Effect of Number of Neurons of a Neural-Network on Compensation Performance of SPM Non-linear Waveform Distortion.

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Abstract—**We investigated the effect of the number of neurons of a neural-network (NN) on the equalization performance of nonlinear waveform distortion caused by self-phase modulation (SPM). Numerical simulations revealed that the heavier waveform distortion requires the more neurons in hidden layer of the NN, whereas the performance is not improved by changing the number of input-layer neurons.**

Keywords-Nonlinear equalization, Self-phase modulation, Digital signal processing, Naural network, 16QAM

I. INTRODUCTION

Waveform distortion caused by nonlinear effects such as self-phase modulation (SPM) and cross-phase modulation (XPM) is one of the important issue to realize higher-performance optical fiber networks. Some methods have been proposed for compensating for the nonlinear effects, including optical phase conjugation [1], digital back propagation [2] and Volterra filters [3]. However, these methods require enormous amount of calculation or complicated optical components. Digital signal processing based on neural networks (NNs) have been investigated to compensate for nonlinear effects in wireless communication systems because NNs can adaptively compensate for nonlinear distortion by using supervised learning algorithms [4,5]. In optical communications systems, NNs has been studied for Intensity Modulation-Direct Detection (IM-DD) transmission systems [6, 7]. Recently, NNs were used for nonlinear equalization in coherent optical orthogonal frequency division multiplexing (CO-OFDM) [8, 9]. We proposed a novel nonlinear equalization method using an NN to compensate optical multi-level signals distorted by SPM [10-12]. In this paper, we investigated the effect of input-layer and hidden-layer size of an NN on the performance of nonlinear equalization. Error vector magnitude (EVM) performance after the nonlinear equalization was evaluated by numerical simulations, changing the number of neuron elements in the input layer and the hidden layer of the NN.

II. NOLINEAR EQUALIZATION USING AN NN

Figure 1 shows the construction of the NN which we used in the nonlinear equalization. The NN have a three-layer structure consisting of an input layer, a hidden layer, and an output layer. The input layer of the NN has feedforward tapped delay lines. Input signals of in-phase (I) and quadrature (Q) components are fed into the delay lines. Neurons in the hidden layer has sigmoidal output function. Output layer have 2 neurons for I- and Q-signal components. Output of neurons y_i is described as

$$y = \sum_{k=1}^{n} f(x_k w_k + b) \ , \tag{1}$$

where x_k is the input from k-th neuron, w_k is the weight, b is the bias, and f is the output function of the neuron. In order to minimize the difference between supervised signal and output of the NN, the values of weight and bias are calculated by Back Propagation (BP) algorithms. The error e can be expressed as

$$e = \sum_{k=1}^{n} (y_i - d_i)^2, \tag{2}$$

where d_i is the supervised signal.

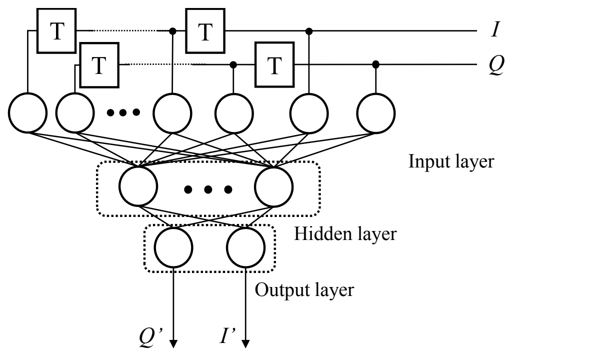


Fig. 1. Construction of NN.

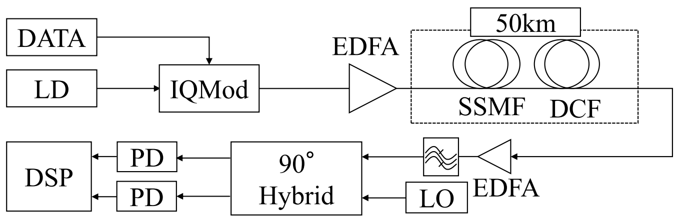


Fig. 2. System setup

III. SYSTEM SETUP

Figure 2 shows 50-km 16QAM signal transmission system used in our simulation of nonlinear equalization. 10-Gsymbol/s

