Progress In Electromagnetics Research M, Vol. 72, 79–88, 2018

Multi-Physics Parametric Modeling of Microwave Passive Components Using Artificial Neural Networks

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Abstract—In this paper, a novel multi-physics parametric modeling approach using artificial neural networks (ANNs) for microwave passive components is proposed. In the proposed approach, the ANN is used to learn the nonlinear relationships between electromagnetic (EM) behaviors and multi-physics design variables. The trained model can accurately represent the EM responses of the passive components with respect to the multi-physics input parameters. Therefore, the proposed model can provide accurate and fast prediction of EM responses using low computational cost and little time for multi-physics design. The advantage of the proposed model is demonstrated by two microwave examples: the proposed model can save about 98% computational cost compared with the EM model, and the CPU time of the proposed model is less than 0.1 s while that of the EM model needs many minutes.

1. INTRODUCTION

Parametric modeling of electromagnetic (EM) behavior has become important for EM design of microwave passive components [1, 2]. For high performance RF/microwave component and system design, we often require considerations of the operation in a real-world multi-physics environment which includes other physics domains besides the EM domain [3]. EM centric multi-physics design, which involves EM analysis coupled with the effects of multi-physics areas such as thermal and structural mechanics, is time consuming because it usually requires repetitive EM simulations with multi-physics parameters as design variables. Multi-physics parametric modeling becomes essential, which can develop parametric models to represent the EM responses as functions of multi-physics parameters [4].

Researches have been focused on multi-physics parametric modeling for microwave passive components. In [5], a multi-physics model has been constructed with finite element methods (FEMs) for Light Emitting Diode which works in different temperature and humidity environments. The authors in [6] have presented a multi-physics model of through-silicon vias with an equivalent-circuit approach. Most of the researches have used circuit methods and FEMs for multi-physics modeling of microwave passive components [7–9]. However, recently, the structure of microwave passive components has become more complex. Although the existing methods are suitable for modeling existing components, they are often time-consuming and computationally expensive for new components. New multi-physics modeling methods with high efficiency and low cost are needed urgently.

Artificial neural networks (ANNs) can be trained to learn any arbitrary nonlinear input-output relationships from corresponding data, which lead to ANNs being applied to many fields, especially in modeling area [10–12]. Recently, ANNs have been recognized as an effective vehicle for EM-based modeling and optimization in microwave area. Through an automatic training process, ANN can

Received 4 July 2018, Accepted 6 August 2018, Scheduled 20 August 2018
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learn the relationship between EM responses and geometrical parameters. The trained model provides accurate and fast prediction for the EM behavior of microwave components with geometrical parameters as variables and can be subsequently implemented in circuit and system designs [13, 14]. However, how to develop multi-physics parametric models using ANN techniques remains an open topic.

In this paper, we propose a new multi-physics parametric modeling method using ANN for microwave passive components. In the proposed method, ANN is trained to learn the relationships between the EM behaviors and multi-physics design parameters. The trained ANN can provide an effective and fast prediction of EM responses with respect to multi-physics design parameters. The proposed multi-physics parametric model using ANN can achieve high accuracy of the EM responses using low computational cost and little time. A tunable evanescent mode cavity filter example and a four-pole waveguide filter example are used to illustrate the feasibility of the proposed multi-physics parametric modeling approach.

2. PROPOSED MULTI-PHYSICS MODEL

In this paper, we propose to create a multi-physics parametric model using ANN to learn the EM response of microwave passive components with respect to multi-physics design parameters. The proposed multi-physics model which learns the behavior of the components is developed through the process illustrated using the flowchart in Figure 1. Design of experiments (DOE) method [15] is used as the sampling method. The data for modeling are generated using FEM simulations. All EM data are divided into two groups: one is the training data used for training the ANN model; the other is the test data used for verifying the ANN model. In order to improve the modeling accuracy, the scaling method is used for training data [16]. The trained multi-physics parametric model can be used for fast and accurate EM centric multi-physics analysis.

