Distance and spectral power profile shaping using machine learning enabled Raman amplifiers

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***Abstract*—We propose a Convolutional Neural Network (CNN) to learn the mapping between the 2D power profiles, (distance and frequency), and the Raman pumps. Using the CNN, the pump powers and wavelengths for arbitrary 2D profiles can be determined with high accuracy.**

I. Introduction

Recently, Raman amplifiers have been extensively researched for optical wideband communication scenarios due to their high flexibility for gain and power profile design, and for their low noise figure because of the distributed amplification [1], [2].

The main research focus for Raman amplifiers has been on optimizing the pumping configuration to achieve a desired gain spectrum at the amplifier output. This is a complex optimization problem and requires solving a system of nonlinear differential equations. Several methods based on either genetic algorithms [3] or neural networks (NNs) [4]–[6] have aimed at solving the inverse mapping between the desired spectral gain profile and the pump parameters.

However, Raman amplifiers, in addition to enabling spectral shaping of the signal gain by controlling the pump parameters, also allow to control the signal power evolution along the fiber. Controlling the power evolution jointly in frequency (spectral) and distance (spatial) domain can be beneficial in terms of noise reduction and thus yield improved transmission performance. For instance, approaching a lossless transmission has been a clear goal for optical communication systems but that presents itself as a challenging task. A lossless transmission not only minimizes the amplified spontaneous emission (ASE) noise level [7], [8], it would also help several of the Kerr nonlinearity mitigation techniques currently being investigated. The nonlinear Fourier transform theory ideally enables nonlinear distortion free transmission, however only under the strong assumption of a lossless transmission [9], [10]. Furthermore, nonlinearity mitigation using mid-link optical phase conjugation which requires a symmetric power distribution is not possible without having a precise control over the power evolution along the span [11]. A significant effort has been already devoted to numerical or experimental demonstrations of a uniform [13] or symmetric [12] signal power evolution along the distance. Impressive results have been reported, with power variations below 3 dB/100 km [7], by combining second-order Raman pumping with grating mirrors creating a ultra-long fiber cavity for the first-order Raman pump. However, the complexity of the problem, and the challenge in terms of grating mirrors allowed considering only a few pump wavelengths, limiting the frequency band over which quasi-lossless transmission could be demonstrated.

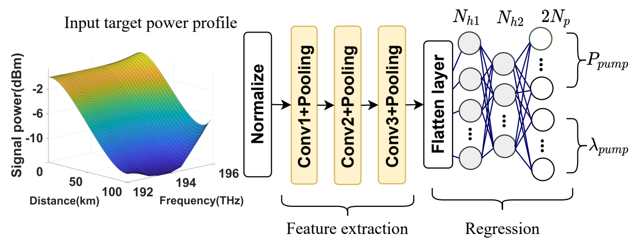

Fig. 1. Diagram of the proposed CNN-based model.

In this paper, we focus on standard distributed amplifiers, relying on simpler first and second-order pumping but without additional components (grating) and we review our recent contribution for inverse designing Raman power evolution jointly in frequency and distance along the fiber using a Convolutional Neural Network (CNN) model [14].

II. CNN-based Raman amplifier design

Considering an 100-km long single-mode fiber (SMF) link, we design a Raman amplification scheme by finding the pump powers and wavelengths of the amplifier which provide a target signal power evolution $\mathbf{P}_s(f, z)$ jointly in frequency (f) and distance (z) along the fiber. We propose a CNN-based architecture due to its outstanding performance in various pattern recognition problems by capturing correlations within 2D data forms, like images. With this in mind, we resemble the input power profile to the network as a 2D image and propose this modelling as two cascaded learning stages, a feature extraction and a regression problem, as shown in Fig.1.

