Off-Line Monitoring of OSNR/CD/PMD Degradation Effects Using Neural-Network-Based Training Sequences

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Abstract

A technique using artificial neural networks to simultaneously identify OSNR, CD, and PMD from eye-diagram parameters is demonstrated both via simulation and experimentally in 40 Gb/s OOK and DPSK systems. A correlation coefficient of 0.99 is obtained for the testing data of both systems.

Introduction

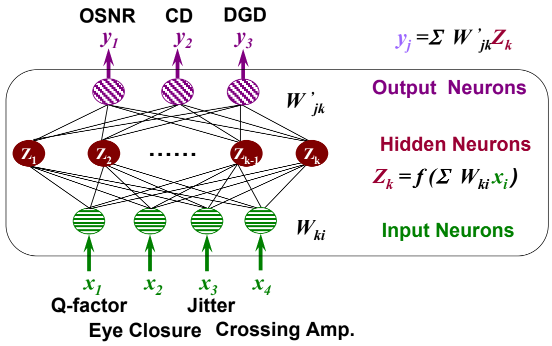
High-performance optical networks are susceptible to various degrading effects that can change over time. Knowledge of the data channel degradation can be used to diagnose the network, repair the damage, drive a compensator/equalizer, or reroute traffic around a non-optimal link [1]. Therefore, it is valuable to monitor the channels for optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD).

Optical performance monitoring has generally taken two different forms. The first type uses an optical technique to monitor a specific channel parameter that can be used to extract degradation information, such as using optical off-center bandpass filtering to monitor PMD [2]. The second type employs off-line digital signal processing of the received data signal, where various impairments will uniquely distort the data bits and eye diagram [3-7]. Using digital signal processing requires that the relationship is known between various non-ideal eye-diagram shapes and the underlying physical degradation effects [8].

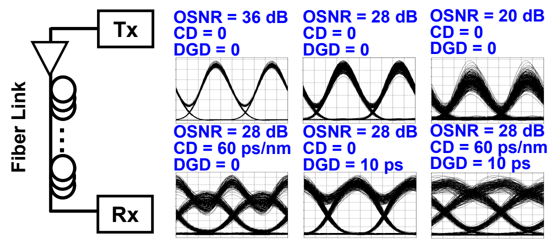
In this paper, we use a neural-network-based approach to "train" the receivers in an optical network as to the relationship between OSNR, CD, and first-order PMD (referred as differential group delay (DGD)) and the resultant shapes of the data channel's eye diagrams. The coefficients of the neural network algorithm are derived in several iteration steps before live traffic is sent into the network. We first verify this approach for 40-Gbit/s OOK and DPSK data via simulation. Then we demonstrate this technique by obtaining eye diagrams from the experiment and doing the training and testing afterwards. The experimental results match well with the simulation.

Concept and Simulations

Artificial neural networks (ANNs) are information processing systems that learn from observations and generalize by abstraction [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, as shown in Fig.1 (a). ANNs learn the 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 reach prescribed values. In our case, the outputs are OSNR, CD, and PMD, and the inputs are Q-factor, eye-closure, jitter, and crossing amplitude. After training, another set of data is used to test the ANN.



(a) The structure of an artificial neural network (ANN)



(b) The degradation effects

Fig.1 Concept of ANN and the impact of degradation effects.

The ANN architecture used in this work is a feed-forward, three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer. The hidden layer consists of 12 hidden neurons. We first verify the concept via simulation in 40 Gb/s RZ-OOK and RZ-DPSK systems. The conjugate gradient method is used for training. The training data are obtained from the eye diagrams using one set of 125 samples (OSNR = 32, 28, 24, 20, 16 dB; CD = 0, 15, 30, 45, 60 ps/nm; DGD = 0, 2.5, 5, 7.5, 10 ps). Fig. 1 (b) shows some corresponding eye diagrams. Another set of 64 samples (OSNR = 30, 26, 22, 18 dB; CD = 7.5, 22.5, 37.5, 52.5 ps/nm; DGD = 1.25, 3.75, 6.25, 8.75 ps) is used for testing. The ANN

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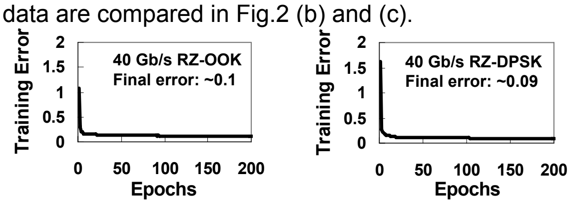
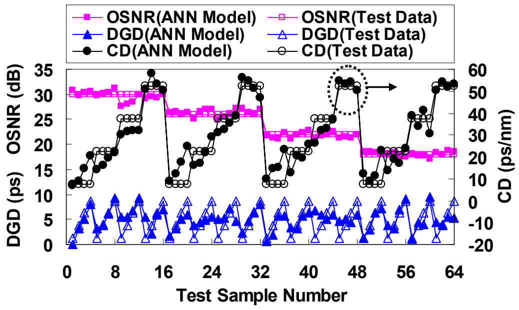
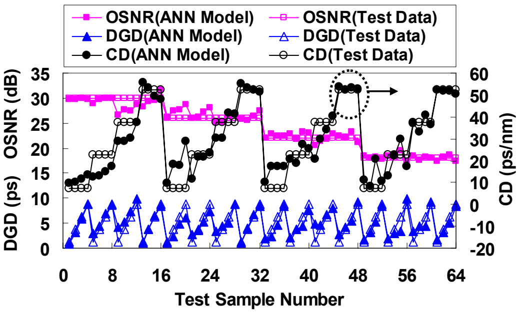
reports a correlation coefficient of 0.97 and 0.96 for OOK and DPSK systems, respectively. Fig. 2 (a) shows the training error. The test and ANN-model data are compared in Fig.2 (b) and (c).



