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Methods for compensation of nonlinear effects in multichannel data transfer systems based on dynamic neural networks

O.S. Sidelnikov, A.A. Redyuk, S. Sygletos, M.P. Fedoruk

Abstract. **A scheme for compensation of nonlinear effects in multichannel data transfer systems based on dynamic neural networks is proposed. An improved quality of optical signal transfer in this scheme in comparison with the signal transfer in a scheme based on a neural network using symbols from only one channel is demonstrated.**

Keywords: *optical fibre, nonlinear effects, neural networks, mathematical simulation, wavelength division multiplexing.*

1. Introduction

Nonlinear effects are one of the main factors limiting the throughput of modern fibre-optic communication lines. The operation of modern multichannel communication systems with a multiplexed band suggests an increase in the total signal power in fibre, due to which the influence of nonlinear transfer effects increases [1 – 3]. The operation of optical communication lines in these nonlinear regimes differs significantly from the conventional linear regime and calls for new approaches and methods for processing received high-power signals. To date, the most efficient scheme for compensation of nonlinear distortions is the digital back-propagation, which models the backward propagation of signals through an optical fibre using the split-step Fourier method [4]. However, this method generally calls for fairly high computational resources and can be used in only static data transfer systems, because its application implies preliminary knowledge of all communication line parameters. Among other ways to compensate for nonlinear signal distortions, we can select a set of methods based on application of functional Volterra series [5], digital methods based on perturbation theory elements [6, 7], nonlinear Schrödinger filter and the "reception in general with bit-by-bit decision making" algorithm [8], and the optical methods with signal phase matching [9]. In the last five years machine learning methods have been especially actively utilised in the field of fibre-optic communication lines [10 – 15]. These methods are powerful statistical tools for developing adaptive equalisers, capable of compensating for nonlinear transfer effects at a relatively low computational complexity. These nonlinear equalisers can be based on the support-vector machine [10], method of k nearest neighbours [11], and static [12, 13] and dynamic neural networks [14, 15]. In addition, due to the possibility of periodic retraining, schemes of processing received signals based on machine learning methods can also be applied in dynamically changing communication lines.

In this study, the scheme for compensation of nonlinear distortions based on dynamic neural networks (NNs) that was proposed in [15] is expanded for the case of a communication system with wavelength division multiplexing (WDM). The developed scheme, which uses symbols from several frequency channels on the NN input layer, is compared with a linear compensator and the previous version of the scheme, which utilises symbols from only one channel.

2. Mathematical simulation

The data transfer system under study is schematically shown in Fig. 1. The communication line consists of a transmitter, 20 spans (100 km each) of a standard single-mode fibre, erbium-doped optical amplifiers (inserted after each span), and a receiver. 16-QAM-signals with a symbolic rate R_s = 32 Gbaud, which corresponds to a bit transfer rate of 128 Gbit s^{-1} in one polarisation of one channel, are generated on the transmitter. Pulses are shaped using a raised-cosine filter with a smoothing coefficient of 0.01. A data transfer system with three frequency channels and 32-GHz interchannel spacing (corresponding to the symbolic rate) was investigated. The centre wavelength of the emitted-signal band was taken to be λ = 1550 nm. The noise generated by the EDFA amplifier (NF = 4.5 dB) was added to the optical signal after each span.

The signal propagation through an optical fibre is described by the nonlinear Schrödinger equation [1]

$$\frac{\partial A}{\partial z} = -\frac{\alpha}{2}A - \mathrm{i}\frac{\beta_2}{2}\frac{\partial^2 A}{\partial t^2} + \mathrm{i}\gamma|A|^2 A,$$

where $A(z,t)$ is a slowly varying envelope of optical signal, α = 0.2 dB km^{-1} is the fibre loss, $\beta_2 = -25$ ps^2 km^{-1} is the chromatic dispersion, and γ = 1.4 W^{-1} km^{-1} is the fibre nonlinear parameter. This equation was solved numerically using the symmetric split-step Fourier method at a sampling rate of 16 samples per symbol.

