

High Dynamic Range 100 Gbit/s PAM4 PON with SOA Preamplifier using Gated Recurrent Neural Network Equaliser

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Abstract We investigate parallel multi-symbol equalisation scheme for 100Gb/s/λ PAM4 using Gated Recurrent Neural Networks and exploit SOA preamplifier gain suppression to achieve 27 dB system dynamic range below hard-decision FEC BER limit of 3.8×10^{-3} using a receiver with two gain settings.
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Introduction

Recently published ITU-T Higher Speed Passive Optical Network (PON) standards outline the requirements for next generation 50G PON aimed at meeting ever-increasing demand for high-speed Fiber-to-the-Premises [1]. Future PON standards targeting single channel 100 Gb/s and beyond operation may need to transition to new solutions based on either coherent modulation and reception techniques or Intensity Modulation with Direct Detection (IM/DD) with the addition of optical amplification to meet the challenging minimum optical loss budget for PON of 29 dB [1]. In this paper, we present a potential IM/DD solution based on 50 Gbaud, 4-level Pulse Amplitude Modulation (PAM4) for 100Gb/s operation. Compared to non-return-to-zero (NRZ) modulation, PAM-4 is an attractive solution due to its reduced electro-optic bandwidth requirements, albeit at the cost of reduced receiver sensitivity. However, the latter can be compensated by using Semiconductor Optical Amplifiers (SOAs) as receiver pre-amplifiers. SOAs are attractive solutions as they are readily integrable, can operate in the C- and O-bands, and are relatively low-cost.

However, the impact of SOA non-linearities such as gain saturation-induced patterning effects is a concern, especially in the upstream direction in PONs. This is due to the high Dynamic Range (DR), burst mode nature of the signalling, with the new 50G PON standards specifying values as high as 19.5 dB DR for loud-soft burst ratio [1]. It has been shown that PAM4 signalling is highly sensitive to SOA gain saturation-induced patterning effects [2], which makes it difficult to avoid large power penalties for the high power, loud bursts. However, Machine Learning (ML) based equalisation techniques such as Recurrent Neural Networks (RNNs) have been shown to be capable of compensating these impairments, among others [3, 4]. This suggests an intriguing further possibility; if such an equaliser can enable the

SOA to operate in gain saturation with tolerable patterning impairments, can the associated SOA gain suppression be exploited to reduce the input optical DR to the following photo-receiver? This could be particularly advantageous given the challenges of designing 50 Gbaud-, high dynamic range-capable burst mode receivers (BMRx) with sufficient linearity to support PAM-4 modulation. Such a BMRx for 25Gbaud operation is discussed in [5]. Furthermore, can the ML equaliser also compensate for electronic non-linearities in the adjustable gain trans-impedance amplifier (TIA) of the BMRx?

In this work we demonstrate a 100 Gbit/s PAM4 system that achieves 30 dB optical loss budget, and up to 28 dB back-to-back (B2B) DR using a fixed bias SOA optical preamplifier followed by an Rx with two gain settings. The SOA gain suppression is exploited by using the GRU-based RNN equalisation scheme proposed by us in [6]. However, as others have noted, there exists difficulties in implementing neural network equalisers in hardware [7], and so we extend our analysis of the RNN equaliser to include parallel multi-symbol output schemes as seen in [4, 8, 9]. These are advantageous for future real-time FPGA or ASIC hardware implementations due to reduced multiply-accumulate operations per equalised symbol, and GRU feedback rate

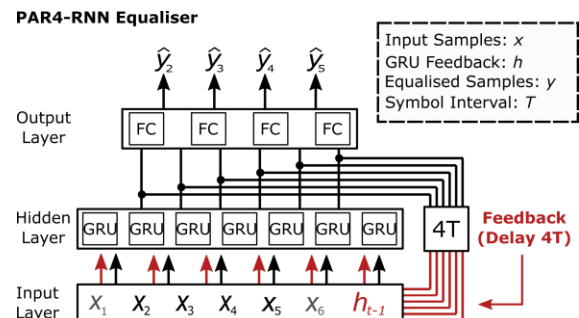


Fig. 1: PAR4-RNN equaliser predicts four consecutive symbols simultaneously. Feedback is only required once every four symbols thus relaxing DSP timing requirements.

