Neural-network-based MDG and Optical SNR Estimation in SDM Transmission

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Abstract: We propose a neural network model for MDG and optical SNR estimation in SDM transmission. We show that the proposed neural-network-based solution estimates MDG and SNR with high accuracy and low complexity from features extracted after DSP.

1. Introduction

Space division multiplexing (SDM) is currently regarded as the only solution to cope with the exponential growth of data traffic in optical transmission networks [1, 2]. In coupled SDM transmission, mode coupling can be compensated by multiple-input multiple-output (MIMO) equalizers at the receiver. In contrast, mode dependent gain (MDG) generated in inline amplifiers cannot be compensated by digital signal processing (DSP). The random power variations of the guided modes induced by MDG turn the channel capacity into a random variable, reducing the average capacity and generating outages [3–5]. The combined effect of MDG and amplified spontaneous emission (ASE) noise generated in amplifiers poses fundamental performance limitations to high-capacity SDM systems deployed at long distances.

MDG estimation based on the transfer function of MIMO equalizers has been widely used in recent works [6, 7] to assess the link quality. However, we show in [8] that, as adaptive MIMO equalizers typically use the minimum mean square error (MMSE) criterion [9], the MDG estimation accuracy is affected by the signal to noise ratio (SNR), mainly for high levels of MDG and low SNRs [8]. Based on a known SNR, we also propose and validate a correction factor to partially compensate for the MDG estimation errors [10, 11]. However, measuring the SNR at the coherent receiver input may not be feasible in particular scenarios, limiting the scope of the proposed solution. Furthermore, although SNR estimation can be easily carried out in polarization-multiplexed optical systems from the signal after polarization demultiplexing, in mode-multiplexed systems this task is not straightforward, as the output signal-to-interference-plus-noise ratio (SINR) is MDG-dependent.

Currently, machine learning (ML) techniques are being considered for optical performance monitoring in both single-mode [12] and mode-multiplexed systems [13]. Nevertheless, to the best of our knowledge, the study of the joint MDG and SNR estimation in SDM systems based on ML has not been yet reported. In this paper, we propose a neural-network (NN) model to estimate MDG and SNR in coupled SDM transmission systems. The model is validated experimentally in a 3-mode transmission system with polarization multiplexing over a 32.5 m few-mode fiber (FMF) link.

2. Feature extraction for neural-network-based MDG and SNR estimation

The MDG of a link can be computed from the eigenvalues, $\lambda_i^2$, of $HH^H$, where $H$ is the channel transfer matrix, and $(.)^H$ is the Hermitian transpose operator [3, 4]. The standard deviation of the overall MDG, $\sigma_{\text{mdg}} = \text{std}(\log(\lambda_i^2))$, is widely used to quantify the accumulated MDG at the end of the link. For an unknown $H$, $\sigma_{\text{mdg}}$ is conventionally computed from the eigenvalues, $\lambda_i^2_{\text{MMSE}}$, of $W_{\text{MMSE}}^{-1}(W_{\text{MMSE}}^{-1})^H$, where the inverse transfer matrix of the MIMO MMSE equalizer, $W_{\text{MMSE}}^{-1}$, is used as an estimate of $H$. The transfer matrices $W_{\text{MMSE}}$ and $H$ are related by [14]

$$W_{\text{MMSE}} = \left( \frac{I}{\text{SNR}} + H^H H \right)^{-1} H^H ,$$

where the SNR is computed at the coherent receiver input. From (1), the estimated $\sigma_{\text{mdg}}$ depends clearly on SNR [8].

1We denote SNR as the ratio of total signal optical power and total optical noise power in the channel bandwidth, considering all supported spatial and polarization modes.
Conventionally, in single-mode coherent optical systems, the optical SNR can be easily estimated after DSP from the electrical SNR. In SDM systems, however, the combined effect of MDG and ASE noise complicates this task. In coherent optical systems that use MMSE equalizers, the so-called electrical SNR is actually the signal-to-noise-plus-interference ratio, SINR. The SINR in data stream \( i \) can be calculated as [14]

\[
\text{SINR}_i = \frac{1}{\left( I + \text{SNR}' H^H H \right)^{-1}} - 1,
\]

where \([ , ]_{i,i}\) indicates the \( i \)-th element in the main diagonal. To account for the implementation penalty present in practical receivers, and mitigate imprecisions at high SNRs, the SNR' in (2) is defined as \( 1/(\text{SNR}^{-1} + \text{SNR}_{\text{imp}}^{-1}) \), where \( \text{SNR}_{\text{imp}} \) is computed in a practical receiver in the absence of MDG and ASE noise.

