Monitoring I/Q Data and Pulse Carving Misalignments in RZ-DQPSK Transmitters Using a Neural Network Approach

Xiaoxia Wu[1*], Jeffrey Jargon[2], Louis Christen[1], Loukas Paraschis[3], Alan Willner[1]
1. Dept. of Electrical Engineering - Systems, University of Southern California Email: xiaoxia@usc.edu
2. Department of Commerce, National Institute of Standards and Technology (NIST)
3. Optical Networking, Advanced Technology and Planning, Cisco Systems, Inc.

Abstract We propose a technique using artificial neural networks (ANNs) to simultaneously identify I/Q data misalignment and data/carver misalignment in both parallel-type and serial-type RZ-DQPSK transmitters. A correlation coefficient of 0.99 is obtained by using a 3-input ANN for the parallel case and a 2-input ANN for the serial case.

Ⅰ. Introduction

Advanced modulation formats are increasingly important in the optical communications community due to their ability to provide increased spectral efficiency, higher receiver sensitivity (i.e., lower optical signal-to-noise-ratio (OSNR) requirement), and better tolerance to fiber-based chromatic dispersion and nonlinear effects [1]. In particular, return-to-zero (RZ) quadrature-phase-shift-keying (QPSK) has been shown to provide quite high system performance results; in QPSK, the in-phase (I) and quadrature-phase (Q) data streams are simultaneously transmitted during a single symbol period. The above is true for both noncoherent differential QPSK (DQPSK) as well as the more robust coherent version.

As the modulation format becomes more advanced, the transmitter tends to become more complex in terms of number of components and time synchronization among the components [2]. Due to unavoidable optical/electronic device aging, imperfections and temperature variations, maintaining the correct timing within the data transmitter is quite difficult and yet crucial to proper system performance. Therefore, a laudable goal would be to monitor the relative time misalignment in order to provide a feedback signal and maintain proper synchronization. For an RZ-QPSK transmitter, the following are important: (i) I and Q data must be temporally aligned with each other, and (ii) the RZ pulse carver must be synchronized to the data.

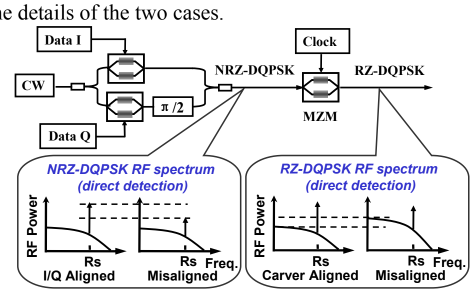
There have been reports of measurements of time misalignment/synchronization for serial and parallel types of RZ-DQPSK transmitters [3-4]. In these techniques, a specific parameter is measured, such as power in a radio frequency (RF) tone or power in one part of the channel spectrum. These parameters will either increase or decrease with temporal misalignment. One could use a simple feedback loop that would either maximize or minimize these measured values. However, it would be more valuable if the transmitter could be "trained" to recognize and directly relate RF tone power or spectral power to a specific temporal misalignment cause and value.

Artificial neural networks (ANNs) are information processing systems that learn from observations and generalize by abstraction [5]. ANNs learn the relationships among sets of input-output data that are characteristic of the device or system under consideration and then apply the relationship to any testing data within the range of interest.

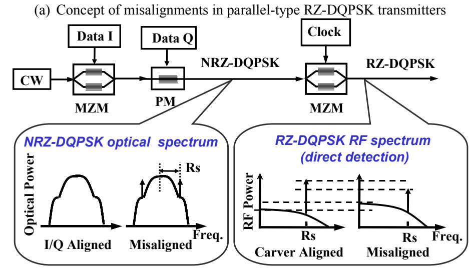
In this paper, we use the measured parameters to initially train the ANN to recognize what parameters are temporally misaligned, and by how much, in the DQPSK transmitters. A correlation coefficient of 0.99 is obtained by using a 3-input ANN for the parallel-type RZ-DQPSK transmitter and a 2-input ANN for the serial-type transmitter.

Ⅱ. Concept

Fig. 1 (a) shows the concept of misalignments in parallel-type RZ-DQPSK transmitters. When data streams I and Q are misaligned, the clock tone power at the symbol rate decreases with the increase of the misalignment. When data I/Q are aligned, the RF power at low frequencies increases with the data/pulse carving misalignment. Fig. 1 (b) shows the misalignments in a serial-type RZ-DQPSK transmitter. By monitoring the optical clock tone at the symbol rate, we can determine the I/Q misalignment, and the misalignment between data and carver can be monitored by measuring the power change in RF clock tone. See Refs. 3 and 4 for the details of the two cases.



(a) Concept of misalignments in parallel-type RZ-DQPSK transmitters



(b) Concept of misalignments in serial-type RZ-DQPSK transmitters

Fig. 1. Conceptual diagram of the misalignments in parallel/serial-type RZ-DQPSK transmitters.

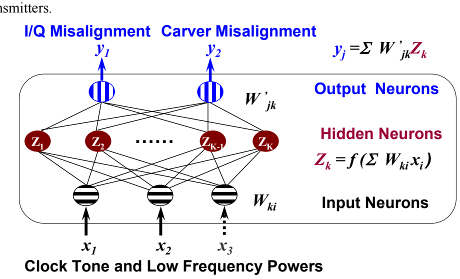


Fig. 2. Conceptual diagram of an artificial neural network (ANN).

