Synergetical use of analytical models and machine-learning for data transport abstraction in open optical networks

Synergetical use of analytical models and machine-learning for data transport abstraction in open optical networks

Vittorio Curri[1]**, Andrea D'Amico**[1]**, Stefano Straullu**[2]

[1]*DET, Politecnico di Torino, Torino, Italy;* [2]*LINKS Foundation, Torino, Italy*

vittorio.curri@polito.it

Abstract: The key-operation to enabling an effective data transport abstraction in open optical line systems (OLS) is the capability to predict the quality of transmission (QoT), that is given by the generalized signal-to-noise ratio (GSNR), including both the effects of the ASE noise and the nonlinear interference (NLI) accumulation. Among the two impairing effects, the estimation of the ASE noise is the most challenging task, because of the spectrally resolved working point of the erbium-doped fiber amplifiers (EDFA) depending on the spectral load, given the overall gain. While, the computation of the NLI is well addressed by mathematical models based on the knowledge of parameters and spectral load of fiber spans. So, the NLI prediction is mainly impaired by the uncertainties on insertion losses an spectral tilting. An accurate and spectrally resolved GSNR estimation enables to optimize the power control and to reliably and automatically deploy lightpaths with minimum margin, consequently maximizing the transmission capacity. We address the potentialities of machine-learning (ML) methods combined with analytic models for the NLI computation to improve the accuracy in the QoT estimation. We also analyze an experimental data-set showing the main uncertainties and addressing the use of ML to predict their effect on the QoT estimation.

1. Introduction

Data traffic will experience a dramatic increase over the next years, driven by the implementation of 5G access and by the expansion of bandwidth hungry applications such as high definition video, virtual and augmented-reality contents [1]. Backbone networks are already carrying massive amount of data and will be required to sustain such a growth . A key operators request is to exploit the existing infrastructure to maximize their returns over investments. Such a need is directly related to the capability of orchestrating all the network layers to *squeeze* all the available capacity from the data transport [2]. The optimal exploitation of DWDM data transport is enabled by an accurate generalized SNR (GSNR) [3, 4] estimation on Open Optical Line Systems (OLS), including both the effects of ASE noise and nonlinear interference (NLI) accumulation.

SDN controllers rely on a network abstraction where the GSNR degradation on OLSs is given by the capability of OLS controllers to operate at the optimal working point [3, 5]. Among the two disturbances, the most challenging to estimate is the ASE noise setting the OSNR, because it is the dominant one [3] at the optimum, and because it is set by the working point of EDFAs[6], that is spectral-load dependent [7]. The NLI can be accurately predicted when the ASE noise accumulation is well characterized [8]. We suppose the worst case of a completely agnostic scenario, by relying only on data coming from the optical channel monitor (OCM) available at the end of the OLS. The uncertainty on the EDFAs' working point is typically induced by a mixed effect of physical phenomena [7] and implementation issues. So, a pure mathematical model approach is quite challenging and almost impossible in an open environment. Because of this, we address to using machine learning (ML) techniques, that has been already effectively tested in managing optical networks; see [9–12] for performance monitoring applications; [13, 14] for prediction estimation of the ML approach and [15] for both. An overall survey of ML applied in optical networks can be found in [16].

2. Physical layer abstraction and optimization in transparent optical networks

An optical network is an infrastructure connecting sites where traffic is added/dropped or routed. Links are OLSs implemented by fiber pairs amplified by in-line amplifiers set to operate at the optimal working point by the OLS controller. Spectral slots[17] enabling transparent source-to-destination optical transport are defined as lightpaths (LP). Signals propagates over LPs impaired by the ASE noise added by the amplifiers, by the fiber nonlinear propagation effects and by the ROADM filtering effects. The fiber propagation on uncompensated OLS impairs the QoT of LP operated with coherent technologies by introducing some amount of phase and amplitude noise. The phase noise is well compensated by the carrier phase estimator (CPE) module [18], while, the nonlinear interference (NLI), always

