Emmanuel Gooskens Photonics Research Group Ghent University-IMEC Gent, Belgium Emmanuel.Gooskens@UGent.be Stijn Sackesyn Photonics Research Group Ghent University-IMEC Gent, Belgium Stijn.Sackesyn@UGent.be Sarah Masaad Photonics Research Group Ghent University-IMEC Gent, Belgium Sarah.Masaad@UGent.be Joni Dambre Computer Systems Laboratory Ghent University Gent, Belgium Joni.Dambre@UGent.be

Peter Bienstman Photonics Research Group Ghent University-IMEC Gent, Belgium Peter.Bienstman@UGent.be

Abstract—We seek to improve nonlinear fiber distortion mitigation for wavelength multiplexed telecommunications in terms of both processing speed and energy efficiency. We propose a photonic reservoir computing hardware implementation maximizing the chip footprint to processing power ratio by employing a single readout for all wavelengths.

Index Terms—photonics, reservoir computing, signal equalization, wavelength division multiplexing

I. INTRODUCTION

Reservoir computing (RC) employs a randomly initialised fixed recurrent neural network (RNN), called the reservoir, which is left untrained and to which a simple linear readout layer is added. We show that a single-readout photonic reservoir system can perform with $< 10^{-3}$ BER on several wavelength division multiplexing (WDM) channels in parallel for nonlinear fiber distortion mitigation. There are many potential photonics-based reservoir computing hardware implementations. Among those investigated are systems consisting of a single non-linear node with feedback and free-space reservoir systems [1]–[10]. The former use only a single node, which limits data bandwidth, while the latter is not as compact, fast or cost-efficient as integrated systems. Here, we will focus on a multi-node waveguide-based integrated RC system. Such systems have been proven to perform well for various tasks such as bit-level tasks, nonlinear dispersion compensation and isolated spoken digit recognition [11]-[14]. However, the footprint of waveguide-based photonic reservoirs, where waveguides form the interconnects and nodes consists of optical elements such as multimode interferometers [10], is typically on the order of one to a few tens of mm^2 . This large footprint translates into added cost, which negatively impacts economic viability. In this paper we make more efficient use of a given chip area by exploiting wavelength division multiplexing. Similar ideas have been explored in e.g. [15]-[17], although using different reservoir architectures and

This research is funded by Fonds Wetenschappelijk Onderzoek (3S044419).

technologies. We want to use a single set of weights for all wavelengths, as having a separate sets of weights for each wavelength would eliminate all the chip area savings.

II. OVERVIEW MEASUREMENT SETUP AND RESERVOIR

The measurement setup is shown in figure 1. The reservoir nodes are optically probed and detected by a photodiode one at a time. The signal is repeated in time entirely for each node to accomplish this. These electrical time traces are saved on a computer and the linear combination of these traces is done in post-processing on a computer. The amplifier in front of the fiber is an artificial means of increasing nonlinear distortion effects in the fiber and thus specifying the difficulty of the task to be solved by our reservoir computer. For these experiments the input power to the fiber $\approx 5 dBm$.



Fig. 1. Schematic illustration of the setup used in the experiment.

The architecture that is used is the four-port architecture [18]. It refers to the four ports of each node that are connected to other nodes in the reservoir, following the network connection scheme, as shown schematically in figure 2. The nodes consist of 3x3 multimode interferometers (MMIs). The nonlinearity required for nonlinear tasks is supplied by the inherent nonlinearity of the photodetector.



Fig. 2. four-port architecture schematic

III. WDM WITH SINGLE READOUT

The main reason why reservoir performance depends on input wavelength is the resulting variation in phase shifts in the waveguide interconnections. This leads to altered signal mixing for which the readout was not trained, leading to an incorrect weighting and recombination of node outputs. It is thus necessary to include all different target wavelengths in training. The training of the weights consists mainly of a ridge regression algorithm [19] in which normalization is allowed. The labels used for training are the digital on-off keying bit stream [20]. We investigate 2 wavelengths seperated by a standard dense WDM frequency spacing of 12.5 GHz in the C band. Results are shown in figure 3.



Fig. 3. a) distorted signal b) result for single wavelength training c) result for 2 wavelength training

Note that the number of test bits used, 10^5 , limits the statistically relevant BER resolution to roughly 10^{-3} .

IV. CONCLUSION

we demonstrated experimentally that a single-readout photonic RC system can perform nonlinear fiber distortion mitigation with $< 10^{-3}$ BER at several wavelength channels for nonlinear fiber distortion mitigation. This clears the way toward commercial viability of photonic RC systems for nonlinear fiber distortion mitigation of WDM signals as the same chip footprint now has significantly increased processing power and reliability.

V. ACKNOWLEDGEMENTS

This research is funded by Fonds Wetenschappelijk Onderzoek (3S044419). Parts of this work were performed under the EU H2020 program under grant agreements 871658 (Nebula), 871330 (NEoteRIC) and 101017237 (PHOENICS).

