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Machine learning Assisted Accurate Estimation of QoT Impairments of Photonics Switching System on 400ZR

Ihtesham Khan[(1)], Lorenzo Tunesi[(1)], M Umar Masood[(1)], Enrico Ghillino[(2)], Paolo Bardella [(1)], Andrea Carena[(1)], Vittorio Curri[(1)],

[(1)] Politecnico di Torino, Corso Duca degli Abruzzi, 24, 10129, Torino, Italy,
[(2)] Synopsys, Inc., 400 Executive Blvd Ste 101, Ossining, NY 10562, United States
ihtesham.khan@polito.it

Abstract: We propose a machine learning-based technique that accurately estimates quality-of-transmission (QoT) impairments of an optical switch on 400ZR. The proposed scheme works in an entirely agnostic way reduces inaccuracy in QoT impairments estimation by 1.5 dB. © 2021 The Author(s)

1. Introduction

With the present-day rise in capacity and traffic demands, the key network operators always welcome novel solutions that try to exploit the residual capacity of existing infrastructures to maximize their capex. The newly evolved concept of disaggregated and open network infrastructure has been recognized as a potential candidate that provides more flexibility to the network and defines a path for a multi-vendor system [1, 2]. In this context, optical software-defined networking (SDN) applications may be implemented on each layer to control and manage the optical network. This deployment of SDN down to the transmission and physical layer enables the full virtualization operation of wavelength division multiplexed (WDM) optical transport with a standard application programming interface (API) in order to manage network subsystems and components independently [3]. To accomplish this, a quality of transmission estimator (QoT-E) plays an essential role by computing the generalize signal-to-noise ratio (GSNR) of transparent lightpath (LPs) to maximize the deployed capacity by accumulating the GSNR degradation of noisy elements and filtering penalties of switches.

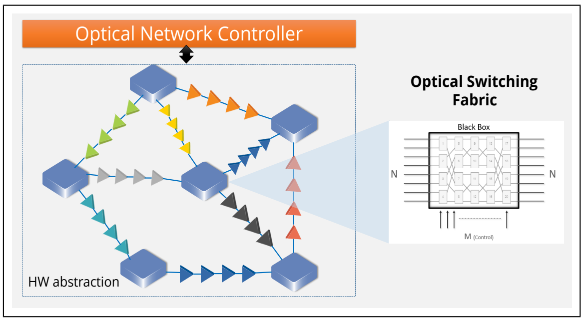
To avoid out-of-service (OOS), the network operators must guarantee that the QoT never falls below a given threshold; this introduces the provisioning of a certain degree of margin that quantifies the uncertainties on the computed QoT. Typically, the provisioned margin ranges to several dB due to conservative overestimation [4]. Cutting the uncertainties in QoT-E allows margin reduction with considerable increase in traffic deployment using the existing network infrastructure. The modern optical networks extensively exploit photonic integrated circuits (PICs) for switching operations due to their wide-band capabilities, minimal latency and low power consumption. Hence, requests for a generic softwareized control model for photonic switches to enable their complete control by a centralized controller as shown in Fig. 1a. Such a model includes the switches control states and the filtering penalty degrading the GSNR of the routed LP.

This work extends our previous investigation related to model control states of $N\times N$ photonics switching system using a topology-agnostic blind approach based on inverse ML technique [5]. In this work, we exploit ML techniques with a direct design method to accurately predicting the filtering penalties of an optical switching system on LP deploying 400ZR [6]. The proposed method can be easily extended to model $N\times N$ optical switch performance on the network layer metrics. The presented data-driven scheme is trained by a dataset obtained by considering any $N\times N$ photonics switch under test as a black-box. The training dataset can either be acquired experimentally or synthetically by using a software simulator for components [7], as for the presented results

