ANN Performance for the Prediction of High-Speed Digital Interconnects over Multiple PCBs

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***Abstract*—In this paper the performance and the accuracy of artificial neural networks for the prediction of high-speed digital interconnects up to 100 GHz on printed circuit boards are analyzed and evaluated. The prediction accuracy is evaluated both for scattering parameters in frequency domain as well as weighted power sums thereof. The interconnects considered all contain a backplane connected to a daughtercard, showing two via arrays each. Several parameter variations of the basic setup lead to a wide range of possible transmission and crosstalk parameters. Training data sets are obtained using physics-based via modeling up to 100 GHz. Approximately 7000 data sets were made available in total for this study. Neural networks are able to predict the overall link behavior.**

***Index Terms*—Signal Integrity, Machine Learning, High-Speed Links, Physics-Based Modeling**

I. Introduction

With increasing data rates of modern high-speed links come new requirements for the simulation environments that are used for their design. Even though hardware capabilities have increased, it is often not feasible to use time-consuming full-wave simulation methods. In this context, Machine learning (ML) can become an important element in the link design toolbox.

Recently, several works have studied the applicability of ML. It has been shown how to predict properties of the passive link such as via impedances ([1]) or stripline parameters ([2], [3]). In [4] the eye opening is predicted. In [5] eye opening predictions for a SATA 3.0 example up to 9 GHz are shown. Another example of eye opening prediction is given in [6].

From these previous works it is clear that artificial neural networks (ANNs) can indeed be used for tasks in signal integrity engineering. Still, ANNs are not yet able to replace physics-based simulation tools, such as full-wave solvers. The aim of this contribution is to explore the applicability of ANNs for a more complicated high-speed interconnect that shows full-wave effects and therefore high parameter sensitivities. An example of such a link is shown in Fig. 1. It consists of a backplane that is connected to a daughtercard via a connector. In this work different variations of this link are simulated up to 100 GHz with an efficient modeling technique called the physics-based via modeling (PBV) [7]. Based on the PBV simulations, an ANN is trained to predict the S-parameters. The frequency-dependent S-parameter analysis of the SI behavior is extended by an analysis of frequency domain figures of merit (FOMs), the weighted power sums [8].

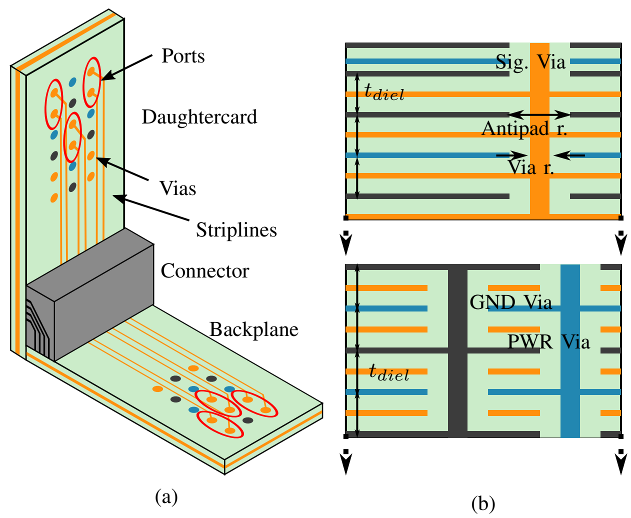

Fig. 1. Complete model consisting of backplane and daughtercard. Only a section of the via arrays is shown. The connector is modeled as a thru, connecting backplane and daughtercard. (a) Model. (b) Upper part of the stackup of backplane and daughtercard. The lower part is symmetrical to the upper half.

II. Link Model and Physics-Based Simulation

The complete link model consists of a backplane and an attached daughtercard (see Fig. 1). The connector is not included in the modeling process, instead both parts are simulated separately and concatenated directly based on network parameters. The vertical stack-ups are shown in Figs. 1 (b) and (c), respectively. The individual board layouts are shown in Figs. 2 (a) and 2 (b) respectively. The differential stripline pairs are routed to avoid skew that could impair the differential transmission. On both boards perfectly matched layer boundaries are assumed.

The boards are simulated with the physics-based via modeling [7], and a 2D trace model. For similar links a good correlation with full-wave simulations up to 100 GHz has been observed [9].

