300-Gbit/s/λ PAM8 Modulation with a Silicon Microring Modulator using Long Short Term Memory Regression and Deep Neural Network Classification

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Abstract: We demonstrate a 300-Gbit/s PAM8 modulation using a 55-GHz bandwidth silicon-microring-modulator (SiMRM) with a driving voltage of 1.8-Vpp. To achieve high-order PAM8 modulation, long-short-term-memory (LSTM) and deep-neural-network (DNN) are used for regression and classification respectively. © 2024 Author(s)

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1. Introduction

For optical transceivers (TRx) operating beyond 1 Tbit/s transmission [1], single lane data rate at or above 200 Gbit/s should be needed [2]. Optical transceivers using silicon photonics (SiPh) has attracted widespread interest because SiPh benefits from the mature and high-yield fabrication processes of complementary metal-oxide-semiconductor (CMOS) [3]. Silicon micro-ring modulator (SiMRM) provides many advantages, including high electrical-to-optical (EO) bandwidth, compact size and low power consumption [4]. These advantages enable SiMRM to be ideal for space limited and energy efficient data center application. To further increase the data rates beyond 200 Gbit/s, one way is to increase the TRx bandwidth. This requires upgrading and redesigning both optical and electrical components, such as SiPh modulators, modulator drivers and amplifiers. Another way to increase the data rate is by utilizing higher-order modulations, such as 4-level pulse-amplitude-modulation (PAM4) or PAM8 [5]. Notwithstanding the cost and power considerations, owing to the high bandwidth and efficiency demands, digital signal processing (DSP) is considered as a promising enabler in the future optical communications [6] to mitigate transmission impairments, such as chromatic dispersion (CD), polarization mode dispersion (PMD), as well as improving the transmission capacity. For example, Volterra equalizer [7], feed-forward equalizer (FFE), decision feedback equalizer (DFE), and polynomial non-linear equalizer (PNLE) [8] were employed to improve the transmission performances.

In this work, we experimentally demonstrate a long-short-term-memory (LSTM) and deep-neural-network (DNN) enabled 300-Gbit/s (i.e. 100 Gbaud) PAM8 modulation generated by a single 55-GHz bandwidth SiMRM with a driving voltage of 1.8-Vpp. Experimental results show that 300 Gbit/s PAM8 modulation is achieved at back-to-back (B2B) and 270 Gbit/s PAM8 is achieved after 1 km standard single-mode-fiber (SSMF) transmission satisfying the soft-decision forward error correction (SD-FEC) requirement (i.e. bit-error-rate, BER = 2.4×10^{-2}).

2. SiMRM Design and Experiment

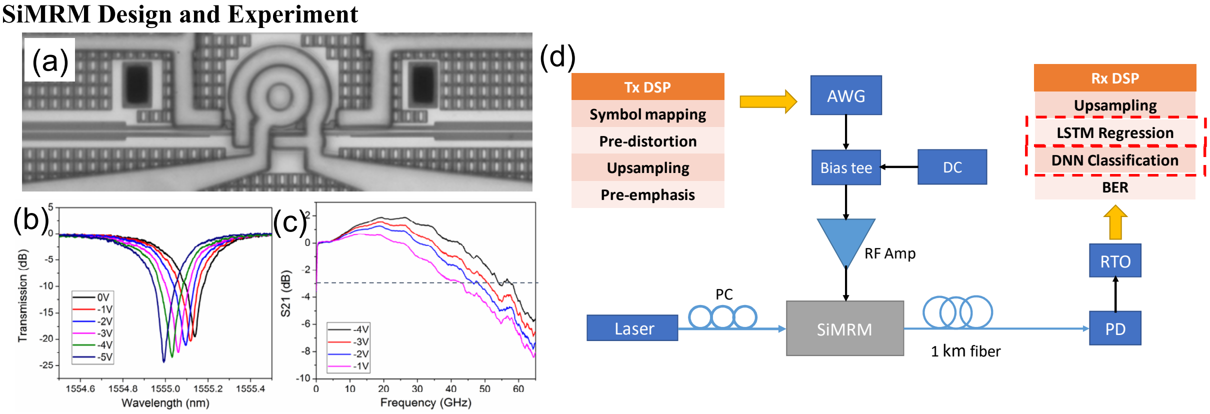

Fig. 1. (a) Photo our SiMRM design with ring radius of 7.5 µm. (b) SiMRM transmission curves and (c) S21 parameters at different biases. (d) Experiment of the PAM8 modulation using the proposed SiMRM. AWG: arbitrary waveform generator; EDFA: erbium-doped fiber amplifier; PD: photo-detector; RTO: real time oscilloscope.

