Channel Inverse Design Using Tandem Neural Network

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***Abstract*—A tandem neural network (NN) with R^2 score-based loss function is proposed in this paper for channel inverse design. Tandem NN consists of an inverse neural network from target performance to design parameters and a pre-trained forward neural network from design parameters to design targets. The training of the actual INN uses the fixed pre-trained forward model to evaluate the inverse design output. A channel inverse design example for target impedance and attenuation at multiple frequency points is applied in this paper to evaluate the performance of tandem NN. Numerical results show that tandem NN achieves a good design result compared with target performance and regular NN.**

Keywords—high-speed link; inverse design; neural network; impedance and attenuation

I. Introduction

Channel design is one of the most critical problems in modern electronic integrated systems. Inverse design of high-speed channel for target performance often needs to consider high-dimensional design parameters. Utilizing machine learning technology as an automatic method is a recent research trend to solve the problem of inverse design. Optimization methods, such as genetic algorithm [1] and Bayesian optimization [2-4], are widely used to find the optimal design for target specifications. Since the optimization step is always time-consuming, finding the direct inverse mapping architecture from target performance to design parameters also attracts the attention of researchers. Deep neural network (NN) [5] least-squares support vector machine [6], support-vector-regression based active subspace method [7-8] are employed for this purpose.

Considering that directly training a regular NN model from target performance to design parameters suffers from a “one-to-many” property. This paper utilizes tandem NN to help overcome the training confusion, which consists of an inverse neural network (INN) and a pre-trained forward neural network (FNN). FNN is trained as a physics predictor at the first step. An R^2 score-based loss function calculated in the physics domain by pre-trained FNN is used to evaluated INN design outputs and update INN neural weights. After training, additional target performance can be fed into INN and calculate corresponding design parameters. A channel inverse design example for target impedance and attenuation at multiple frequency points is demonstrated to evaluate the performance of TNN in this work.

This paper is organized as follows: Section II presents the tandem neural network structure methods with its training and testing steps. Section III evaluates the tandem NN method with its application to a channel inverse design problem. Meanwhile, inverse design results of the example are illustrated as well in Section III with a comparison of the regular NN method. This paper concludes in Section IV.

II. Methodology

A. Neural Network

Finding a mapping from design targets $\boldsymbol{X}=\{x_1,\ldots,x_n\}$ to design parameters $\boldsymbol{Y}=\{y_1,\ldots,y_m\}$ is a direct way for inverse design. NN, as a popular surrogate model, is widely used for this kind of design problem. As shown in Fig. 1, regular NN structure design takes design targets as inputs and design parameters as outputs and then utilizes the error between expected and predicted design parameters as a loss function to update the neural weights during training.

However, a NN model in reality used for directly calculating the design parameters from desired targets always fails due to the “one-to-many” property of the inverse problem. In other words, the fact that several nonunique solutions exist for the same design target makes NN confused in the training process.

B. Tandem Neural Networks

To overcome the above captioned problem, tandem NN [9] is applied for inverse design which consists of a pre-trained FNN as a physics predictor in neural network training. As shown in Fig. 2, a tandem neural network consists of a normal INN and a pre-trained FNN. In tandem NN, the loss function does not compare ambiguous design layouts but operates in the physics domain (e.g., the characteristic impedance rather than the design parameters). In this way, different design parameters which lead to a similar physical response no longer confuse the NN, and all correct solutions to a given design problem yield positive training feedback.

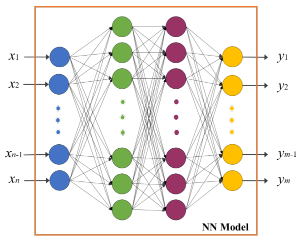

Fig. 1. NN for inverse design.

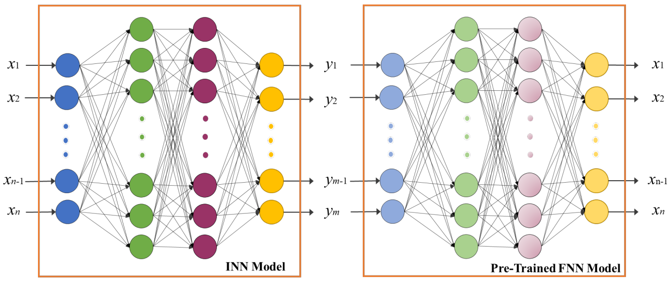

Fig. 2. Tandem neural network for inverse design.

The tandem NN training and testing steps are as follows:

- A forward NN from design parameters to target performance is trained at first.
- The training of the actual INN subsequently uses the fixed pre-trained forward model to evaluate the inverse design output.
- New testing data uses trained INN to get inverse design parameters.

