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Local vs. Global Optimization for Optical Line System Control in Disaggregated Networks

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***Abstract*—Setting the operating point of optical amplifiers of optical line systems (OLS)s within transparent, disaggregated and reconfigurable networks is a crucial task that determines the optical transmission performance of the specific infrastructure. In this work, four optimization strategies for OLS control are compared through a simulation campaign, where a realistic physical layer is replicated using a machine-learning model derived from an experimental dataset on commercial devices for the Erbium-doped fiber amplifiers (EDFA)s and a characterized set of fiber spans. In particular, two distinct objective functions are evaluated, both at the end of the line (global approach), and, in turn, at the end of each single span (local approach).**

***Index Terms*—Optical networks, optical line system, optimization, disaggregation.**

I. Introduction

In recent years, driven by the telecom operator demand, the implementation of the concepts of disaggregation and openness in the field of optical communication networks has gradually taken hold in order to improve the aspects of automation, sharing, maintenance/updating and optimization of already installed and future infrastructure [1]. The related practical implications are crucial in the management of optical networks as regards the control of the optical amplifiers within the various optical line systems (OLS)s, where their operating point determines the transmission performance of the specific network. A common metric utilized to quantify the quality of transmission (QoT) of a deployed lightpath is the generalized signal-to-noise ratio (GSNR) [2]. At the same time, also the signal power per channel has to be properly managed in order to avoid a further degradation due to the transceiver (TRX) sensibility or saturation. The QoT estimation and the network element modeling can be performed using a large variety of approaches, i.e. deterministic, statistical models or machine-learning (ML) techniques. The degree of complexity of a given model is related to the possibility to accurately describe the behaviour of a specific feature. In particular, more resources are needed to intercept frequency-dependent behaviors, both in computational and experimental data terms.

Focusing on a single band scenario and considering a simplified modeling without the inclusion of frequency-dependent effects in both amplifier and fiber optic transmission, a simple optical line system (OLS) optimization method is the local-optimization global-optimization (LOGO) strategy [3], where each in-line amplifier (ILA) operating point is set fixing the amount of amplified spontaneous emission (ASE) noise at double the estimated nonlinear interference (NLI) contribution starting from the optical pre-amplifier (PRE) and going back until the booster (BST) [4] in order to maximize the GSNR. The authors experimentally demonstrated the maximization and equalization of the GSNR of an OLS in a full wavelength division multiplexing (WDM) C-band scenario setting the operative point of each optical amplifier exploiting a frequency-dependent modeling for both the Erbium-doped fiber amplifier (EDFA) and fiber [5]. The first of the two proposed objective functions was focused on the global observation of the GSNR at the end of the optical line, while the second was a local LOGO-inspired strategy aiming to progressively optimize each span starting from the BST. In this work, these optimization strategies are investigated in an accurate and controlled simulation environment using an ML EDFA model derived from an experimental dataset on commercial devices and a characterized set of fiber spans, enlarging the previous collection of proposed methodologies and providing directions on their utilization. In particular, the two objective functions are combined with the different observation of the metrics of interest both at the end of the line and the end of a single span, comparing the obtained results and analyzing the overall behaviour.

II. Network Architecture

The general representation of the optical network architecture considered in this work is depicted in Fig. 1. For the purposes of determining the route-wavelength and deploying the lightpath, it is assumed in this framework that the optical network controller has direct access to the TRXs and reconfigurable optical add & drop multiplexers (ROADM)s. Whereas, the optical line controllers, which have direct access to the telemetry from the available network element monitors, are responsible for managing the OLSs, which are identifiable by the ROADM-to-ROADM physical connections, including BSTs and PREs integrated in each ROADM. In addition, every optical line controller independently assesses and determines the optimal operative point for the controlled OLS amplifiers, giving the optical network controller the QoT metrics neces-

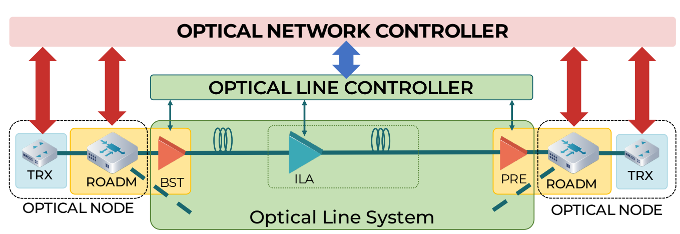

Fig. 1. Sketch of an open and partially disaggregated optical network architecture supporting the management of ROADM-to-ROADM optical line systems.

