Load aware Raman gain profile prediction in dynamic multi-band optical networks

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Abstract: We introduce a load aware machine learning method for prediction of Raman gain profiles. It enables future network controllers to manage seamless upgrades toward multi-band optical line systems with dynamic loads. © 2020 The Author(s)

OCIS codes: (060.0060) Fiber optics and optical communication, (060.2320) Fiber optics amplifiers.

1. Introduction

Raman amplification exploiting the Stimulated Raman Scattering (SRS) is an attractive solution capable of delivering gain at any wavelength with low-noise because of its distributed nature. It will be an important tool for the implementation of future multi-band optical line systems that will extend beyond the conventional C-band [1] to satisfy the ever increasing capacity demand. The management of these future optical networks will require high level of automation to provide fast routing, self-adaptation and efficient resources allocation with low-latency. SRS interplay between channels and pumps is described by a system of nonlinear ordinary differential equations (ODEs) [2], whose analytical solution is computationally challenging and time-consuming, in particular when the number of both channels and pumps is large as in the case of multi-band systems.

Ultra-fast methods for predicting gain profile of Raman amplification will be an essential component for future real-time network controllers. An early study based on machine learning (ML) has been presented in [3] with a limited set of results and applications. Recently, a more comprehensive analysis has been introduced in [4] and [5] but in both cases the designed neural networks (NNs) are completely load unaware, as they are trained under the full load condition. This assumption is valid for a limited class of networks where the traffic is almost static. Future networks will be required to manage dynamic allocation of traffic to satisfy increasing capacity. In particular, an upgrade is envisioned from a condition where the C-band is only partially loaded toward the exploitation of the full C+L band.

In this paper, we first show that a load unaware neural network (LU-NN) fails in predicting gain profiles when employed in a scenario where load can dynamically change. Then, we propose an improved solution, the load aware neural network (LA-NN), that is trained with a data–set considering different load conditions added at the input of the LA-NN. In the analyzed scenario covering the C+L band the number of channels is very large (more than 200 considering 50 GHz frequency slots), generating an unmanageable dimension of the input cases ($> 2^{200}$). To solve this issue, the key idea is to reduce the dimension of the input space to be visited for the data-set generation by considering sub-bands composed of 10 channels each. Moreover, we also propose a smart solution for the input load selection in the data-set generation. A comprehensive statistical analysis over several thousands cases with different input load shows that the LA-NN can always predict gain profiles with a high level of accuracy (maximum error always below 0.5 dB with an average of 0.12 dB). We also show an application to the upgrade from a C-band only system to a full C+L band demonstrating the superior performance of the LA-NN.

2. Data–set generation and neural networks training

We analyze a distributed Raman amplifier (RA) based on a single standard single mode fiber (SSMF) span with $N_\text{p} = 5$ counter-propagating pumps. The fiber span length is $L_\text{span} = 100$ km and the attenuation coefficients are $\alpha_\text{s} = 0.21$ dB/km and $\alpha_\text{p} = 0.25$ dB/km, for the input signal and for the pumps, respectively. As in standard commercial modules, pumps are set at fixed frequencies ($f_1 = 210.37$ THz, $f_2 = 207.14$ THz, $f_3 = 204.01$ THz, $f_4 = 200.97$ THz, $f_5 = 198.03$ THz) to enable gain profiles across the entire C+L band, spanning 11 THz from 185 THz to 196 THz. The input WDM comb is based on 220 channel slots, on the 50 GHz WDM grid. To reduce the dimension of the space to be visited for the data-set generation we consider $N_\text{sb} = 22$ sub-bands, each carrying 10 channel slots, for a total band of 500 GHz. We have 12 sub-bands in the L–band and 10 sub-bands in C–band.

The data–set generation is based on a numerical solver of the ODEs describing the Raman effect [2], available within the open source library GNPy [6]. Input load conditions are based on the fact that each sub-band can assume

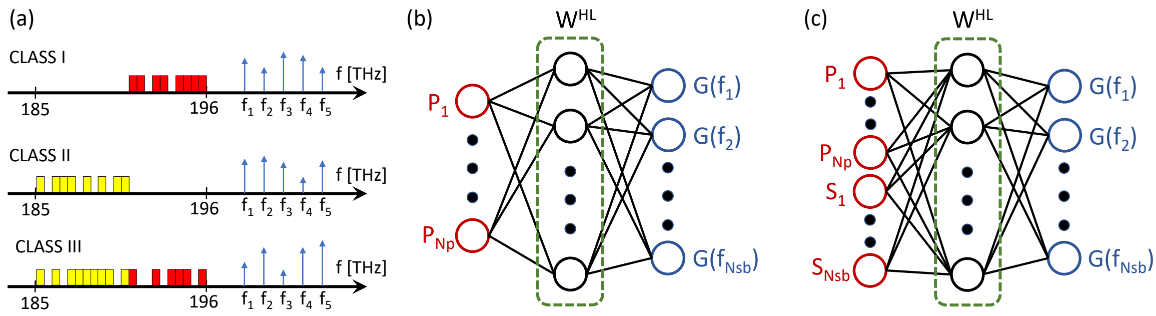

Fig. 1: Three selected data–set cases (a). Neural network models: load unaware NN (b) and load aware NN (c).

