Digital Twin of Unrepeatered Line Based on Raman and Remote Optically Pumped Amplifier Machine Learning Models

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Abstract: We demonstrate an accurate digital representation of an unrepeatered line based on separate measurement-based machine learning models of Remote Optically Pumped Amplifier and Raman amplification. We assess the accuracy via OSNR measurements in the line. © 2023 Nokia

1. Introduction

The current era of optical communications offers a vast variety of tools, network components, and transponder types so one could design an optical network with the required capacity and durability at the right cost. In that context, one should be aware of generic one-for-all approaches, as they may result in network designs that are challenging from the cost/bit perspective. A good example would be the design of low-range (several hundred kilometers) submarine optical lines. If one decides to adopt a usual for long-range submarine lines approach with the placement of electrically powered erbium-doped fiber amplifiers (EDFA), then the cost/bit becomes high. Yet less expensive solutions exist that do not require high-cost optical cables with electric cabling to power an EDFA. Such solutions would be *unrepeatered* optical lines that deliver high capacity without recourse to active in-line elements [1].

Unrepeatered lines mainly rely on the amplification of optical signal via Raman amplification [2]. In the case of cables with very high span-loss, in-line amplification may be required but done by means of Remote Optically Pumped Amplifiers (ROPA) [3]. ROPA represents an EDFA that is pumped by an optical pump delivered from a remote location, potentially through the same fiber as used for communication channels. In that context, it is important to correctly design and optimize such unrepeated lines to deliver the best performance possible. In this paper, we demonstrate a digital representation/twin of an unrepeated line shown in Fig. 1 based on separate Machine Learning (ML) models of ROPA and Counter-Raman amplification operating jointly. Such digital twin represented in Fig. 2 can be used for monitoring purposes and for the further design of unrepeatered lines.

In literature one can find proposals for ML [4-6] and measurement-based [7] models for Gain representation of EDFA and these models are suitable for ROPA modelling as well. However, we propose our own ML model of ROPA/EDFA, that is similarly precise as [4,6] but simpler in terms of computation complexity due to simplicity of neural network structure; and more flexible in channel placement, as not tied to a fixed channel grid. In comparison to [7], our ROPA ML model is less precise, but offers differentiability of Gain function needed for optimization purposes. Also, we demonstrate ROPA ML model for Noise Figure (NF), that is on-par precise as [8], but with simpler ML model and without fixed channel grid. ML models for Raman amplification have been reported [9-10], however, as we consider only 2nd order Raman pump, we can use simpler ML model delivering $Gain_{on/off}$ and NF (not considered in [9-10]). If consider joint operation of several ML models, one finds few examples of such tests: we note [11] that use ML EDFA models for a suite of EDFAs, and [12] that considers them in a network.

We demonstrate joint operation of ML models of ROPA and Counter-Raman amplification for the first time, to the best of our knowledge. We verify experimentally such ML models interworking by comparing with OSNRs in the unrepeatered line and achieving up to 0.13 dB of Mean Absolute Error (MAE).

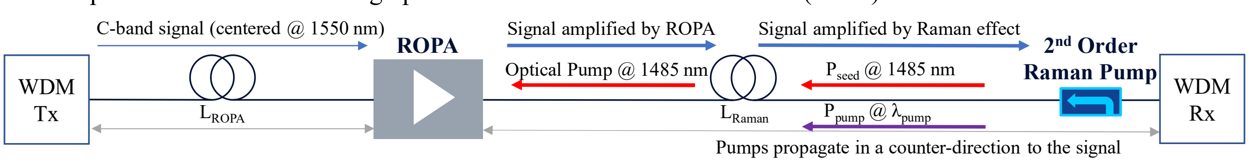

Fig. 1 Unrepeatered line consisting of Counter-Raman amplification, that is also pumping ROPA.

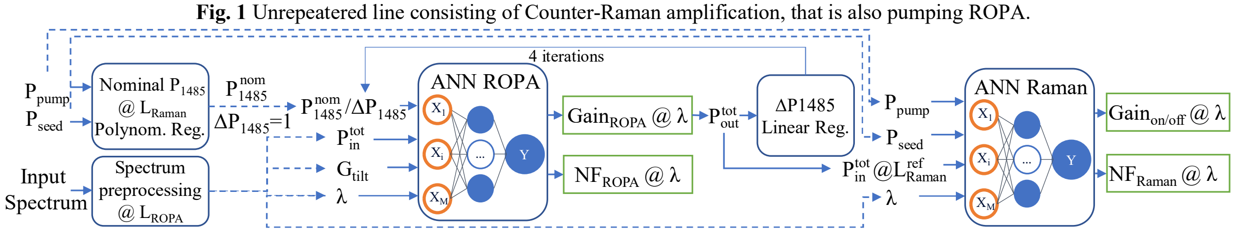

Fig. 2 Representation of digital twin of unrepeated line based on separate ML models of ROPA and Raman Amplification.

