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***Abstract*—It has been recently demonstrated that neural networks can learn the complex pump–signal relations in Raman amplifiers. Here we experimentally show how these neural network models are applied to provide highly–accurate Raman amplifier designs and flexible configuration for ultra–wideband optical communication systems.**

***Index Terms*—optical communications, machine learning, inverse system design, optimization**

I. Introduction

The research in optical amplifiers is currently facing two major challenges: data–rate increase and dynamic operation in optical communication systems [1]. Erbium-doped fiber amplifiers (EDFAs), the most mature and widely commercially deployed amplification technology, have enabled bit rates approaching 1 Tb/s per fiber in the 90s by exploiting the wavelength division multiplexing (WDM) transmission [2]. However, EDFAs have a limited operating bandwidth, covering the C–band and part of the L–band (ITU-T grid). Therefore, to explore the full 53 THz low loss spectra of the optical fibers, other technologies have been investigated and experimentally validated. Among the candidates, Raman amplifiers (RAs) have recently gained renewed interest due to their broadband amplification when operating in a multiple pump lasers scheme [3]. They also present a low noise figure when providing distributed amplification. Another interesting feature that is exclusive to RAs is the possibility to arbitrarily shape their gain profile by properly adjusting the pump powers and wavelengths [4]. This adds a new level of flexibility and dynamic adaptability to the optical amplifier, and thus to optical communication systems.

The RA design consists of properly selecting the pump configuration, i.e. the number of pumps, their wavelengths, and power distribution, to provide the desired gain profile. Due to the complex interactions between pumps and signals, the RA design is not a trivial task. Recently, machine learning (ML) tools have been proposed to address this problem [4]–[8]. These works exploit the neural networks (NN) capabilities of universal function approximators to learn, from a given data set, the underlying mapping from gain profiles to pump powers/wavelengths, i.e. the RA inverse mapping. After trained, the NN inverse model can instantaneously deliver the corresponding pump configuration for any desired gain profile, providing a fast programmable gain profile tool simply relying on matrix multiplications.

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Here, we will provide an overview of our recent works on ML-based RA inverse design and optimization [4]–[6]. In these works, artificial NNs were employed to design RAs in different scenarios, with bandwidths ranging from 4 THz (C–band) to 17.6 THz (S+C+L–band). Highly accurate designs were obtained, showing that ML-enabled RA can potentially unlock the high capacity of the already deployed optical fibers by providing both ultra–wideband transmission and flexible gain profile operation.

II. ML-enabled Raman amplifier design

Fig. 1 summarizes our recently proposed ML framework for the RA inverse design [4]. The process to develop, apply and validate such an ML framework has four steps. (1) *Experimental data acquisition*: different pump configurations are applied to an experimental RA setup and the corresponding Raman gains are measured. This step is not illustrated in Fig. 1. (2) *Model training*: the ML framework is based on two NN models: NN_{fwd} (Fig. 1(a)) and NN_{inv} (Fig. 1(b)). They use the experimental data–set generated in step 1 to learn the inverse ($\mathbf{G} \mapsto \mathbf{P}$) and forward ($\mathbf{P} \mapsto \mathbf{G}$) mappings for the RA system. $\mathbf{P}$ is the pump configuration vector and can contain information about the pump powers, wavelengths, currents, etc. In Fig. 1(a-b), to exemplify, we consider the pump power: $\mathbf{P} = [P_1, P_2, ..., P_n]^T$ for n pumps. $\mathbf{G} = [G_1, G_2, ..., G_N]^T$ is the gain vector describing the gain profile over N frequency channels. (3) *Gain design*: after training, NN_{inv} receives a target gain profile $\mathbf{G_{TARG}}$ and returns the pump configuration $\mathbf{P_{DESIGN}}$ needed to achieve the corresponding $\mathbf{G_{TARG}}$, as shown in Fig. 1(c). If $\mathbf{P_{DESIGN}}$ is not sufficiently accurate, it can be finely optimized. This optional fine design procedure is depicted in Fig. 1(d) and consists of using NN_{fwd} in a gradient descent (GD) loop that minimizes the mean squared error (MSE) between $\mathbf{G_{PRED}}$ and $\mathbf{G_{TARG}}$. During the fine

