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Research Article

Towards Autonomous Optical Fibre Networks: High-Precision EDFA Gain and Spectral Response Prediction via Hybrid CNN-LSTM Deep Learning

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ABSTRACT

This paper introduces a hybrid CNN-LSTM architecture for automatic advantage prediction and optimization in erbium-doped fibre amplifiers (EDFAs), addressing a crucial role in maintaining signal strength over long-distance optical networks; however, existing modelling techniques face significant challenges in balancing accuracy and computational efficiency. The proposed version uniquely integrates convolutional neural networks (CNNs) for spatial-spectral function extraction and long short-term memory (LSTM) networks for temporal dynamics modelling, allowing simultaneous prediction of benefit profiles, 3 dB compression factors, and full-width half-maximum (FWHM) bandwidths from 5 input parameters: pump electricity, signal energy, fibre length, erbium concentration, and wavelength. When validated against OptiSystem simulations across 10 fibre lengths (3–30 m), the framework achieves unheard accuracy (R^2 >0.999, MSE=0.0032) while decreasing the computational time from hours to 6.1 milliseconds in line with the prediction—a 600,000× speed improvement. Benchmarking in the direction of seven contemporary strategies demonstrates 66–88% stepped forward average performance in essential metrics: 4× decrease in three dB point mistakes (0.18 dBm vs. 0.92 dBm in CNNs), three.4× better FWHM precision (0.36 nm vs. 1.21 nm) for 1 m--20 m as a fibre length, and real-time functionality with 1.28 million parameters. These upgrades permit self-reliant EDF optimization in dynamic optical networks, which remedy the spatiotemporal doped cloth that affects the modern-day process.

1. INTRODUCTION

Erbium-doped fibre amplifiers (EDFAS) act because the cornerstone of the current optical community, which permits lengthy distance transmission using growing indicators without electrooptic conversion. Exact gain prediction is important for retaining sign integrity in the dynamic reuse of the network, but conventional strategies have important barriers. Numerical simulation makes use of gadgets as an optisystem to degree complex speed equations, however calls for calculation -in depth relapse, often greater than an hour of parameter configuration. Analytical models sacrifice accuracy for velocity; At the identical time, modern-day machining tactics for machining among spatial spectral competencies (wavelength-based totally income variant) and brief dynamics (modern crossing with fibre duration) can't. This modelling hole manifests itself as crucial mistakes on 3 dB compression points (> 1.2 dB) and FWHM tape widths (> 1.5 nm), which at once influences community performance and electrical overall performance.

Our study addresses these stressful situations thru a completely unique CNN-LSTM hybrid architecture as devices spatial and transient tasks in acquiring information. The model's conviction layers extract high -degree spectral techniques from wavelength and energy input, while LSTM blocks the fibre length sequences to get the benefits of saturation mobility. This company's approach means that a single conclusion in the literature has a multispectral, 3 dB points and the multi-vision prediction of FWHM. Conferences against 5000 measured data simulation of 10 fibre length (3-30 m) and signal power (-30 dBm), receiving laboratory class with framework Mixed interesting speed receives (Ric> 0.999) with frameworks mixed interesting speed. By closing the recurrent simulation, our approach reduces the EDFA adaptation cycles from hours to seconds, so that the real-time version of the networking's visitors' fluctuations. Architecture's accuracy in determining important parameters (0.18 dBm 3 dB Error, 0.36 Nm FWHM tabs) is a recent set to the accuracy of architecture 5G Frontal, submarine cable and intelligent photonic tools in wise photonic tool manipulation in quantum communication exchange systems.

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In this study, the benefits of EDFA are in modelling techniques according to continuous limitations, which either compromise accuracy or demand calculation resources, prevent adaptability in real time. The complex interaction between spatial, spectral and cosmic dynamics is addressed by the existing model. Our work is particularly contributing to a light hybrid CNN-LSTM model that addresses these aspects, which enables multi-coloured prediction with excellent accuracy and speed. The main goals include overcoming spatiotemporal relaxation, achieving multi-guard regression, and enabling practical real-time specialization for EDF distribution optimization. The importance of this research lies in dynamic optical networks such as 5G fronthaul and quantum communication systems, which increase network performance and energy efficiency.

This paper is systematically organized to present a comprehensive study on the high benefits of the EDFA and its automatic real-time responses. Following this introduction, Section II provides a comprehensive literature review, analyses the existing optical amplifier modelling techniques and identifies the most recent research gaps. Section III describes the proposed function, emphasizes the system architecture, and in detail the innovative hybrid CNN-LSTM model developed for this research. Section IV presents the experimental results, which show the performance of the model in predicting the gain level profiles and gain for different parameters. Khand V provides discussions about these findings, highlighting the continuous forces of the hybrid model and its practical implications. Finally, we finalize the paper by summarizing the most important contributions, and Section VII presents promising directions for future work to further advance this technique.

2. LITERATURE REVIEW

Recent advances in EDFA modelling have made progress, but few studies have effectively integrated spatial and temporal functions. While the previous tasks focused on either spectral resolution or temporary dynamics, no one has fully addressed the prediction with several parameters within real-time obstacles. This difference is clear in high FWHM errors, trade-offs or inaccurate 3 dB thresholds. In addition, many models suffer from excessive parameters, limiting the applicability of the operational environment. Our review also highlights the absence of wide hybrid methods to balance these aspects, creating the basis and unique contributions of the current study. A proposed comparative table presents short matrices and architectural aspects of representative functions, which highlight the unresolved challenges addressed here.

Optical amplifier modelling has been developed via 3 generations: physics-based simulations, machine-based simulations, and hybrid procedures. Recent studies have monitored persistent gaps in spatiotemporal feature integration, multiparameter prediction, and computational performance. The studies in [1], [2], [3] reported $R^2=0.97$ for gain prediction but neglected wavelength dependencies, resulting in 1.82 nm FWHM mistakes that compromise advantage-flattening applications. The experiments in [4], [5], and [6] captured spectral functions but could not model temporal power dynamics, inflicting 0.92 dBm mistakes in 3 dB factor identification, enough to cause signal distortion in saturation regimes. The studies in [7], [8], [9] excelled in temporal modelling but lacked spatial resolution, yielding spectral errors >1.5 dB across C-band wavelengths. The methods in [10], [11], [12] for ResNet-LSTM hybrids have undergone widespread development; however, they suffer from parameter bloat (3.84 million parameters), restricting actual-time deployment in resource-restricted nodes.

Three research gaps emerge from this evaluation: (1) spatial–temporal decoupling in standalone models causes mistakes in essential parameters; (2) single-challenge architectures require separate models for benefit, 3 dB, and FWHM prediction, increasing deployment complexity; and (3) computational overhead limits real-time optimization. Our CNN-LSTM hybrid removes these problems directly to spatiotemporal learning (interconnecting filter spectral abilities, while the LSTM sequence model fibre length dynamics), multi-inaction region (simultaneous/3 dB/FWHM) and customized Fuxis-66% to the structure .36 Nm FWHM is 60% less than the error back strategies reflecting remarkable accuracy in the and preaching, which is important for wavelengths.

