Fast Design of Metasurface-based Microwave Absorber Using the Neuro-TF Approach

Yuheng Tu, **Jianan Liu**, **Tian Qiu**, **Yunlang Cai**,
Jianan Zhang, **Jian Wei You**, **and Tie Jun Cui**
State Key Laboratory of Millimeter Waves, Southeast University, Nanjing, China

Abstract— Due to its great capability in manipulating electromagnetic (EM) waves, metasurfaces have broad application prospects. Conventional approaches for metasurfaces design demand huge amounts of full-wave EM simulations to obtain the optimal geometric parameter values, leading to a CPU-intensive and time-consuming optimization process. Parametric modeling is an important part of achieving fast design optimization of microwave components. Recently, an advanced technique which combines neural networks and pole-residue-based transfer function (i.e., the neuro-TF approach) shows great potential in parametric modeling, which is so far mostly applied to microwave passive components. However, how to apply the neuro-TF method to parametric modeling and fast design of metasurfaces remains an open project. The main contribution in this paper is the development of the neuro-TF model which provides accurate and fast prediction of the EM behavior of a metasurface and thus greatly accelerate the design optimization process. The model can then be utilized to achieve fast design of metasurfaces-based components such as microwave absorbers. A frequency-selected microwave absorber is used as an example to demonstrate the superior performance of the neuro-TF approach.

2023 Photonics & Electromagnetics Research Symposium (PIERS) | 979-8-3503-1284-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/PIERS59004.2023.10221266

1. INTRODUCTION

Metasurfaces have made significant advancement over the past decade and are considered to be one of the most promising technologies for next-generation communication systems [1]. In terms of fast metasurface design, parametric modeling is a crucial but challenging task, which is conventionally fulfilled in commercial EM simulation software demanding a large number of full-wave electromagnetic (EM) simulations of repetitively changing geometrical parameter values [2, 3]. As a result, the mission is usually finished at the cost of tremendous time, computer memory and engineers' energy. To solve the above problems, machine learning (ML)-based methods prove available to fast and intelligent metasurface design. The neuro-transfer function (neuro-TF) method is one of the most powerful tools [4, 5], in which the EM response of microwave structures versus frequency is represented by transfer functions of the pole-residue format. Recent years have witnessed successful applications of neuro-TF to parametric modeling and yield-driven design of microwave passive components [6–8], but the usage of neuro-TF on the parametric modeling of metasurfaces is still a blank. In this paper, successful completion of the neuro-TF-based parametric modeling of metasurfaces is the main contribution. The trained neuro-TF model can provide fast and accurate predictions of the EM behavior of metasurfaces, thereby greatly increasing the efficiency in metasurface design.

In this paper, we first review the neuro-TF approach combining the neural network technique and the pole-residue-based transfer function. Then, a neuro-TF model is trained for fast prediction of the EM responses of the metasurface, which is further implemented for the design of a metasurfaces-based frequency-selected microwave absorber. Finally, the performance comparison between neuro-TF and traditional approach is provided. It has been demonstrated that the neuro-TF method achieves the superior performances in both tasks, saving a lot of CPU time and at the same time achieving satisfying accuracy.

2. INTRODUCTION TO THE NEURO-TF APPROACH

In this section, we will provide a brief introduction to the pole-residue-based neuro-TF Model formulation and its training process.

As depicted in Fig. 1, the pole-residue-based neuro-TF model comprises neural networks and a pole-residue-based transfer function, which is employed for the computation of the absorbance of the metafurface. The inputs to the model are represented by the vector $\mathbf{x}$ comprising of the geometrical variables along with the frequency ω. The output of the model is denoted by y, which specifically signifies the absorbance of the metasurface corresponding to $\mathbf{x}$ and ω.

