Machine Learning-based Raman Tilt Prediction in a ROADM Transmission System

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Abstract *We develop a machine learning-based model to predict the Raman tilt induced in a multi-wavelength signal propagating through a 50km optical fiber deployed in the COSMOS testbed. The neural network model achieves a mean prediction error of 0.02–0.13 dB for randomly loaded channels.*

Introduction

In recent years, there has been much interest in the use of data-driven control and management methods in optical transmission systems. Physical phenomena that affect signal performance and system operation depend on the cumulative influence of the numerous components within the system. Component characteristics often vary not only due to different internal architectures and materials, but also due to time-dependent effects such as mechanical stress and temperature. Conventionally, these factors are accounted for through lab measurements and margin engineering to allow for component characteristic variations and uncertainty. With the use of disaggregated systems, such methods become problematic and unscalable as a single vendor does not control and test the end-to-end system and its variations. Low margin engineering has also received interest as a means to reduce the cost of engineering systems with large margins[1]. Increased data collection and data-driven methods, potentially leveraging machine learning (ML) techniques, which are designed to use such data are important to make progress in these low margin and/or disaggregated systems.

This paper examines the potential for the use of deep learning to model the stimulated Raman scattering (SRS) effect in a wavelength division multiplexed (WDM) optical transmission system. A deep neural network (DNN) is developed to obtain the tilt due to the SRS effect. The DNN model is trained and tested for randomly loaded WDM transmission. Its error performance is compared with that of existing analytical models.

Data-driven System Models

Data-driven methods have explored the use of both lab-based and field-based data collection. One approach is to collect datasets on components in the lab and then build models that can be efficiently implemented on the aggregate system in the field, e.g., using inference on a DNN trained on the component. Often these methods include the use of transfer learning so that numerous components can be rapidly characterized in the lab and/or retrained in the field. This approach has been used for neural network models of optical amplifiers to predict end to end signal power dynamics[2]. Another approach is to use in-field tools and measurements to collect data and develop or re-train models based on this live or real time data. Such methods have been studied using end-to-end characterization and component-wise characterization[3]. In each of these cases, a key question is to what extent physics-based models should be used or data-based models in which the system is treated like a “black box”. The physics of optical transmission is well understood and accurate models are routinely used to control and manage optical systems. Physics-based models can themselves be augmented with data-driven methods to incorporate more accurate or real-time data for better predictions.

SRS is an example of a well-understood physical effect in optical transmission systems in which optical power from short wavelength signals is transferred to longer wavelength signals through the fibre Raman interaction, resulting in a tilted spectrum at the fibre output. This tilt depends on the total power of the aggregate signals, the distribution of that power across the spectrum (i.e., the wavelength locations of the signals)[4], and is modified by the wavelength dependent (linear) fibre loss. Previous studies have shown that the tilt can be accurately predicted for a set of uniformly distributed WDM channels using a simple analytical formula based on a few basic as-

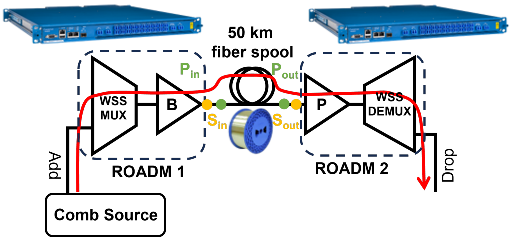

Fig. 1: Measurement setup for fibre-induced Raman tilt. ROADM: Reconfigurable optical add-drop multiplexer; WSS: Wavelength selective switch; B: Booster, P: Pre-amplifier.

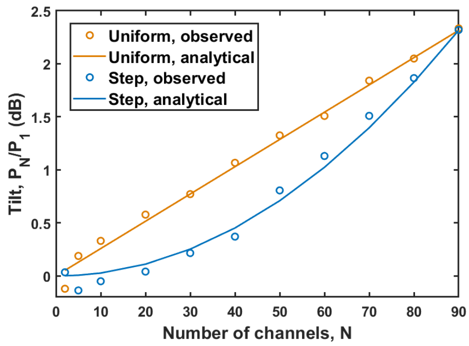

Fig. 2: Observed and analytical values of Raman tilt in case of uniform and step loading.

sumptions[4]–[7]. The wavelength dependent Raman gain coefficient is assumed to be a triangular (ramp) function with respect to wavelength and the fibre is assumed to be uniform along its length. With a few simple measurements, the Raman gain coefficient and wavelength-dependent loss can be roughly measured for a given fibre span. However, a transmission span might have a highly variable loss (due to splices and other defects) along its length and the distribution of WDM channels, in general, is not uniform and channel powers vary due to wavelength-dependent power dynamics or engineering rules for different modulation format signals. This can lead to significant errors in the analytical model predictions.

