Fully-blind Neural Network Based Equalization for Severe Nonlinear Distortions in 112 Gbit/s Passive Optical Networks

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Abstract: We demonstrate and evaluate a fully-blind digital signal processing (DSP) chain for 100G passive optical networks (PONs), and analyze different equalizer topologies based on neural networks with low hardware complexity. © 2023 The Author(s)

1. Introduction

In recent decades, passive optical networks (PONs) have been the key technology to enable broadband internet access in cities worldwide. Since PONs are primarily used for fiber-to-the-home (FTTH), the end-user transceivers must be cheap and power efficient while covering the increasing demand of data rates. For this reasons, they typically rely on intensity-modulation and direct-detection (IM/DD) of the optical signal. Current research is focusing on data rates beyond recent 50G-PON standardization efforts [1], i.e., towards PONs which are capable of delivering $100\,\mathrm{Gbit/s}$ [2]. Since cost-effective hardware hinders increasing the symbol rate, the focus shifts towards higher-order modulation formats such as 4-ary pulse amplitude modulation (PAM4). However, compared to conventional on-off-keying (OOK), which is used until 50G-PON, multi-level modulation formats are more prone to nonlinerities and, due to its reduced signal-to-noise ratio (SNR) tolerance, require optical amplification. The utilized low-cost semiconductor optical amplifiers (SOA) distort the signal at high received optical power (ROP) due to nonlinear gain saturation, which reduces the dynamic range [3]. Additionally, electro-absorption modulators (EAMs) distort the signal at the transmitter due to their nonlinear electro-optical power transfer function and, chromatic dispersion (CD) corresponds to a nonlinear effect in an IM/DD link, which limits high-speed PONs, even in the O-band [1].

Digital linear equalization, as introduced in the 50G-PON standard, can compensate for such nonlinear distortions only to a certain extent. Thus, nonlinear equalization methods draw attention of the community. In particular, machine learning using neural networks (NNs), which proved to be highly capable of compensating for nonlinear impairments, is a contender for future equalizers. Current work focuses on the correction of isolated effects such as distortions by the SOA [3], or CD [4, 5]. However, all of these works considered supervised learning meaning that they require known training sequences or intense offline learning. Hence, these algorithms cannot adapt to varying transmission parameters or require pilot sequences, which significantly reduce the net data rate.

This work contains two major contributions. Firstly, we apply a novel blind adaptive learning algorithm inspired by a vector-quantized variational autoencoder (VQVAE) [6] and combine it with a blind digital signal processing (DSP) chain [7], which allows us to transmit fully-blindly $112\,\mathrm{Gbit/s}$ through a PON upstream with an EAM at the optical network unit (ONU) and with an SOA at the optical line terminal (OLT). Precisely, we transmit PAM4 at $56\,\mathrm{GBd}$ for a distance of $2.2\,\mathrm{km}$ in C-band ($D \approx 15.5\,\mathrm{ps/nm/km}$), which corresponds to approx. $9\,\mathrm{km}$ in O-band upstream at $1270\,\mathrm{nm}$ ($D \approx -3.7\,\mathrm{ps/nm/km}$), and investigate the equalization algorithm under all impairments mentioned above. Secondly, we investigate NN topologies which are reasonable from a hardware implementation perspective, and compare them to other state-of-the-art NN topologies such as gated recurrent units (GRUs).

