ARTIFICIAL INTELLIGENCE OR REAL ENGINEER, WHICH IS BETTER?

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Abstract: Artificial Intelligence (AI) has found applications in many areas, but does it have a future in subsea communications? Current generations of subsea amplifiers are extending bandwidth from the C-band into the L-band, employing either hybrid Raman-EDFA or dual-EDFA solutions, and branching units are offering flexible wavelength routing. The extra capacity and flexibility, however, comes with extra complexity which risks increasing the difficulty of both initial commissioning and long-term operation.

As optical networks move towards more complex and dynamic networks, it becomes important to be able to adapt system parameters such as tilt and optical output power. These need to be adjusted in response to changing conditions in the network, such as wavelength re-configuration and repairs. This paper demonstrates a practical neural network solution for the configuration of a complex multi-pump broadband amplifier.

1. INTRODUCTION

Subsea links are growing and expanding into mesh-like systems with added complexity both in the physical layer (i.e. fiber count expansion, C+L bandwidth extension, ROADMs), as well as in the associated control and configuration requirements of amplifiers and terminal equipment. With added increases in complexity, it becomes more and more challenging for engineers to design, configure and optimize such systems. The future evolution of subsea networks requires control and bandwidth optimization, as a minimum.

There is therefore a clear potential for these new challenges to be addressed with the aid of machine learning algorithms, neural networks (NN) being one approach. The explosive increase in popularity of neural networks in a multitude of fields over the last decade is explained by their potential to solve increasingly complex problems. Within the context of optical communications, the applicability of NNs has already been successfully demonstrated by the research community in a variety of areas, such as optical transmission impairment mitigation, performance monitoring, software-defined networking [1-3].

The realm of optical amplifier design can also benefit from these new AI approaches to tackle the added complexities due to scaling. A neural network for learning the pump powers and wavelength settings required in achieving a targeted gain profile over the C-band was proposed and demonstrated [4]. This approach can prove to be useful in the design stage of a Raman-based amplifier, where the pump wavelengths need to be selected such that the desired amplification spectrum is obtained. A maximum gain prediction error of 0.6 dB was obtained. An alternative approach, combining NNs with a differential evolution algorithm, was used in designing a Raman amplifier with minimum gain ripple of 0.4 dB over the C+L band [5]. Machine learning can give a lower estimation error than the analytical predictors, when determining the gain spectrum of EDFAs based on given input power profiles [6].

In practice, another strong incentive to applying machine learning to optical amplifiers is the simplification of the amplifier configuration process, during deployment and operation. The optimal operating point of an EDFA can be adaptively adjusted to minimize the noise figure and gain ripple through machine learning [7, 8]. This feature is particularly important when configuring a cascade of optical amplifiers with varying input conditions, such as it is the case when employing ROADMs.

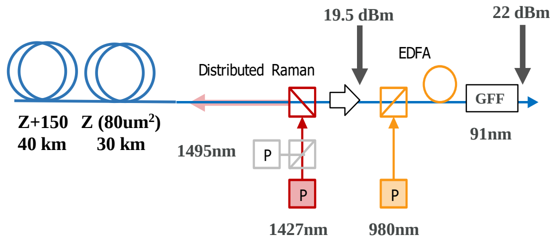
In this paper we propose and demonstrate the application of a deep NN to the optimization of amplifier pump powers to achieve a target optical output power and spectral tilt. Further, a second simplified single-layer NN is proposed to extend the problem in obtaining an improved prediction of the output spectrum for a set of known pump powers. Output spectrum prediction means a virtualization of the amplifier, which can be used jointly with gradient-descent algorithms to perform performance analyses, predictions and further pump optimization. To the best of the authors' knowledge, this approach is shown on hybrid amplifiers for the first time.

2. HYBRID AMPLIFIER DESIGN

Distributed Raman amplification (DRA) when used in a hybrid configuration with EDFAs can improve both the noise figure and bandwidth of the amplifier.

This experiment employed a single hybrid Raman EDFA (HRE) amplifier based on five pumps (one 980 nm, two 1427 nm and two

Fig 1: C+L hybrid EDFA/Distributed Raman Amplifier With hybrid fibre span.



1495 nm) to obtain a continuous amplification gain in the C+L bands, between 1525 nm and 1616 nm, as Figure 1 shows. The pump powers were varied up to 650 mW for the 980 nm pumps and up to 310 mW for the Raman pumps.

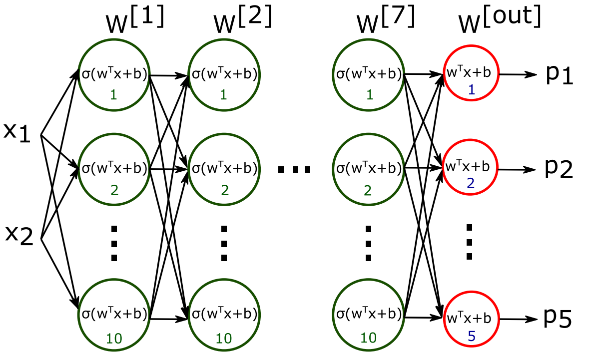
The fiber span used were a combination of 40 km of 150 µm2 high effective core area (Sumitomo Z+150) at the transmit end, that limits the impact of nonlinearities and 30 km of standard 80 µm2 fiber (Sumitomo Z) at the receive end, to maximize the Raman gain. An additional benefit of this approach is that 80 micron fiber can significantly reduce the cost of the span. The input signal into the fiber was provided by a 97 nm ASE noise source.

