Recurrent Neural Network Equalizer to Extend Input Power Dynamic Range of SOA in 100Gb/s/λ PON

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Abstract: We propose a novel equalization scheme for 100Gb/s/λ PAM4 PON based on Gated Recurrent Neural Network to increase SOA preamplifier input power dynamic range tolerance to 30 dB below hard-decision FEC BER limit of 3.8×10^{-3}.

1. Introduction

Passive Optical Networks (PONs) continue to be the dominant optical access technology addressing network operator demand for higher speed Fiber-to-the-Premises and mobile backhaul solutions. Looking beyond the recently published 50G PON standards, future networks will need to contend with limited electro-optic device bandwidths, and so four-level pulse amplitude modulation (PAM4) is being considered for single channel 100Gb/s PON due to its spectral efficiency. However, the recommendations of ITU-T G.9804.3 commit to supporting existing optical distribution network infrastructure, meaning a minimum optical loss budget of 29 dB, which is a challenge for PAM4's high SNR requirements. Semiconductor optical amplifiers (SOAs) offer a compelling solution as pre-amplification units at the optical line terminal, being low cost, integrable, and operating in both C- and O- wavelength bands. But this raises another concern, as the SOA input power dynamic range cannot meet the minimum required PON dynamic range of 19.5 dB without equalization because of gain saturation induced patterning. Recently neural network-based equalizers (NNEs) have been suggested for pre-equalization to overcome SOA patterning effects in 50G PAM4 PON and extend system dynamic range [1]. Further, Recurrent Neural Networks (RNN) incorporating feedback have been proposed as efficient post-equalizers for 100 Gb/s PAM4 PON with O-band SOA preamplifiers achieving sufficient receiver sensitivity for 30 dB optical loss budget [2]. However the impact of SOA saturation, which is critical for high dynamic range operation, was not considered.

Here, we demonstrate 100 Gb/s PAM4 33 dB power budget with 30 dB input power dynamic range using an SOA preamplifier. We implement an advanced RNN equalization scheme based on Gated Recurrent Units (GRUs) [3] to overcome SOA patterning and compare performance with a feed forward equalizer (FFE) and a standard neural network equalizer (NNE). Our results show that the GRU gated feedback mechanism enables the same SOA input power dynamic range as a NNE but with far fewer equalizer taps, leading to reduced memory footprint and computational complexity evaluated in terms of multiply-accumulate operations per equalised symbol [4].

2. Experimental Setup and Recurrent Neural Network Equalizer

The experiment setup is shown in Fig. 1 (b): 50 Gbaud PAM4 signal with 6-dB extinction ratio is generated in the C-band with 100 GSa/s DAC with differential output driving a Mach Zehnder modulator and boosted by EDFA to emulate an ideal high-power Tx. Digital pre-compensation corrects for setup linear bandwidth restrictions. A photoreceiver with integrated TIA was unavailable for this study and so a 50 GHz photodiode combined with EDFA is substituted. To investigate signal performance with saturated and unsaturated SOA preamplifier (CIP SOA-S), a variable optical attenuator is placed before the SOA to emulate optical distribution network losses, see Fig. 1 (a). Signals are captured using a 200 GSa/s real time scope, and a 25GHz 4th-order Bessel filter is applied digitally to mimic the bandwidth limitation that would arise from the use of lower cost 25G class optoelectronics.

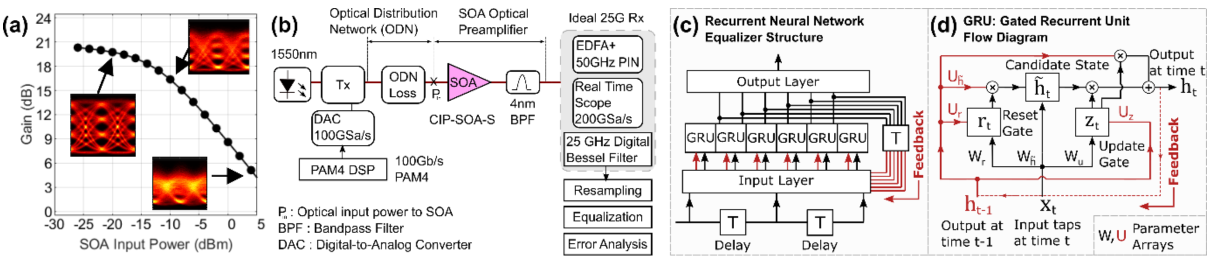

Fig. 1: (a) CIP-SOA-S gain curve with eye diagrams (inset) showing extent of inter-symbol interference (ISI), (b) experimental setup, (c) RNN equalizer structure with (d) Gated Recurrent Units making up recurrent hidden layer.

