Machine Learning Assisted Hybrid EDFA-Raman Amplifier Design for C+L Bands

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Abstract *We address the different design challenges and applications of machine learning to modeling optical amplifiers. The problem of accuracy in designing neural networks cannot be simplified to the requirement of large training data sets, but it is specific to the application and the model selection.*

Introduction

Recent years have seen a surge of interest in Machine Learning (ML) applied to modelling, designing and optimizing optical transmission systems and components[1,2]. One application of ML is in modelling optical amplifiers[3]–[19], whose gain is a nonlinear function of the parameters of the fiber providing the gain medium, pump current, pump wavelengths, input signal power levels and bandwidth. The modeling of amplifier physics is paramount in the prediction and optimization of the overall system throughput, particularly when considering the recent applications of per-channel power optimization transmitting non-flat spectra[20]–[22], and has conventionally relied on the development of accurate analytical models of erbium-doped fiber amplifiers (EDFAs)[23] or semi-analytical models of distributed Raman amplifiers (DRAs)[24], the most commonly used types of amplifiers in optical transmission links. Model prediction accuracy is important as any errors in the model will translate to the practical system implementation

While (semi-)analytical models offer the advantage of computational speed, they can be challenging to implement. This is especially the case when employing DRAs or hybrid Raman/EDFA (HRE) type of amplifiers, to broaden the transmission bandwidth over the C+L bands. With distributed amplification the gain estimation requires a semi-numerical solution to solving partial differential equations that describe the signal and pump powers evolution along the transmission fiber medium. Moreover, the management of multiple Raman pumps adds to the complexity of designing and operating DRA and HRE amplifiers towards achieving a target gain response.

Neural networks (NN) can be a more practical alternative in simulating the gain response of such amplifiers. With knowledge of input parameters and the output signal, learning directly from amplifier-generated data is possible while the model's implementation complexity is simplified. Such models have been applied to various types of amplifiers including EDFAs[3]–[8], all-Raman[10]–[17] or HREs[9]. However, to achieve estimation performances comparable to the analytical models, large numbers of data sets are often used when training the NNs, increasing their time complexity. Hybrid models[18],[19], comprising ML and analytical techniques, or reduced-complexity parameter-fitting techniques[25] that avoid NNs, have been proposed to improve the estimation time.

However, in this paper, we address the fact that the performance and complexity of the NNs strongly depend not only on the chosen NN architecture and optimization procedure, but also on the amplifier being emulated. Hence, this might suggest that there is no ubiquitous NN design to model various optical amplifiers. As a result, the comparison between the different model types (i.e. NN, analytical, or a hybrid of the two) is not straightforward and requires a preliminary thorough investigation of the optimal NN model design.

Machine Learning Amplifier Models

A commonly addressed problem of ML-assisted amplifier models is gain prediction. The initial interest was addressing EDFA's gain prediction in elastic optical networks or network topologies employing reconfigurable add-drop multiplexers (ROADMs), where a cascade of amplifiers with varying input conditions can lead to undesirable gain fluctuations across different wavelength-division multiplexed (WDM) channels. Configuring constant gain-operation of EDFAs through ML can achieve an improved QoT and a reduction from 1.02dB to 0.08dB in OSNR margin[8].

The conventional performance metrics for the ML-based amplifier gain estimators is the root-mean-squared error (RMSE) or the maximum error over the output features (power or gain per wavelength) and sample number (across all measurements) in the test set. A maximum EDFA gain error of 0.11 dB was reported[6] using 5000 experimental measurements to train and test a 2-hidden layer NN. The network was designed to take as input the signal power per channel, total input power and target gain.

In contrast with EDFAs which requires a single pump wavelength for its operation, Raman amplifiers require multiple pump wavelengths (i.e. more than 4 typically) to control and extend the bandwidth of operation into the L-band. ML can reduce the complexity of predicting the gain of all-Raman amplifiers. Similar performances have been reported[10],[11] with maximum errors of 0.5 dB over 3000 data samples[11] and 0.4 dB[10] over 5000 data samples. For HREs, spectral estimation with maximum errors of 0.33 dB over C+L band channels covering 90 nm was recorded[9]. All these different results[9]-[11] were obtained with almost identical NN hidden-layer designs: 1-2 hidden layers,10-nodes, hyperbolic tangent sigmoid activation functions and trained using the Levenberg-Marquardt optimizer. However, the HRE model reports lower overall errors for significantly lower number of measurements (only 826 experimental measurements were required). With ML techniques, it is usually expected to have a lower estimation error (variance) as the training data set size increases, unless the estimation bias is high. The explanation for the discrepancy could be stemming from the very different amplifiers used, number of channels, and the ensuing input/output layers configurations, leading to different performance results. Therefore, for each application and amplifier design, performing a ML architecture search is necessary in ensuring the highest model accuracy.

When selecting a NN model that could replace an analytical or hybrid model, the aim is simultaneously achieving reduced-complexity and high-accuracy requirements. An optimal NN model selection requires trying different activation functions (i.e. sine, hyperbolic tangent, rectified linear unit etc.), different nodes and layers configurations and optimizers (i.e. stochastic gradient descent with momentum, Adam, Levenberg-Marquardt etc.) to minimize the RMSE.

For DRAs and HREs the inverse problem has also been studied[9],[13]-[17], where, the required pump powers are determined by a neural network to achieve a target spectral shape or tilt at the output of the amplifier. This inverse mapping approach has applications in amplifier design and spectral optimization to maximize system throughput. The main challenge here is accounting for the nonlinear interactions between Raman pumps and signal powers, which is numerically expensive in a semi-analytical model, but simplified in the ML implementation. When configuring a ultra-wideband HRE by means of a NN[9], the pump powers were estimated with RMSE as low as 6.9 mW (on average across all experimental measurements for which the pumps settings were varied between 0-310 mW for the Raman pumps and 0-650 mW for the 980 nm pumps). The ML design of DRAs including optimal pump powers and wavelengths selection to obtain a target gain over the C+L bands was shown numerically[14] to perform with mean gain errors of 0.46 dB and 0.2 dB standard deviation. These results demonstrate the applicability of ML to solving the inverse mapping problem for C+L amplifiers.

In practice, another strong incentive to using ML in the inverse design of optical amplifiers is the simplification of the amplifier configuration process, both during deployment and operation. A real-time configuration process can take between an hour and a full day by a field engineer, after system deployment. ML-assisted configuration could be instantaneous once fully trained. While the training process is time consuming due to the need to gather data sets, these measurements could be integrated as part of the amplifier testing phase during deployment. Moreover, a practical demonstration has shown[9] that less than 1000 measurements can potentially achieve better performance than a lab engineer in performing the pump configuration of a HRE.

Conclusions

Machine Learning offers an alternative to analytical models, through neural networks, which can improve the estimation accuracy of nonlinear functions. The computational complexity during training is often regarded as the main limitation of these techniques. However, the optimization criteria of NNs depends on its various application, therefore performing a NN architecture search is essential in determining the best-fit ML model of an optical amplifier and thus take advantage of their properties to provide simplified implementation and highly accurate predictions.

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