Let the frequency response of the metasurfae (i.e., S_{11}) be a function of poles/residues, the definition of which is established by means of a transfer function that relies on poles and residues

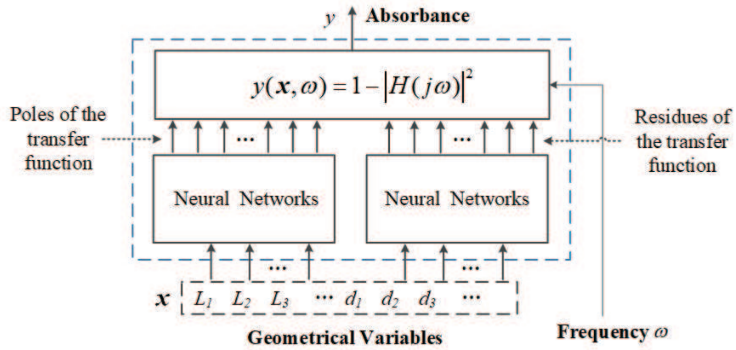

Figure 1: Structure of the pole-residue-based neuro-TF model.

and is expressed in the subsequent manner:

$$H(j\omega)=\sum_{i=1}^{N}\frac{r_i}{j\omega-p_i} \tag{1}$$

where p_i and r_i represent the poles and residues of the transfer function respectively, and N represents the order of the transfer function.

A two-stage training process is proposed whereby, in the first stage, separate neural networks are preliminarily trained to learn the nonlinear relationship between the poles and residues and the geometrical parameters. The training data for this stage comprises of (x, p_i) and (x, r_i) respectively, i.e., samples of geometrical parameters as model inputs and poles/residues as model outputs. The outputs of the neural network for poles (residues) are represented as p_{NN} (r_{NN}) with corresponding neural network weights denoted by $\mathbf{w}_p$ $(\mathbf{w}_r)$. A small number of hidden neurons in the neural networks can be employed by making use of relaxed error criteria [4].

During the second stage, model refinement is conducted. The training data utilized for this phase consists of samples of geometrical parameters as model inputs and EM-simulated absorbances as model outputs. The model itself comprises the pole-residue-based transfer function of (1), alongside neural networks whose initial values are the optimal solutions from the preliminary training. The refinement process encompasses both model training and testing. The training aspect aims to optimize the weights within the neural networks to minimize the error function:

$$E_{T_r}\left(\mathbf{w}_p,\mathbf{w}_r\right)=\frac{1}{2n_s}\sum_{k\in T_r}\sum_{i\in\Omega}\left|y\left(p_{NN}\left(\mathbf{x}_k,\mathbf{w}_p\right),r_{NN}\left(\mathbf{x}_k,\mathbf{w}_r\right),s_i\right)-d_{k,i}\right|^2 \tag{2}$$

where n_s is the total number of training samples. The index set T_r pertains to the training data of diverse geometrical parameters, while k serves as the index that specifies the k-th sample of training data. The index set Ω pertains to the frequency samples. The output of the entire model is designated by y, and ultimately depends on the geometrical parameters $\mathbf{x}_k$, frequency s_i, and neural network weights $\mathbf{w}_p$ and $\mathbf{w}_r$.

After a certain number of iterations, the training process is halted, and an unused independent set of testing data is utilized to evaluate the quality of the trained model. The training and testing errors are computed as the difference between the model response and the training/testing data. If both the training and testing errors are sufficiently low, the refinement process of the model will terminate, indicating that the model is suitable for high-level metasurface design applications.

3. EXAMPLES

In this part, the fast design for a metasurfaces-based frequency-selected microwave absorber is carried out using the neuro-TF method, with the unit cell shown in Fig. 2. The unit cell has a length of $a = 200$ mm along the x-axis and a height of 3 mm along z-axis.

3.1. Parametric Modeling of a Microwave Absorber With two Ribbons

The training and testing data ranges for the two distinct cases are specified in Table 1. We scale and shift the frequency range from 2 GHz–4 GHz to 0.9 GHz–1.1 GHz during the vector fitting progress

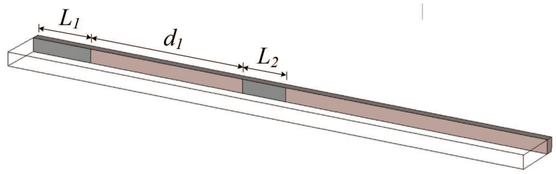

Figure 2: EM structure of the unit cell of the microwave absorber.

and set the order $N = 8$, which is the maximum order. We compare the modeling performance of the neuro-TF method with pure neural networks (MLP3, also referred to as the data-driven method), as shown in Table 1. From the table, one can see that the neuro-TF method achieves better modeling accuracy than the data-driven method for both cases. We obtain the neuro-TF model outputs in Case 2 at one geometrical testing sample, and compare them with CST-simulated responses and MLP3 predictions, as illustrated in Fig. 3. We can see that the neuro-TF model outputs match the CST-simulated responses better than the pure neural network model outputs.

