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Multiphysics Parametric Modeling of Microwave Components Using Combined Neural Networks and Transfer Function

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ABSTRACT This paper proposes a new technique to develop an accurate multiphysics parametric model for microwave components to speed up the multiphysics modeling process. In the proposed technique, the artificial neural networks (ANNs) and pole/residue based transfer function are incorporated to represent the highly non-linear relationships between electromagnetic centric (EM-centric) multiphysics behaviors and multiphysics geometrical/non-geometrical design parameters. Vector fitting technique is utilized to obtain the poles/residues of the transfer function for each multiphysics sample. Since the relationship between multiphysics design parameters and the pole/residues of the transfer function is non-linear and unknown, two mapping functions are proposed to establish the mathematical links between the multiphysics design parameters and poles/residues. Parallel multiphysics data generation is proposed to generate the training and testing data for establishing the proposed multiphysics parametric model. A two stage training algorithm is proposed to guide the multiphysics training process. Once an accurate overall model is developed, it can be used to provide accurate and fast prediction of the multiphysics behavior of microwave components with geometrical and non-geometrical parameters as variables, and further can be used in the high level design. Compared with the existing multiphysics modeling methods, the proposed technique can achieve better model accuracy with high efficiency. The proposed technique provides an accurate and efficient methodology even when the coarse model or empirical model is unavailable. Two microwave examples are used to illustrate the validity of the proposed multiphysics parametric modeling technique.

INDEX TERMS Artificial neural networks, multiphysics, parametric modeling, parallel computation, transfer function.

I. INTRODUCTION

Accurate parametric modeling of multiphysics behavior is very important and essential for high performance radio frequency (RF)/microwave design. Multiphysics analysis typically encompasses several physics domain analysis, for example electromagnetic (EM), structural mechanics and thermal [1]–[6]. Multiple coupled physical domain analysis makes the multiphysics simulation very computationally expensive. For multiphysics design, the computational cost of directly using the multiphysics simulation is even more expensive considering that it requires repetitively multiphysics simulations due to the adjustments of the values of design parameters. Parametric modeling can be used to efficiently and accurately predict the multiphysics behavior and perform the high level multiphysics design. To build an accurate parametric model and reduce the computational cost, many parametric modeling techniques have been introduced.

Space mapping techniques [7]–[13] have gained recognition in computer-aided design (CAD). Space mapping

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considers the existence of coarse models and fine models [7]–[10]. The coarse models usually represent the equivalent circuits or the empirical functions. They are computationally very efficient but not accurate enough. While the fine models, such as 3D EM simulator, are typically very accurate but computationally very intensive. By using space mapping technique, we can combine the accuracy of the fine models with the computational efficiency of the coarse models [11], [12]. A neuro-space mapping algorithm which uses the neural networks to build the relationships between the fine models and the coarse models is introduced in [13].

Recent years, artificial neural network (ANN) has become a powerful technique for solving the EM-based design, such as parametric modeling and optimization design with different values of geometrical variables. Neural networks can be used to build the complex and nonlinear links between the EM responses (such as S-parameter) and geometrical parameters. After the neural network training process, we can obtain the quick evaluations of the problem it has learned. As a further approach, a knowledge-based neural network (KBNN) is introduced in [17], [18]. The empirical functions or analytical equations are embedded into the KBNN model so that we can reduce the training data to further improve the efficiency of the parametric model. In [19]–[22], the combined artificial neural networks and transfer function (Neuro-TF) is presented to solve the high order EM problems. In [21], the pole-and-residue-based transfer function has been introduced to model the pure EM behavior with wider geometrical ranges. This method is still applicable when there is no prior knowledge or empirical functions. In [22], the EM behavior modeling using adjoint neural networks and pole-residue transfer functions with EM sensitivity analysis is introduced to further improve the modeling accuracy and efficiency. A passivity enforcement technique for passive component modeling subject to variations of geometrical parameters using combined neural networks and rational functions is introduced in [23].

The EM-centric multiphysics problem involves EM analysis combined with other physical domain analysis, such as structural and thermal analysis, i.e., the EM analysis obtained from multiphysics analysis. Multiphysics has become a hot topic in microwave design area. Several multiphysics related works have been introduced to improve the multiphysics design efficiency. In [25], a multiphysics model which combines the EM and thermal analysis with the non-linear electro-thermal transistor models is introduced. In [26], a correlating mapping is developed so that the multiphysics non-geometrical design variables can be mapped to the geometrical design variables for the simple EM structure. A multiphysics parametric modeling method is introduced using artificial neural networks in [27]. In [28], a space mapping approach is used to build the links between the multiphysics domain and the pure EM domain in an effort to reduce the multiphysics model development time. However, this method requires the existence of the coarse model to build the mapping. When the coarse model is not available, this technique is not applicable.

In this paper, for the first time, the combined neural networks and transfer function is proposed to develop an accurate and efficient EM-centric multiphysics parametric model to speed up the multiphysics modeling process. The model inputs of the proposed parametric model include the geometrical design variables and non-geometrical design variables. The model output represents the behavior of EM-centric multiphysics response evaluated by multiple physical domain simulations. Vector fitting process is exploited to obtain the poles/residues of the transfer function for each multiphysics training sample. Two neural network mapping modules are exploited to establish the mathematical links between multiphysics parameters and poles/residues, respectively. Considering that multiphysics simulation is very time-consuming and computationally expensive, we propose to use parallel computational technique so that multiple EM-centric multiphysics evaluations can are performed simultaneously to obtain the training samples for establishing the EM-centric multiphysics parametric model. We propose a two stage training algorithm to make the multiphysics training more efficient. After the model development process, the proposed EM-centric multiphysics parametric model can provide fast and accurate predictions of multiphysics responses. It can be further exploited to perform the multiphysics design. The proposed technique can provide more accurate multiphysics solutions even with less hidden neurons compared with the existing parametric models. The proposed technique provides an accurate and efficient multiphysics solution even when the coarse model or empirical model is unavailable.

