Optical Signal-To-Noise Ratio Monitoring Based on Delay Tap Sampling Using Artificial Neural Network

Feng Wang, Shencheng Ni, Shuying Han, Shanhong You

***Abstract*—**With the development of optical communication, optical performance monitoring (OPM) has received more and more attentions. Since optical signal-to-noise ratio (OSNR) is directly related to bit error rate (BER), it is one of the important parameters in optical networks. Recently, artificial neural network (ANN) has been greatly developed. ANN has strong learning and generalization ability. In this paper, a method of OSNR monitoring based on delay-tap sampling (DTS) and ANN has been proposed. DTS technique is used to extract the eigenvalues of the signal. Then, the eigenvalues are input into the ANN to realize the OSNR monitoring. The experiments of 10 Gb/s non-return-to-zero (NRZ) on–off keying (OOK), 20 Gb/s pulse amplitude modulation (PAM4) and 20 Gb/s return-to-zero (RZ) differential phase-shift keying (DPSK) systems are demonstrated for the OSNR monitoring based on the proposed method. The experimental results show that the range of OSNR monitoring is from 15 to 30 dB and the root-mean-square errors (RMSEs) for 10 Gb/s NRZ-OOK, 20 Gb/s PAM4 and 20 Gb/s RZ-DPSK systems are 0.36 dB, 0.45 dB and 0.48 dB respectively. The impact of chromatic dispersion (CD) on the accuracy of OSNR monitoring is also investigated in the three experimental systems mentioned above.

***Keywords*—**Artificial neural network, ANN, chromatic dispersion, delay-tap sampling, optical signal-to-noise ratio, OSNR.

I. Introduction

WITH the rapid development of data capacity, the optical communication networks experience explosive growth. However, the dynamic and flexible optical networks also bring about various optical signal damages, which affect the quality of signal transmission seriously. Hence, OPM is an important element in network management and it is essential for ensuring robust and high-quality system performance. Channel impairments include CD, polarization-mode dispersion (PMD), OSNR and so on. OSNR is one of important parameters because it is directly related to the bit error rate (BER).

Many OSNR monitoring methods have been proposed and verified for optical networks, such as delay-line interferometer (DLI), DTS technique [1], polarization nulling technique [2] and so on. DTS techniques have received considerable attentions, which are easy to implement and do not need to consider clock recovery. Nevertheless, these traditional techniques always have some inevitable drawbacks.

Recently, the use of ANN is proposed for simultaneous monitoring of various channel impairments [3]. In particular, parameters derived from either eye diagrams or asynchronous constellation diagrams are used as input to ANNs for training and testing [4]. The development of ANN brings a new dawn to OPM.

In this paper, we propose an OSNR monitoring method based on DTS in combination with ANN in NRZ-OOK, PAM4 and RZ-DPSK systems. In the proposed method, based on DTS, we analyze the amplitude histogram (AHs) by fitting samples located not only along the delay-tap plots diagonal but also with an appropriate region to enhance the accuracy. After obtaining the data, we send the datasets into the ANN model for training. The OSNR monitoring range is from 15 to 30 dB and the rms errors of NRZ-OOK, PAM4 and RZ-DPSK systems are 0.36 dB, 0.45 dB and 0.48 dB respectively. The results show that the OSNR can be estimated successfully.

II. Operating Principle

In the DTS technique, the signal waveform is sampled at two instants separated by a delay [5]. Subsequently, sample values are used as rectangular coordinates X and Y to form a delay-tap plot (DTP). The plot is created by overlapping the coordinates from consecutive sampling pairs. This enables a graphical decomposition of the waveform and analysis of impairment. Fig. 1 (a) displays two-DTP with 0.1 B delay and a corresponding DTP, B is bit period. If the distributions are assumed to be Gaussian, their mean values and standard deviations can be indicated respectively as $\mu 0$ and $\sigma 0$ for low signal level and $\mu 1$ and $\sigma 1$ for high signal level, as shown in Fig. 1 (b).

In the proposed method, we find that two-DTP can expand when the corresponding OSNR changes, so we perform histogram fitting for some regions that change significantly with the change of OSNR. We also analyze the histogram plots by fitting samples located not only along the DTP diagonal but also with an appropriate region to enhance the accuracy. Fig. 2 (a) displays two-DTP with 0.1 B delay and OSNR is 23 dB. A is the diagonal of plots, which means the distribution of points that Y is equal to X. Z represents the intersected point of midcourt line. Take Z as the center, A rotates up and down with an angle α forming two regions with low and high signal levels respectively. The plot allows separating samples from waveform peak and waveform valley. The occurrence of sample pairs in overlap regions forms a histogram with two peaks as shown in Fig. 2 (b).