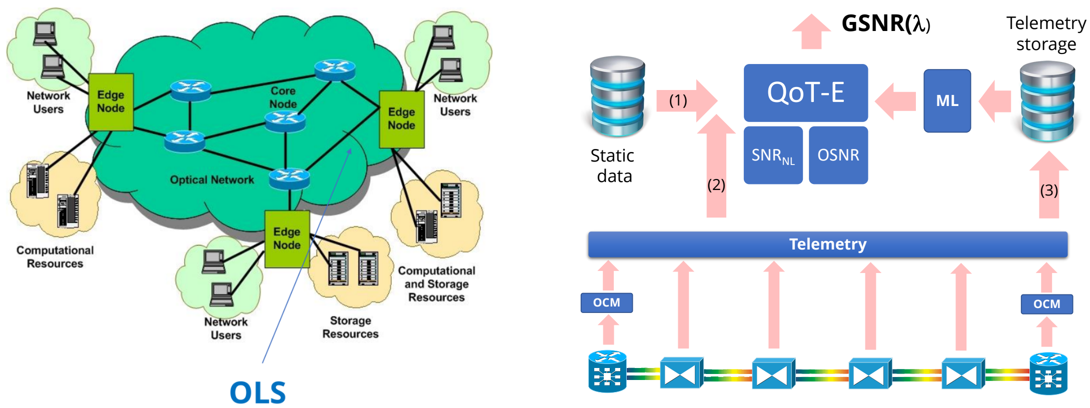

Fig. 1: (a) Schematic description of an optical network as a topology of ROADM nodes connected by optical line systems. The inset shows a general setup for an OLS that in this case is supposed to be open. (b) General scheme for a QoT-E module predicting the GSNR(Λ). The three possibly available set of data are shown: Static data from factory characterizations of network element (1), data from telemetry (2) and stored data from feeding a ML module (3).

impairs performance as a Gaussian disturbance that adds up to the ASE noise at the receiver [3]. Filtering effects of ROADMs impact as extra losses.

The QoT is given by the GSNR that includes the accumulated ASE noise and NLI disturbance, and is defined as: $GSNR = P_{Rx}/(P_{ASE}+P_{NLI}) = (OSNR^{-1}+SNR_{NL}^{-1})^{-1}$, where $OSNR = P_{Rx}/P_{ASE}$, $SNR_{NL} = P_{Rx}/P_{NLI}$, P_{Rx}, P_{ASE} and P_{NLI} are the channel, ASE and NLI intensities, respectively. Each LP experiences the cascade of all the passed OLSs. So, if the OLS controllers keep the optimal working point, the OLSs can be abstracted by the GSNR degradation that in general varies with λ: ISNR(λ)=1/GSNR(λ). Thus, for the operations related to the QoT, a network can be abstracted as a graph weighted by GSNR degradations. Once the network abstraction is available and reliable for the network management, LPs can be deployed at the maximum rate relying on the GSNR of the assigned route and wavelength, either in case of traffic deployment or in case of traffic recovery. Therefore, we need to keep physical layer fluctuations under control to expose a reliable GSNR.

It is useful to separately observe how to calculate the two contributions to the OLS impairments: the NLI generation and the ASE noise accumulation. The NLI power can be reliably calculated with different levels of accuracy by mathematical models [19–23]. To this purpose, the required data are the spectral load of the fiber span and its characteristics, including Raman pumps, if used. Among these requested data, the only one affected by some considerable uncertainty is the input connector loss to each fiber span that sets the actual spectral load exciting nonlinearities. Consequently, the prediction capability of P_{NLI} is in general very good and affected by limited uncertainty.

A much more delicate scenario is the one related to the prediction of the effect of the EDFAs cascade, each characterized by a $G_i(\lambda)$ and $F_i(\lambda)$, depending on the sectral load.

