Deep Learning Gain and Tilt Adaptive Digital Twin Modeling of Optical Line Systems for Accurate OSNR Predictions

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1st Rocco D'Ingillo
Politecnico di Torino
Turin, Italy
rocco.dingillo@polito.it

2nd Andrea D'Amico
NEC Labs America
Princeton, NJ, USA
adamico@nec-labs.com

3rd Renato Ambrosone
Politecnico di Torino
Turin, Italy
renato.ambrosone@polito.it

4th Emanuele Virgillito
Politecnico di Torino
Turin, Italy
emanuele.virgillito@polito.it

5th Vittorio Gatto
Politecnico di Torino
Turin, Italy
vittorio.gatto@studenti.polito.it

6th Stefano Straullu
LINKS Foundation
Turin, Italy
stefano.straullu@linksfoundation.com

7th Francesco Aquilino
LINKS Foundation
Turin, Italy
francesco.aquilino@linksfoundation.com

8th Vittorio Curri
Politecnico di Torino
Turin, Italy
vittorio.curri@polito.it

***Abstract*—We propose a deep learning algorithm trained on varied spectral loads and EDFA working points to generate a digital twin of an optical line system able to optimize line control and to enhance OSNR predictions.**

***Index Terms*—EDFA, deep learning, digital twin, GNPy**

I. Introduction

As the demand for network capacity continues to rise [1], network operators are exploring innovative solutions to maximize transmission speeds and capacities. Disaggregated and open optical infrastructures offer flexibility and support multi-vendor approaches, enabling a software-defined networking (SDN) approach to control and manage optical networks, allowing dynamic assignment of lightpaths (LPs) for wavelength division multiplexed (WDM) optical transport. [2] Quality of transmission estimation (QoT-E) is crucial for assessing network performance, considering factors such as amplified spontaneous emission (ASE) noise and nonlinear interference (NLI). The ASE noise is the main contributor to QoT degradation, depending on the working points of the erbium-doped fiber amplifiers (EDFAs) present in the optical line system (OLS) [4]. To minimize downtime, network operators establish a minimum QoT threshold, often incorporating conservative design margins, which can sometimes reach multiple dB due to cautious estimations [5]. Streamlining these margins has the potential to significantly enhance traffic capacity, all without requiring modifications of the network infrastructure. To achieve this objective, this study focuses on a partially disaggregated optical network framework using SDN with reconfigurable optical wavelength selective switches (WSSs) and an independent optical line systems (OLS). The two components of the optical signal-to-noise ratio (OSNR), namely the transmitted signal and ASE powers, both experience significant fluctuations when the spectral load is modified. Deep learning and artificial intelligence (AI) approaches have shown outstanding results for signal and ASE power fluctuations due to a varying spectral load [7], [8], providing a significant enhancement of the prediction capabilities of a digital model such as GNPy, and in general machine learning (ML) techniques have been leveraged for QoT-E accuracy improvements and system margin reduction [3], [6]. Extending the results presented in [7], system response fluctuations induced by a varying spectral load have been measured for an extensive set of working points, *i.e.* gain and tilt values for each amplifier, in order to enable an adaptive control of the OLS. Remarkably, the proposed methodology is based on a optical system digital twin (DT) approach, where data collection is automatized and managed by an OLS controller with a direct access to EDFAs and the optical channel monitoring (OCM) within the WSSs through device vendor interfaces.

II. Telemetry of the Optical Line System

In Fig. 1 the testbed in use for measurements is presented. The OLS consists of 10 commercial EDFAs (one booster (BST) at transmitter side (TX), one pre-amplifier (PREAMP) at receiver side (RX) and 8 in-line amplifiers (ILAs)), interconnected by 9 standard single mode fiber (SSMF) spans with a nominal length of 100 km. A 96-channels C-band WDM comb is generated at BST input with 50 GHz spacing between channels. A commercial waveshaper is responsible to shape the amplitude of an ASE noise for the generation of 92 channels. These channels are combined with 4 additional equally spaced modulated channels under test (CUT) (centered at 191.5, 193.0, 194.5 and 196 THz, respectively),

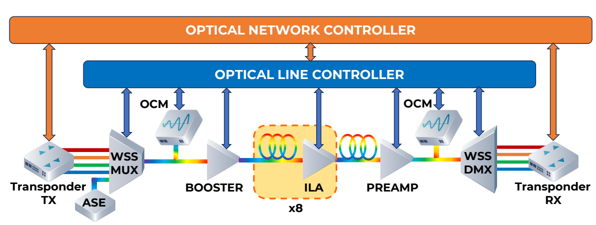

Fig. 1: Framework in use for gathering telemetry data in the WDM optical line system.

