Highly Accurate Measurement-Based Gain Model for Constant-Pump EDFA for non-Flat WDM Inputs

Alexis Carbo Meseguer[1], Jean-Christophe Antona[1], Alberto Bononi[2], Junho Cho[3], Stephen Grubb[4], Pascal Pecci[1], Olivier Courtois[1] and Vincent Letellier[1]

[1]Alcatel Submarine Networks, Nokia Paris-Saclay, 96120 Nozay (France), [2]Università di Parma, Dip. Ingegneria e Architettura, 43124 Parma (Italy), [3] Nokia-Bell Labs, Holmdel, NJ (United States), [4] Facebook, Menlo Park, CA (United States)

alexis.carbo_meseguer@asn.com

Abstract: We develop a simple and accurate measurement-based model to predict the gain of wideband erbium-doped fiber amplifiers with a root mean square error of 0.05 dB, lower than state-of-the-art models based on machine learning techniques. © 2021 The Author(s)

1. Introduction

Energy efficiency has become critical in modern subsea networks, due to the increase of traffic demand and intrinsic cable voltage limitations. The recent introduction of Spatial Division Multiplexing with multi-amplifier optical pump sharing has enabled to a paradigm shift from capacity optimization per fiber to capacity optimization per multi-fiber cable. This amounts to optimize energy efficiency per fiber, i.e. maximizing the cable capacity for a given limited electrical feeding. Besides, the widespread use of rate-adaptive transceivers operating close to the Shannon limit enables to consider cable capacity with non-uniform channel performance. In that context, link optimization deserves reconsideration with new degrees of freedom such as amplifier spacing, powering, waterfilling pre-emphasis techniques [1,2], and non-conventional inline equalization schemes departing from "flat" equalized spans by re-evaluating the transfer function and periodicity of inline Gain Shaping Filters [3,4]. To explore these new degrees of freedom, simple amplifier characterizations under nominal input power profiles seem insufficient while multi-parameter physical models of erbium-doped fiber amplifiers (EDFA) suffer from their complexity computation speeds [5]. Recent, Machine Learning (ML) techniques seem particularly suitable since they enable, after a training period, to emulate optical amplifiers and/or perform system optimization very rapidly, nonetheless possibly at the expense of physical understanding or accuracy [3,4,6].

In this study we introduce a hybrid EDFA gain model, based on both ML techniques and physics theory, adapted to any arbitrary full C-band input spectrum with significantly improved accuracy (0.05dB RMS) with respect to state-of-the-art techniques [3,4,6,7], combining very limited amplifier experimental measurements and homogenous gain assumptions. In details, after experimentally comparing the EDFA gain curve evolutions versus input powers for flat and non-flat input spectrum conditions, we exploit the homogeneous gain Saleh's model [5] to convert a calibrated EDFA gain model for flat input spectra into a model applicable to arbitrary spectra, without the need of EDF physical parameters. Model is assessed in output spectrum and signal-to-noise ratio (SNR) predictions after both 1 and 12 amplified spans for hundreds of non-flat input spectra. Last, we discuss system optimization with insight on possibly hidden power efficiency gains using specific spectra into the EDFAs.

2. Experimental test-bed

The experimental set-up used in this study is summarized in fig.1a) where a commercial 39-nm full C-band EDFA is characterized. It is labeled as device under test (DUT), operated at a constant bias current of 550 mA and loaded with a noise emulated wavelength-division multiplexed (WDM) spectrum. A 40-nm noise source together with a waveshaper are used to emulate this comb composed of 50 channels of 20 GHz bandwidth and 100 GHz spacing. With this configuration we can easily access to the noise floor between channels and estimate the SNR. A second waveshaper follows to filter out again the channels and assure maximal extinction ratio and therefore high input SNR.