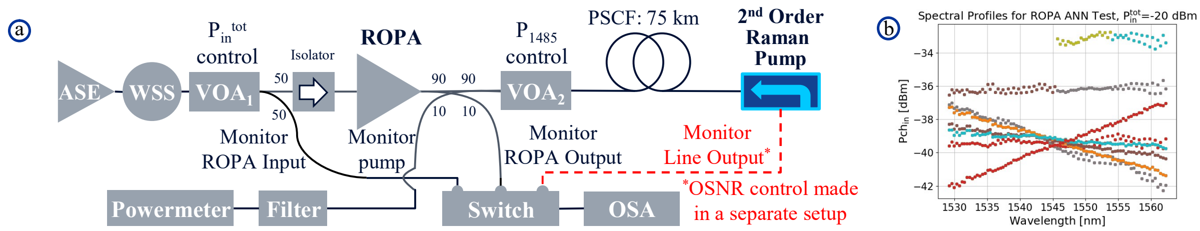

Fig. 3: a) Setup used for ROPA characterization and digital twin verification of unrepeatered line; b) spectral loadings for ANN_{ROPA} test.

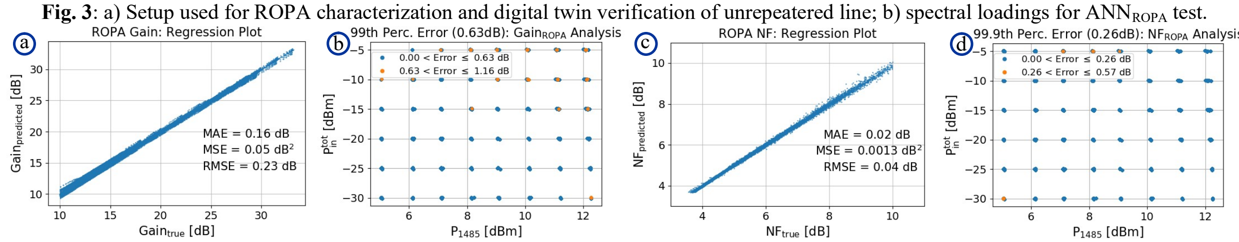

Fig. 4: ML models of ROPA Gain and NF: a) regression plot for Gain, b) Gain error analysis, c) regression plot for NF, d) NF error analysis.

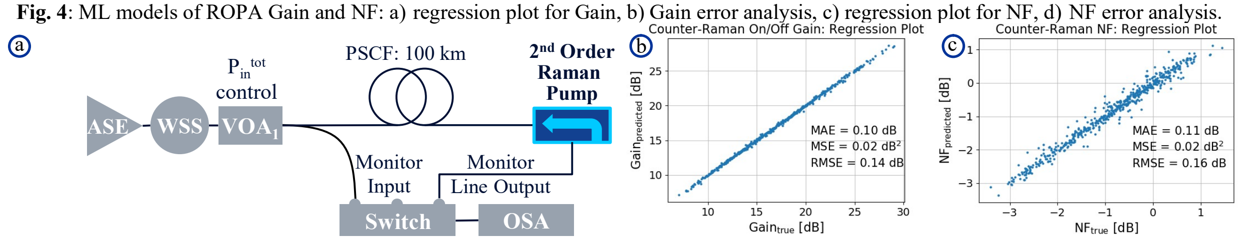

Fig.5: ML model for Counter-Raman amplification: a) Raman Pump characterization setup, b) $Gain_{on/off}$ regression plot, c) NF regression plot.

2. Digital Twin of Unrepeatered Line: ML models or ROPA and Counter-Raman Amplification.

We consider an unrepeatered line presented on Fig. 1 that consists of a ROPA and a Raman pump. We study 2nd order Raman pump, i.e., of two wavelengths: *pump* at λ_{pump} sent with P_{pump} power and *seed* at 1485 nm sent with P_{seed} power. First, Raman pump amplifies optical signal via Counter-Raman amplification. Second, the power at 1485 nm, denoted as P_{1485} at ROPA location, optically pumps the doped fiber embedded in the ROPA, resulting in complimentary to Counter-Raman amplification. We note that output power after ROPA may influence Counter-Raman amplification and affect P_{1485}, making the interaction between the Raman pump and ROPA interdependent. Below we describe ROPA and Raman amplification ML models and join them to form a digital twin (Fig. 2).

