Space Mapping Approach to Electromagnetic Centric Multiphysics Parametric Modeling of Microwave Components

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***Abstract*— This paper proposes a novel technique to develop a low-cost electromagnetic (EM) centric multiphysics parametric model for microwave components. In the proposed method, we use space mapping techniques to combine the computational efficiency of EM single physics (EM only) simulation with the accuracy of the multiphysics simulation. The EM responses with respect to different values of geometrical parameters in nondeformed structures without considering other physics domains are regarded as coarse model. The coarse model is developed using the parametric modeling methods such as artificial neural networks or neuro-transfer function techniques. The EM responses with geometrical and nongeometrical design parameters as variables in the practical deformed structures due to thermal and structural mechanical stress factors are regarded as fine model. The fine model represents the behavior of EM centric multiphysics responses. The proposed model includes the EM domain coarse model and two mapping neural networks to map the EM domain (single physics) to the multiphysics domain. Our proposed technique can achieve good accuracy for multiphysics parametric modeling with fewer multiphysics training data and less computational cost. After the modeling process, the proposed model can be used to provide accurate and fast prediction of EM centric multiphysics responses of microwave components with respect to the changes of design parameters within the training ranges. The proposed technique is illustrated by a tunable four-pole waveguide filter example at 10.5–11.5 GHz and an iris coupled microwave cavity filter example at 690–720 MHz.**

***Index Terms*— Artificial neural networks (ANNs), microwave component, multiphysics modeling, neuro-transfer function (Neuro-TF), parametric modeling, space mapping (SM).**

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I. Introduction

SPACE mapping (SM) techniques [1]–[13] have gained recognition in microwave computer-aided design area addressing the growing computational challenges in 3-D field optimization with geometrical parameters as variables. SM assumes the existence of fine and coarse models [1]. The fine models are usually very accurate but CPU intensive such as 3-D field electromagnetic (EM) simulations, while the coarse models are typically empirical functions or equivalent circuits, which are computationally very efficient but not very accurate. SM technique allows expensive EM optimizations to be performed efficiently with the help of fast and approximate surrogates [2]–[8]. Neuro-SM [9] techniques use neural network learning capabilities to establish a mathematical link between the coarse and the fine models. Recent efforts on SM have focused on several areas, such as output SM [10], tuning SM [11], aggressive SM [12], and parallel SM [13].

For EM-simulation-driven design, the computational cost of directly using fine models can be very expensive because EM-simulation-driven design requires repetitive fine model evaluations due to the adjustments of the values of the geometrical parameters. To reduce the computational cost, the equivalent circuit models [14], [15] and mathematical equations [16], [17] are presented as fast approximate models for the EM structure. In recent years, artificial neural networks (ANNs) have emerged as powerful techniques for parametric modeling and design optimization of EM-based microwave components with geometrical parameters as variables [18]–[20]. Furthermore, the knowledge-based neural network is also studied where microwave empirical or semianalytical information is incorporated into the model structure. The microwave knowledge complements the capability of learning and generalization of neural networks by providing additional information such as analytical expressions [21], empirical models [22], or equivalent circuits [23], [24]. A study, which combines neural networks and transfer functions (Neuro-TF), is presented to model the EM behavior of embedded passives [25], [26]. This approach can be used even if accurate prior knowledge is unavailable.

In this paper, we consider a more challenging scenario. For high performance RF/microwave component and system design, besides the EM domain (single physics), we often require considerations of the operation in a real-world multiphysics environment [27], [28] which includes other physics domains. Understanding the interaction between multiple physics domains is essential for an accurate system analysis. In this paper, we focus on the EM centric multiphysics problem which involves EM analysis coupled with the effects of other physics domains such as thermal and structural mechanics. EM centric multiphysics simulation of microwave components involves the simultaneous solutions of EM and other physics domains which can provide the accurate evaluation of EM behavior. The EM centric multiphysics analysis becomes necessary for a growing number of microwave components and systems because EM single physics (EM only) analysis may not be sufficiently accurate in a real world. As examples of multiphysics related research, recently a 3-D electromagnetic-thermal-mechanical coupling finite element model of a gas-insulated bus plug-in connector is studied in [27]. In [29], the effects of the input power on microwave planar devices are studied involving the electro-thermal-mechanical coupling which shows that for moderate input powers, the device transfer function can be altered by increasing the losses and frequency shift. In [30], the electromagnetic-thermal characteristics of interconnects are investigated. A set of modified formulas and appropriate thermal models are presented to consider the thermal effects. The computational cost of the multiphysics simulations is very expensive because it involves multiple domains, coupling between domains, and often deals with the deformed structure. This problem becomes even more challenging when repetitive multiphysics evaluations are required due to adjustments of the physical geometrical design parameters of the structure. To address this problem, a recent work on multiphysics parametric modeling using the Neuro-TF modeling method is presented in [31]. The input classification and correlating mapping are introduced to map the multiphysics input parameters onto geometrical input parameters. The parametric model in [31] is much faster than directly using the multiphysics simulator for highly repetitive multiphysics evaluations due to the adjustments of the values of design parameters.

