Machine Learning Based EDFA Channel In-band Gain Ripple Modeling

Zhiping Jiang[1*], Jiachuan Lin[1], Hangting Hu[2]
[1]*Huawei Technologies Canada, 303 Terry Fox Dr., Ottawa, Canada*
[2]*Optical Technologies Engineering Dept, NW, Huawei Technologies Co., Ltd., Wuhan, China*
zhiping.jiang@huawei.com

Abstract: For the first time, a framework is proposed to model EDFA's channel in-band gain ripple by machine learning. The achieved model accuracy (standard deviation) is 0.022dB/nm for gain tilt and 0.053dB for overall gain. © 2021 The Author(s)

1. Introduction

To meet ever increasing traffic demand and reduce cost, the channel baud rate is increasing rapidly. Recently 130Gbd~140Gbd modules have been announced commercially available by some vendors [1], and 200Gbd solutions are also being actively discussed [2]. In the low baud rate era, EDFA's gain difference within a channel, or in-band gain ripple (IGR) is largely negligible. However, for high baud rate, IGR is no longer negligible. Through multiple span propagation, significant in-band power/OSNR ripple can be accumulated, leading to severe performance degradation if this in-band ripple is not properly dealt with.

Accurate EDFA gain model is essential in predicting performance change during channel add/drop. It is also the basis for inline equalization, as flex WSS (wavelength selective switch) can greatly mitigate inter-channel gain difference, as well as intra-channel gain ripple. EDFA's gain profile is an extremely complicated function of channel loading, there has not been a physical model with acceptable accuracy. In recent years, machine learning (ML) based EDFA modeling has been demonstrated with good accuracy [3-7]. However, IGR modeling has not been reported so far.

In this paper, a machine learning (ML) based EDFA's channel IGR modeling is proposed for the first time. We extend our previous model from channelized average gain only to including IGR. Aspects, such as effective representation of IGR, data collection, model performance are discussed.

2. In-band Gain Ripple

Fig. 1(a) shows the EDFA gain profile under a few channel loading conditions. Each color represents a channel loading condition, with the present channels indicated by the dots. As is seen, the gain profile is not flat, and is a very complicated function of channel loading. On the one hand, the EDFA gain modeling is essential to optical link performance modeling/prediction; on the other hand, largely due to the lack of accurate SHB (spectral hole burning) model, no gain profile model based on physical principle with acceptable accuracy has been reported. This problem is well suited for machine learning: it is too complicated for physical model, or empirical curve fitting; and yet, it is deterministic, and a large number of data sets can be obtained easily and accurately in the lab.

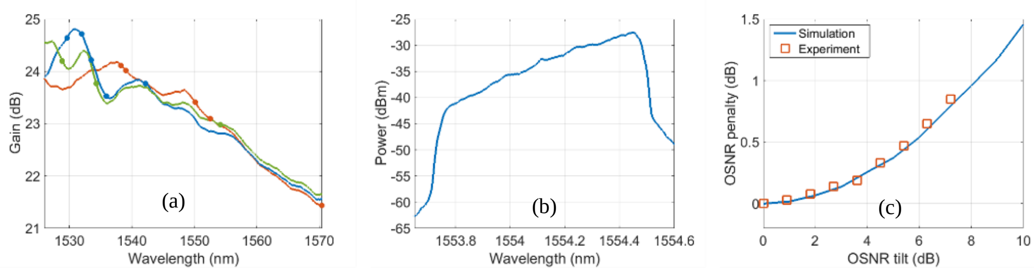


Fig. 1. (a) Measured EDFA gain profiles of three partial loading conditions (b) Received signal spectrum after 35 EDFAs showing ~15 dB accumulated in-band power tilt; (c) OSNR penalty vs. in-band OSNR tilt.

The IGR has significant impact when the signal baud rate is high. An example is shown in Fig. 1(b), about 15 dB accumulated in-band power tilt are observed after 35 EDFAs for a 90 Gbd signal. The signal's power tilt is accompanied by OSNR tilt, which is approximately half of the power tilt due to the fact that the ASE noise is distributed added to the signal in the optical link. Fig. 1(c) is the measured and simulated OSNR penalty as a function of in-band OSNR tilt for a single carrier signal. About 1dB OSNR penalty can be seen when OSNR tilt is around 8dB. It is worth mentioning that the penalty could be much higher for digital multi-carrier signal, which is becoming popular [8].

