

# Neuromorphic reservoir for nonlinear optical signal equalization

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## ABSTRACT

The upcoming optical telecommunication networks face a significant challenge due to a massive increase in internet traffic. To handle this, higher-capacity transmission schemes are being implemented. To increase the optical signal-to-noise ratios (OSNR), higher launch powers are used, which are limited by nonlinear distortions caused by the Kerr effect in the transmission fibers. Currently, expensive and power-hungry digital signal processing (DSP) solutions are used to tackle this problem.

Our proposal offers an alternative solution using a neural network based on a photonic reservoir to address the nonlinear distortions in transmission links. This approach is potentially more cost-effective and consumes less energy. The photonic reservoir design is based on a four-port architecture incorporating multimode interferometers (MMIs), Mach-Zehnder-Interferometers (MZIs), and semiconductor optical amplifiers (SOAs). Inside the reservoir, the optical signals from past and current transmissions are mixed, providing the network with a memory-like capability. The training process focuses solely on driving the MZI and SOA arrays, resulting in accurate outcomes with reduced training time and energy consumption.

We numerically demonstrate the mitigation of nonlinearities in high-order transmission links using a photonic reservoir. By comparing various configurations of the neural network (NN), we highlight the specific advantages of each implementation. Looking ahead, we aim to implement this approach using a photonic integrated circuit (PIC) to further enhance its practicality and efficiency.

**Keywords:** photonic reservoir, nonlinearities mitigation, neural network, signal equalization, photonic integrated circuit, digital signal processing, semiconductor optical amplifiers

## 1. INTRODUCTION

To cope with the ever-growing capacity requirements for future optical communication networks, new approaches are needed which can overcome current limitations. The Kerr effect is the main driver of nonlinearities in optical fibers, which distort the signals and disrupt the orderly reception at the endpoint. Optical amplifiers, which are embedded in the backbone network to compensate for the signal attenuation over large distances, will also contribute to the distortions.

NNs are showing great potential as part of a new approach to mitigate such unwanted distortions and improve on current transmission systems [1]. In particular, neuromorphic photonics has a key advantage in comparison to digitally implemented NNs, given the fact that they can be directly applied to the signals in the optical domain without the need for expensive hardware. Such photonic NN can potentially process several wavelengths in parallel and with significantly lower latency and energy consumption. NNs have been demonstrated to perform several DSP functions and show a lot of potential going forward. Our approach envisions a device incorporating a hybrid PIC, which can equalize the optical signals and mitigate the nonlinear distortions, without the need for any electro-optical conversion.

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## 2. PHOTONIC NEURAL NETWORK

### 2.1 Model

The photonic NN model includes a reservoir based on a four-port architecture [2] and one fully connected layer with activation functions. The single optical input is split equally and fed to each node inside the reservoir. The nodes are implemented as 3x3 MMIs, each having 4 connections to other nodes, a general input, and an output to the next layer.

The trainable portion of the NN is composed of one layer with activation functions, connected to the output of the photonic reservoir with complex weights, and one combiner layer. The number of activations functions is equal to the number of nodes in the reservoir. The introduction of a nonlinear activation function inside a NN can improve its capability to solve nonlinear problems [3] [4]. The data signals are then combined with complex weights into a single output. The combination of these three layers enables a large learning potential while keeping the complexity of the NN low.

In our previous works, we have experimentally demonstrated the modulation format identification (MFI) capabilities of a neuromorphic PIC based on the same type of reservoir architecture [5] [6].

