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Multi–band programmable gain Raman amplifier for high–capacity optical networks

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Abstract

The paper presents recent advances in the design of controllable, highly accurate, and multi-–band Raman gain profiles. The ultra-–wideband programmable gain profiles are implemented using a machine learning approach based on the mapping between gain profiles and pump powers.

I. INTRODUCTION

Increasing the system throughput by expanding the optical transmission bandwidth is a viable solution to accommodate the constant traffic growth in our modern society [1]. This means going beyond the traditional C–band transmission and deploying all (or most of) O, E, S, C, and L–bands. However, multi-band transmission systems require new amplification schemes able to operate across the different bands [2].

New technologies have been recently explored to cover transmission beyond the C–band. They are doped fiber amplifiers (DFAs) such as bismuth, thulium, neodymium, and praseodymium [3], semiconductor optical amplifiers (SOAs) [4], optical parametric amplifier (OPA) [5], and Raman amplifiers (RAs) [6]. Among these new technologies, Raman amplifiers (RAs) have the advantages of being commercially mature and able to provide gain at any band provided the correct pump lasers' frequency allocation. Moreover, it is possible to obtain arbitrary Raman gain profile shapes in a controlled way, by properly adjusting pump powers and wavelengths. The generation of arbitrary gain profiles has a wide range of potential applications such as 1) in multi-band systems, with non-linear interactions between bands, an uneven gain along the channels is needed to maximize the information throughput; 2) in hybrid amplification subsystems, an adjustable non-flat gain profile can compensate for the wavelength-dependent gains of DFA and SOAs [7]; and 3) within the field of integrated optical frequency combs (OFC), programmable gain optical amplifiers could be very useful to flatten the OFC lines or shape its spectrum as desired. All these applications would minimize additional attenuation from currently static and lossy gain flattening filters.

Configuring the RA pumps to provide a specific target gain profile can be considered as an inverse design problem. Machine learning (ML) has proved to be an innovative and efficient approach for the inverse design of a wide range of photonic structures [8]. In the field of optical communications, we have recently proposed and experimentally demonstrated that ML can be used to learn the complex pump–signal relations in RAs [9]–[11]. In these works, we develop an ML–framework that employs an artificial neural network (NN) to learn the inverse mapping relating the pumps configuration (NN's output) to the gain profile (NN's input). After training, the NN is able to provide ultra-fast and high-accurate gain designs in a wide range of scenarios, from simple C-band [9], [11] to complex S+C and S+C+L-bands [9], [10] transmissions. Here, we summarize the results presented in [10], where the ML-framework is applied to program more than 1000 arbitrary gain profiles over an ultra–wide bandwidth of 17.6–THz. These designs show a very low average maximum error, defined between target and realized gain profiles, of 0.28 dB. This value corresponds to $1.6 \cdot 10^{-2}$ dB/THz when normalized by the total bandwidth. The obtained results demonstrate a high and accurate degree of flexibility in high-capacity and multi-band systems, providing the basis for system end-to-end optimization in dynamic transmission scenarios.

