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Abstract: Experimentally-trained neural network models are used to optimize the 12 Raman pumps of a C+L band hybrid EDFA-Raman amplifier, targeting gains with improved flatness. Gain ripples are decreased from 6.7 to 1.9 dB.

1. Introduction

Optical amplifiers are key components in communication systems as they define the transmission bandwidth and determine the system performance through their gain profile and noise characteristic. As demand for connectivity keeps growing, migrating from C- to C+L-band systems with appropriate amplification may double the data rate [1]. This upgrade can leverage the mature technology of erbium-doped fiber amplifiers (EDFAs). However, gain ripples of EDFAs cause unequal performance among frequency channels. Gain-flattening filters (GFFs) enable flattening these ripples but at the expense of power losses and a limited operation regime of the EDFA.

Alternatively, hybrid amplifiers (HAs) combining EDFAs and distributed Raman amplifiers (DRAs) may be applied to decrease gain ripples and enhance the transmission performance [2,3]. To achieve this goal, optimization of the HA's pumps is required and that is a non-trivial problem as the response of HAs is a nonlinear function of its pumps, the transmission bandwidth, the link configuration, the presence of GFFs, etc. Numerical optimization of HA has been shown through e.g. exhaustive grid-search [3] or genetic algorithms [2]. These methods have limited generalization beyond the specific target profile, and require re-optimizing if the target profile changes.

Recently, a neural-network (NN) model of a HA combing an EDFA and a dual-pump DRA was proposed, showing potential for fast reconfiguration and high accuracy by optimizing both DRA and EDFA pumping [4]. However, only profiles within the measured dataset were tested without clear improvement of gain ripples. Furthermore, for an application targeting the upgrade of EDFA-based deployed systems, it is desirable to focus only on the optimization of the DRA pumps. The EDFA in the HA defines the launch power into the transmission span, therefore its output power should be kept fixed.

In this paper, we apply a machine learning (ML) framework proposed for DRA modeling [6] and experimentally train NN-based models of a C+L band HA. The HA combines C- and L- band EDFAs and a 12-pump DRA. The EDFAs operate in constant output power, outside their specified regime for flat gain, and only the Raman pumps are optimized by approximating the direct and inverse mappings from DRA pump currents to HA gain profile with NNs trained on experimental data. The accuracy of the models' predictions is experimentally evaluated for both arbitrary gain profiles and by optimizing for flat gain spectra. The optimization decreases the gain ripples both comparing to the EDFA-only and to a naive manual optimization where all pumps are set to the same power level.

2. Hybrid EDFA-Raman amplifier

The setup of the HA is shown in Fig. 1. A broadband amplified spontaneous emission (ASE) source is split into C and L bands using a wavelength-division multiplexing (WDM) coupler. Each band is independently amplified by EDFAs preceded by wavelength selective switches (WSS) for spectral flattening. The recombined bands at a total launch power P_{in} = 18 dBm act as a spectrally flat test signal for the HA (Fig. 1(inset)). The HA consists of 80 km of standard single-mode fiber (SSMF), counter-propagating DRA, and EDFAs. At the SSMF output, a WDM coupler is used to combine the transmitted test signal with the 12 Raman pumps. After the coupler, C and L bands are split, separately amplified into two EDFAs, and recombined to form the output of the transmission span. The 12 Raman pumps have frequencies of [199.5 200.5 203.5 204.5 205.5 206.5 207.5 208.5 209.5 210.5 211.5 212.5] THz and adjustable power up to 80 mW. The control system of the EDFAs is operated in constant

output power mode. These amplifiers are equipped with GFFs and designed to operate standalone at a specified output power of 22 dBm with a flat gain for an input power of 9 dBm.

Two operation regimes for the HA are considered: case1 - the EDFAs output power is set to match the launch power into the fiber, P_{out} =18 dBm, effectively forcing a zero net gain of the span; case2 - the EDFAs output power is increased to reach a total P_{out} =22 dBm, e.g. considering pre-compensating the loss of an add-drop multiplexer. In both cases, the EDFAs operate outside the specified regime for flat gain (output < 21 dBm and input < 8 dBm), which invalidates the gain compensation of the GFFs.