We propose to use ANN as the multi-physics parametric model structure because ANN can learn the highly nonlinear relationship between input and output, and the trained ANN model is able to provide fast output solutions to the problems that they have learned. The three-layer multilayer perceptron (MLP) as one of the ANN structures, which can get the nonlinear relationship effectively and accurately,

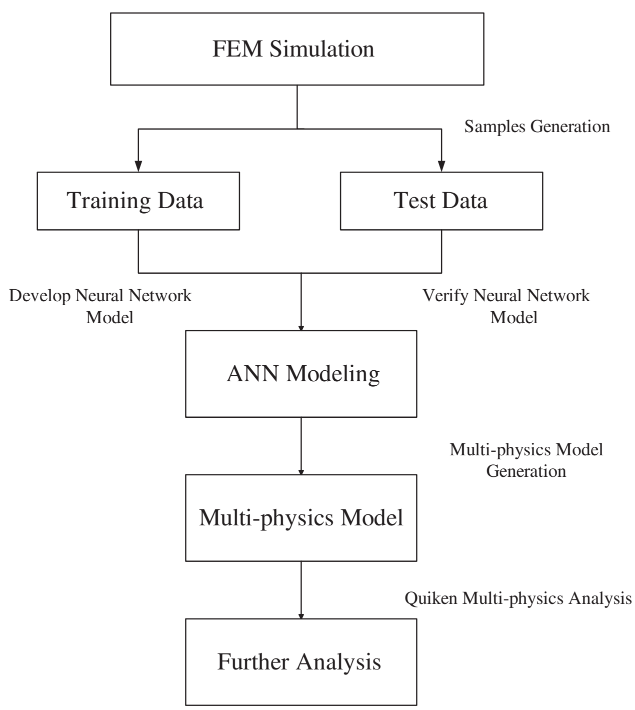

Figure 1. Flowchart demonstrating the multi-physics model development.

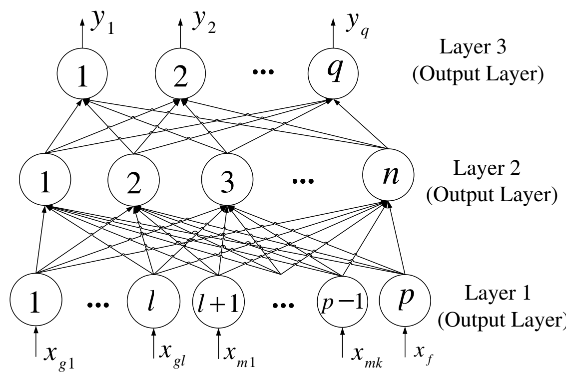

Figure 2. The proposed multi-physics parametric model using ANN.

is proposed to be used in this paper. For ANN modeling, let $\mathbf{x}$ be a set including all the input variables of a given passive component, which is divided into geometrical parameters $\mathbf{x_g}$, multi-physics parameters $\mathbf{x_m}$ and frequency $\mathbf{x_f}$. Let $\mathbf{y}$ be a set including all the output responses of the given passive component, which represents the EM behavior of the multi-physics problem. The ANN structure of the proposed multi-physics parametric model is illustrated in Figure 2. Layer 1 is the input layer ($\mathbf{x}$), which receives the external inputs including $\mathbf{x_g}, \mathbf{x_m}$ and $\mathbf{x_f}$ by the input neurons. Layer 2 is a hidden layer of the neural network, which handles $\mathbf{x_g}, \mathbf{x_m}$ and $\mathbf{x_f}$ according to activation functions. Based on the neural network model in Figure 2, we propose to use the sigmoid function as the activation function for the hidden neurons, which is a smooth switch function and can be defined as

$$\sigma(\gamma) = \frac{1}{1+e^{-\gamma}}, \tag{1}$$

Layer 3 is the output layer ($\mathbf{y}$), which represents the output responses of the proposed model. In Figure 2, p and q represent the numbers of input and output neurons, respectively. l and k represent the numbers of $\mathbf{x_g}$ and $\mathbf{x_m}$, respectively, i.e., $l + k = p - 1$. n represents the number of hidden neurons, which is determined during the ANN training.