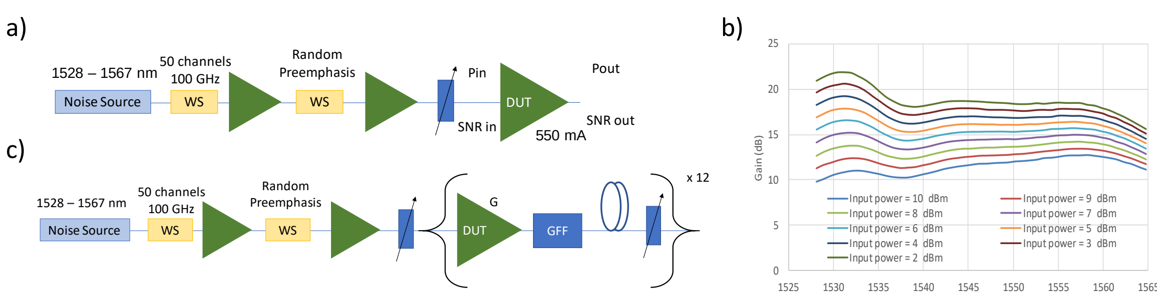

Fig. 1: (a) The experimental set-up used to assess the EDFA model, (b) EDFA gain experimentally measured at 550 mA of bias current for different total input powers in flat WDM regime and (c) the experimental set-up for the chain of 12 EDFAs

An EDFA is then inserted after each waveshaper to compensate for the losses of these two devices. The second waveshaper is also used to equalize the input spectrum to flat profile or to any given non-flat preemphasis. A variable optical attenuator (VOA) is placed after the DUT to measure the gain. For this experiment 13 total input power levels were tested, ranging from 0 dBm to 12 dBm by steps of 1 dB. These input powers are centered on 6 dBm, the input power level that the EDFA exhibits flat gain after the insertion of the GFF at 550 mA. Input-output power and noise levels are measured using an optical spectrum analyzer. Gain and noise figure are estimated from these measurements for each emulated noise channel. In fig.1b) the gain shapes in flat regime are shown for all the input powers.
Then 200 random 39-nm input WDM non-flat preemphases were generated with a maximum of 12 dB power variation and plotted in fig.2a). We repeated the measurement for the 13 total input powers, leading to a total of 2600 measures. In fig.1c), a test bed composed of 12 amplified spans is depicted. Each span is composed of an EDFA identical to the DUT from fig.1a), a gain-flattening filter (GFF), and a ~59km fiber section of 9.2dB loss and 125µm² effective area. Finally, a VOA is inserted to recover the original input power for next stages.

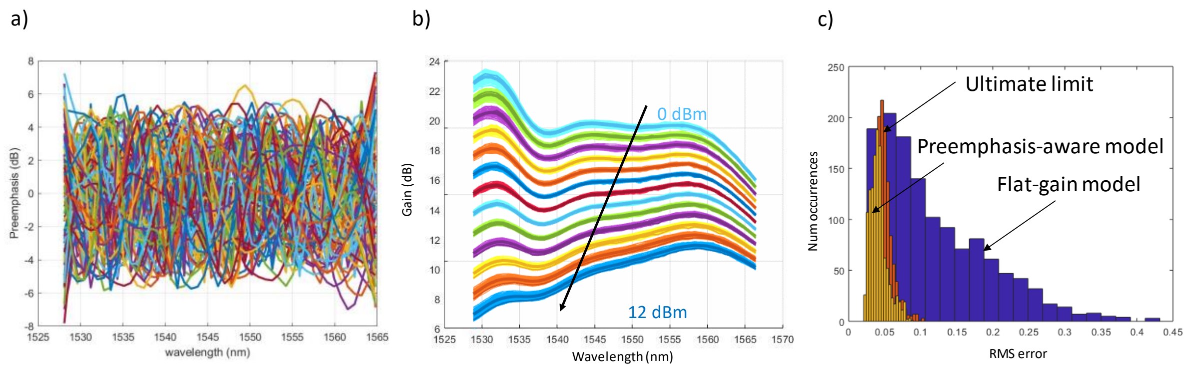

Fig. 2: (a) 200 random input WDM preemphases used in the experimental validation of the model, (b) the gains measured for the 2600 input random preemphases and (c) the histogram of measured root mean square errors