ML-based models provide an alternative, however, their potential for accurately predicting SRS in WDM transmission systems has not yet been studied. A first step in this direction is to explore the use of ML models for the case of variable channel configurations and to compare such methods with the established analytical models. In this work, the SRS effect is systematically studied in a 50 km standard single-mode fibre (SSMF) span that carries WDM signals with varying numbers and wavelength configurations.

Experimental Setup and Results

We conduct experiments and collected fiber measurements using the open-access optical-wireless PAWR COSMOS testbed deployed in Manhattan, New York City[8],[9]. The testbed includes eight Lumentum ROADM-20 graybox units which can be interconnected using various lengths of fiber spools, and dark fibre connections between Columbia University, 32 Avenue of the Americas (32 AoA), and City College of New York.

Fig. 1 depicts the experimental setup in the COSMOS testbed using two ROADM units and one fiber spool. A comb source is used to generate 90 channels spaced at 50 GHz to emulate a WDM spectrum in the C-band from $\lambda_1 = 1,529.16$ nm (196.05 THz) to $\lambda_{90} = 1,564.68$ nm (191.60 THz). The output of the comb source is connected to an add port of the ROADM MUX WSS, which selects different channels and flattens the channel powers at the booster output (line-out) such that the average power per channel is P_0 with a maximum deviation of 0.2 dB from the mean. The WDM signal then traverses a 50 km fibre spool and is received at the pre-amplifier input (line-in) of the other ROADM unit, and it is dropped after a DEMUX WSS.

We perform a calibration test with a per channel launch power $P_0 = -20$ dBm into the fibre, where the difference between the spectra at the output (S_{out}) and input (S_{in}) of the fiber, gives the wavelength-dependent linear loss of the fiber. For all other cases, we fix $P_0 = +3.5$ dBm to maximize the Raman effect. We also conduct another calibration test where all the 90 channels are loaded in the input spectrum (S_{in}). The output spectrum (S_{out}) in this test is used to calculate the normalised Raman gain coefficient. To study the Raman tilt, we consider a varying number of channels loaded at the input of the fiber, $N \in \{2, 5, 10, 20, 30, \ldots, 80, 90\}$.

We first consider two types of channel loading configurations: (i) N channels uniformly loaded across the spectrum with the same total bandwidth (**Uniform**); (ii) N channels loaded in steps with a fixed spacing of 50 GHz from one side of the spectrum, λ_1 (**Step**). The tilt in the output spectrum due to SRS is measured as the ratio of the output power of the N^{th} channel to that of the first channel, i.e., P_N/P_1. The variations in the SRS tilts observed for the two loading cases are depicted in Fig. 2. We show that our experimental observations agree with the calculated values obtained using the analytical model for SRS tilt presented by Bigo et al.[4]:

$$(P_N/P_1)_{\text{dB}} = 2.17(g'/A_e)P_0N(N-1)L_e\Delta f, \quad (1)$$

where Δf is the channel spacing, g' is the normalised Raman gain coefficient, and A_e/L_e is the effective area/length of the fibre.

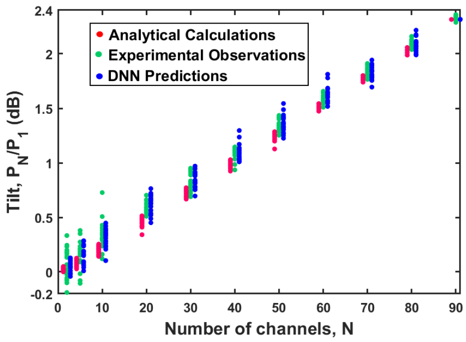

Fig. 3: Observed, analytical and predicted values of Raman tilt in case of random loading.

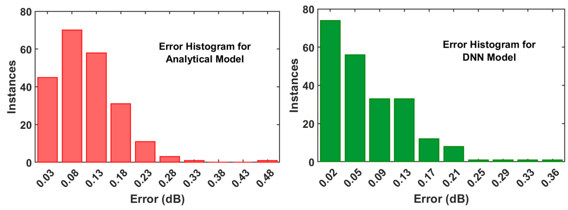

Fig. 4: Histograms of the errors in Raman tilt values obtained using the analytical model (left) and DNN model (right).

Note that the results for $N = 90$ overlap because when all channels are loaded, the input spectrum S_{in} is the same for both loading cases but for $N < 90$, the tilt is higher with uniform loading due to larger channel spacing. However, in general the channel loading is random. To analyze such scenarios, we consider randomly loaded channels across the spectrum with the same fixed 50 GHz spacing. For each value of N, we consider 100 random channel configurations, and the measured and calculated values of the SRS tilt are shown in Fig. 3. Evidently, there are considerable variations in the observed values that are not reflected in the analytical results obtained using Eqn. (1). To address this issue, we develop a DNN model to predict the SRS tilt in arbitrarily loaded channel conditions in a ROADM transmission system.

