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An Optical Performance Monitoring Model Based on RBF-ANN Trained with Eye-Diagram

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Abstract

An optical performance monitoring model based on radial basis functions artificial neural network was proposed in this paper. This proposed model can simultaneously identify three kinds of impairments, namely optical signal-to-noise ratio, chromatic dispersion, and polarization-mode dispersion. These impairments were the main cause for optical channels quality deterioration in high bit-rate and transparent optical communication systems. Firstly, the structure of the network was optimized by appliance of Gram-Schmidt rule. Optimization of the network's parameters was realized based on particle swarm optimization method. Then this optimized network was trained and validated with two different data sets derived from eye-diagrams under different levels of aforementioned impairments and bit rates, respective. Finally, the effectiveness of the model was verified by two different optical signals, namely 10 Gb/s non-return-to-zero on-off keying and 40Gb/s return-to-zero differential phase shift keying. The simulation results show that this model had improved performance compared with OPM based on BP-ANN and be transparent for modulation schemes.

Keyword: optical performance monitoring, artificial neural networks, eye-diagram, simulation

1. Introduction

Over the past years, optical communication networks have developed into high-capacity and been shifted to transparent optical networks with the implementation of spectral-efficient modulation formats such as multi-level differential quadrature phase-shift keying (DQPSK). These come at the price of much

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more complicated and problematic approach to performance monitoring in optical domain and on real-time basis to enable robust, cost-effective self-managed operation. So the optical networks should be able to agilely monitor the physical state of the network and the quality of propagating data signals [1-3].For this purpose, optical performance monitoring (OPM) systems should be able to identify the cause of performance degradation, estimate the levels of different types of impairments at the same time in order to sectionalize and locate the faulty equipments. Additionally, from a carrier's perspective, interested OPM models will need to be developed that have sophisticated diagnostic capability, low-cost components, and transparency to bit-rate and modulation schemes.

This paper identifies an improved OPM model that could make these goals achievable based on improved artificial neural networks (ANNs) [1, 3, 4]. Application of error back-propagation ANNs (BP-ANNs) trained with eye-diagram parameters of monitored optical channels for identifying and estimating three crucial kinds of impairments, namely ion (CD), and polarization mode dispersion (PMD), was firstly presented by J.A. Jargons and et al [5]. Based on ANNs' intelligence, the models had features of monitoring and isolating different types of impairment simultaneously, being transparent to modulation, having applicability to high-rate data and being cost-effective with two major drawbacks. Firstly, the number of neurons in hidden layer and values of weight originally determined in random. Then, ANN's output tends to localized optimization. The aforementioned shortcomings could be overcome by using radial basis function ANNs (RBF-ANN) trained with eye-diagram parameters by combination of different levels and kinds of impairments. The training data, eye diagrams with different types and level of crucial impairment in optical networks, was generated by a commercial optical communication system simulation packages for two different bit-rate and modulation schemes signals, namely 10-Gb/s non-return to zero ON-OFF keying (NRZ-OOK) and 40 GB/s return to zero DPSK (RZ-DPSK). PMD was replaced with its first-order differential group delay (DGD). For testing efficacy of the trained RBF-ANNs, measured data from real optical signals was used instead of cross validation. And the validation results were compared with that based on BP-ANNs.

2. Methodology

As an efficient testing tool for data communication system, eye-diagram's features can distinctly reflect the influence more than one impairments combination on signal quality. Based on theoretic analysis and simulation results, Q-factor, closure, root-mean-square (RMS) jitter, and crossing amplitude were selected to feature the impairments in optical networks from all eye-diagram parameters because the selected parameters change significantly with varying impairment combinations, as shown in Fig.1 for aforementioned 10-Gb/s (NRZ-OOK), similar situation to the second signal.

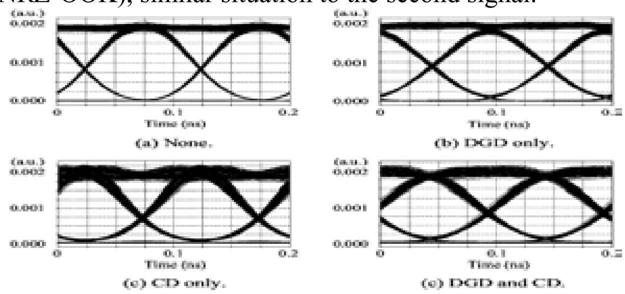

Fig.1 Eye-diagrams of the 10Gb/s NRX-OOK channel with various impairments(OSNR=32dB) (a) None, (b) DGD only(40ps),(c) CD only(800ps/nm),(d) DGD(40 ps) and CD(800ps/nm).

