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Effectiveness of Machine Learning in Assessing QoT Impairments of Photonics Integrated Circuits to Reduce System Margin

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Abstract— **We propose machine learning technique for assessment of QoT impairments of integrated circuits. We consider margin reduction problem applied to a switching component. Overall results and data sets for machine-learning training are obtained by leveraging the integrated software environment of the Synopsys Photonic Design Suite.**

Keywords— Machine learning; Photonic Integrated Circuits; Q-factor

I. INTRODUCTION

In the field of optical communications, network components are progressively exploiting photonic integrated circuits (PICs) to execute complex functions at the photonic level, circumventing the bottleneck of opto-electronic conversion. As this trajectory increases the complexity of such devices [1], more sophisticated optimization and modeling tools are needed. Thanks to the advanced simulation tools, the behavior of PICs can be abstracted with high accuracy and precision. This permits to consider it within the software-defined networking (SDN) paradigm for network planning and management. Using this method, we obtain a full network disaggregation and softwarization down to below layer-0.

In this work, taking advantage of the capability of the Synopsys multi-layer design environment [2], [3], we demonstrate an application of machine learning (ML) based extension of the abstraction paradigm below the transmission layer -- layer-0 --, bringing the network abstraction to the component-design layer. We use ML technique to deliver an augmented knowledge of the physical parameters as in [4]. Here, we focus on predicting performance impairments of PICs to be used for more accurate assessment of QoT of lightpaths within a transparent optical network, consequently reducing the amount of system margin needed to avoid out-of-services. As a proof of concept, this work is based on the optical Benes Switch presented in [5] based on silicon photonics using analog photonics (AP) process design kit (PDK) [6].

II. SIMULATION MODEL & DATA SET ANALYSIS

In this section, the design and simulating environment for the considered 4x4 multi-stage switch based on a Benes layout [4] along with data set building are illustrated. The synergic use of Synopsys design and simulation environment; Opto-Designer and Optsim enable a vertical abstraction below layer-0. This vertical abstraction allows to analyze the Benes structure from physical layout up to the system level performance when employed to PM-MQAM signal. The system level performance is measured based on BER through an error counting approach, but we have reported it using a Q-factor. The 4x4 Benes Switch can redirect any of the four wavelengths (λ_1, λ_2, λ_3, λ_4) at its inputs to any of the four outputs; achieved by varying 6 internal voltages signal, each one controlling a single ring resonator. Considering simulation parameters defined in [5], nominal voltages for cross and bar states are 0V and 8.4V, respectively. In this study, we consider that control signals may suffer a perturbation, in the range of ±1V. Such a perturbation induces a random effect on QoT when deploying such a component within a transmission system, that needs system margin to avoid out-of-service events.

Along with this perturbation, we consider two distinct working modes of Benes Switch out of 26. The first mode corresponds to the output sequence λ_1, λ_2, λ_3, λ_4 (combination A) while the second mode corresponds to the output sequence λ_1, λ_3, λ_2, λ_4 (combination B) at the Output-1, Output-2, Output-3 and Output-4 respectively. The proposed simulating environment for any PICs (Benes) is depicted in Fig. 1a. Furthermore, to obtain a data set, the perturbated nominal voltage implies different filtering through the paths inside the Benes Switch by varying the Q-factor. A single realization of data set consists of six input voltages and four output Q-factor values, one for each channel processed. Exploiting the data set, we draw some basic considerations by computing the average of the Q-factor for each output port for all the realizations. In Fig. 1b, we show results referring to the particular combination A, similar results have also been obtained for combination B. The average values of Q-factor (purple dots) is comprised between 2.68 dB and 2.75 dB, with standard deviation (purple error bar) of about 0.20 dB. Green line shows the minimum value for each output where 1.79 dB (red dotted line) is the global minimum. The nominal values of Q-factor (orange dotted line) is comprised between 2.88 dB and 2.95 dB. Considering a scenario with only knowledge of nominal control voltage, so that the corresponding nominal Q-factor must be enforced for each output ports. In this approach, due to the fluctuations in Q-factor values it creates up to 1.13 dB of average margin in Q-factor. The major challenge in the present environment is to decrease the needed margin on top of Q-factor prediction in the absence of exact knowledge of driving conditions of Benes Switch.