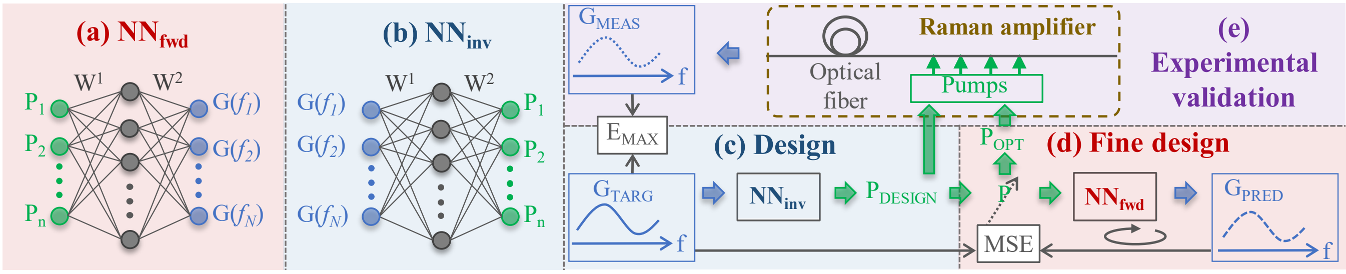

Fig. 1. Neural network models for the (a) forward (NN_{fwd}) and (b) inverse (NN_{inv}) Raman amplifier mappings; full machine learning framework composed of the (c) design and (d) gradient descent-based fine design to finely optimize NN_{inv} predictions; and (e) experimental design validation procedure applying the pump configurations from design and fine design to the Raman amplifier.

design, NN_{fwd} is used for fast gain predictions and gradient computations. The optimized pump $\mathbf{P_{OPT}}$ is obtained after a few iterations since the process started from an already optimized solution provided by $\mathbf{P_{DESIGN}}$. (4) *Experimental validation*: $\mathbf{P_{DESIGN}}$ and $\mathbf{P_{OPT}}$ are applied to the experimental RA and the measured gain profile $\mathbf{G_{MEAS}}$ is compared to $\mathbf{G_{TARG}}$ in terms of maximum absolute error along the frequency channels $E_{MAX} = max(|\mathbf{G_{MEAS}} - \mathbf{G_{TARG}}|)$.

In Fig. 2, we show the experimental results for: C–band distributed RA (4 THz, n=4, N=40) [5], C+L–band discrete RA (9.4 THz, n=5, N=90) [6], and S+C+L–band discrete RA (17.6 THz, n=8, N=148) [6] in terms of probability density functions (PDF) and the cumulative distribution functions (CDF) for E_{MAX} (with mean and standard deviation in the legend). Details about the experimental setups and NN_{fwd}/NN_{inv} model selection and training can be found in [5], [6].

These results show highly–accurate pump prediction for NN_{inv} (Fig. 2(a)). In fact, mean E_{MAX} slightly degrades when applying the fine design as seen in Fig. 2(b). This occurs for the widest bandwidths (mainly S+C+L–band) and it is because the fine design relies on the NN_{fwd} model that has a certain prediction error. Since NN_{inv} has already found the pump configuration that minimizes the MSE, the fine design ends up worsening the performance by adding some random deviations around the minimum [6]. However, for high E_{MAX} ($\geqslant$1 dB) cases, the fine design considerably improves the performance, as observed by the significantly maximum E_{MAX} values reduction from Fig. 2(a) to Fig. 2(b). For most cases the pump configuration for arbitrary gain profiles can be performed in a low–complex way as applying NN_{inv} requires only matrix multiplications. Therefore, the NN–based RA provides fast gain profile reconfigurability, which is essential to support the dynamic operation in future ultra–wideband systems.

III. Summary

Machine learning has proved to be a powerful tool for Raman amplifier design and optimization. By learning the complex signal–pump mapping from experimental data, it can provide ultra–fast, low–complexity, and high–accuracy pump configuration for an arbitrary gain profile. The ability

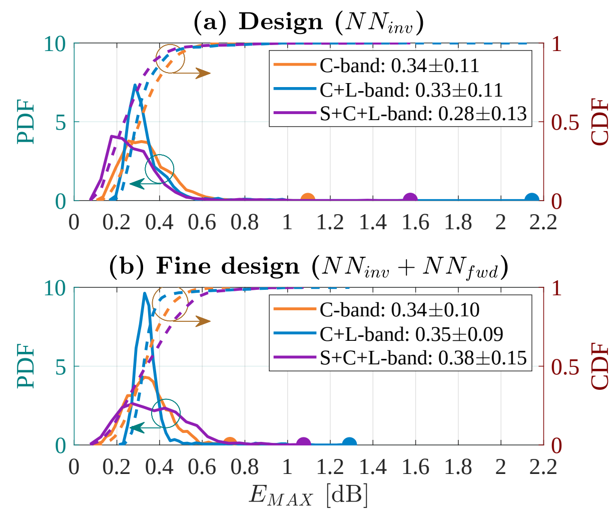

Fig. 2. Machine learning framework experimental validation for the three investigated Raman amplifiers showing the probability density functions (PDF) and cumulative distribution functions (CDF) of the maximum absolute error E_{MAX} over the frequency channels for the (a) design and (b) fine design. Mean and standard deviation values are shown in the legends.

to finely tune the amplifier gain profiles over such an ultra–wideband is a remarkable achievement that will enable the use of the unexplored optical fiber broadband in an intelligent and flexible way.

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