We consider an experimental setup shown in Fig. 3a) which we used to characterize the ROPA and create its ML model. Raman pump is set with P_{seed}=100 mW, P_{pump}=1600 mW and connected via 75 km Pure Silica Core Fiber (PSCF) fiber to the ROPA. Up to 84 optical channels at 50GHz in C-band are emulated by Amplified Spontaneous Emission (ASE) source, carved at 50 GHz by Wavelength Selective Switch (WSS) and sent through the ROPA. To characterize ROPA and build representable ML model we consider special spectral profiles, like those in [5]. Two Variable Optical Attenuators (VOA) are used to control the setup configurations. We adjust the total power of channels P_{in}^{tot} passed through ROPA via VOA_1, and the pump P_{1485} passed to ROPA through VOA_2. While changing channels spectral profile, P_{in}^{tot} and P_{1485} we measure per-channel values of Gain and NF.

We base ML ROPA models for Gain and NF on 3-layer artificial neural network (ANN) [13] of 30, 20, 10 neurons/layer with *tanh(x)* activation function. We use 4 standardly scaled inputs for ANN_{ROPA}: P_{in}^{tot}, P_{1485}, λ and G_{tilt}. P_{in}^{tot} (mW) represents total power of channels in C-band, P_{1485} (mW) represents optical pump, λ (nm) means the central wavelength of a channel, and G_{tilt} is a parameter that we call $Generalized_{tilt}$ linked to geometrical form of spectral profile, G_{tilt} is proportional to spectral Tilt. To train ANN we use 15 spectral profiles with nominal $P_{in}^{tot} \in [-30, -5]$ dBm at 5 dB step and $P_{1485} \in [5, 12]$ dBm at 1 dB step. To validate ANN we use 5 spectral profiles with -20, -15, -10, 10, 15 dB of Tilt with $P_{in}^{tot} \in [-30, -5]$ dBm at 5 dB step and $P_{1485} \in [5, 12]$ dBm at 1 dB step. For ANN test we employ 5 tilted spectral profiles with Tilts of -5, -4, -2, -1, 5 dB and 5 flat profiles: full-band, 1st and 2nd halfs, 3rd and 4th quarters of C-band in λ (Fig.3b). We train $ANN_{ROPA\text{-}G}$ for Gain and $ANN_{ROPA\text{-}NF}$ for NF via LBFGS [13] Mean Squared Error (MSE) optimization, we stop training when validation dataset achieves minimum MSE.

We present performance of two ANN_{ROPA} for Gain and NF in Fig. 4 on test data, we show realistic cases only with Gain > 10 dB and NF < 10 dB limits respectively. On Fig. 4a) we make a Gain regression plot, i.e., correspondence of $Gain_{predicted}$ to $Gain_{true}$, we observe "y=x" type straight line meaning ANN predicts Gain correctly: we achieve MSE=0.05 dB^2, MAE=0.16 dB and Root MSE (RMSE)=0.23 dB. On Fig. 4b) we attempt to analyze errors on Gain prediction: in 2D we plot "P_{in}^{tot} & P_{1485}" configurations and color with orange points where the error on prediction gets bigger than 99th percentile (0.63 dB). We attest that the majority of "P_{in}^{tot} & P_{1485}" configurations

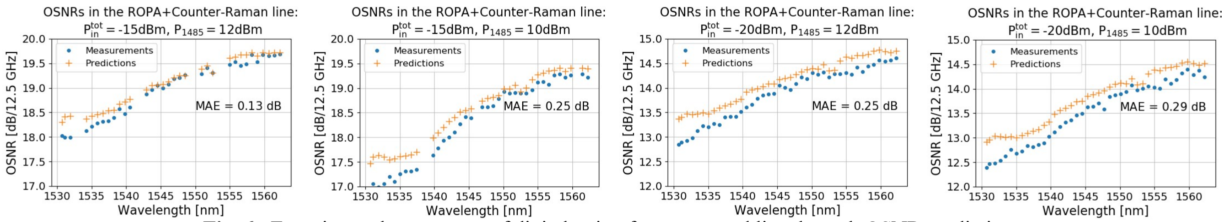

Fig. 6 : Experimental assessment of digital twin of unrepeatered line through OSNR predictions.

don't exceed 0.63 dB limits, and those that do exceed, they are located outside of normal ROPA functioning. On Fig. 4c) we make a NF regression plot and attest correct predictive performance with MSE=0.0013 dB^2, MAE=0.02 and RMSE=0.04 dB that is better than [8]. We analyze NF prediction error on Fig. 4d), due to high ANN precision we apply 99.9th percentile threshold: we see that almost all "P_{in}^{tot} & P_{1485}" configurations don't exceed 0.26 dB error.