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sary for the lightpath computations. The ROADM provides at the BST input a full C-band WDM comb with constant power spectral density. The operative point of each optical amplifier working in fixed gain mode is defined by a couple of parameters, which are the average gain, G, and tilt, T.

III. Problem Formulation

The analysis performed in this work is focused on the formulation of four different optimization problems, defining the operative points of the EDFA collection, {G, T}, according to two objective functions.

The first one, labeled as *GSNR* objective function, evaluates the GSNR profile aiming to maximize its average, $\overline{\mathrm{GSNR}}$, and minimize the standard deviation, σ_{GSNR}:

$$\max_{\{\mathrm{G},\,\mathrm{T}\}} \left\{ \overline{\mathrm{GSNR}^{\mathrm{dB}}} - \sigma_{\mathrm{GSNR}^{\mathrm{dB}}} - |m_{P^{\mathrm{dBm}}_{\mathrm{SIG}}}| \right\} , \quad (1)$$

where $m_{P^{\mathrm{dBm}}_{\mathrm{SIG}}}$ is the linear regression angular coefficient of the signal power profile expressed in dB/THz.

The second expression, named *NOISE* objective function, which is based on a similar methodology to the LOGO technique, assesses the relative impact of the ASE, $P_{\mathrm{ASE}}(f)$, and NLI, $P_{\mathrm{NLI}}(f)$, noise power profiles:

$$\min_{\{\mathrm{G},\,\mathrm{T}\}} \left\{ |m_{P^{\mathrm{dBm}}_{\mathrm{SIG}}}| + \frac{1}{N_{ch}} \sum_{i=1}^{N_{ch}} \left| P^{\mathrm{dBm}}_{\mathrm{ASE}}(f_i) - P^{\mathrm{dBm}}_{\mathrm{NLI}}(f_i) + 3 \right| \right\} , \quad (2)$$

where i is the channel ordinal number within the specified grid that goes from 1 to the number of channels, N_{ch}.

The two mentioned objective functions are combined with two different observation strategies. The first one consists in the evaluation of the specific objective function at the end of the line (*global* approach) formulating an optimization problem with a total number of variables to optimize equal to 2 times the number of the optical amplifiers within the OLS, where 2 represents the number of parameters that define each amplifier's operating point, gain and tilt. On the contrary, the second one starts with the BST span and executes a series of forward optimizations, one for each span and one for the PRE alone, using as the input for the span being evaluated the state of the WDM comb propagated with the optimized amplifier configurations collected in the earlier phases (*local* approach). This formulation provides for the division of the problem into many optimizations equal to the number of amplifiers present within the OLS, each with a fixed number of variables to be optimized equal to 2.

IV. Simulation Framework

Recalling the optical network architecture defined in the previous section, the four formulated optimization problems are tackled using a simulation framework consisting of an OLS of 10 fiber spans (11 amplifiers and 10 fiber spools). The considered full C-band WDM spectrum starts from a channel with a central frequency of 191.31 THz and it is composed of 64 channels with 64 GBd of symbol rate, 75 GHz of spacing and 0.15% of roll-off, presenting a flat signal profile with a total power of 0 dBm at the input of the BST.