This paper is a significant advance over the work of [31] in an effort to further improve the efficiency of the parametric multiphysics modeling by reducing the number of multiphysics training data samples. A new SM technique is introduced to map the EM domain to the multiphysics domain, as opposed to use direct modeling method in [31]. Our proposed technique can work well even when the correlating information needed in [31] is not available. In this paper, for the first time, we elevate the SM techniques from solving EM modeling problem to solving the multiphysics modeling problem. We propose to formulate the SM techniques to build the mapping between the multiphysics domain and EM domain (single physics) considering that EM domain responses are approximate solutions to the EM centric multiphysics responses but are much faster than the multiphysics simulations. In our proposed technique, the EM data from EM single physics (EM only) simulation are used to construct a coarse model. The coarse model with geometrical parameters as variables is represented either by ANN model or Neuro-TF model. The fine model represents the behaviors of EM centric multiphysics responses. The inputs of the fine model include the geometrical parameters and nongeometrical parameters. Two mapping modules are proposed to map the EM domain responses to the multiphysics domain responses. One module is the mapping between the multiphysics domain design parameters and EM domain design parameters, and the other module represents the mapping relationship between the nongeometrical design parameters along with frequency parameter of the multiphysics model and the frequency parameter of the coarse model. An adjoint multiphysics model is proposed to guide the gradient-based training and optimization process. Our proposed technique can achieve good accuracy of the EM centric multiphysics model using fewer multiphysics training data compared to the direct parametric modeling method. Thereby, the proposed method can reduce the design cycle and increase the design efficiency. Once an accurate overall model is developed, it can be used to provide accurate and fast prediction of EM centric multiphysics responses with geometrical parameters of microwave components as variables and can be used for higher level design. A tunable four-pole waveguide filter example and an iris coupled microwave cavity filter example are used to demonstrate the efficiency of the proposed parametric modeling technique.

II. Description of the EM centric Multiphysics Problem for Microwave Components

Multiphysics analysis usually involves multiply physics domain analysis such as EM, thermal and structural mechanics. The outputs the multiphysics analysis have many responses such as the EM behavior and thermal distribution. In this paper, we propose to develop a parametric modeling technique for multiphysics modeling with the EM behavior (e.g., S-parameter) as the primary output of the model. But in order to calculate the accurate S-parameter, the other physical domain effects need to be considered, such as thermal and structural mechanics. The proposed multiphysics model, i.e., EM behavior solved from multiphysics analysis, is called as the EM centric multiphysics model. For the convenience of the subsequent explanation, the proposed model is simply called as the multiphysics model. Multiphysics analysis can mimic the behaviors of the EM structures in the real-world environment including thermal and other effects. Multiphysics analysis for microwave components is essential for RF designers to gain a better understanding of entire system performance.

To accurately predict the EM behavior in a real-world environment, a two-way feedback between multiple physics domains is required. Fig. 1 shows an illustration of an iterative process of a multiphysics simulation for a waveguide filter. S-parameters are the output responses with respect to different values of geometrical parameters for the filter example.

In EM single physics (EM only) analysis, i.e., single physics analysis, the S-parameters are independent of the input power. Therefore, for the EM single physics (EM only) analysis, the S-parameter is not affected by the change of the value of the input power. However, during the multiphysics analysis,

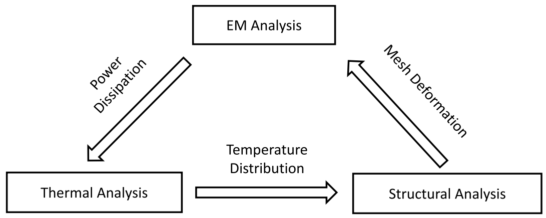


Fig. 1. Iterative process of multiphysics analysis of the waveguide filter. This multiphysics analysis includes three physics domains: EM, thermal, and structure mechanics.

the input power will be considered by the other physics domains, and thereby, influence the EM responses. The input power to the filter generates the RF losses in the structure. These RF losses are evaluated using the electric and magnetic fields computed over the entire surface or volume of the device. The RF losses become the heat source which will create the temperature distribution. Thermal analysis is used to calculate the temperature distribution in the structure. Different temperatures at different positions in the structure will create the thermal stress and cause the deformation of the structure. Furthermore, the structural analysis is used to calculate the deformation based on the temperature distribution. The resultant structural deformation of the microwave device is looped back to the EM simulator to reperform the meshing and analyze the structure again. Therefore, the S-parameter computation is affected by the input power in the multiphysics environment. This process is repeated iteratively until a steady-state final solution is obtained, i.e., until the amount of deformation or changes in temperature between two consecutive iterations are less than a user defined threshold.

This iterative process takes several iterations to converge to a steady solution. For each iteration, we perform the analysis in multiple physics domains and deal with the deformed structure. This makes the multiphysics simulation highly time-consuming and computationally expensive. However, for the EM single physics (EM only) simulation (single physics), it is a one-time EM analysis in nondeformed structure, which makes it much cheaper than the multiphysics simulation. In this paper, a parametric modeling technique for multiphysics modeling problem is developed to address an even more challenging case of multiphysics simulation where the repetitive evaluations are required due to the adjustments of the values of the design parameters.

III. Proposed EM Centric Multiphysics Parametric Modeling Technique

In this section, we propose the structure of the multiphysics model which contains the EM domain coarse model and two mapping functions. We propose to formulate the SM techniques to establish the relationships between the EM domain coarse model and multiphysics domain fine model. We develop the EM single physics (EM only) domain coarse model which can be used as the prior knowledge to establish the proposed multiphysics model. We propose the multiphysics model training process with respect to different values of geometrical and nongeometrical input parameters and formulate the equations of the adjoint model which can be used to guide the training and optimization process.

