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• **Supplementary File** •

Linear Shallow Neural Network to Accelerate Transmitter Dispersion Eye Closure Quaternary (TDECQ) Assessment

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Appendix A Simulation setup and results

As shown in Fig. A1, the transmitter dispersion eye closure quaternary (TDECQ) assessment system is numerically developed under the condition of a back-to-back (B2B) transmission, including both transmitter (Tx) and receiver (Rx). At the Tx, an electrical 25 and 50 Gbaud four-level pulse amplitude modulation (PAM-4) signal is generated by a short stress pattern random quaternary (SSPRQ) pattern with a length of 2^{16}-1. Then, the electrical 25 and 50 Gbaud PAM-4 signals are converted to corresponding PAM-4 optical signals by a Mach-Zehnder modulator (MZM). At the Rx, a single photodetector (PD) is used to realize the direct detection. After the analog-to-digital conversion (ADC), the amplitude histogram (AH) of individual TDECQ value is collected. The resolution of ADC is ideally set during the numerical simulation, in order to avoid the distortion during the PAM-4 signal received. The TDECQ value is calculated by the traditional assessment method of IEEE standard, with a range of 1.5-4.0 dB. To improve the robustness of model, various TDECQ values are obtained, by adjusting the bias voltage of MZM, the swing of digital-to-analog conversion (DAC), and the bandwidth of DAC. Finally, 400 AHs are used for training, while 200 AHs are reserved for testing.

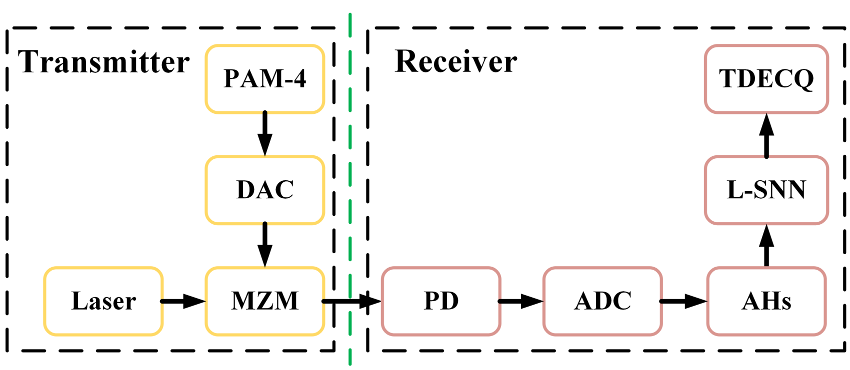

Figure A1 Simulation setup of TDECQ assessment.

Since the complexity of linear shallow neural network (L-SNN) is only determined by the number of input neural units, which is the same as the number of bins of AH, its impact is investigated first. As shown in Fig. A2(a), by taking the 25 Gbaud PAM-4 signals under a sampling rate of 2 samples per symbol (Sa/s) as an example, the TDECQ assessment performance gradually improves, when the number of bins increases. It gradually becomes stable after the use of 150 bins. Since the number of bins corresponds to the number of input neural units of L-SNN, more neural units will enhance the implementation complexity of L-SNN. Meanwhile, when more bins are involved, the stronger representation ability can be secured, leading to a learning capability enhancement of L-SNN. The neural network (NN) performance is approaching the stable state. Finally, we decided to generate the AH with 210 bins. Meanwhile, the sampling rate of ADC to generate the AH with 210 bins on the L-SNN performance is investigated, as shown in Fig. A2(b). It indicates that, a higher sampling rate is helpful to improve the performance of L-SNN. This is because the AH

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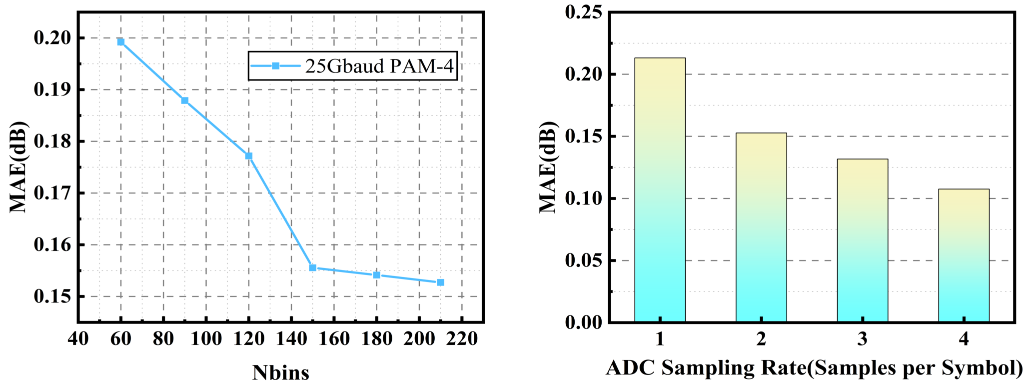

Figure A2 (a)Impact of the bin numbers on the TDECQ assessment. (b) Impact of the ADC sampling rate on the TDECQ assessment.