To list the possibilities to reduce the uncertainty on the GSNR, Fig. 1 schematically shows the possible levels of knowledge of OLS behavior. Typically, some data are available from static characterization of devices – the (1) option in Fig. 1 – and are highly significant for closed systems. In case we suppose to operate an OLS in an agnostic way as required in open OLS, we have to mainly rely on data from telemetry, coming from the OCM and EDFA telemetry. We can suppose that these data are available only from the network status, without any stored training data-set: case (2) in in Fig. 1. Relying on this option, from the statistical characterization of the data-set, we can evaluate the uncertainty on the OSNR and the consequent needed margin. The third option, summarized by the (3) option in Fig. 1, is the availability of a data-set that has been generated before the in-service operation of the OLS. We can suppose that before deploying traffic, each OLS of a network is characterized by a random spectral load and telemetry data acquisition. For this option, the data-set can be used to train a ML algorithm that will be used to predict the QoT in actual LP deployment and in controlling the OLS power levels. We analyze the (2) and (3) options, being the ones characterizing an agnostic operation of the OLS. Moreover, we focus on OCM data only to assess fundamental limits and to address further investigations considering also telemetry data from the amplifiers.

3. Statistical Analysis of Experimental Data

In this study, we schematize the EDFAs cascade as a black box that, from a specific input, produces a fixed output. The main purpose of this analysis is to characterize the OSNR fluctuations of this process due to the specific spectral

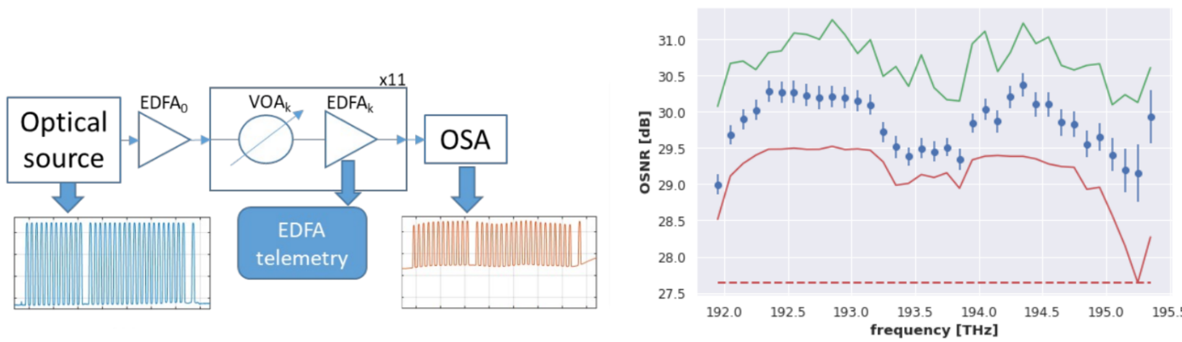

Fig. 2: (a) Experimental setup. EDFA: Erbium-Doped Fiber Amplifier; VOA: Variable Optical Attenuator; OSA: Optical Spectrum Analyzer. (b) Blue dots plot the mean value over the whole sample of the OSNR measured on each channel; the errorbars are equal to the standard deviations. In green and red, respectively, the maximum and the minimum for each channel are outlined. The dashed line indicates the overall OSNR minimum.