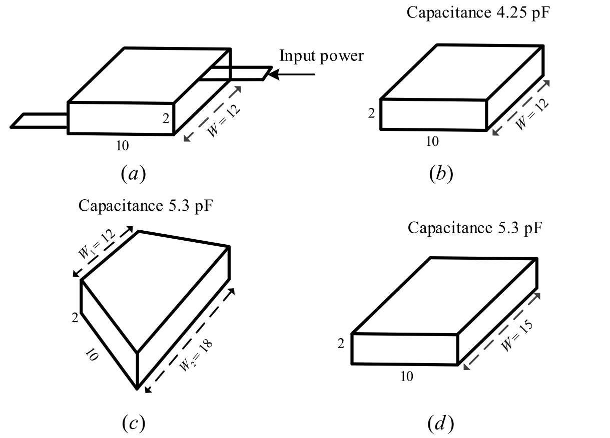


Fig. 2. Simple illustration of the idea of using SM techniques to build the mapping relationship between the multiphysics domain and single physics domain. (a) Original structure of a film capacitor. (b) Structure for electric analysis, i.e., the coarse model. (c) Deformed structure due to high power at one side of the capacitor used for multiphysics analysis, i.e., the fine model. (d) Electric analysis with a different width such that the capacitance of this nondeformed structure (i.e., the mapped coarse model) is the same as the capacitance of deformed structure shown in (c). W is changed from 12 to 15 mm by mapping.

A. Structure of the Proposed Space Mapped EM Centric Multiphysics Parametric Model

Here, we use a simple fictitious example to illustrate the idea. Fig. 2(a) shows a film capacitor with the length of 10 mm, height of 2 mm, and width (W) of 12 mm. The length and height of the structure are fixed in this example. The relative permittivity is 8. The width (W) of the capacitor is the geometrical variable in this example. A high input power is given from the upper plate to the lower plate. Suppose our model output is the capacitance of the structure.

In pure electric analysis, the capacitance is independent of the input power and the capacitance of the device is 4.25 pF, as shown in Fig. 2(b). While for multiphysics analysis, we include the electrical, thermal, and structural analysis in this example. The high input power is considered by the thermal analysis and transformed into the temperature distribution along the device. Here, we suppose that temperature is linearly distributed along the length of this device. This temperature distribution becomes the input to the structural analysis. After the structural analysis, the geometrical structure of the device is changed due to the uneven temperature in the structure shown in Fig. 2(c). The capacitance of the deformed structure is changed from 4.25 to 5.3 pF. The multiphysics simulation is much more expensive than the pure electric (single physics) analysis. When performing the multiphysics analysis, we need to use the entire deformed mesh information to calculate the capacitance of the device.

In this example, the coarse model is the nondeformed structure shown in Fig. 2(b), the fine model is the deformed structure shown in Fig. 2(c). The capacitance of the coarse model is not accurate enough to represent the capacitance of

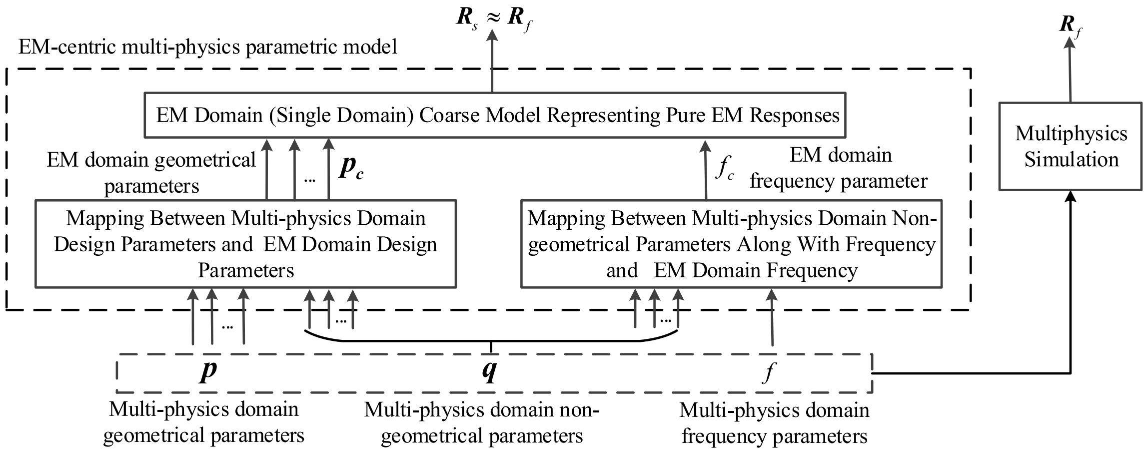


Fig. 3. Structure of the proposed space-mapped multiphysics parametric model exploiting coarse model and SM techniques. $\boldsymbol{R}_s$ represents the real and imaginary parts of the outputs of the overall multiphysics model (e.g., S-parameters). $\boldsymbol{R}_f$ represents the outputs of fine model multiphysics analysis. The first mapping module represents the relationship between the multiphysics domain design parameters and EM domain design parameters. The second mapping module represents the SM between the nongeometrical input parameters along with the frequency parameter of the multiphysics model and the frequency parameter of the EM domain coarse model.

the fine model. However, if we change the width W from 12 to 15 mm, as shown in Fig. 2(d), the capacitance of this nondeformed structure is the same as the capacitance of the deformed structure shown in Fig. 2(c). SM can be used to map W from 12 to 15 mm. In other words, the EM domain coarse model has been mapped to the multiphysics domain fine model.

