Flexible Bias Control for a Mach-Zehnder Modulator Based on a Two-Layer Neural Network Algorithm

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Abstract: We propose and experimentally demonstrate a neural network-based flexible bias control algorithm. The proposed algorithm is experimentally demonstrated with an MZM driven by a 56-Gb/s PAM4 signal and a 28-Gb/s BPSK signal, respectively.
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1. Introduction

Mach-Zehnder modulators (MZMs) have been widely used in optical communication systems and microwave photonic links due to their remarkable performances. An MZM requires a bias voltage to maintain its operating point that depends on the application scenario. In an intensity modulation-direct detection (IM-DD) system, the bias of the MZM is usually set to the quadrature point of its transmission curve [1]. In other transmission systems, e.g., systems employing phase-shift keying (PSK) signal, the MZM bias needs to be set to its transmission null [2]. It is highly desired that the bias of an MZM can be easily adjusted and locked to obtain an optimum performance. Furthermore, the optimum bias of an MZM could drift due to the variations of the environmental temperature, humidity and stress [3]. Thus, an effective control algorithm to correct the drifted bias of an MZM is necessary.

In recent years, various techniques have been proposed for the bias locking of an MZM [4-7], including optical power monitoring techniques [4,5], and dithering signal-based techniques [6,7]. In the first case, the control algorithm adjusts the bias according to the monitor power variation of the MZM. Such algorithms have been demonstrated at the quadrature points in [4], but require complicated control circuits if they work at the null points [5]. In a dithering signal-based control system, a dithering signal is applied to the MZM to generate the first and the second order harmonics, and the algorithm can adjust the bias according to their power ratio. The second scheme can achieve the bias control at any point of the transmission curve. However, the dithering signal needs to be strong enough to ensure an accurate bias control, which may induce an optical signal noise ratio (OSNR) penalty [6]. Besides, a dithering signal-based system requires additional devices to generate the dithering tone and filter out the harmonics, resulting in increased complexity and power consumption [4].

In this paper, we propose and experimentally demonstrate a neural network (NN)-based control algorithm to realize any bias locking for an MZM. A two-layer NN is employed to learn the nonlinear relationship between the output power of the MZM and its bias voltage, then the desired bias is predicted according to the output power in one cycle of the transmission curve. Compared to the dithering signal-based scheme, the proposed scheme reduces the control circuit complexity. The feasibility of the proposed scheme is experimentally verified by using an MZM driven by a 56-Gb/s four-level pulse amplitude modulation (PAM4) signal and a 28-Gbaud binary phase-shift keying (BPSK) signal, respectively.

2. Operation Principle

The average output optical power of an MZM in a period time of T can be expressed as follows [7]:

$$\left\langle P_o(t) \right\rangle = \frac{\alpha P_i}{2}\left(1 + \frac{1}{T}\int_0^T \cos\left(\frac{\pi(V_{bias} + V(t))}{V_\pi}\right)dt\right), \tag{1}$$

where P_o is the output optical power of the MZM and P_i is the input optical power, $V(t)$ is the radio frequency (RF) signal, α and V_π are the insertion loss and the half-cycle voltage of the modulator, respectively. According to (1), for an MZM driven by a given RF signal, the average output optical power of the MZM is independent of $V(t)$, and shows a nonlinear relationship with the bias voltage. Thus, it is possible to design an effective algorithm to learn the nonlinear relationship between the average output optical power of the MZM and its bias voltage. Here we use an artificial neural network (ANN) to learn the relationship. Figure 1(a) shows the block diagram of the ANN in our proposed algorithm. It is a fully connected two-layer NN with a single hidden layer. In the input layer and the output layer, we use a single neuron with a linear activation function. In the hidden layer, we use three neurons with a hyperbolic tangent (tanh) function as the activation function, which shows a good trade-off between the predicted error and computational complexity. The training method is the error backpropagation (BP) algorithm [8].

Figure 1(c) depicts the flow charts of the proposed algorithm, which can be divided into three stages, i.e., a training set building stage, a NN training stage, and a power monitoring and bias adjusting stage. In the first stage, we apply a set of bias voltages that are uniformly distributed between the peak and the null of the transmission curve of the MZM, and measure their corresponding monitor powers to build the training set, as shown in Fig. 1(b). In the training stage, the training set is used to train the neural network. After sufficient training processes, the ANN can quickly predict the voltage difference between an arbitrary point and the reference point according to its monitor power. Finally, the control circuit estimates the output optical power of the MZM and compares it to the target power. Here, we set a threshold to determine whether the bias is drifted or not. If the power fluctuation reaches the threshold, the algorithm will adjust the bias according to the calculation output of the network.

