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# Enhancing Optical Multiplex Section QoT Estimation Using Scalable Gray-box DNN

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***Abstract*—In Optical Multiplex Section (OMS) control and optimization framework, end-to-end (Global) and span-by-span (Local) DNN gray-box strategies are compared in terms of scalability and accuracy of the output signal and noise power predictions. Experimental measurements are carried out in OMSs with increasing number of spans.** 

***Index Terms*—QoT estimation, deep learning, optical networks**

## I. Introduction

In today's rapidly evolving digital landscape, optical networks are witnessing an unprecedented surge in traffic demand due to emerging Internet applications such as virtual and augmented reality, cloud services and video streaming. As transmission transceivers' technologies are already close to the theoretical Shannon limit [1], to cope with these increasing capacity needs, efficient network control and management strategies are required. In this perspective, the partially disaggregated approach reduces the optimization complexity separating the control of individual optical multiplex sections (OMS) enabling a software-defined networking management and dynamic lightpath assignment for wavelength division multiplexed optical transport [2]. In this context, accurate physical layer models are crucial, particularly for erbium-doped fiber amplifiers (EDFAs), which directly impact the optical signal-to-noise ratio (OSNR) and overall quality of transmission (QoT) [3]. Physical layer abstraction is particularly challenging in variable spectral load scenarios due to EDFA response fluctuations. Recent advancements in deep learning, especially using deep neural networks (DNNs), have shown promising results for power spectrum prediction in multi-span systems [4]–[8] and EDFA gain modeling [9]. This study focuses on enhancing power spectra prediction accuracy in OMS systems through scalable DNN models combined with simple analytical models for EDFAs and fiber losses, namely *gray-box* approach [3], [9], proposing two strategies: span-by-span (Local) and end-to-end (Global) gray-box DNN Models.

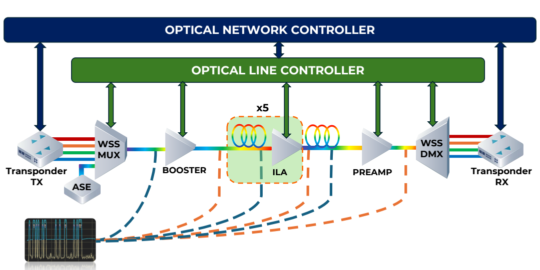



Fig. 1: Framework employed for collecting OMS telemetry data.

## II. Telemetry Setup & DNN Model

The experimental setup for data acquisition and DNN training consists of a multi-span OMS system, as shown in Fig. 1. It includes a booster amplifier (BST) at the input, a pre-amplifier (PREAMP) at the output, and five in-line amplifiers (ILA), all connected by six 65 km standard single-mode fiber (SSMF) spans. A 64-channel C-band wavelength division multiplexed (WDM) comb, with a spacing of 75 GHz between channels, is generated at the BST input using an amplified spontaneous emission (ASE) source shaped with a Wavelength Selective Switch (WSS). Control and telemetry of all EDFAs are managed through vendor-proprietary interfaces, allowing adjustments of operational parameters like gain and tilt values. A Python-based optical line controller (OLC) manages the EDFAs and retrieves telemetry from the EDFAs and transceivers. Laboratory measurements involve varying spectral loads propagated through the OMS, resulting in 500 unique spectral configurations, each with constant launch power at 2dBm, setting EDFAs in constant gain condition. Channel powers are measured at the OMS terminations and at each EDFA input and output for all the spectral configurations using an optical spectrum analyzer (OSA), as shown in Fig. 1. In particular, signal or noise power levels are measured if the channel is switched on or off, respectively. The entire set of measurements can be framed in two distinct monitoring scenarios: a span-by-span and an end-to-end power-

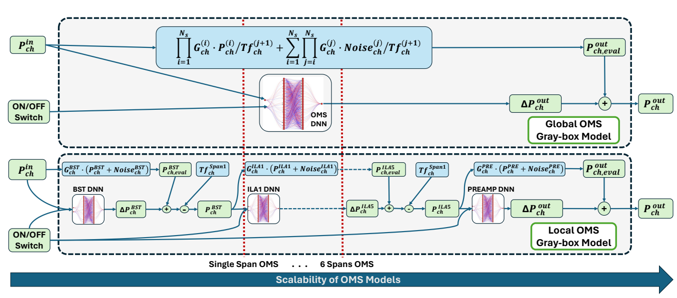
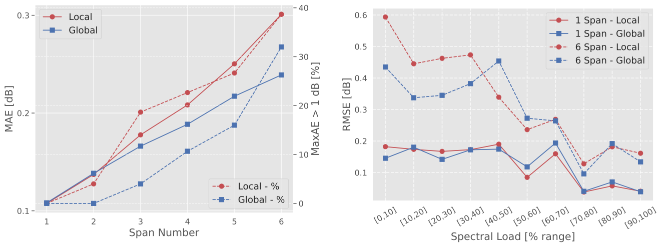



