Novel Electro-optic Components for Integrated Photonic Neural Networks

Pascal Stark[1], Jacqueline Geler-Kremer[1,2], Felix Eltes[1], Daniele Caimi[1], Jean Fompeyrine[1], B. J. Offrein[1], Stefan Abel[1]

[1]IBM Research – Zurich, Säumerstrasse 4, 8803 Rüschlikon, Switzerland
[2]Empa, Swiss Federal Laboratories for Materials Science and Technology
sab@zurich.ibm.com

Abstract:
We demonstrate PIC-based non-volatile optical synaptic elements, an essential building block in large non-von Neumann circuits realized in integrated photonics. The impact of non-idealities on the performance of a photonic recurrent neural networks is evaluated.

1. Computing with photonic circuits

Integrated photonic circuits efficiently combine multiple optical functions on a single physical platform, such as guiding, modulating, splitting, or detection of light. The integration of these functions removes barriers for designing and realizing large optical circuits, as present when using discrete components like bulky lenses or mirrors in tabletop optical networks. With the rise of silicon photonics, integrated photonic circuits (PICs) are becoming increasingly large and highly functional, eventually allowing unprecedented concepts of photonic computing. Examples are integrated photonic quantum processors [1], microwave photonic filters and processors [2], and optical accelerators to train and execute neural networks [3].

The development of circuits for efficiently solving computational tasks in the field of artificial intelligence are among the new use cases for PICs. A series of early demonstrator for vector-matrix multiplication [3] or non-von Neumann computing architectures such as photonic Ising Machines [4] or optical reservoir computing platforms [5] have only recently been shown. In many cases, photonic implementations offer benefits in speed, latency, and power-efficiency compared to executing the networks in software or in electronic circuits. However, the building blocks currently available in integrated photonic platforms are not yet sufficient for realizing a fully photonic neural network. New elements like photonic non-volatile transmission elements, efficient phase shifters, amplifiers, and nonlinear optical components are needed in order to scale up the size of the networks. In particular, storing the synaptic weights within the photonic domain, and enabling efficient neuronal activation functions are important functions that need to be executed in the optical domain. The realization of these new elements requires co-integration of new materials and technologies with the silicon photonics platform, such as III-V materials to achieve optical gain and nonlinearity [6], and phase-change materials (PCM) [7] or ferroelectrics [8] to achieve non-volatile optical storage.

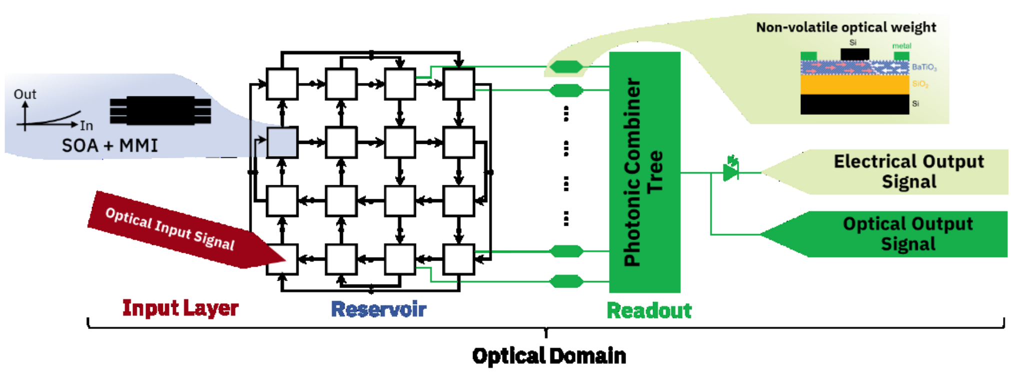

Fig. 1. Schematics of a photonic reservoir computing scheme. The optical signal is injected (red arrow) into a network of delay lines (black squares) made from long waveguides, which are connected via MMIs. SOAs are ideally inserted into the network to serve as non-linear activation functions in the network. The output states are collected with waveguides (green lines), which are coupled to non-volatile optical weights before combining them to a single output state. This state can either be send optically to the next layer (dark green) or converted into the electrical domain (bright green) using a detector.