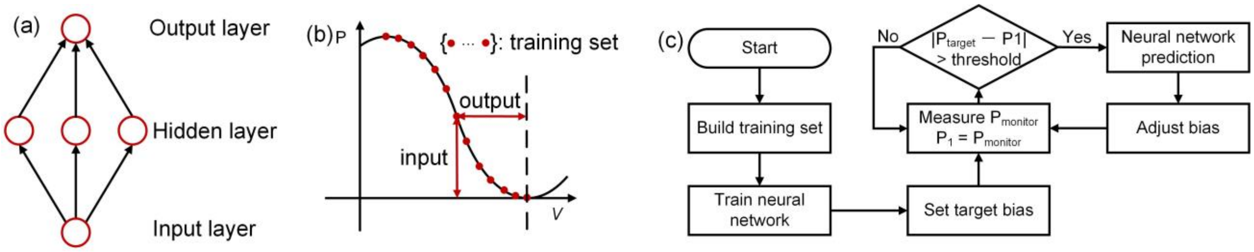

Fig. 1. (a) Two-layer neural network model. (b)Illustration of the training set. (c) Algorithm flow charts.

3. Experimental Results

The experimental setup is illustrated in Fig. 2. At the transmitter, a 25-GHz arbitrary waveform generator (AWG) (Keysight M8195A) is used to generate a 56-Gb/s PAM4 signal or a 28-Gb/s BPSK signal that drives an MZM (Fujitsu FTM7939EK). A continuous-wave (CW) light at 1550 nm is fed into the MZM. A small proportion of the output of the MZM is first tapped by a 10:90 coupler and then monitored by the control circuit. In the bias control sub-system, a ~300-MHz monitor photodetector (PD) is used to detect the optical signal. The output current of the monitor PD is converted to a voltage signal and filtered by a low pass filter consists of a capacitor and a resistor. The voltage signal is sampled by an analog-to-digital converter (ADC) integrated in a commercial microcontroller unit (MCU) (STM32F407). Then the digital signals are processed in the MCU. Finally, the output of the algorithm is delivered to the digital-to-analog converter (DAC) and amplified by an amplifying circuit with a gain of 2.2. At the receiver, a 40-GHz PD is used to detect the optical signal. After the detection, the eye diagram of the signal is measured by a 30-GHz sampling oscilloscope (Keysight 86100D).

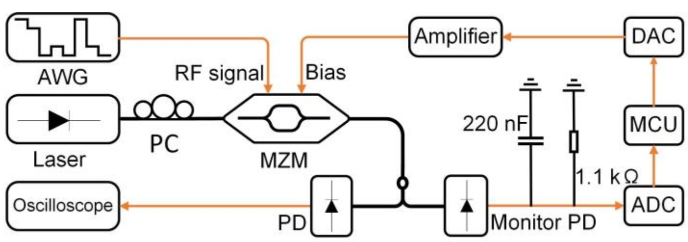

Fig. 2. Experimental setup.

In the experiment, the bias of the MZM was set to the quadrature point of its transmission curve for the PAM4 signal, and the null point for the BPSK signal, respectively. After the signal was modulated, the control algorithm adjusted the bias of the MZM to build the training set. Note that the power-voltage relation may change due to the variation of the RF signal amplitude or the input optical power. In these cases, we need to build the training set and train the NN again. At the beginning of the training stage, all the thresholds and weights of the neurons were initialized with random numbers from 0 to 1. The learning rate in our NN was initialized to 0.47 and decayed when the iteration number increased. After sufficient training, the bias was set to the target voltage and its corresponding optical power was measured as the target power. A hot air blower was used to increase the temperature of the MZM by more than 15 ℃ in a few minutes, which otherwise would take much longer time in practical applications. The results for the quadrature bias setting are provided in Fig. 3(a) and (b). Without the bias control, the bias voltage applied to the MZM remains constant, while the monitor voltage in proportion to the monitor power increases as the temperature rises. If the control circuit is turned on, the monitor voltage and therefore the monitor signal power become stable. The mean error and maximum error of the monitored voltage are less than 0.79% and 2.4% compared to the target value, respectively. Note that the time interval between the adjacent execution loops may be different, since the control algorithm operates only when the bias drifts over the threshold. The eye diagrams of the PAM4 signal with and without the bias control process are provided in the insets of Fig. 3(b), showing the effectiveness of the control algorithm and the good quality of the signal.

To verify the feasibility of the proposed algorithm at the transmission null of the MZM, we also conducted an experiment with a BPSK signal. The results for the null bias setting are provided in Fig. 3(c) and (d). The dash curves show that, without the bias control, the bias voltage remains constant while the monitor voltage increases as the temperature rises. And as depicted by the solid curves, the control algorithm can adjust the bias voltage to keep the monitor voltage stable. The mean error and maximum error of the monitor voltage are less than 1.1% and 3% compared to the target value, respectively. Due to the zero slope at the transmission null, a relatively large temperature variation is needed to induce an error signal above the threshold in Fig. 1(c), thus step-like changes of the bias voltage can be observed in Fig. 3(c). The eye diagrams of the BPSK signal of different states are provided in the insets of Fig. 3(d).