For the sake of perspicuity, the calculation of the proposed model is formulated as

$$y_j = \sum_{i=1}^{n} w_{ij}^{(2)} \sigma \left(\sum_{h=1}^{l} w_{hi}^{(1)} x_{gh} + \sum_{r=l+1}^{k+l} w_{ri}^{(1)} x_{mr} + w_{pi}^{(1)} x_f + w_{0i}^{(1)} \right) + w_{0j}^{(2)}, \tag{2}$$

where $w_{hi}^{(1)}$, $w_{ri}^{(1)}$ and $w_{pi}^{(1)}$ are the weight parameters between the respective (hth, rth or pth) input neuron and the ith hidden neuron, while $w_{ij}^{(2)}$ is the weight parameters between the ith neuron in the hidden layer and the jth neuron in the output layer. $w_{0i}^{(1)}$ and $w_{0j}^{(2)}$ denote bias values of the ith hidden neuron and the jth output neuron, respectively. Those weight parameters determine the nonlinear relationship between input and output variables.

The proposed ANN model cannot predict EM behaviors of the components accurately until it is well trained using the EM data. Therefore, the ANN training is a significant step during the proposed model development. In the training process, the weight parameters and the number of hidden neurons in the ANN model are optimized and adjusted so that the outputs of the ANN model can fit the EM data accurately. In general, the initial number of hidden neurons is chosen based on the experiences, and the appropriate number of the hidden neurons can be obtained through trial-and-error processes. The weight parameters are changed to make the error between neural network prediction and the training sample as small as possible with Quasi-Newton training method [16]. For training purposes, we use the training error to measure the learning performance of the ANN model and the test error to measure the predictive ability of the ANN model. The training process is performed until both the training error calculated with the training data and the test error calculated with the test data meet the accuracy requirements. The same error function is defined as [17]

$$E(\mathbf{w}) = \frac{1}{2}\sum_{t=1}^{T}\sum_{j=1}^{q}\left\|y_j^t(\mathbf{x},\mathbf{w}) - y_{jD}^t(\mathbf{x})\right\|^2, \tag{3}$$

where $y_j^t(\mathbf{x},\mathbf{w})$ and $y_{jD}^t(\mathbf{w})$ are the EM response of the proposed model and the FEM simulations data, respectively. The subscript t is the training or test data index, and T is the total number of the training or test data. The training and test processes of the proposed multi-physics model are completed using the flowchart in Figure 3.

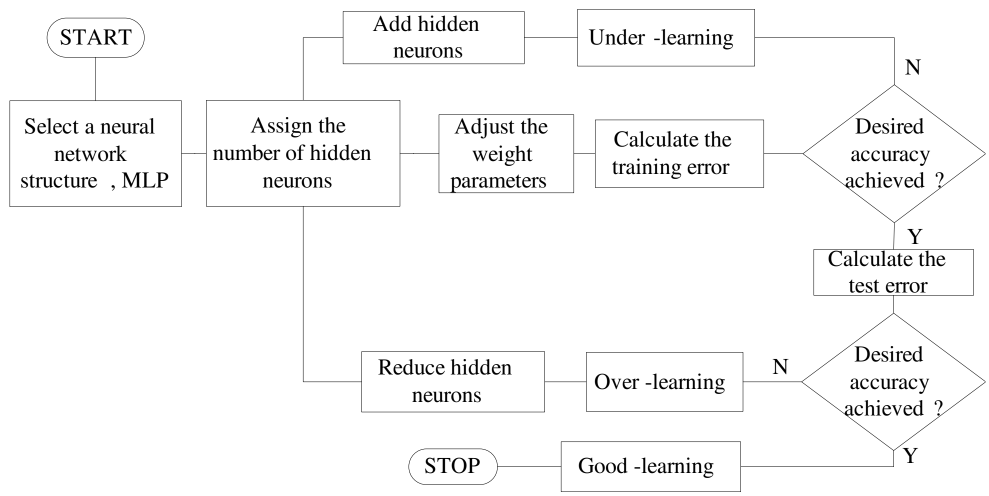

Figure 3. The training and testing process of the proposed multi-physics model.

3. EXAMPLES

3.1. Tunable Evanescent Mode Cavity Filter

A tunable evanescent mode cavity filter [18] is used as the first example, whose structure is illustrated in Figure 4. In this example, the displacement and deformation of piezo actuator can change the magnitude of a small air gap which offers the tunability of the resonant frequency. There are 3 geometrical parameters for the filter: length (L), width (W) of the tuning post, and the gap (H) between the top of the post and the bottom side of the piezo actuator, i.e., $\mathbf{x}_g = [L\ W\ H]^T$. It has one multi-physics variable: bias voltage (V), which is applied on the piezo actuator, causes the deformation and displacement, i.e., $\mathbf{x}_m = [V]$. There is an additional input: frequency ($\mathbf{x}_f$), with the range from 3 GHz to 3.06 GHz. The input parameters of the proposed model for this example are defined as: $\mathbf{x} = [L\ W\ H\ V\ f]^T$. The model has one output: the magnitude in decibels of S_{11} of the filter response, i.e., $\mathbf{y} = [S_{11}]$.