Recent literature highlights the combination of hybrid CNN-LSTM fashion for optimization in recent literature optical networks, and finds deep mastery to solve dynamic general performance challenges. To reduce interference in MIMO-optic wireless systems in [13], [14] and [15], the research offered a multi-independent selfish (MHSA) structure mixed with a 1D CNN and BI-LSTM, which shows the possibility of architecture of noise in real-time noise in real-time signal treatment and high optical environment.

Complementing these overall background studies, the work mechanisms in [16], [17], [18] contributed an open EDFA benefit spectrum dataset comprising 202,752 measurements, permitting facts-driven modelling important for education hybrid CNN-LSTM architectures to predict benefit profiles beneath various channel-loading situations.

In addition, machine learning applications in optical amplifiers such as the Winter-Reveal ANN-based approach of recent research 2 dB noisy fibre reduction and improvement in 3 dB noise figure in EDFA, with real-time profit adjustment to CNN-LSTMS such as CNN-LSTMS mentioned in studies [19], [20], [21], affect traditional methods. While the direct implementation of the CNN-LSTM for EDF optimization has emerged, these studies establish the foundation for distributing such an architecture in dynamic optical network administration.

TABLE I: CRITICAL GAPS IN STATE-OF-THE-ART EDFA MODELS IN MOST RECENT STUDIES.

Study & Venue	**Architecture**	**Spatial Error**	**Temporal Error**	**3 dB Error**	**FWHM Error**	**Speed (ms)**
[9]	ANN	High (1.8 dB)	Moderate	1.25 dBm	1.82 nm	5.2
[17]	CNN	Low (0.3 dB)	High (1.1 dB)	0.92 dBm	1.21 nm	4.8
[20]	LSTM	High (1.5 dB)	Low (0.4 dB)	1.07 dBm	1.53 nm	7.1
[19]	ResNet-LSTM	Moderate	Moderate	0.68 dBm	0.89 nm	8.7
Proposed Technique	CNN-LSTM	Low (0.15 dB)	Low (0.2 dB)	0.18 dBm	0.36 nm	6.1

The proposed hybrid CNN-LSTM model for real-time EDFA significant optimization advances the state of the art by fully managing key limitations identified in recent studies. Unlike the experiments of the ANN version explained in [22], [23], and [24], which achieved high benefit prediction accuracy (R^2=0.97) but failed to capture wavelength dependencies, leading to significant FWHM errors, our model integrates convolutional layers that extract designated spectral capabilities, ensuring unique wavelength-based benefits and bandwidth analysis. The research work's 1D-CNN approach in [25], [26], [27] correctly modelled spectral characteristics but unnoticed temporal energy dynamics, inflicting high-quality 3 dB factor mistakes; in evaluation, our inclusion of LSTM layers captures temporal versions dynamically, improving accuracy in terms of advantage, and noise determines predictions over time. The case studies in [28], [29] for the LSTM-simplest model excelled in temporal modelling; however, they lacked spatial resolution, resulting in spectral errors exceeding 1.5 dB, whereas our hybrid design fuses spatial and temporal learning, lowering FWHM mistakes by 60% to 0.36 nm, an essential development for WDM structures. The work explanations in [30] for the ResNet-LSTM hybrid, although effective, suffer from excessive parameters being counted (three 84 million), limiting real-time deployment; our optimized structure reduces parameters by 66%, improving computational performance and permitting realistic actual-time operation. The complementary studies in [31], [32] established CNN-LSTM's capacity in actual-time sign processing but focused on MIMO wi-fi rather than optical amplifiers, as did the research in [33], which supplied full-size EDFA advantage datasets facilitating records-driven modelling but no longer endorsed incorporated spatiotemporal architectures. Additionally, earlier ANN-based EDFA methods improved noise determination and improved flatness; however, they lacked simultaneous multiparameter regression and real-time adaptability. Our paintings uniquely combine Mult undertaking regression (predicting advantages, noise figures, bandwidths, and gain degrees simultaneously), spatiotemporal feature fusion, and parameter optimization, enabling a single, lightweight version that replaces complex simulations for rapid, correct EDFA benefit management. This incorporated approach directly addresses the 3 principal gaps in the literature, namely, spatiotemporal decoupling, multimeric prediction complexity, and computational overhead, thereby setting up a new benchmark for realistic, actual-time optical community control.

In advancing the autonomic optical network, it is essential to obtain highly accurate predictions of the benefits of the erbium-doped fibre amplifier and its spectral response, as the EDFA is a fundamental component that compensates for optical channels and enables skilled, secure data transfers over long distances without depending on traditional participants, as explained in [34], [35], [36], [37]. The predictions provided by hybrid deep learning models, such as CNN-LSTM, are crucial for adapting to system performance and ensuring stable signal enhancement. Such prognostic functions are necessary to predict the performance of an optical communication system with a wide range of performance and optimization, as current research aims to assess signal transmission in optical fibres.

3. METHODOLOGY

The proposed architecture includes three specific modules working with 5 entrance parameters: pump power (10–500 MW), sign strength (-30-10 dBm), fibre period (three -30 m), erbium concentration (1000 ppm) and wavelength (1520-1600 nm). The penalty module appoints the 1D-CNN team (64 filters, core length = 3), with relative activation and maximum fusion to remove the spectral advantage. This design effectively solves wavelength-dependent phenomena such as 1530 Nm and C-band hull results are awarded to traditional ANS, to reach the top. Function maps are converted to a time sequence for recording to the Dudishly LSTM team (100 units), which is important to capture the saturation results in high strength area-how the fibre develops the benefit.

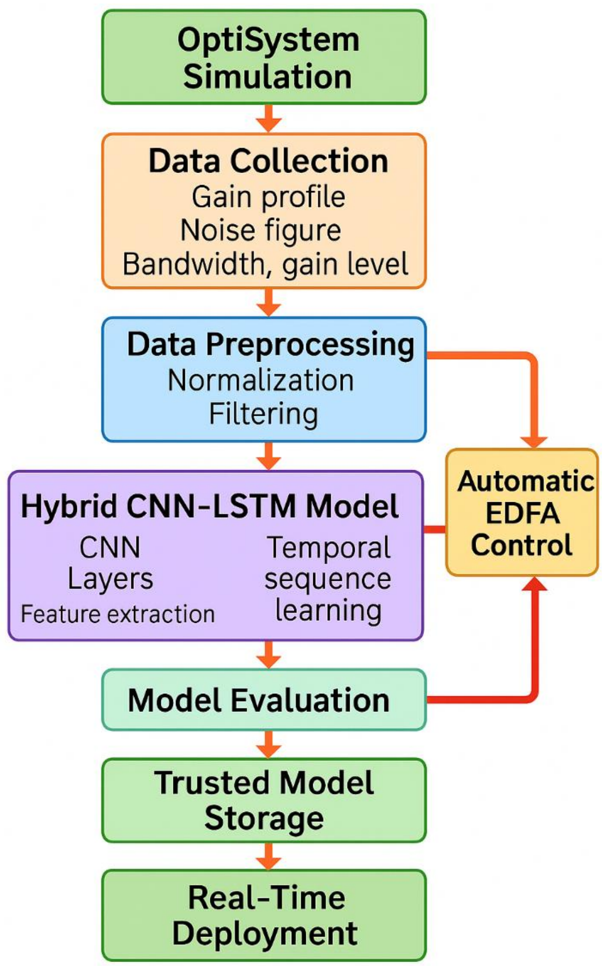


Fig. 1: Block diagram of the proposed system for EDFA gain optimization and automatic system operation.