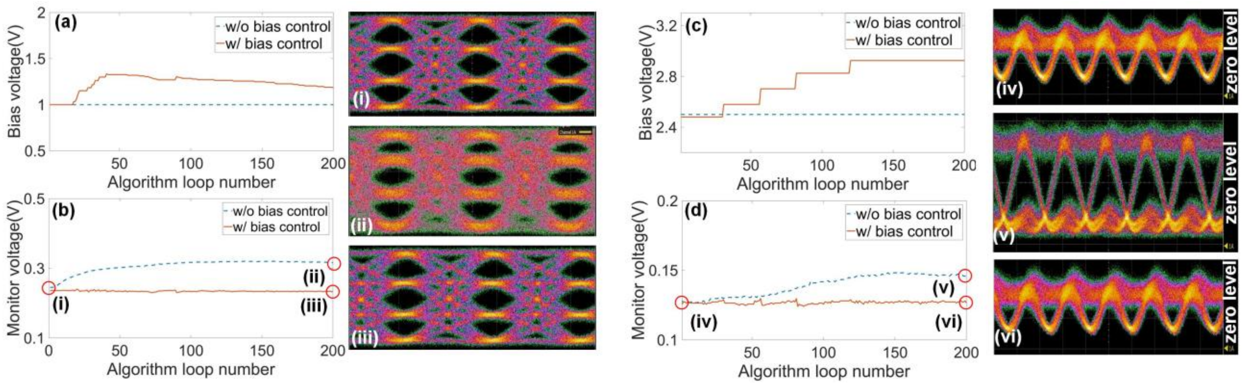

Fig. 3. Experimental results with quadrature bias setting and null bias setting: (a) Bias voltage of the MZM versus execution loop number. (b) Voltage of the monitor versus execution loop number. Insets: eye diagrams of the PAM4 signal (i) before the temperature increases, (ii) after the temperature increases without the bias control and (iii) after the temperature increases with the bias control. (c), (d) same as (a), (b) but with BPSK signal.

4. Conclusions

A flexible bias control based on a two-layer neural network algorithm is proposed and experimentally demonstrated for an MZM with quadrature bias setting and null bias setting. The algorithm can achieve a long term and accuracy bias control for an MZM in one cycle of its transmission curve.

References

[1] S. H. An, Q. M. Zhu, J. C. Li, H. X. Pang, and Y. K. Su, "Experimental Demonstration of Single-wavelength, Single-polarization 102-Gb/s DMT Signal Transmission over 105-km Single-span SMF in an IM-DD System," in 2018 International Photonics and OptoElectronics Meetings (POEM), 2018, OT4A.10.

[2] Q. J. Chang, Y. Tian, J. M. Gao, T. Ye, Q. Li, and Y. K. Su, “Generation and Transmission of Optical Carrier Suppressed-Optical Differential (Quadrature) Phase-Shift Keying (OCS-OD(Q)PSK) Signals in Radio Over Fiber Systems,” Journal of Lightwave Technology, vol. 26, no. 15, pp. 2611-2618, Aug, 2008.

[3] J. P. Salvestrini, L. Guilbert, M. Fontana, M. Abarkan, and S. Gille, “Analysis and Control of the DC Drift in LiNbO3-Based Mach-Zehnder Modulators,” Journal of Lightwave Technology, vol. 29, no. 10, pp. 1522-1534, May, 2011.

[4] M. H. Kim, B. M. Yu, and W. Y. Choi, “A Mach-Zehnder Modulator Bias Controller Based on OMA and Average Power Monitoring,” IEEE Photonics Technology Letters, vol. 29, no. 23, pp. 2043-2046, Dec, 2017.

[5] K. Sekine, C. Hasegawa, N. Kikuchi, and S. Sasaki, "A Novel Bias Control Technique for MZ Modulator with Monitoring Power of Backward Light for Advanced Modulation Formats." Optical Fiber Communications Conference and Exposition, OFC 2007, pp.1-3.

[6] L. L. Wang, and T. Kowalcyzk, “A Versatile Bias Control Technique for Any-Point Locking in Lithium Niobate Mach-Zehnder Modulators,” Journal of Lightwave Technology, vol. 28, no. 11, pp. 1703-1706, Jun, 2010.

[7] X. Yuan, Y. A. Zhang, J. Zhang, and M. Zhang, “Any point bias control technique for MZ modulator,” Optik, vol. 178, pp. 918-922, 2019.

[8] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, “Learning representations by back-propagating errors,” Nature, vol. 323, no. 6088, pp. 533-536, Oct, 1986.