Enabling Optical Modulation Format Identification Using an Integrated Photonic Reservoir and a Digital Multiclass Classifier

Guillermo von Hünefeld(1,2), Gregor Ronniger(1), Pooyan Safari(1), Isaac Sackey(1), Rijil Thomas(3), Enes Seker(3,4), Piotr Cegielski(3), Stephan Suckow(3), Max Lemme(3,4), David Stahl(5), Sarah Masaad(6), Emmanuel Gooskens(6), Peter Bienstman(6), Colja Schubert(1), Johannes Karl Fischer(1), and Ronald Freund(1,2)

(1) Fraunhofer Institute for Telecommunications, HHI, Einsteinufer 37, 10587 Berlin, Germany
(Email: guillermo.von.huenefeld@hhi.fraunhofer.de)
(2) Technical University of Berlin, Photonic Communication Systems, 10587 Berlin, Germany
(3) AMO GmbH, Advanced Microelectronic Center Aachen, 52074 Aachen, Germany
(4) RWTH Aachen University, Chair of Electronic Devices, 52074 Aachen, Germany
(5) ID Photonics GmbH, 85579 Neubiberg, Germany
(6) Ghent University, Photonics Research Group, Department of Information Technology - imec, Belgium.

Abstract *We numerically show modulation format identification in the optical domain using Silicon-on-Insulator-based Photonic-Integrated-Circuit (PIC) reservoir. We fabricate the reservoir's building-blocks and use the experimental results to model the PIC layout. Identification of 32 GBd single-polarization signals of OOK, PAM4, BPSK and QPSK is successfully achieved.*

Introduction

Reducing power consumption and latency represent essential requirements for optical networks in 5G and beyond. The recent advances in hardware-based artificial Neural Networks (NN) technologies provides promising energy-efficient solutions compared to the traditional computing approaches based on von Neumann architectures [1]. Reservoir computing presents an attractive low cost alternative to other NN architectures primarily due to the reduced complexity in the training of its weights [2-3].

To achieve a more efficient transmission, a better use of the existing infrastructure at any given moment and for any given throughput requirement, current optical networks employ different modulation formats. This approach creates the demand for devices which can identify the modulation format present in an optical link. Current solutions to this problem include expensive equipment on the receiver side which increase the complexity system [4]. Thus, both the capital expenditure and operational cost can scale up significantly. Furthermore, digital domain solutions for format identification [4-5] will suffer from scaling limitations of CMOS.

However, photonic reservoirs have the potential of providing an all-optical solution and as such benefit from ultra-high processing speeds and parallelism compared to their electronic-domain counterparts [6-8]. Still better, realization of a photonic reservoir on standard planar waveguides such as Silicon-on-Insulator (SOI) is a promising approach due to its smaller footprint and the possibility to utilize the commercially available CMOS technologies.

In this paper, we present a numerical analysis and evaluation of a photonic domain NN that is capable of identifying optical modulation formats. We exploit SOI waveguides on a PIC to realize the reservoir, and its building blocks have practical parameters obtained from AMO's nanophotonic SOI platform, available as foundry offering [9]. To train, validate and test our Modulation Format Identification (MFI) NN model, we use 32 GBd single-polarization data of four different modulation formats (i.e., On-Off Keying (OOK), 4-level Pulse-Amplitude