Table 1: Definition of training and testing data for the parametric modeling of the microwave absorber.

	Geometrical Variables	Training Data Min	Training Data Max	Training Data Step	Testing Data Min	Testing Data Max	Testing Data Step	MLP3 Training Error	MLP3 Testing Error	neuro-TF Training Error	neuro-TF Testing Error
Case1 (small range)	L_1(mm)	16	18	0.2	16.1	17.9	0.2	1.444%	1.2844%	0.7513%	0.8259%
	L_2(mm)	16	18	0.2	16.1	17.9	0.2				
	d_1(mm)	10	11	0.2	10.1	0.2	10.9				
Case2 (large range)	L_1(mm)	13	30	1	13.5	29.5	1	7.8417%	7.618%	4.9497%	4.1678%
	L_2(mm)	13	30	1	13.5	29.5	1				
	d_1(mm)	1	171	5	3	168	5				

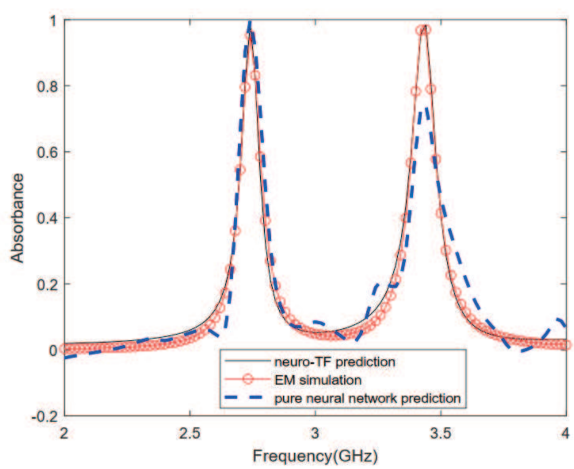

Figure 3: Comparison between the responses predicted by the neuro-TF model and the CST simulated data at the testing sample $[L_1\ L_2\ d_1] = [16\ 22\ 80]^T$ (mm).

3.2. Neuro-TF-Based Design Optimization of a Frequency-Selected Microwave Absorber

Subsequently, the trained neuro-TF model is utilized to the design of a metasurfaces-based frequency-selected absorber, with design specifications: absorbance greater than 0.7 at specified frequencies of 3.17 GHz and 3.41 GHz. The initial geometrical parameter values are given as $[L_1\ L_2\ d_1] =$

$[17.2\ 16.8\ 10.5]^T$ (mm), and the optimal geometric parameter values for the absorber obtained are $[L_1\ L_2\ d_1] = [16.1287\ 17.9641\ 10.0]^T$ (mm). Fig. 4 shows the CST-simulated responses at the initial and optimal designs, demonstrating that the optimal design can satisfy the desired design specification. It can be observed from Fig. 4 that the absorbance predicted by the neuro-TF model exhibits remarkable conformity with the EM data. To facilitate a comparative evaluation, we leveraged CST to undertake direct EM optimization of the frequency-selected absorber using identical initial design parameter values and design specifications. The neuro-TF-based optimization was achieved in a mere 0.134 seconds, while the CST optimization costs 1h 10min. The more we re-use the neuro-TF model, the more time savings will be achieved.

