DNN-based QoT Estimation Using Topological Inputs and Training with Synthetic-Physical Data

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***Abstract*—We propose a DNN-based QoT estimation technique that operates on a network-wide scale. The DNN training data is composed of connection paths, frequency slots, and OSNR transponder telemetry, collected from both synthetic and physical connections. Simulation results indicate effective and low-complexity QoT estimation.**

***Keywords*—QoT estimation, optical networks, machine learning, deep learning.**

I. Introduction

Estimating the quality of transmission (QoT) of unestablished lightpaths has been an active field of research in recent years [1]. Contrasting with the common practice of estimating QoT based on analytical formulas and applying margins, new approaches leverage advances in network operation to improve QoT estimates based on the telemetry of installed devices. Most recent QoT estimation algorithms based on machine learning (ML) rely on techniques such as artificial neural networks (ANNs), support vector machines (SVMs), and extreme gradient Boosting (XGBoost). Although these algorithms have black-box characteristics, they can straightforwardly incorporate practical discrepancies into the QoT model.

Kruse et al. [2] implement spectral data-driven long short-term memory (LSTM) neural networks for QoT estimation, obtaining 1.1 dB improvement in established lightpaths. Amirabadi et al. [3] compare deep neural network (DNN) regressors with other well-known ML algorithms for generalized signal-to-noise ratio (GSNR) estimation with transmission and topology features, such as channel index, modulation format of the channel under test and neighbor channels, number of empty neighbor channels, number of occupied channels, traffic volume, and number of spans and their length. Usmani et al. [4] evaluate QoT estimation using ML models trained with the number of spans, distance, signal power, nonlinear distortion, and amplified spontaneous emission (ASE) noise. Morais et al. [5] adopt a topology feature space to train ML algorithms to estimate residual margins.

This paper proposes a QoT estimation algorithm based on a DNN fed with only topological data. For a specific lightpath, the DNN inference inputs are simply the traversed links and the selected frequency slots. Differently from [2]–[4], the training phase only relies on topological data and simple optical signal-to-noise ratio (OSNR) transponder telemetry. Unlike [5], the proposed work adopts fewer input topology features, increasing its applicability. The smaller input dataset is compensated by extensive training using physical telemetry and synthetic telemetry generated by the GN model. Having the synthetic telemetry ensures reasonable QoT estimation, approximating the GN model when the network is only lightly populated. The role of the synthetic data is then diminished as more physical connections are installed in the network. We show that the DNN trained with mixed synthetic-physical data is able to track the OSNR with non-biased error, even when only a few physical samples are available.

II. Proposed Framework

The proposed framework considers an optical network with $2L$ unidirectional links, each supporting N_{fs} frequency slots. The QoT estimation scheme is based on the DNN shown in Fig. 1. Its $2L + N_{wc}$ inputs correspond to all $2L$ unidirectional network links and N_{wc} wavelength clusters, and its output corresponds to a link OSNR (or GSNR). We denote a wavelength cluster as a set of contiguous neighboring frequency slots. Clustering frequency slots into a lower number of inputs helps to reduce sparsity and improve performance. The inputs are binary variables set to one if the corresponding link or wavelength cluster is used by the connection whose QoT (OSNR) is being evaluated. The remaining inputs are set to zero. The proposed framework works with a training dataset composed of a mixture of synthetic data, whose OSNR is generated by the GN model, and a physical dataset, whose OSNR is collected by telemetry. This approach enables the algorithm to yield relatively accurate estimates even in a lightly loaded network. In this paper, the physical dataset is also computationally emulated by incorporating imperfections.

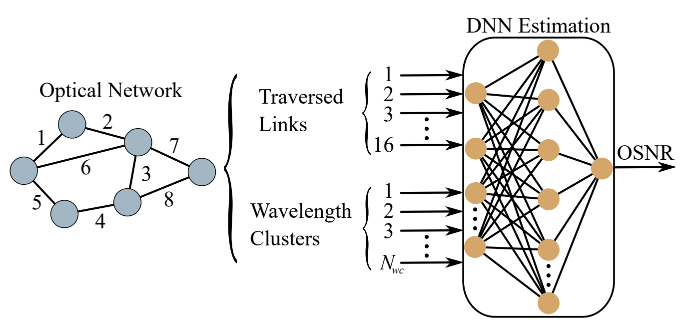

Fig. 1. Example of the proposed OSNR estimation architecture for an optical network with 8 nodes, 8 links (bidirectional), and N_{wc} wavelength clusters.

III. Results

Table I depicts the simulation parameters. Demands are uniformly distributed in the network, with a symbol rate $k \times 10$ Gbaud, where k is an integer uniformly distributed between 4 and 8. The signal bandwidth considers Nyquist pulse shaping with 0.15 roll-off factor. Simulated route-and-select (R&S) reconfigurable add-drop multiplexers (ROADMs) are equipped with a per-channel power control loop based on optical channel monitors (OCMs) and wavelength selective switches (WSSs), ensuring a -6-dBm launch power per slot (equivalent to 0-dBm launch power for a 50-GHz channel). We assume 80-km spans with 0.2-dB/km attenuation, except for the last one, which ranges between 50 km and 120 km, to achieve the desired total span length. Synthetic connections are generated considering flat inline amplifier (ILA) gains and noise figures (NFs) equal to 16 dB and 5.5 dB, respectively.