2. Optical reservoir computing

The need of such new building blocks can be illustrated in the example of reservoir computing (RC), a type of a recurrent neural network well-suited to solve time-dependent and dynamic problems like speech recognition or bitwise operations [9]. Integrated photonic RC offers energy-efficient, ultra-fast signal processing capabilities [9,10], which can be applied to equalize signals in high-speed optical communication links to reduce the link error rate [11]. RC systems need to fulfill the approximation and separation property, they must have fading memory and a nonlinear activation function. The fading memory property can be realized in silicon photonics by a network of optical delay lines, connected with conventional splitters (e.g. multi-mode interferometers, MMIs) (**Error! Reference source not found.**). The nonlinear activation function requires an optical element with an optical-power dependent transmission function, as for example present in semiconductor optical amplifiers operated close to saturation [12]. The challenge here is to co-integrate III-V materials with silicon photonics, which can for example be achieved by wafer scale integration [6] or transfer printing [13].

Finally, a reservoir computing system needs, similar to any neural network, synaptic elements to store information acquired during the training phase at the output of the network. All current implementations of integrated photonic neural networks convert the output of the network into the electronic domain, where weighting and summation of the signals is performed. While this approach offers ideal weights with high precision and zero drift, the conversion to the electronic domain limits the processing speed, latency, and the energy efficiency of the RC system [2]. To fully benefit from photonic processing, the output layer needs to be implemented in the optical domain.

3. Integrated, non-volatile photonic weights

In integrated photonic technologies, no component to non-volatilely store optical information is readily available today. The integration of PCM materials represents a first possible solution that has only recently been demonstrated experimentally [7,14]. By means of optical control signals, the crystalline state of a thin $Ge_2Sb_2Te_5$ (GST) layer close to the optical mode is modified, which results in a change of the complex refractive index. Consequently, multiple transmission states of straight waveguides can be stabilized. The change of the transmission is predominantly caused by the change of the absorption in the PCM. To reduce the overall optical power consumption in particular for large PIC-based neural networks, only the real part of the refractive index should be altered, for example by using optical phase shifters, which act as synaptic elements.

Using ferroelectric thin layers of barium titanate (BTO), we demonstrate such non-volatile phase shifters on a silicon photonics platform. In these BTO-based devices, we exploit ferroelectric domain flipping in the BTO layer to non-volatilely change the propagation index of the optical mode. To show this new concept, we use photonic resonators made from a silicon photonic waveguide on top of a few hundred nanometer thick BTO layer as a memory element (**Error! Reference source not found.**) [8]. The index of the optical mode depends on the ferroelectric domain pattern in the BTO film, which is modified by applying electrical pulses to electrodes parallel to the waveguide. Changing the ferroelectric domains varies the effective electro-optic Pockels effect in the BTO layer. Consequently, the refractive index in BTO non-volatilely changes when biasing the film.

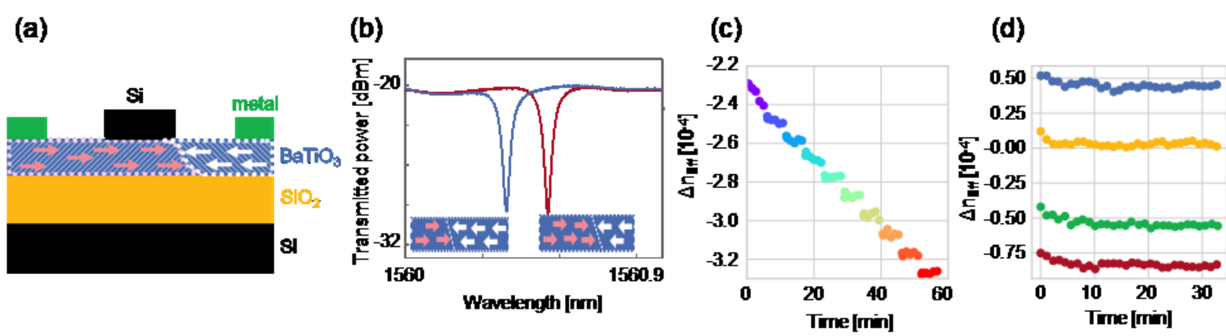

Fig. 2. (a) Schematic of the cross section of a non-volatile optical phase shifter using ferroelectric barium titanate thin layers. Arrows indicate ferroelectric domains. (b) By applying electrical pulses, the domain configuration is altered, and the transmission spectrum is changed due to (c) multiple different refractive indices present in the waveguide at constant bias. (d) the states are stable in time but do show imperfections compared to weights implemented in software, such as drift and noise.