only two states, ON and OFF, with same probability. When a sub-band is OFF, it does not carry any power, while when it is ON, it carries 10 mW: the equivalent of 1 mW per channel slot. According to the input load, the data–set is composed of three classes: I) only C–band, II) only L–band and III) C+L–band (some examples in Fig. 1(a)). Then, in each class, we define sub-classes where a controlled number of sub-bands is ON: spectral position is randomized. Each sub-class is characterized by a fixed even number of sub-bands turned ON, respectively from 2 to 10 for class I, from 2 to 12 for class II and from 2 to 22 for class III. For every single case considered in each class and sub-class, pump powers values are drawn from a uniform distribution, $P_i \sim [0, 250]$ mW with $i \in \{1, \ldots, 5\}$. For each sub-class we have generated 500 cases, resulting in a dynamic-load training data-set of 11000 cases. A second and independent data–set, with same dimensions, has been generated for validation.

We start analyzing the same NN introduced in [5], simplified by avoiding the pump wavelengths as inputs: this is the LU-NN with input the pump powers $\mathbf{P} = [P_1, \ldots, P_{\mathrm{N_p}}]$ and output the gains $\mathbf{G} = [G(f_1), \ldots, G(f_{\mathrm{N_{sb}}})]$ evaluated for each sub-band. Then, we move to the proposed LA-NN that adds as inputs the load on a sub-band basis: $\mathbf{S} = [S_1, \ldots, S_{\mathrm{N_{sb}}}]$. Both NNs are a single-hidden layer models, as shown in Fig. 1(b-c). The LU-NN, as proposed in [5] because is load unaware, has been trained using the data–set of full-load cases (class III for C+L band and sub-class with all 22 sub-bands ON) enlarged to 5000 cases. The LA-NN is trained with the full dynamic-load data-set considering all classes and sub-classes, properly scrambled with a randomized ordering. Both LA-NN and LU-NN have been trained using the Random Projection method, performing the optimization of the hyper-parameters. The activation function is the hyperbolic tangent, and the optimum number of hidden nodes are 580 and 1900 for LU-NN and LA-NN, respectively .

3. Validation results

Using the validation-data set, completely independent from the training one, we carry out first a comprehensive statistical analysis of the accuracy of both the LU-NN and the LA-NN. The method performance is evaluated by defining the error as the difference between the gain profile predicted by the NN and the target gain evaluated using the numerical solver [6]. We determine both the maximum error ($Error_{MAX}$) and the root-mean-square-error ($RMSE$) over all the sub-bands ON. In Fig. 2, we report probability density functions (pdfs) of both errors for different conditions. Fig. 2(a) refers to the LU-NN when validation is carried out considering only full-load conditions. As expected, we obtained results in agreement with [5]: the average $Error_{MAX}$ is 0.14 dB, while the $RMSE$ is even lower. Then, we test and validate the LU-NN with respect to the dynamic-load data–set (containing also cases that are not fully-loaded). In Fig. 2(b), we observe that the LU-NN fails in delivering accurate predictions. The average $Error_{MAX}$ is 0.57 dB with pdf tail going well above 1 dB. Finally, we consider the novel LA-NN

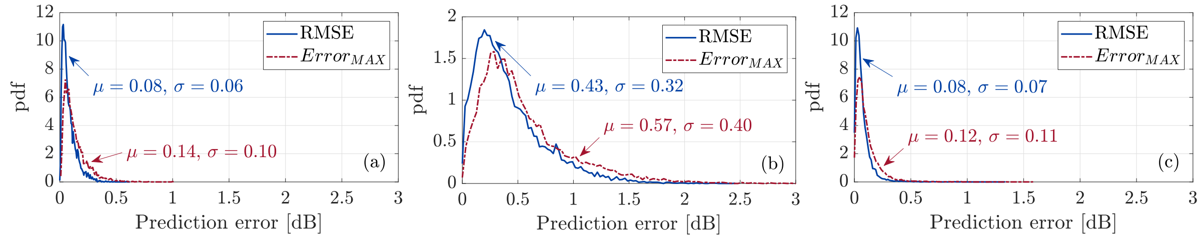

Fig. 2: Probability density functions of $RMSE$ and $Error_{\mathrm{MAX}}$ for: (a) LU-NN validated over full load cases only, (b) LU-NN validated over the entire data-set, and (c) LA-NN validated over the entire data-set.