In details, Q-factor is defined as the difference of the mean upper and lower levels divided by the sum of the upper and lower level standard deviations; closure is the ratio of the outer eye height to the inner eye height; crossing amplitude is the point on the vertical scale where the rising and falling edges intersect; and RMS jitter is usually defined as the standard deviation of the time data calculated in a narrow window surrounding the crossing amplitude.

ANNs are neuroscience-inspired computational tools that are trained by use of input-output data to generate a desired mapping from an input stimulus to the targeted output. It has been proved that a feed forward three-layer perceptron structure (MLP3) ANN, as shown in Fig. 2, can model almost any physical function with any degree of accuracy, provided that a sufficient number of hidden neurons are available.

So, using the four selected eye-diagram parameters; OSNR, CD, and DGD as the input vector and output vector of RBF-ANN respectively, the optimized and trained RBF-ANN should model and map the relationship between eye-diagram parameters and impairment simultaneously with satisfied modelling accuracy, which essentially being determined by the optimization effect for RBF-ANN.

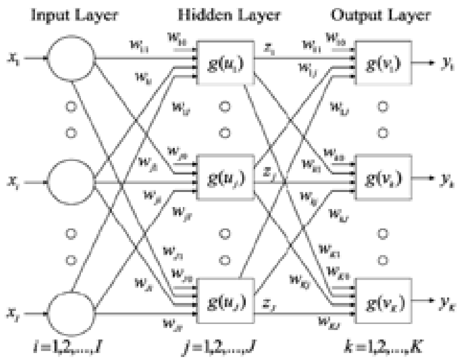

Fig. 2 Schematic architecture of ANN

Two steps were arranged to optimize the RBF-ANNs. Firstly, RBF-ANN architecture, mainly determined by the number of neuron in hidden layer, was optimized [5-7,9].As shown in Fig.2; the output may be expressed as

$$y(x) = \sum w_i g(\|X - c_i\|) \tag{1}$$

where $g(\|X - c_i\|) = \exp(-\|X - c_i\|^2 / \sigma_i^2)$; $X \in R_n$ being input vector; w_i being network weight coefficient being the number of neuron in hidden layer; c_i and σ_i being the centre and width of Gaussian function, respectively.

According to Eq. (1), performance of RBF-ANNs would be essentially determined by n, c_i , and σ_i .Then, orthogonal square law was used to determine n according to input testing data set. For this aim, Eq. (1) was arranged in matrix as $Y = \Phi\Theta$, where Φ being matrix of output determined by input vector of first layer and output matrix of hidden layer. When Φ was divided as Gram-Schmidt orthogonal rule

$$\Phi = WU \tag{2}$$

where, U being upper triangle matrix; W being orthogonal matrix. After defining the weight coefficient vector as $G = U\Theta$, Eq. (2) should be rewritten as $Y = (\Phi U^{-1})(U\Theta) = WG$.

So, the error degradation ratio was expressed as

$$[e]_i = \frac{g_i^2 w_i^T w_i}{Y^T Y} \tag{3}$$

where, $[e]_i, g_i$, and w_i was modelling error of RBF-ANN, line vectors of G and W, respectively.

Proposed the training error as $0 < \xi < 1$, and queued all calculated $[e]_i$ in down sequence. And to stop the training process when the condition expressed as Eq. (4) was accomplished. And this determined value of n was the optimized number of neurons in hidden layer, i.e., the optimization for the RBF-ANN structure was completed.

$$1 - \sum_{i=1}^{n} [e]_i < \xi \tag{4}$$

Second kind of key structure parameters of RBF-ANN were c_i and σ_i, that may be determined by application of particle swarm optimization (PSO) [7-9].

3. Simulation Results and Discussion

For training data sets, two types of simulation optical signal that were of characteristics including a laser with a centre wavelength of 1550 nm and a full-width at half maximum line width of 10 MHz, the same as in [5] for convenience to compare the modelling results with different selected ANNs. The simulation results and comparison between tested data, BP-ANN and RBF-ANN modelled data for two different types of optical signal were shown in Fig.3