Both boards have variable parameters, whose ranges are given in Table I. To match their footprints, both boards have the same pitch inside the via arrays. Via and antipad radius are the same for backplane and daughtercard. This yields a total of 13 variable parameters. The transmission line width and the separation inside a differential pair are chosen to achieve a differential impedance of 100Ω. Parameter combinations that are impossible, such as a via radius larger than the antipad

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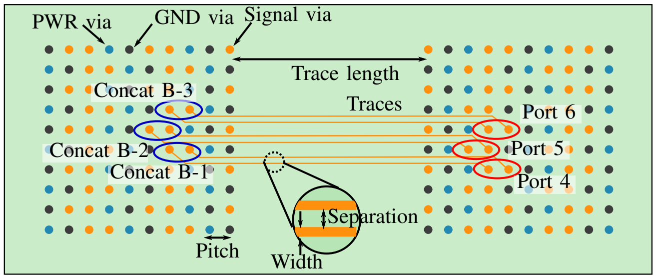
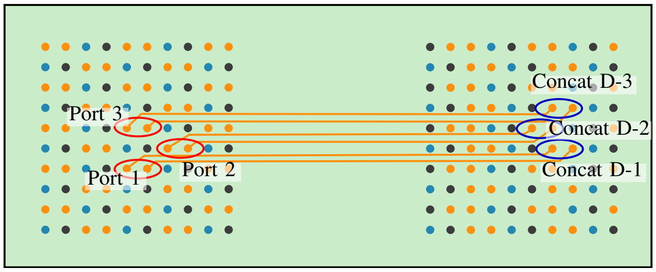


(a)



(b)

Fig. 2. Top view of the backplane and daughtercard boards. Differential ports are indicated with a circle. The blue ports "Concat B-1" to "B-3" are concatenated with the blue ports "Concat D-1" to "D-3" of the daughtercard. The port numbers of the red ports refer to the port labels of the concatenated link. The dimensions are not drawn to scale. (a) Backplane. (b) Daughtercard.

Table I
RANGE OF GEOMETRICAL PARAMETERS OF THE INTERCONNECT MODEL.

Parameter	**Range Backpl.**	**Range Daughterc.**
pitch	[40,80] mil	*same as backplane*
via r.	[3,9] mil	[3,9] mil
antipad r.	[6,18] mil	[6,18] mil
ε_r	[3.6,4.4]	[3.6,4.4]
$\tan\delta$	[0.0,0.02]	[0.0,0.02]
diel. h.	[6,14] mil	[6,14] mil
trace len.	[500,5000] mil	[500,2000] mil

radius, are excluded. The exception is the stripline separation. If the calculated separation is not achievable due to the via pitch, the separation is set to the maximum possible value.

The S-parameters under consideration are the transmission and the far-end crosstalk (FEXT). The transmission is taken between ports 5 and 2 (S_{d5d2}) and the FEXT is taken between ports 5 and 1 (S_{d5d1}) and ports 5 and 3 (S_{d5d3}).

Besides S-parameters, the links are also evaluated based on the weighted power sums, which are FOMs in frequency domain. They can represent transmission, crosstalk, and also a weighted signal to crosstalk ratio. Details can be found in [8].

III. Design of ANN Models

The design of the ANN can be found manually with a grid search or with an optimization algorithm. The ANNs found with the Bayesian Optimization (BO) do not perform significantly better than the ANNs from the manual search.

Both the S-parameters as well as the weighted power sums could be predicted with an ANN model. In case of the S-parameters, the target is the magnitude vector which is sampled at 200 frequency steps. Only the magnitude is predicted because this part is required for the calculation of the weighted power sums. To predict the phase, an extended ANN would be required. In case of the FOM, the target is a 6 element vector, where the sampling points correspond to 6 different bitrates.

Table II
ANN CONFIGURATIONS FOR DIFFERENT PREDICTION TARGETS.

