PINN for Power Evolution Prediction and Raman Gain Spectrum Identification in C+L-Band Transmission System

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Abstract: We experimentally demonstrate multi-channel power evolution prediction and identification of frequency-dependent fiber characteristics using PINN. A maximum absolute error of 0.3 dB for power prediction is observed on C+L-band transmission under different loadings. © 2023 The Author(s)

1. Introduction

Multi-band transmission promises to further improve the capacity of communications with existing optical fiber infrastructures, and the upgradation from the conventional C-band to the L-band is being extensively investigated and deployed [1]. In wideband scenarios, the signal on different channels is unequally distorted due to frequency-dependent characteristics of optical fibers and wideband nonlinear effects, such as stimulated Raman scattering (SRS). The SRS transfers power from high-frequency to low-frequency channels upon signal propagation along fiber and its efficiency, described by the Raman gain spectrum, is maximum for channels with a frequency separation of approximately 10 THz. To have a high-fidelity power evolution model for fiber channel in C+L-band systems, it is required to obtain the accurate frequency-dependent fiber characteristics, of which the effect of the attenuation coefficient α_f dominates over others, and the fiber Raman gain spectrum g_R. In practice, α_f can be derived using low level launch power on all the transmitted channels, where the effect of SRS is negligible. To obtain g_R, the classical technique is using ultrashort pluses [2], which is complex and not feasible on deployed links. Recently, it was proposed to identify the g_R and other fiber characteristics using DSP based techniques [3]. However, such techniques require processing of long sequences of signals with heavy computation. Optical channel monitor (OCM) is widely used in practical optical networks and embedded in many link components, such as erbium-doped fiber amplifier (EDFA). This makes the query of power spectrum of WDM channels a regular thing, and thus it is much more beneficial to use only measured power spectrum to identify these key characteristics.

Physics-informed neural networks (PINNs) has been proposed to solve the differential equations directly by using them as constraints in the loss function, and the neural networks (NN) are parameterized as the solution function in the training process [4]. Combining the prior knowledge of physics and the learning ability of NNs, PINNs have shown its power in many areas, such as solving the Navier-Stokes equations in fluid [5], and the NLSE in optical fiber [6]. PINN alleviates the burden of collecting labeled data and makes NNs more explainable.

In this paper, we propose a PINN based multi-channel power evolution model accounting for the SRS, which can also be used to simultaneously identify the α_f and g_R of fiber using only several pairs of OCM measured input and output power spectra. We showcase the performance of the proposed model for power evolution prediction and fiber characteristics identification on C+L-band transmission experiments. After fiber characteristics identification, the accuracy of power evolution prediction can be improved with a maximum absolute error below 0.3 dB for C+L-band transmission experiments under full and partial loadings.

2. Principle of wideband power evolution and PINN

In wideband transmission with bandwidth larger than the conventional C-band, the SRS cannot be neglected. The power evolution accounting for the SRS is described by the following ordinary differential equations (ODEs):

$$\frac{\partial P_n(z)}{\partial z} + 2\alpha_f P_n(z) + \sum_{m=1}^{N} \frac{g_R\left(f_m - f_n\right)}{A_{\text{eff}}} P_n(z) P_m(z) = 0 \tag{1}$$

where N denotes the number of transmitted channels, α_f the frequency-dependent attenuation and g_R the fiber Raman gain spectrum. A_{eff} is the fiber effective area and f_n denotes the frequency of the n^{th} channel. This equation can be solved numerically using split-step methods, which will consume much computational resource under small step size and long transmission conditions. Furthermore, such numerical methods cannot be directly used for parameter identification.

The PINN can be used to solve Eq. (1) in an unsupervised way as illustrated in Fig. 1. Standard multi-layer feedforward neural network is selected to establish the map from transmission distance z to transmitted powers of N