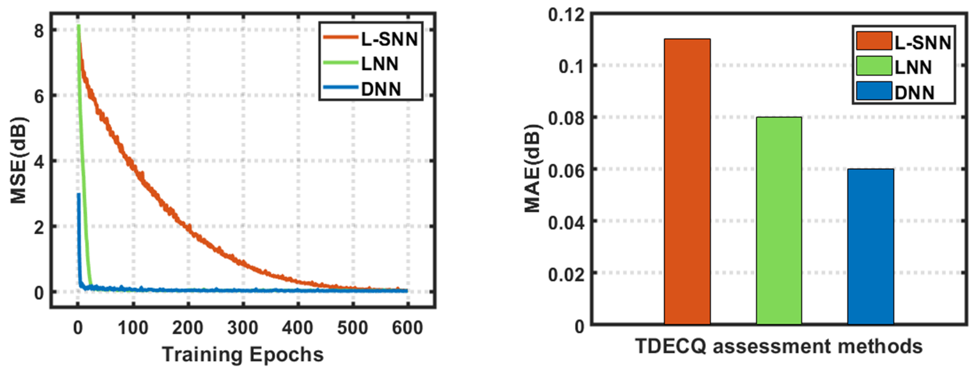

Figure A3 (a)The training loss among L-SNN, LNN and DNN. (b) TDECQ assessment results among L-SNN, LNN and DNN.

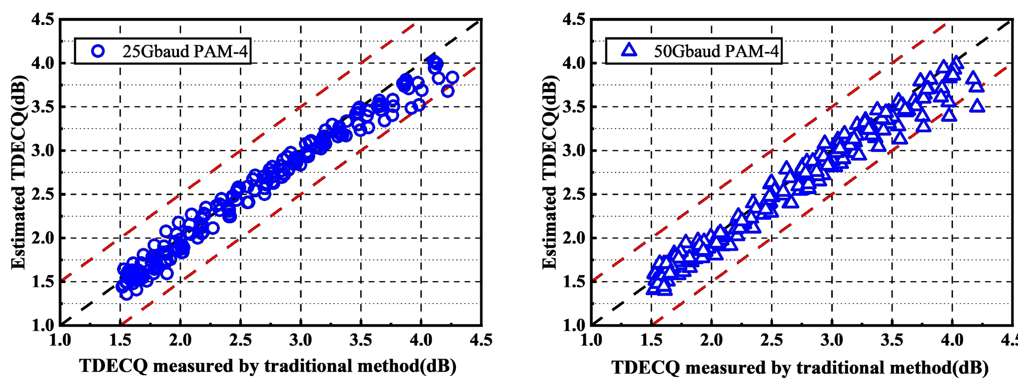

Figure A4 Calculated TDECQ assessment results for (a)25 Gbaud signals, (b) 50 Gbaud signals.

generated with a higher sampling rate has more information to be extracted by the L-SNN. Since the mean absolute error (MAE) of TDECQ assessment must satisfy the standard threshold, the sampling rate of 4 Sa/s is good enough to waive the hardware complexity. In both simulation and experiment setup, the operation parameters keep consistent.

Next, we carry out a performance comparison among deep neural network (DNN), linear neural network (LNN), L-SNN enabled TDECQ assessment schemes. When DNN is evolved to L-SNN, the advantage of L-SNN becomes clear. For the ease of fair comparison, the neural unit sizes of DNN are 210, 100, and 1, respectively. The neural unit sizes of LNN are the same as that of DNN. The input neural unit of L-SNN is 210, while the output neural unit is 1. As for the L-SNN, there occur both no hidden layer and no NAF. Furthermore, all training parameters of various NNs keep the same, including the iteration number and the learning rate. As shown in Fig. A3(a), in terms of training, we can see that the convergence speed of DNN is faster than that of L-SNN. The multiple-layer structure together with the use of NAF is helpful to speed up the convergence. Since we only need a well-trained model during the testing, the low convergence speed during the training is acceptable. As shown in Fig. A3(b), the MAE values of DNN, LNN, and L-SNN enabled TDECQ assessment schemes are 0.06dB, 0.08dB, and 0.11dB, respectively. Considering the standard accuracy threshold of 0.25 dB, all TDECQ assessment schemes can realize the precise TDECQ assessment. The experimental TDECQ assessment results of 25 and 50 Gbaud PAM-4 signals are presened in Fig. A4. The corresponding MAE values are 0.11 dB and 0.12 dB, respectively.

Appendix B Complexity for various TDECQ assessment schemes

We investigate the computation complexity of DNN, LNN, L-SNN and other existing schemes [1–3]. The number of multipliers for DNN is 21100, the number of multipliers for LNN is 21100, while it is 210 for L-SNN. Although the L-SNN enabled assessment has a slight performance penalty than that of DNN, its computation complexity is two orders of magnitude lower than that of DNN. The performance of long short-term memory neural network (LSTM-NN) strongly depends on what part of the SSPRQ is selected, its complexity needs to be optimized. Moreover, since the input of LSTM-NN is a digitalized waveform of PAM-4 signals, the number of multipliers for LSTM-NN is severe. Finally, the computation complexity of various DL-enabled TDECQ assessment schemes is summarized in Tabel B1. When the accuracy threshold of the traditional TDECQ assessment is chosen as a benchmark, our proposed L-SNN has the lowest computation complexity.

Table B1 Comparison of implementation complexity for various TDECQ assessment schemes

	Method	Activation function	Multiplier
[1]	$Tradition\ method$	$--$	10^{10}
[2]	$2D-CNN$	$ReLU$	2.5×10^7
[3]	$LSTM-NN$	$Sigmoid, Tanh$	$--$
[3]	$1D-CNN$	$ReLU$	10^9
ours	DNN	$ReLU$	21100
ours	LNN	LAF	21100
ours	$L-SNN$	LAF	210

References

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