II. PROPOSED MULTIPHYSICS PARAMETRIC MODEL INCORPORATING ARTIFICIAL NEURAL NETWORKS WITH TRANSFER FUNCTION

In this section, the proposed EM-centric multiphysics parametric model structure which includes the pole-and-residue-based transfer function and two neural network mapping modules is introduced. In our proposed technique, we exploit the vector fitting techniques [29] to generate the poles/residues of the transfer function from the multiphysics frequency responses. Since the relationship between multiphysics design parameters and the pole/residues of the transfer function is non-linear and unknown, we develop the two mapping modules to build the relationships between the multiphysics domain design parameters and the poles/residues of the transfer function by exploiting artificial neural networks. Parallel computational technique is implemented to accelerate the model development process. We proposed a two stage training algorithm to guide the multiphysics training process. The first stage is the preliminary training and the second stage is the model refinement training. Finally, an accurate and efficient multiphysics parametric model is developed.

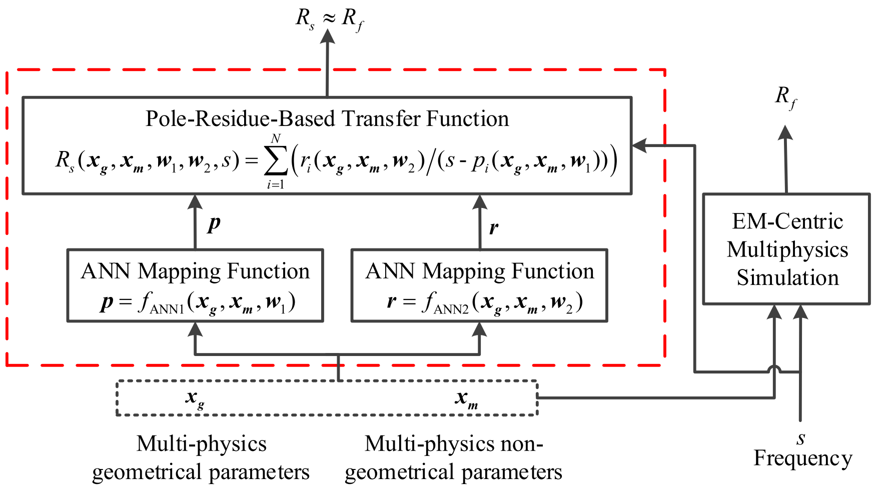


FIGURE 1. **The structure of the proposed multiphysics parametric model with the transfer function in pole/residue format. The model consists of the pole/residue based transfer function and two mapping neural network functions. w_1 and w_2 represent the weighting parameters in the two mapping functions; R_f represents the frequency responses from EM-centric multiphysics simulation; R_s represents the frequency responses of the proposed EM-centric multiphysics parametric model. Two mapping functions are used to map the multiphysics domain design parameters to the poles and residues of the transfer function by exploiting the artificial neural networks.**

A. STRUCTURE OF THE EM-CENTRIC MULTIPHYSICS PARAMETRIC MODEL

Fig. 1 demonstrates the proposed multiphysics parametric model structure. The model includes two parts, the first part is the pole/residue based transfer function, two second part is two neural network mapping functions. The model inputs are the multiphysics design variables and the frequency. The model outputs are the EM-centric responses (for example, the S-parameter). For multiphysics simulation, the design variables usually contains not only the geometrical variables, but also the non-geometrical variables which represent the other physical domain parameters. Let $\boldsymbol{x}$ represent the vector of all the multiphysics design parameters which include the geometrical and non-geometrical variables. Let $\boldsymbol{x}_g$ represent the vector containing all the geometrical variables in $\boldsymbol{x}$. Let $\boldsymbol{x}_m$ represent the vector containing all the non-geometrical variables in $\boldsymbol{x}$. $\boldsymbol{x}_m$ are the variables in other multiphysics domains besides geometrical variables.

Let s represent complex angular frequency which is the extra input of the multiphysics model. Let R_f represent the frequency response of the multiphysics simulation (multiphysics analysis). Let R_s represent the response of the proposed EM-centric multiphysics parametric model. In our technique, R_s can be expressed by the transfer function, formulated as

$$R_s(\boldsymbol{x}_g, \boldsymbol{x}_m, \boldsymbol{w}_1, \boldsymbol{w}_2, s) = \sum_{i=1}^{N} \frac{r_i(\boldsymbol{x}_g, \boldsymbol{x}_m, \boldsymbol{w}_2)}{s - p_i(\boldsymbol{x}_g, \boldsymbol{x}_m, \boldsymbol{w}_1)} \qquad (1)$$

where the variables p_i and r_i represent the i^{th} pole and residue of the transfer function, respectively. N represents the number of orders for the pole/residue based transfer function.

Let $\boldsymbol{p}$ be a vector containing all the poles of the pole/residue based transfer function, defined as

$$\boldsymbol{p} = [\, p_1 \quad p_2 \ \cdots \ p_N \,]^T. \qquad (2)$$

Let $\boldsymbol{r}$ be a vector containing all the residues of the pole/residue based transfer function, defined as

$$\boldsymbol{r} = [\, r_1 \quad r_2 \ \cdots \ r_N \,]^T. \qquad (3)$$

Multiply training samples are needed to develop the accurate EM-centric multiphysics model. For different training samples, the poles/residues for the transfer function is different. There is no empirical or analytical equations between multiphysics parameters and poles/residues of the transfer function. To obtain this nonlinear and unknown relationships, two neural network mapping modules are proposed.