In our proposed method, we use the EM single physics (EM only) domain responses in nondeformed structure without considering other physics domains to construct a coarse model. The fine model is the EM responses in the practical deformed structure including thermal and structural mechanic factors. By mapping the coarse model to the fine model, we can get the accurate surrogate model. Let $\boldsymbol{R}_f$ represent the vector containing the responses of multiphysics analysis for a microwave component (fine model). Let $\boldsymbol{\phi}$ represent the design parameters for the multiphysics problem. Let f represent the frequency parameter which is an extra input of the fine model. The task is to construct a surrogate model which is computationally very efficient and also as accurate as the fine model. Let $\boldsymbol{R}_s$ represent a response vector of the surrogate model which is required to be

$$\boldsymbol{R}_s(\boldsymbol{\phi}, f) = \boldsymbol{R}_f(\boldsymbol{\phi}, f). \quad (1)$$

Here, we propose a multiphysics parametric model (surrogate model) using SM technique which is illustrated in Fig. 3. The surrogate model consists of EM domain-based coarse model with geometrical parameters as variables and two SM module functions. The EM domain coarse model represents the EM single physics (EM only) behaviors of microwave components, which can be used as the prior knowledge to establish the proposed multiphysics model. Two mapping modules are used to map the EM domain responses to the multiphysics domain responses. The first mapping module is trained to represent the relationship between the multiphysics domain design parameters and EM domain design parameters. The second mapping module is developed to represent the mapping between the nongeometrical design parameters along with frequency parameter of the multiphysics model and the frequency parameter of the coarse model. If the coarse model and fine model use the same value of inputs, the output responses will be misaligned. The two proposed mapping modules are used to reduce the misalignment between EM domain (single physics) coarse model and multiphysics domain fine model. After training process, the outputs for the surrogate model with respect to different values of geometrical and nongeometrical input parameters can represent the EM responses (e.g., S-parameters) simulated in multiphysics simulator.

To illustrate the proposed multiphysics SM technique effectively, we first define the input parameters of the EM domain (single physics) coarse model and multiphysics domain fine model. Let $\boldsymbol{p}$ represent the geometrical parameters of the fine model. The geometrical parameters $\boldsymbol{p}$ are independent of the frequency which is an extra input of the fine model. The design parameters $\boldsymbol{\phi}$ for the multiphysics problem include not only the geometrical parameters $\boldsymbol{p}$ but also other physics domain parameters such as temperature, input power, input voltage, and structural stress. Let $\boldsymbol{q}$ represent other physics domain parameters which are considered as nongeometrical design variables. Therefore, the entire input parameters for the multiphysics model are defined as

$$\boldsymbol{\phi} = \begin{bmatrix} \boldsymbol{p} \\ \boldsymbol{q} \end{bmatrix}. \quad (2)$$

For the coarse model, let $\boldsymbol{p}_c$ represents the geometrical parameters of EM domain and f_c represent the frequency parameter of EM domain. The input parameters of the EM domain coarse model include only the geometrical parameters, i.e., $\boldsymbol{p}_c$ is the inputs to the coarse model. Let $\boldsymbol{R}_c$ represent the response vector of the EM domain coarse model as a function of $\boldsymbol{p}_c$ and f_c, defined as $\boldsymbol{R}_c(\boldsymbol{p}_c, f_c)$.

To correct the changes in the EM responses due to other physics domain parameters, two SM modules are proposed. The same nongeometrical parameters $\boldsymbol{q}$ are used as inputs for both mapping modules. For the first mapping module, since the relationship between EM domain design parameters and the multiphysics domain design parameters is nonlinear and unknown, we propose to use the neural network to learn this relationship. Let $\boldsymbol{f}_{\mathrm{ANN1}}$ be the neural network mapping function. The multiphysics design parameters containing geometrical parameters $\boldsymbol{p}$ and nongeometrical parameters $\boldsymbol{q}$ are mapped to the geometrical variables $\boldsymbol{p}_c$, which are the EM domain design parameters. The mapping function implemented using neural network function is proposed as

$$\boldsymbol{p}_c = \boldsymbol{f}_{\mathrm{ANN1}}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{w}_1) \tag{3}$$

where $\boldsymbol{p}$ and $\boldsymbol{q}$ are the inputs to the neural network, $\boldsymbol{p}_c$ is the output of the neural network, and $\boldsymbol{w}_1$ represent a vector containing all the weight parameters of this mapping neural network.

Similarly, for the second mapping module, since the relationship between the frequency parameter of the coarse model and the nongeometrical input parameters along with frequency parameter of the multiphysics model is nonlinear and unknown, we propose to use the second neural network to learn this relationship. Let f_{ANN2} be the mapping function. The frequency parameter f and nongeometrical parameters $\boldsymbol{q}$ of the multiphysics model are mapped directly to the input frequency f_c of the EM domain (single physics)-based coarse model. The frequency mapping function is proposed as

$$f_c = f_{\mathrm{ANN2}}(\boldsymbol{q}, f, \boldsymbol{w}_2) \tag{4}$$

where $\boldsymbol{q}$ and f are the inputs to the neural network, f_c is the output of the neural network, and $\boldsymbol{w}_2$ represent a vector containing all the weight parameters in this frequency mapping network. The responses of the proposed model with geometrical and nongeometrical parameters as variables are defined as

$$\begin{aligned}\boldsymbol{R}_s\big(\boldsymbol{p}, \boldsymbol{q}, f, \boldsymbol{w}_1^*, \boldsymbol{w}_2^*\big) &= \\ &\boldsymbol{R}_c\big(\boldsymbol{f}_{\mathrm{ANN1}}\big(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{w}_1^*\big), \quad f_{\mathrm{ANN2}}\big(f, \boldsymbol{q}, \boldsymbol{w}_2^*\big)\big)\end{aligned} \tag{5}$$

where $\boldsymbol{w}_1^*$ and $\boldsymbol{w}_2^*$ are the solutions from the following optimization problem:

$$\min_{[\boldsymbol{w}_1, \boldsymbol{w}_2]} \sum_{j \in T_r} \sum_{l \in \Omega} \|\boldsymbol{R}_s(\boldsymbol{p}_j, \boldsymbol{q}_j, f_l, \boldsymbol{w}_1, \boldsymbol{w}_2) - \boldsymbol{d}_{j,l}\| \tag{6}$$