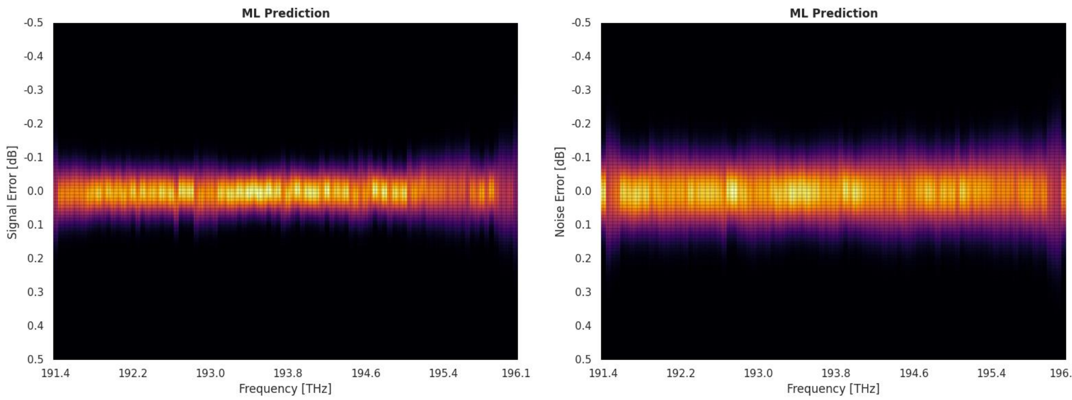

Fig. 2: Error distribution of signal and noise powers evaluated with the ML model.

at 32 GBd rate, through a commercial WSS multiplexer (MUX). The 4 CUTs are modulated by 4 commercial coherent pluggable transceivers plugged into two Cassini whiteboxes. The whiteboxes exploit OcNOS operating system developed by IP Infusion, which provides NETCONF interfaces that enable both data retrieval and the configuration of parameters necessary for conducting measurements on the devices. All EDFAs are controlled through vendor-proprietary interfaces which allow the operative working points of the devices to be read and set managing gain and tilt (G&T) values. The OLS is controlled by a single optical line controller (OLC) developed in Python language in charge to get and set the EDFA (G&T) values independently and to manage and retrieve the telemetry from the EDFAs and OCM of the WSSs MUX and demultiplexer (DMX) at TX and RX side. In the scope of this study, 8 different EDFA working point conditions have been taken into account. Additionally, the spectral load in line is varied considering 1030 different combinations of ON/OFF channels in the 96-channels WDM comb, going from a minimum of 4 ON channels, given by the CUTs coming from the Cassini whitebox, up to the full spectral load. The data collection performed in the telemetry campaign is fed to a deep neural network (DNN) able to provide accurate predictions of signal and noise profiles of the OLS considering all the different working point condition of the EDFAs and for each spectral load configuration. The time necessary for data collection settled around 16 hours considering all 1030 channel spectral load combinations for G&T EDFA working point case, for a total amount of 128 hours. Remarkably, the main driver of the data collection time is the OCM estimation and register update speed, which exceeds 1 minute in the investigated testbed.

III. Deep Neural Network Modeling and Training

The proposed methodology involves the implementation of a ML algorithm to enhance the QoT assessment for the OLS under investigation. This implementation aims to reduce inaccuracies in OSNR component estimation. In order to create a ready-to-use training dataset for the DNN to satisfy this condition, collected telemetry data are processed in order to detect and treat outliers. In the implementation of the ML algorithm within this study, we standardize and partition the dataset into training, validation, and testing subsets, comprising 80%, 10%, and 10% of the total dataset size, respectively. We utilize the open-source Keras high-level API from TensorFlow library to construct a sequential DNN model consisting of an input layer of the same size of the input features, one single hidden layer composed by 1024 hidden neurons, with rectifying linear unit (ReLU) activation function, and one output layer of the output label size, with linear activation function. These values have been determined as optimal through a validation process, striking a balance between the accuracy of ML predictions and the overall training time. The entire measured dataset is prepared in order to use the diverse G&T EDFA configurations, the input power and the ON/OFF spectral load channel configurations as *features* of the DNN , whereas, the output power of each channel, including the channel cross-talk (XT) and ASE noise, as DNN *label*. As spectral load and G&T EDFAs configurations vary for each measurement within the dataset, the selection of appropriate features for DNN input and output is crucial. The feature selection must be finalized before the training process begins and remains constant throughout the training. The features used for training must correspond to known system variables, as individual DNN predictions rely on these inputs. Consequently, the complete set of power measurements can be used exclusively as DNN outputs, as they are unknown for any given spectral load. The main challenge is described in the following: when a channel is active, the signal power can be measured, but the ASE and, if present, XT noise powers cannot. Conversely, when a channel is inactive, by definition, there is no signal power, but ASE noise or XT powers can be measured. To overcome this issue, we applied a data augmentation procedure leveraging the system similarities between adjacent channels. Each DNN then features a total of 136 inputs and 96 outputs, with precise signal and ASE noise power predictions, leading to accurate signal and ASE power estimations.