R^2 score as a statistical measure for the regression model is the proportion of the variation in the dependent variable that is predictable from the independent variables, which is always in the range from 0 to 1. In the best case, the prediction values from the regression model exactly match the expected values, which results in an R^2 score equal to 1. The closer the R^2 score gets to 0, the worse the model predicts. Previous work [10] shows that for regression analysis evaluation, the R^2 score is more informative than other commonly used indicators, such as mean squared error (MSE), mean absolute error (MAE), et. al.

Thus, in this work, a loss function based R^2 score is defined for neuron weights updating in the NN training process:

$$\begin{aligned} Loss &= 1 - R^2 = \frac{SS_{res}}{SS_{tot}}, \\ SS_{res} &= \sum_i (y_i - f_i)^2, \\ SS_{tot} &= \sum_i \left(y_i - \frac{1}{n} \sum_i y_i \right) \end{aligned} \tag{1}$$

where f_i is the prediction result of y_i.

III. Results and Discussion

To evaluate the performance of tandem NN with its application to signal integrity, we consider an example of channel inverse design example for target impedance and attenuation.

Fig. 3 describes an embedded microstrip line with four geometry parameters, for which we consider the characteristic impedance and attendance of the trace in the middle. TABLE I shows nominal value and range for these four parameters. Channel Impedance and attenuation at 2 GHz, 3 GHz, 4 GHz, 5 GHz, and 6 GHz under nominal design parameters are shown in Fig. 4 and utilized as target performances. In this way, tandem NN is applied in this example to design channel geometry parameters from target impedance and attenuation at multi-frequency points.

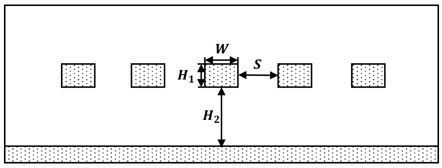

Fig. 3. Embedded Microstrip lines.

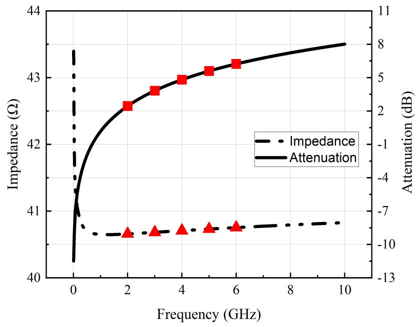

Fig. 4. Impedance and attenuation of the embedded microstrip line.

TABLE I. Channel Design Parameters

Parameter	Nominal Value	Range	Unit
W	140	70-210	um
S	150	75-225	um
H_1	30	15-45	um
H_2	100	50-150	um

A tandem NN consists of a 3-hidden-layer INN and a pre-trained 3-hidden-layer FNN is utilized in this example. The neurons of the input layer, three hidden layers, and the output layer for INN are 10, 50, 50, 10, 4, while in FNN are 4, 50, 50, 10, 10. Rectified Linear Unit (ReLU) is an activation function to help increase the nonlinear relationship in hidden layers. Adaptive Moments Estimation (Adam) optimization method is applied to update neuron weights based on the defined loss function.

There are 300 training samples and 300 validation samples generated from ANSYS Q2D Extractor. Pre-trained FNN achieves 0.0232 training loss and 0.0254 validation loss. The final training loss and validation loss for tandem NN are 0.0052 and 0.0064.

Additional 50 target performance requirements are used for the model test, which applied well-trained INN in Tandem NN to calculate design parameters. These inverse design parameters are fed into ANSYS to calculate its impedance and attenuation performance. Fig. 5 compares the performance results from the tandem NN inverse design with a target performance. Results show that tandem NN can successfully help design channel parameters from target requirements.

In the meanwhile, a regular NN with the same hyper-parameters settings as INN is utilized as a comparison method. Numerical results of mean squared error (MSE) and R^2 score shown in TABLE II found that tandem NN that utilizes a pre-