Having passed through a channel, optical signals arrived at a receiver, in which ideal compensation of chromatic dispersion was performed after separating frequency channels. A linear compensation scheme and schemes based on dynamic

O.S. Sidelnikov, A.A. Redyuk, M.P. Fedoruk Novosibirsk State University, ul. Pirogova 1, 630090 Novosibirsk, Russia; Institute of Computational Technologies, Siberian Branch, Russian Academy of Sciences, prosp. Akad. Lavrent'eva 6, 630090 Novosibirsk, Russia; e-mail: o.s.sidelnikov@gmail.com, alexey.redyuk@gmail.com, mifester@gmail.com;
S. Sygletos Aston University, England, Birmingham, B4 7ET; e-mail: s.sygletos@aston.ac.uk

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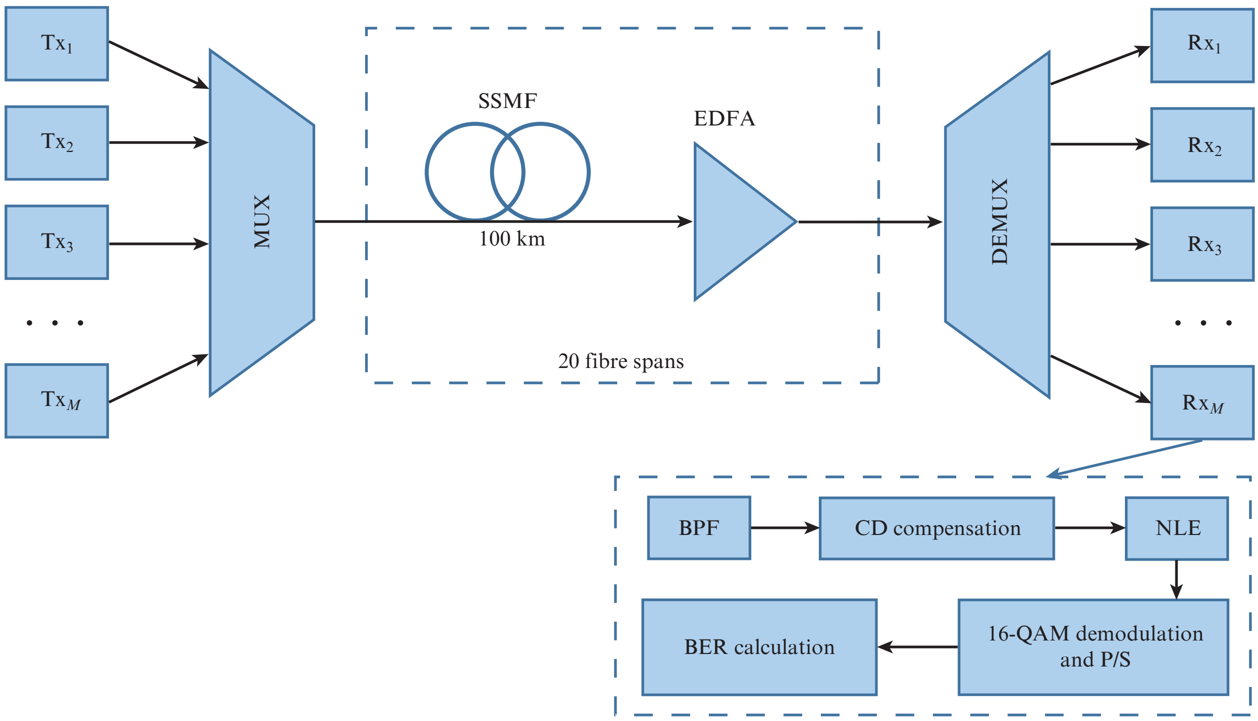

Figure 1. Schematic of the communication line under study: (Tx) transmitter for one channel; (MUX) WDM multiplexer; (EDFA) erbium-doped fibre amplifier; (DEMUX) WDM demultiplexer; (Rx) receiver for one channel; (BPF) bandpass filtering; (NLE) nonlinear effect compensation.