For the first mapping function, we propose to exploit the artificial neural network to establish the mathematical links between the multiphysics design parameters and pole vector $\boldsymbol{p}$ of the pole/residue based transfer function. Let f_{ANN1} represent the proposed mapping function. The input parameters of the first mapping function includes not only the geometrical variables $\boldsymbol{x}_g$, but also non-geometrical variables $\boldsymbol{x}_m$. The outputs are the poles of the transfer function, which are formulated as

$$\boldsymbol{p} = f_{\mathrm{ANN1}}(\boldsymbol{x}_g, \ \boldsymbol{x}_m, \ \boldsymbol{w}_1) \qquad (4)$$

where $\boldsymbol{w}_1$ is a vector which contains all the weighting variables in the neural network.

Similarly, for the second mapping function, we propose to exploit the artificial neural network to establish the mathematical links between the multiphysics design parameters and residue vector $\boldsymbol{r}$ of the pole/residue based transfer function. Let f_{ANN2} represent the proposed mapping function. The input parameters of the second mapping function includes not only the geometrical variables $\boldsymbol{x}_g$, but also non-geometrical variables $\boldsymbol{x}_m$. The outputs are the residues of the transfer function, which are formulated as

$$\boldsymbol{r} = f_{\mathrm{ANN2}}(\boldsymbol{x}_g,\ \boldsymbol{x}_m,\ \boldsymbol{w}_2) \tag{5}$$

where $\boldsymbol{w}_2$ is a vector which contains all the weighting variables in the neural network. From Fig. 1 we can see that frequency is the input to the transfer function, while the inputs of the two mapping functions only contain the multiphysics design parameters. This can contribute to simple artificial neural network structure with less hidden neurons. To obtain the initial training data for two mapping neural networks where the inputs are the geometrical parameters and the outputs are the poles/residues of the transfer function, we exploit the vector fitting techniques [29] to generate the poles/residues of the transfer function from the multiphysics frequency responses. We use the pole-residue tracking technique [21] to solve the discontinuity of poles/residues to obtain the transfer functions of constant order w.r.t. the multiphysics design variables.

B. MULTIPHYSICS DATA GENERATION USING PARALLEL TECHNIQUES

In our proposed technique, the first step of the multiphysics modeling process is to generate EM-centric multiphysics training samples. There are various distribution methods for generating the data, such as grid distribution, star distribution and orthogonal distribution. In the proposed technique, orthogonal distribution [30], i.e., a specific type of design of experiment (DOE) sampling distribution, is applied to generate the multiple samples where the subspace divisions are sampled with the same density and are orthogonal. Orthogonal distribution around the central point requires fewer samples compared with the grid distribution and enables the multiphysics model to be valid in much larger neighborhood compared to star distribution. We define the number of training samples which are needed to construct the proposed model as n_s. Let $T_r = \{1,\ 2,\ \ldots,\ n_s\}$ be the index set of all the training sampling points.

In the proposed technique, multiple EM-centric multiphysics evaluations for constructing the multiphysics model take the major computational burden of the total computational time. Sequential EM-centric multiphysics evaluations of the samples requires n_s times the computational time of one EM-centric multiphysics evaluation. Therefore, to reduce the overall computational time, parallel computational approach for the EM-centric multiphysics evaluations is proposed. We generate the EM-centric multiphysics responses $R_f(\boldsymbol{x}_g^{(j)}, \boldsymbol{x}_m^{(j)}, s)$ for all the sampling points, i.e., $j = 1, 2, \cdots, n_s$, simultaneously by performing the multiple EM-centric multiphysics simulations using parallel techniques, formulated as

$$\begin{aligned}&\left\{R_f(\boldsymbol{x}_g^{(j)}, \boldsymbol{x}_m^{(j)}, s) | j = 1, 2, \cdots, n_s\right\}\\ &\quad = \left\{R_f(\boldsymbol{x}_g^{(1)}, \boldsymbol{x}_m^{(1)}, s), R_f(\boldsymbol{x}_g^{(2)}, \boldsymbol{x}_m^{(2)}, s),\right.\\ &\qquad \left.\cdots, R_f(\boldsymbol{x}_g^{(n_s)}, \boldsymbol{x}_m^{(n_s)}, s)\right\}. \end{aligned} \tag{6}$$

After the parallel data generation, the generated multiple EM-centric multiphysics samples can be used for developing the multiphysics model.

C. PROPOSED TWO STAGE TRAINING ALGORITHM

To build an efficient and accurate EM-centric multiphysics parametric model, we propose a new training algorithm which contains two training stages. For the first stage, we perform the preliminary training of the two mapping modules by adjusting the weighting parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ to build the mathematical links between the poles/residues of the transfer function and the multiphysics geometrical/non-geometrical design variables. In the preliminary training stage, a relatively relaxed training error criteria (such as 4% to 10%) is used to increase the robustness of the proposed technique and decrease the non-linearity and complexity. To avoid over learning of the neural network, the number of hidden neurons of the two mapping functions is initialized to be a small number. .