Fig. 1(a) shows the photo of our SiMRM design, which was fabricated in a commercial foundry using CMOS-compatible processes on silicon-on-insulator (SOI) platform. The thickness of the silicon layer and the buried oxide layer are 220 nm and 2 µm respectively. The ring radius is 7.5 µm to have an optimal Q factor and to ensure sufficient EO bandwidth for high data rate operation at the same time. Three doping concentrations were utilized to construct the PN diode in order to reduce the waveguide loss. The lowest concentration is at the strip region, higher concentration is at the slab region, and the highest concentration is for the metal contacts. TiN heater is placed in the oxide above the SiMRM for thermal tuning of the resonant wavelength. The dark rectangles shown in Fig. 1(a) are the deep trenches for thermal isolation. Fig. 1(b) shows the SiMRM transmission curves at different biases. It has an extinction ratio (ER) of 25 dB at 0 V and a loaded Q factor of ~ 5,200. Fig. 1(c) shows the S21 parameter measured by a 67-GHz light wave component analyzer (Keysight® N5227A). The 3-dB bandwidth is ~ 55 GHz at -4V bias. The bandwidth variation at different biases is due to depletion width widening in the PN junction under strong applied voltage. Fig. 1(d) shows the experimental setup of the PAM8 modulation using the proposed SiMRM. An arbitrary waveform generator (AWG, Keysight® M8199A) has a nominal sampling rate of 128 GSa/s. It can run at 256 GSa/s by using the included passive interleaver. The AWG output is amplified by a 60-GHz broadband RF amplifier (SHF® S804B) at 1.8 Vpp and applied to the SiMRM via a bias-tee with –3V DC bias. The optical signal is generated by a tunable laser at wavelength of 1555 nm. The optical signal is coupled into and out of the SiMRM via grating couplers (GCs). The generated optical PAM8 signal is then transmitted in 1 km SSMF. It is then received by a 70-GHz photo-detector (PD) and digitized using an 80-GHz analog bandwidth real time oscilloscope (RTO, Keysight® UXR0802A) with 256-GSa/s sampling rate. In the transmitter (Tx) DSP, symbol mapping is first performed to map the data into PAM8 format. Pre-distortion and pre-emphasis are used respectively, to compensate for the SiMRM transmission curve non-linearity and the high-frequency roll-off. The receiver (Rx) DSP includes the upsampling, LSTM regression, DNN classification and BER analysis. Since PAM8 doubles the number of amplitude levels compared to PAM4, it is more susceptible to SiMRM non-linear transmission curve. Utilizing LSTM with DNN could be an effective mitigation scheme since the PAM8 data can be directly decoded without the need to know the specific parameters of Tx DSP.

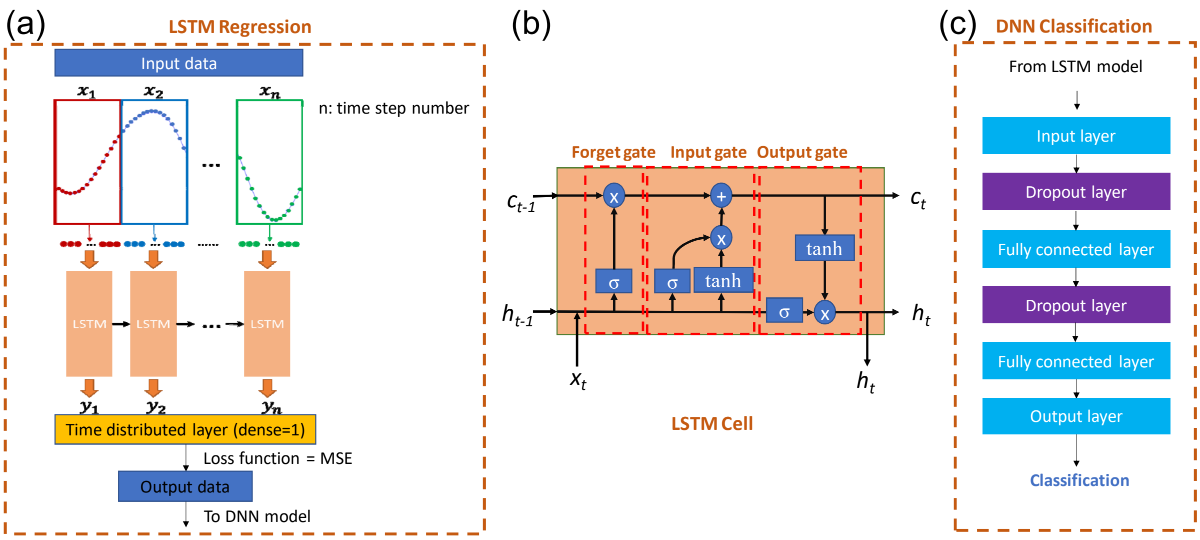

Fig. 2. Architectures of (a) LSTM regression model, (b) LSTM cell, (c) DNN classification model.