II. RAMAN AMPLIFIER INVERSE DESIGN

The core of our recently proposed ML–framework for the RA inverse design is the NN NN_{inv} depicted in Fig. 1(a). NN_{inv} learns the RA *inverse* mapping, i.e. the function $f^{-1} : \mathbf{G} \mapsto \mathbf{P}$. $f(\cdot)$ is a differential equation operator for the direct mapping $f : \mathbf{P} \mapsto \mathbf{G}$ relating pump $\mathbf{P}$ and gain $\mathbf{G}$ in the Raman amplification process. More specifically, $\mathbf{P}$ is the pumps configuration vector with pumps wavelengths and/or powers, and $\mathbf{G}$ is the gain vector describing the gain profile over the frequency channels. Here, the RA considers $\mathbf{P} = [P_1, ..., P_8]^T$ and $\mathbf{G} = [G_1, ..., G_{148}]^T$, i.e., 8 pumps and 148 frequency channels.
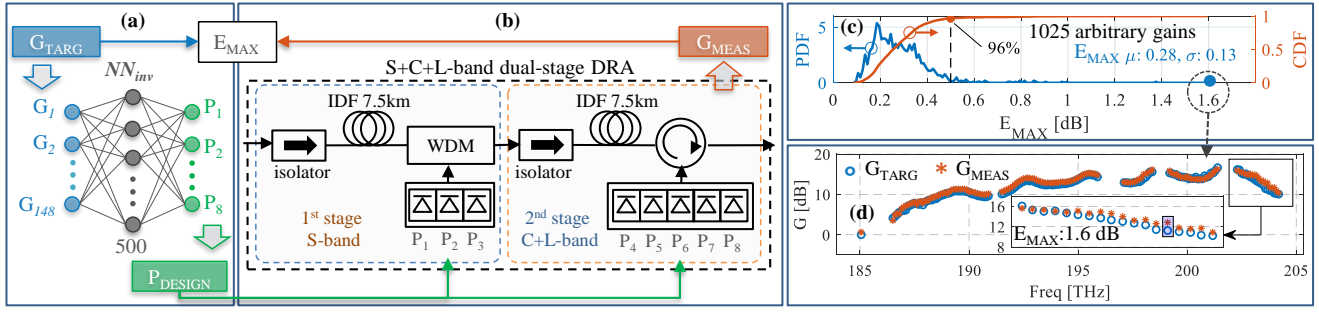
Fig. 1. (a) Neural network model for the inverse Raman amplifier mapping; (b) S+C+L–band dual–stage discrete Raman amplifier (DRA) experimental setup (IDF: inverse dispersion fiber); (c) Probability density function (PDF) and cumulative distribution function (CDF) for the maximum error (E_{MAX}) showing mean (μ) and standard deviation (σ); and (d) comparing target and designed gain profiles for arbitrary gain worst case (maximum E_{MAX}).

The ML–framework is applied to the dual–stage discrete RA (DRA) shown in Fig.1(b). Details about the experimental setup can be found in [10]. Programmable RA gain profiles are obtained according to the following steps. 1) *Experimental data acquisition*, to train NN_{inv}, is performed by applying a total of 4025 different pumps powers (drawn from uniform distributions) to the experimental setup in Fig.1(b) and measuring the corresponding RA gain profiles. The experimental data–set is split into training and test sets, with 3000 and 1025 cases, respectively. 2) *Model selection and training* considering 10-fold cross–validation (using 10% of the training set as validation set) and extreme learning machine, respectively. The optimized model (Fig. 1(a)) is a single-layer NN with 500 hidden nodes. The activation function is sine for the hidden layer and linear for the output layer. 3) The *gain design/programming*, also illustrated in Fig. 1(a), is a single-step process that consists in applying NN_{inv} to instantaneously provide the pumps configuration $\mathbf{P_{DESIGN}}$ given a target gain $\mathbf{G_{TARG}}$. NN_{inv} performs an ultra-fast RA inverse design, relying on a simple and fast matrix multiplication. 4) The *experimental validation*, illustrated in Fig. 1(a-b), consists in applying the $\mathbf{P_{DESIGN}}$ to the experimental DRA setup. The measured gain profile $\mathbf{G_{MEAS}}$ is compared to $\mathbf{G_{TARG}}$ in terms of maximum error along the frequency channels, defined as $E_{MAX} = max(|G_{MEAS} - G_{TARG}|)$.

Fig. 1(c) presents the probability density function (PDF) and the cumulative distribution function (CDF) for E_{MAX} over 1025 arbitrary gain profile designs. These gain profiles are within the pumps wavelengths and power limits available for the experimental DRA. E_{MAX} values are concentrated around a very low mean (μ) of 0.28 dB, with a standard deviation (σ) of 0.13 dB. Moreover, 96% of the designs have E_{MAX} lower than 0.5 dB. Fig. 1(d) shows $\mathbf{G_{TARG}}$ and $\mathbf{G_{MEAS}}$ for the worst design case (E_{MAX} = 1.6 dB). Slight differences occur along the entire bandwidth, with higher values for the S–band. However, the overall gain profile presents an excellent match, even for the worst case, with an acceptable approximation of the target gain. These results show an extremely fast and highly accurate gain profile programming for a multi–band DRA.

III. CONCLUSIONS

Recent works demonstrated that machine learning is a powerful tool for Raman amplifier design and optimization. Here, we show that it can be successfully applied to generate multi–band programmable gain profiles on demand, in an accurate and controlled way. The ability to realize signal spectrum shaping over such an ultra–wideband has potential applications in many different areas of optics ranging from maximization of spectral efficiency versus distance product, gain compensation in hybrid optical amplification technologies, and flattening of optical frequency combs lines. The proposed machine learning framework has therefore great potential to provide the desired degree of freedom for the intelligent operation in dynamic optical networks.

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