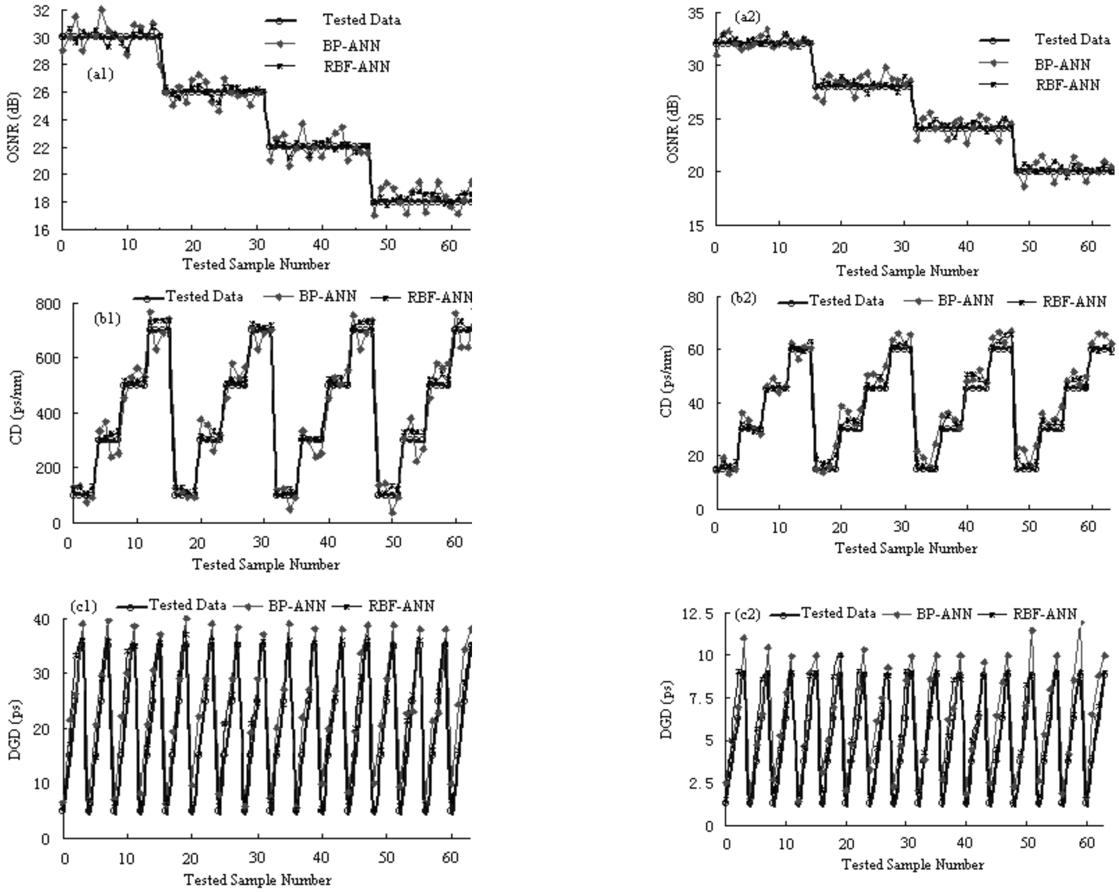

Fig. 3 Comparison of testing, BP-ANN and RBF-ANN modeled data (a1-c1)OSNR,CD and DGD for 10 Gb/s NRZ-OOK;(a2-c2) OSNR,CD and DGD for 40 Gb/s RZ-DPSK.

Shown as in Fig. 3, the training data sets were arranged as the following:For 10Gb/s NRZ-OOK signal, 125 simulations using the following impairment combinations:OSNR-16,20,24,28, and 32dB; CD-0,200,400,600, and 800 ps/nm; and PMD with values of DGD equal to 0,10,20,30,and 40 ps. For 40Gb/s RZ-DPSK signal, also selected 125 simulations with the following impairment combinations: OSNR-16,20,24,28, and 32dB; CD-0,15,30,45, and 60 ps/nm; and DGD-0,2.5,5,7.5,and 10ps.

Accomplishing the training process, the 64 simulation data sets used for validating the accuracy, selected as, 10Gb/s NRZ-OOK signal:OSNR-18,22,26, and 30dB; CD-100,300,500, and 700 ps/nm; and DGD- 5,15,25,and 35 ps; for 40Gb/s RZ-DPSK signal: OSNR-18,22,26, and 30dB; CD-7.5,22.5,37.5, and 52.5 ps/nm; and DGD-1.25,3.75,6.25,and 8.75ps.

Indicated by the two groups of figuration, OPM based on optimized RBF-ANNs could estimate three kinds of impairments simultaneously with sufficient accuracy and of efficiency compared with that based on BP-ANN.

4. Conclusion

In this paper, OPM models based on RBF-ANNs trained with eye-diagram parameters, which could be used to simultaneously identify levels of ONSR, CD, and DGD, for two types of different bit-rate and modulation scheme, were presented. According to simulation results, they had more modelling efficiency and mapping accuracy compared with OPM models based on BP-ANNs. This improvement resulted from optimized ANNs' structure and parameters. The capabilities presented here show significant potential for enabling the development of cost-effect OPMS with significant diagnostic capabilities in determining different kinds of impairments transparent to modulation schemes and bit-rates.

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