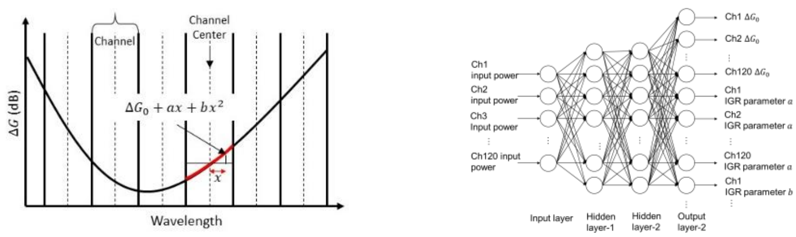
3. Machine Learning Based In-band Gain Ripple Modeling

In our previous EDFA gain modeling, the transmission band (e.g. C band) is divided into channels (e.g. 50GHz or 100GHz spaced grid), and only the averaged channel gain profile is modelled. There is no information about the gain shape within a channel. In order to obtain the gain shape information within a channel, one way is to do the modeling similarly, but with much smaller channel bandwidth. However this brute force approach greatly increases the modeling workload, and is not practical. Alternatively, we here propose to approximate each channel's in-band gain profile by a low order polynomial function. As in [3], to avoid the impact of the gain flattening filter (GFF), the differential gain profile (deviation from full-fill channel loading condition) $\Delta G(i) = G_{PF}(i) - G_{FF}(i)$ is modelled, with $G_{PF}(i)$ the partial-fill and $G_{FF}(i)$ the full-fill gain profile, i the channel index. As illustrated in Fig. 2(a), the transmission band is divided into channels (solid line), and for each channel, its differential gain profile can be expressed as

$$\Delta G(i,x) = \Delta G_0(i) + a(i)x + b(i)x^2, \tag{1}$$

where ΔG_0 is the differential gain at the channel center (dash line), x is the wavelength offset from the channel center, a and b are the parameters to describe IGR (1st and 2nd order coefficients, respectively). Higher order terms can also be added if necessary. All the parameters are a function of channel power loading condition.

The structure of our ML model is shown in Fig. 2(b), it is a multi-layer perceptron (MLP) with 1 input layer, 2 hidden layers and 1 output layer. The difference with prior model is that in addition to average channel differential gain ΔG_0, the 1st and 2nd order parameters a and b are also modelled at the outputs.

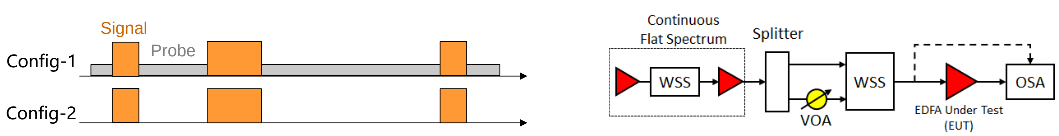


(a) (b)

Fig. 2. (a) Differential channel gain ripple illustration; (b) ML model for EDFA center gain and in-band gain ripple.

4. Data Acqusition, Results and Discussion

As in any ML modeling, large amount of accurate data is the key. Compared to the average gain, the accurate measurement of IGR is harder. The data collection and processing in our prior work have to be modified to obtain average channel gain as well as IGR parameters. In order to do so, continuous gain profile, rather than the channelized gain profile [3], should be measured. To be able to measure the gain at all spectrum, low spectral power density probe is used for non-signal channels. The input spectrum is made as continuous as possible, there is no spectral gap between consecutive signal channels or consecutive probe channels. Since the ASE noise generated by the EDFA under test (EUT) has significant contribution to the output probe power, this ASE noise must be properly measured and subtracted to yield an accurate gain profile. This can be done by blocking the probe spectrum, allowing the EUT's ASE noise measurement. Fig. 3(a) shows 2 input spectra: Config-1 for gain profile measurement, Config-2 for measuring the EUT generated ASE power at probe wavelength.



(a) (b)

Fig. 3. (a) Input spectrum for gain profile measurement. To account for the influence of the generated ASE noise by the EDFA under test, signal with probe (Config-1) and without probe (Config-2) are used; (b) Experiment setup for data acquisition.

Fig. 3(b) shows the data collection setup, a WSS and two EDFAs are used to generate continuous flat spectrum. The spectrum is then split by a splitter into two paths, one path (upper path) is for signal channels, and the other (lower path) is for probe channels. A second WSS is used to select light either from the signal path or the probe path. Due to limited attenuation capability, a VOA in the probe path is used to attenuate the probe light power. The power of probe channels is kept ~30dB lower than signal one, so that it does not affect the EDFA gain profile, but is high enough to allow accurate gain measurement. An optical spectrum analyzer (OSA) is used to measure the input and output spectra of the EUT, which is operated in the constant gain control mode.

The EUT generated ASE noise profile P_n is obtained by measuring the spectral power at probe wavelength for Config-2 input. The gain profile is calculated by $G = (P_{out} - P_n)/P_{in}$, where P_{out} and P_{in} are the output spetrum and input spectrum with input spectrum of Config-1. The differential gain profile ΔG is obtained by substracting the full-fill gain profile. Finally we extract the channelized parameters of $\Delta G_0, a, b$.

The gain profiles of a total of 900 channel loading conditions are collected. Of them, 800 are used for training, and the rest 100 are used to verify the model. For the 2nd order IGR parameter b, we only model in the short wavelength region, where the SHB effect is strong. In long wavelength region, the 2nd order parameter is very small. Excluding longer wavelength region can actually improve the model accuracy for the shorter wavelength region.