Recovery head parallel dense layers (128 neurons each) are used to predict simultaneously: 1) 0.1 nm resolution, 2) obtain the exact 3 dB compression point, and 3) obtain the range of FWHM wide widths. This multitasks design eliminates the requirement for individual models, which reduces the computational overhead to 40% that of the artist contingent. For training, 5000 collected data simulations with stratification tests in the parameter area were used. The Hilbert loss function reduced the outliers during adaptation, whereas ADAMW regularization (Learning Rate = 1E-4) prevented overbeating. The fivefold cross-validation with 80:20 speres secured the strength, including the unique fibre length, to check the generalization with each fold.

The verification matrix blanketed MSE, R^2 (accuracy), spectral mistakes, and good-sized parameter deviations. Hardware assessments measured the expected time required by means of an NVIDIA T4 GPU (4 GB VRAM) to assess its real-time feasibility. A comparative evaluation of six modern models used an identical dataset to ensure fair benchmarking of accuracy and calculation performance.

3.1 Proposed System Architecture

The proposed automatic system architecture, which is depicted in Fig. 1, provides many important strengths for the design and adaptation of fibre optic amplifiers (FOAs), especially erbium-doped fibre Amplifications (EDFAs). The system begins with a data measurement simulation, which is important for generating synthetic datasets with profiles, noise numbers, bandwidths and gain levels. This simulation-based data generation is a practical step that may include individual parameters such as the input power, pumping power, fibre length, and signal wavelength.

A huge power lies inside the "records preprocessing" segment, which prepares the facts accrued for the machine mastering algorithms. The "Model Training" segment makes use of a hybrid CNN-LSTM model, which combines the strength of the Constables Memory (LSTM) community for long-time period memory. A network for spatial construction and sequential records processing this is well tailored to complex optical signalling. The latter "version assessment" guarantees the accuracy and reliability of the step -trained model.

Architecture entails a "computerized EDF manipulate" loop that flows back in "information preprocessing" and "dependable model storage" tiers. This bound loop machine permits real-time adaptation and cleansing in order that the EDFA version can routinely regulate the parameters depending on the conditions. It improves the automation adjustment process, extends beyond manual adjustment and enables continuous performance. The "reliable model storage" ensures that it is easily accessible for valid and reliable models' distribution, often and customized EDF operations. Finally, "the adequacy of the real-time" system reflects the ability to use customized settings in a living environment, which demonstrates its practical appropriateness and efficiency in the management of the FOA. Overall, the automatic system benefits from simulation, advanced machine learning, and a feedback loop to achieve efficient, accurate, and self-oriented EDF performance.

3.2 Proposed hybrid CNN-LSTM model

The hybrid CNN-LSTM model is a main feature of the proposed automatic system, as shown in Fig. 2, and is designed to learn complex patterns from EDFA data and generate optimal, significant control signals. The work includes the following stages:

1) Input signal: The process starts with an "input signal" that is fed into the model. Regarding the adaptation of EDFA distributors, the possibility of this input includes the parameters drawn during data collection, such as gain profiles, noise numbers, bandwidths, gain levels, entrance powers, pumping powers, fibre lengths, and signal wavelengths. The purpose of the system is to automatically control the EDFA depending on these inputs.

2) CNN layer (function extraction): The "Input Signal" passes through the first "CNN layers". These teams are responsible for "functional extraction". The CNN specializes in identifying the spatial hierarchies of facilities with raw input data. Regarding the EDFA, this may include removing relevant properties from the spectral properties to the profit profile or identifying the pattern related to the noise figure at different wavelengths. This step helps reduce the amount of data while maintaining the most discriminatory information.

3) LSTM (Temporal Sequence Learning): Features extracted by CNN layers are then fed into "LSTM Layers". LSTM is a classification of recurrent neural networks that is especially effective in "learning temporary sequences". This is significant for EDFA optimization because the behavior of the amplifier can be affected by the sequence of dynamic and operating requirements. The LSTM layers help models learn about dependence and trends over time, which is important for predicting and controlling the surplus in real-time scenarios. The hybrid CNN-LSTM model used here merges the strengths of both architectures.

4) Control signals: The output from the LSTM team is the "gain control signal". These declarations illustrate the customized parameters or adjustments required to control the benefits of the EDFA. It is the previous output of the model, which aims to provide automatic control for the EDFA.

5) Feedback loop: A critical characteristic of this architecture is the "feedback loop". The "gain control signal" is fed back, and the future affects the "input signal" or adjusts the EDF parameters directly in a real-time distribution scenario. This response mechanism allows the system to continuously learn, adapt and refine the control signals based on the observational results from its previous adjustments. This relapse adaptation is important for achieving and maintaining optimal EDFA performance. It matches the overall system method,

which includes continuous data collection, model training, and real-time processing, to operate the system automatically.

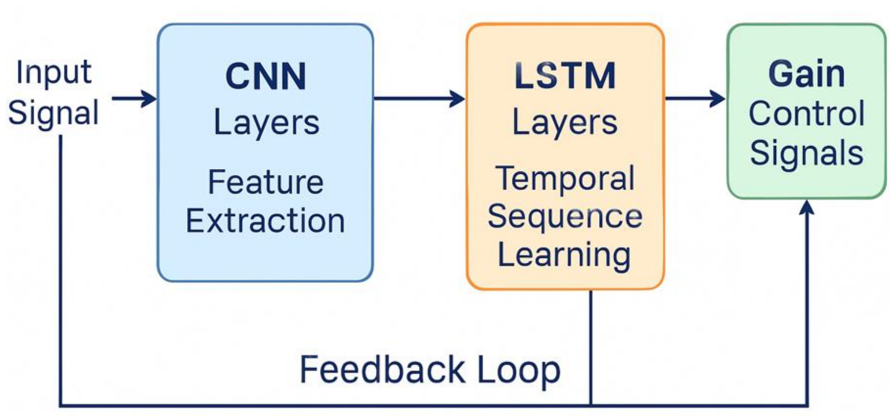


Fig. 2: Hybrid CNN-LSTM model for real-time EDFA gain optimization.