AHs exhibit unique and distinctive patterns for different optical signal [6]. AHs with 80 bins are generated from the samples. Fig. 3 shows different modulation format and OSNR will lead to different AHs features.

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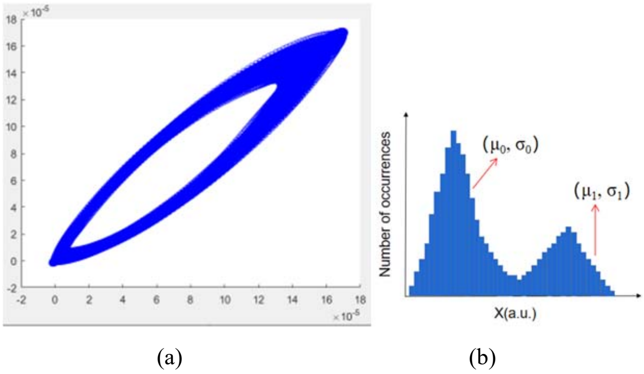


Fig.1 (a) Two-DTP with 0.1 B delay, (b) bimodal distribution of samples

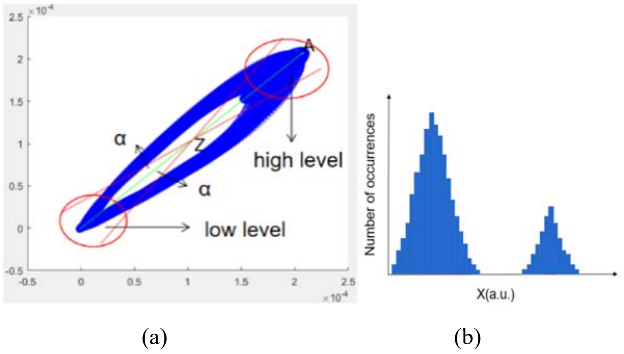


Fig.2 (a) Two-DTP with 0.1 B delay and overlap regions, (b) bimodal distribution of samples

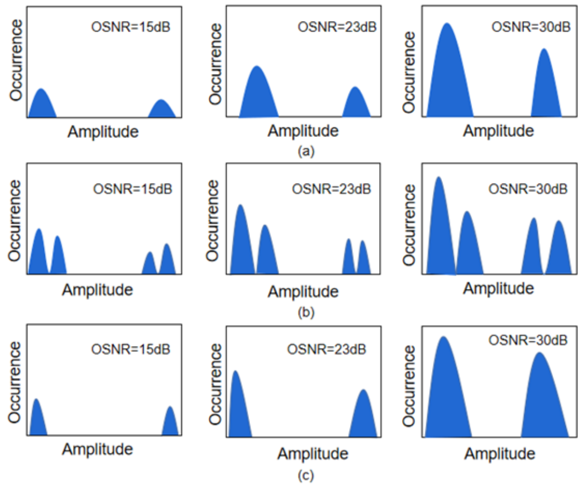


Fig. 3 AHs under different OSNR, (a) NRZ-OOK, (b) PAM4, (c) RZ-DPSK

ANN is a mathematical model or computational model that mimics the structure and function of a biological neural network for estimating or approximating functions. It can be trained by using input-output data to generate a desired mapping from an input stimulus to the targeted output. As shown in Fig. 4, an ANN generally consists of an input layer, an output layer, and a hidden layer. In each layer, the processing element is called neuron, which is linked to other neurons in the neighboring layers by varying coefficients that represent the strength of these connections. In this method, the ANN is optimized by momentum descent algorithm, which can reach the global minimum of the model quickly. The momentum descent algorithm is a method to calculate the gradient of the loss function with respect to the weights in an ANN. It is commonly used as a part of algorithms that optimize the performance of the network. The momentum descent algorithm has two hyper-parameters, namely α and β. Parameter α is learning rate, which determines the magnitude of each parameter update. Parameter β represents the magnitude of momentum, which controls the exponential weighted average.