The physical model of the fiber is taken from the open-source Python library GNPy [6], while the EDFA model

TABLE I
Fiber Physical Layer Parameters

UID	L_S [km]	C_R [(W·km)$^{-1}$]	$l(z=0)$ [dB]	$l(z=L_S)$ [dB]
1	106.179	0.34	3.60	0.24
2	107.510	0.44	1.25	0.71
3	106.179	0.44	1.54	0.12
4	108.825	0.42	0.60	0.11
5	108.278	0.42	0.18	0.12
6	106.195	0.42	1.11	0.22
7	106.791	0.34	0.10	0.12
8	106.424	0.34	0.16	0.71
9	107.273	0.42	0.21	0.13
10	108.319	0.42	0.52	2.31

is based on the ML technique presented in [7]. The fiber objects are described through a set of physical layer parameters characterized from an experimental laboratory setup composed by 10 standard single-mode fiber (SSMF) spans and reported in Fig. 2 and Tab. I, where L_S is the fiber span length, C_R is the maximum Raman efficiency, $l(z = 0)$ is the input connector loss and $l(z = L_S)$ is the output connector loss. The values of dispersion and nonlinear coefficient are fixed for all the fibers at 17.7 ps^2·km^{-1} and 1.27 W^{-1}·km^{-1}, respectively. The NLI impairment is computed considering 7 channels under test equally distributed along the C-band and linearly interpolating between them and using the generalized Gaussian noise (GGN) model approximation described in [8]. The ML EDFA model is obtained characterizing in full-spectral load condition the gain and the introduced ASE noise profiles of a commercial device with maximum output power of 23 dBm, gain operative range from 12 to 27 dB and tilt operative range from -5 to 5 dB, and it is used for all the OLS amplifiers. On the basis of the created dataset, two neural networks are generated, one for the gain and one for the introduced ASE noise respectively, which predict a profile having as input parameters the total input power, the gain and the tilt target. Starting from the channels defined in the measurements, the profiles are adapted to the channels used in the simulation by linearly interpolating in logarithmic units of measure.

A stochastic optimization method based on an evolutionary approach called covariance matrix adaptation evolution strategy (CMA-ES) [9] is employed since each optimization problem provides a high computational cost from the perspective of the physical model and a sizable number of variables.

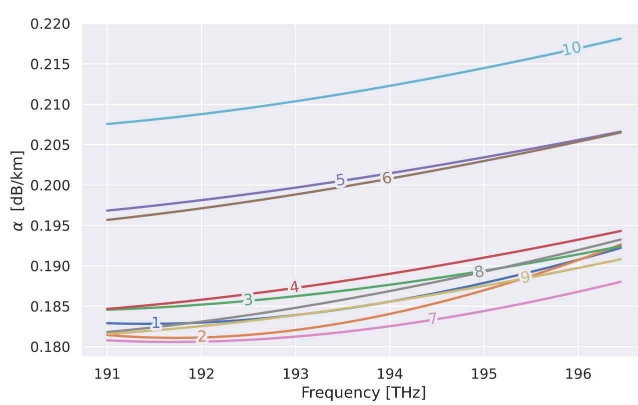

Fig. 2. Fiber loss coefficient functions, $\alpha(f)$.