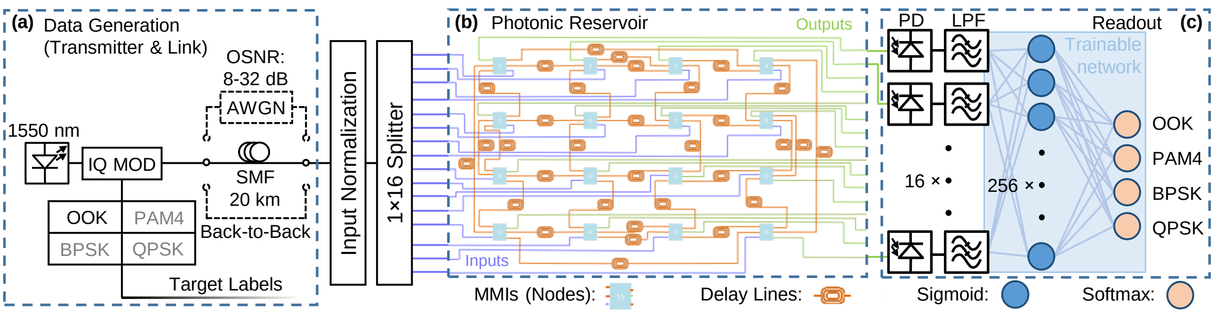

Fig. 1: Depiction of the simulation setup showing: (a) the data generation stage for 4 different modulation formats, (b) a four-port 16-node SOI-based photonic integrated circuit reservoir and (c) a multiclass classifier assisted readout layer.

Modulation (PAM4), Binary Phase-Shift Keying (BSPK), and Quadrature Phase-Shift Keying (QPSK)).

Generation of Test Data

Fig. 1(a) shows the implemented simulation setup of the transmitter using *VPIphotonics Design Suite 11.1* [10]. The investigations were conducted for four different modulation formats (OOK, PAM4, BPSK and QPSK). For each modulation format, six different scenarios were simulated, namely; one back-to-back (b2b) scenario, four scenarios with different levels of Additive White Gaussian Noise (AWGN) and finally one scenario with a 20 km Standard Single-Mode fiber (SSMF), to allow the introduction of polarization mode dispersion and chromatic dispersion. The goal was to compare the accuracy of the format predictions under these different conditions. All the signals have a symbol rate of 32 GBd. For each format and scenario, 2^{19} symbols were generated and transmitted, making the total number of symbols in the dataset around 12.6 million. The data collected after the links is what we consider as the actual input for our PIC-based SOI photonic reservoir for the MFI. At the input of the reservoir, the optical signals were normalized to have the same average power for each format and were split equally into all nodes.

SOI-based Photonic Reservoir

Reservoir networks are a type of recurrent network in which the signals from current and previous symbols mix together. Contrary to a recurrent NN, all connections inside the reservoir are fix. The intersymbol mixing is driven by delay lines which determine its timescale (typically on the order of symbol duration).

We translated the logical layout sketched in Fig. 1(b) into a physical PIC layout. We fabricated and characterized its main components (waveguides and Multi-Mode Interferometer (MMI) splitters) and used these measurement results as inputs for a circuit level simulation of the PIC. The used architecture has a four-port topology as reported in Ref. [7], [12]. The computational structure of this topology has been shown to be capable of solving key known complex tasks including XOR calculation and header recognition [7-8], [11-12]. Each node in the reservoir was realized by a 3×3 MMI, and connected to four neighbouring MMIs via fixed-delay waveguides. One of the remaining two ports of each MMI served as input whereas the last port was connected to the output of the reservoir as shown in Fig. 1(b). Note that for this particular task, we used a 16-node architecture (with 16 inputs and 16 outputs). The design was optimized for 1-channel signals with a center wavelength of 1550 nm and a symbol rate of 32 GBd. We performed a parameter sweep of the delay lengths to optimize MFI performance, and the optimum length of the interconnecting waveguide between the MMIs was found to be 3.68 mm (i.e., a group delay of 47 ps). The reservoir was implemented using the *Photontorch* photonic simulator developed at Ghent University [13].