Fig. 1 (c) shows the structure of our proposed RNN equalizer solution: it comprises one hidden layer with 6 GRUs incorporating layer feedback, while the output layer is a single fully connected (FC) unit. The GRU feedback mechanism is superior to that of standard RNNs as it exploits “reset” and “update” gates, which are used to determine relevant feedback and input state information for the current symbol equalization; the complete operation of a single GRU is shown in Fig. 1 (d). The backpropagation through time (BPTT) algorithm [5] with Adam optimizer is used to train the equalizer by “unrolling” the RNN for 40 sequential input times. For each SOA input power, a single captured PRBS14 waveform is used for training, while bit-error-ratio (BER) estimation is carried out on repeated acquisitions of PRBS15 (~130k symbols). We generate a PRBS14 PAM4 sequence by combining two binary PRBS14 sequences with a relative shift of $\lfloor (2^{14}-1)/2 \rfloor = 8191$ symbols, thus avoiding neural network overfitting to the training pattern.

3. Results

From Fig. 2 (a) we achieve baseline receiver sensitivity of −25 dBm at the hard decision FEC (HD-FEC) threshold BER of 3.8 x 10^{-3} and therefore meet the required 29 dB PON loss budget assuming +8 dBm launch power. As the input power increases beyond −15 dBm we drive the SOA into gain saturation leading to nonlinear ISI due to patterning, with only 12.5 dB maximum achievable input power dynamic range with no equalizer, and 19 dB with 40T (symbol spaced) tap FFE. However, our RNN equalizer using only 3T taps achieves a BER of 10^{-4}, well below the HD-FEC limit up to +5 dBm input power to the SOA and corresponding to >30 dB input power dynamic range. For comparison we also implemented a 40T tap NNE with two hidden layers of 6 and 4 neurons, which achieves the same performance as our 3T tap RNN equalizer.

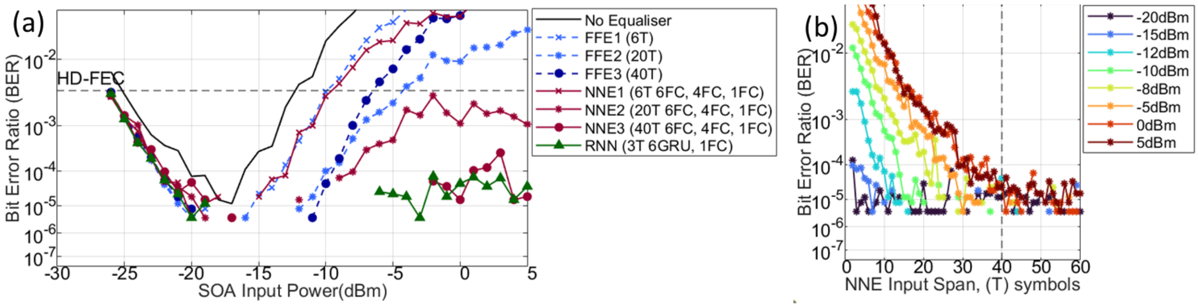

Fig. 2: BER plotted against: (a) SOA input power with equalization; (b) symbol spaced input taps to NNE for different SOA input powers.

Although a single GRU unit is more complex than a standard neural network neuron, the advantage of a GRU based RNN is clear as it effectively leverages its gated feedback mechanism to mitigate a range of nonlinear ISI extending beyond its immediate input taps. In contrast, Fig. 2 (b) shows a NNE is strongly dependent on a large numbers of input taps for the same ISI. Table 1 compares RNN and NNE equaliser performance in terms of SOA input power dynamic range achieved and computational complexity. The 3T RNN achieves 30 dB dynamic range, while a similar complexity 20T NNE only achieves 23 dB. To match the 3T RNN performance, NNE requires 40T input taps, leading to a significant overall increase in equaliser parameters and multiply-accumulate operations.

Table 1: Comparison of neural network equalizer parameters and associated multiply-accumulate operations.

Equalizer	Input Taps	Structure	Parameters	Multiply-Accumulate Operations per Symbol	SOA Input Power Dynamic Range [dB]
NNE	20T	(6FC, 4FC, 1FC)	159	148	23
NNE	40T	(6FC, 4FC, 1FC)	279	268	30
RNN	3T	(6GRU, 1FC)	187	168	30

4. Conclusion

In summary, we demonstrate >30 dB SOA input power dynamic range is possible in a 100 Gb/s PAM4 system using a recurrent neural network equalization scheme based on Gated Recurrent Units to mitigate SOA patterning. A computational complexity advantage over standard neural network equalizer structures is also shown.

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5. References

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