Fast and Accurate DNN-Based Approach in Maximizing Ultra-Wideband Fiber-Optic Systems Throughput

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Abstract: We present a fast and accurate physical layer model assisted by a neural network to maximize the throughput for ultra-wideband systems. The proposed approach significantly saves computation time and keeps the same precision.

1. Introduction

The incoming growth in the demand for high data rate is pressing to solve. Expanding optical bandwidth in wavelength-division multiplexing (WDM) systems is one of the solutions. The throughput is mainly limited by the available signal-to-noise ratio (SNR), which is constrained due to a combination of the amplified spontaneous emission (ASE) noise and the Kerr nonlinearity associated with optical power. In ultra-wideband (UWB) transmission, inelastic inter-channel stimulated Raman scattering (ISRS) effect is non-negligible which causes power transfer from shorter-wavelength channels to longer-wavelength channels. Thus, managing launch power is substantial to improve the overall performance.

The Gaussian noise (GN) model derived from perturbation analysis in [1] can provide an efficient analytic approximation of fiber nonlinear interference (NLI) to enable fast launch power optimization algorithms. The closed-form approximation of NLI with the presence of the ISRS is proposed in [2]. The impact of the per wavelength launch power optimization on the UWB point-to-point transmission performance has been recently investigated in [3]. In [4], a simulated annealing (SA) algorithm is proposed to search for the optimal power slopes and offsets of $(C{+}L{+}S)-$ band. Machine learning (ML) is recently exploited to be a scalable and efficient approach in optical fiber communication systems [5]. ML-based approaches are proposed to predict the characteristics of fiber-optic systems including the stimulated Raman scattering effect in [6,7]. A launch power controlled, digital twin assisted flat SNR optimization approach is proposed in [8] for $(C{+}L)-$ band.

With this work we investigate the way to reduce the computational complexity by using a surrogate model to replace the time-consuming optical network physical layer calculations. We propose a novel more effective deep neural network (DNN) based approach in conjunction with particle swarm optimization (PSO) for launch power optimization in point-to-point optical transmission to increase the overall throughput. The performance is evaluated by bench-marking with the numerical approach. The proposed approach is comparable with the numerical approach without performance degradation and outperforms it in terms of computational complexity.

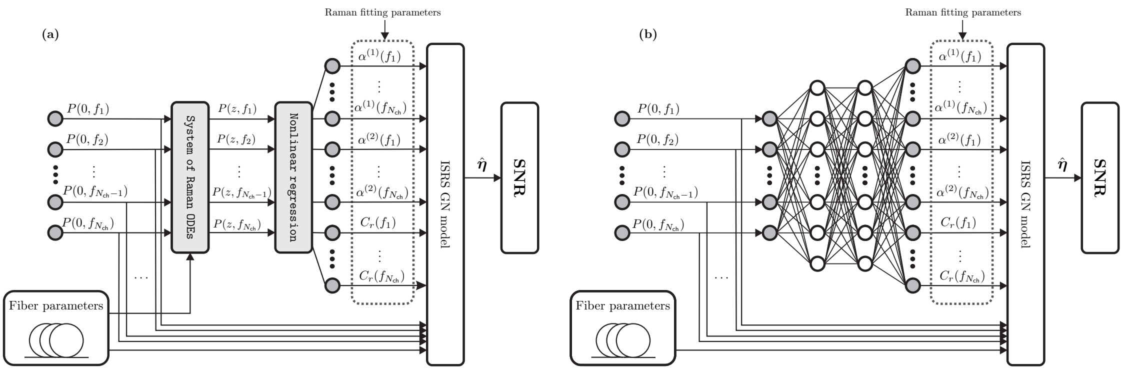

Fig. 1: Schematics for SNR prediction using ISRS GN model with f-dependent parameters $C_r(f_k)$, $\alpha^{(1)}(f_k)$ and $\alpha^{(2)}(f_k)$ in Eq. (2) by (a) numerically solving Raman ODEs followed a nonlinear regression and (b) a fully-connected DNN.

2. Physical layer

It is customary to introduce the effective signal-to-noise ratio (SNR) vector $\mathbf{SNR} \triangleq \mathrm{SNR}_k \, \forall k = \{1,\ldots,N_{\mathrm{ch}}\}$ under the locally-white noise assumption can be decomposed as follows:

$$\mathrm{SNR}_k \approx P(f_k)\left[N_{\mathrm{s}}\sigma^2_{\mathrm{ASE}}(f_k) + N_{\mathrm{s}}^{\varepsilon(f_k)+1}\,\eta^{(\mathrm{SPM})}_{kk}P^3(f_k) + N_{\mathrm{s}}\,P(f_k)\sum_{l\neq k}\eta^{(\mathrm{XPM})}_{kl}P^2(f_l)\right]^{-1}, \tag{1}$$