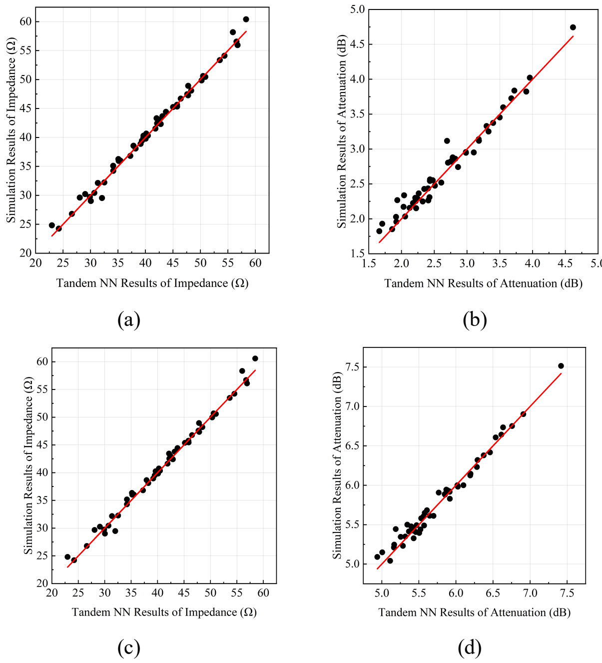

Fig. 5. Comparison between inverse design results and expected design targets: (a) impedance at 2 GHz; (b) attenuation at 2 GHz; (c) impedance at 5GHz; (d) attenuation at 5GHz.

TABLE II. COMPARISON RESULTS OF TANDEM NN AND REGULAR NN

Parameter		Tandem NN		Traditional NN	
		MSE (Ω^2)	R^2 score	MSE (dB^2)	R^2 score
2GHz	Impedance	0.729	0.991	2.660	0.967
	Attenuation	0.015	0.964	0.035	0.914
3GHz	Impedance	0.732	0.991	2.672	0.967
	Attenuation	0.010	0.974	0.030	0.913
4GHz	Impedance	0.734	0.991	2.680	0.967
	Attenuation	0.007	0.976	0.028	0.910
5GHz	Impedance	0.736	0.991	2.687	0.967
	Attenuation	0.006	0.977	0.027	0.904
6GHz	Impedance	0.737	0.991	2.692	0.967
	Attenuation	0.006	0.977	0.026	0.898

trained NN to evaluate inverse design help solve the training confusion in regular NN and leads to better results.

IV. CONCLUSION

The tandem NN with R^2 score-based loss function is implemented in this work for channel inverse design which consists of an INN from target performance to channel design parameter and a pre-trained FNN from channel to performance evaluation. Neuron weights in tandem NN are trained from the loss function evaluated by fixed pre-trained FNN with the INN design outputs. A channel inverse design example for target impedance and attenuation at multiple frequency points is applied in this paper to evaluate the performance of tandem NN. Numerical results show that tandem NN achieves a good design result compared with target performance and regular NN. The different NN evaluation methods in the training step with pre-trained NN help tandem NN overcome the "one-to-many" inverse confusion in regular NN.

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REFERENCES

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

[2] D. Lho, J. Park, H. Park, S. Park, S. Kim, H. Kang, S. Kim, G. Park, K. Son, and J. Kim, "Bayesian optimization of high-speed channel for signal integrity analysis," *in 2019 IEEE 28th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)*, Montreal, QC, Canada, Oct. 2019.

[3] X. Yang, H. M. Torun, J. Tang, P. R. Paladhi, Y. Zhang, W. D. Becker, J. A. Hejase, and M. Swaminathan, "Parallel bayesian active learning using dropout for optimizing high-speed channel equalization," *in 2021 IEEE 30th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)*, Oct. 2021.

[4] H. M. Torun and M. Swaminathan, "High-dimensional global optimization method for high-frequency electronic design," *IEEE Transactions on Microwave Theory and Techniques*, vol. 67, no. 6, pp. 2128–2142, Jun. 2019.

[5] K. Roy, M. A. Dolatsara, H. M. Torun, R. Trinchero, and M. Swaminathan, "Inverse design of transmission lines with deep learning," *in 2019 IEEE 28th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)*, Montreal, QC, Canada, Oct. 2019.

[6] R. Trinchero, M. A. Dolatsara, K. Roy, M. Swaminathan, and F. G. Canavero, "Design of high-speed links via a machine learning surrogate model for the inverse problem," *in 2019 Electrical Design of Advanced Packaging and Systems (EDAPS)*, KAOHSIUNG, Taiwan, Dec. 2019.

[7] H. Ma, E.-P. Li, A. C. Cangellaris, and X. Chen, "Support vector regression-based active subspace (SVR-AS) modeling of high-speed links for fast and accurate sensitivity analysis," *IEEE Access*, vol. 8, pp. 74 339–74 348, 2020.

[8] H. Ma, E.-P. Li, A. C. Cangellaris, and X. Chen, "High-speed link design optimization using machine learning SVR-AS method," *in 2020 IEEE 29th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)*, San Jose, CA, USA, Oct. 2020.

[9] I. Malkiel, M. Mrejen, A. Nagler, U. Arieli, L. Wolf, and H. Suchowski, "Plasmonic nanostructure design and characterization via deep learning," *Light Sci. Appl.* vol. 7, no. 60, 2018.

[10] D. Chicco, M. J. Warrens, G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Computer Science* vol. 7:e623, 2021.