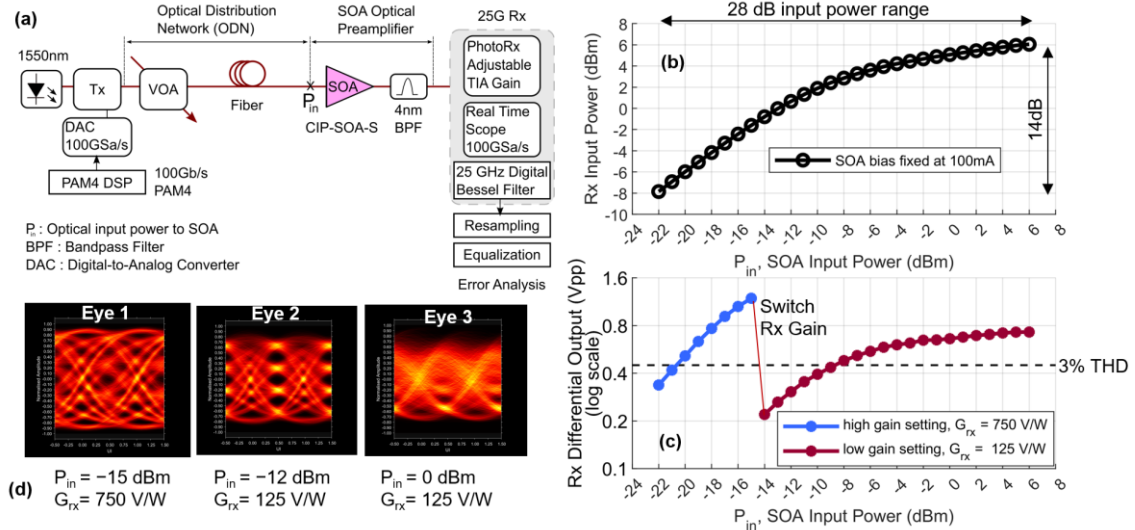


Fig. 2: (a) Experimental setup of a 100Gb/s PAM4 link with SOA pre-amplified 25G Rx, (b and c) shows SOA and PhotoRx output saturating as SOA input power increases and (d) Rx output electrical eyes at various operating points showing effects of Rx electrical nonlinearities and SOA gain saturation.

requirements. Finally, we investigate DR performance penalties induced by dispersion of up to 91.8 ps/nm.

Recurrent Neural Network Equaliser

This work implements parallel multi-symbol RNN equalisers based on gated recurrent units (GRUs) [10], as shown in Fig. 1. The equalisers have a single hidden layer comprised of 6- or 7-GRUs implementing a “gated” feedback mechanism which is more stable than that in standard recurrent neural network units, and is defined by the equations:

$$\begin{aligned} z_t &= \sigma(W_z x_t + U_z h_{t-1} + b_z) \\ r_t &= \sigma(W_r x_t + U_r h_{t-1} + b_r) \\ \hat{h}_t &= \tanh(W_h x_t + U_h (r_t \circ h_{t-1}) + b_h) \\ h_t &= (1 - z_t) \circ h_{t-1} + z_t \circ \hat{h}_t \end{aligned}$$

where W_i, U_i, b_i are learned parameter matrices and bias vectors, σ is the sigmoid function, \circ is the Hadamard product, and x_t, h_t denote current input / output samples respectively at time t . The update, reset, and candidate “gating” operation outputs are z_t, r_t, \hat{h}_t . The equaliser output layer is composed of fully connected (FCs) units and outputs equalised symbols \hat{y} . If the RNN has n FC units in its output layer then it equalises n symbols per equalisation cycle and we label it PAR n -RNN. We choose the number of input taps to be $n + 2$, while feedback is required only once every n symbols. PAR-RNN equalisers can therefore efficiently share GRU computation simultaneously among consecutive symbol equalisations. The parameter matrices and vectors are trained using the back-propagation-through-time algorithm [11] with Adam optimizer by “unrolling” the RNN for up to 40 sequential past inputs. This ensures the equaliser learns

SOA patterning and Rx saturation impairments sufficiently. During training a single PRBS14 waveform is used for each input power to the SOA preamplifier, while repeated acquisitions of PRBS15 waveforms totalling $\sim 130k$ symbols are used for BER estimation. Overfitting to the training pattern is avoided by combining two PRBS14 sequences with a relative shift of $\lfloor (2^{14} - 1)/2 \rfloor = 8191$ symbols to generate a PRBS14 PAM4 sequence.

Experimental Setup

Fig. 2 (a) shows the experimental setup used to emulate an upstream 100G PON scenario. A high-power Tx is realised in the C-band using an EDFA booster amplifier in conjunction with a Mach Zehnder modulator. This is driven by a differential output DAC operating at 100 GSa/s, generating a 50 Gbd PAM4 signal with 6 dB extinction ratio. Linear pre-compensation corrects for system bandwidth limitations up to 33 GHz. A Variable Optical Attenuator (VOA) emulates optical distribution network losses, while standard single mode fibre introduces dispersion of up to 91.8 ps/nm. The OLT comprises an SOA preamplifier (CIP SOA-S) and a photoreceiver with integrated adjustable conversion gain (Thor Labs RXM42AF).