2. Blind Adaptive NN-based Equalizers

A promising algorithm to blindly and adaptively update NN-based equalizers is the recently-proposed VQVAE-inspired learning algorithm [6]. While it can be derived from statistics and the concept of variational inference, which enables maximum likelihood (ML) approximating estimation, it boils down to a rather simple loss function used to update the equalizer parameters, $\mathcal{L} = \beta\,||\tilde{\boldsymbol{x}} - \hat{\boldsymbol{x}}||^2 + (1-\beta)\,||\boldsymbol{y} - f_\theta(\hat{\boldsymbol{x}})||^2$, where β is a weighting factor, $\boldsymbol{y}$ are the received samples, $\tilde{\boldsymbol{x}}$ is the equalizer output, $\hat{\boldsymbol{x}}$ are the expected symbols after hard decision, and $f_\theta(\cdot)$ is a channel estimator, e.g., another NN, which is also learned during training. As a byproduct, latter provides valuable information for, e.g., quality of service (QoS) estimation. In fact, the loss function consists of two terms, where the first (commitment loss) comes down to a decision-directed (DD) least mean squares (LMS) loss while the second term (reconstruction loss) tries to reconstruct the received signal from the detected signal using the learned channel estimate. While the latter is especially important for the startup phase, the weighting factor β allows to shift more towards the DD-LMS loss after convergence. For this reason, we employ a scheduler which increases β by a factor of a_β after every N_β-th training iteration. We use Adam [8], a gradient descent based optimizer,

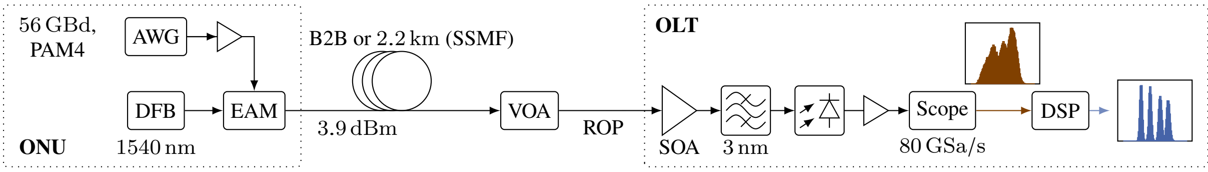

Fig. 1: Experimental setup for the 112 Gbit/s (56 GBd) PON upstream through a standard single mode fiber (SSMF) in the C-band.

and another scheduler with a_{lr} and N_{lr} to control the learning rate. Per sequence, we have 7600 training iterations of 720 samples each at two samples per symbol (sps) per iteration. All remaining hyperparameters have been optimized at $\mathrm{ROP} = -2\,\mathrm{dBm}$ using a Bayesian search.

We consider two main types of NNs, namely GRUs and convolutional neural networks (CNNs), which are compared to a commonly-used linear finite impulse response (FIR) filter. The NN sizes are chosen to be still feasible for practical implementation. For the GRU, we took the suggested topology from [3], where it was also analyzed for PONs. Precisely, we chose a large GRU with 180 real-valued multiplications (rvms) per symbol (3 input taps, 6 hidden GRU cells and one output tap), and a small with 51 rvms (8 input taps, 6 hidden GRU cells and 6 output taps). Note that latter has more learnable parameters, but reduces the rvms by moving the input block by six samples (instead of one sample) each time and outputting six equalized symbols at once. To accommodate for the oversampled input, the output sequence of the GRU is downsampled by sps = 2. It also should be mentioned that GRUs have in general an overhead in the required hardware resources due to the necessity of storing the state, the need of a hyperbolic tangent (tanh) and two sigmoid activation functions and the recurrent paths which constrain parallelization and introduce a routing overhead [9]. In contrast, the CNNs are easily implementable on a field-programmable gate array (FPGA) [10] and consist of three one-dimensional layers with simple rectified linear unit (ReLU) activation (after the first and second layer). The CNNs reduce the required rvms by strided convolutions with stride = $(2, 2, 2+\mathrm{sps})$ and output 8 equalized samples simultaneously. In fact, we choose a small CNN of 49 rvms with a kernel size $K = (7, 5, 7)$ and $C = (4, 4, 8)$ output channels per layer in a way that it allows implementation on the high-performance FPGA Xilinx XCVU13-P with the required throughput of 56 GBd [10]. For comparison, we also implemented a large CNN of 180 rvms with a kernel size $K = (11, 9, 9)$ and a number of output channels per layer $C = (7, 7, 8)$, as well as FIR filters of similar complexity with 51 taps and 181 taps.

The channel estimator of the VQVAE equalizer is implemented as two-layer CNN with $K = (11, 15)$, and $C = (5, 1)$, which is large enough to ensure proper channel estimation capabilities.