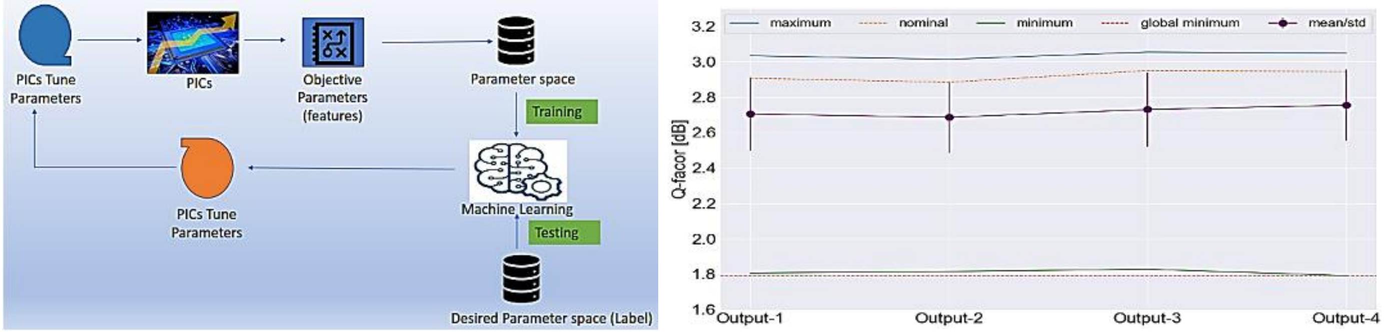

Fig .1. (a) Model Orchestration (b) Overall Q-factor measurements for a single combination A

III. Machine Learning architectonics

The proposed ML technique, specifically a deep neural network (DNN) is developed by using TensorFlow© platform that consists of 2 hidden-layers along with 10 neurons for each hidden-layer, having *ReLU* as activation function that allows translation of the given input features into the prediction of label of our point of interest with less complexity [7]. The proposed DNN model is evaluated by mean square error (*MSE*) as a loss function. The DNN model is configured for training, validation and testing by the conventional rule 70/15/15 having training-steps of 10,000 and *learning-rate* of 0.01. The training set for each mode in the present scenario consists of 600 realizations, while the test set consists of 100 realizations. The manipulated features in the proposed scenario include voltage measurements delivered to the six input configuration ports, while the exploit label is Q-factor of the particular output port.

IV. Results & Conclusion

In this section, we exploit the performance of the proposed ML module in-order to reduce the margin in Q-factor of Benes Switch . The metric to quantify this ability is defined by ΔQ-factor, where ΔQ-factor = Q-fator^{predicted}- Q-fator^{actual} in case of using ML while without-ML it is defined as Q-fator^{nominal} - Q-fator^{actual}. The reliability of the module is verified by testing it on both combination A and B.

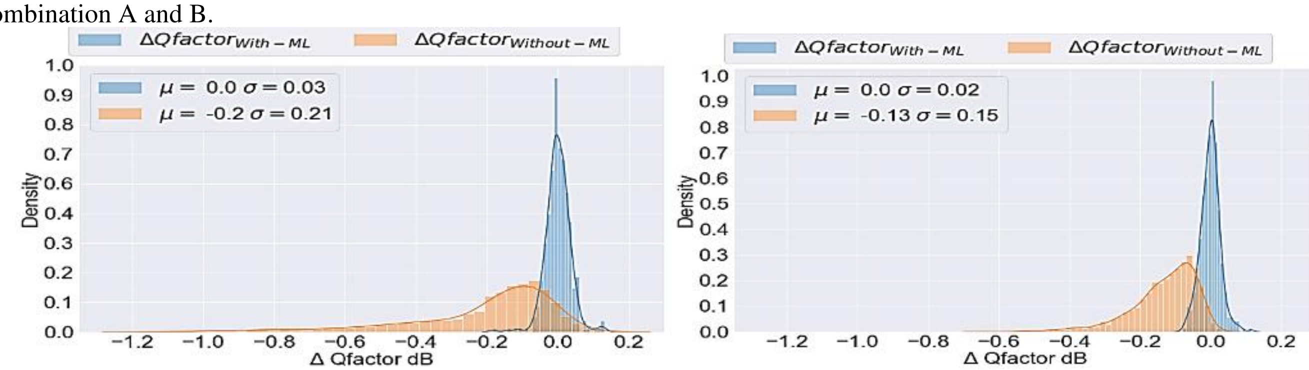

Fig .2. (a) Combination A ΔQ-factor Distribution (b) Combination B ΔQ-factor Distribution

The combine distribution of all the four ΔQ-factors with and without-ML along with the mean (μ) and standard deviation (σ) statistics of the Benes Switch for both the combinations A and B are shown in Fig. 2. Analyzing the statistics of μ and σ, to be more confident and conservative we considered the needed margin twice the average σ value of ΔQ-factor of all output ports. Demonstrating the results related to combination A, the margin due to the uncertainty in the Q-factor prediction is reduced from 1.13 dB (without-ML) to 0.06 dB (with-ML) while for combination B it is reduced from 0.8 dB (without-ML) to 0.04 dB (with-ML). The dramatic decrease in the margin needed by the Q-factor uncertainty shows that ML , together with the capability of fully abstract PICs by simulation, played a promising role to yield a high degree of information related to physical parameters of Benes Switch. The provided knowledge not only operated to accurately characterize the PIC but also to deliver its complete software abstraction of optical transport below layer-0.

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