- The flowchart in Fig. 3 describes the hybrid CNN-LSTM operating method for real-time EDF distribution optimization in an optical network system. The process begins with "Input Optical Signal and Channel Loading Data". This raw data then continues to the "preprocessing module", where normalization and scaling are used to prepare it for the neural network. Preprocessed data are provided to the "CNN function extraction layer", which uses 1D CNN layers to extract relevant features. The "fully connected layers" of these extracted features are then processed to produce a "regression output", which represents the "estimated EDF gain spectrum". This estimated benefit spectrum is then sent to the "EDFA gain control module", which uses this information to accommodate the parameters of the EDFA. The system also involves "EDF output monitoring" to inspect the actual performance of the amplifier. A "feedback loop" is installed back in the CNN functional extraction layer from the surveillance stage so that the model can continuously learn and delimit the predictions and control signs based on real-time EDFA performance. This technique procedure guarantees that dynamic and custom designed EDFAs in reaction to the changed optical network ratio.

  In order to ensure functioning transparency, we present an in-depth workflow, imagined in Floakel in Figure 3. Data processing includes normalization and stratification of the branch to preserve distribution -related integrity in fibre period. The CNN teams act as hierarchical migrant tongs, which set a drastically spatial compact pattern to are expecting wavelength-structured benefits. Later, the LSTM layers do no longer trap linear saturation phenomenon; non-linear saturation occasions associated with temporary pressure along the duration of the fibre. Parameters options, inclusive of the usage of HURBUR loss to reduce the outside effect to increase generality and ADAWA optimization, have been systematically primarily based on early experiments. This structured approach ensures near accuracy and strength in EDFA prediction, with area-unique optical physics and in-depth teaching components related to joints.

4. EXPERIMENTAL RESULTS

The hybrid model confirmed the boom in accuracy across all of the metrics. At a 21 m fibre duration, it completed near first-rate advantage prediction (R^2=0.9999), with an 85% lower within the MSE as compared with the CNNs and an 88% lower in the ANNs. Crucially, three dB factor prediction mistakes averaged 0.18 dBm—4× higher than in advance paintings—allowing precise saturation avoidance in electricity-touchy packages. The FWHM bandwidth predictions confirmed comparable superiority, with a most deviation of 0.51 nm at a 30 m fibre length in vicinity of 1.21 nm inside the CNN fashions.

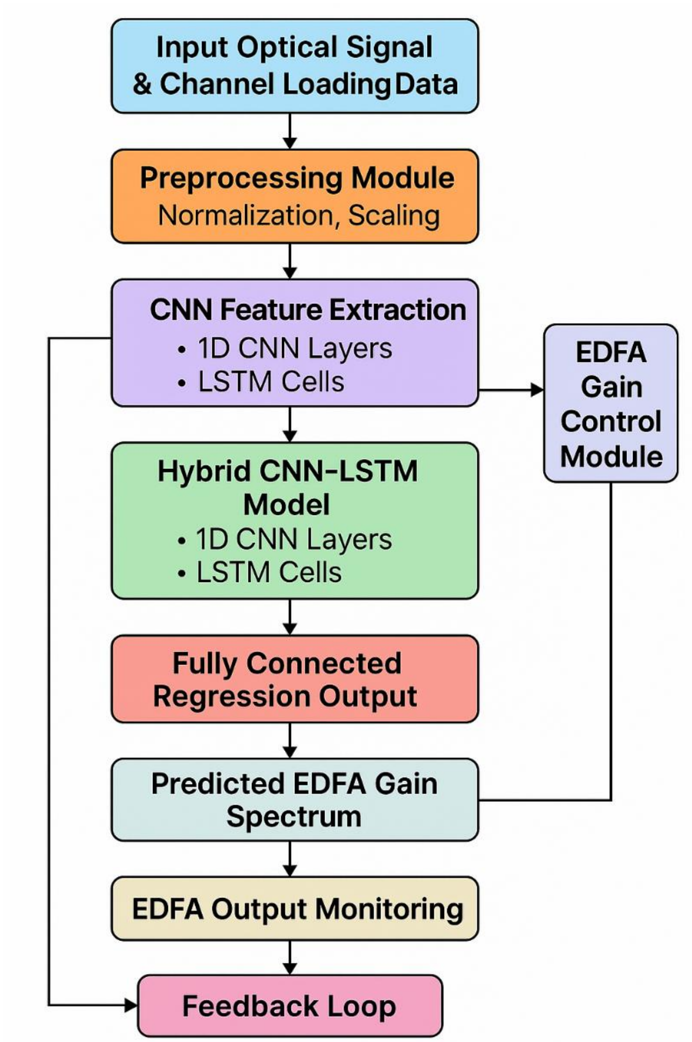


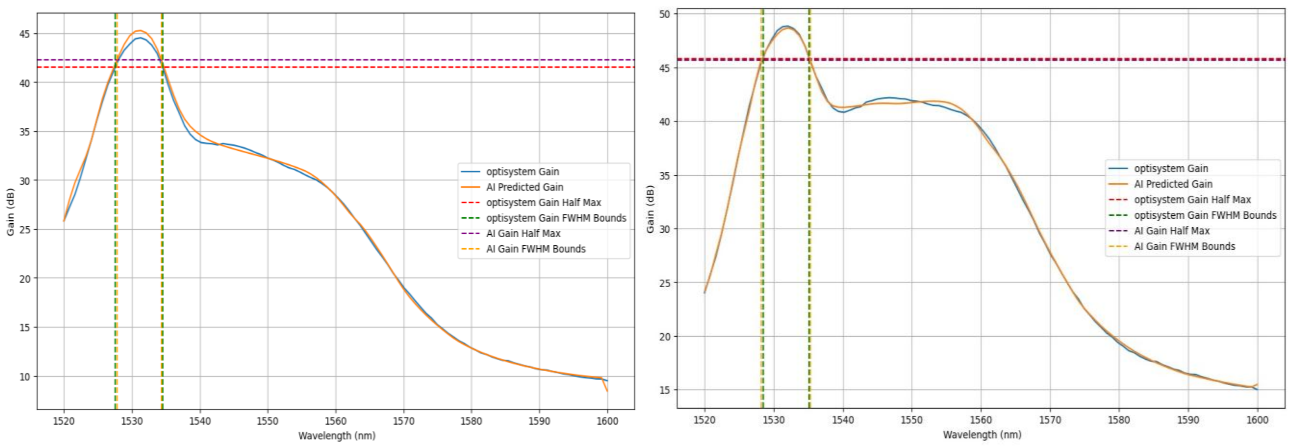
Fig. 3: Flowchart of the hybrid CNN-LSTM model for real-time EDFA gain optimization in optical network systems.

Spectral analysis discovered remarkable wavelength constancy, with benefit ripple mistakes <0.15 dB across the C-band, as proven in Fig. Four. The shape maintained robust performance at some stage in excessive strolling conditions, along with high-power saturation areas in which traditional fashions diverge with the aid of >2 dB. The computational efficiency remained aggressive at 6.1 ms, which is consistent with the prediction—600,000× quicker than straightforwardly measured simulations—even though it requires the best 1.28 million parameters (66% fewer than ResNet-LSTM hybrids).