The SOA preamplifier and photoreceiver characteristics are shown in Fig. 2 (b) and (c). The SOA is kept at constant bias and driven into saturation by large input powers causing gain suppression. This compresses the system optical power DR from 28 dB to 14 dB at the SOA output but introduces patterning effects above SOA saturation input power of -8 dBm. Only two Rx gain settings are used at the photoreceiver, to potentially simplify the requirements for gain

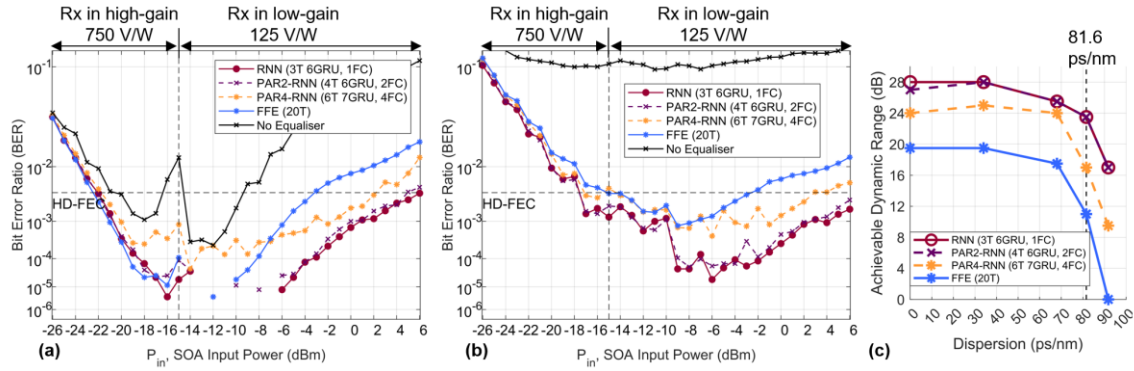


Fig. 3: BER performance for various equalisers in (a) back-to-back and (b) transmission over a fibre length with 81.6ps/nm dispersion. Achievable dynamic range for various dispersion values shown in (c).

adaptation in a PON Rx, and the gain is changed from low to high setting at -14 dBm input to the SOA / OLT as shown in Fig. 2 (c). The photoreceiver electrical output is also shown, representing the amplitude swing between the PAM4 outer symbols. The Rx has linear response ($< 3\%$ THD - Total Harmonic Distortion) up to a differential output swing of 450 mV, and the eye diagrams in Fig. 2 (d) show clear degradation due to Rx non-linearities and SOA patterning.

Waveforms are captured using a 100 GSa/s real time scope with 33 GHz bandwidth, while a 4th-order Bessel filter is applied digitally to imitate 25G class opto-electronics. Offline processing is then carried out, before DSP using 1 sample per symbol is applied and final error analysis occurs.

Results

Fig. 3 (a) shows the 100 Gb/s PAM4 system back-to-back (B2B) performance for PAR2- and PAR4-RNN equalisers, as well as single output RNN and 20-tap (20T) FFE for comparison. The optically preamplified Rx sensitivity is measured to be -22 dBm at the hard-decision forward error correction (HD-FEC) threshold BER of 3.8×10^{-3} . Assuming +8 dBm launch power, this corresponds to an optical power budget of 30 dB. Rx non-linearities result in the distinctive “W” performance curve seen in Fig. 3 (a) for the no equaliser case, meaning DSP is required to enable two gain settings operation at the Rx. The PAR2- and PAR4-RNN equalisers overcome the combination of bandwidth limitation, SOA patterning, and Rx non-linearities to achieve 27 dB and 24 dB optical DR respectively. This approaches the RNN equaliser performance of

28 dB DR, while preserving similar equaliser structure and reduced complexity, as detailed in Table 1.

Fig. 3 (b) shows equaliser performance over total system DR for fibre transmission totalling 81.6 ps/nm in the C-band. The RNN equalisers achieve below HD-FEC threshold BER up to +6dBm input to the OLT, and consistently achieve higher DR than FFE over a wide range of dispersion values as seen in Fig. 3 (c).

Table 1 compares equaliser complexities in terms of trained parameters and multiply-accumulate operations per symbol, where the parallel RNNs show competitive performance. By going from single-symbol output RNN equaliser to PAR4-RNN which predicts simultaneously 4 consecutive symbols, the number of parameters increases by only a factor of 1.75, and the multiply-accumulate operations per equalised symbol decreases by 55%.

Conclusions

In summary, we demonstrate a 100 Gb/s PAM4 system with 28 dB dynamic range by exploiting SOA preamplifier gain suppression and using two gain setting scheme at the Rx. Equalisation based on Gated Recurrent Units is shown to overcome associated SOA patterning and Rx non-linearities, and we further demonstrate computational advantage of PAR-RNN equalizers.

Acknowledgements

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Table 1: Comparison of neural network equaliser performance, parameters and associated multiply-accumulate operations.

Equaliser	Input Taps	Structure	Parallel Outputs	Parameters	Multiply-Accumulate Operations per Symbol	SOA Input Power Dynamic Range		
						0ps/nm	81.6ps/nm	91.8ps/nm
RNN	3T	(6GRU, 1FC)	1	187	168	28dB	23.5dB	17dB
PAR2-RNN	4T	(6GRU, 2FC)	2	212	96	27dB	23.5dB	17dB
PAR4-RNN	6T	(7GRU, 4FC)	4	326	75.25	24dB	17dB	9.5dB

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