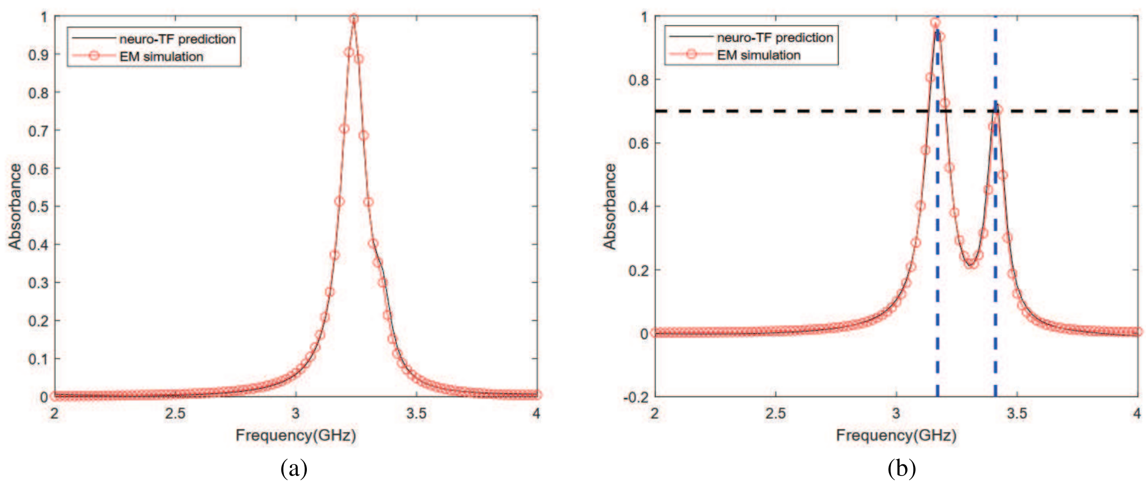

Figure 4: Comparison between the absorbances in the magnitude of neuro-TF model and CST simulation. (a) Before optimization $[L_1\ L_2\ d_1] = [17.2\ 16.8\ 10.5]^T$ (mm). (b) After optimization $[L_1\ L_2\ d_1] = [16.1287\ 17.9641\ 11.0]^T$ (mm).

4. CONCLUSION

The use of the neuro-TF model in the parametric modeling of metasurfaces has resulted in significant benefits, including fast and accurate predictions of electromagnetic (EM) responses. This has enabled a faster design process, addressing the disadvantages of traditional methods that are time-consuming and CPU-intensive. The trained model has been utilized for the purpose of expediting metasurface design optimization of frequency-selected absorbers. This approach has presented possibilities for the progression of advanced intelligent physics-driven machine learning (ML) techniques within the field of metasurface design.

ACKNOWLEDGMENT

This work was supported by the Natural Science Foundation of Jiangsu Province (BK20220808, BK20210209), the Fundamental Research Funds for the Central Universities under Grant 2242023 K5002, the Basic Scientific Center of Information Metamaterials of the National Natural Science Foundation of China (6228810001), the National Key Research and Development Program of China (2017YFA0700201, 2017YFA0700202, 2017YFA0700203), the National Natural Science Foundation of China (62101124), and the 111 Project (111-2-05).

REFERENCES

1. Cui, T. J., D. R. Smith, and R. Liu, *Metamaterials: Theory, Design, and Applications*, Springer, New York, NY, USA, 2010.
2. You, J. W., J. F. Zhang, W. X. Jiang, H. F. Ma, W. Z. Cui, and T. J. Cui, "Accurate analysis of finite-volume lumped elements in metamaterial absorber design," *IEEE Trans. Microw. Theory Techn.*, Vol. 64, No. 7, 1966–1975, Jul. 2016.
3. You, J. W., S. Tan, J. Zhang, W. Cui, and T. J. Cui, "A uniform time-domain finite integration technique (TDFIT) using an efficient extraction of conformal information," *IEEE Antennas Propag. Mag*, Vol. 56, No. 2, 63–75, Apr. 2014.

4. Feng, F., C. Zhang, J. Ma, and Q. J. Zhang, "Parametric modeling of EM behavior of microwave components using combined neural networks and pole-residue-based transfer functions," *IEEE Trans. Microw. Theory Techn.*, Vol. 64, No. 1, 60–77, Jan. 2016.
5. Xiao, L.-Y., W. Shao, X. Ding, and B.-Z. Wang, "Dynamic adjustment kernel extreme learning machine for microwave component design," *IEEE Trans. Microw. Theory Techn.*, Vol. 66, No. 10, 4452–4461, Oct. 2018.
6. Zhang, J., F. Feng, and Q. J. Zhang, "Rapid yield estimation of microwave passive components using model-order reduction based neuro-transfer function models," *IEEE Microw. Wireless Compon. Lett.*, Vol. 31, No. 4, 333–336, Apr. 2021.
7. Zhang J., et al., "Adaptively weighted yield-driven EM optimization incorporating neurotransfer function surrogate with applications to microwave filters," *IEEE Trans. Microw. Theory Techn.*, Vol. 69, No. 1, 518–528, Jan. 2021.
8. Zhang, J., F. Feng, W. Zhang, J. Jin, and Q. J. Zhang, "Parametric modeling of microwave passive components using combined neural networks and reduced-order models," *IEEE Trans. Microw. Theory Techn.*, Vol. 68, No. 6, 2215–2233, Jun. 2020.