load features. The experimental data-set consists of measurements produced by the 11-span OLS depicted in Fig. 2(a) based on commercial EDFAs. VOA attenuation is set to 10 dB and chanel power to -1 dBm. The channel combs spectrally loading the OLS have been obtained by shaping ASE noise (Finisar 1000 S), to generate a 100 GHz-spaced 35-channel WDM comb centered at 1550 nm and amplified by a booster amplifier (EDFA_0 in Fig. 2(a)). We measured the overall power in the spectral slot, i.e., the noise floor in case of channel *off*, and the channel power in case of channel *on*. Thanks to the 100 GHz spacing choice, we were also able to measure the *exact* OSNR for each spectra load, for each channel *on*. We experimentally generate a data-set made of 2291 cases: almost 70 for each spectral load with 2 to 34 *on* channels; 35 cases with only one channel *on* and the all channel *on* scenario. The set of considered configurations is uniform over all the channels and the number of total *on* channels. Through the whole analysis, we have not taken into account any uncertainty in the measurements, since it is negligible with respect to the variances due to the lack of information. Since the sample has a relative limited dimension, in what follows we address to the standard deviation calculated with the weight $N-1$, in order to obtain a less biased estimator of any quantity variance. From an overall observation of the OSNRs calculated for each channel on the whole sample, we obtain the statistical description shown in Fig. 2(b). The average values of the OSNR (dots in the figure) sketch a characteristic figure of the EDFAs amplification process and take place between 29 and 30.5 dB with standard deviations from 0.13 to 0.4 dB. The green and red lines outline, respectively, the maximum and minimum values of the measured OSNRs for each channel. In general terms, the OSNR measurements experience an excursion up to 3.6 dB with respect to the overall minimum (dashed red line in the Fig. 2(b)). To be more specific, the OSNR values and fluctuations vary distinctly for each channel, covering the above mentioned characteristic figure of the EDFAs amplification process; the OSNR range measured for each channel has an average value of almost 1.5 dB. Let us underline that, as expected, the channels with frequency bandwidths near 195.25 THz suffer the severest variances due to the well known spectral hole burning, see reference [7]. In order to deepen our investigation of the EDFAs cascade behaviour, it is necessary to resolve the aspects that tie the measured OSNR values with the configurations features. In Figs.3, the distributions enclosed in the previous picture are unfolded, for a subset of channels, with regard to the total number of on channels in the configurations. Due to this additional division of the data-set in investigation chunks, the reliability of the averaged quantities decrease substantially. This consideration justifies the scattered aspect of the standard deviation plots in Fig. 3(b), in particular in the region of configurations with a low number of on channels. Nevertheless, the trends of the OSNR in Fig. 3(a) outline an unquestionable increment of the performances of the line approaching the fully load configuration. Channel number 15 seems to be an exception; however, through a closer investigation, it can be verified that its OSNR remains constant for all configurations but those ones with a low number of on channels, which are statistical irrelevant.

Beyond these considerations, finding the best procedure to further characterize the OSNRs response to a certain configuration is not straightforward, given the lack of information of the EDFAs cascade features. In fact, in spite of a precise physical description of the emission phenomenon that is involved in the amplification process, it is not possible to determine the evolution of the spectral load through the EDFAs cascade. In a general scenario, this obstacle occurs mainly because of the embedded software controller of the EDFAs which, in order to maintain specific requirements, changes the spectral powers at the output of the amplifiers with an unknown algorithm.

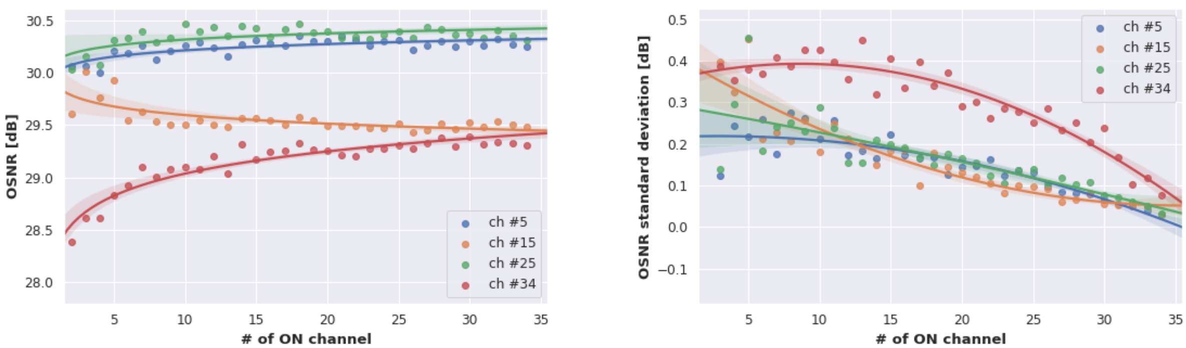

Fig. 3: Overall statistical behaviours of the OSNR fluctuations with respect to configurations with an increasing number of on channels. In the legends the channels numbers address the occupation in the spectral division. OSNR mean values (a) and standard deviations (b).