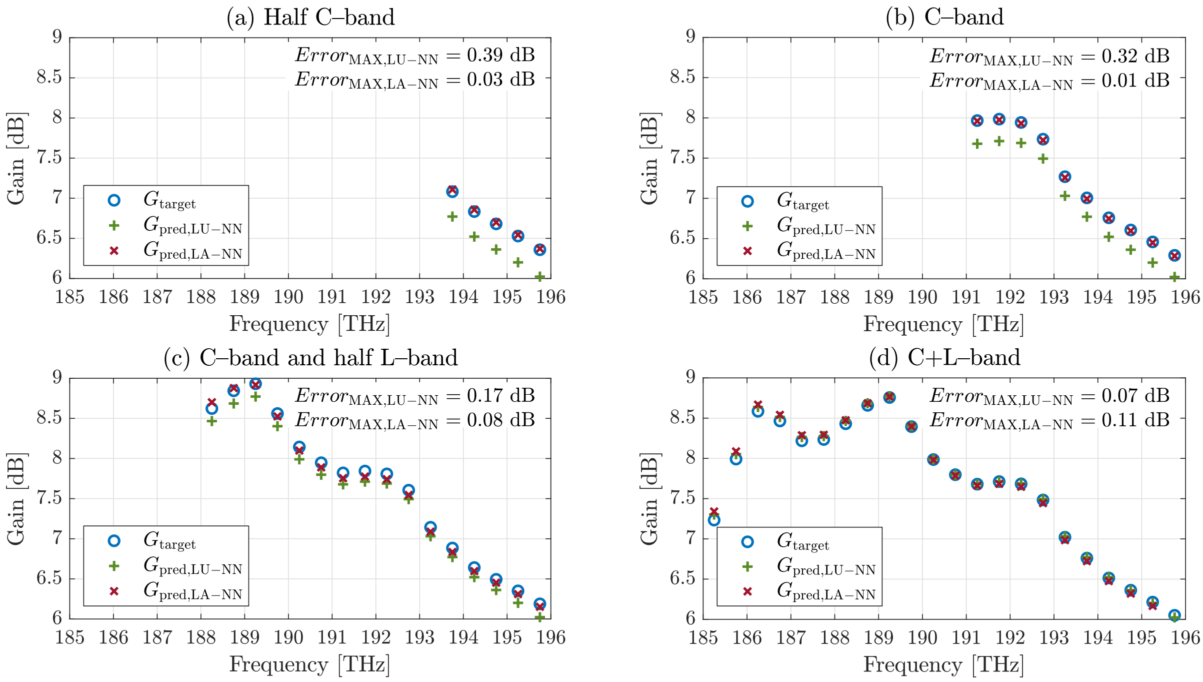

Fig. 3: Target and predicted gain profiles by means of LU-NN and LA-NN over: (a) half C-band, (b) C-band, (c) C-band and half L-band, and (d) C+L-band.

introduced in this paper. In Fig. 2(c), we note that accuracy is guaranteed at the same level of the LU-NN, when considering full load. The average $Error_{MAX}$ is less than 0.12 dB and the pdf tail does not exceed 0.5 dB, meaning that the entire population experiences small errors.

To further validate the newly proposed LA-NN in a practical scenario, we conduct the study of a possible network upgrade. We start from a condition where traffic has been deployed only on half the C-band, to a final scenario with full C+L load, passing through intermediate loads: full C-band and full C-band plus half L-band. In all cases, we suppose all five pumps powers set to 100 mW. In Fig. 3, we show the gain profiles of the four cases with increasing traffic load from Fig. 3(a) to Fig. 3(d). Similarly to previous results, the LA-NN can handle all load conditions, always delivering a gain prediction with $Error_{MAX}$ lower than 0.11 dB. While, the LU-NN can not reach such level of accuracy for all the four load cases, but only for the full C+L load.

4. Conclusions

We propose for the first time a load aware neural network for Raman gain prediction in dynamic multi-band optical line systems. The proposed solution is capable of handling any random input load condition: it has been tested over a large validation data–set always showing a maximum error lower that 0.5 dB.

Acknowledgements
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 754462 and the European Research Council through the ERC-CoG FRECOM project (grant agreement no. 771878).

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