The emulated physical dataset is generated considering inline amplifiers with wavelength-dependent gain. To create wavelength dependency, the ILA gains on the spectrum left edge, right edge, and position n, $g(\lambda_0)$, $g(\lambda_n)$, $g(\lambda_{N_{fs}-1})$, are randomly selected following $\mathcal{U} \sim \{15, 16\}$ dB, in which n is randomly chosen in the interval $(0, N_{fs} - 1)$. The in-between gains are quadratically interpolated, and white Gaussian noise ($\mathcal{N}\{0, 0.0001\}$ dB) is added to each gain. The noise figures (NFs) are also a function of the gains, i.e., $\mathrm{NF}(\lambda_n) = [5.5 + 16 - \mathrm{g}(\lambda_n)]$ dB, $n \in [0, \cdots, N_{fs} - 1]$. The accepted demands are randomly split into training and inference datasets (50% each). A normalization between 0 and 1 is applied at the output to improve numerical stability.

QoT estimation is carried out by a DNN composed of four layers. The first layer has 202 (GNet) and 194 (NSFNet) inputs (corresponding to all unidirectional links and $N_{wc} = 150$ wavelength clusters[1]), the hidden layers have 200 neurons each, with hyperbolic tangent activation functions, and the output layer has 1 nonlinear neuron with rectified linear unit (ReLU) activation function, corresponding to the estimated OSNR. We use a mean squared error (MSE) loss function to minimize the DNN output error. The Adamax optimization is applied to the backpropagation process [6]. The training was performed for 120 epochs with a batch size equal to 20.

TABLE I
Simulation parameters

Topology	GNet and NSFNet [7]
Optical wavelength band	C-band (4.8 THz - 384 FSs)
Grid	12.5 GHz
Symbol rate	$k \times 10$ GBaud, $k = 4, 5, 6, 7, 8$
Accepted demands	831 (GNet) 810 (NSFNet)
Routing	Djkistra
Wavelength assignment	First-fit
Shaping filter	Root-raised cosine ($\alpha = 0.15$)

[1]Wavelength cluster m is created considering ranges $\left[(m-1)N_{fs}/N_{wc}, mN_{fs}/N_{wc}\right]$, $m = 1, 2, ..., N_{wc}$. An FS is assigned to cluster m if its index matches the range of m.

Fig. 2 presents the error quartiles for the GNet and NSFNet. The resulting quartiles represent the error distribution depending on the training strategy: Figs. 2(a) and 2(c) for physical connections only, and Figs. 2(b) and 2(d) for synthetic and physical connections. In Figs. 2(a) and 2(c), the lower and upper whiskers are reduced in modulus when increasing the number of physical samples for training. However, even with several physical samples, some outliers reach high error values. In Figs. 2(b) and 2(d), for 0-physical samples (i.e., only synthetic data), there is an error bias of approximately 5 dB for both networks. Notwithstanding, with only 50 physical samples, there is a significant error reduction in all quartiles, centering Q2 around 0 dB.

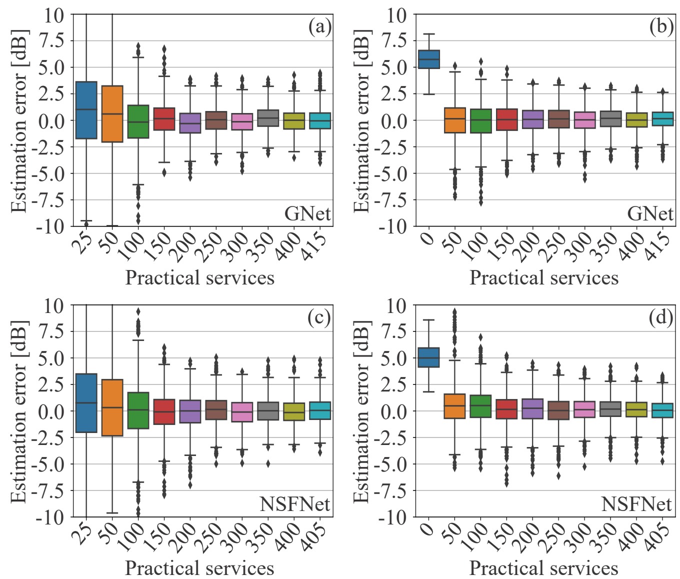

Fig. 2. OSNR estimation error ($e = \mathrm{OSNR}_{\mathrm{true}} - \mathrm{OSNR}_{\mathrm{estimated}}$ [dB]). (a-b) GNet; (c-d) NSFNet. (a-c) using only physical connections; (b-d) using mixed synthetic-physical connections.

Acknowledgments

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