Readout

Fig.1(c) depicts the used electrical readout of our model, where optical signals are first translated into the electrical domain using photodiodes (PDs), subsequently linearly combined and weighted in the digital domain. Several approaches can be used to realize the readout [8], [11-12], [14]. For a practical implementation, that would require analog-to-digital converters, but for this numerical evaluations the data is already in the digital domain. This approach allows for a simplified prototyping with simpler optical components as also shown in [12]. The digital part can be trained by conventional methods such as offline computing, online evaluations using a Field Programmable Gate Array (FPGA), or using a specifically developed electrical circuit. The electrical data at the output of each PD was normalized, filtered by Finite Impulse Response (FIR) Low-Pass Filter (LPF) and down sampled to a single data point for every 320 received symbols. Note that we intentionally identified the modulation formats at a rate of 100 MHz. The resampled signals for all 16 outputs were then sent to the NN designed as a multiclass classifier [15]. In this implementation, the multiclass classifier consisted of a hidden layer with 256 nodes and a sigmoid activation function, followed by the output layer with 4 nodes and a *Softmax* function [15]. Each node in the output layer corresponded to one of the modulation formats to be identified, and the output with the largest value was taken as the actual prediction for the current input signal.

Training of Classifier for MFI

The training of our model was exclusively done on the multiclass classifier stage. The whole model was implemented combining the use of the *Pytorch* [16] and *Scikit-learn* frameworks [17].

A cross-validation scheme was used on the dataset with 10 stratified folds for each case. Each was divided into approximately 80% training, 10% validation and 10% testing subsets, while maintaining a balance of the classes throughout each partition. The training was arranged in up to 100 epochs for each fold, each using a batch size of 64 data points. To avoid

Tab. 1: Results for models trained and tested for different scenarios, averaged over all 10 folds.

Link distortion	OSNR	Prediction Precision				Prediction Accuracy	Cross-Validation Standard Deviation
		OOK	PAM4	BPSK	QPSK		
Back-to-Back	ideal	99.94%	100%	95.23%	95.97%	97.78%	0.787
White Gaussian Noise	32 dB	99.94%	100%	99.76%	98.05%	99.44%	0.322
	24 dB	99.94%	100%	95.48%	94.99%	97.60%	0.738
	16 dB	89.50%	100%	92.67%	87.73%	92.48%	0.404
	8 dB	93.35%	97.68%	73.87%	60.38%	81.32%	7.680
Polarization Mode and Chromatic Dispersion	ideal	99.88%	100%	97.74%	97.25%	98.72%	0.395

overfitting and speed up the training, after the first 50 epochs, we implemented early-stopping when there was no improvement for 10 consecutive epochs. Adam was chosen as the optimizer [18]. The cross-entropy loss was computed on the last layer and minimized during the training. Both learning rate and weight decay were set to 0.001.

Results

The average results over all 10 folds show that, independently from the scenario, the predictions in relation to the two amplitude modulation formats, OOK and PAM4, have a better precision compared to the phase modulated ones, BPSK and QPSK. Most of the incorrect predictions occur when a QPSK signal was incorrectly identified as BPSK, and vice versa. This can be clearly seen in Tab.1 and 2.

When comparing the performance with AWGN present in the link, one can clearly see a trend, where a lower Optical Signal-to-Noise Ratio (OSNR) translates directly to a drop in the accuracy of the predictions. For this comparison, we trained our model independently with subsets of our data with different OSNR levels. One interesting result is that a certain level of dispersion and noise in the signals will improve the accuracy of the predictions. When dispersion occurs, consecutive symbols on the signal will begin to overlap and mix, also increasing the level of intersymbol interference inside the reservoir, which could be the reason for the

Labels \ Predictions	OOK	PAM4	BPSK	QPSK
OOK	99.94 %	0.06 %	0 %	0 %
PAM4	0 %	100 %	0 %	0 %
BPSK	0 %	0 %	95.23 %	4.77 %
QPSK	0 %	0 %	4.03 %	95.97 %

Tab. 2: Confusion matrix of the model trained and tested using the back-to-back scenario.