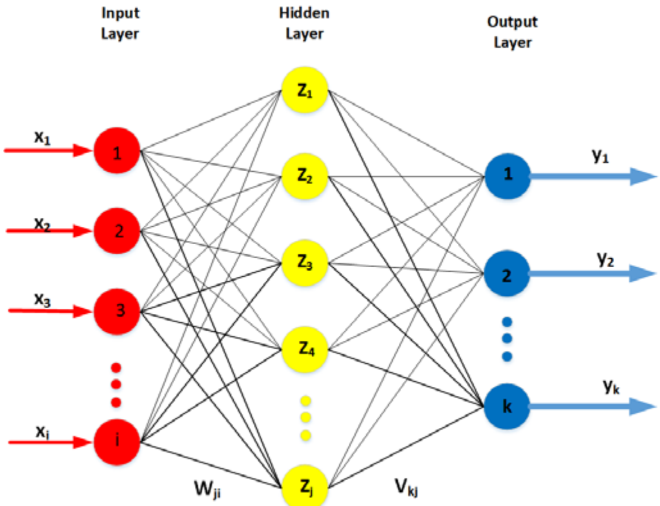


Fig. 4 The ANN architecture

III. Experimental Setup

The experimental setup for OSNR monitoring with ANN is shown in Fig. 5. Three modulation formats, NRZ-OOK, PAM4, and RZ-DPSK are generated for OSNR monitoring and analyzing. The bit-rate of the three modulation formats are 10 Gb/s, 20 Gb/s and 20 Gb/s respectively. The transmitted optical signal is amplified by the first erbium-doped fiber amplifier (EDFA) and then launched into the fiber links of 80-km standard single-mode fiber (SSMF). The second EDFA is used to compensate the transmission loss. The CD emulator can simulate CD in the range of (0,900) ps/nm. When passing through an optical bandpass filter (OBPF), the signal is direct detected by a photodetector (PD). After optics-electronics (O/E) conversion, the delayed and non-delayed signals are sampled as two measurements (X and Y), separated by a fixed delay length τ (0.1B, B is bit period). The obtained sample points are from the same pulse or the adjacent pulses; they can reflect the pulse shape information which has a strong relationship with the impairments. The samples are normalized and plotted as (X, Y) pairs, producing a two-tap plot. Besides, the additional CD effect is also imposed on the testing sets. At the offline processing, we obtain 80 bins for each set of data using AHs. The training sets (80-feature for one sample) are sent into the ANN model for training.

In this study, the ANN consists of 80 neurons in input layer and one neuron in output layer to estimate OSNR. Some important network parameters of ANN in the proposed method are given in Fig. 6. In the ANN, the number of hidden layers is set to 2. Each layer has 45, 10 neurons that have an activation function of sigmoid. The activation function of output neuron is rectified linear unit (ReLU). Before the training of ANN, we preprocess all the features by initial normalization. The ANN is trained by using Tensorflow library [7]. To prevent overfitting and vanishing or exploding gradient problem, batch normalization technique [8] is also used in this method. In the study, α and β of the momentum descent algorithm are set to 0.01 and 0.9.