Beside a statistical description of the sample, different methods for the estimation of an OSNRs threshold arise from this analysis, addressing various level of awareness. Looking back at the general scheme in Fig. 1, without any stored data-set (situation (2)) the same OSNR threshold has to be placed, for all the channels, at least underneath an overall expected minimum; this solution creates a margin up to 3.6 dB over a set of realizations equivalent to our sample. Given an available data storage (situation (3)) it is possible to produce a frequency resolved threshold that yields a margin average around 1.5 dB, over the same set of realizations. This result can be further improved by means of the characterization of the OSNRs fluctuation dependency on the channels configurations. These improvements would reduce effectively the margin but, being deeply closed to the sample features, their accuracy is widely bounded to the statistical incidence of the sample over reality. It means that, a large instances collection could be required to have a reliable value for each spectrum slice. This scenario is a perfect ground for a ML approach, since it can compensate both the lack of information due to the hidden behaviour of the EDFAs cascade and the relatively reduced dimension of a suitable sample, which is restricted by the feasibility of the measurements on a real line.

4. Conclusions

We analyze the issues related to the uncertainties impairing on the GSNR estimation in OLSs, showing that the NLI component can be calculated by analytic models, while the estimation of the ASE noise effect is a perfect application ground for machine learning techniques. As an example, we experimentally obtained a data-set from an 11-EDFAs OLS and analyzed the statistics of the OSNR, showing a large uncertainties and addressing the use of ML techniques to dramatically reduce it.

Acknowledgment

This work was funded by Cisco within a SRA project, the authors would like to thank Alessio Ferrari, Emanuele Virgillito and Dr. Mattia Cantono for the fruitful suggestions.

References

[1] Cisco, tech. rep., Cisco Visual Networking Index: Forecast and Trends, 2017-2022, 2017.
[2] V. Curri et al., *J. of Lightwave Tech.* 35.6 (2017), pp. 1211–1221.
[3] V. Curri et al., *J. of Lightwave Tech.* 33.18 (2015), pp. 3921–3932.
[4] M. Filer et al., *J. of Lightwave Tech.* 36.15 (2018), pp. 3073–3082.
[5] R. Pastorelli, *OFC Conference*, IEEE, 2015, pp. 1–3.
[6] B. D. Taylor et al., *OFC Conference*, OSA, 2018, Tu3E–4.
[7] M. Bolshtyansky, *J. of Lightwave Tech.* 21.4 (2003), pp. 1032–1038.
[8] G. Grammel et al., *OFC Conference*, OSA, 2018, pp. M1D–3.
[9] M. Freire et al., *2018 Asia Communications and Photonics Conference (ACP)*, IEEE, pp. 1–3.
[10] J. Thrane et al., *J. of Lightwave Tech.* 35.4 (2017), pp. 868–875.
[11] F. N. Khan et al., *OFC Conference*, IEEE, 2018, pp. 1–3.
[12] L. Barletta et al., *OFC Conference*, OSA, 2017, Th1J–1.
[13] I. Sartzetakis et al., *J. of Optical Comm. and Networking* 11.3 (2019), pp. 140–150.
[14] W. Mo et al., *OFC Conference*, IEEE, 2018, pp. 1–3.
[15] C. Rottondi et al., *J. of Optical Comm. and Networking* 10.2 (2018), A286–A297.
[16] J. Mata et al., *Optical Switching and Networking* 28 (2018), pp. 43–57.
[17] "https://www.itu.int/rec/T-REC-G.694.1/en".
[18] D. Pilori et al., *OFC Conference*, IEEE, 2018, pp. 1–3.
[19] R.-J. Essiambre et al., *Proceedings of the IEEE* 100.5 (2012), pp. 1035–1055.
[20] A. Carena et al., *J. of Lightwave Tech.* 30.10 (2012), pp. 1524–1539.
[21] M. Cantono et al., *J. of Lightwave Tech.* 36.15 (2018), pp. 3131–3141.
[22] R. Dar et al., *Optics Express* 21.22 (2013), p. 25685.
[23] E. Virgillito et al., *ICTON*, IEEE, 2019.