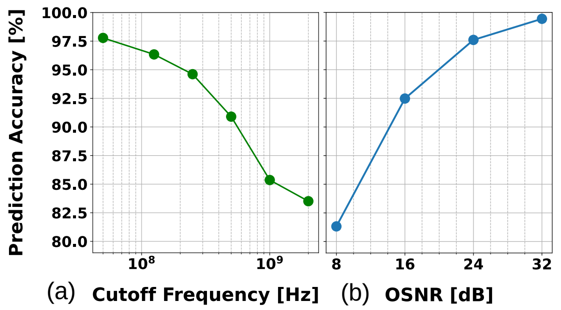

Fig. 2: (a) Prediction Accuracy vs cutoff frequency of the FIR filter on b2b. (b) Prediction Accuracy vs OSNR (in 0.1 nm). Each model was trained and tested with a different OSNR.

increase in the performance. The results, which include the standard deviation of prediction accuracy across the 10 folds for the cross-validation, are shown in Tab. 1. Lowering the cutoff frequency on the FIR filter inside the readout, which corresponds to a wider impulse response in time domain, resulted in an increased performance as shown in Fig. 2(a). The impact of the OSNR level on the accuracy of the prediction can be seen in Fig. 2(b).

Conclusions

In this paper, we have presented the accuracy of the predictions of a reservoir network regarding modulation format identification on optical telecommunication systems. We focus our analysis on signals with a symbol rate of 32 GBd. The network can correctly predict the modulation format of links using OOK, PAM4, BPSK and QPSK with very high accuracy. In future works, we plan to extend the amount of identifiable modulation formats, beyond this proof-of-concept approach, to include more widely utilized schemes with higher-order constellation that allow the transmission of more bits per symbol.

Acknowledgements

Funded by the German Bundesministerium für Bildung und Forschung (BMBF) under the CELTIC-NEXT AI-NET-PROTECT project with grants 16KIS1281, 16KIS1291, 16KIS1301, and under 6G-RIC project with grants 16KISK020K and 16KISK030.

References

[1] A. S. Cassidy, R. Alvarez-Icaza, F. Akopyan, J. Sawada, J. V. Arthur, P. A. Merolla, P. Datta, M. G. Tallada, B. Taba, A. Andreopoulos, A. Amir, S. K. Esser, J. Kusnitz, R. Appuswamy, C. Haymes, B. Brezzo, R. Moussalli, R. Bellofatto, C. Baks, M. Mastro, K. Schleupen, C. E. Cox, K. Inoue, S. Millman, N. Imam, E. McQuinn, Y. Y. Nakamura, I. Vo, , C. Guo, D. Nguyen, S. Lekuch, S. Asaad, D. Friedman, B. L. Jackson, M. D. Flickner, W. P. Risk, R. Manohar and D. S. Modha, ''Real-time Scalable Cortical Computing at 46 Giga-Synaptic OPS/Watt with ~100× Speedup in Time-to-Solution and ~100,000× Reduction in Energy-to-Solution, '' International Conference for High Performance Computing, Networking, Storage and Analysis, vol. 2015-January, pp. 27-38, IEEE Computer Society, 2014, DOI: https://doi.org/10.1109/SC.2014.8

[2] S. Li, and S. Pachnicke, "Photonic reservoir computing in optical transmission systems", *ieee photonics society summer topicals meeting series (sum)*, pp. 1-2, 2020, DOI: https://doi.org/10.1109/SUM48678.2020.9161045

[3] A. Argyris, J. Cantero, M. Galletero, E. Pereda, C. R. Mirasso, I. Fischer, and M. C. Soriano, "Comparison of photonic reservoir computing systems for fiber transmission equalization, *IEEE Journal of Selected Topics in Quantum Electronics*, *26*(1), pp. 1-9, 2019, DOI: https://doi.org/10.1109/JSTQE.2019.2936947

[4] F.N. Khan, K. Zhong, W. H. Al-Arashi, C. Yu, C. Lu, and A. P. T. Lau, "Modulation format identification in coherent receivers using deep machine learning", *IEEE Photonics Technology Letters*, *28*(17), pp. 1886-1889, 2016, DOI: https://doi.org/10.1109/LPT.2016.2574800