In this example, the training data and testing data are generated using COMSOL Multiphysics. The range of input variables of the proposed method is shown in Table 1. The same 2025 training samples and 1600 testing samples which are sampled by DOE are used to finish the modeling process. The process of training and testing is completed using NEUROMODELERPLUS.

Table 2 gives the training and test errors under different hidden neurons. According to Table 2, the proposed model with 45 hidden neurons has both the smallest training error 0.72% and the smallest test error 1.40%. Therefore, the ANN structure with 45 hidden neurons is chosen in the neural model by comparing all the errors. To show the detailed results, Figure 5 gives the S_{11} comparison between the COMSOL Multiphysics data and the output responses of the proposed model with respect to two different sets of input variables. From Figure 5, the proposed model has a good agreement with the EM data.

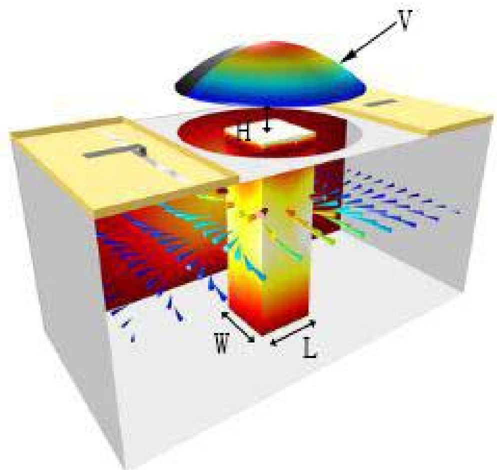

Figure 4. Structure of the tunable evanescent mode cavity filter.

Table 1. Definition of training and testing data.

Input variables	**Training data**			**Test data**		
	Min	**Max**	**Step**	**Min**	**Max**	**Step**
L (mm)	12	18.4	0.8	12.4	18	0.8
W (mm)	10	16.4	0.8	10.4	16	0.8
H (um)	100	148	6	103	145	6
V (V)	−200	200	50	−175	175	50

Table 2. Training and test errors under different hidden neurons.

Hidden neurons	**Training error (%)**	**Test error (%)**
35	1.19	1.91
40	0.93	1.60
45	0.72	1.40
50	0.80	1.60
55	0.78	1.67

The comparison of modeling time between the FEM simulations and the proposed approach is shown in the first column of Table 3. The total modeling CPU time is 2.75 h in the COMSOL Multiphysics, while it is only about 0.35 h in the proposed method. By this comparison, it is clear that the cost in the proposed method is insignificant with a similar accuracy requirement. In other words, it is so highly efficient that the proposed approach constructs the model if the data are prepared.

After building the model, we apply a new set of input to evaluate the performances of two models. The performance comparison of two models in practical application is illustrated in the second and third columns of Table 3. The FEM simulations model gets the corresponding output which costs the CPU time and computational memory about 2.5 minutes and 2.83 GB, respectively. However, the proposed model only costs 0.031 s and 40 MB with a similar accuracy. The proposed approach can save about 98.6% computational memory compared with the FEM simulations. We can see that the proposed model provides effective and fast prediction of EM responses for component design in multi-physics environment. Once the proposed multi-physics model is constructed, it is used over and over again so that the benefit accumulates continuously during this process.