First, a point-wise normalization is performed on the input power profile as a pre-processing step and afterwards, the normalized profile is passed through the feature extraction network which consists of three CNN layers. Each CNN layer is followed by a rectified linear unit (ReLU) as an activation function and an average pooling layer. The role of the pooling layers is to reduce the dimension of the input feature maps resulting in lower amount of parameters and computations in

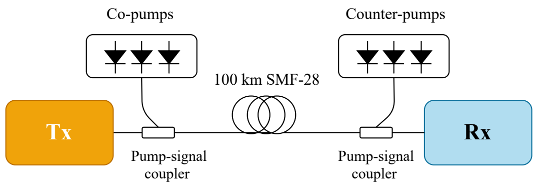

Fig. 2. Schematic of the proposed pumping set-up for the fiber span.

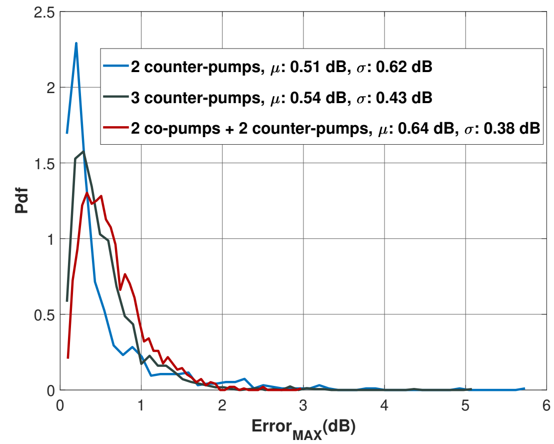

Fig. 3. Probability density function (pdf) of the $Error_{max}$. Mean μ and standard deviation σ are shown for 2, 3 and 4 pumps.

the network. The output of the last CNN layer is flattened and passed to the regression network. The objective of this network, modeled as a deep fully-connected, is to map the extracted features to the pumping setup. This network has four layers including the flatten layer, two hidden layers of size N_{h1} and N_{h2} and the last layer of size $2N_p$, representing the pumping configuration vector. The values of N_{h1} and N_{h2} are optimized depending on the proposed pump configuration.

III. Simulation Results

In this section the simulation results are presented for Raman amplifier design based on the CNN-based architecture presented in the previous section. We consider a single span and analyze the evolution of the power profile jointly over the distance and the entire C-band (40 100-GHz spaced channels). Moreover, three propagation cases are deployed for the evaluation of the proposed method: two counter-propagating cases with 2 and 3 pumps and a bidirectional propagating case with 4 pumps (2co+2counter). A schematic of the proposed pumping configuration is shown in Fig. 2 and it includes both co and counter-propagating pumps launched from opposite ends of the span made up of a 100-km SMF. For each pumping case, the data-sets for the training and evaluation of the proposed method are generated by solving the Raman differential equations with the GNPy framework [15]. After training the network for each case, the trained model is evaluated based on the maximum absolute error ($Error_{max}$) between the input test power profile and the reconstructed one which has been generated using GNPy with the predicted pump parameters by the network. Fig.3 indicates the probability density function (pdf) of $Error_{max}$ beside its mean (μ) and standard deviation (σ) for all pumping cases. Reported results assert that the proposed method is highly accurate for designing Raman amplifiers based on the signal power profile over a wide band and along the span.

IV. Conclusion

The problem of designing a distributed Raman amplifier both in distance and frequency is addressed by presenting a machine learning framework based on the desired 2-D (fiber distance$\times$frequency) power profile as the input. The inverse mapping is modeled as a cascade of two networks trained end-to-end. The first network is a CNN-based architecture proposed for feature extraction of the power profile, followed by a fully-connected network, aiming at finding the pump powers and wavelengths based on the extracted features. Numerical simulations show that the proposed framework provide high accuracy in terms of predicting the pump parameters for both counter and bidirectional propagating pumps in C-band.

Acknowledgment

This work was supported by the European Research Council (ERC-CoG FRECOM grant no. 771878), the Villum Foundation (OPTIC-AI grant no. 29334), and the Italian Ministry for University and Research (PRIN 2017, project FIRST).

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