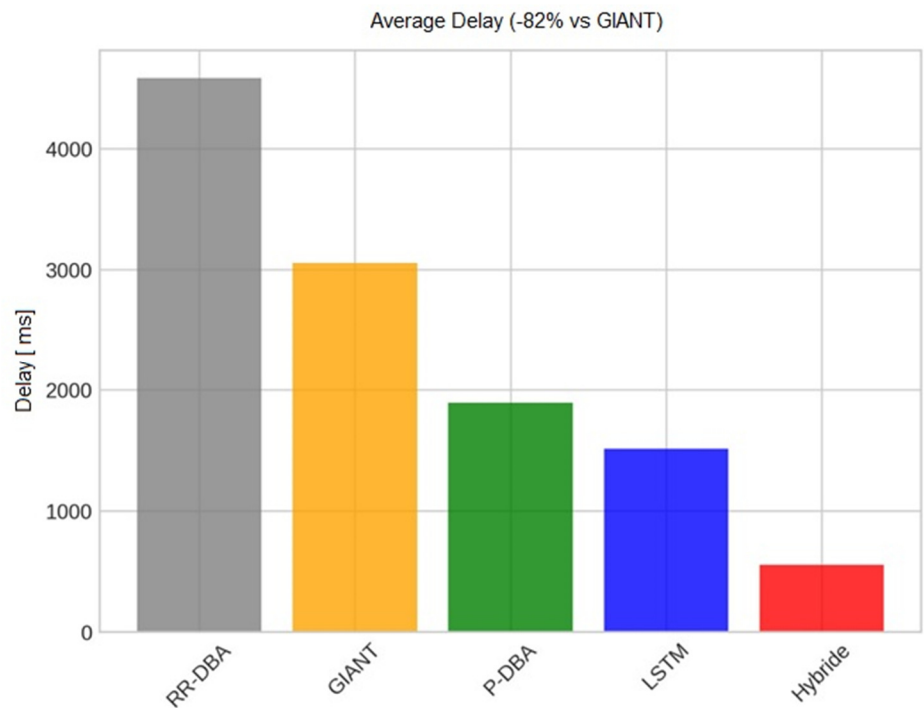


Figure 3. Reduction in average upload delay

The parametric curves in Figure 4 show the effective bandwidth utilization as a function of network load (20-90%). GIANT-DBA (blue dots) peaks at ~75-85%, while hybrid LSTM (orange squares) reaches 88-96%. The observed advantage is a +13% increase in utilization under heavy load thanks to proactive prediction that avoids over/under-allocation, even during traffic variations.