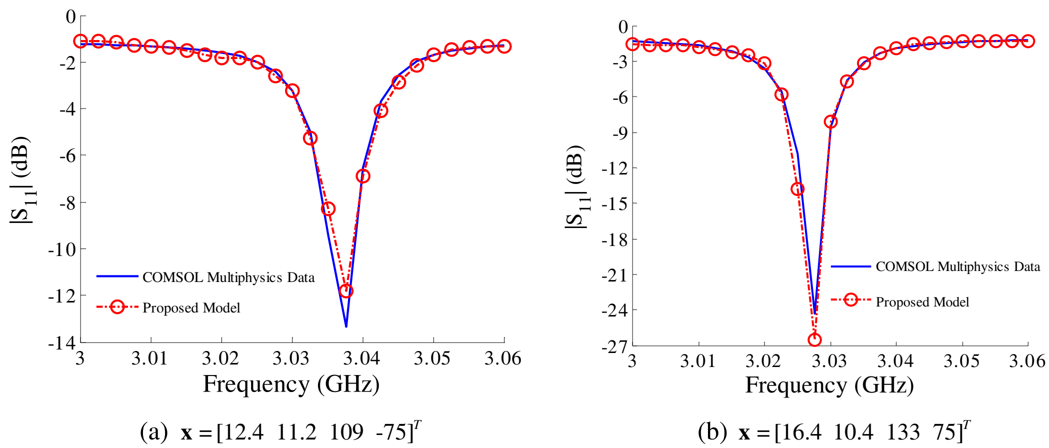

Figure 5. Comparison of the magnitude in decibels of S_{11} between the proposed model and the COMSOL Multiphysics data.

Table 3. Comparison of the cost and time between two modeling approaches for the tunable evanescent mode cavity filter.

Modeling Method	Modeling time(h)	CPU time	Computational memory	Memory saving (%)
FEM simulations	2.75	2.5 minutes	2.83 GB	98.6%
Proposed	$2.75 + 0.3$	0.031 s	40 MB	

3.2. Four-Pole Waveguide Filter

A four-pole waveguide filter [19] is used as the second example, whose structure is illustrated in Figure 6. In this example, the displacement and deformation of four piezo actuators can change the magnitude of the small air gap which offers the tunability of the resonant frequency. There are 4 geometrical parameters for the filter: height (H_1) and height (H_2) of the tuning posts in the coupling windows, and height (H_3) and height (H_4) of the square cross section, i.e., $\mathbf{x_g} = [H_1\ H_2\ H_3\ H_4]^T$. It has 2 multi-physics variables: bias voltage (V_1, V_2), which is applied across the piezo actuator, i.e., $\mathbf{x_m} = [V_1\ V_2]^T$, and there is an additional input: frequency ($\mathbf{x_f}$), with the range from 10 GHz to 11 GHz. The input parameters of the model for this example are defined as: $\mathbf{x} = [H_1\ H_2\ H_3\ H_4\ V_1\ V_2\ f]^T$. The model has one output: the magnitude in decibels of S_{11} of the filter response, i.e., $\mathbf{y} = [S_{11}]$.

In this example, the training data and testing data are generated using COMSOL Multiphysics. The range of input variables of the proposed method is shown in Table 4. The same 8181 training samples and 1919 testing samples which are sampled by DOE are used to finish the modeling process. The process of training and testing is completed using NEUROMODELERPLUS.

Table 5 gives the training and test errors under different hidden neurons. According to Table 5, the proposed model with 55 hidden neurons has both smallest training error 1.68% and smallest test error 1.89%. Therefore, the ANN structure with 55 hidden neurons is chosen in the neural model by comparing all the errors. To show the detailed results, Figure 7 gives the S_{11} comparison between the COMSOL Multiphysics data and the output responses of the proposed model with respect to one set input variable. From Figure 7, the proposed model has a good agreement with the EM data.

The comparison of modeling time between the FEM simulations and the proposed approach is shown in the first column of Table 6. The total modeling CPU time is 41.75 h in the COMSOL Multiphysics while it is only about 1.2 h in the proposed method. By this comparison, it is clear that the cost in the proposed method is insignificant with a similar accuracy requirement. In other words, it is so highly efficient that the proposed approach constructs the model if the data are prepared.

After building the model, we apply a new set of input to evaluate the performances of two models.