The output power spectrum and total optical output power were recorded over a set of 826 distinct measurements. For every measurement, random pump powers were selected for all 5 pumps, then after allowing the pumps to settle, a 60001-point spectrum was recorded using an OSA (2 pm resolution). The spectrum was then resampled down to 45-points covering only the pass-band of the amplifiers (2 nm resolution) to increase the computation speed of the proposed algorithms. The spectral tilt was estimated from the recorded spectrum, while the output power measured from a monitoring diode inside the amplifier.

For example, as required in a previously conducted experiment [9] using the same HRE amplifiers, the target total output power was 22 dBm and the spectral tilt was -2dB over the transmission bandwidth. The next section explains the different ways of adjusting the pumps to achieve these targets, with their particular advantages and disadvantages.

3. PUMP OPTIMIZATION

Fig 2: 7-layer neural network to estimate pump powers from amplifier output power and spectral tilt



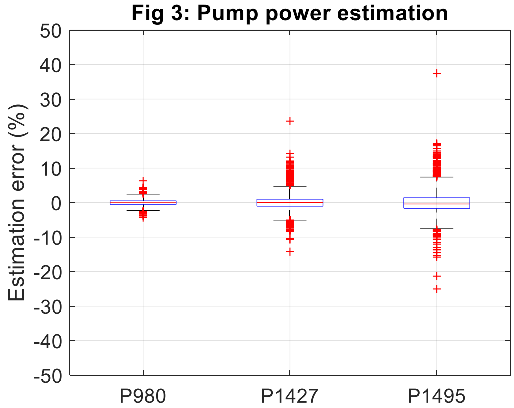
In determining the amplifier pump powers with respect to the output power and spectral tilt, a 10-nodes 7-layer "deep" NN, as depicted in Fig. 2, was trained. The input vector x contains two values: x_1 the output power (dB) and x_2 the tilt (dB). The green nodes represent the "hidden" layers of the network, and the red nodes form the "output" layer. At each hidden network layer the inputs are transformed by: $z = W^T x + b$, where W^T is the transposed weight matrix, b the bias vector. The output to the next layer is activated by a hyperbolic tangent function σ(z). The final outer layer is activated by a linear function to obtain the pump powers estimates vector p = [P_{980nm}, $P_{1427nm}^{(1)}$, $P_{1427nm}^{(2)}$, $P_{1495nm}^{(1)}$, $P_{1495nm}^{(2)}$].

The Levenberg-Marquardt optimization algorithm is used to train the network. After training, feed-forward propagation through the network predicts the pumps that satisfy arbitrary amplifier output power and tilt conditions. The 826 measurement data is split randomly between training, validation and testing by 90%, 5% and 5% respectively.

The neural network, once trained, was then used to give estimates of the pump powers such that the target power and tilt values were achieved. To qualify the method, we looked at the errors between the estimated values and the measured values. Figure 3 shows the percentage error distribution: the blue boxes corresponds to 50% of errors, the black lines delimits 99.3% of the errors and the red markers are the outliers. An estimation error of less than 7.4% is obtained for 99.3% of all tested data. The overall average root-mean-squared (RMS) error is 6.9 mW, where for each pump n from data set m we defined:

$$RMSE = \frac{1}{4130} \sum_{m=1}^{826} \sum_{n=1}^{5} (\hat{p}_{n,m} - p_{n,m})^2$$

Fig 3: Pump power estimation



The two extreme errors at around 24 % and 38% for the 1427 nm and 1495 nm Raman pumps are owing to the NN not perfectly matching on two data sets. These errors might well be improved with additional training data.

To evaluate the model further, the network was tested for a target of 22 dBm output power and -2dB/91nm spectral tilt, comparing the NN performance with that of an engineer. These results are summarized in Table 1. The first row labelled "Human" are the settings that we have found through manual iterative optimization. The NN estimated the pump powers within 11.2 mW of the expected "Best fit" measured values; the RMS error was 8.02 mW. The engineer's configuration, on the other hand, gave a maximum error of 29.7 mW and RMS error of 14.1 mW. The neural network thus providing a better solution.

Table 1: Pump values settings (all in mW) for 22dBm output power and -2dB spectral tilt.