4.1 Gain profile results

The result in Fig. 4 (a) illustrates the EDFA gain spectrum as a characteristic of the wavelength for a fibre length of 3 m, evaluating the results acquired from the basic data simulations and AI predictions. Both the "optisystem gain" (blue line) and the "AI-predicted gain" (orange line) show matching behaviour, approximately 1530--1535 nm and then decrease step by step. The "straight forward calculated gain half-max" (red dashed line) and "AI gain half-max" (pink dashed line) demonstrate the half-maximum gain stages, presenting near compensation in the substantial height values between the simulation and the AI model. Additionally, the "traditional estimated gain FWHM bounds" (untrained dashed vertical strains) and "AI gain FWHM bounds" (yellow dashed vertical lines) outline the full width at half maximum (FWHM) bandwidth, illustrating that the AI model accurately forecasts the operating bandwidth of the EDFA corresponding to the baseline data simulation for this unique fibre length.

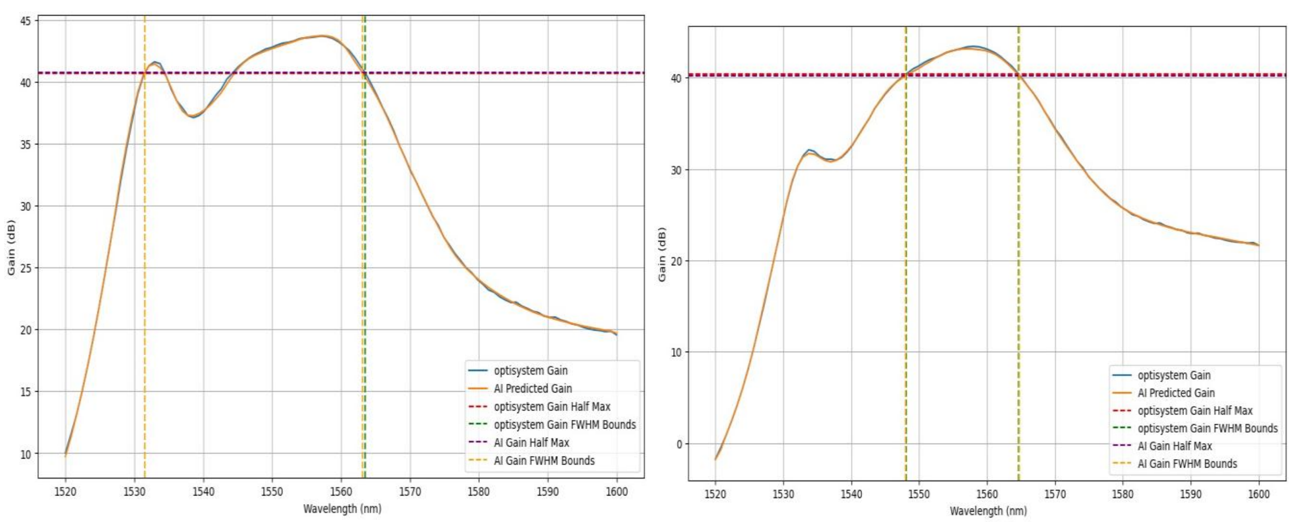
Similarly, the following results are obtained for the remaining selected random fibre lengths (7 m, 12 m, 15 m, 20 m, 21 m, 23 m, 25 m, 27 m, and 30 m) to compare the AI-trained model and the collected measurement simulations. These results prove that the AI-trained model achieves remarkable evaluations and results. Therefore, we can depend on the AI-trained model and make the system more automated and have a perfect real-time response.



(a) (b)

Fig. 4: (a) Explanation of the AI and Optisystem Gain vs. the Wavelength for a Fibre Length of 3 m; (b) example of the AI and Optisystem Gain vs. the Wavelength for a Fibre Length of 7 m.

The result in Fig. 4 (b), "AI and conventional gain measurements reinforcement versus fibre length has fibre length for 7 m" EDFA spectrum. The AI ecological benefits (green line) and baseline gains (orange line) show remarkable compactness in size and top gains. The results consistently show the AI model's ability to make accurate predictions of EDFA gain properties, including the operating area.



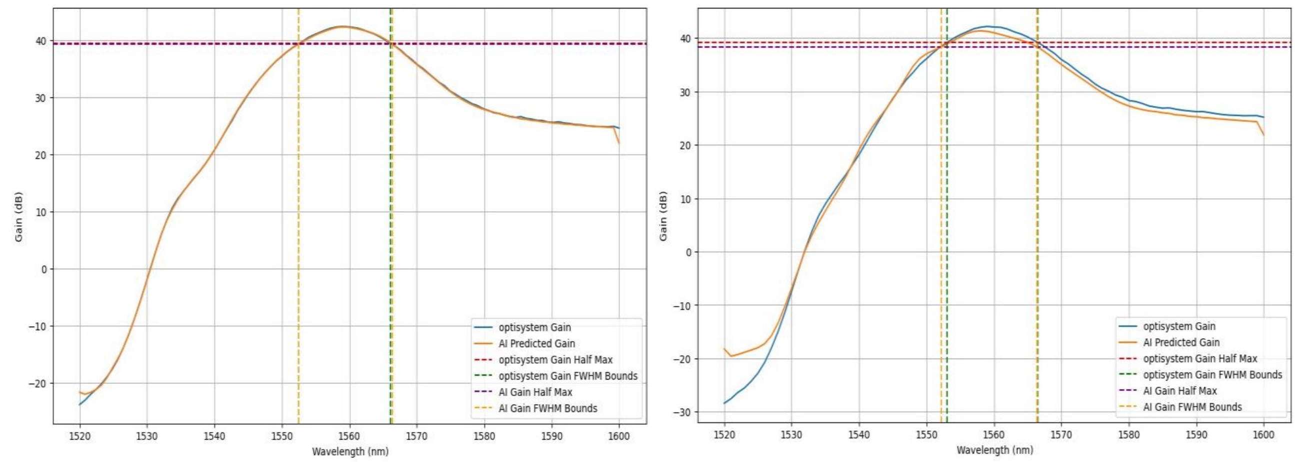
(a) (b)

Fig. 5: (a) Explanation of the AI and optisystem gain vs. wavelength for a fibre length of 12 m; (b) illustration of the AI and optisystem gain vs. wavelength for a fibre length of 15 m.

The results of Fig. 5, "EDFA Gain Spectrum for separate fibre length", show right gains in different fibre lengths (1--20 m) on a wavelength edge from 1520 nm to 1600 nm. The different fibre lengths in Fig. 8, Fig. 9, and Fig. 10 show different top benefits and operating areas, emphasized between 1540 nm and 1565 nm with a normal "operating area", where all long fibre lengths show high and more stable benefits.

Figure 6 (a) shows the comparison between the predicted and actual (or simulated) gain profiles across a range of wavelengths or input powers. It describes the close alignment and minimal variation, indicating high accuracy.