A DNN-based Raman Tilt Prediction Model

The collected random SRS tilt dataset for 50 km fibre is divided into the training and test sets with a split ratio of 80%–20%. The training set also includes uniform and step channel loading configurations (refer Fig. 2). We create a DNN model of the fiber spool for predicting its SRS tilt using the following architecture. The DNN consists of ten fully connected layers: one input layer, eight hidden layers with 128/128/64/64/32/32/16/16 neurons, and one output layer. The input features include the total input power P_{in} and the total output power P_{out} of the fiber, input power spectrum S_{in} to the fiber, and a 90-dimensional binary vector indicating the channel loading configuration. Then, the output layer predicts the fibre's SRS tilt as a function of the wavelength channels. The DNN model is trained using the mean square error (MSE) and Adam optimizer, with the exponential linear unit (ELU) activation function at all layers and a learning rate of 5e-5 over 800 epochs.

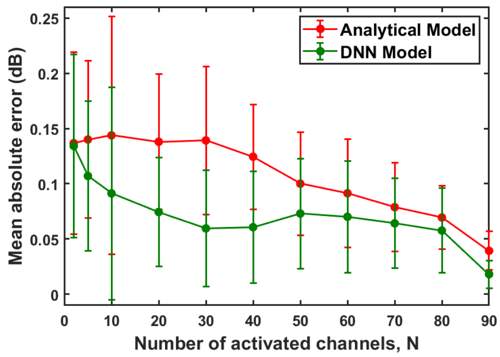

Fig. 5: MAE with the standard deviation of the Raman tilt values obtained by the analytical and DNN models.

We compare the experimental measurements with the DNN predictions and analytical calculations (Eqn. (1)) using the absolute errors. Fig. 4 shows the histograms for the errors incurred using the analytical and DNN models, where we observe that the error for the DNN model has a larger spread over lower values when compared to the analytical counterpart. We also calculate the mean absolute error (MAE) in the two cases, Fig. 5, where the bars represent the standard deviations. It can be seen that the DNN model achieves significantly lower MAEs in predicting the SRS tilt when compared to the analytical model. For example, with $N = 40$ randomly loaded channels, the MAE obtained by the DNN and analytical models are 0.06 dB and 0.13 dB, respectively.

Conclusions

The SRS tilt induced in WDM signal propagation through SSMF is measured using built-in ROADM OCMs. Analytical and DNN-based models are used to predict the SRS tilt in randomly loaded channel configurations, where the latter incurs lower prediction errors. In future work, we will analyse the effects of different system parameters on the SRS tilt and prediction errors of the DNN model.

Acknowledgements

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References

[1] Y. Pointurier, "Design of low-margin optical networks", *Journal of Optical Communications and Networking*, vol. 9, no. 1, A9–A17, Jan. 2017. DOI: 10.1364/JOCN.9.0000A9.

[2] Z. Wang, D. Kilper, and T. Chen, "Transfer learning-based ROADM EDFA wavelength dependent gain prediction using minimized data collection", in *Optical Fiber Communication Conference (OFC) 2023*, Th2A.1.

[3] N. Morette, I. F. de Jauregui Ruiz, H. Hafermann, and Y. Pointurier, "On the robustness of a ML-based method for QoT tool parameter refinement in partially loaded networks", in *Optical Fiber Communication Conference (OFC) 2022*. DOI: 10.1364/OFC.2022.M3F.1.

[4] S. Bigo, S. Gauchard, A. Bertaina, and J.-P. Hamaide, "Experimental investigation of stimulated Raman scattering limitation on WDM transmission over various types of fiber infrastructures", *IEEE Photonics Technology Letters*, vol. 11, pp. 671–673, 1999. DOI: 10.1109/68.766780.

[5] K. Torii, T. Tanaka, M. Yuki, H. Nakamoto, T. Naito, and I. Yokota, "Impact of stimulated Raman scattering between WDM signals over an ultra-wide bandwidth", in *Optical Fiber Communications Conference (OFC) 2003*, pp. 332–334. DOI: 10.1109/68.766780.

[6] F. Vanholsbeeck, S. Coen, P. Emplit, M. Haelterman, and T. Sylvestre, "Raman-induced power tilt in arbitrarily large wavelength-division-multiplexed systems", *IEEE Photonics Technology Letters*, vol. 17, no. 1, pp. 88–90, 2004. DOI: 10.1109/LPT.2004.837726.

[7] M. Zirngibl, "Analytical model of Raman gain effects in massive wavelength division multiplexed transmission systems", *Electronics Letters*, vol. 34, no. 8, pp. 789–790, 1998. DOI: 10.1049/el:19980555.

[8] D. Raychaudhuri, I. Seskar, G. Zussman, *et al.*, "Challenge: COSMOS: A city-scale programmable testbed for experimentation with advanced wireless", in *Mobile Computing and Networking (MobiCom) 2020*. DOI: 10.1145/3372224.3380891.

[9] T. Chen, J. Yu, A. Minakhmetov, *et al.*, "A software-defined programmable testbed for beyond-5G optical-wireless experimentation at city-scale", *IEEE Network*, vol. 36, no. 2, 2022.