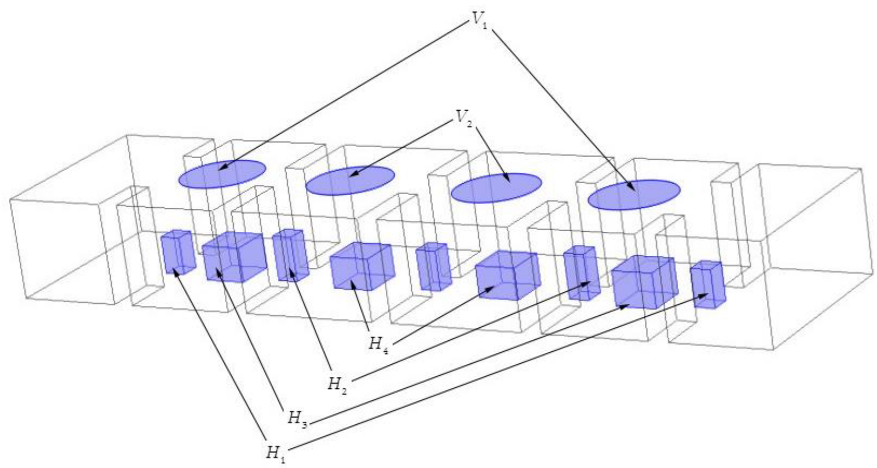

Figure 6. Structure of the four-pole waveguide filter.

Table 4. Definition of training and testing data.

Input variables	Training data			Test data		
	Min	Max	Step	Min	Max	Step
H_1 (mm)	3.04	3.44	0.05	3.065	3.415	0.05
H_2 (mm)	3.10	3.50	0.05	3.125	3.475	0.05
H_3 (mm)	3.52	3.84	0.04	3.54	3.82	0.04
H_4 (mm)	3.28	3.52	0.03	3.295	3.505	0.03
V_1 (V)	-120	120	30	-105	105	30
V_2 (V)	-120	120	30	-105	105	30

Table 5. Training and test errors under different hidden neurons.

Hidden neurons	Training error (%)	Test error (%)
45	2.27	3.10
50	2.24	2.77
55	1.68	1.89
60	2.14	3.01
70	2.22	3.17

Table 6. Comparison of the cost and time between two modeling approaches for the four-pole waveguide filter.

Modeling Method	Modeling time(h)	CPU time	Computational memory	Memory saving (%)
FEM simulations	41.75	23.5 minutes	2.8 GB	98.2%
Proposed	41.75 + 1.2	0.058 s	52 MB	

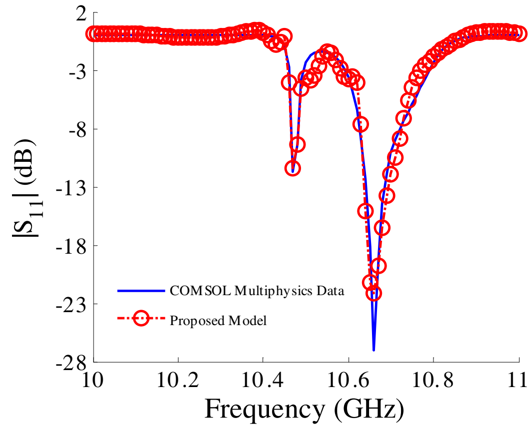

Figure 7. Comparison of the magnitude in decibels of S_{11} between the proposed model and the COMSOL Multiphysics data with the test sample: $\mathbf{x} = [3.115\ 3.125\ 3.58\ 3.325\ \ -75\ \ -75]^T$.

The performance comparison of two models in practical application is illustrated in the second and third columns of Table 6. The FEM simulations model gets the corresponding output which costs the time and computational memory about 23 minutes and 2.8 GB, respectively. However, the proposed model only costs 0.058 s and 52 MB with a similar accuracy. The proposed approach can save about 98.2% computational memory compared with the FEM simulations. We can see that the proposed model provides effective and fast prediction of EM responses for passive component design in multi-physics environment. Once the proposed multi-physics model is constructed, it is used over and over again so that the benefit accumulates continuously during this process.

4. CONCLUSIONS

In this paper, an effective multi-physics parametric modeling approach using ANN for microwave passive components has been proposed. Compared with FEM simulations, the proposed approach achieves similar accuracy using less computational cost and time. The two examples results show that the more complex the component structure is, the more obvious the advantage of the proposed method is in saving calculation time and cost. The trained model can accurately represent the EM responses of the microwave passive components with respect to the multi-physics input parameters. The proposed model can be used to provide accurate and fast prediction of EM responses for multi-physics design process, which can further shorten the design cycle.

In the future, we will try to use various advanced modeling methods to construct the multi-physics model of microwave passive components. Support vector machine (SVM), space mapping (SM), and radial basis function neural network (RBF) could be useful future directions.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (Grant No. 61601323) and the Scientific Research Project of Tianjin Education Commission (Grant No. 2017KJ088).

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