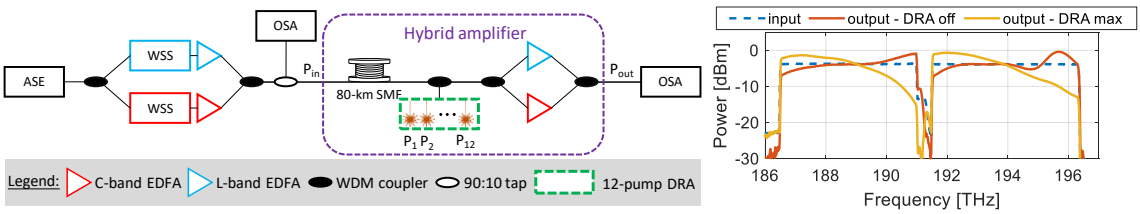

Fig. 1. Experimental setup and examples of input and output spectra for a P_{out}=18 dBm.

Optical spectra are collected with an optical spectrum analyzer (OSA) at the input and output of the HA (examples in Fig. 1(inset)), and the gain (output-input) is extracted. Measurements datasets are built by independently varying the pump currents uniformly between 0 and 500 mA (0-80 mW in pump power), and collecting the corresponding gains. The gain spectra are downsampled on a 100-GHz grid (47 points and 45 points for C and L-band, respectively) and combined with the 12 pump currents to build two experimental datasets, one per case.

3. Neural-network-based amplifier models

The ML framework used to optimize the HA gain flatness follows the scheme proposed in [6]. The framework relies on the NN models shown in Fig 2. The NNs learn the direct (pump current to gain, NN_{fwd}) and inverse (gain to pump current, NN_{inv}) models of the HA. Both NNs have a single hidden layer with 2000 hidden nodes and are trained with random projection/extreme learning machine, making the training nearly instantaneous (<0.5 s on a standard laptop). The prediction accuracy of both models is increased through averaging the output of 20 NNs, trained in parallel (ensemble averaging) without any additional time required [6].

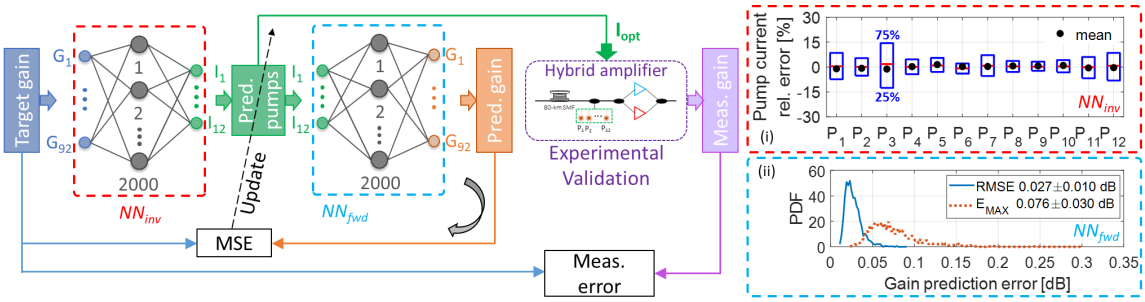

Fig. 2. Inverse (NN_{inv}) and direct (NN_{fwd}) NN models combined for a fast iterative optimization of the HA, followed by experimental validation and performance evaluation. Prediction errors for (i) NN_{inv}: pump currents ($(I_{pred} - I_{real})/I_{real}$) and (ii) NN_{fwd}: gain profile (G_{pred} vs. G_{real}).

The measured datasets are split into training/testing data (5000/1000 for case1 and 3300/232 for case2). After training, the models are tested and the errors are shown in Fig. 2(i) and (ii) for NN_{inv} and NN_{fwd}, respectively (case1). High accuracy is shown for both NNs and nearly identical performance is achieved for case2.