where Ω represents the index set of the frequency samples. T_r represents the index set of training samples, i.e., $T_r = \{1, 2, \ldots, n_s\}$, where n_s is the total number of multiphysics training data samples. $\boldsymbol{d}$ represents the data from multiphysics simulation with respect to different values of geometrical and nongeometrical design parameters. $\boldsymbol{d}_{j,l}$ represents the multiphysics data from the jth training sample at the lth frequency sample. The parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ are trained to make the outputs of the proposed model match the multiphysics data at each frequency and each geometrical sample. Since we use much of the EM single physics (EM only) data samples to build the coarse model, the total number of multiphysics training samples n_s is relatively smaller than that in the direct methods which use the multiphysics training data to build the multiphysics model. Therefore, the proposed multiphysics model can be developed with relatively fewer multiphysics training data and less computational cost.

B. EM Domain Coarse Model Construction

To develop the proposed multiphysics parametric model using SM technique, the first step is to build the EM domain (single physics) coarse model with respect to different values of geometrical parameters. The output responses of the EM single physics (EM only) domain (single physics) simulation can be considered as the available knowledge for the computationally expensive multiphysics simulation. The relatively inexpensive EM simulation data from the EM domain analysis can be used to construct an EM domain coarse model. The expensive multiphysics simulation can be replaced by the relatively inexpensive EM domain simulation.

The first step for constructing the EM single physics (EM only)-based coarse model is data generation. To generate the EM domain training data, we need to first classify the multiphysics input parameters into three sets of parameters: the geometrical parameters $\boldsymbol{p}$, the frequency parameter f, and other physics domain nongeometrical parameters $\boldsymbol{q}$. Once the multiphysics parameter classification is finished, we can determine the variables of the inputs $\boldsymbol{p}_c$ which contain the same geometrical variables as the overall model geometrical inputs $\boldsymbol{p}$. To guarantee the accuracy of the overall multiphysics model, the ranges of geometrical parameters for the EM domain (single physics) coarse model are selected to be slightly larger than those in the overall multiphysics model.

After data generation, an EM domain coarse model with geometrical parameters as variables is developed using the parametric modeling methods such as ANN modeling method [20] or Neuro-TF technique [26]. Pure ANN is a simpler technique to learn EM behavior without having to rely on the complicated internal details of passive components. Neuro-TF technique is more efficient when the frequency responses have sharp resonances. After training process, the trained EM domain (single physics) coarse model can be used to represent the behavior of EM single physics (EM only) responses and is ready to be used as a prior knowledge for the overall multiphysics model development.

C. Proposed Space-Mapped EM Centric Multiphysics Parametric Model Training Process

To develop an accurate space-mapped multiphysics parametric model, we propose to perform a two-stage training process. The first stage is the EM domain (single physics) coarse model training which is defined in Section III-B. After the EM domain coarse model is trained, the parameters in the coarse model are fixed. We can construct the proposed multiphysics parametric model with respect to different values of geometrical and nongeometrical input parameters. The second stage is the multiphysics domain model training. We use design of experiments (DOE) sampling method [32] to generate the multiphysics data. We perform multiphysics simulations to generate multiphysics training data for the proposed surrogate model. We first perform the unit mapping for the two mapping networks by setting the values of EM domain inputs to be equal to the values of multiphysics inputs. The purpose of the unit mapping is to provide good initial values for the mapping neural networks before training them. After the unit mappings are established, the overall multiphysics model training process is performed to obtain the final surrogate model. The training data for this step are the samples with the multiphysics input parameters as the model input data and EM responses by multiphysics analysis as the target data for model outputs. During this stage, we optimize the weight parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ of the two mapping modules to reduce the misalignment between the proposed multiphysics model and the multiphysics training data.

During the proposed multiphysics parametric model training process, the first-order derivatives $\partial \boldsymbol{R}_s^T/\partial \boldsymbol{w}_1$ and $\partial \boldsymbol{R}_s^T/\partial \boldsymbol{w}_2$ are required to guide the gradient-based training process. In order to get the derivative information for the weighting parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$, we need the derivative information of $\partial \boldsymbol{R}_c^T/\partial \boldsymbol{p}_c$ and $\partial \boldsymbol{R}_c^T/\partial f_c$. For this purpose, we propose to establish an adjoint multiphysics model. Once the adjoint model is developed, the outputs of the adjoint model will provide the first order derivative to guide the gradient-based training process. The adjoint multiphysics model consists of the adjoint EM domain coarse model and two adjoint neural network models [33]. Since the coarse model is represented by either the ANN model or the Neuro-TF model, the adjoint EM domain coarse model is represented by either the adjoint neural network [33] or adjoint Neuro-TF model [34]. After the neural network model is trained, the weighting parameters are fixed. We create an adjoint neural network [33] based on a similar structure with the same weighting parameters as the trained neural network, i.e., the adjoint model. Let $\boldsymbol{G}_{\mathrm{EM}}$ represent the derivative information of the EM domain outputs with respect to the EM domain design parameters. Let $\boldsymbol{F}_{\mathrm{EM}}$ represent the derivative information of the EM domain outputs with respect to the EM domain frequency parameter [33]. Let $\boldsymbol{G}_{\mathrm{MP}}$ and $\boldsymbol{M}_{\mathrm{MP}}$ be the outputs of the adjoint model of the first mapping function with respect to the variables $\boldsymbol{p}$, $\boldsymbol{q}$, and f. More specifically, $\boldsymbol{G}_{\mathrm{MP}}$ represents the derivative information of the EM domain design parameters with respect to the multiphysics domain geometrical parameters. $\boldsymbol{M}_{\mathrm{MP}}$ represents the derivative information of the EM domain design parameters with respect to the multiphysics domain nongeometrical parameters. Let $\boldsymbol{F}_{\mathrm{MP}}$ be the outputs of the adjoint model of the second mapping function. $\boldsymbol{F}_{\mathrm{MP}}$ represents the derivative information of the EM domain frequency parameter with respect to the multiphysics domain nongeometrical parameters. The proposed adjoint multiphysics model is shown in Fig. 4.