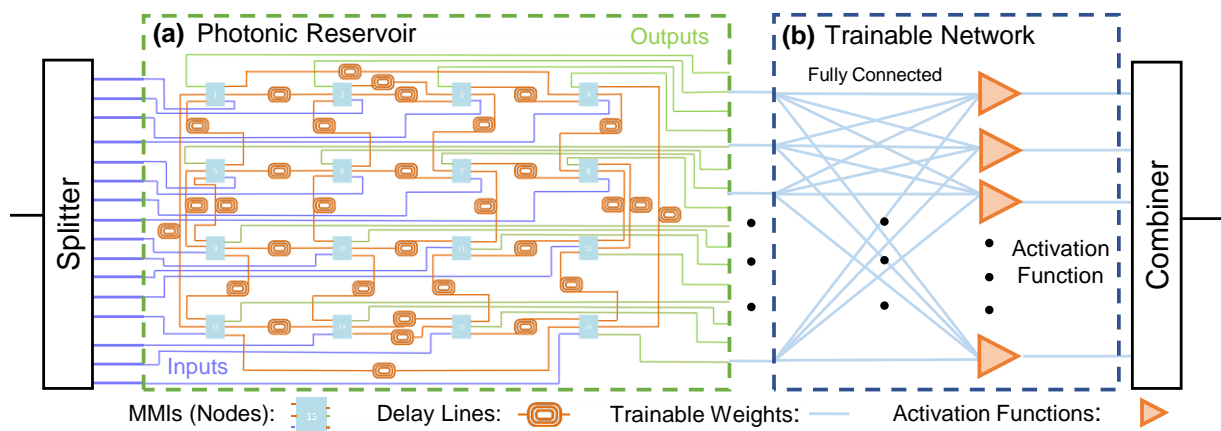


Figure 1. Model of the photonic NN. (a) Photonic reservoir based on a four-port architecture. Each node is a 3x3 MMI, is connected to other nodes with delay waveguides. (b) The trainable part of the NN includes a fully connected layer with complex weights and activation functions.

### 2.2 Hybrid-PIC Architecture

The first component of the hybrid architecture is envisioned as a silicon nitride (SiNx) PIC, which includes a photonic reservoir and a trainable fully connected layer implemented using an MZI array. With the use of electrical microstrips on top of the MZI array, one can adjust the weight in this layer by varying the corresponding electrical currents. The single optical input is split equally using a single MMI.

The second component is envisioned as an indium phosphide (InP) PIC, which includes an SOA array. The output signals of the SOA array are then combined using another MMI. One can also adjust the current feeding the SOA array, therefore adjusting the amplification of the optical signals and the amount of extra nonlinearities introduced to the NN. The envisioned architecture is depicted in Figure 2.

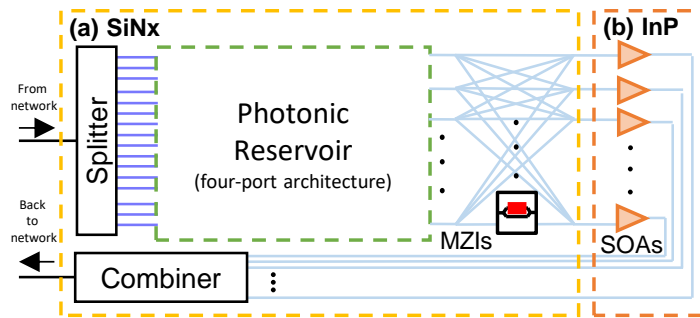


Figure 2. Architecture of the photonic NN. This figure depicts the envisioned hybrid PIC and its individual components. (a) The envisioned passive SiNx PIC, which includes the reservoir, the MZI array, as well as the input splitter and output combiner. (b) The envisioned active InP PIC which includes the SOA array, which introduces extra nonlinearities and works as activation function of the NN.

### 2.3 Test Data

The experimental dataset used for this work was generated in our lab at the Fraunhofer Heinrich Hertz Institute (HHI). We transmitted 32 GBaud 16QAM single polarization data signals over an 800 km link using standard single mode fiber (SSMF). Several measurements using optical launch powers between -1 and 2 dBm were done, which corresponded to OSNR levels from 18 up to 21.4 dB at the receiver. Over 6 million samples were recorded for each measurement scenario.