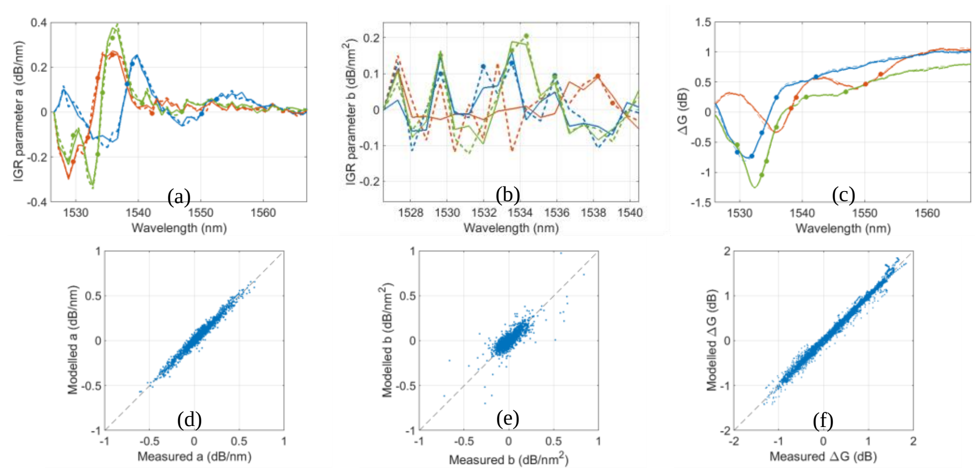


Fig. 4. (a) Predicted and measured results of (a) 1st order IGR parameter a for all channels; (b) 2nd order parameter b for SHB region; (c) overall differential gain spectra for all wavelength (0.01nm step); scatterplots of all loading conditions for (d) measured and predicted a; (e) measured and predicted b; (f) measured and predicted overall differential gain ΔG

Fig. 4(a) and (b) plot the predicted IGR parameters a and b for 3 channel loading conditions. By interpolating modelled $\Delta G_0, a, b$, the modelled ΔG spectrum can be obtained at a fine wavelength step. Fig. 4(c) shows the corresponding three modelled ΔG spectra at a wavelength step size of 0.01nm. In these three plots, the dashed lines are the measured results, the solid lines are model predictions, and the dots mark the positions of signal channels.

Fig. 4(d) shows the prediction vs. measurement of the IGR parameter a for all channels under all channel loading conditions. The agreement is excellent with a maximum observed difference around 0.17dB/nm, and a standard deviation of 0.022dB/nm. Fig. 4(e) shows the prediction vs. measurement of the 2nd order IGR parameter b for SHB region under all channel loading conditions. The maximum difference is around 0.6dB/nm^2, and the standard deviation is 0.067dB/nm^2. At first glance, it appears that the percentage error of the 2nd order parameter b is significantly larger than that of the 1st order parameter a, however, the contribution of the 2nd order parameter to IGR is small, the overall accuracy of the IGR model is still high. Fig. 4(f) shows the overall IGR accuracy, i.e. the prediction vs. measurement of the ΔG for all wavelength points (0.01nm step) for all loading conditions. The standard deviation is 0.053dB.

6. Conclusion

Realizing the importance of IGR in future high baud rate systems, we proposed a machine learning based EDFA IGR modeling framework. A polynomial function is proposed to represent IGR. The data collection setup is modified to obtain average channel gain, as well as IGR parameters. The MLP model is modified, so that both the center gain and IGR parameters can be predicted. Preliminary results show excellent accuracy, with standard deviations of 0.022dB/nm for 1st order IGR parameter, and 0.053dB for overall differential gain.

Acknowledgement

The authors would thank Dr. Wing-Chau Ng and Dr. Yuren You for useful discussions on ML optimization.

References

[1] Coherent Interconnect Module 8, “The CIM 8 powered by Jannu is a 140Gbaud solution,” https://acacia-inc.com/product/coherent-interconnect-module-8/.

[2] M. Nakamura *et al.*, “High Symbol-Rate Signal Optimization for Long-Haul Transmission Systems over 1-Tbps/λ Net-Data Rate,” in ECOC (2021).

[3] Y. You, Z. Jiang, and C. Janz, “Machine Learning-Based EDFA Gain Model,” in ECOC (2018), Mo3E.5.

[4] Y. You, Z. Jiang, and C. Janz, “OSNR prediction using machine learning-based EDFA models,” in ECOC (2019).

[5] S. Zhu *et al.*, “Machine learning based prediction of erbium-doped fiber WDM line amplifier gain spectra,” in ECOC (2018).

[6] S. Zhu *et al.*, “Hybrid machine learning EDFA model,” in OFC (2020).

[7] Jiakai Yu *et al.*, “Machine-learning-based EDFA gain estimation,” J. Opt. Commun. Netw. **13**(4), B83 (2021).

[8] H. Sun *et al.*, "800G DSP ASIC Design Using Probabilistic Shaping and Digital Sub-Carrier Multiplexing, " J. Lightwave Technol., **38**(17), 4744-4756 (2020)