where the matrix $\hat{\eta} \triangleq \eta_{kl} \, \forall \{k,l\} = \{1,\ldots,N_{\mathrm{ch}}\}$ evaluates the amount of noise due to NLI and indicated in Fig. 1, N_{ch} is the total number of WDM channels, $\varepsilon(f_k)$ denotes the NLI noise coherence factor, and N_{s} is the number of fiber spans in a link. The approximate closed-form expressions for SPM $\eta^{(\mathrm{SPM})}$, XPM $\eta^{(\mathrm{XPM})}$ NLI noise coefficients spectral profiles, as well as for the coherence factor ε in Eq. (1) can be readily found in [2]. The impact of FWM is neglected owing to the presence of a large amount of chromatic dispersion in a link. The spectrum of ASE noise power per fiber span can be expressed as $\sigma^2_{\mathrm{ASE}}(f_k) = 10^{\mathrm{NF}(f_k)/10}\,h(f_0+f_k)\,[G(L_{\mathrm{s}},f_k)-1]\,(1+r)R_S$, where NF stands for the noise factor, h is the Planck constant, f_0 is the carrier signal frequency, α is the $f-$dependent fiber loss coefficient, L_{s} is the fiber span length, and r is the roll-off factor. The amplifier gain to entirely compensate the power spectral tilt due to fiber loss and inter-channel SRS effect can be approximated as follows [2]

$$\begin{aligned} G(z,f_k) &\triangleq P(0,f_k)\,P^{-1}(z,f_k) \\ &\approx \left[\left(1-\frac{P_{\mathrm{tot}}f_kC_r(f_k)}{\alpha^{(2)}(f_k)}\right)\exp\left(-\alpha^{(1)}(f_k)z\right)+\frac{P_{\mathrm{tot}}f_kC_r(f_k)}{\alpha^{(2)}(f_k)}\exp\left[-\left(\alpha^{(1)}(f_k)+\alpha^{(2)}(f_k)\right)z\right]\right]^{-1} \end{aligned} \tag{2}$$

where $P_{\mathrm{tot}} = \sum_{k=1}^{N_{\mathrm{ch}}} P(f_k)$ defines the total optical launch power with N_{ch} being the total number of WDM channels, $C_r(f_k)$, $\alpha^{(1)}(f_k)$ and $\alpha^{(2)}(f_k)$ are the $f-$dependent nonlinear regression fitting parameters, which account for the actual the Raman gain spectrum. The $f-$dependent signal distance evaluation $P(z,f_k)$ in Eq. (2) obeys the Raman coupled ordinary differential equations (ODEs) [9]. In this paper, we propose to use a DNN to significantly reduce the computation time at the physical layer as an efficient alternative method of numerically solving coupled Raman ODEs via the Runge-Kutta (RK) method in conjunction with the nonlinear regression (NLR) to find the f-dependent parameters $C_r(f_k)$, $\alpha^{(1)}(f_k)$ and $\alpha^{(2)}(f_k)$ for ISRS GN model, as shown in Fig. 1, which is conventionally a fairly time-consuming process.

3. Results

In the simulation, we consider a 10×100 km optical long-haul transmission system within $(C+L+S)-$band. The overall modulated bandwidth is 20 THz from 1464.8 nm to 1623.3 nm centered at 1540 nm. including practically relevant a 10 nm S/C guard band and a 5 nm C/L guard band. It has total $N_{\mathrm{ch}} = 181$ WDM channels and each channel is set to be modulated at a symbol rate of 96 GBd with a 100 GHz spacing in between. We consider a flat noise figure spectrum for each band, which are 7 dB for $S-$band, 4 dB for $C-$band, and 5 dB for $L-$band.

The overall data contains 10^4 launch power profiles from -6 to 6 dBm generated by smoothed random Gaussian walk as input and the corresponding fitted parameters as labels. We used 70% data in the training process and the rest in the validation process. We optimize the hyper-parameters of the DNN by Optuna [10]. The optimized DNN has an architecture of an input layer with 181 neurons corresponding to the launch power profile for each channel, 3 hidden layers with 350 neurons following a *sigmoid* activation function, and an output layer with 543 neurons to predict the 3 parameters of each channel. The *Adam* optimizer with a learning rate of $1.08 \cdot 10^{-3}$ is used. The training process contains 1000 epochs and a batch size of 140. We consider the mean absolute error (MAE) between the predicted and labeled fitted parameters as the loss. The training and validation curve of the DNN is shown in the inset figure in Fig. 2a. Then, we compare the mean SNR achieved by the launch power profiles from the validation dataset in one span calculated by using labels, predictions, and triangle approximation in Fig. 2a and the corresponding MAE of the SNR with respect to the value calculated from labels in Fig. 2b. The maximum MAE of SNR along all channels is always less than 0.004 dB which provides an accurate prediction for proposed DNN. If we apply the triangle-approximation beyond 15 THz, the mean SNR will have a maximum 0.56 dB and an average 0.42 dB deviation in $L-$band and an average 0.19 dB across the modulated bandwidth.