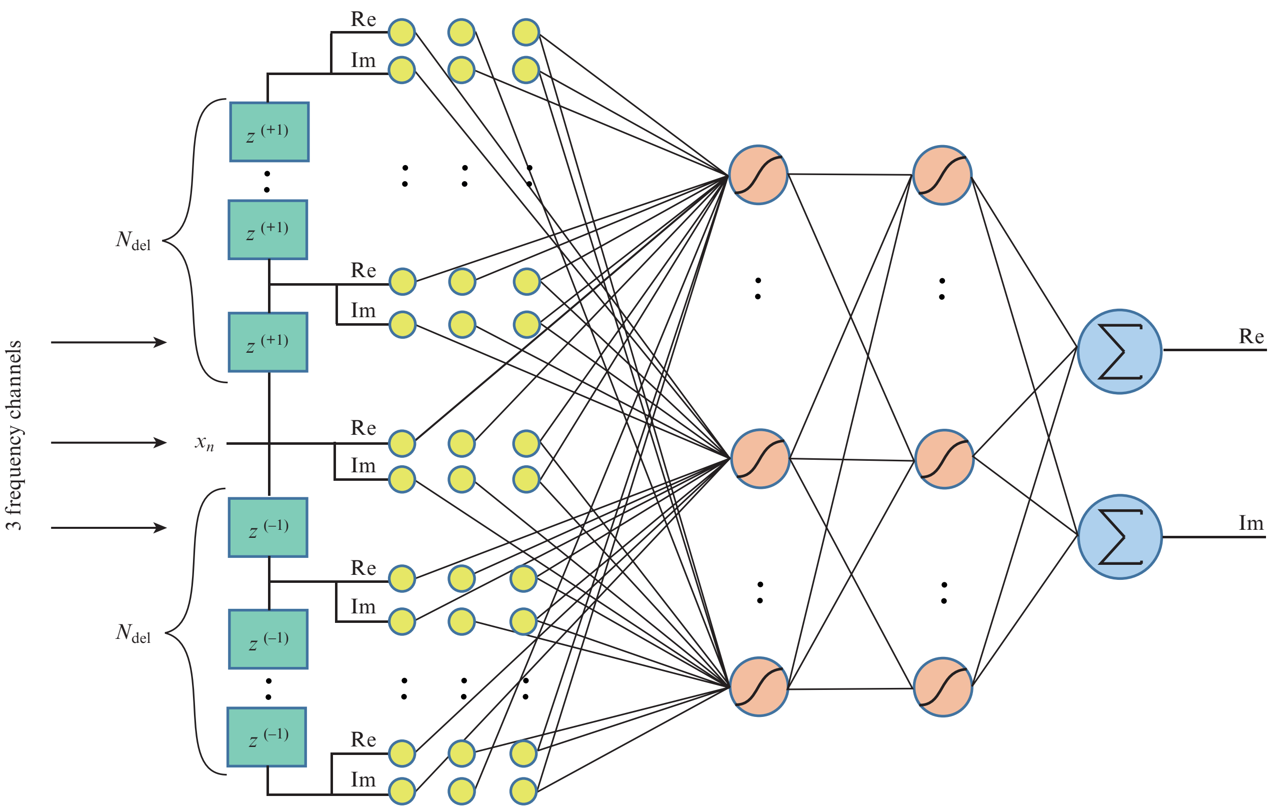

Figure 2. Architecture of a dynamic neural network.

neural networks, using all frequency channels or only the central channel, were applied to compensate for nonlinear distortions. The target function of the methods under consideration is the bit error rate (BER).

3. Scheme for compensation of nonlinear effects based on dynamic neural networks

The architecture of the proposed neural network is presented in Fig. 2. Here, in contrast to the scheme considered in [15], symbols from all frequency channels are applied at the neural network input. To take into account the channel memory effect, delay units are used in the neural network scheme, due to which both previous and subsequent symbols can be used at the NN input. This neural network is referred to as dynamic.

Since the object of our study was neural networks dealing with real numbers, complex symbols arriving at the input were separated into real (Re) and imaginary (Im) parts. The number of neurons on the NN input layer is $3 \times 2 \times (2 \times N_{\rm del} + 1)$, where $N_{\rm del}$ is the number of neighbouring symbols used in each direction. The factor of 3 corresponds to the number of channels applied at the NN input. The network contains also two hidden layers and an output layer with two neurons, corresponding to the real and imaginary parts of a symbol processed. Hyperbolic tangent was used as an activation function on hidden layers, while a linear transfer function was applied at the output layer. The network weights were determined using the adaptive moment estimation (Adam) optimisation algorithm on a training set of transmitted and received symbols. The trained neural network was tested on a test set in order to process received symbols. To calculate the BER value, we carried out 10 runs with 2^{18} symbols in each; 2^{16} symbols were used for learning, and others served to calculate BER.

4. Results of application of the scheme for compensation of nonlinear effects based on dynamic neural networks

First we considered an NN where symbols from only one channel are applied at the input. The influence of the number of delay units on the efficiency of nonlinear distortions compensation was investigated for such NNs with different architectures. Figure 3 shows the dependences of the BER on the number of neighbouring symbols applied at the NN input in each direction for networks with 64 and 192 neurons on each of the hidden layers.