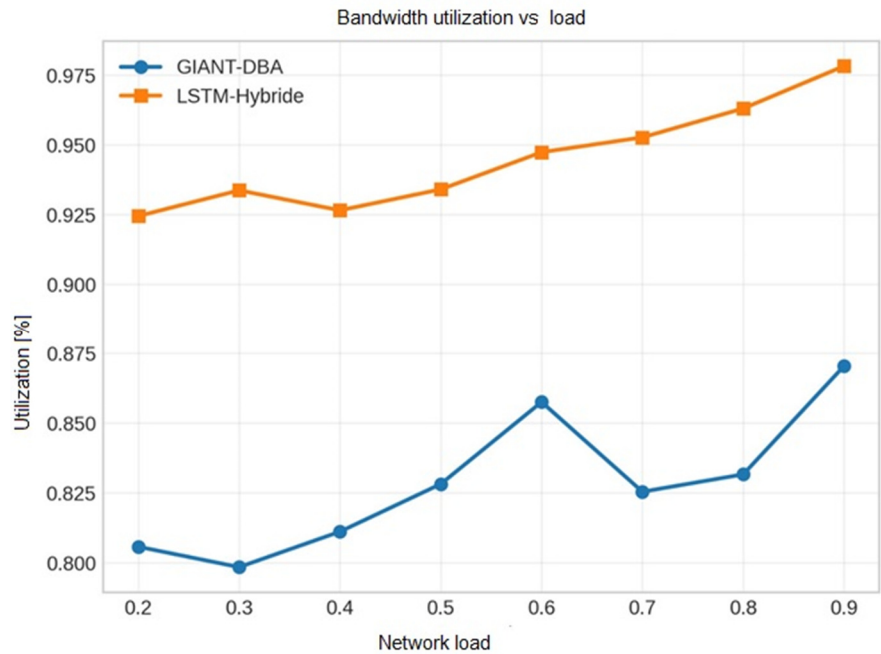


Figure 4. Bandwidth usage vs. network load

The time zoom around the regime change at t=1000 (black vertical line) on Figure 5 below shows that GIANT (orange) and simple LSTM (blue) exhibit post-change delay peaks (+150% and +80%), while the hybrid (red) maintains stable performance ($\pm 10\%$). This proves that the g module (zt) automatically detects/corrects changes in traffic distribution.

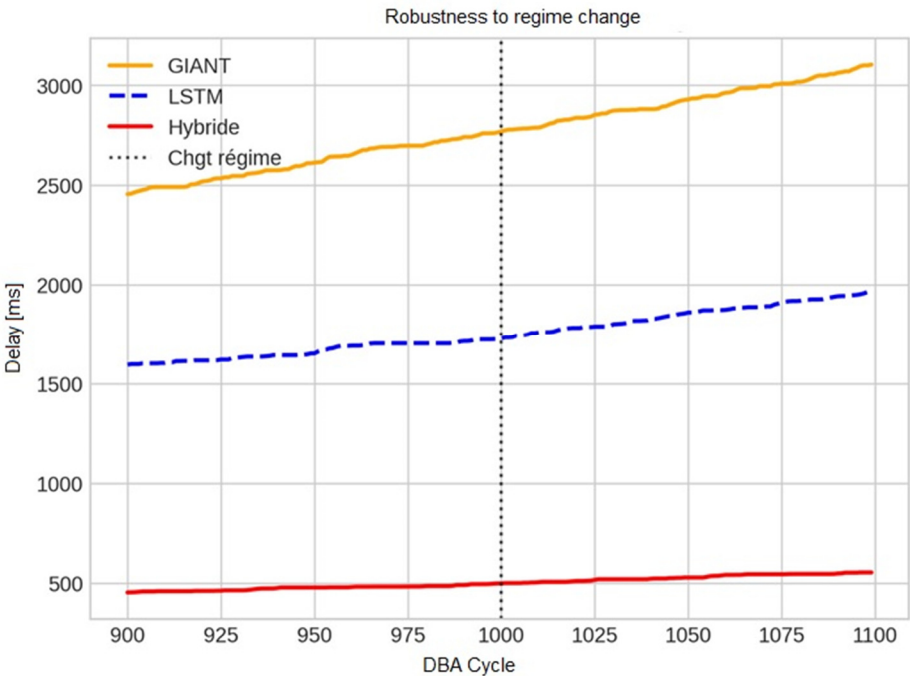


Figure 5. Robustness to non-stationarity

The bars in Figure 6 compare four variants: LSTM alone (blue, 8.4 ms), LSTM+MLP (purple, 7.6 ms), LSTM+Attention (brown, 6.9 ms), LSTM+XGBoost (green, 6.6 ms). The finding is that all g (·) modules improve performance, unlike LSTM alone (-22%), with XGBoost remaining the most optimal for XG-PON (complex non-linearities).