During the overall model training process, the neural network internal parameters $\boldsymbol{w}_1$ and $\boldsymbol{w}_2$ are the optimization variables. The first-order derivatives of the overall multiphysics model output $\boldsymbol{R}_s$ with respect to the neural network internal parameters are required for training technique. The derivatives of the $\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)/\partial \boldsymbol{p}_c$ and $\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)/\partial f_c$ can be obtained from the outputs of the adjoint multiphysics model shown as

$$\frac{\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)}{\partial \boldsymbol{p}_c} = \boldsymbol{G}_{\mathrm{EM}} \tag{7}$$

$$\frac{\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)}{\partial f_c} = \boldsymbol{F}_{\mathrm{EM}}. \tag{8}$$

The first-order derivatives of the overall multiphysics model output $\boldsymbol{R}_s$ with respect to weight parameters $\boldsymbol{w}_1$ of the first mapping module are formulated by

$$\begin{aligned}\frac{\partial \boldsymbol{R}_s^T(\boldsymbol{p}, \boldsymbol{q}, f, \boldsymbol{w}_1, \boldsymbol{w}_2)}{\partial \boldsymbol{w}_1} &= \frac{\partial \boldsymbol{p}_c^T(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{w}_1)}{\partial \boldsymbol{w}_1}\frac{\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)}{\partial \boldsymbol{p}_c}\\ &= \frac{\partial \boldsymbol{p}_c^T(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{w}_1)}{\partial \boldsymbol{w}_1} \cdot \boldsymbol{G}_{\mathrm{EM}}\end{aligned} \tag{9}$$

where $\boldsymbol{G}_{\mathrm{EM}}$ is the output of the adjoint EM domain coarse model. $\partial \boldsymbol{p}_c^T(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{w}_1)/\partial \boldsymbol{w}_1$ represents the derivative information of EM domain design parameters with respect to the weighting parameters of the first mapping function $\boldsymbol{f}_{\mathrm{ANN1}}$ calculated by the back propagation [35]. Similarly, the first-order derivatives of the overall multiphysics model output $\boldsymbol{R}_s$ with respect to weight parameters $\boldsymbol{w}_2$ of the second mapping module are derived by

$$\begin{aligned}\frac{\partial \boldsymbol{R}_s^T(\boldsymbol{p}, \boldsymbol{q}, f, \boldsymbol{w}_1, \boldsymbol{w}_2)}{\partial \boldsymbol{w}_2} &= \frac{\partial f_c(\boldsymbol{q}, f, \boldsymbol{w}_2)}{\partial \boldsymbol{w}_2}\frac{\partial \boldsymbol{R}_c^T(\boldsymbol{p}_c, f_c)}{\partial f_c}\\ &= \frac{\partial f_c(\boldsymbol{q}, f, \boldsymbol{w}_2)}{\partial \boldsymbol{w}_2} \cdot \boldsymbol{F}_{\mathrm{EM}}\end{aligned} \tag{10}$$

where $\boldsymbol{F}_{\mathrm{EM}}$ is the output of the adjoint EM domain coarse model. $\partial f_c(\boldsymbol{q}, f, \boldsymbol{w}_2)/\partial \boldsymbol{w}_2$ represents the derivative information of EM domain mapped frequency with respect to the weighting parameters of the second mapping function f_{ANN2} calculated by the back propagation [35].

The detailed multiphysics training mechanism of the overall multiphysics parametric model exploiting SM technique is illustrated in Fig. 5. The overall multiphysics model training process is performed by adjusting the neural network weights of the two mapping modules to minimize the training error between the proposed model and multiphysics data, formulated as

$$E_{\mathrm{Tr}}(\boldsymbol{w}_1, \boldsymbol{w}_2) = \frac{1}{2n_s}\sum_{j\in T_r}\sum_{l\in\Omega}\|\boldsymbol{R}_s(\boldsymbol{p}_j, \boldsymbol{q}_j, f_l, \boldsymbol{w}_1, \boldsymbol{w}_2) - \boldsymbol{d}_{j,l}\|^2. \tag{11}$$

After training, an independent set of multiphysics testing data are used to test the trained overall multiphysics parametric model. If the testing error E_{Te} is lower than a user define threshold ε, the training process terminates and the overall model has been developed. Otherwise, the overall multiphysics model training process will be repeated by adjusting the

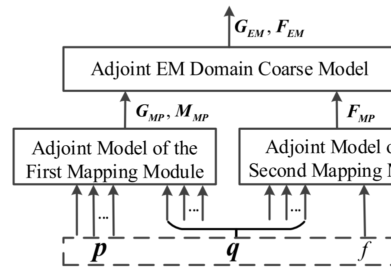


Fig. 4. Structure of the proposed adjoint multiphysics model including the adjoint EM domain coarse model and two adjoint neural network models. The adjoint model of the first mapping module is the adjoint neural network of f_{ANN1} and the adjoint model of the second mapping module is the adjoint neural network of f_{ANN2}. The purpose of this adjoint model is to provide the derivative information to guide the training and optimization process.