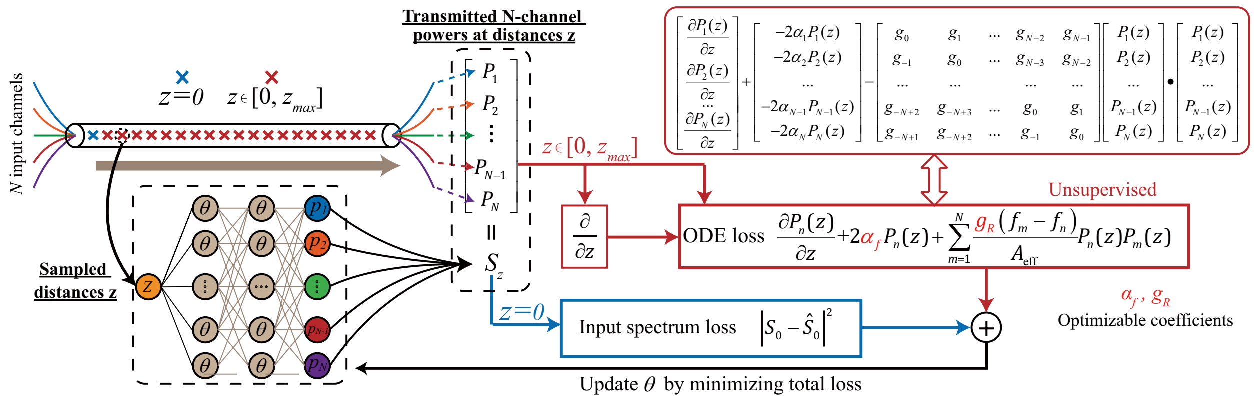

Fig. 1 Schematic of the PINN for multi-channel power evolution accounting for SRS. The ODE loss function is a matrix of the power evolution ODEs. θ denote the parameters of NNs to be optimized. $\hat{s}_0$ denotes the input power spectrum of fiber.

channels at the distance z. First, the input power spectrum $\hat{s}_0$ of fiber is required as initial conditions of Eq. (1) and is learned by the PINN when z=0. The difference from data-driven NNs lies in the loss function, where the ODE residual of Eq. (1) is embedded to constrain the outputs of NNs in an unsupervised way. The ODE loss function is in fact a matrix with dimensions the same as the number of transmission channels and is minimized at sampled distances from z=0 to z_{max}. It should be emphasized that the first-order differential terms in the ODE loss function, which are the derivates of NN outputs with respect to the input, can be calculated efficiently using the automatic differentiation built in deep learning libraries. The NN parameters θ is updated by minimizing the total loss via gradient-based optimizers. After the training, transmitted powers for these N transmitted channels from z=0 to z_{max} can be obtained.

In the training of PINN, we introduce the spatio-temporal causal structure which has been shown to be effective in wave propagation problems [7]. Regard optical signal propagation in fiber, this principle of causality dictates that changes in input spectrum is reflected in its corresponding states at later transmission distances. We apply a re-formulation of the training objective of the PINN (details can be found in [7]), which ensures the loss of all the sampled transmission distances close to z=0 is minimized properly before optimizing on later sampled distances.

Benefitting from the fact that all the results are continuously learned at all transmission distance z and the constraints of ODEs, the frequency-dependent coefficients of α_f and g_R in Eq. (1) can be optimized during the training with the knowledge of transmitted spectrum at the input and output of fiber. First, several pairs of initial conditions (input spectrum) and final conditions (transmitted spectrum) are collected for an uninvestigated fiber and used to train the PINN at z=0 and z_{max}, respectively. Then the ODE loss is minimized by updating θ of NNs at z range from 0 to z_{max}. Note that at the beginning of training the coefficients of α_f and g_R in the ODEs are manually assumed, which deviate from their actual values. Therefore, the ODE loss cannot be minimized properly as long as the corresponding initial and final conditions are rigorously learned. After every 100 epochs for minimizing the ODE loss by updating θ, the assumed α_f and g_R are updating towards their actual values to minimize the ODE loss.

In conclusion, when the input power spectrum and ODEs are known, the transmitted power spectrum at (z, z_{max}] can be learned; when some pairs of input and output spectra are known, the coefficients of ODEs can be identified.

3. Experimental setup for C+L-band transmission and results

The experimental setup is depicted in Fig. 2, and it consists of eight spans of 75-km standard single mode fiber (SSMF) except for the second span with a length of 85 km. The transmission bandwidth occupies the L-band, from 186.1 THz to 190.8 THz, and the C-band, from 191.4 THz to 196.1 THz. A total of 96 channels with 100 GHz channel bandwidth are configured. Two commercial frequency-tunable transponders of 400-Gb/s DP-16QAM

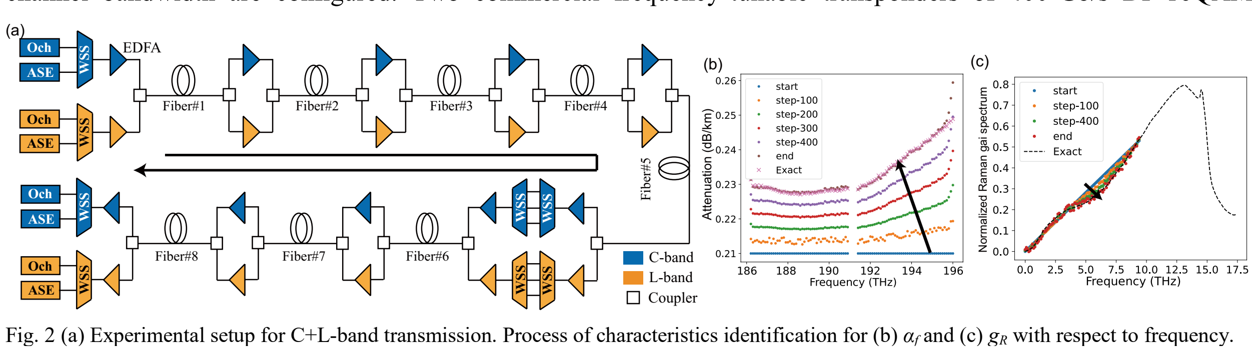

Fig. 2 (a) Experimental setup for C+L-band transmission. Process of characteristics identification for (b) α_f and (c) g_R with respect to frequency.