3. EDFA model for non-flat WDM input powers

Fig.1b) depicts the gain profile versus wavelength of the DUT for 13 different flat WDM input spectra and a fixed current. Under those conditions changing the input optical power amounts to bi-univocally changing the average population inversion and hence the gain profile. Fig.2b) depicts the gain profile versus wavelength of the tested EDFA for the 2600 different random spectrum shapes. The different gain curves form a continuum, where curves change because of total input power or spectrum shape. Indeed, this is easily explained assuming the EDFA has a homogenous gain, hence each gain curve corresponds to a given average population inversion.
In the following, we build our EDFA model based on this homogeneous gain assumption. In particular, we associate each gain profile generated from an arbitrary spectrum to a specific *equivalent* flat input power $P_{in,eq}$ producing the same gain response and through the same average population inversion and we use Saleh EDFA model with ASE self-saturation [1,2] to determine this *equivalent* flat input power.
In the steady-state regime, the extended Saleh equation [5] sets the balances between input fluxes, of N_{Ch} WDM channels, and output fluxes including amplified signal, amplified spontaneous emission and fluorescence. It is defined as $\sum_{i=1}^{Nch} Q_i^{in}\,(G_i(x)-1) = K(x, Q_p)$ where Q_i^{in} is the input flux from the i-th channel, Q_p is the input pump flux and K is the function that balances output fluxes. At an equilibrium population inversion x, the amplifier gain profile is set to $G_i(x)$. Let us now consider an input signal into an EDFA of total power $P_{in,tot}$ and deviation from average ΔP_i for each channel i. We search the *equivalent* flat input power, yielding the same EDFA population inversion x, with total power per channel denoted as $P_{ch} = P_{in,tot}/N_{ch}$ and $P_{in,eq} = P_{in,tot} + N_{ch}\,\Delta P_{in,eq}$. We can then derive that $\sum_{i=1}^{Nch} \lambda_j * (P_{ch} + \Delta P_i)\,(G_i(x)-1) = \sum_{i=1}^{Nch} \lambda_i * \left(P_{ch} + \Delta P_{in,eq}\right)(G_i(x)-1)$, reaching to:

$$\Delta P_{in,eq} = \frac{\sum_{i=1}^{N_{ch}} \lambda_i\, \Delta P_i (G_i(x)\ -1)}{\sum_{i=1}^{N_{ch}} \lambda_i\, (G_i(x)\ -1)}$$

Note that the *equivalent* channel power correction $\Delta P_{in,eq}$ solely depends on the EDF gain at population inversion x. We can approximate x as the population inversion corresponding to a flat input with average channel power P_{ch}. Therefore, we only need to know the EDF gain profile at average channel power P_{ch} that can be deduced from EDFA measurements with flat spectrum input signals, along with an estimation of the EDFA input/output coupling losses (CL<1) of weak impact in practice for typical subsea gains. This formula also holds with relative power excursions.
In the following we build and test the following pre-emphasis aware EDFA gain model for the DUT. With the 13 flat WDM input power measurements, we first build a simple gain prediction function $G_{flat\ input}(\lambda\ , P_{in,tot})$ based on a

look up table of gain profiles versus wavelength λ for the different flat input powers $P_{in,tot}$ and use linear regressions for intermediate wavelengths and powers. Then for any arbitrary input spectrum, we estimate the gain from:

$$G_{pre\ aware}(\lambda, P_{in,tot}, \Delta\bar{P}) \triangleq G_{flat\ input}(\lambda, P_{in,tot} + \mathrm{N_{ch}}\ \Delta \mathrm{P_{in,eq}}) \text{ and } \Delta \mathrm{P_{in,eq}} = \frac{\sum_{i=1}^{N_{ch}} \lambda_i\, \Delta P_i\, (G_{flat\ input}(\lambda_i, P_{in,tot}) * CL - 1)}{\sum_{i=1}^{N_{ch}} \lambda_i\, (G_{flat\ input}(\lambda_i, P_{in,tot}) * CL - 1)}$$

The model is extended to estimate SNR by using similar look-up tables with total power dependent noise figure values.