In this paper, we propose a NN model to estimate \( \sigma_{\text{mdg}} \) and SNR from features extracted after DSP. The block diagram of the proposed solution is depicted in Fig. 1. The training dataset is generated according to Inset (a). Using the multisection model presented in [3], \( 6 \times 6 \) matrices \( H \) are generated to simulate a 3-mode transmission with polarization multiplexing over a 2,500 km FMF link with 0.2 dB < \( \sigma_{\text{mdg}} \) < 6.2 dB. For each \( H \), the SNR is swept from 5 dB to 22 dB to generate 6 \( \lambda_{\text{MMSE}}^{2} \) values and 6 SINR\(_{i}\) values through equations (1) and (2). The labelled set of \( \lambda_{\text{MMSE}}^{2} \) and SINR\(_{i}\) values is fed into Inset (c) as input features for NN training. The NN, implemented in \( \text{keras/tensorflow} \), receives 6 \( \lambda_{\text{MMSE}}^{2} \) values and 6 SINR\(_{i}\) values, and provides an estimate of \( \sigma_{\text{mdg}} \) or SNR. A hidden layer with 6 neurons, and an output layer with 1 neuron, learn the relation between the input features and the output based on the training samples generated analytically. The NN is trained using Adam optimizer [15] during 500 epochs and a batch size of 5 samples.

The NN model is validated using experimental data captured from the 3-mode transmission setup depicted in Inset (b). Three linearly polarized modes, \( \text{LP}_{01} \), \( \text{LP}_{11a} \) and \( \text{LP}_{11b} \), each one with two polarizations, are transmitted over 32.5 m of FMF. Variable optical attenuators (VOAs) are used to control the \( \sigma_{\text{mdg}} \) of the link. The optical SNR is varied at the coherent receiver input by a noise loading stage. The SNR is computed as \( \text{SNR} = \text{OSNR} \times T_s / 12.5\text{GHz} \) where \( T_s = 40\text{ps} \) is the symbol time, and the OSNR is the traditional optical signal to noise ratio computed by an optical spectrum analyzer at the 12.5 GHz bandwidth. Additional details of the experimental setup can be found in [11]. After DSP, the eigenvalues, \( \lambda_{\text{MMSE}}^{2} \), are computed at each frequency of \( W_{\text{MMSE}} \) and averaged across the signal band. The SINR\(_{i}\) is computed from each one of the 6 equalized data streams using a single-coefficient least-squares (LS) estimator [16].

### 3. Neural-network-based \( \sigma_{\text{mdg}} \) and SNR estimation results

The NN is fed with 12,300 analytical samples. 90% of the samples are used for model training and the remainder for model testing. After training, model validation is performed from 936 experimental samples. Figs. 2a,d show the estimated versus actual values for \( \sigma_{\text{mdg}} \) and SNR, respectively. The estimated values satisfactorily track the actual values, resulting in a mean squared error (MSE) of 0.019 for \( \sigma_{\text{mdg}} \) and 0.462 for SNR.

Figs. 2b,e show the estimation error of the conventional method in dB, defined as the difference between the actual value and the estimated value. The conventional method for SNR estimation applies an LS estimator to the data flows after DSP, and for \( \sigma_{\text{mdg}} \) estimation uses the eigenvalues of the equalizer transfer function. The imple-
SNR [dB]

Figure 2. (a) NN-estimated $\sigma_{\text{mdg}}$ as a function of the actual $\sigma_{\text{mdg}}$. (b) $\sigma_{\text{mdg}}$ estimation error in dB generated by the conventional method as a function of the actual $\sigma_{\text{mdg}}$ and SNR. (c) $\sigma_{\text{mdg}}$ estimation error in dB generated by the NN as a function of the actual $\sigma_{\text{mdg}}$ and SNR. (d) NN-estimated SNR as a function of the actual SNR. (e) SNR estimation error in dB generated by the conventional method as a function of the actual $\sigma_{\text{mdg}}$ and SNR. (f) SNR estimation error in dB generated by the NN as a function of the actual $\sigma_{\text{mdg}}$ and SNR.

4. Conclusion

We propose a NN model to estimate MDG and SNR in SDM systems with coupled channels, based on features extracted after DSP. The proposed model is evaluated in an experimental 3-mode transmission setup with polarization multiplexing. The results show that the NN-based solution estimates both MDG and SNR with high accuracy and low complexity, largely exceeding the performance provided by conventional methods.

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