Fig. 2: Global and Local gray-box DNN Models diagrams. Input features, output labels and transfer functions in use for the gray-box approach are shown. Vertical red lines represent the scalability of the models for the different number of spans under test (from 1 to 6).




a) b)

Fig. 3: a) MAE and percentage of channels with MaxAE greater than 1 dB vs. OMS number of spans Local and Global gray-box models; b) RMSE vs. Spectral Load range for Local and Global gray-box model, with 1 span (solid line) and 6 spans (dashed line) OMS cases.

per-channel monitoring where the Local and Global gray-box DNN models can be employed, respectively. The objective is to compare the scalability and accuracy of the two models in predicting fluctuations in the response of EDFA to variable input spectral loads. Therefore, in this work, fiber propagation is modeled by applying transfer functions, $Tf$, derived from span-by-span OSA measurements. In real-world applications, these transfer functions may be evaluated using dedicated optical transmission tools such as GNPy [10]. Additionally, considering span-by-span OSA measurements up to the $n$-th span enables analysis of OMSs with variable number of spans (from 1 to 6), $N_s$. The objective of the gray-box DNN models is the signal and noise power value predictions at the output termination of the considered OMSs; these quantities can be used for OSNR estimations. In particular, the gray-box approach is implemented by leveraging a combination of data-driven techniques and domain knowledge, considering a simplified EDFA model that applies a simplified transfer function evaluated using total input and output powers, and the nominal gain and tilt of each EDFA telemetry, as shown in Fig. 2. In this perspective, DNN model predictions are limited to the output power per channel variation ($\Delta P_{ch}^{out}$) with respect to the simplified output power evaluation, $P_{ch,eval}^{out}$. In detail, the DNNs are configured by considering the input powers and configurations of switched on/off channels (128 features) as input features, $\Delta P_{ch}^{out}$ as output labels (64 labels), and including two hidden layers, each with 1024 neurons. The DNNs are trained using the Adam optimizer and ReLU activation function, iterating over 2000 epochs, considering as training, test and validation sets a percentage division of 70/15/15, respectively. DNNs training are performed monitoring the mean squared error loss function. Performance metrics as mean absolute error (MAE), maximum absolute error (MaxAE) and root mean squared error (RMSE) per channel are chosen to quantify the models' predictive capabilities and accuracy.

## III. Results & Conclusions

Fig. 3 a), with double vertical axes, illustrates the comparison between the Local and Global gray-box OMS DNN models in terms of MAE (left axis), and percentage of channels with a MaxAE greater than 1 dB (right axis), across different spans. The Global gray-box model exhibits a lower MAE across all spans compared to the Local gray-box model. The MAE for the Global model remains below 0.2 dB up to 5 spans, while the Local model's MAE fluctuates more widely, reaching up to 0.3 dB. The percentage of channels with a MaxAE greater than 1 dB is also lower for the Global gray-box model, which maintains this percentage below 20% up to 5 fiber spans, whereas the Local model can go as high as 40% in the 6-spans case. These results demonstrate that the Global gray-box model can lead to more accurate and reliable QoT predictions for the OMS even increasing its complexity. Figure 3 b) presents the RMSE for both the Local and Global DNN models across different spectral load ranges, considering only the single-span and the 6-spans cases under investigation. For single-span setups, both models perform similarly at lower spectral loads, with a RMSE around 0.1 to 0.2 dB. As the spectral load increases, both RMSE reach higher accuracy, with values below 0.1 dB. Considering the opposite extreme case of 6-spans, RMSE sharply increases for lower spectral densities, moving down to the range between 0.2 and 0.1 dB for higher spectral loads. The RMSE for the Global model remains generally lower with respect to the Local model, across different spectral loads, indicating its higher robustness.

These findings demonstrate that the Global gray-box model provides more accurate and reliable predictions, especially in multi-span configurations, due to its end-to-end OMS approach. Overall, this study highlights the potential of scalable DNN models combined with the gray-box approach for enhancing power spectra prediction accuracy in OMS systems, contributing to the advancement of predictive modeling in optical networks with a mixed analytical and deep-learning approach, enhancing the QoT estimation for more accurate OSNR and, integrating the proposed techniques with already existing QoT estimators like GNPy, improving GSNR predictions' accuracy.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