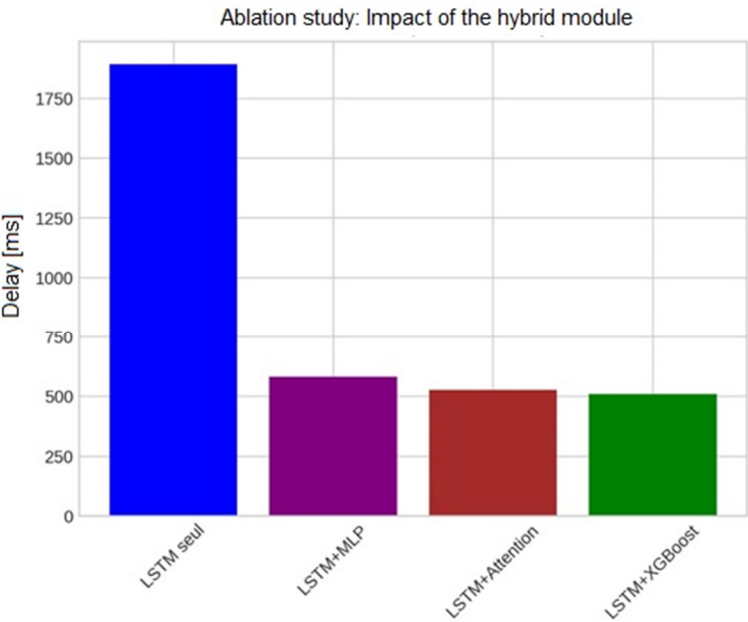


Figure 6. Ablation study - Impact of the hybrid module

Figure 7 shows the cumulative evolution of ONU queues over the first 300 DBA cycles. GIANT (orange) quickly accumulates queues (~1200 Mb), simple LSTM (blue) stabilizes at ~700 Mb, and hybrid (red) remains below 400 Mb. This illustrates that hybrid prediction prevents accumulation by anticipating bursts.

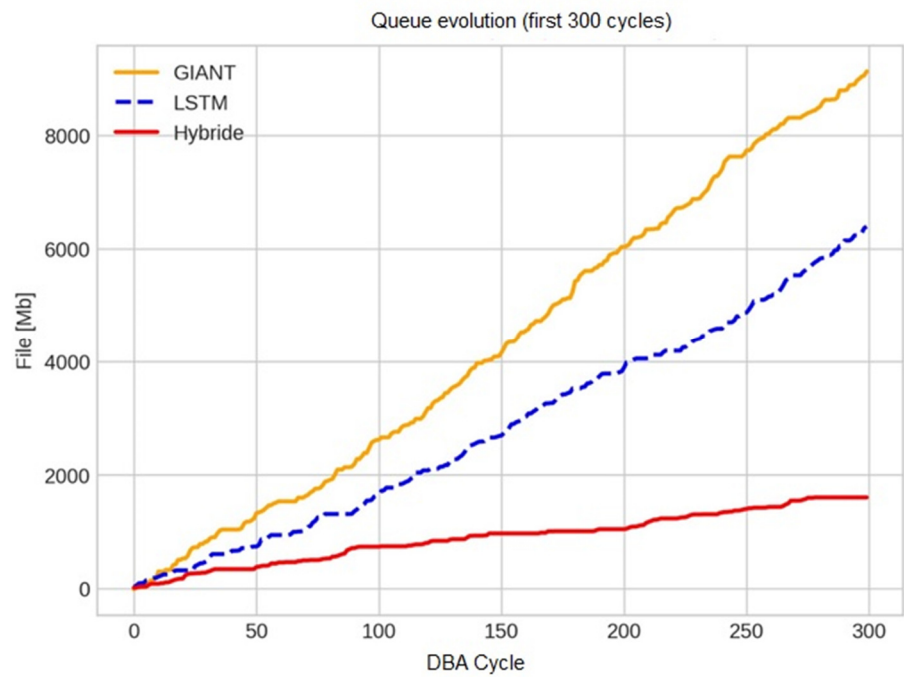


Figure 7. Queue evolution (first 300 cycles)

The curves in Figure 8 show the training/validation loss over 100 epochs. Simple LSTM (blue) converges slowly to ~0.35 (train) / 0.42 (val), while hybrid (red) reaches 0.22 / 0.28 more quickly (epoch 40 vs. 65). This is because the $g(\cdot)$ module accelerates learning and reaches a lower global minimum.