IV. Results

We present the ML prediction results for a test dataset containing 824 different combinations of spectral load and EDFA G&T configurations (before data augmentation). The accuracy metric used is the mean-square error (MSE) between

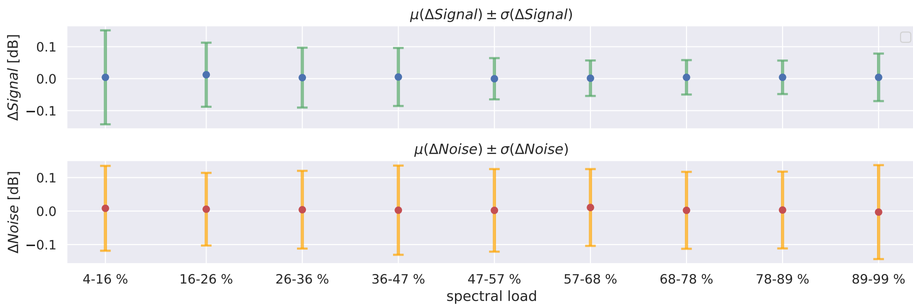

Fig. 3: Signal and Noise errors (Δ Signal, Δ Noise) over different ranges of spectral load percentage: dots represent the mean absolute error (μ), the vertical lines the standard deviation of the error (σ), in dB.

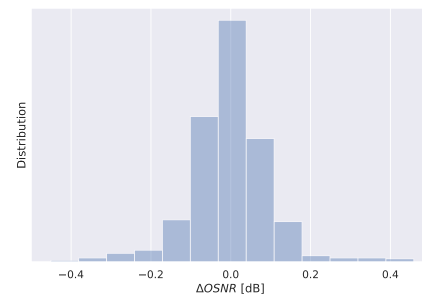

Fig. 4: Distribution of the error on the OSNR (Δ OSNR) between measured and predicted cases, in dB.

measured and predicted quantities, which is robust to outliers [9], used as difference between measured and predicted values. Also mean absolute error (MAE), standard deviation of the absolute error (STD) and maximum absolute error (MaxAE) between predicted and measured data are monitored, in order to stop the training only for a STD lower than 0.2 dB and a MaxAE lower than 1 dB, per channel. To show the benefits of using a machine learning approach, we assess the DNN accuracy in predicting output DMX power levels across the full WDM comb for all the different configurations in the test dataset. The predicted signal and noise power model of the OLS is obtained after 45 minutes of training time, with a MaxAE of 0.9 dB, maximum STD of 0.1 dB and with a minimum accuracy R2 score (R2S) parameter of 97.98%, per channel. To provide a qualitative evaluation of the model accuracy, Fig. 2 displays the signal and noise error (Δ Signal, Δ Noise) distribution results after ML prediction, illustrating error distribution as vertical colored strips for each channel. Brighter colors represent higher density, while darker colors indicate lower density. Fig. 3 shows these results in detail, with focus on the mean absolute error μ (represented with dots) and the standard deviation σ (represented with vertical lines) of both errors for different ranges of spectral load percentage, demonstrating the stability of the per-channel results shown in Fig. 2. Finally, the accurate signal and noise power predictions of the ML model can be used for the OSNR estimation. In particular, in this work we assume that the noise level does not change significantly when a single channel is switched off, and the value of a channel OSNR can be measured through this standard procedure. In order to estimate the ML model prediction accuracy of this OSNR measurement, we select throughout the entire test dataset all the pairs of spectral configurations that differs of one single channel switched off. Then, the ML model is applied to the two configuration to predict the signal and the noise, respectively, and the distribution of the error on the OSNR (Δ OSNR) between measured and predicted cases is showcased in Fig. 4, confirming the high accuracy of the ML prediction. This comparison provides a prediction error distributions with 0 dB MAE, 0.1 STD and 0.6 MaxAE, demonstrating the potential of the ML model as an accurate unbiased OSNR estimator. This approach, combined with already existing QoT-E like GNPy can move towards increased accuracy of estimation, reducing error and thresholds in design margins.

V. Conclusion

This study showcase a ML approach to optical network QoT-E for varying spectral load and OLS working points. The study employs a partially disaggregated OLS combined with SDN to dynamically manage optical networks, using deep learning and AI to reduce uncertainties in ASE noise characterization. Considering 8 different configurations of G&T of the EDFAs in the OLS, which are the main source of noise in line, and 1030 spectral load configurations, the OLS telemetry performed is used to train a deep learning model of signal and noise power profiles of the global OLS. ML predictions present a high accuracy, moving error distributions near zero mean. This method, combined with a QoT-E to predict the NLI noise like GNPy is a strong means to enhance the already existing estimation techniques to predict the GSNR with high accuracy, streamlining design margins even in challenging condition of varying working points of the amplifiers in line and with diverse spectral load application.

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