3. Experimental Setup and Results

In Fig. 1, we display the experimental setup, which emulates a PON upstream path. At the ONU side, we use a Keysight USPA DAC3 to generate a 56 Gbaud non-return-to-zero (NRZ) PAM4 signal with a sequence length of 2^{19} symbols and amplify it to a peak-to-peak voltage of 2 V to achieve a sufficient optical modulation amplitude at the low-cost EAM, which outputs an optical transmit power of 3.9 dBm. A distributed-feedback laser (DFB) provides the optical carrier at a wavelength of 1540 nm.

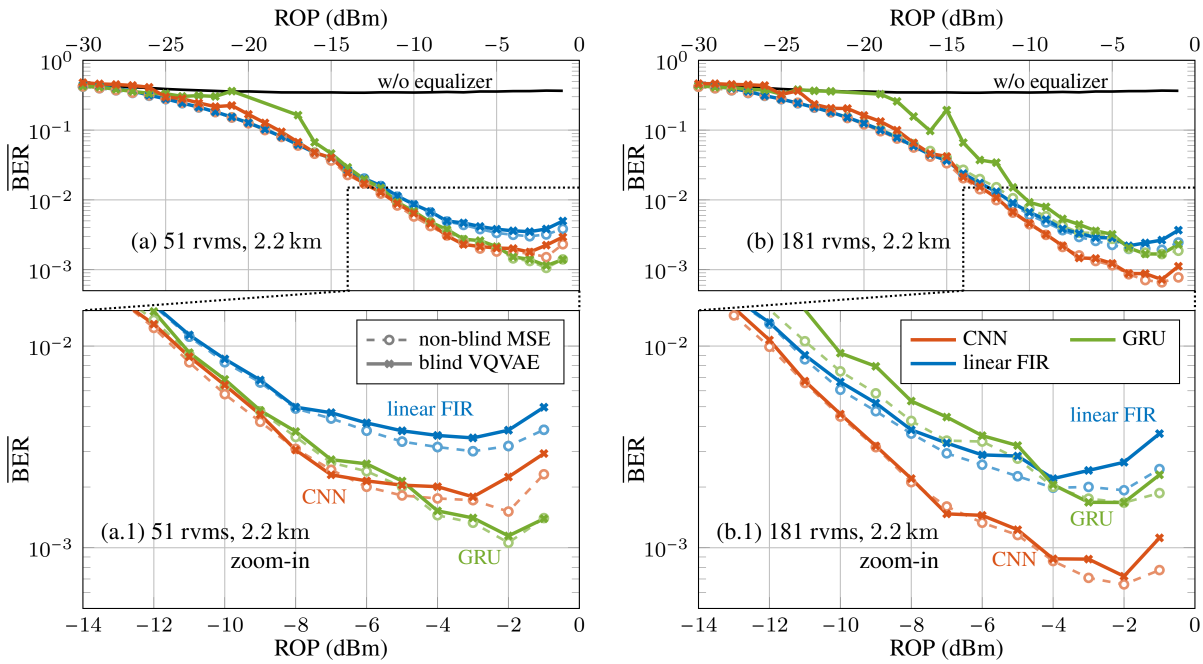

Fig. 2: Median $\overline{\mathrm{BER}}$ for a fiber length of 2.2 km (C-band) with NNs of 51 real-valued multiplications (rvms) (a) and 181 rvms (b) .

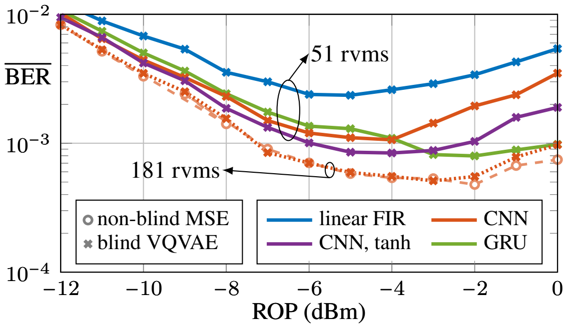

Fig. 3: Median $\overline{\mathrm{BER}}$ for optical back-to-back (B2B).