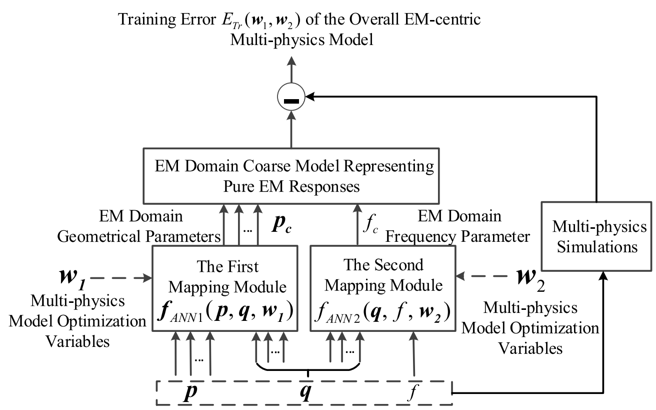


Fig. 5. Detailed training mechanism of the overall multiphysics parametric model exploiting SM technique. The objective is to minimize the training error between the proposed model and multiphysics data. The variables of this training process are the weighting parameters w_1 and w_2 of the two mapping modules between the multiphysics domain and the single physics domain.

numbers of hidden neurons in the neural networks. A flowchart of the proposed multiphysics model development process is shown in Fig. 6. After the overall multiphysics parametric model is developed, it is ready to be used for higher level multiphysics design optimization.

D. Use of Proposed Model for Multiphysics Design Optimization

After training is finished, the proposed multiphysics model can be used for multiphysics design optimization. During the optimization process, our proposed adjoint multiphysics model can be used to obtain the first-order derivative information of the overall model output R_s with respect to the overall model inputs p and q to guide the gradient-based design optimization.

In order to get the derivative information of $\partial R_s^T/\partial p$ and $\partial R_s^T/\partial q$, we need to evaluate the derivatives throughout various parts of the model. The derivatives of the $\partial p_c^T(p, q, w_1)/\partial p$ and $\partial p_c^T(p, q, w_1)/\partial q$ can be obtained directly from the adjoint model of the first mapping model, formulated as

$$\frac{\partial p_c^T(p, q, w_1)}{\partial p} = G_{\mathrm{MP}} \tag{12}$$

$$\frac{\partial p_c^T(p, q, w_1)}{\partial q} = M_{\mathrm{MP}}. \tag{13}$$

Similarly, the derivative of the $\partial f_c(q, f, w_2)/\partial q$ can be obtained directly from the adjoint model of the second mapping model, formulated as

$$\frac{\partial f_c(q, f, w_2)}{\partial q} = F_{\mathrm{MP}}. \tag{14}$$

Based on the proposed adjoint multiphysics model, the detailed derivative formula of R_s with respect to p which is used to guide the optimization process is derived as

$$\frac{\partial R_s^T(p, q, f)}{\partial p} = \frac{\partial p_c^T(p, q)}{\partial p}\frac{\partial R_c^T(p_c, f_c)}{\partial p_c} = G_{\mathrm{MP}} \cdot G_{\mathrm{EM}} \tag{15}$$

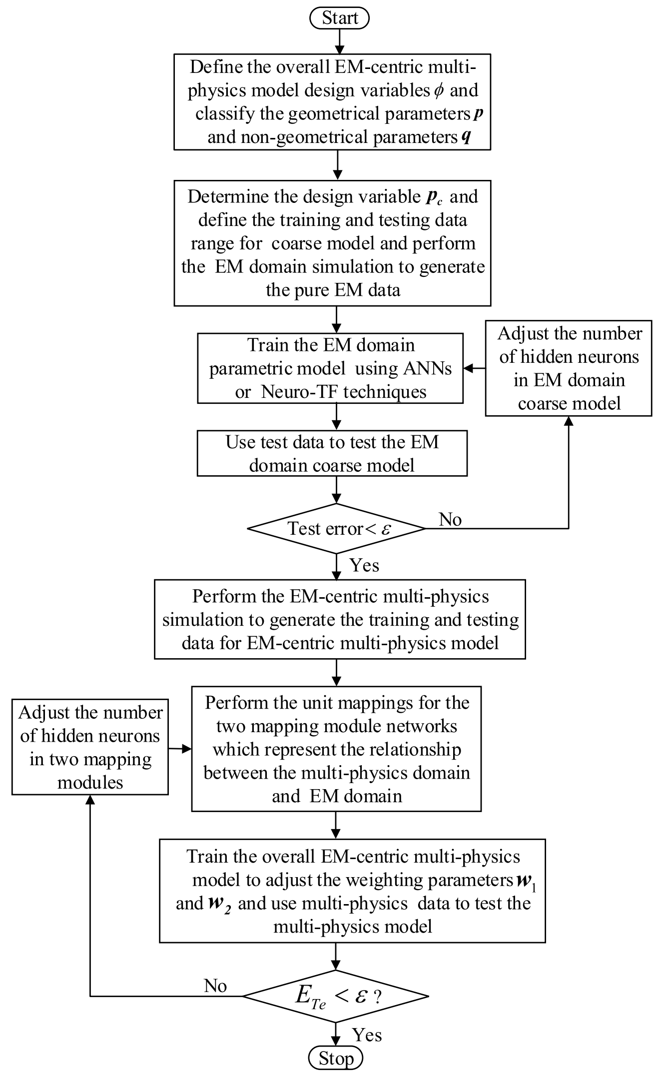


Fig. 6. Flowchart of the development process of the multiphysics parametric model exploiting the EM domain coarse model and SM between the multiphysics domain and the single physics EM domain.