### 2.4 Simulation Setup and Training

The photonic reservoir was simulated using the photontorch platform [7], which enables the simulation of photonic NNs and their components. The fully connected layer with the activation functions, corresponding to the MZI and SOA arrays, was trained using pytorch. The model used for the implementation of the nonlinearity of the SOAs [2] is based on the leaky hyperbolic tangent function ( $\tanh$ ), which is very similar to the SOA transfer function. Both functions are depicted in Figure 3. The training was executed in 20 epochs using the Adam [6] optimizer and mean square error (MSE) as loss function.

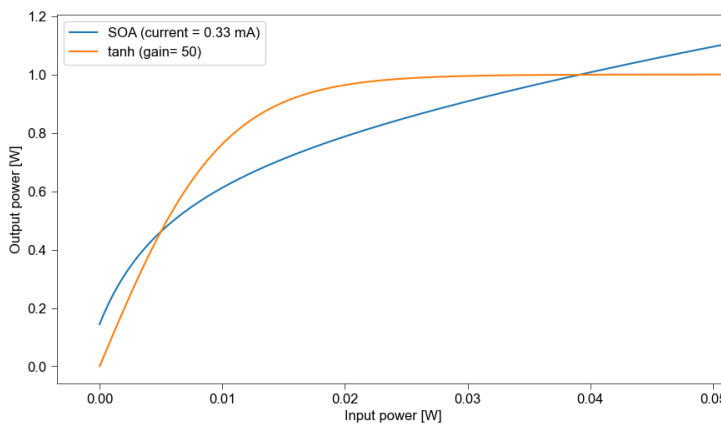


Figure 3. SOAs have been chosen as activation function of the photonic NN given the similarities between their transfer function and a  $\tanh$  function. The bias and driver current need to be set to the right values to achieve the wanted functionality.

### 3. RESULTS

We compared 3 configurations of the NN to evaluate the impact of their size on the overall performance. The results regarding  $Q^2$ -Factor are shown in Figure 4 in comparison to the case without NN ('distorted'). As expected, the configuration with a larger reservoir produces a higher  $Q^2$ -Factor. The larger the reservoir, the more photonic components and connections are needed in the PIC, which will increase the complexity and production costs. The energy consumption will also increase with the size of the NN.

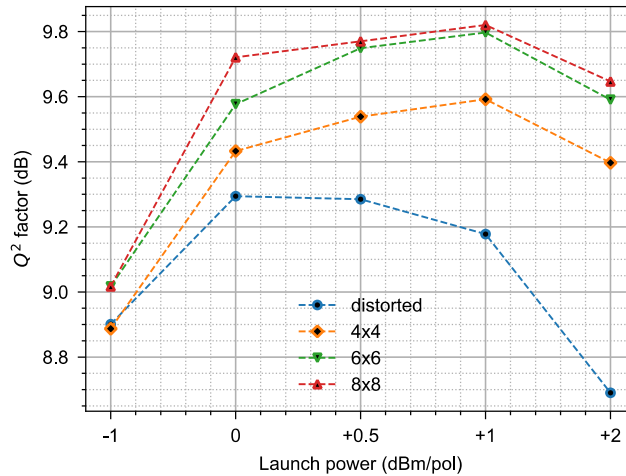


Figure 4.  $Q^2$ -Factor as a function of the optical launch power for different configurations of the photonic NN. '4x4', '6x6' and '8x8' describe the size of the photonic reservoir. The '4x4' configuration will have 16 nodes in the reservoir, 256 MZIs for the fully connected layer, and 16 SOAs as activation functions.

### 4. CONCLUSIONS

We have numerically demonstrated the mitigation of nonlinearities in recorded 32GBaud single polarization 16QAM data signals after transmission over 800 km, corresponding to an optical launch power of 2dBm at a comparable  $Q^2$ -Factor of 0.7 dB, using a purely photonic reservoir NN. Our results show that even a simple NN with a 4x4 photonic reservoir, together with adjustable MZI and SOA arrays, can be used to mitigate distortions in the optical data signals. This paper presents yet another good example of how photonic NNs can achieve good results for problems that are currently challenging for electronic DSP solutions, and show a great potential to reduce energy consumption and costs in the future.

### ACKNOWLEDGMENTS

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