Optical Performance Monitoring Using Artificial Neural Networks Trained With Eye-Diagram Parameters

Jeffrey A. Jargon, *Senior Member, IEEE*, Xiaoxia Wu, and Alan E. Willner, *Fellow, IEEE*

***Abstract*—We developed artificial neural network models to simultaneously identify three separate impairments that can degrade optical channels, namely optical signal-to-noise ratio, chromatic dispersion, and polarization-mode dispersion. The neural networks were trained with parameters derived from eye diagrams to create models that can predict levels of concurrent impairments. This method provides a means of monitoring optical performance with diagnostic capabilities.**

***Index Terms*—Artificial neural network (ANN), chromatic dispersion (CD), eye diagram, optical performance monitoring (OPM), optical signal-to-noise ratio (OSNR), polarization-mode dispersion (PMD).**

I. Introduction

As optical fiber transmission systems become more transparent and reconfigurable, optical performance monitoring (OPM) is essential for ensuring high quality-of-service [1]. Crucial impairments in optical networks include optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD).

Recently, several techniques have been proposed for monitoring optical performance [2]–[6]. Three of these methods [2], [3], [5] utilize amplitude histograms or power distributions to estimate bit-error rate (BER); one [4] employs delay-tap plots to distinguish among impairments; and one [6] uses pattern classification techniques for the same purpose. None of them, however, have been shown to concurrently quantify three different impairments. Of these five monitoring techniques, three [2]–[4] exploit asynchronous sampling, and two [5], [6] require synchronous sampling. In asynchronous sampling, the signal of interest is sampled without regard to an instant relative to a decision time, and thus clock recovery is not necessary. Synchronous sampling, however, necessitates a standard receiver with clock recovery, but can easily be used to generate eye diagrams from which numerous performance parameters may be derived.

Here, we present a method for simultaneously estimating the impairments of OSNR, CD, and PMD using artificial neural networks (ANNs) trained with parameters derived from eye diagrams. These eye diagrams can be generated either from a synchronized sampler, or by a technique that regenerates such diagrams from asynchronous samples [7]. In Sections II and III, we present a brief overview of ANNs and provide examples of our proposed method with simulated data by use of two different bit-rates and modulation schemes, namely 10-Gb/s nonreturn-to-zero, ON–OFF keying (NRZ-OOK) and 40-Gb/s return-to-zero, differential phase-shift keying (RZ-DPSK).

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J. A. Jargon is with the National Institute of Standards and Technology, Boulder, CO 80305 USA (e-mail: jargon@boulder.nist.gov).

X. Wu and A. E. Willner are with the University of Southern California, Los Angeles, CA 90089 USA (e-mail: xiaoxia@usc.edu, willner@usc.edu).

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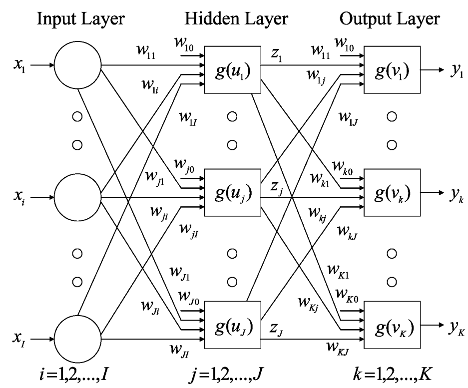

Fig. 1. ANN architecture.

II. ANNs

ANNs are neuroscience-inspired computational tools that are trained by use of input–output data to generate a desired mapping from an input stimulus to the targeted output [8], [9]. ANNs consist of multiple layers of processing elements called neurons. Each neuron is linked to other neurons in neighboring layers by varying coefficients that represent the strengths of these connections. ANNs learn relationships among sets of input–output data that are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and output vectors are computed, the ANN outputs are compared to the desired outputs and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors drop below prescribed values.

The ANN architecture used in this letter is a feedforward three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer, as shown in Fig. 1.

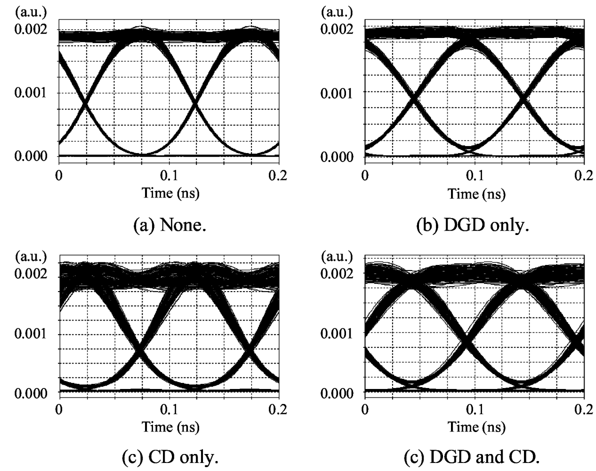

Fig. 2. Eye diagrams of the 10-Gb/s NRZ-OOK channel with various impairments ($\mathrm{OSNR} = 32$ dB). (a) None. (b) DGD only (40 ps). (c) CD only (800 ps/nm). (d) DGD (40 ps) and CD (800 ps/nm).