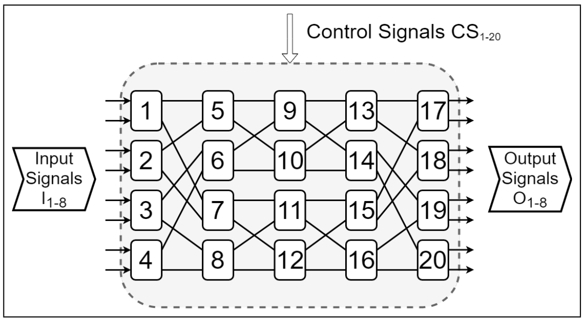
2. Switching Topology and Data Generation

The switching device used in the analysis is based on the Beneš network topology, due to the architecture widespread applications, and is defined as a 8×8 non-blocking multistage switching network. The circuit is made of $M = 20$ 2×2 crossbar optical switching elements (OSE). The OSEs have been modelled as micro-ring resonator filters [8], with the capability of routing optical signals in the C-band transmission window, with free spectral range (FSR) of 100 GHz. The switching network state is controlled through a binary vector $M \in \mathbb{R}^{1,20}$, which describes the state of each OSE i: each crossbar element can be in one of two possible states, representing the signal permutation at the output of the device, with the BAR state represented as $\mathrm{CS}_i = 0,\ [I_1, I_2] \rightarrow [O_1, O_2]$, and the CROSS state as $\mathrm{CS}_i = 1,\ [I_1, I_2] \rightarrow [O_2, O_1]$

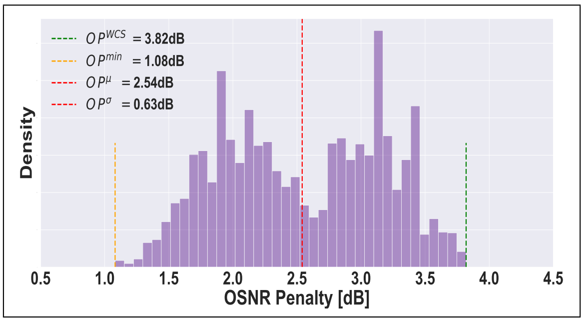
The device and its components have been implemented as a simulation-ready models through the Optsim Photonic Circuit Design Suite [9], allowing the simulation of transmission penalties, with each input port handling a different channel of the WDM comb. The channel frequencies are centered at $f = (193.1 + 0.1 \times x)$ THz for $x \in$



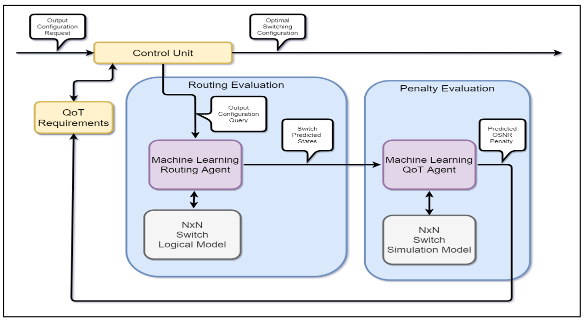
(a) Abstraction of the photonic switch in optical-SDN.



(b) 8×8 Beneš switch topology



(c) Statistical Analysis of OP.



(d) Control Unit block model

Fig. 1

[1,8], with each input signal representing a dual-polarization 16-QAM modulated stream at symbol rate of 59.8 Gbaud as per the 400ZR implementation agreement [6].

The dataset of the OSNR filtering penalties were gathered from a random set of 1000 control vector configurations, measuring the needed extra OSNR with respect to the back-to-back characterization to obtain the target BER under different input-output routings.

The overall filtering penalty distribution obtained with 500 random configurations, is shown in Fig. 1c. Results show a statistics of penalties as a bi-modal distribution with mean (μ) = 2.5 dB and standard deviation (σ) = 0.6 dB. In order to define the maximum operative OSNR degradation to be considered as model for the switching penalty, we always have to consider the worst-case scenario (WCS) in the absence of any information related to the switch characteristics to avoid any OOS. The resulting WCS OSNR penalty (OP) is as large as $\mathrm{OP}^{WCS} = 3.8\,dB$, and this is the value to be considered for QoT-E in the absence of a more advanced model.