After preliminary training of the two mapping neural networks, a second stage training process is proposed. In this training stage, we perform the entire multiphysics refinement training to further improve the accuracy of the proposed model. The training samples at the refinement stage are $(\boldsymbol{x}_g^{(j)},\ \boldsymbol{x}_m^{(j)},\ R_f{}^{(j)})$, $j \in T_r$, i.e., samples of geometrical and non-geometrical variables as the model inputs and EM-centric multiphysics responses as model outputs. The mechanism for the model refinement process is illustrated in Fig. 2. It consists of the pole/residue based transfer function and the two mapping neural networks whose initial values are the optimal solutions from the preliminary training process stage. At this stage, we perform both training and testing for the proposed model. The training process is performed by optimizing the weighting parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ inside the two mapping functions so that we can minimize the error function

$$\begin{aligned}&E_{Tr}(\boldsymbol{w}_1,\ \boldsymbol{w}_2)\\ &\quad = \frac{1}{2n_s}\sum_{j\in T_r}\sum_{l\in\Omega}\left\|R_s(\boldsymbol{x}_g^{(j)},\ \boldsymbol{x}_m^{(j)},\ \boldsymbol{w}_1,\ \boldsymbol{w}_2,\ s^{(l)}) - R_f^{(j,l)}\right\|^2\end{aligned} \tag{7}$$

where T_r is the index set of all the training sampling points of various geometrical and non-geometrical parameters, and n_s is the number of training data. Ω is the index set of frequency samples.

Let E_t represent the user defined threshold error (such as 2%). When the training error is lower than E_t, the training algorithm stops. After the training process finished, we use the testing samples which are independent to the training

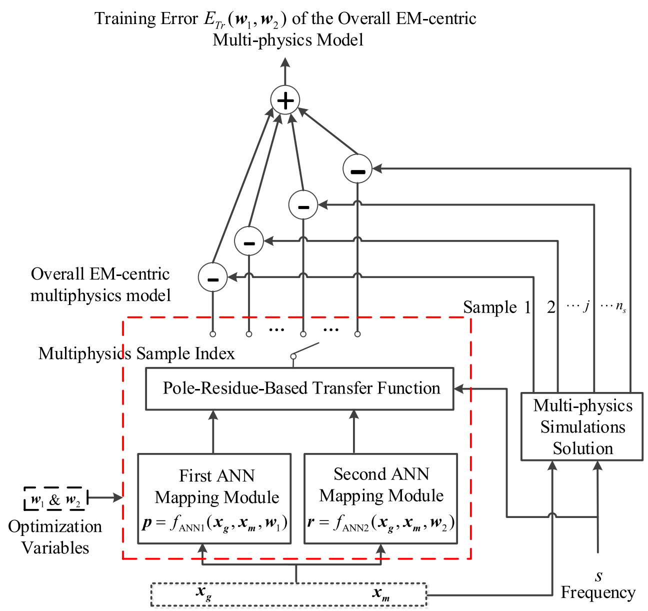


FIGURE 2. The mechanism of the model refinement process for the EM-centric multiphysics parametric model. The training process is performed by optimizing the weighting parameters w_1 and w_2 inside the two mapping functions so that we can minimize the error function. It consists of the pole/residue based transfer function and the two mapping neural networks whose initial values are the optimal solutions from the preliminary training process stage.

samples, i.e., never used in training, to test the overall multiphysics model. Let E_{T_e} represent the testing error. If E_{T_e} is lower than E_t, our proposed multiphysics parametric model is developed with good accuracy. Otherwise, we add the number of hidden neurons in the two mapping modules and repeat the training algorithm until we obtain a good testing error which is lower than E_t. In this way, we can obtain a good training and testing error with a simple neural network sturcture.

D. PROPOSED EM-CENTRIC MULTIPHYSICS PARAMETRIC MODELING ALGORITHM

we summarize our proposed modeling development algorithm as follows

- Step 1) Define the overall EM-centric multiphysics model design parameters which include the geometrical parameters x_g and non-geometrical parameters x_m.
- Step 2) Evaluate multiphysics simulations $R_f(x_g^{(j)}, x_m^{(j)}, s)$ at all the Training samples (i.e., $j = 1, 2, \cdots, n_s$) using parallel computational techniques.
- Step 3) Use vector fitting techniques to get the poles p and residues r of the transfer function. Use the pole-residue tracking technique to obtain the transfer functions of constant order w.r.t. the multiphysics design variables.
- Step 4) Perform the first stage preliminary training of the two mapping neural networks to learn the relationships of the poles/residues of the transfer function w.r.t. the multiphysics geometrical and non-geometrical variables.

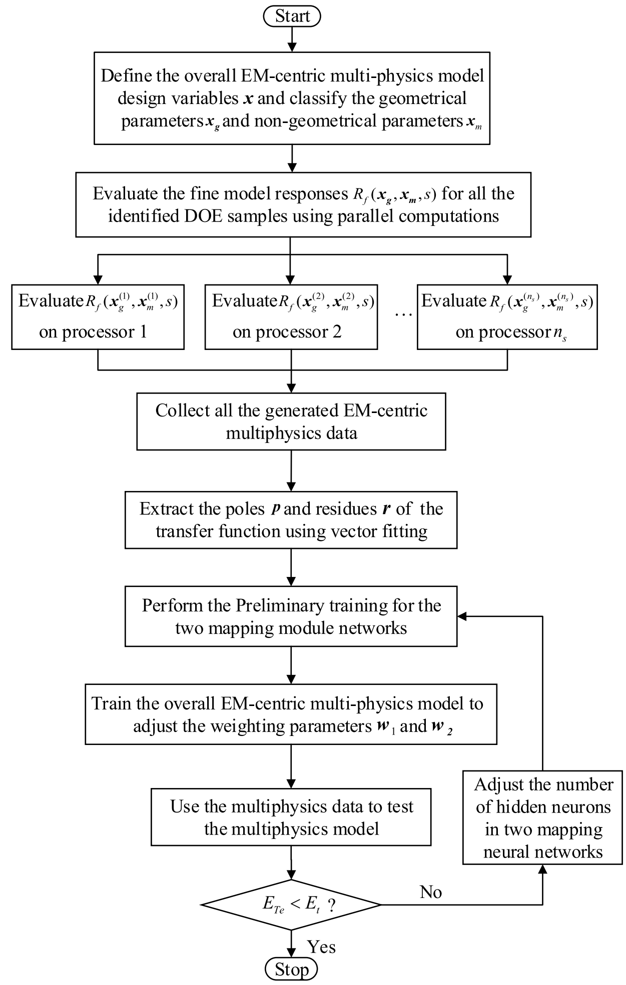


FIGURE 3. The flowchart of the overall pole/residue based neuro-TF multiphysics parametric model development process. The proposed technique includes parallel multiphysics data generation, preliminary training, and overall model refinement training.