We compare the following three cases in launch power optimization using PSO in terms of performance and time complexity: (1) using the semi-closed-form ISRS GN model at the physical layer with numerically solving the Raman ODEs via Runge-Kutta method and nonlinear regression which is referred to RK+NLR in the following content; (2) using the semi-closed-form ISRS GN model with DNN; (3) using the fully closed-form ISRS GN model under triangle-approximation. For the PSO, we set the swarm size of $10 \cdot N_{\mathrm{ch}}$ and the maximum iteration of 10^4 with a function tolerance of 10^{-8}. The optimized launch power profiles are shown in Fig. 2c. The throughput values achieved by the optimized launch power profiles are 163.02, 163.02, and 162.05 Tbps for cases 1, 2, and

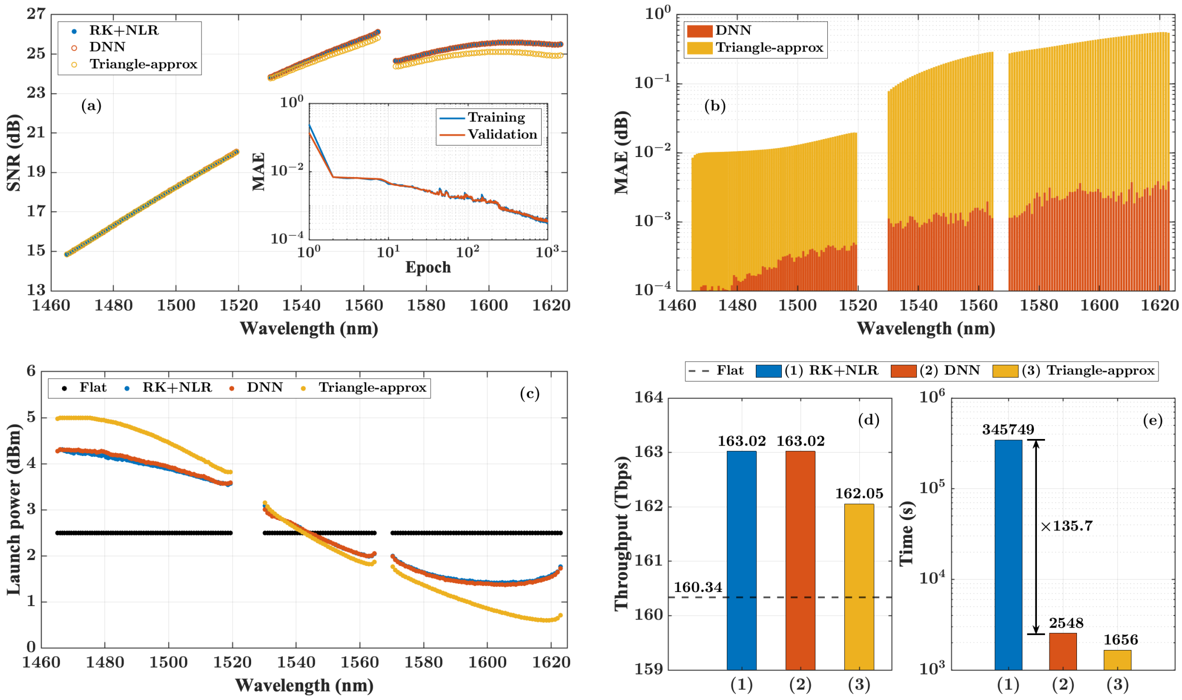

Fig. 2: Performance evaluation of RK+NLR, proposed DNN, and triangle-approximation on: (a) mean SNR per channel of the validation dataset; (b) MAE of the mean SNR with respect to the labeled dataset; (c) flat and optimized launch power profiles by PSO and (d) their corresponding achieved throughput and (e) computational time.

3 respectively as shown in Fig. 2d. The computational time taken by each approach is shown in Fig. 2e. Every approach runs on a machine with a 3.0 GHZ 8-core CPU under the same conditions. Using DNN in the physical layer can reduce the time in seconds by more than 2 orders of magnitudes without performance degradation.

4. Conclusions

We presented an effective launch power assignment approach for UWB systems for combining effective learning capabilities from surrogate machine learning models with realistic optical transmission physical layer modeling. The proposed approach has achieved a near-optimal launch power profile exhibiting the potential of DNN to learn from the power-dependent and f-dependent physical layer. Moreover, the proposed approach has significantly reduced the computational time by a magnitude of 2 compared to conventional physical layer estimation using numerical methods while the accuracy is preserved within the range of $99.99\% - 100\%$.

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