While propagating through the fiber, the signal accumulates CD and is attenuated by a variable optical attenuator (VOA) to set a certain ROP. At the receiver on the OLT-side, an SOA with a $3\,\mathrm{nm}$-bandpass filter accounts for the higher SNR requirements of PAM4 compared to OOK. We use a $40\,\mathrm{GHz}$-photodiode with conventional amplifier since there was no avalanche photodiode with transimpedance amplifier available in our lab during the time of the experiments, which would further improve the receiver sensitivity. Finally, the electrical signal is captured by a $33\,\mathrm{GHz}$-real-time oscilloscope at $80\,\mathrm{GSa/s}$ and resampled to two sps for the subsequent blind feed-forward clock recovery suitable for PONs [7] and the equalization. Either the blind VQVAE (indicated by cross markers) learning algorithm or, as a reference, the standard supervised (non-blind) mean squared error (MSE) loss (indicated by circle markers) is used to update the equalizer taps. The colors indicate different equalizer topologies. After every one-hundredth training iteration, the bit error rate (BER) is estimated over a test set of $50\,000$ symbols (cut from the same recorded sequence) and the last 10 estimates are averaged to get the mean $\overline{\mathrm{BER}}_{\mathrm{Seq}}$ per sequence. In total, 15 sequences are recorded per working point, and the median $\overline{\mathrm{BER}}$ is displayed in Fig. 2.

For the same number of rvms, the NN based equalizers outperform the linear FIR filters. In the strongly non-linear regime of ROP $> -3\,\mathrm{dBm}$, the GRU with 51 rvms reaches the lowest $\overline{\mathrm{BER}}$, while the CNN, which has a less complex ReLU activation function, has advantage in the more linear regime. Overall, the CNN with 180 rvms performs the best. For all topologies, the blind VQVAE algorithm approaches the performance of the non-blind MSE loss. Similar results can be seen in Fig. 3 for optical B2B. For the CNN with 49 rvms, the usage of a tanh activation function (purple) increases the performance.

Different channel estimator topologies for the VQVAE algorithm at $2.2\,\mathrm{km}$ and $-2\,\mathrm{dBm}$ are analyzed in Fig. 4 for the proposed equalizer topologies. The markers indicate the different estimators, which topologies are based on the similarly-named equalizers. *NetEst* corresponds to the above-described two-layered estimator CNN, which has been used so far along with the VQVAE. Different estimators work well for different equalizers, while the FIR based estimator with only 51 rvms performs good in general. This indicates that the estimator can be significantly simplified and optimized.

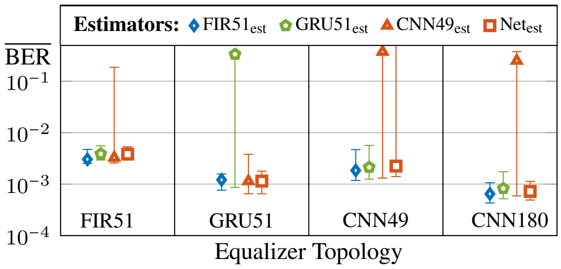

Fig. 4: Median $\overline{\mathrm{BER}}$ (markers) and the corresponding error bars (to the best and worst estimates per 15 captured sequences) at $2.2\,\mathrm{km}$, $-2\,\mathrm{dBm}$ for the proposed equalizers, trained by the blind VQVAE with different channel estimator nets.

4. Conclusion

We demonstrate the fully-blind transmission of $112\,\mathrm{Gbit/s}$ through a PON uplink path with NN topologies, which complexity is low enough for implemention on state-of-the-art FPGAs. Furthermore, we show that appropriate NN topologies reach a lower BER as classical linear FIR filters of similar computational complexity, and that the novel blind and adaptive VQVAE-based learning algorithm is capable of approaching the performance of the non-blind MSE loss.

Acknowledgements: This work was carried out in the framework of the CELTIC-NEXT project AI-NET-ANTILLAS (C2019/3-3, grant 16KIS1316 and 16KIS1317) and the project KIGLIS (grant 16KIS1228), both funded by the German Federal Ministry of Education and Research (BMBF). The authors thank Jinxiang Song from Chalmers University of Technology for valuable discussions.

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