[5] S. Zhang, Y. Peng, Q. Sui, J. Li, Z. and Li, "Modulation format identification in heterogeneous fiber-optic networks using artificial neural networks and genetic algorithms", *Photonic Network Communications*, *32*(2), pp. 246-252, 2016,
DOI: https://doi.org/10.1364/OE.20.012422

[6] L. Appeltant, M. C. Soriano, G. Van der Sande, J. Danckaert, S. Massar, J. Dambre, and I. Fischer, "Information processing using a single dynamical node as complex system", *Nature communications*, *2*(1), pp. 1-6, 2011,
DOI: https://doi.org/10.1038/ncomms1476

[7] A. Katumba, "Energy-efficient photonic neuromorphic computing for telecommunication applications", *Doctoral dissertation*, Ghent University, 2019.

[8] M. Freiberger, A. Katumba, P. Bienstman, and J. Dambre, "On-chip passive photonic reservoir computing with integrated optical readout", *IEEE International Conference on Rebooting Computing (ICRC)*, pp. 1-4, 2017,
DOI: https://doi.org/10.1109/ICRC.2017.8123673

[9] A. Rahim, J. Goyvaerts, B. Szelag, J. M. Fedeli, P. Absil, T. Aalto, and R. Baets, "Open-access silicon photonics platforms in Europe", *IEEE Journal of Selected Topics in Quantum Electronics*, *25*(5), pp 1-18, 2019, DOI: https://doi.org/10.1109/JSTQE.2019.2915949

[10] VPIphotonics, "VPItransmissionMaker Optical Systems", [online] Available: https://www.vpiphotonics.com/Tools/OpticalSystems/.

[11] K. Vandoorne, P. Mechet, T. Van Vaerenbergh, M. Fiers, G. Morthier, D. Verstraeten, P. and Bienstman, "Experimental demonstration of reservoir computing on a silicon photonics chip", *Nature communications*, *5*(1), pp. 1-6, 2014,
DOI: https://doi.org/10.1038/ncomms4541

[12] S. Sackesyn, C. Ma, J. Dambre, and P. Bienstman, "Experimental Demonstration of Nonlinear fibre Distortion Compensation with Integrated Photonic Reservoir Computing", *European Conference on Optical Communication (ECOC)*, pp. 1-4, IEEE, 2021, DOI: https://doi.org/10.1109/ECOC52684.2021.9606162

[13] R. Khan, Y. Qiang, A. B. Tufail, and A. Noor, "Multiclass Classification of Modulation Formats in the presence of Rayleigh and Rician Channel Noise using Deep Learning Methods", *3rd International Conference on Information and Communications Technology (ICOIACT),* pp. 297-301, IEEE, 2020, DOI: https://doi.org/10.1109/ICOIACT50329.2020.9332035

[14] Q. Cai, Y. Guo, P. Li, A. Bogris, K. A. Shore, Y. Zhang, and Y. Wang, "Modulation format identification in fiber communications using single dynamical node-based photonic reservoir computing", *Photonics Research*, 9(1), pp. B1-B8, 2021, DOI: https://doi.org/10.1364/PRJ.409114

[15] F. Laporte, J. Dambre, and P. Bienstman, "Highly parallel simulation and optimization of photonic circuits in time and frequency domain based on the deep-learning framework pytorch", *Scientific reports*, 9(1), pp. 1-9, 2019, DOI: https://doi.org/10.1038/s41598-019-42408-2

[16] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, and S. Chintala, "Pytorch: An imperative style, high-performance deep learning library", *Advances in neural information processing systems*, pp. *32*, 2019, DOI: https://doi.org/10.48550/arXiv.1912.01703

[17] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, and E. Duchesnay, "Scikit-learn: Machine learning in Python", *The Journal of machine Learning research*, 12, pp. 2825-2830, 2011,
DOI: https://doi.org/10.48550/arXiv.1201.0490

[18] D. P. Kingma, and J. Ba, "Adam: A method for stochastic optimization", *International Conference on Learning Representations (ICLR)*, 2014.