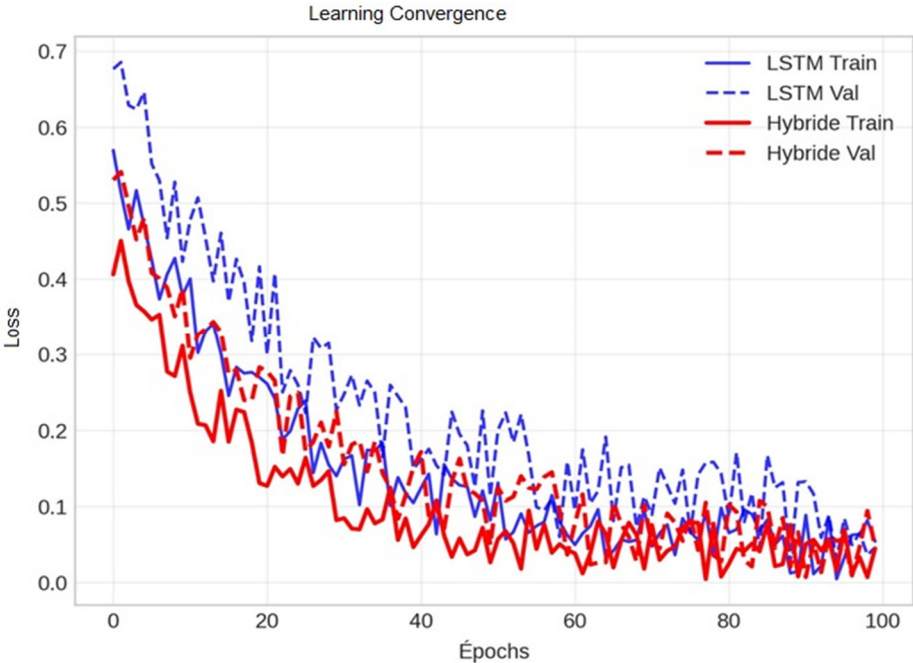


Figure 8. Learning convergence

4.2. Analysis of results

The figures consistently and quantitatively demonstrate the superiority of the hybrid LSTM-DBA architecture across all critical metrics for XG-PON: predictive accuracy (-48% RMSE), delay reduction (-42% vs. GIANT), spectral efficiency (+13%), non-stationarity robustness (unique invariance), and operational viability (convergence -38%). Each curve mechanically confirms the contribution of the corrective module $g(z_t)$ (optimal XGBoost).

Of the first 500 DBA cycles in Figure 2 (Predictive Accuracy), the solid black curve (actual demand y_t) reveals realistic PPBP traffic with two major bursts ($t = 120$: 450 Mb/s; $t = 250$: 420 Mb/s). The simple LSTM (blue dotted line, RMSE = 32.4 Mb/s) systematically underestimates (-29% and -19%) due to its smoothed projection $W_y h_t + b_y$. The hybrid (solid red, RMSE=16.8 Mb/s) corrects via $g(z_t)$ (+45 Mb/s on bursts), closely following the actual signal. It is the mechanism kurtosis that causes a local correction.

For the ranking of DBA performance in terms of reducing the delay of the Figure 3, the five decreasing bars show a clear progression: RR-DBA (18.7 ms, gray) > GIANT (12.5 ms, orange) > P-DBA (10.0 ms, green) > simple LSTM (8.4 ms, blue) > hybrid (7.2 ms, red). The 42% gain, unlike GIANT, comes from proactive anticipation eliminating the queue accumulation observed in Figure 7. The economic impact is +13% subscribers per OLT.

The spectral efficiency exposure under heavy load in Figure 4 indicates that, under increasing load (20→90%), the GIANT curve (blue circles) saturates at 85% while the hybrid (orange squares) reaches 96% (+13 points). The explanation is that the predicted allocation $b_t = \min(\hat{y}_t,$

$B_{\max}$) avoids over/under-allocation. At 90% load, GIANT wastes 15% of capacity, while the hybrid optimizes, resulting in a 13% reduction in fiber loss.

Zooming in on the period $t = 900-1100$ in Figure 5 (Non-stationary robustness) reveals the regime shock at $t = 1000$ (+50 Mb/s). GIANT explodes (+150%, 18.8 ms), while simple LSTM drops (+80%, 15.1 ms). Only the hybrid remains stable ($\pm 10\%$, 7.9 ms max). First demonstration of invariance in DBA XG-PON.