3. Machine Learning Black Box

As an alternative to modeling the filtering penalty as described in the previous section, we propose to exploit ML techniques to accurately predict the QoT impairment. The proposed data-driven system consists of two ML networks: the initial network works inversely to determine the M control states given the required switching condition. In contrast, the subsequent ML network gets the output of the first ML network and works in a direct method for the estimation of the QoT penalty of the $N\times N$ photonic switch on 400ZR LPs, considered as the black-box shown in Fig. 1d.

A deep neural network (DNN) is considered for both the proposed ML networks. The DNN is built using higher-level APIs of the TensorFlow© library. The DNN is trained and tested on a separate subset of the dataset: the conventional rule of 70% and 30% has been opted to split the available dataset. To avoid over-fitting, the *training steps* is set as the ceasing factor and the *mean square error* (MSE) as the loss function defined as:

$$\mathrm{RT}_{\mathrm{MSE}} = \frac{1}{n}\sum_{i=0}^{n}\left(\sum_{m=1}^{M}\left|\mathrm{CS}^{p}_{i,\mathrm{m}} - \mathrm{CS}^{a}_{i,\mathrm{m}}\right|\right)^2 \quad (1) \qquad \mathrm{QoT}_{\mathrm{MSE}} = \frac{1}{n}\sum_{i=0}^{n}\left(\sum_{k=1}^{N}\left|\mathrm{OP}^{p}_{i,\mathrm{k}} - \mathrm{OP}^{a}_{i,\mathrm{k}}\right|\right)^2 \quad (2)$$

where $\mathrm{RT}_{\mathrm{MSE}}$ and $\mathrm{QoT}_{\mathrm{MSE}}$ is the routing and QoT agent MSE. n is the number of test combinations, M is the overall number of switching elements in the definite $N\times N$ switching system, while for each tested instance i, $\mathrm{CS}^{p}_{i,\mathrm{m}}$ and $\mathrm{CS}^{a}_{i,\mathrm{m}}$ are the predicted and actual control states of the m-th switching element of the considered topology. Similarly, N is the total number of input/output ports of the specific $N\times N$ switching system and $\mathrm{OP}^{p}_{i,\mathrm{k}}, \mathrm{OP}^{a}_{i,\mathrm{k}}$ are the predicted and actual OP of the k-th output port of the considered architectures.

Furthermore, the DNN engines of both networks are tuned by various parametric values that have been optimized (such as the *training steps*, set to 1000), loaded with the *adaptive gradient algorithm (ADAGRAD)* Keras optimizer, with *learning rate* set to 10^{-2} and L_1 regularization set to 10^{-3}. Moreover, *Relu* has been selected as an activation function. For the *hidden-layers* we performed a trade-off between precision and computational time,

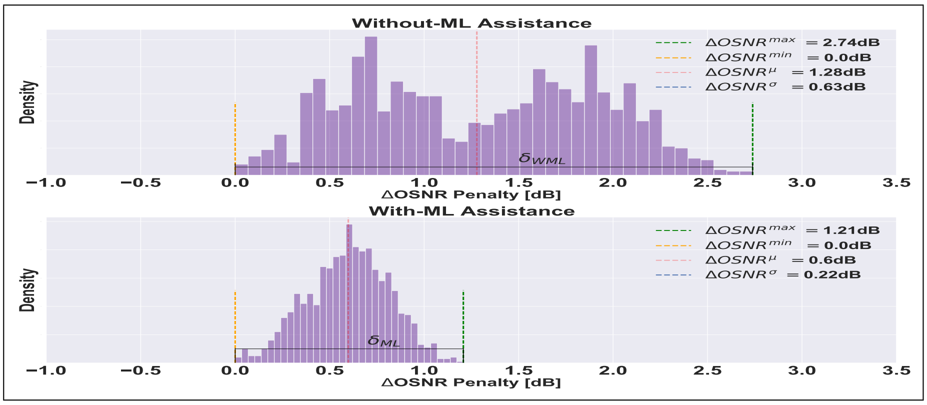


Fig. 2: ΔOSNR with and without ML of the 8x8 Beneš switch.