We demonstrate the concept of that new component by applying electrical voltage pulses of 100 ns duration to resonant weighting devices and by analyzing the transmission spectra. We achieve multiple transmission states that are stable for hours. Still, the physical weights suffer from setting and reading noise, as well as long-term drifts. Such non-idealities impact the performance of any neural network when used as synaptic weight. We analyze the influence of these physical imperfections on the performance of a photonic reservoir system and compare the performance with ideal software weights [15].

4. Conclusion

Recently, novel computing concepts such as optical neural networks have been mapped into PICs. These circuits show great potential for fast and low-power data processing with very low latency. While many of the building blocks needed for such circuits already exists in a scalable way today, storage of information in the optical circuits is still an unsolved challenge. We demonstrate an option to realize such function by integrating ferroelectric barium titanate thin films into a silicon photonic platform. We show the working principle of these new synaptic elements and estimate the influence of physical imperfections such as noise and drift on the performance of reservoir computing system, a special implementation of a recurrent optical neural network.

5. References

[1] J. Wang *et al.*, "Multidimensional quantum entanglement with large-scale integrated optics," *Science (80-.).*, vol. 291, no. April, pp. 285–291, 2018.

[2] J. S. Fandiño, P. Muñoz, D. Doménech, and J. Capmany, "A monolithic integrated photonic microwave fi lter," *Nat. Photonics*, vol. 11, no. 2, pp. 124–129, 2016.

[3] Y. Shen *et al.*, "Deep Learning with Coherent Nanophotonic Circuits," *Nat. Photonics*, vol. 1, no. June, pp. 441–446, Jun. 2017.

[4] D. Kielpinski *et al.*, "Information processing with large-scale optical integrated circuits," *2016 IEEE Int. Conf. Rebooting Comput. ICRC 2016 - Conf. Proc.*, pp. 1–4, 2016.

[5] K. Vandoorne *et al.*, "Experimental demonstration of reservoir computing on a silicon photonics chip," *Nat. Commun.*, vol. 5, p. 3541, Mar. 2014.

[6] M. Seifried *et al.*, "Monolithically Integrated CMOS-Compatible III – V on Silicon Lasers," vol. 24, no. 6, 2018.

[7] C. Ríos *et al.*, "Integrated all-photonic non-volatile multi-level memory," *Nat. Photonics*, vol. 9, no. September, pp. 725–732, 2015.

[8] S. Abel *et al.*, "Large Pockels effect in micro- and nano- structured barium titanate integrated on silicon," *Nat. Mater.*, vol. 18, no. 1, pp. 42–47, 2019.

[9] A. Katumba *et al.*, "Neuromorphic Computing Based on Silicon Photonics and Reservoir Computing," *IEEE J. Sel. Top. Quantum Electron.*, vol. 24, no. 6, pp. 1–10, 2018.

[10] M. Freiberger, A. Katumba, P. Bienstman, and J. Dambre, "Training Passive Photonic Reservoirs With Integrated Optical Readout," *IEEE Trans. Neural Networks Learn. Syst.*, vol. PP, pp. 1–11, 2018.

[11] A. Katumba, X. Yin, J. Dambre, and P. Bienstman, "A Neuromorphic Silicon Photonics Nonlinear Equalizer for Optical Communications with Intensity Modulation and Direct Detection," *J. Light. Technol.*, vol. 37, no. 10, pp. 2232–2239, 2019.

[12] P. R. Prucnal, B. J. Shastri, T. Ferreira de Lima, M. A. Nahmias, and A. N. Tait, "Recent progress in semiconductor excitable lasers for photonic spike processing," *Adv. Opt. Photonics*, vol. 8, no. 2, p. 228, 2016.

[13] J. Zhang *et al.*, "Transfer-printing-based integration of a III-V-on-silicon distributed feedback laser," *Opt. Express*, vol. 26, no. 7, p. 8821, 2018.

[14] Z. Cheng, C. Ríos, W. H. P. Pernice, C. D. Wright, and H. Bhaskaran, "On-chip photonic synapse," vol. 2, no. September, pp. 1–7, 2017.

[15] P. Stark *et al.*, "Non-Volatile Photonic Weights and Their Impact on Photonic Reservoir Computing Systems," in *Conference on Lasers and Electro-Optics Europe and European Quantum Electronics Conference*, 2019, p. jsi_1_3.