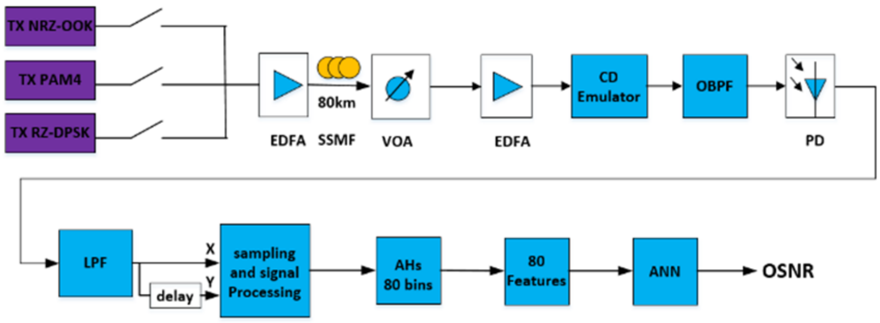


Fig. 5 Experimental setup for OSNR monitoring

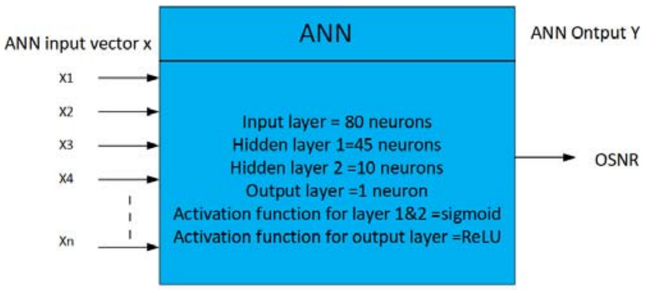


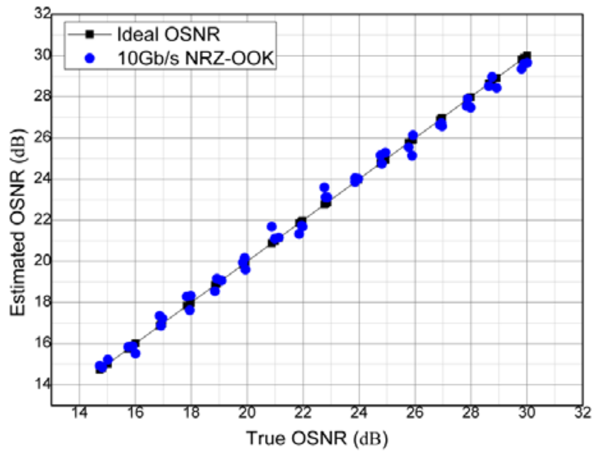
Fig. 6 Network parameters of ANN in the proposed method

IV. Results and Discussions

A. OSNR Monitoring Results

At offline sampling processing, we should choose appropriate α. To express the linear fitting degree for different α values in detail, the α value is changing from 0 to 45 degree. Through histogram fitting of the sampled signal, it can be seen that there will be non-Gaussian cases in histogram fitting and measurement error will be larger, when the α value keeps increasing. Through data analysis, it is feasible to fit when the α is less than 2. In order to reduce the measurement error, the number of points fitted should include as many regions as possible where the scatter diagram changes caused by OSNR. Hence, the appropriate α is 2.

In the experiment, the OSNR interval is from 15 to 30 dB in step of 1 dB. After extracting AHs with 80 bins features, we divide all the samples into training and testing sets by randomly selecting 70% and 30% of overall datasets. The OSNR monitoring results are shown in Fig. 7. It is obvious that OSNRs can be estimated accurately and the rms errors for 10 Gb/s NRZ-OOK, 20 Gb/s PAM4 and 20 Gb/s RZ-DPSK system are 0.36 dB, 0.45and 0.48 dB respectively.



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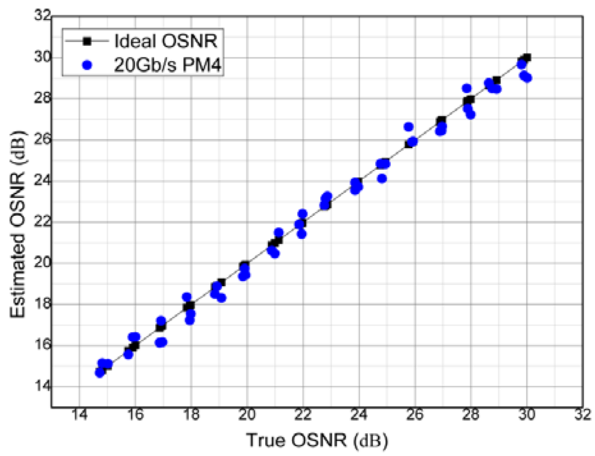

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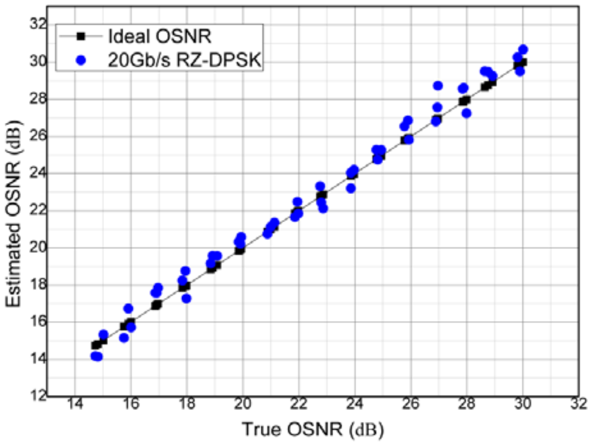