The hidden layer allows complex models of input–output relationships. The mapping of these relationships is given by $\mathbf{Y} = g[\mathbf{W}_2 \cdot g(\mathbf{W}_1 \cdot \mathbf{X})]$, where $\mathbf{X}$ is the input vector, $\mathbf{Y}$ is the output vector, and $\mathbf{W}_1$ and $\mathbf{W}_2$ are, respectively, the weight matrices between the input and hidden layers and between the hidden and output layers. The function $g(u)$ is a nonlinear sigmoidal activation function given by $g(u) = 1/[1 + \exp(-u)]$, where u is the input to a hidden neuron. According to [10], an MLP3 with one hidden sigmoidal layer is able to model almost any physical function accurately, provided that a sufficient number of hidden neurons are available.

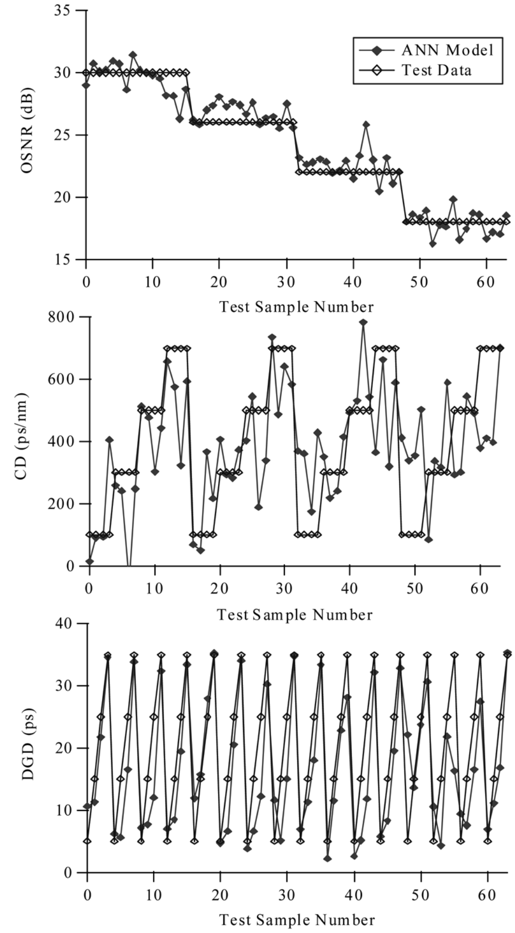

Fig. 3. Comparison of testing and ANN-modeled data for the 10-Gb/s NRZ-OOK channel.

III. Methodology

A. 10-Gb/s NRZ-OOK

Fig. 2 shows simulated eye diagrams for a 10-Gb/s NRZ-OOK signal at a few select combinations of CD and PMD for a given value of OSNR. Visually, it is obvious that these impairments produce distinct features. To quantify these attributes, we can calculate various eye-diagram parameters. For this first example, we chose four such parameters, including Q-factor, closure, root-mean-square (rms) jitter, and crossing amplitude. Q-factor is defined as the difference of the mean upper and lower levels divided by the sum of the upper and lower level standard deviations; closure is the ratio of the outer eye height to the inner eye height; crossing amplitude is the point on the vertical scale where the rising and falling edges intersect; and rms jitter is usually defined as the standard deviation of the time data calculated in a narrow window surrounding the crossing amplitude. These four inputs were chosen since they change significantly with varying impairment combinations.

To illustrate our method, we performed 125 simulations using the following impairment combinations: OSNR—16, 20, 24, 28, and 32 dB; CD—0, 200, 400, 600, and 800 ps/nm; and PMD with values of differential group delay (DGD) equal to 0, 10, 20, 30, and 40 ps. The simulated fiber channel included a laser with a center wavelength of 1550 nm and a full-width at half-maximum (FWHM) linewidth of 10 MHz; a 10 Gb/s logic source; a single-arm, Mach–Zehnder, optical modulator biased at the quadrature point with a $V\pi$ drive voltage; and a fourth-order Bessel–Thomson filter.

The ANN consisted of four inputs (Q-factor, closure, jitter, and crossing-amplitude), three outputs (OSNR, CD, and DGD), and 12 hidden neurons. The ANN was trained by use of a software package developed by Zhang *et al.* [11]. Although alternatives were explored, a conjugate-gradient technique was chosen since it offers a nice compromise in terms of memory requirements and implementation effort.