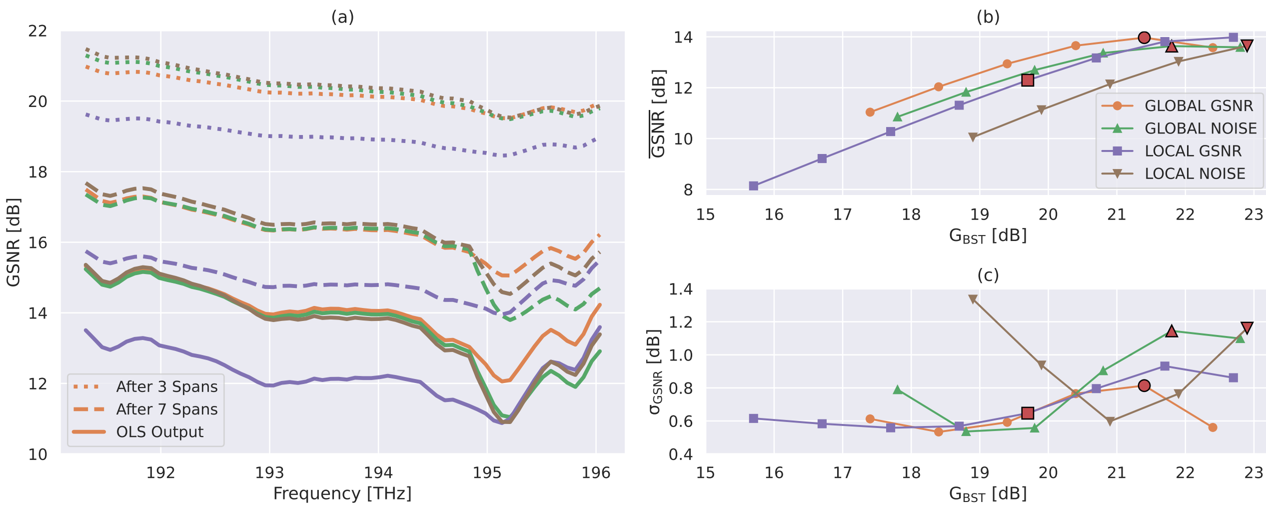

Fig. 3. Simulation results for the different optimization strategies: (a) GSNR profiles accumulated at different points of the OLS for the optimal configurations; GSNR aggregated metrics – (b) average, and (c) standard deviation – with respect to the BST gain varied in 1 dB steps (power sweep) at the end of the OLS.

In each optimization, the steps leading to the evaluation of a single function are first the propagation of the defined WDM spectrum through the OLS using the current extracted configuration of gain and tilt parameters for the optical amplifiers, and then the estimation of the output metrics with the described physical layer model.

V. Results & Conclusion

The optimized EDFA configurations found applying the four strategies are reported in Tab. II, while the corresponding results in terms of GSNR are depicted in Fig. 3. Repeating the optimization process, the execution time of the global strategies is more than one order of magnitude with respect to the corresponding local ones for the considered scenario, given the significant reduction of the number of variables and the complexity of the optimization space in the latter approach. Observing the obtained GSNR profiles (Fig. 3-a), it is evident how the high-frequency spectral zone undergoes the characteristic rippled behaviour of the EDFAs [10], resulting in a more wrinkled trend of the performance accumulated as the WDM spectrum is propagating through the OLS. Moreover, the curves of GSNR average and standard deviation versus the BST gain, G_{BST}, give a perception of how the behavior of the space of the optimization problem is around the found heuristic solution. The metrics for the optimal configurations in Tab. II are represented by the red larger markers with outline. The BST maximum gain cannot be higher than 23 dB as the amplifier will saturate given the total input power value.

Comparing the obtained results, the *global GNSR* strategy allows to achieve the best performance in terms of average and flatness over the whole C-band. The *local* and *global NOISE* strategies achieve similar outcomes, outlining the choice of the first one as more advantageous given the lower complexity of the optimization problem and the savings in terms of execution time. The *local GNSR* strategy does not bring to an effective OLS optimal operative point. A further refinement of the BST gain allows the system to achieve a performance comparable to the result of the *global GNSR* strategy.

TABLE II
Optimized EDFA Configurations

	GLOBAL GSNR		GLOBAL NOISE		LOCAL GSNR		LOCAL NOISE	
[dB]	**G**	**T**	**G**	**T**	**G**	**T**	**G**	**T**
BST	21.4	-1.6	21.9	0.8	19.7	-1.8	22.9	-2.4
ILA-1	26.4	-4.8	26.5	-4.4	24.8	-2.5	26.3	-3.9
ILA-2	21.4	-0.8	21.0	-4.0	22.6	-2.1	20.6	-2.6
ILA-3	22.3	-0.7	22.1	-2.8	21.3	-2.2	21.9	-3.0
ILA-4	22.1	-4.8	22.2	0.1	21.9	-2.2	22.0	-2.9
ILA-5	24.7	-0.9	25.4	-4.9	24.8	-2.4	25.2	-3.3
ILA-6	21.6	-4.4	20.2	-1.6	21.9	-1.9	21.0	-2.4
ILA-7	23.0	0.3	22.8	-5.0	22.3	-2.3	22.1	-2.8
ILA-8	23.5	-4.4	25.8	-4.7	24.0	-2.3	25.0	-3.2
ILA-9	21.8	-2.4	19.9	-3.8	20.8	-2.2	19.5	-2.6
PRE	23.0	-5.0	23.6	-0.2	25.0	-0.7	25.0	-0.7

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