Parameter	**Trans.**	**FEXT**	**WPSXT**	**WPT**	**WSXTR**
N. of hidden layers	4	4	3	3	4
N. of neurons per layer	2000	2000	2000	2000	2000
Activation function	relu	relu	relu	relu	relu
Learning rate	0.001	0.0005	0.001	0.001	0.005
Train RSME	0.0211	0.0040	2.5962	141.6727	6.06405
Test RSME	0.0258	0.0043	10.3185	194.2862	17.4680
Training time (s)	202.75	165.16	263.30	511.37	1094.70

The samples are simulated with the PBV. Samples that are not physical realizable are excluded. In total 7030 samples are generated. Each sample is a concatenation of backplane and daughtercard model. The simulation of one sample requires approximately $8\,m\ 56\,s$. The total simulation time for all samples (without parallelization) would be approximately 44 days. The parameters are chosen within the ranges specified in Table I. The samples are chosen based on latin hypercube sampling (LHS) to achieve an even distribution of parameters within the parameter space. The data split into an 80% training batch and a 20% test batch. Only the training samples are seen by the ANN model during the training. The final model quality is determined by the test batch.

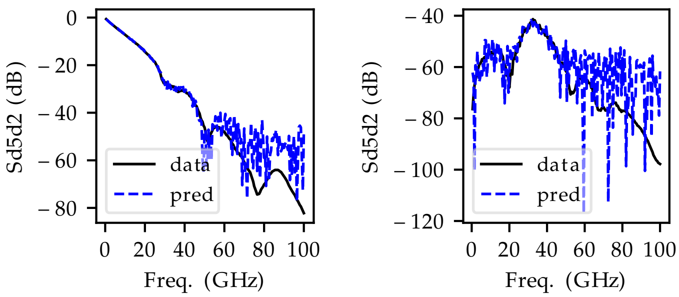
The ANNs are implemented with the open source python package *scikit-learn* which uses the Adam solver [10]. The hyperparameters are tuned by manually testing different parameter combinations (grid search). This requires a lot of manual tuning but if similar problems have been studied before, the knowledge of the solutions can be applied. The final ANN design for all five predictions can be found in Table II.

IV. Evaluation of ANN Performance

This section analyzes the errors of the predictions, both for S-parameter and FOM prediction. The ANN topologies are given in Table II.

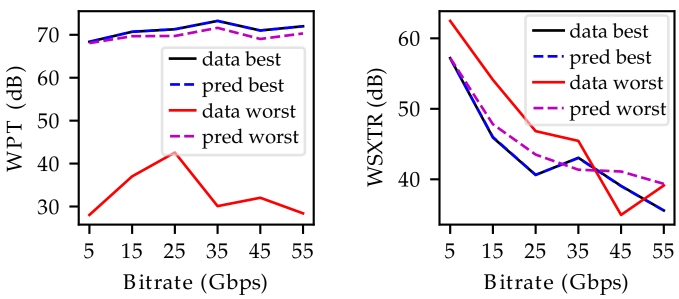
Fig. 3 shows the S-parameters that are obtained from the PBV, and the predicted S-parameters from the ANN model. Figs. 3 (a) and (b) show the predictions with the lowest mean squared error (MSE) for transmission and FEXT. The predicted results show large variations and are less smooth than the original data. A few datasets show an unexpected S-parameter behavior that also lead to a very poor prediction performance. This could be due to unfavorable link parameter combinations and is still under investigation. Furthermore, the predicted S-parameters are not guaranteed to be passive.

ANNs can also predict the FOMs. Their configurations for the prediction of weighted power sum of crosstalk (WPSXT),



(a) (b)

Fig. 3. Comparison of Transmission and FEXT with best prediction results. (a) Transmission. (b) FEXT.



(a) (b)

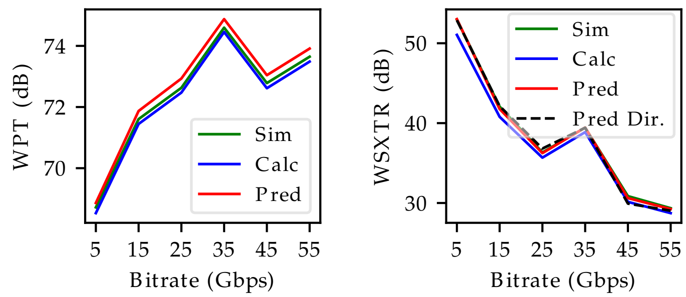
Fig. 4. Prediction results for FOMs. (a) WPT best and worst prediction. (b) WSXTR best and worst prediction.

weighted power sum of transmission (WPT), and weighted signal to crosstalk ratio (WSXTR) are given in Table II. Fig. 4 shows the samples with the best prediction results for WPT and WSXTR. The best predictions match the simulated data almost perfectly. The worst predictions (not shown here) show very large deviations. For the prediction of the WSXTR the worst prediction still represents the main behavior of the data. As the WSXTR is the division of WPT and WPSXT, it is possible that this division cancels out some differences.