- Step 5) Perform the overall model refinement process to further improve the accuracy of the final model. The training data for this phase is$(x_g^{(j)}, x_m^{(j)}, R_f^{(j)})$, $j \in T_r$, i.e., samples of geometrical $x_g^{(j)}$ and non-geometrical parameters $x_m^{(j)}$ as model inputs and EM-centric multiphysics responses as model outputs.
- Step 6) After training, test the refined multiphysics parametric model. If the testing error $E_{T_e} \leq E_t$, the model development process terminates and the proposed multiphysics parametric model is ready to be used for higher level design. Otherwise (i.e., $E_{T_e} > E_t$), adjust the number of hidden neurons in the two mapping neural networks f_{ANN1} and f_{ANN2} and go back to Step 4).
- Step 7) Stop the pole/residue based neuro-TF multiphysics parametric model development process.

The flowchart of the overall pole/residue based neuro-TF multiphysics parametric model development process is illustrated in Fig. 3.

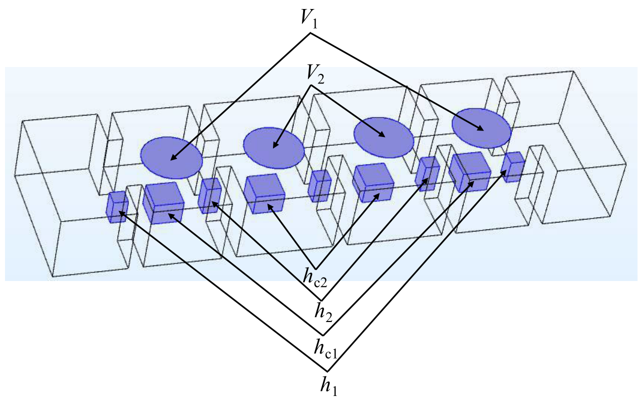


FIGURE 4. **The four pole waveguide filter structure with EM-centric multiphysics design parameters $x = [h_1\ h_2\ h_{c1}\ h_{c2}\ V_1\ V_2]^T$. The two voltages ($V_1$) and ($V_2$) represent the electronic potentials which are supplied to the piezo actuator. These two voltages can generate the deformation on the piezo actuator due to piezo electric effect and therefore affect the EM-centric multiphysics responses.**

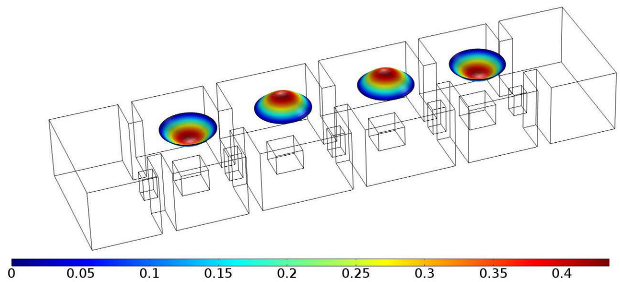


FIGURE 5. **The deformed structure of the four pole waveguide filter due to the piezo electric effects.**

TABLE 1. **The ranges of training sample and testing sample of the EM-centric multiphysics parametric model for the four pole waveguide filter example.**

Design Variables to the Model		Training Sample Range		Testing Data Range	
		Min	Max	Min	Max
Multi-physics Data	h_1 (mm)	3.24	3.48	3.25	3.47
	h_2 (mm)	4	4.24	4.01	4.23
	h_{c1} (mm)	3.12	3.38	3.13	3.37
	h_{c2} (mm)	2.82	3.08	2.83	3.07
	V_1 (V)	110	250	120	240
	V_2 (V)	10	150	20	140

III. MICROWAVE EXAMPLES

A. EM-CENTRIC MULTIPHYSICS PARAMETRIC MODELING FOR THE TUNABLE WAVEGUIDE FILTER APPLYING THE PIEZO ACTUATOR

In order to illustrate the validity of the proposed technique, we consider a four pole waveguide filter [31] example. The tuning parameters are the heights of posts of the square cross section which are located at the central parts of the cavities and coupling windows. Due to the piezo electric effect [32], the piezo actuator can generate a geometrical strain which is proportional to the applied electric field. For our example, the piezo actuator is applied to control the distance between the post and the piezo actuator, this provides the tunability for the four pole waveguide filter. Fig. 4 shows the structure of this tunable filter where the heights (h_1) and (h_2) represent the heights of the tuning post of the square cross section. Heights (h_{c1}) and (h_{c2}) represent the heights of the square cross section which is located at the center of the resonator cavity. The two voltages (V_1) and (V_2) represent the electronic potentials which are supplied to the piezo actuator. These two voltages can generate the deformation on the piezo actuator due to piezo electric effect and therefore affect the EM-centric multiphysics responses. For the resonant cavity, the input waveguide and output waveguide are the standard WR-75 waveguides, i.e., a = 19.050 mm, b = 9.525 mm. The thickness for all the coupling windows in this example is fixed to 2 mm. The frequency parameter f is an additional model input parameter. The total design variables for the four pole waveguide filter example have six parameters, i.e., $\boldsymbol{x} = [h_1\ h_2\ h_{c1}\ h_{c2}\ V_1\ V_2]^T$. The geometrical design parameters for the proposed multiphysics parametric model are $\boldsymbol{x_g} = [h_1\ h_2\ h_{c1}\ h_{c2}]^T$. The non-geometrical design parameters for the parametric model are $\boldsymbol{x}_m = [V_1\ V_2]^T$. The proposed multiphysics model has two output responses for this example, one is the real part of S_{11}, the other is the imaginary part of S_{11}.