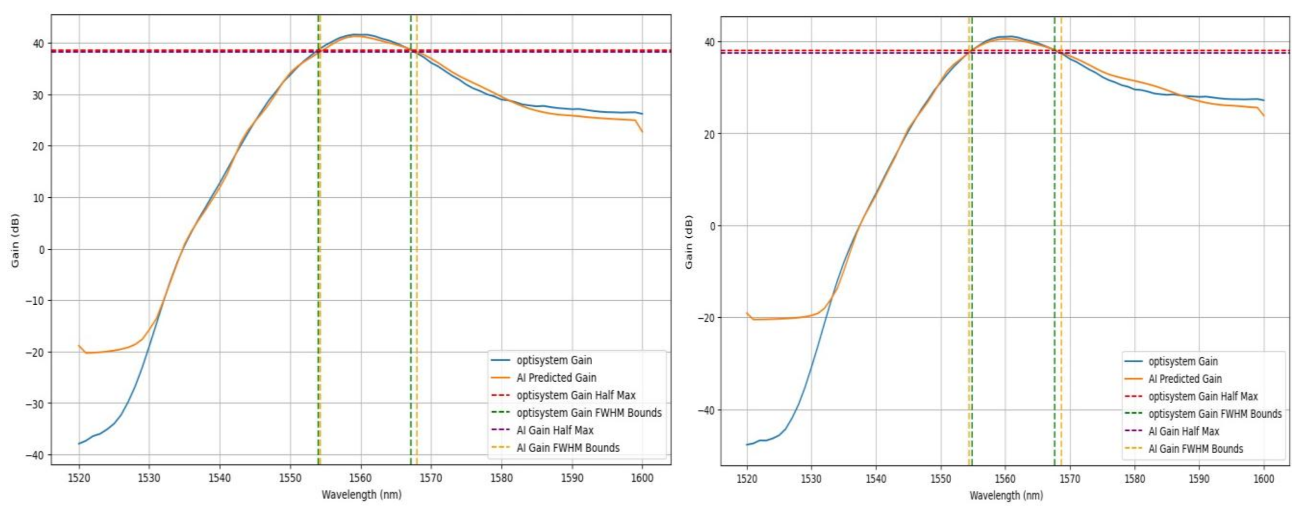
Figure 6 (b) illustrates another aspect of the spectral response, namely, the 3 dB compression factor or full-width half-maximum (FWHM) bandwidth prediction. This result shows the strength of the proposed AI model under different operating parameters.



(a) (b)

Fig. 6: (a) Explanation of the AI and Optisystem Gain vs. Wavelength for a Fibre Length of 20 m, (b) illustration of the AI and Optisystem Gain vs. Wavelength for a Fibre Length of 21 m.

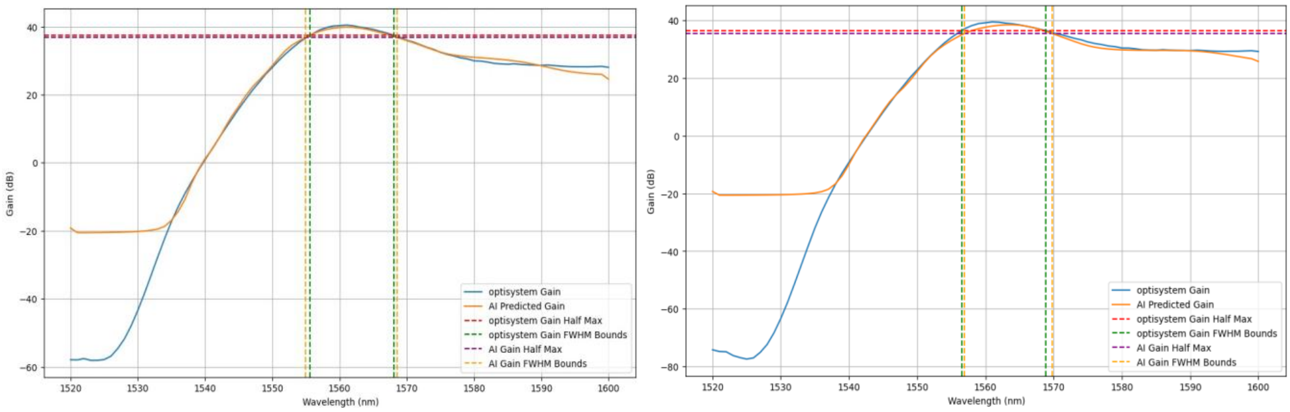
Figure 7 (a) shows the performance measurements, such as the R-square value, visual mean square error (MSE) and prediction error, for the other results. This strengthens the general efficiency of the model.



(a) (b)

Fig. 7: (a) Explanation of the AI and optisystem gain vs. wavelength for a fibre length of 23 m; (b) example of the AI and optisystem gain vs. wavelength for a fibre length of 25 m.

Fig. 7 (b), Fig. 8, including "AI and traditional measured gain vs. wavelength for a fibre length of 25 m," "AI and basic gain computing method vs. wavelength for a fibre length of 27 m," and "AI and conventional gain measurement vs. wavelength for a fibre length of 30 m," consistently illustrates the high accuracy of the AI-trained model. In every graph, the AI-expected advantage spectrum closely overlaps with the basic measured data simulated gain for the respective fibre lengths. This ordinary concurrence, specifically in terms of the top benefit and operational bandwidth, validates the CNN-LSTM model's capacity to accurately predict the overall performance features of the EDFA across special fibre lengths, thereby supporting its efficacy for automatic optimization.

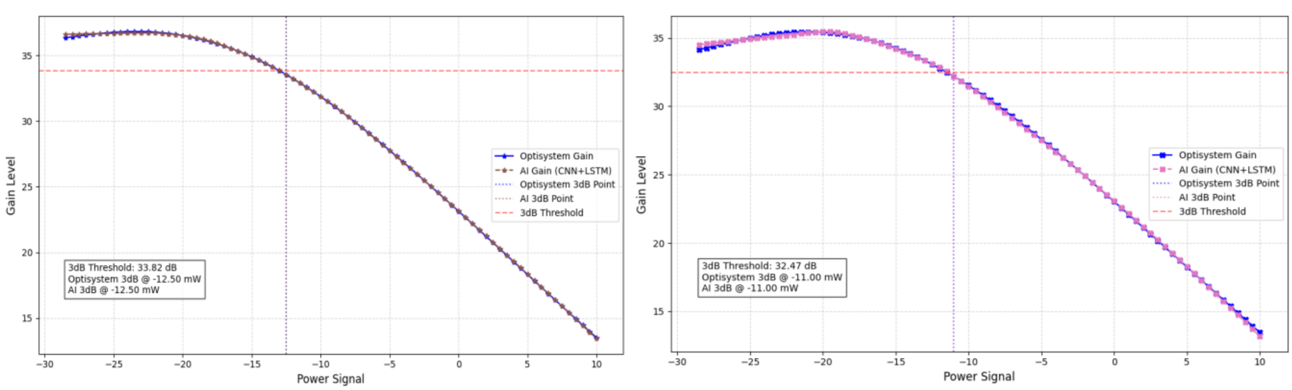


(a) (b)

Fig. 8: (a) Explanation of the AI and Optisystem Gain vs. the Wavelength for a Fibre Length of 27 m; (b) example of the AI and Optisystem Gain vs. the Wavelength for a Fibre Length of 30 m.