(a) Training error



(b) 40 Gb/s RZ-OOK testing results



(c) 40 Gb/s RZ-DPSK testing results

Fig.2 Simulation results.

Experiment and Results

The experimental setup is shown in Fig. 3. 40 Gb/s DPSK or OOK signals are generated using two cascaded Mach-Zehnder modulators (MZM). The signal then goes through a tunable dispersion compensating module (TDCM) with +/- 400 ps/nm tuning range and 10 ps/nm tuning resolution, which serves as the CD emulator. The output of the TDCM is sent to an Erbium-doped fiber amplifier (EDFA) with a variable optical attenuator (VOA) in front to adjust the received OSNR. The noise-loaded signal is then filtered by a bandpass filter (BPF) with 1 nm bandwidth, and sent to the scope, where the eye diagram parameters are extracted.

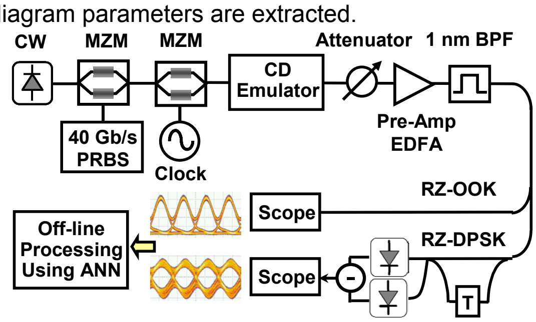
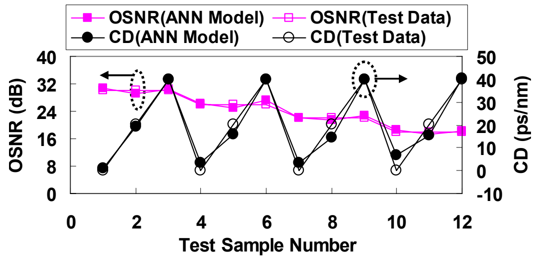
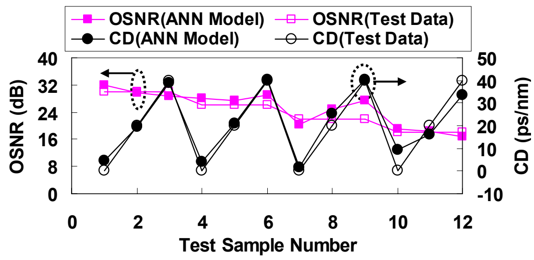


Fig.3 Experimental setup. ANN: artificial neural network.

In our experiment, we vary OSNR and CD for both 40 Gb/s RZ-DPSK and RZ-OOK signals to get two sets of eye diagram parameters, including extinction ratio, eye opening factor and signal-to-noise ratio. One set with 20 samples (OSNR = 32, 28, 24, 20, 16 dB; CD = 0, 10, 30, 50 ps/nm) is sent to the ANN model for training and the other set with 12 samples (OSNR = 30, 26, 22, 18 dB; CD = 10, 20, 40 ps/nm) is used for testing. The final training errors for the OOK and DPSK data are ~0.03 and ~0.04, respectively. Fig. 4 shows testing results with the experimental data. For the RZ-DPSK signal, we use the eye of the destructive port of the delay line interferometer to extract information since we cannot estimate balanced eye diagrams with the scope. The ANN reports a correlation coefficient of 0.99 for both of the 40 Gb/s RZ-OOK and RZ-DPSK systems. Fig. 4 compares the testing and ANN-model data.



(a) 40 Gb/s RZ-OOK testing results



(b) 40 Gb/s RZ-DPSK testing results

Fig.4 Experimental results.

Acknowledgements

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References

1. D. C. Kilper, et al, JLT, 22(1), 2004.
2. T. Luo, et al, OFC'03, ThY3, 2003.
3. I. Shake, et al, Electro. Lett., 34(22), 1998.
4. S. Ohteru, et al, PTL, 11(10), 1999.
5. N. Hanik, et al, Electro. Lett., 35(5), 1999.
6. I. Shake, et al, JLT, 22(5), 2004.
7. S. D. Dods, et al, OFC'06, OThP5, 2006.
8. R. A. Skoog, et al, PTL, 18(22), 2006.
9. Q. J. Zhang, et al, Neural Networks for RF and Microwave Design, Norwood, MA: Artech House, 2000.