In this example, to build the accurate multiphysics parametric model, we use the COMSOL MULTIPHYSICS software to evaluate EM-centric multiphysics analysis to obtain the training and testing data with different values of all the design parameters including the geometrical and non-geometrical variables. To observe the piezo electric effects, we perform the multiphysics simulation with the design variables $\boldsymbol{x} = [3.414.213.243.02200 - 200]^T$ (mm mm mm mm V V). The deformed structure of the four pole waveguide filter is illustrated in Fig. 5. From the figure we can see that with the positive voltage ($V_1 = 200$ V), the piezo actuator will deflect towards the bottom side, while with the negative voltage ($V_2 = -200$ V), the piezo actuator will deflect upwards the bottom side. Table 1 shows the training and testing data ranges for the four pole waveguide filter example. The frequency range for the EM-centric multiphysics parametric model is 10.5 GHz-11.5 GHz.

For multiphysics training data, we use DOE sampling method to generate 49 training samples. For testing data, we use random distribution sampling method to generate 20 testing samples which are never used in training data. In our proposed technique, the pole/residue based transfer function is exploited to build the EM-centric multiphysics parametric model with different values of geometrical and non-geometrical variables. We use the same number of neurons for the two mapping networks which is selected as 4 in this example. After training, the training error for all the training samples is 0.91%. We use testing data to test the proposed model, the testing error for all the testing samples

TABLE 2. Comparisons of different parametric modeling methods of the four pole waveguide filter example.

Training Method	No. of Neurons	Average Training Error	Average Testing Error
ANN Model	10	4.33%	3.87%
ANN Model	20	2.38%	2.89%
ANN Model	30	2.13%	5.95%
Proposed Model	4/4*	0.91%	1.37%

* 4/4 represents the numbers of neurons for two neural network mapping functions are selected as 4 and 4, respectively.

is 1.37%. The proposed multiphysics model including the transfer function and two mapping functions is developed and trained using the software NeuroModelerPlus [33].

For comparison purpose, ANN model is trained to learn multiphysics data using different hidden neurons. In this example, we train the ANN model using 10, 20 and 30 hidden neurons to construct the non-linear relationships between the multiphysics responses and multiphysics geometrical and non-geometrical design parameters. We compare the neural network structures, training error and testing error for different modeling techniques in Table 2. From the table, we can see that when the number of hidden neural is 20, the ANN model can obtain a relatively good training and testing error. While the proposed EM-centric multiphysics model only uses 4 hidden neurons for two mapping modules to obtain a more accurate model compared to the existing parametric models since the transfer function provides rich knowledge to the proposed model. After model construction, the proposed EM-centric multiphysics parametric model can provide fast and accurate predictions of multiphysics responses. Fig. 6 illustrates the comparison of the magnitudes of S_{11} (in decibels) for the proposed model, the ANN model with 20 hidden neurons and the multiphysics simulation responses for two different design parameters. These two samples are selected from the testing data and have never been used during the model development process. The values of the two design parameters of the four pole waveguide filter are listed as follows

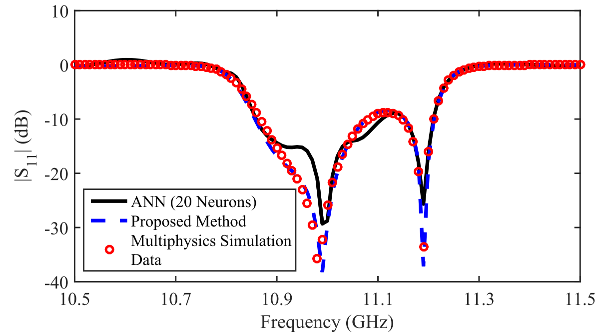
Testing sample 1:

$\boldsymbol{x} = [3.456\ 4.011\ 3.237\ 2.892\ 229.6\ 124.4]^T$ (mm mm mm mm V V)

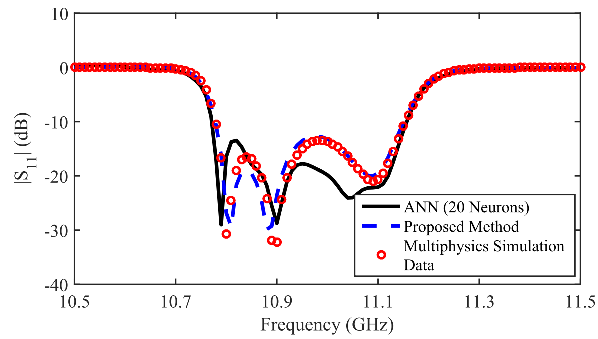
Testing sample 2:

$\boldsymbol{x} = [3.312\ 4.174\ 3.252\ 2.96\ 219\ 47.9]^T$ (mm mm mm mm V V)

From the modeling results, the proposed EM-centric multiphysics model is more accurate even with less hidden neurons than the existing parametric models. After the model development process, the proposed EM-centric multiphysics parametric model can provide fast and accurate predictions of multiphysics responses. It can be further exploited to perform the multiphysics design. Considering the model development process is a one time investment, the benefits of using the proposed multiphysics model accumulates when the model is used over and over again.