Fig. 5 shows the FOMs generated by different means for one link variation. The references are the FOMs calculated from simulated S-parameters (”Sim”). The second set is calculated from S-parameters that are predicted with an ANN from the link parameters (”Calc”). The third set is directly predicted from the link geometry (”Pred”). The WSXTR can be calculated by dividing the predicted WPT and WPSXT (”Pred.”) or it can be predicted directly (”Dir. Pred.”). The presented results show little differences between the different methods. Greater variations can be observed for other link variations (not shown here). It appears that directly predicting the WSXTR leads to worse results than predicting WPT and WPSXT separately. Even though the calculation of the power sums cancel out a part of the noise of S-parameters, there appears to be no clear advantage in predicting the S-parameters instead of directly predicting the FOMs.

V. Conclusion

It was found that ANNs of modest complexity can predict interconnect performance for connected PCBs up to 100 GHz.



(a) (b)

Fig. 5. Comparison of FOMs generated by different means. The simulated parameters are calculated from S-parameters simulated with the PBV (”Sim”). ”Calc.” indicates that the FOM is calculated from predicted S-parameters. ”Pred.” indicates that FOMs are predicted from the link geometry with the ANN. In case of the WSXTR the FOM can be predicted directly (”Dir. Pred.”) or with the WPT and WPSXT (”Pred.”). (a) WPT. (c) WSXTR.

ANN designs found with an optimization lead to a similar performances than manual designs. Both S-parameters and figures of merit can be predicted. A further investigation should focus on extending the range of link models.

References

[1] K.-T. Hsu, W.-D. Guo, G.-H. Shiue, C.-M. Lin, T.-W. Huang, and R.-B. Wu, “Design of reflectionless vias using neural network-based approach,” *IEEE Transactions on Advanced Packaging*, vol. 31, no. 1, p. 211–218, Feb. 2008.

[2] H. Kim, C. Sui, K. Cai, B. Sen, and J. Fan, “Fast and precise high-speed channel modeling and optimization technique based on machine learning,” *IEEE Transactions on Electromagnetic Compatibility*, vol. 60, no. 6, pp. 2049–2052, Dec. 2018.

[3] K. Roy, M. A. Dolatsara, H. M. Torun, R. Trinchero, and M. Swaminathan, “Inverse design of transmission lines with deep learning,” in *IEEE Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)*, Montreal, Canada, Oct. 2019.

[4] T. Lu, J. Sun, K. Wu, and Z. Yang, “High-speed channel modeling with machine learning methods for signal integrity analysis,” *IEEE Transactions on Electromagnetic Compatibility*, vol. 60, no. 6, pp. 1957–1964, Dec. 2018.

[5] N. Ambasana, G. Anand, D. Gope, and B. Mutnury, “S-parameter and frequency identification method for ANN-based eye-height/width prediction,” *IEEE Transactions on Components, Packaging and Manufacturing Technology*, vol. 7, no. 5, pp. 698–709, May 2017.

[6] R. Trinchero and F. G. Canavero, “Modeling of eye diagram height in high-speed links via support vector machine,” in *IEEE Workshop on Signal and Power Integrity (SPI)*, Brest, France, May 2018.

[7] R. Rimolo-Donadio, X. Gu, Y. Kwark, M. Ritter, B. Archambeault, F. de Paulis, Y. Zhang, J. Fan, H.-D. Brüns, and C. Schuster, “Physics-Based Via and Trace Models for Efficient Link Simulation on Multilayer Structures Up to 40 GHz,” *IEEE Transactions on Microwave Theory and Techniques*, vol. 57, no. 8, pp. 2072–2083, Aug. 2009.

[8] K. Scharff, H.-D. Brüns, and C. Schuster, “Performance metrics for crosstalk on printed circuit boards in frequency domain,” in *IEEE Workshop on Signal and Power Integrity (SPI)*, Chambéry, France, June 2019.

[9] ——, “Efficient crosstalk analysis of differential links on printed circuit boards up to 100 GHz,” *IEEE Transactions on Electromagnetic Compatibility*, vol. 61, no. 6, pp. 1849–1859, Dec. 2019.

[10] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, “Scikit-learn: Machine learning in Python,” *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.