It can be seen that the optimal number of neighbouring symbols in use increases with increasing number of neurons on hidden layers. A further rise in the number of neighbouring symbols leads to gradual deterioration of BER.

To estimate the efficiency of the proposed multichannel method for compensating nonlinear effects, it was compared with the linear compensation algorithm and with the scheme based on a neural network using information from only the central channel. Figure 4 shows the dependences of BER on the initial signal power for different schemes for compensating nonlinear distortions: a linear compensation scheme based on the least mean square (LMS) algorithm, which reconstructs only the phase of received signal; a neural network having two hidden layers (with 64 neurons in each), where symbols from only the central channel are used to predict the input symbol; and a dynamic neural network, which uses information from all frequency channels and also has 64 neurons on each hidden layer. Neural networks with $N_{\rm del} = 10$ were considered.

It can be seen in Fig. 4 that the schemes based on dynamic neural networks excel the linear compensator in terms of the bit error rate. However, the use of information from all three channels only slightly improves BER in comparison with the single-channel NN. The reason is that an NN with 64 neurons on hidden layers can efficiently process only 10 neighbouring symbols in each direction (see Fig. 3). A 'single-channel' NN already uses this optimal number of neighbouring pulses; therefore, the proposed multichannel scheme, where 42 additional symbols from neighbouring channels (21 symbols from each channel) are applied at the input, do not allow one to process them efficiently and use for compensation of inter-channel nonlinear effects, which would make it possible to reduce additionally the BER value. Thus, the use of information from all frequency channels does not improve the data transfer quality for these NN architectures.

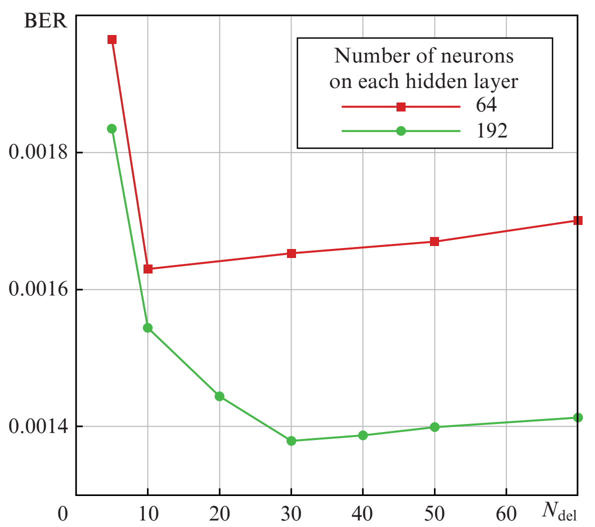

Figure 3. Dependences of BER on the number of neighbouring symbols in use.

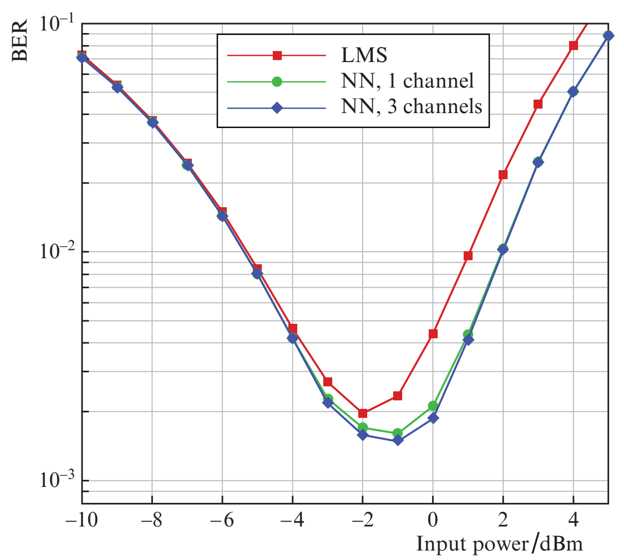

Figure 4. Dependences of BER on the initial signal power for different schemes of nonlinear distortion compensation based on an NN with 64 neurons on hidden layers.