we opted upon a DNN with *three hidden-layers* with 10 cognitive neurons for each hidden layer in the initial ML network. In contrast, for the subsequent ML network, we selected *one hidden-layers* with 11 cognitive neurons. The initial ML routing network considers various permutations of the input signals (I_1, I_2, I_3....I_n) at the output ports of the switch as features while it exploits its M control states as labels. The following ML QoT network exploits the output of the first ML network, i.e., the M controls states as features and utilized the OP of the specific output port of $N \times N$ switching system as a response variable.

4. Results and Conclusion

We explored the performance of the proposed data-driven scheme first in the prediction of the control states and then exploit the predicted control states to accurately predict the QoT impairments in terms of $\mathrm{OP_k}$ for each k port of the considered Beneš network. The ML routing agent delivers excellent accuracy (100%) in predicting the control states of the considered 8x8 Beneš topology. The scalability and detailed analysis of the considered ML routing agent is demonstrated in [5]. Now, to evaluate the effectiveness of the ML QoT agent, we compare its findings with the results obtained considering WCS of OP in Fig. 1c. To this aim, we adopted a common metric $\Delta\mathrm{OSNR}_{i,\mathrm{k}}$ for assessment. The $\Delta\mathrm{OSNR}_{i,\mathrm{k}}$ used for the assessment of ML QoT agent is $\Delta\mathrm{OSNR}_{i,\mathrm{k}}^{ML}$, while for WCS we termed it as $\Delta\mathrm{OSNR}_{i,\mathrm{k}}^{WML}$ defined as:

$$\Delta\mathrm{OSNR}_{i,\mathrm{k}}^{WML} = \mathrm{OP}^{WCS} - \mathrm{OP}_{i,\mathrm{k}}^{a} \qquad (3) \qquad \Delta\mathrm{OSNR}_{i,\mathrm{k}}^{ML} = \left(\left(\mathrm{OP}_{i,\mathrm{k}}^{p} - \mathrm{OP}_{i,\mathrm{k}}^{a}\right) - \min\left(\mathrm{OP}_{i,\mathrm{k}}^{p} - \mathrm{OP}_{i,\mathrm{k}}^{a}\right)\right) \qquad (4)$$

where OP^{WCS} is the worst-case OP (see Fig. 1c). The rest of Eq. 3 and Eq.4 parameters description are same as in Eq. 2.The distributions of $\Delta\mathrm{OSNR}^{WML}$ and $\Delta\mathrm{OSNR}^{ML}$ are shown in Fig. 2 along with μ and σ. The distribution of $\Delta\mathrm{OSNR}^{WML}$ is always positive ($\Delta\mathrm{OSNRs} \geq 0$), so WCS completely avoid the possibility to get into OOS. To avoid any kind possible OOS in ML-assisted approach the term $\min\left(\mathrm{OP}_{i,\mathrm{k}}^{p} - \mathrm{OP}_{i,\mathrm{k}}^{a}\right)$ in Eq.4 is introduced, that actually shifts the distribution of ΔOSNRs towards operative region and thus satisfy the condition of no oos ($\Delta\mathrm{OSNRs} \geq 0$).

Furthermore, observing the general statistics (μ and σ) and visualizing both the distribution, the effectiveness of ML assistance is quite promising. Regarding the numerical assessment, the maximum inaccuracy in estimating OP ($\delta = \Delta\mathrm{OSNR}^{\max}$). The maximum inaccuracy without-ML assistance in estimating OP is $\delta_{WML} \approx 2.74$ dB. Similarly, the maximum inaccuracy with-ML assistance in estimating OP is $\delta_{ML} \approx 1.21$ dB (see Fig. 2).

In conclusion, the use of ML in the proposed scenario significantly reduces the error in estimating the OP by 1.5 dB (δ_{WML} - δ_{ML}) of the considered 8x8 Beneš switch on 400ZR LPs.

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