(a)



(b)

FIGURE 6. Comparison of the magnitudes of S_{11} (in decibels) for the multiphysics models developed using different modeling techniques and COMSOL MULTIPHYSICS simulation responses: (a) Testing sample 1 and (b) Testing sample 2 for the four pole waveguide example.

B. MULTIPHYSICS PARAMETRIC MODELING OF AN IRIS COUPLED MICROWAVE CAVITY FILTER

For the second example, we consider an iris coupled microwave cavity filter [31] to demonstrate the proposed EM-centric multiphysics modeling technique. Fig. 7 shows the structure of this cavity filter. Widths w_1, w_2, w_3 and w_4 represent the widths of the iris. The large input power P_{in} is supplied to the structure. This large input power can affect the multiphysics responses because of the thermal distribution and structural deformation. The frequency parameter f is an additional model input parameter. The total design variables for the iris cavity filter example have five parameters, i.e., $\boldsymbol{x} = [w_1\ \ w_2\ \ w_3\ \ w_4\ \ P_{in}]^T$. The geometrical design parameters for the proposed multiphysics parametric model are $\boldsymbol{x}_g = [w_1\ w_2\ w_3\ w_4]^T$. The non-geometrical design parameter for the parametric model is $\boldsymbol{x}_m = P_{in}$. The proposed multiphysics model has two output responses for this example, one is the real part of S_{11}, the other is the imaginary part of S_{11}.

In this example, to build the accurate multiphysics parametric model, we use the ANSYS WORKBENCH software to evaluate EM-centric multiphysics analysis to obtain the training and testing data with different values of all the design parameters including the geometrical and non-geometrical variables. We use three modules in the software, i.e., HFSS

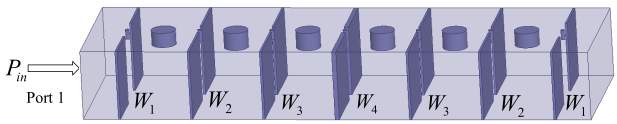


FIGURE 7. The iris coupled cavity filter structure with EM-centric multiphysics design parameters $x = [w_1\ w_2\ w_3\ w_4\ P_{in}]^T$. A high power is supplied to the port 1.

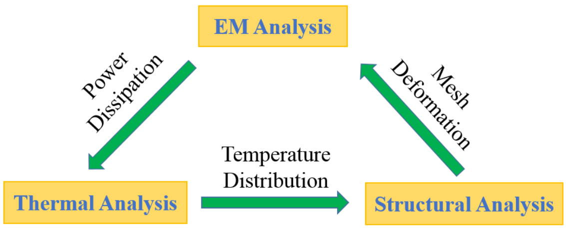


FIGURE 8. The practical process for the multiphysics analysis. The iterative process terminates until we obtain a steady-state solution.

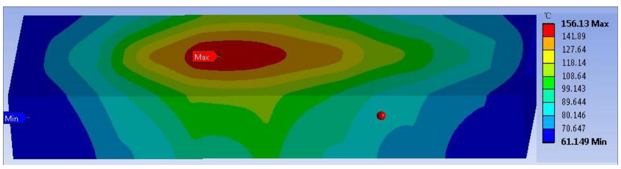


FIGURE 9. The thermal distribution in the filter structure by the thermal analysis.

module, Steady-State Thermal module and Static Structural module. Fig. 8 illustrates the practical process for the multiphysics analysis. When the iris filter is supplied with a high power, this high power can generate the RF losses across the entire filter structure. We can calculate the RF losses by computing the electric and magnetic fields over the entire volume of the cavity filter. After evaluating the RF losses which will become the heat source for the thermal analysis, thermal analysis can compute the thermal distribution in the filter. The thermal distribution will generate the thermal stress which will further create the deformation of the filter. The structural analysis can compute the deformation based on different temperature in the structure. The deformed structure of the iris cavity filter is looped back to the EM analysis to re-simulate the EM responses. The iterative process terminates until we obtain a steady-state solution where the changes of temperature or deformation between the two consecutive iterations are less than the user defined threshold. After the multiphysics simulation, the temperature information and structural deformation information of the iris cavity filter with the design variables $\boldsymbol{x} = [116.549.73543.44548.99536.25]^T$ (mm mm mm mm kW) are illustrated in Fig. 9 and Fig. 10, respectively.

The ranges of training samples and testing samples for the EM-centric multiphysics parametric model are shown in Table 3 for the iris cavity filter example. The frequency range for the EM-centric multiphysics parametric model is 690 MHz-720 MHz. For multiphysics training data, we use DOE sampling method to generate 81 training samples. For

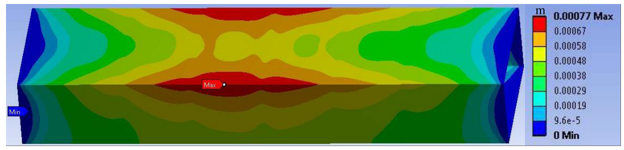


FIGURE 10. The deformed structure of the iris filter by the structural analysis.

TABLE 3. The ranges of training sample and testing sample of the EM-centric multiphysics parametric model for the iris coupled cavity filter example.

Design Variables to the Model		Training Sample Range		Testing Sample Range	
		Min	Max	Min	Max
Multi-physics Data	w_1 (mm)	110.63	120.3	110.73	119.93
	w_2 (mm)	46.15	50.91	46.25	50.81
	w_3 (mm)	42.63	46.43	42.73	46.33
	w_4 (mm)	48.16	52.36	48.26	52.26
	P_{in} (kW)	19	41	20	40

testing data, we use DOE sampling method to generate 64 testing samples which are never used in training data.