Fig. 2(a) shows the detail of the LSTM regression model. The received signal from the RTO will be upsampled to the least common multiple of the transmission data rate. After the upsampling, the data will be input to the LSTM regression model. The LSTM regression model consists of a LSTM layer with 8 neurons and a time distributed layer. The time distributed layer is used to combine the LSTM layer output at each time step. Fig. 2(b) shows the structure of the LSTM cell [9], which consists of multiple nonlinear activation functions and point-wise multiplication operations. C_{t-1}, C_t, x_t, σ, h_{t-1},h_t, are the memory from the previous time step LSTM cell, newly updated memory, current input of this time step, Sigmoid operation, output of previous time step LSTM cell, and current output respectively. In our model, each time step inputs the samples of a symbol from the received signal waveform and outputs a corresponding feature of that symbol. Then, we can use this feature to decode the signal. The loss function of the LSTM regression model is mean-square error (MSE). The model takes the samples of a symbol as input and outputs a feature for this symbol. The output symbol feature will transmit to the next time step and output through the time distributed layer at the same time. The time distributed layer unit number is set to one to allow the symbol feature to be regressed into a single value, representing that particular symbol. The outputs of the LSTM regression model will be input into the DNN model as shown in Fig. 2(c) for the classification of the PAM8 data. It has an input layer with 16 neurons, 2 dropout layers with a dropout rate of 0.05, 2 fully connected (FC) layers with 8 neurons each, and an output layer with 8 states. The activation function used for the FC layers is ReLU function, while the output layer uses the Softmax function. The loss function of the DNN classification model is the sparse categorical cross-entropy function, which can effectively classify data with different targets without requiring one-hot encoding. Finally, the output of the last layer of the classification model will be used to determine the predicted class label, which corresponds to the 8 levels of the PAM8 pattern. This predicted label is then compared with the true label in the source data to obtain the BER.

3. Result and Discussion

Fig. 3(a) shows the BER performance with different input time-steps. We can observe that the BER decreases as the number of time-step increases. This indicates that as the number of time-step increases, our LSTM regression model is able to capture more information from the received signal waveform, allowing it to better mitigating the transmission impairments and decoding the signal. However, increasing the number of time-steps also increases the time required for model training and running. By considering the trade-off between BER and computing time, we decided to select 10 time-steps as the number of input time steps for our model. Fig. 3(b) shows the BER performance of the PAM8 modulation by the SiMRM at B2B. As discussed the necessities of the LSTM regression and DNN classification above, we also include the utilization of DNN classification model only for comparison. It is worth to point out that as the 3-dB bandwidth of the SiMRM is only ~ 55 GHz, PAM8 signal cannot be observed even at 225 Gbit/s, and no BER could be measured at the raw PAM8 signal. When utilizing the DNN model only, data rate of 270 Gbit/s is achieved, satisfying the SD-FEC threshold (i.e. BER = 2×10^{-2}). When utilizing the LSTM with DNN, 300 Gbit/s is achieved, satisfying the SD-FEC threshold. Fig. 3(c) shows the BER performance of the PAM8 modulation by the SiMRM after 1 km SSMF transmission. The proposed LSTM with DNN can successfully decode PAM8 signal at data rate of 270 Gbit/s satisfying the SD-FEC threshold.

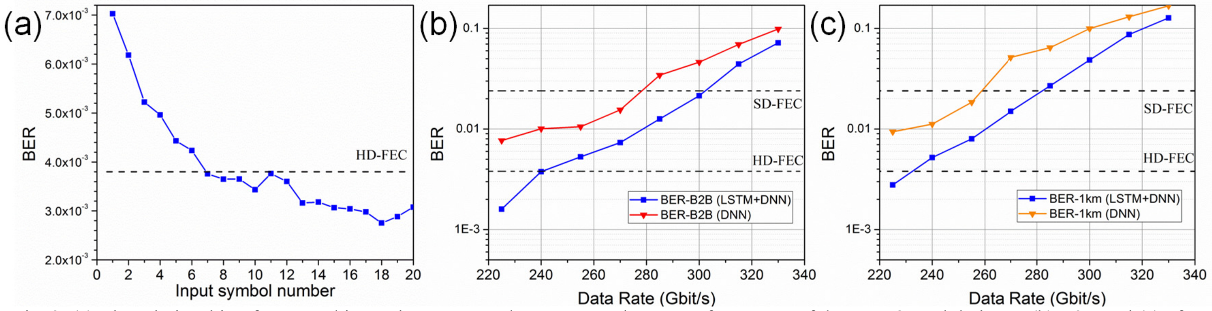

Fig. 3. (a) The relationship of BER and input time step number. Measured BER performances of the PAM8 modulation at (b) B2B and (c) after 1-km SSMF utilizing LSTM with DNN and DNN only.

4. Conclusion

We proposed and experimentally demonstrated a LSTM and DNN enabled 300-Gbit/s (i.e. 100 Gbaud) PAM8 modulation generated by a single 55-GHz bandwidth SiMRM with a driving voltage of 1.8-Vpp. The LSTM possessed memory cells for handling time-domain signal dependencies, with the ability to store, read, and reject data passing through the neural network. Experimental results showed that 300 Gbit/s PAM8 modulation was achieved at B2B and 270 Gbit/s PAM8 was achieved after 1 km SSMF transmission satisfying the SD-FEC requirement (i.e. BER = 2.4×10^{-2}). The design parameters of the SiMRM, LSTM model and DNN model were discussed.

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