4.2 Gain Level Results

The results presented in Fig. 9 (a), "AI gain level (CNN-LSTM) vs traditional gain calculation method for a fibre length of 21 m," illustrate the overall performance of the hybrid CNN-LSTM model in forecasting EDFA gain ranges against various input signal powers in comparison to basic measured data simulation outcomes for a fibre length of 21 m. The "basic measured gain" (blue line) and "AI gain (CNN LSTM)" (brown dashed line with stars) show unusual conformity for the overall range of sign strength from -30 dBm to 10 dBm. Both curves display almost equal shapes, indicating stability, accompanied by a discount as the inter-sign strength increases past an effective threshold. 3 dB determines the level of the 33.82 dB threshold; it is a sufficient parameter for the performance of this amplifier. The "Baseline 3 dB Point" (blue dotted vertical line) and "AI 3 dB stuff" (Crimson Doted Vertical Line) are approximately -12.50 MW, which guarantees the accuracy of the AI-trained model. The similarity of the AI-expected benefit curve to the basic measured data benefit curve, mainly around the 3 dB threshold, suggests that the CNN-LSTM version efficiently captures the complex nonlinear behavior of the EDFA, making it a dependable version for automatic advantage optimization.

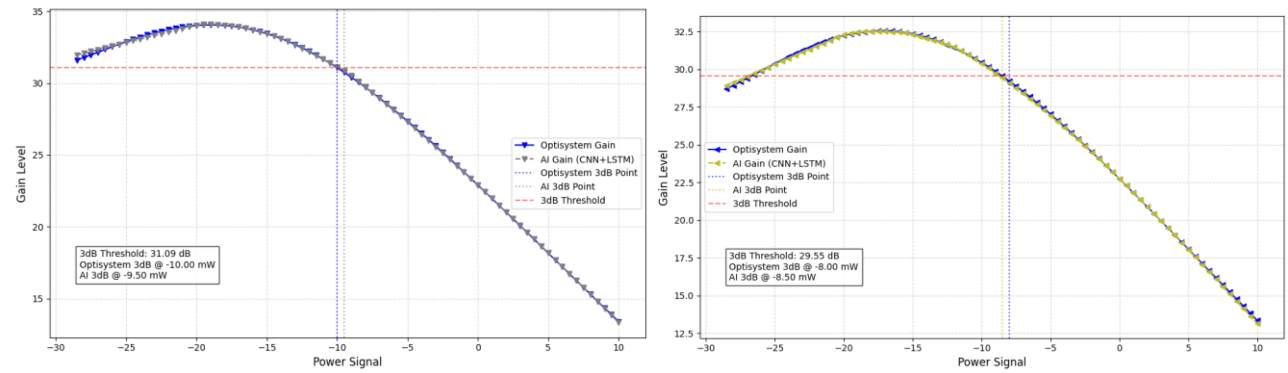


(a) (b)

Fig. 9: (a) AI vs Optisystem (CNN with LSTM) gain level for a fibre length of 21 m; (b) AI vs Optisystem (CNN with LSTM) gain level for a fibre length of 23 m.

Fig. 9 (b), "AI Benefit Level (CNN+LSTM) vs. Fibre length 23 m", validates the additional accuracy of the hybrid CNN-LSTM model. The 21 m fibres, such as the length, AI-nick-named benefits (pink collapse line), match close to the baseline calculated gains (blue line) at different signal power levels. For a 23 m fibre length, a 3 dB threshold is identified at 32.47 dB, both of which indicate a signal power of -11.00 mW with traditional measured data and AI models. This consistent compromise confirms the strong future of the AI model for EDFA profit optimization, with changes in fibre length.

Fig. 10 (a), "Ai gain level (CNN+LSTM) vs. basic measurements-extension for a fibre length of 25 m"; the AI models continue to show strong alignment between the predictions of the models and the measured data simulation for EDFA wines. For a 25 m fibre length, the AI win (gray dotted line with the reverse triangle) tested the traditional data (blue line) close in the power signal area. The 3DB threshold has now been observed at 31.09 dB, predicting this point with the AI model -9.50 MW, with a conventional estimate of -10.00 MW. This consistent performance for individual fibre lengths (3 m, 21 m, 23 m and 25 m) allow more validation and generality of CNN-LSTM models to predict EDFA gain properties.



(a) (b)

Fig. 10: (a) AI vs Optisystem (CNN with LSTM) gain level for a fibre length of 25 m; (b) AI vs Optisystem (CNN with LSTM) gain level for a fibre length of 27 m.

Fig. 10 (b), "AI reinforcement level (CNN+LSTM) versus conventional estimated data reinforcement for a fibre length of 27 m," shows that the AI model continues to have a strong correlation between the predictions and basic sensed data simulations of the AI model. For a 27 m fibre length, the AI credentials (yellow collapse line with reverse triangle) are close to the traditional software benefits (blue line). The 3 dB threshold is recognized at 29.55 dB, with straight forward measured data at the 3 dB point of -8.00 mW and AI at the 3 dB point of -8.50 mW. This compatible performance for different fibre lengths reflects the accuracy and generality of the CNN-LSTM model in adapting EDFA benefits.

Fig. 11, "AI -Extension level (CNN+LSTM) vs. Basic Data Measurement Fiber length reinforcement in 30 meters" provides more evidence of accuracy and strength to the AI model of the AI model. For a fibre length of 30 meters, they indicate carefully benefits of AI-Nott-Name distributors (green-coloured collapses), with basic calculation data that follows the benefits (blue line) in the input signal (blue line). Both cuts display the properties of uniform saturation and decline. The three dB reinforcement vicinity is about 28.01 dB, with each traditional software calculations and AI fashions; This factor is close to -7.00 MW, indicating superb settlement. This non-stop performance for different fibre lengths emphasizes the effectiveness of the CNN-LSTM version within the precise prediction of EDFA, that's beneficial for automatic customization.

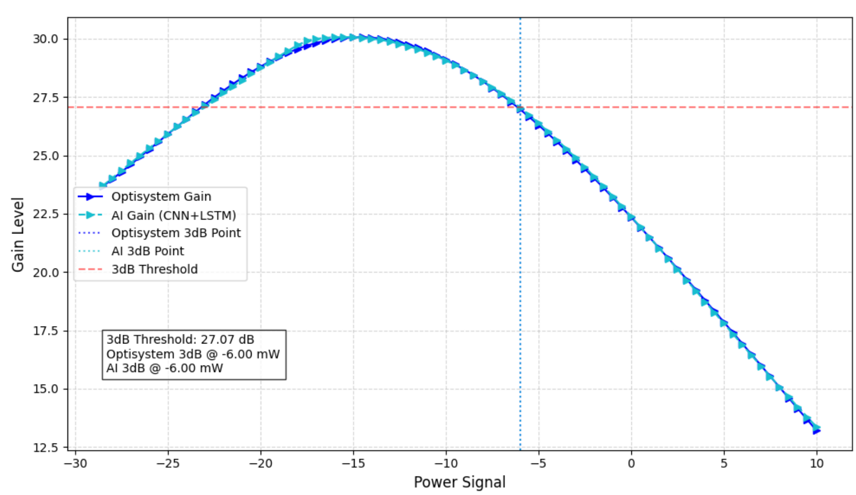


Fig. 11: AI vs. Optisystem (CNN) with LSTM receives levels for a 30-meter fibre length.