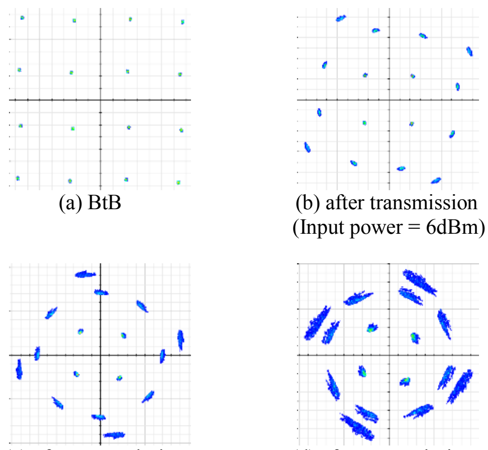
16QAM signal was modulated by random data and transmitted by a standard single mode fiber (SSMF) and a dispersion compression fiber (DCF) having a total length of 50 km, cancelling the chromatic dispersion. After the transmission, the optical signal was received by optical homodyne detection. Here, we assumed that the local oscillator (LO) was ideally synchronized to the optical signal. The distorted signal after the transmission was compensated by the NN in a digital signal processor (DSP), changing the number of neurons in the input and hidden layers. The NN was trained by Levenberg-Marquardt algorithm that is a kind of BP [12].

IV. Result

Figure 3(a) shows the constellation of the received 16QAM signals in back to back (BtB) configuration. Figure 3(b), (c), and (d) show the constellations after the transmission where the input power to the optical fiber was 6 dBm, 10 dBm, and 13 dBm, respectively. Due to the large input power, the transmitted signals were seriously distorted by SPM. Figure 4 shows the EVM performance versus the number of neurons in the hidden layer. The number of neurons in the input-layer was fixed at 3. In the figure, we plotted the result of 10-times trials in each condition and drew straight lines connecting each average. The EVM values were improved by increasing the number of neurons in the hidden layer. When the waveform distortion was serious, more neuron elements were required. Figure 5 shows the EVM performance when the input layer size was changed. The number of neurons in the hidden layer was fixed at 10. Here, ten trials were performed as well as the numerical simulations in Fig. 4. The EVM performance was not improved even when the number of input layer was changed.

V. Conclusions

We investigated the effect of the size of a NN on the performance of the equalization of SPM nonlinear waveform distortion. The results of our numerical simulations show that the heavier waveform distortion requires the more neurons in hidden layer of the NN, whereas the performance is not improved by changing the number of input-layer neurons.


(a) BtB

(b) after transmission (Input power = 6dBm)

(c) after transmission (Input power = 10dBm)

(d) after transmission (Input power = 13dBm)

Fig.3. Constellations without equalization. (Received optical power: -3dBm)

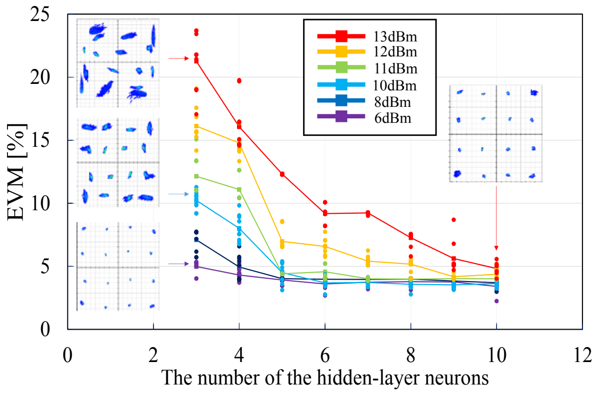


Fig.4. EVM performance versus the number of hidden-layer neurons.

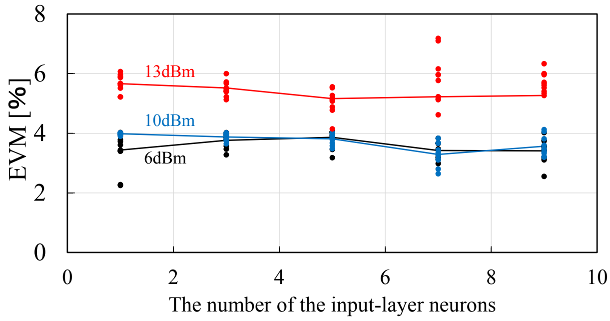


Fig.5. EVM performance versus the number of input-later neurons.

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