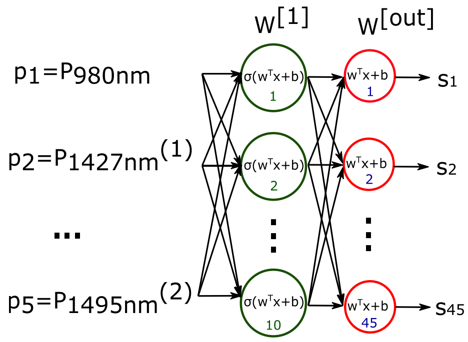
	P_{980}	P_{1427}	P_{1427}	P_{1495}	$P1_{495}$
Best fit	529.7	225.5	226.7	235.7	237.1
Human	500	230	230	230	230
NN	519.1	223.5	224.2	246.8	245.7

In terms of optimization time, the NN solution can additionally offer a clear advantage. While it could take a field engineer somewhere between an hour and a day to fully configure the pumps on a system during deployment, the NN gives instant results after it has been trained. The only caveat is the need of gathering training data which can be a time consuming process. However, these measurements could be automated and performed during the cable splicing and amplifier testing phase of deployment.

4. SPECTRAL ESTIMATION

By reversing the problem, a 10-node single layer NN was used to learn the power spectral density (PSD) response of the HRE, for a given set of input pump powers. The same Levenberg-Marquardt optimization algorithm was used for training, validation and testing. In this setup, the pump powers were the inputs into the NN and the spectrum measured across 45 wavelengths was the output. The 826 measurement data is split

Fig 4: Single layer neural network to estimate spectrum from pump powers.



randomly between training, validation and testing by 70%, 15% and 15% respectively.

Figure 5 shows that there is a close match between the predicted and measured spectra, for the pump settings that would give 22dBm output power and -2dB spectral tilt (“Best fit” settings in Table 1). In estimating the PSD 99.3% of errors are less than 0.27 dB, as Figure 6 shows. The maximum recorded error was 0.33 dB an improvement from previous results [1]. However, the average RMS error across all estimated spectral power points was only 0.044 dB.

NN-based spectral estimation would be useful in performing the analysis and configurations of individual amplifiers in an optical system link. However, it is expected that the output spectrum to change not only with the pump powers but also with the input spectrum. A more complete NN model could thus require the inclusion of the input spectrum to the training data, as well.

Fig. 5: Spectrum of HRE

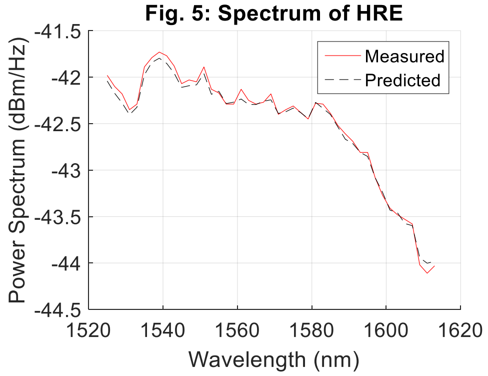
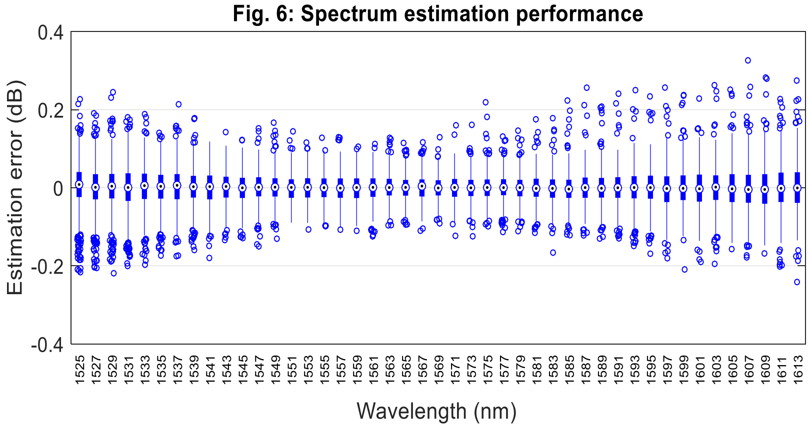


Fig. 6: Spectrum estimation performance



5. CONCLUSIONS

As the design of optical amplifiers has become more complex and the adjustments of the pumps have become more difficult, with the introduction of AI techniques such as those presented herein, it becomes possible to find solutions for the adjustments of the pumps, making operations with minimal human effort feasible.

In this paper, we proposed and demonstrated the practical application of neural networks to amplifiers that have already been designed, but require continuing configuration during and after deployment. Setting up the amplifiers to give a desired output power and spectral gain across the transmission bandwidth, is a challenging and time-consuming task for a field engineer. We showed that the neural networks outperform a human in setting up the pump values to an optimum solution. Since training can be done in tens of milliseconds (or less on a fast GPU), the main time consuming stage of the method is recording data for training. The best time to do this is during deployment when performing amplifier characterization.

While these results assumed a fixed input spectrum, this is unlikely to be the case in practice, especially in a chain of amplifiers. Therefore the input spectrum might additionally be used as an input to train the neural network, which makes the scope of future work.

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