Targeting a flat gain profile, e.g. a profile outside the testing dataset, the NN_{inv} predicts the required pump currents following the flow shown in Fig 2. However, the target gain may not be achievable by the constraints of the HA (pump power/frequency) [7]. The currents prediction is consequently refined to approach the target through an iterative optimization which uses the NN_{fwd} and the predicted currents as initial conditions [6]. The mean square error (MSE) between the gain predicted by NN_{fwd} and the target gain is used to update the pump currents in a gradient-descent-based optimization. The optimization relies on the good initial condition provided by NN_{inv} and converges in less than 30 iterations. The optimized pump currents (I_{opt}) are applied to the experimental setup (Fig. 2) and the error between target and measured gains is computed.

4. Experimental validation: gain ripple and test error

The decrease in gain ripples ($\Delta G = max(\text{Gain}) - min(\text{Gain})$) achieved for case1 are shown in Fig. 3(a). The optimized profiles are compared with the EDFA-only (I_{off}) and with a naive DRA optimization consisting of setting all pump currents to the same value (I_0) which is then optimized. This naive approach reduces a 12-dimensional (12D) optimization into a 1D optimization, at the cost of a sub-optimal solution. Here, 30 values uniformly-spaced between 50 and 500 mA are considered.

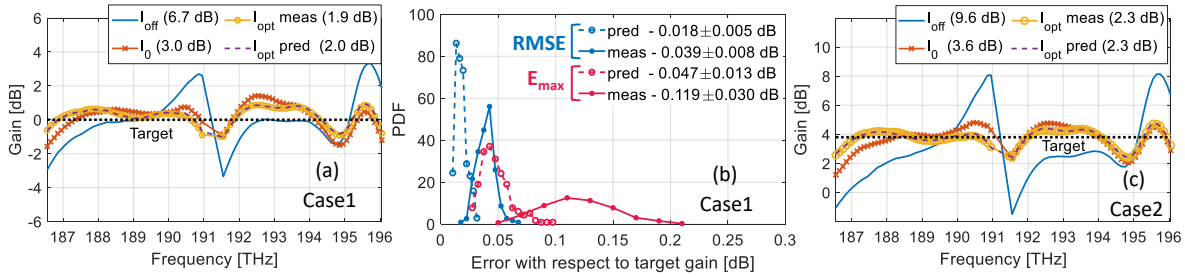

Fig. 3. (a) Gain ripples comparison for EDFA only (I_{off}), naive optimization (all pumps at I_0), and NN-based optimization (I_{opt}, predicted and measured); and (b) PDF of RMSE and error max for prediction and experimental validation using 232 *arbitrary* profiles, for case1. (c) Gain ripples comparison for case2. For (a) and (c), gain ripples (ΔG) values are reported in the legend in brackets.

Fig. 3(a) shows a reduction in grain ripples (ΔG =6.7 dB without DRA, ΔG =3.0 dB after naive optimization, ΔG =1.9 dB with NN-based optimization) and great agreement between predicted and measured NN-optimized gains. The residual gain ripple is due to constraints of the experimental setup (pump power/frequency) and not due to inaccuracies in the models. Fig. 3(b) shows the probability density function (PDF) of both maximum error and root MSE (RMSE) between target and measured arbitrary gains for the testing profiles (i.e. achievable within the setup [7]), clearly highlighting the high accuracy after experimental validation. The mean and standard deviation values of each PDF are reported in the legend of Fig.3(b). Finally, Fig. 3(c) shows the gain ripples performance for case2. The higher P_{out} yields worse flatness from the EDFAs alone (ΔG =9.6 dB) and naive optimization (ΔG =3.6 dB), whereas the NN-based optimization provides nearly identical performance (ΔG =2.3 dB).

5. Conclusions

We applied a ML framework for the optimization of a C+L HA based on EDFAs and a 12-pump DRA. Only the DRA is optimized, emulating an upgrade of a deployed system already using EDFAs. The NN models used for the optimization showed high accuracy and enabled to significantly decrease the gain ripples of the EDFAs. It also provided a clear improvement over a naive 1D optimization approach. This scheme can be further extended to include noise figure performance and system throughput optimization.

Acknowledgments

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