Once the model was trained, we validated its accuracy with a different set of testing data. We used 64 simulations with the following impairment combinations: OSNR—18, 22, 26, and 30 dB; CD—100, 300, 500, and 700 ps/nm; and DGD—5, 15, 25, and 35 ps. The software reported a correlation coefficient of 0.91 for the testing data. Fig. 3 compares the testing and ANN-modeled data for OSNR, CD, and DGD.

B. 40-Gb/s RZ-DPSK

Fig. 4 shows simulated eye diagrams for a 40-Gb/s RZ-DPSK signal at a few select combinations of CD and DGD for a given value of OSNR. Once again, it is obvious that these impairments

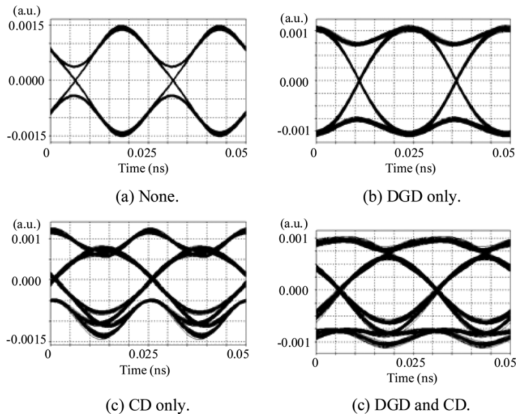

Fig. 4. Eye diagrams of the 40-Gb/s RZ-DPSK channel with various impairments ($\mathrm{OSNR} = 32$ dB). (a) None. (b) DGD only (10 ps). (c) CD only (60 ps/nm). (d) DGD (10 ps) and CD (60 ps/nm).

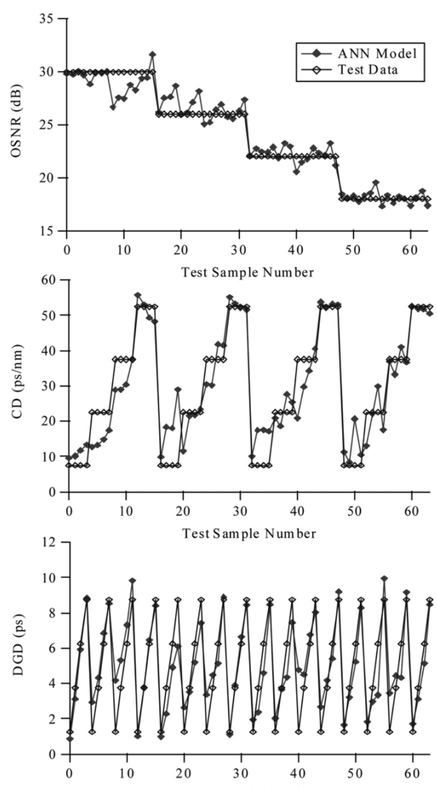

Fig. 5. Comparison of testing and ANN-modeled data for the 40-Gb/s RZ-DPSK channel.

produce distinct features. In this case, we also chose four parameters to train our ANN, namely Q-factor, closure, rms jitter, and the level of transition between adjacent zeroes (as opposed to crossing amplitude).

In this example, we performed 125 simulations with the following impairment combinations: OSNR—16, 20, 24, 28, and 32 dB; CD—0, 15, 30, 45, and 60 ps/nm; and DGD—0, 2.5, 5, 7.5, and 10 ps. The simulated fiber channel included a laser with a center wavelength of 1550 nm and a FWHM linewidth of 10 MHz; a 40 Gb/s logic source; a single-arm, Mach–Zehnder, optical modulator biased at the minimum point with a $2V\pi$ drive voltage; and a fourth-order Bessel–Thomson filter. Once again, the ANN consisted of four inputs, three outputs, and 12 hidden neurons, and was trained with a conjugate-gradient technique.

Once the model was trained, we validated its accuracy using a different set of testing data. We used 64 simulations with the following impairment combinations: OSNR—18, 22, 26, and 30 dB; CD—7.5, 22.5, 37.5, and 52.5 ps/nm; and DGD—1.25, 3.75, 6.25, and 8.75 ps. The software reported a correlation coefficient of 0.96 for the testing data. Fig. 5 compares the testing and ANN-modeled data.

IV. Conclusion

We have shown how ANN models, trained with parameters derived from eye diagrams, can be used to simultaneously identify levels of OSNR, CD, and DGD for 10-Gb/s NRZ-OOK and 40-Gb/s RZ-DPSK signals. This method provides a powerful new technique for monitoring the performance of optical channels. It should be noted that the most severe impairments should be included when training ANNs since these models are generally only valid when interpolating. In the near future, we plan on developing new models with other modulation schemes and using measured data.

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