In our proposed technique, the pole/residue based transfer function is exploited to build the EM-centric multiphysics parametric model with different values of geometrical and non-geometrical variables. We use the same number of neurons for the two mapping networks which is selected as 8 in this example. After training, the training error for all the training samples is 1.55%. We use testing data to test the proposed model, the testing error for all the testing samples is 1.63%. The proposed multiphysics model including the transfer function and two mapping functions is developed and trained using the software NeuroModelerPlus [33].

For comparison purpose, ANN model is trained to learn multiphysics data using different hidden neurons. In this example, we train the ANN model using 30, 40 and 50 hidden neurons to construct the non-linear relationships between the multiphysics responses and multiphysics geometrical and non-geometrical design parameters. We compare the neural network structures, training error and testing error for different modeling techniques in Table 4. From the table, we can see that when the number of hidden neural is 40, the ANN model can obtain a relatively good training and testing error. While the proposed EM-centric multiphysics model only uses 8 hidden neurons for two mapping modules to obtain a more accurate model compared to the existing parametric models since the transfer function provides rich knowledge to the proposed model. After model construction, the proposed EM-centric multiphysics parametric model can provide fast and accurate predictions of multiphysics responses. It can be further exploited to perform the multiphysics design. Fig. 11 illustrates the comparison of the magnitudes of S_{11} (in decibels) for the proposed model, the ANN model with 40 hidden neurons and the multiphysics simulation responses for two

TABLE 4. Comparisons of different parametric modeling methods of the iris coupled cavity filter example.

Training Method	No. of Hidden Neurons	Average Training Error	Average Testing Error
ANN Model	30	2.82%	3.76%
ANN Model	40	2.08%	3.38%
ANN Model	50	2.09%	3.46%
Proposed Model	8/8*	1.55%	1.63%

* 8/8 represents the numbers of neurons for two neural network mapping functions are selected as 8 and 8, respectively.

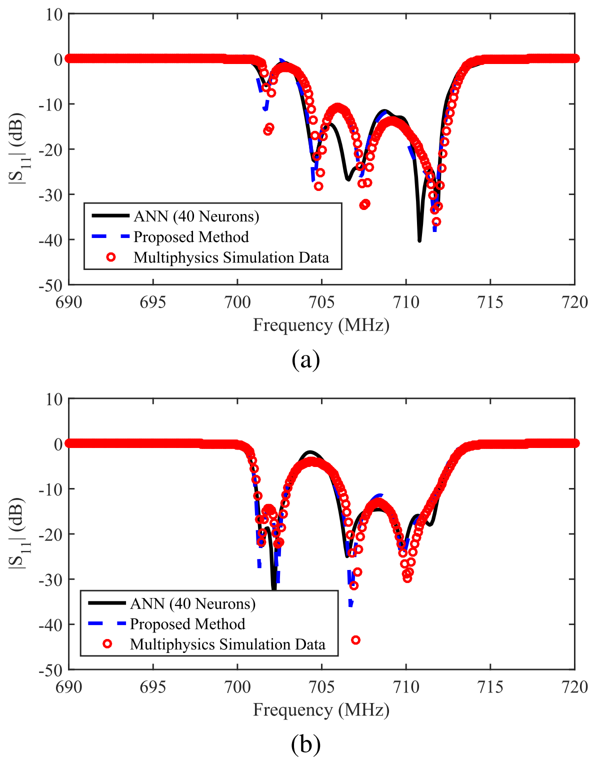


FIGURE 11. Comparison of the magnitudes of S_{11} (in decibels) for the multiphysics models developed using different modeling techniques and ANSYS WORKBENCH simulation responses: (a) Testing sample 1 and (b) Testing sample 2 for the iris coupled cavity filter example.

different design parameters. These two samples are selected from the testing data and have never been used during the model development process. The values of the two design parameters of the iris coupled cavity filter are listed as follows

Testing sample 1:

$\boldsymbol{x} = [113.0348.2644.5350.0935]^T$ (mm mm mm mm kW).

Testing sample 2:

$\boldsymbol{x} = [113.0351.2646.3347.2130]^T$ (mm mm mm mm kW).

From the modeling results, the proposed EM-centric multiphysics model is more accurate even with less hidden neurons than the existing parametric models. After the model development process, the proposed EM-centric multiphysics parametric model can provide fast and accurate predictions of multiphysics responses. It can be further exploited to perform the multiphysics design.

IV. CONCLUSION

In this paper, we have proposed a new technique to utilize the combined neural networks and transfer function to develop a novel EM-centric multiphysics parametric model to accelerate the multiphysics modeling process. In the proposed method, the artificial neural networks and pole/residue based transfer function have been incorporated to represent the high non-linear relationships between EM-centric multiphysics behaviors and multiphysics design parameters. We have proposed to use parallel computational technique so that multiple EM-centric multiphysics evaluations can are performed simultaneously to generate the training data for establishing the proposed parametric model. Two mapping neural networks have been proposed to represent the unknown relationships between the poles/residues of the transfer function and multiphysics design parameters. A two stage training algorithm has been proposed to guide the multiphysics training process. Compared to the conventional multiphysics modeling methods, the proposed technique could obtain better and more consistent accuracy. Two microwave examples have been presented to illustrate the advantages of the proposed EM-centric multiphysics parametric modeling technique.

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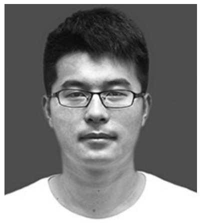

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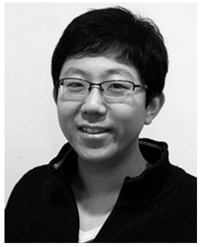

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