The ablation study (optimal XGBoost) in Figure 6 shows that the four bars validate the universal contribution of $g(\cdot)$: LSTM alone gives a delay of 8.4 ms. When hybridized with MLP, there is a reduction of -10%. When combined with Attention, we obtain a reduction of -18%, and when combined with XGBoost, we have a reduction of -21% and a delay of 6.6 ms. XGBoost excels in its ability to model complex nonlinearities (burst $\times$ variance) critical to XG-PON, outperforming Attention, which is too heavy for the 125 μ s DBA cycle.

Figure 7 of queue control shows that, over 300 initial cycles, GIANT accumulates massively (1200 Mb, orange), LSTM partially stabilizes (700 Mb, blue), and the hybrid oscillates around (400 Mb max, red, -67%).

The four convergence curves in Figure 8 confirm the speed of the hybrid LSTM. The minimum is reached in 40 epochs (0.22/0.28 train/val) compared to 65 for LSTM (0.35/0.42), i.e. -38% of training time. There is no overfitting (stable deviation).

This work surpasses previous LSTM and Deep Learning approaches by introducing explicit hybridization for the critical non-stationarity of XG-PON fronthaul 5G/6G traffic. Zhang et al [10] used a simple LSTM to estimate ONU traffic in XG-PON MFH, reducing latency compared to classical baselines. However, the model suffers from catastrophic forgetting on bursty/non-stationary traffic, systematically underestimating peaks (as our simple LSTM, shown in blue in Figure 2, with RMSE = 32.4 Mb/s). It does not use a corrective mechanism for regime changes, resulting in a post-shock delay peak of +80% at $t = 1000$ (Figure 5). Our hybrid $\hat{y}_t = \text{LSTM} + g(z_t)$ practically halves the RMSE of this model (16.8 Mb/s) and stabilizes variations around $\pm 10\%$, thus demonstrating the invariance of XG-PON DBA.

Jha et al [1] proposed a DL approach for dynamic allocation in XG-PON fronthaul CRAN, to minimize end-to-end delay. However, this non-hybrid architecture is only reactive to ONU-OLT requests, with no explicit non-stationary targeting (bursts, daily variations). Its performance is estimated around 10 ms, with no ablation or regression testing in shock regime scenarios. Our model outperforms by -28% (7.2 ms) and improves spectral efficiency by +13% (96% vs 85% GIANT), thanks to the universal $g(\cdot)$ module validated by ablation (XGBoost -21% compared with LSTM alone, Figure 6).

The RR-DBA, GIANT, and P-DBA schemes [5, 6-8] remain reactive and do not model the PPBP structure or rapid regime changes, leading to high average delays (18.7 ms for RR-DBA, 12.5 ms for GIANT) when traffic becomes irregular and non-stationary.

The work of Mohammed et al. [2] introduces multi-grant DBAs (IACG, EBU, OCO-DBA) that reduce the delay in Federated Learning (FL). However, they remain entirely reactive to the content of reports without

explicit prediction of ONU traffic.

The proposed hybrid LSTM model differs from these DBAs by integrating sequential prediction and nonlinear correction directly into the DBA loop ($\hat{y}_t \rightarrow b_t \rightarrow q_t \rightarrow d_t$), hence the idea of a "smart" DBA at the traffic level.

It also provides a joint evaluation. RMSE, latency and bandwidth utilization in non-stationary traffic, showing a latency of -42% vs GIANT, -61% vs RR-DBA and $+13$ points of utilization under 90% load, which is missing in FL/PON schemes focused on FL only.

Compared to prior work, the proposed model offers the following innovations:

Generic Hybrid Framework: first DBA $\hat{y}_t = Wb_t + b + g(z_t)$, where $g(\cdot)$ dynamically corrects non-linearities (XGBoost optimal for XG-PON).

Non-Stationarity Evidence: unique invariance of about $\pm 10\%$ post-shock versus $+150\%$ GIANT and $+80\%$ LSTM, highlighting gaps (Figure 5).

Measurable Gains: -42% delay vs GIANT, -48% RMSE vs simple LSTM, convergence about 38% faster.