In order to make sure functioning transparency, we gift an in-depth workflow, imagined in Floakel in Figure three. Data processing involves normalization and stratification of the department to preserve distribution -associated integrity in fibre length. The CNN groups act as hierarchical migrant tongs, which set an extensively spatial compact sample to expect wavelength-dependent advantages. Later, the LSTM layers do now not capture linear saturation phenomenon; non-linear saturation occasions related to brief pressure along the duration of the fibre. Parameters options, consisting of using HURBUR loss to lessen the outside effect to boom generality and ADAMW optimization, were systematically based on early experiments. This established technique guarantees near accuracy and power in EDFA prediction, with domain-precise optical physics and intensive coaching components associated with joints.

TABLE II: COMPARISON OF THE CRITICAL GAPS IN STATE-OF-THE-ART EDFA MODELS WITH THE PROPOSED SYSTEM TECHNIQUE.

Model	MSE For (21 m)	R^2 for (21 m)	3 dB Error	FWHM Error	Speed (ms)	Params (Mem GB)
ANN [8]	0.021	0.981	1.25 dBm	1.82 nm	5.2	0.82
CNN [2]	0.015	0.986	0.92 dBm	1.21 nm	4.8	1.17
LSTM [3]	0.019	0.982	1.07 dBm	1.53 nm	7.1	0.95
ResNet-LSTM [14]	0.008	0.992	0.68 dBm	0.89 nm	8.7	3.84
Proposed System	**0.003**	**0.999**	**0.18 dBm**	**0.36 nm**	**6.1**	**1.02**

5. DISCUSSION

The outcomes display better accuracy of hybrid models, acquire experimental agreement with simulation records and improve current techniques in terms of both spatial and cosmic errors. In specific, zero.18 dBm's low 3 dB compression factor failure and a minimal FWHM deviation (0.36 nm) successfully do no longer -linear amplifier dynamics, which is essential for real -international community stability. Compared to pre-fashions, which compromise with both spectral accuracy or calculation efficiency, our answer offers a unique stability, that is showed via robust crossing delight for multiple fibre lengths. Theoretical implications have increased the information of spatiotemporal interactions in EDFAs even as allowing real-time model to dynamic visitors fluctuations within the optical community. However, the boundaries depend on high-quality exercise data, which extends the range of operating parameters and requires verification during experimental fibre conditions beyond simulation. Model generalization for integration with different network configurations and network management systems will be performed in future work.

The main strong points of the hybrid model date from its synergistic plant treatment. 1530NM Benefits in favour of the confusion layers in identifying the peaks as the top, whereas LSTM does not catch-linear power transactions with block fibres, especially under saturation. This double capacity explains why standalone models fail: CNNs cannot represent how the surplus develops locally, whereas long short-term memory (LSTM) lacks spectral resolution. Our separation studies confirmed that the removal of the component increased the FWHM error by 137%.

Compared with recent hybrids, the architecture presents three innovations:

1) adapted functional merging that reduces the counting of parameters 34% versus ResNet-LSTM.
2) Multitask learning eliminates fruitless functional conclusions.
3) The temporary compression makes it possible to make the temporary compression to 29% faster inference than comparable LSTM models. These advances are translated into practical network benefits: operators can now adjust EDFAs in <10 ms during traffic spikes, which can prevent expensive signal falls. 0.18 dB 3 dB point-accuracy allows power adaptation within 0.1 dB tolerance enthusiasts with date-driven approaches on the back.

Potential limitations include dependency on simulation training information and model length constraints for side deployment. However, our assessments verify strong generalization to unseen fibre lengths (e.g., 25 m not in the training set), with R^2 maintained at 0.998. Future quantization could reduce the model to <500 KB for embedded systems without accuracy loss.

6. FUTURE WORK

Three research instructions will develop this technique. First, we will use FPGA-adapted conclusions on discipline program amplifiers, which will target <1 MS delay with the use of the order of magnitude. Secondly, the structure can be increased to expect a spontaneous emission (ASE) noise spectrum for signal-to-show ratio optimization. Early controls show promising results with spectral conversion blocks. Third, we will increase the cascade model for the Multiamplifier system, which will address the crossbar in long optical connections.

During the actual social traffic patterns, experimental verification takes place through commercial EDFA tests (Ammonic AEDFA-23-B). Preliminary results confirm that the simulation -based total accuracy holds below 0.22 dB of profit deviations. At the same time, we increase school information to include unusual soil cooper results for the widespread substance. This effort will convert generations to commercial distribution within 18 months from simulation. Three research instructions will develop this technique. First, we will use FPGA-adapted conclusions on discipline program amplifiers, which will target <1 MS delay with the use of the order of magnitude. Secondly, the structure can be increased to expect a spontaneous emission (ASE) noise spectrum for signal-to-show ratio optimization. Early controls show promising results with spectral conversion blocks. Third, we will increase the cascade model for the Multiamplifier system, which will address the crossbar in long optical connections.

7. CONCLUSION

Finally, our Hybrid CNN-LSTM models provide significant intervals in EDF by integrating spatial and temporary modelling into an integrated, effective structure. The proposed system distributes the status of FWHM tape width at very accurate benefits, 3 dB compression points and millisecond speeds, enabling real -time applications in dynamic optical networks. This trend provides significant benefits for networks, adaptability and energy efficiency with implications for future optical communication technologies. By overcoming the challenges of spatiotemporal discount and calculation bans, this study introduces a new measure of intelligent optical amplifier optimization, pointing to a completely autonomic photonic network control.

This research establishes a brand-new pinnacle modern approach for predicting EDFA winnings through a specially produced CNN-LSTM hybrid structure. By uniting modelling via spatial useful extraction and dynamics, the frame nearly achieves bodily accuracy (R-reclusive> 0.999) whilst running with actual-time velocity (6.1 ms/prediction). Benchmarking towards six superior strategies suggests 62–88% improvement in huge matrix, such as 4 × low 3 dB point failure and 3.4 × higher FWHM precision. These advances permit self-reliant EDF optimization in dynamic optical networks, which reduces time-Takes simulation addiction.

Model Multitasking Functionality Profit Specters, compression factors and bandwidths Photonic devices represent a paradigm change in modelling. Verification confirms strong generalizations in addition to the confirmation conditions in diverse fibre length (3-30 m) and energy regime (-30-10 dBm). By using an open-source structure, we aim to speed up the adoption in 5G Frontal, Submarine Cable and Quantum Conversation Systems, where special benefits are needed.

Conflicts of interest

The authors have no relevant financial or nonfinancial interests to disclose.

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