4. Experimental assessment

To assess the accuracy of our EDFA model, the gain measured experimentally is compared with the gain predicted by our model for all the 2600 measures with random preemphases. Fig.2c) shows the histograms of the root mean square (RMS) error defined as $\sqrt{\frac{1}{N_C}(e_1^2 + \cdots + e_{N_C}^2)}$, where e_i is the error for the i-th channel for three different cases. In blue, the histogram of RMS error of the preemphasis unaware model given by $G_{flat\ input}$ is plotted. This error corresponds to the model that does not take the non-flatness of the input power into account, only the total input power. The RMS error averaged over the 2600 measurements shown by this preemphasis unaware model is 0.12 dB. On the other hand, we plot in yellow the RMS error using the estimated value of $P_{in,eq}$ that minimizes the error obtained directly from experimental data. It is indeed the lowest error we can attain given the hypothesis that the gain is already well-defined from $P_{in,eq}$, so we call it the *ultimate limit*. The averaged RMS error is 0.04 dB for this case. The remaining error may be attributed to measurement uncertainty and to the contribution of other effects that cannot be modeled by our homogeneous model. Finally, in orange we show the RMS error for the model presented in this study given by $G_{pre\ aware}$ with an averaged RMS error of 0.05 dB. This value is much lower than EDFA models developed with ML techniques [3,4,6] and, as far as we know, is the one which shows the lowest RMS error.

Eventually we also experimentally validated the accuracy of the model in the cascade of 12 EDFAs shown in fig.1c). We observed than after 12 spans, the averaged RMS error in output power is about 0.15 dB, confirming that the model can be extended to a chain of EDFAs with high accuracy. Output SNR values showed similar RMS errors of 0.18 dB.

5. System optimization

We used the $\Delta P_{in,eq}$ concept introduced in this paper to explain the possible benefit of working in non-flat WDM input regimes. As discussed previously, the population inversion of the EDFA can be modified by changing the input preemphasis, obtaining EDFA gains which correspond to a different equivalent flat system for the same input powers. We can exploit it when working with input preemphases that show negative $\Delta P_{in,eq}$ values. In this regime, the gain experienced by the EDFA is higher than the one corresponding to the total power, since the flat equivalent system works at a lower equivalent input power, making it possible to artificially increase the EDFA output power by 1dB at fixed pump power. An optimization function was defined taking this idea into account to search the WDM input preemphasis that maximizes system capacity based in this approach. We reached, following a different path, the same results as the ones obtained in [4] verifying that gain-shaped waterfilling is an efficient technique to address this issue.

6. Conclusions

We developed an agnostic measure-based model that predicts the gain of an EDFA with only 0.05 dB of root mean square error when a full-C band non-flat WDM input is provided with a power variation between channels up to 12 dB. To the best of our knowledge, this is the smallest error found in literature and is much lower than other models completely based on ML learning techniques. On the other hand, this model can be extended to estimate the output spectrum and SNR after a chain of 12 EDFAs, showing 0.15 dB of RMS error, and can be used for optimizing optical links with non-flat WDM inputs or GFF suppression.

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7. References

[1] A. Bononi, P. Serena and J-C. Antona, "Gain-shaped Waterfilling is Quasi-optimal for Constant-pump Flattened-EDFA Submarine Links," in Proc. ECOC 2020, Tu1-F5.

[2] J. K. Perin *et al*. "Importance of Amplifier Physics in Maximizing the Capacity of Submarine Links," J. Lightw. Technol. vol. 37, pp. 2076-2085, May 2019.

[3] M. Ionescu *et al*., "Design Optimisation of Power-Efficient Submarine Line through Machine Learning", in Conference on Lasers and Electro-Optics, STh4M.5, 2020.

[4] J. Cho *et al*., "*Supply-Power-Constrained Cable Capacity Maximization Using Multi-Layer Neural Networks*", in Journal of Lightwave Technology, Vol. 38, No. 14, pp. 3652-3662, 15 July15, 2020

[5] A. A. M. Saleh *et al*. "Modeling of gain in erbium-doped fiber amplifiers," Photon. Technol. Lett. vol. 2, pp. 714- 717, Oct. 1990.

[6] F. Da Ros, U. de Moura and M. Yankov, "Machine learning-based EDFA Gain Model Generalizable to Multiple Physical Devices", Proc ECOC 2020, Tu1A-4

[7] J. Cho *et al*., "*Data-Driven Characterization of EDFA In Constant Current Operation*", Proc OECC 2020