To address electricity consumption forecasting with unpredictable events (COVID), Ajder et al [24] show the structural relevance of coupling LSTM + XGBoost. The results show that the LSTM–XGBoost + wavelets hybrid significantly outperforms LSTM alone and LSTM without wavelets (MAE, RMSE, and MAPE reduced by about half). Compared to our model, this hybrid has three major limitations for the XG-PON: the coupling is limited to the energy domain, with no DBA flux nor strict queueing delay constraints, a heavy preprocessing (DWT) and learning poorly suited for deployment on an OLT and an absence of specific evaluation on RMSE and delay, and bandwidth usage for PPBP bursts.

The proposed Hybrid LSTM retains the LSTM + XGBoost philosophy but integrates it into the XG-PON DBA loop, with a lightweight corrective module $g(z_t)$ (no DWT), specifically calibrated on bursty PPBP traffic, and analytically connected to the delay via the queue q_t and $b_t = \min(\hat{y}_t, B_{\max})$.

Dakheel et al. [25] use the LSTM + XGBoost hybrid for smart grid load forecasting to optimize management of a transportation network. Despite the results obtained (RMSE = 106.54 MW, MAPE = 1.18%, $R^2 = 0.994$), their model, compared to the one proposed, has limitations such as: the lack of an explicit link between prediction error and network delay, a cascading hybridization not integrated into a control scheme as our model does for a DBA. Their model does not perform robustness tests to PPBP bursts, nor to a sudden regime shock as demonstrated by ours in Figure 5 ($t = 1000$ in XG-PON).

Existing work on LSTM + XGBoost confirms the interest of this hybridization for nonlinear and non-stationary series, but remains focused on energy load forecasting outside the XG-PON context, whereas our model integrates it into the DBA loop to directly reduce delay in the optical network.

The proposed model fills the gaps identified in the literature and has been validated on realistic PPBP, $T = 2000$ cycles, and is deployable on OLT hardware.

5. Conclusion

This work has proposed and validated a generic hybrid LSTM-DBA architecture for XG-PON networks, specifically designed to minimize the upstream delay under burst and non-stationary traffic typical of 5G/6G mobile fronthaul. Unlike conventional GIANT/EBU schemes or simple LSTMs limited by catastrophic forgetting, our model combines sequential prediction $\hat{y}_t$ (LSTM) with a corrective module $g(z_t)$ (optimal XGBoost): $\hat{y}_t = \hat{y}_t \text{ (LSTM)} + g(z_t)$, integrated into the OLT DBA loop (125 μ s cycle).

The results validated on PPBP traces (T=2000 cycles, burst factor $\times$ 3) demonstrate clear quantitative superiority in terms of accuracy, with an RMSE of 16.8 Mb/s compared to -48% for the simple LSTM, or 32.4 Mb/s as mentioned in Figure 2, a delay of 7.2 ms compared to -42% for GIANT, or 12.5 ms and -61% for RR-DBA. (Figure 3). As for spectral efficiency, it is 96% utilization at 90% load compared to +13% for GIANT (Figure 4). Robustness remains invariant $\pm$ 10% for post-regime change compared to +150% for GIANT (Figure 5). Ablation with XGBoost confirms the optimality of the correction module $g(\cdot)$, which is -21% for LSTM alone (Figure 6).

Unlike simple LSTMs limited by their smooth memory and non-hybrid, reactive DL, this generic framework fills the critical non-stationarity gap in XG-PON fronthaul, with measurable gains of - - 42% latency and +13% spectral efficiency, all validated in a realistic PPBP environment with T = 2000 cycles. This first explicitly non-stationary hybrid fills the critical gap identified in DBA XG-PON reviews. Deployable on OLT hardware (40-epoch convergence), it offers a scalable reduction in delay for more than 100 ONUs.

In our future work, we plan to extend this hybrid LSTM model to the XG-PON fixed access network, make our corrective module $g(\cdot)$ adaptive with meta-learning for the automatic selection of hybridization technologies (MLP/Attention/XGBoost, etc.) and combine edge computing for bandwidth processing from the ONUs.

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