The next object of our study was neural networks with 192 neurons on each hidden layer and the number $N_{\rm del}$ of neighbouring symbols used in each direction equal to 30. Figure 5 shows the dependences of BER on the initial signal power for a linear compensator and for schemes based on dynamic neu-

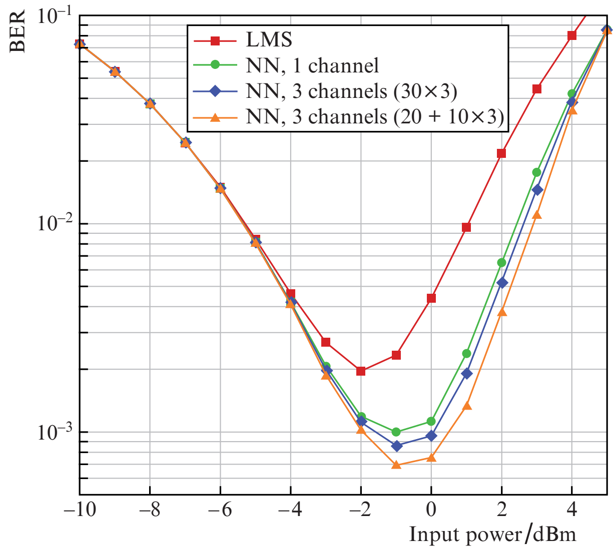

Figure 5. Dependences of BER on the initial signal power for different schemes of nonlinear distortion compensation based on an NN with 192 neurons on hidden layers.

ral networks using all frequency channels or only the central one.

Here, the use of data from all channels also improves only slightly the BER value in comparison with a single-channel NN. Nevertheless, the gain in BER in this case is somewhat larger than for an NN with 64 neurons on each hidden layer. However, if we consider a neural network using 20 neighbouring symbols in each direction from the central channel, 10 neighbouring symbols from the first channel, and 10 neighbouring symbols from the third channel [NN, 3 channels (20 + 10 × 3)], the nonlinearity compensation efficiency will increase, and the BER will decrease by 65% in comparison with the linear compensation scheme and by 31% as compared with the single-channel NN. This can be explained by the fact that the number of symbols applied at the NN input is close to optimal. Therefore, the scheme under consideration can use efficiently symbols from neighbouring frequency channels to compensate for the phase cross modulation and four-wave mixing effects, which positively affects the signal reconstruction quality. A further increase in the number of neurons on hidden layers is expected to provide even higher gain (when using symbols from all frequency channels) in comparison with a single-channel neural network.

5. Conclusions

A new scheme for processing optical signals in a communication system receiver is proposed. The scheme is based on dynamic neural networks and uses symbols from several frequency channels to compensate for nonlinear distortions. The influence of the NN architecture on the signal processing efficiency was investigated for this scheme. Different methods for compensating nonlinearity were compared in terms of the data transfer quality. It was shown that the proposed scheme is superior over the single-channel neural network (with the hidden-layer architecture preserved).

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References

1. Agrawal G.P. *Nonlinear Fiber Optics* (Boston: Academic Press, 2013).
2. Temprana E. et al. *Science*, **348**, 1445 (2015).
3. Zhitelev A.E. et al. *Quantum Electron.*, **47**, 1135 (2017) [*Kvantovaya Elektron.*, **47**, 1135 (2017)].
4. Ip E. *J. Lightwave Technol.*, **28**, 6 (2010).
5. Liu L. et al. *J. Lightwave Technol.*, **30**, 310 (2012).
6. Sorokina M. et al. *Opt. Express*, **24**, 30433 (2016).
7. Redyuk A.A. et al. *Prikl. Foton.*, **5**, 265 (2018).
8. Burdin V.A. et al. *Quantum Electron.*, **47**, 1144 (2017) [*Kvantovaya Elektron.*, **47**, 1144 (2017)].
9. Ellis A.D. et al. *Opt. Express*, **23**, 20381 (2015).
10. Li M. et al. *IEEE Photonics J.*, **5**, 6 (2013).
11. Wang D. et al. *IEEE Photonics Technol. Lett.*, **28**, 19 (2016).
12. Jarajreh M. et al. *IEEE Photonics Technol. Lett.*, **27**, 4 (2015).
13. Giacoumidis E. et al. *Opt. Lett.*, **40**, 21 (2015).
14. Sidelnikov O.S. et al. *Quantum Electron.*, **47**, 1147 (2017) [*Kvantovaya Elektron.*, **47**, 1147 (2017)].
15. Sidelnikov O. et al. *Opt. Express*, **26**, 25 (2018).