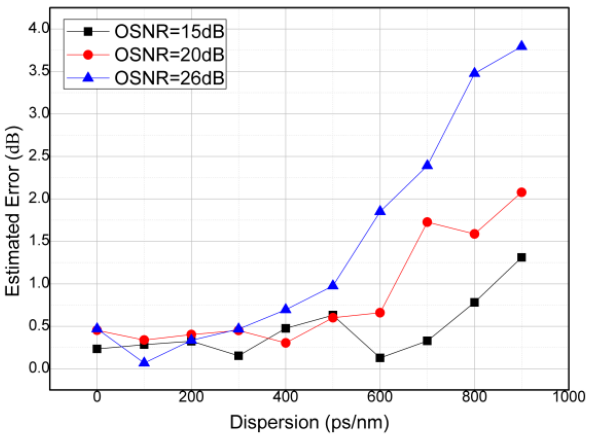
(c)

Fig. 7 Estimated versus true OSNRs, (a) NRZ-OOK, (b) PAM4, (c) RZ-DPSK

B. Impact of CD on Monitoring Results

To investigate the impact of CD on OSNR monitoring by using this method, numerical experiments are performed according to the change of CD. The CD is adjusted from 0 to 900 ps/nm, in step of 100 ps/nm. The reference OSNRs are different. In different CD cases, the OSNR is monitored by using the proposed method. The estimated errors of three modulation formats of signals are shown in Fig. 8.

It is clear that the estimated error is less than 1 dB when CD is less than 500 ps/nm for OSNR of 15 dB, 20 dB and 26 dB in the NRZ-OOK system. However, the error is more than 1 dB when the OSNR is larger and CD is greater than 500 ps/nm. In the PM4 system, the estimated error is less than 1dB when CD is less than 400 ps/nm for both OSNR of 17 dB, 21 dB and 27 dB, when the CD is larger, the error is more than 1 dB. In the RZ-DPSK system, the estimated error is less than 1 dB when CD is less than 600 ps/nm for both OSNR of 18 dB, 23 dB and 28 dB, when the CD is larger, the error is more than 1 dB.



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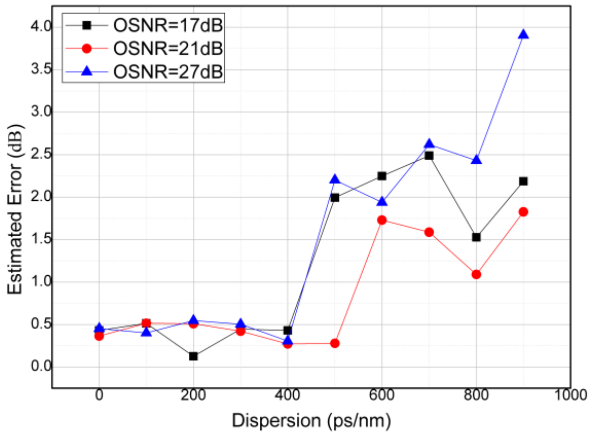

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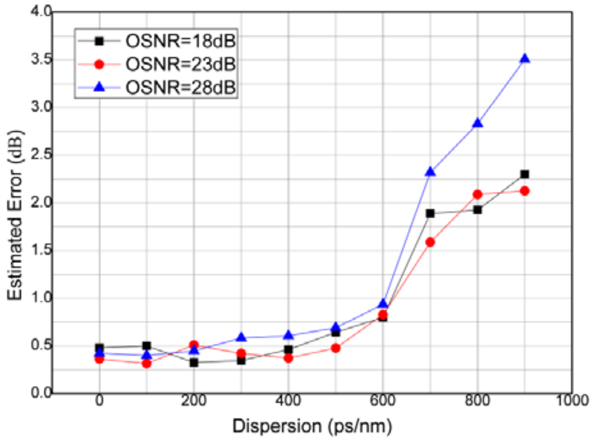

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Fig. 8 Impact of CD on OSNR monitoring, (a) NRZ-OOK, (b) PAM4, (c) RZ-DPSK

V. Conclusion

In the paper, the OSNR monitoring of NRZ-OOK, PAM4 and RZ-DPSK signals based on DTS in combination with ANN trained with AHs are analyzed. By extracting the features in histogram plots, the OSNR can be monitored accurately in different modulation formats. Besides, the OSNR monitoring for NRZ-OOK, PAM4 and RZ-DPSK signals using the proposed method can work well under a certain degree of CD.

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