REFERENCES

- D. Brunner, B. Penkovsky, B. A. Marquez, M. Jacquot, I. Fischer, and L. Larger, "Tutorial: Photonic neural networks in delay systems", Journal of Applied Physics, vol. 124, no. 15, p. 152 004, 2018.
- [2] Q. Vinckier, F. Duport, A. Smerieri, et al., "Highperformance photonic reservoir computer based on a coherently driven passive cavity", Optica, vol. 2, no. 5, pp. 438–446, 2015.
- [3] A. Dejonckheere, A. Smerieri, L. Fang, J. I. Oudar, M. Haelterman, and S. Massar, "All-optical reservoir computer based on saturation of absorption", Optics Express, vol. 22, no. 9, pp. 10 868–10 881, 2014.
- [4] R. M. Nguimdo, G. Verschaffelt, J. Danckaert, and G. V. der Sande, "Fast photonic information processing using semiconductor lasers with delayed optical feedback: Role of phase dynamics", Optics Express, vol. 22, no. 7, pp. 8672–8686, 2014.
- [5] R. M. Nguimdo and T. Erneux, "Enhanced performances of a photonic reservoir computer based on a single delayed quantum cascade laser", Optics Letters, vol. 44, no. 1, pp. 49–52, 2019.
- [6] Y. Hou, G. Xia, W. Yang, et al., "Prediction performance of reservoir computing system based on a semiconductor laser subject to double optical feedback and optical injection", Optics Express, vol. 26, no. 8, pp. 10211–10219, 2018.
- [7] J. Vatin, D. Rontani, and M. Sciamanna, "Enhanced performance of a reservoir computer using polarization dynamics in vcsels", Optics Letters, vol. 43, no. 18, pp. 4497–4500, 2018.
- [8] G. Mourgias-Alexandris, G. Dabos, N. Passalis, A. TotoviA, A. Tefas, and N. Pleros, "All-optical wdm recurrent neural networks with gating", IEEE Journal of Selected Topics in Quantum Electronics, vol. 26, no. 5, pp. 1–7, 2020.
- [9] A. Argyris, J. Bueno, and I. Fischer, "Photonic machine learning implementation for signal recovery in optical communications", Scientific Reports, vol. 8, no. 8487, p. 8487, 2018.
- [10] A. Lugnan, A. Katumba, F. Laporte, et al., "Photonic neuromorphic information processing and reservoir computing", APL Photonics, vol. 5, no. 2, p. 020 901, 2020.
- [11] C. Mesaritakis, V. Papataxiarhis, and D. Syvridis, "Micro ring resonators as building blocks for an all-optical high-speed reservoir-computing bitpatternrecognition system", Journal of the Optical Society of America B, vol. 30, no. 11, pp. 3048–3055, 2013.
- [12] C. Mesaritakis, A. Kapsalis, and D. Syvridis, "All-optical reservoir computing system based on ingaasp ring resonators for high-speed identification and optical routing in optical networks", Proceedings of SPIE, vol. 9370, no. 937033, p. 937 033, 2015.
- [13] A. Katumba, M. Freiberger, F. Laporte, et al., "Neuromorphic computing based on silicon photonics and reservoir computing", IEEE Journal of Selected Topics in Quantum Electronics, vol. 24, no. 6, pp. 1–10, 2018.
- [14] E. Gooskens, F. Laporte, C. Ma, S. Sackesyn, J. Dambre, and P. Bienstman, "Wavelength dimension in waveguide-based photonic reservoir computing", Optics Express, vol. 30, no. 9, pp. 15 634–15 647, 2022.
- [15] R. M. Nguimdo, G. Verschaffelt, J. Danckaert, and G. V. der Sande, "Simultaneous computation of two independent tasks using reservoir computing based on a single photonic nonlinear node with optical feedback", IEEE Transactions on Neural Networks and Learning Systems, vol. 26, no. 12, pp. 3301–3307, 2015.
- [16] F. Duport, A. Smerieri, A. Akrout, M. Haelterman, and S. Massar, "Virtualization of a photonic reservoir computer", Journal of Lightwave Technology, vol. 34, no. 9, pp. 2085–2091, 2016.
- [17] A. Akrout, A. Bouwens, F. Duport, Q. Vinckier, M. Haelterman, and S. Massar, Parallel photonic reservoir computing using frequency multiplexing of neurons, https: //arxiv.org/abs/1612.08606.
- [18] Stijn Sackesyn and Chonghuai Ma and Joni Dambre and Peter Bienstman, An enhanced architecture for silicon photonic reservoir computing, Cognitive Computing 2018 - Merging Concepts with Hardware (2018), pp.1-2.
- [19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research 12(85), 2825–2830 (2011).
- [20] S. Sackesyn, C. Ma, J. Dambre, and P. Bienstman, "Experimental realization of integrated photonic reservoir computing for nonlinear fiber distortion compensation", Optics Express, vol. 29, no. 20, pp. 30991– 30997, 2021.