signals are deployed to scan the transmission performance for each channel, and all other 94 channels are loaded with filtered ASE noise to emulate effects of interfering channels in a cost-effective way. The WSS after the fifth span is not activated and all channels experience equal attenuation through it. Signals in the C-band and L-band are decoupled at the end of each span, amplified by separate C- and L-band EDFA, and then combined again before launching into the next span. Due to the device limitation, the gain at low frequencies of L-band EDFA is not working adequately, and some aged fibers are used. The connector losses for each coupler and frequency-dependent gain profiles of each EDFA are measured in advance.

To identify the accurate α_f and g_R of each fiber, several pairs of input and output power spectrum were measured under different regular input power distributions. Here we take fiber#7 as an example, three pairs of input and output spectra were used to identify the α_f and g_R simultaneously. The actual α_f of fiber#7 was measured using low input power in advance, and it can be observed in Fig. 2(b) that the initial assumed α_f, which is constant at 0.21 dB/km, is optimized towards the actual α_f, and coincides well with the actual one in the end. For the optimization of g_R, the initial assumed linear function with respect to frequency is optimized to nonlinear functions as shown in Fig. 2(c), where the measured default fiber Raman gain spectrum [2] is plotted as black dash line. To visualize the importance of the accuracy of these coefficients, we conduct PINN predictions for four different scenarios and compared them with experimental measurements. In the first one, the assumed incorrect initial α_f and g_R are used; in the second one, the identified g_R and the assumed initial α_f are used; in the third one, the identified α_f and the assumed initial g_R are used; in the last one, both the identified are used. It can be observed in scenario 1 and 2, where the incorrect initial α_f is used, the error is large. In scenario 3, the maximum absolute error is about 1 dB due to the incorrect g_R. It is only in scenario 4, where both the identified α_f and g_R is used, the maximum absolute error is below 0.1 dB, which proves the accuracy of each coefficient is necessary to obtain a high-fidelity power evolution model.

After parameter identification for each of the fibers in the link, we conduct PINN predictions for the entire link and compare the results with the experimental OCM measured ones under the same conditions. As shown in Fig. 3, PINN predictions with identified α_f and g_R for each fiber coincide well that of experiments for various input power distribution and even with partial loaded scenarios, and the maximum power deviation is below 0.3 dB. This proves that the PINN predictions with identified coefficients are accurate enough under various loading conditions. The training of PINN for identification and prediction is less than 5 minutes on a Tesla T4 GPU. It should be noted that other factors affecting the prediction accuracy, such as fluctuating laser power, changing connector losses, and load-dependent EDFA gain profiles, is reduced to the minimum by our best, but is not none.

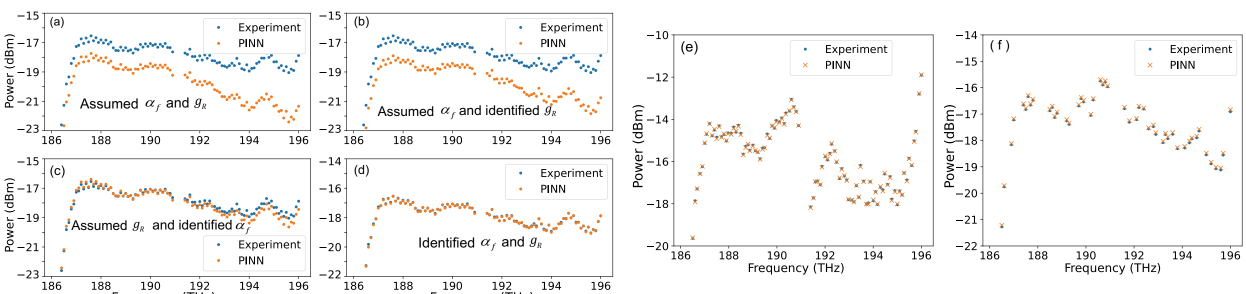

Fig. 3 Four different scenarios (a) assumed α_f and g_R, (b) assumed α_f and identified g_R, (a) identified α_f and assumed g_R (a) identified α_f and g_R. Comparison between PINN predictions and experimental measured ones with different loadings (e) full loading, (f) partial loading.

4. Conclusion

We have proposed and experimentally demonstrated wideband multi-channel power evolution prediction and fiber characteristics identification using the PINN, which is fully driven by the ODEs and requires no labeled data. Below 0.3 dB maximum absolute error for power prediction is observed in C+L-band experiments under full and partial loadings. This physics-informed approach is expected to further improve the accuracy and efficiency of wideband multi-channel power evolution modeling and facilitate the identification of fiber parameters from a new perspective.

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