We characterize Counter-Raman amplification using setup shown on Fig. 5a), it is similar to the setup in Fig. 3a) but without ROPA and with 100 km of fiber. We transmit 80 channels of 50GHz width in C-band and measure $Gain_{on/off}$ and NF for 20 channels. A measurements dataset is based on next configurations: $P_{pump}\in[800, 2000]$ mW at 200 mW step, P_{seed}=[40, 60, 90, 120, 150, 190, 230] mW and $P_{in}^{tot}\in[-10, 10]$ dBm at 5 dB step. We use an ANN_{Raman} of 1-layer with 60 neurons and *tanh(x)* activation function. ANN_{Raman} takes as input P_{in}^{tot}, P_{pump}, P_{seed} and λ delivering $Gain_{on/off}$ and NF. We make 70-15-15% data split for train, validation, and test datasets. We train ANN_{Raman} on train dataset using ANN_{ROPA} optimization technique; validation dataset aids to stop training via early stopping method. On Fig. 5b-c) we report ANN_{Raman} precision on test dataset. For $Gain_{on/off}$ prediction we achieve MSE=0.02 dB^2, MAE=0.1 dB and RMSE=0.14 dB. For NF prediction we get MSE=0.02 dB^2, MAE=0.11 dB and RMSE=0.16 dB.

On Fig. 2 we demonstrate the internal functioning logic of digital twin of unrepeatered line based on ANN_{ROPA} and ANN_{Raman}. As we stated before, the functioning of ROPA and Counter-Raman amplification is interdependent: we discovered that this interdependence can be expressed as $P_{1485}=P_{1485\_nom}/\Delta P_{1485}$ (mW), where $\Delta P_{1485}=f(P_{out}, G_{tilt\_out})$ and $P_{1485\_nom}=g(P_{pump}, P_{seed})$. P_{1485_nom} is the nominal pump power injected in ROPA in the absence of signal, P_{out} is the total power of channels in C-band after ROPA and G_{tilt_out} is the G_{tilt} parameter of spectral profile after ROPA. One can approximate $P_{1485\_nom}=g(P_{pump}, P_{seed})$ using polynomial regression and $\Delta P_{1485}=f(P_{out}, G_{tilt\_out})\approx f^*(P_{out})$ using linear regression. We iteratively evaluate ΔP_{1485} using temporary outputs of ANN_{ROPA} so to calculate P_{out} and G_{tilt_out} and update ΔP_{1485}. We start with ΔP_{1485}=1 and make 4 iterations to converge to P_{1485} to be used in ANN_{ROPA}.

3. Assessment of Digital Twin of Unrepeatered Line

We control the unrepeatered line digital twin via OSNR measurements at the end of the line in a setup like in Fig. 3. It's a separate setup that undergone necessary recalibration. We send to ROPA 80×50GHz flat spectrum C-band channels of P_{in}^{tot}=[-15,-20] dBm but we use only up to 40 channels for OSNR measurements. We set P_{seed}=100 mW, P_{pump}=1600 mW and via VOA_2 vary P_{1485} sent to ROPA. We consider P_{1485}=[12, 10, 9, 8, 7] dBm. In Fig. 6 we show 4 cases: P_{1485}=[12, 10] dBm with P_{in}^{tot}=[-15, -20] dBm. In such cases, MAE varies between 0.13 and 0.29 dB attesting good precision. If consider P_{1485}=[9, 8, 7] dBm: for P_{in}^{tot}=-20 dBm we get MAE=[0.34, 0.46, 0.65] dB; for P_{in}^{tot}=-15 dBm we get MAE=[0.34, 0.51, 0.79] dB respectively. We see that MAE can reach 0.79 dB, however, ROPA-involving applications usually occupy only 1540-1564 nm region, so if we limit analysis to that range, we get better MAE=[0.30, 0.39, 0.54] dB for P_{in}^{tot}=-20 dBm; and MAE=[0.25, 0.39, 0.62] dB for P_{in}^{tot}=-15 dBm.

4. Conclusions

We demonstrated a digital twin of an unrepeatered line based on separate ML models of ROPA and Raman amplification for the first time, to our knowledge. The ROPA/EDFA ML model is a novel model for Gain and NF, offering more flexibility with less complexity. The Raman amplification ML model shows the possibility to use low-complexity ANN for simultaneous $Gain_{on/off}$ and NF prediction. We showed how to resolve interdependence of these models in an unrepeatered line and how to build its digital twin. We verified its good precision in OSNR prediction.

5. References

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