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.2. 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 8 hidden neurons. The conjugate gradient method is used for training. We choose the RF clock tone

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power after direct detection of DQPSK and low-frequency RF power after direct detection of RZ-DQPSK for the parallel case, while for the serial case, we use the optical clock tone power of DQPSK (which can be filtered by an optical filter and detected by an photodiode to convert to RF power) and the RF clock tone power after direct detection of RZ-DQPSK for the inputs to the ANNs. Note that after directly detecting RZ-DQPSK in the parallel case and the low-frequency RF power in the serial case, the clock power can serve as a third parameter for training.

Fig. 3 shows the schematic diagram of using an ANN for feedback control for a parallel-type transmitter. The RF components of interest are filtered by the RF bandpass filters (BPF). Controllable phase shifters will be required to automatically align the transmitter with the misalignment information from the ANN. 600 MHz is used as an example of low frequency components [3].

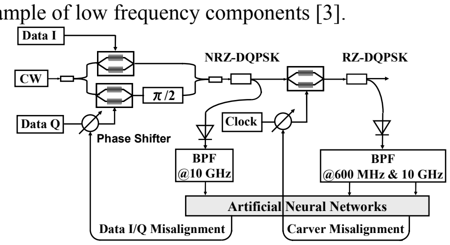
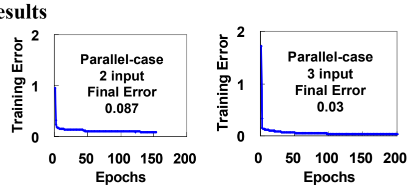
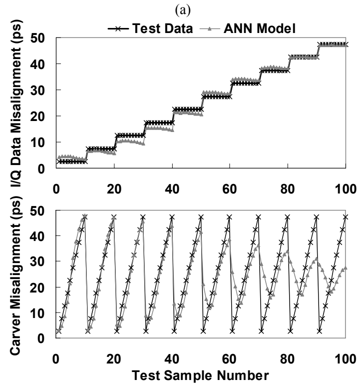


Fig. 3. The feedback control figuration for 20 Gb/s parallel RZ-DQPSK.

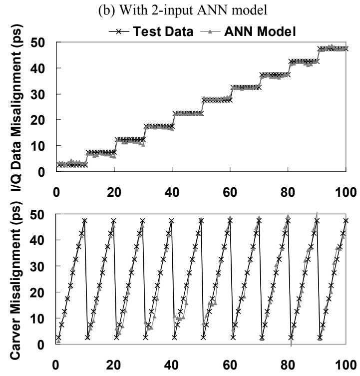
III. Results



(a)



(b) With 2-input ANN model



(c) With 3-input ANN model

Fig. 4. Comparison of testing and ANN-modeled data for 20 Gb/s parallel RZ-DQPSK.

The training data is a set of 121 samples (I/Q misalignment = 0-50 ps in steps of 5 ps; carver misalignment = 0-50 ps in steps of 5 ps). Fig. 4 (a) shows the training error versus epochs for the 20 Gb/s parallel RZ-DQPSK transmitter. An epoch is defined as a stage of ANN training that involves presentation of all the samples in the training data set to the neural network once for the purpose of learning [5]. The final training error is ~0.087 when 2 inputs are used and ~0.03 when 3 inputs are used. Once the model is trained, we validate its accuracy using a different set of testing data that includes 100 samples (I/Q misalignment = 2.5-47.5 ps in steps of 5 ps; carver misalignment = 2.5-47.5 ps in steps of 5 ps). The ANN reports a correlation coefficient of 0.97 and 0.99 for 2-input and 3-input, respectively. Fig. 4 (b) and (c) compare the testing and ANN-modeled data for the 2-input and 3-input models. We observe that the 3-input case gives a better prediction.

Fig. 5 shows the results for the 80 Gb/s serial-type RZ-DQPSK transmitter. A set of 121 samples (I/Q misalignment = 0-12.5 ps in steps of 1.25 ps; carver misalignment = 0-12.5 ps in steps of 1.25 ps) is used for training and another set of 100 samples (I/Q misalignment = 0.625-11.875 ps in steps of 1.25 ps; carver misalignment = 0.625-11.875 ps in steps of 1.25 ps) is used for testing. We observe that 2-input model gives a good prediction, with a correlation coefficient of 0.99. In contrast, the 2-input model in the parallel case does not do as well. The reason is that the RF low-frequency power, which serves as the second input in the parallel-type transmitter depends not only on the carver misalignment but also on the I/Q misalignment, while for the serial case, the second input RF clock tone power depends only on the carver misalignment due to the previous phase modulation.

This technique is shown for direct-detection systems, but should also work for coherent systems, since coherent and noncoherent set-ups can share the same types of transmitters.

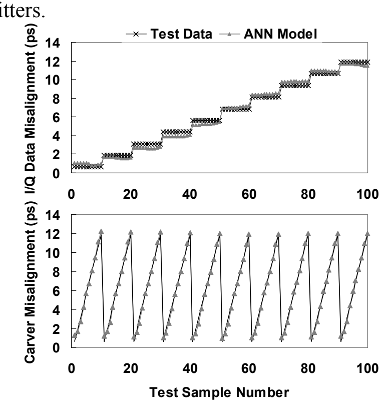


Fig. 5. Comparison of testing and ANN-modeled data for 80 Gb/s serial RZ-DQPSK.

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