where G_{MP} is the output of the adjoint model of the first mapping function and G_{EM} is the output of the adjoint EM domain coarse model. When calculating the derivative information of R_s with respect to q, since the nongeometrical parameters q are the inputs of both of the two mapping module networks, the detailed derivative formula is derived as

$$\begin{aligned}\frac{\partial R_s^T(p, q, f)}{\partial q} &= \frac{\partial p_c^T(q, f)}{\partial q}\frac{\partial R_c^T(p_c, f_c)}{\partial p_c} \\ &\quad + \frac{\partial f_c(q, f)}{\partial q}\frac{\partial R_c^T(p_c, f_c)}{\partial f_c} \\ &= M_{\mathrm{MP}} \cdot G_{\mathrm{EM}} + F_{\mathrm{MP}} \cdot F_{\mathrm{EM}}\end{aligned} \tag{16}$$

where M_{MP} is the output of the adjoint model of the first mapping function. F_{MP} is the output of the adjoint model of the second mapping function. G_{EM} and F_{EM} are the outputs of the adjoint EM domain coarse model. The derivatives calculated in (15) and (16) are, thus, used to guide the gradient-based design optimization with the developed multiphysics parametric model.

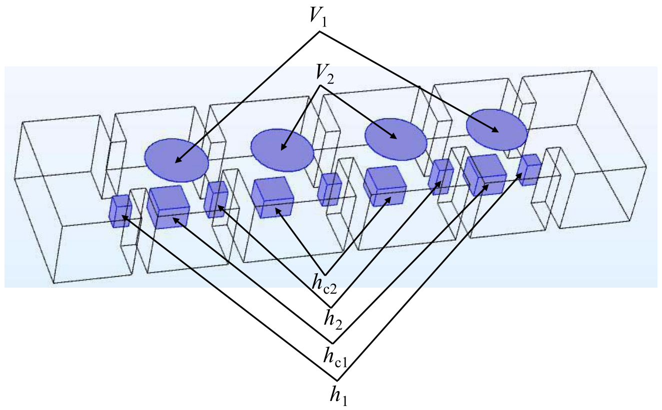


Fig. 7. Structure of the four-pole waveguide filter using piezoactuator with multiphysics model design variables $\boldsymbol{\phi} = [h_1\ h_2\ h_{c1}\ h_{c2}\ V_1\ V_2]^T$. The input and output waveguides, as well as the resonant cavities, are standard WR-75 waveguides (width = 19.050 mm and height = 9.525 mm). The length of the structure is 77.6 mm. The thickness of all the coupling windows is set to 2 mm.

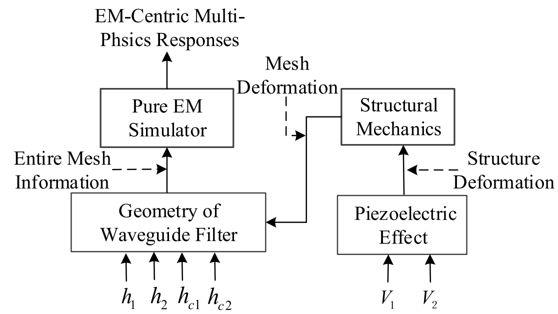


Fig. 8. Actual process of the multiphysics problem for the four-pole waveguide filter example using the COMSOL software.

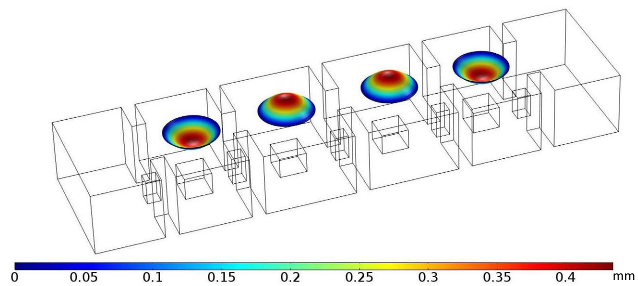


Fig. 9. Structural deformation in the four-pole waveguide filter caused by the input voltages.

IV. Numerical Examples

A. *Multiphysics Parametric Modeling of Tunable Four-Pole Waveguide Filter Using Piezo Actuator*

The first example under consideration is a four-pole waveguide filter [36] with tuning elements as the posts of the square cross section placed at the center of each cavity and each coupling window. The piezoactuator will have a geometric strain proportional to an applied electric field through the piezoelectric effect [37]. The material for the piezoactuator is Lead Zirconate Titanate (PZT-5H). It is z-polarized and generates mainly z-directional deflection of the device. In this example, piezoactuators are used to control the size of a small air gap between the top of the posts and the bottom side of the piezoactuators which provide the tunability for waveguide filter, shown in Fig. 7, where height (h_1) and height (h_2) are the heights of the tuning posts in the coupling windows. Height (h_{c1}) and height (h_{c2}) are the heights of the square cross section placed in the center of the resonator cavities. Voltages (V_1) and (V_2) are the electronic potentials that are applied across the piezoactuator, which will cause the deformation of the piezoactuator, and further change the frequency responses of the device. The input and output waveguides, as well as the resonant cavities, are standard WR-75 waveguides (width = 19.050 mm and height = 9.525 mm) [36]. The length of the structure is 77.6 mm. The thickness of all the coupling windows is set to 2 mm. Frequency f is an additional input. The design parameter for this example has six variables, i.e., $\boldsymbol{\phi} = [h_1\ h_2\ h_{c1}\ h_{c2}\ V_1\ V_2]^T$. The geometrical input variables to the overall multiphysics model are $\boldsymbol{p} = [h_1\ h_2\ h_{c1}\ h_{c2}]^T$. The nongeometrical input variables to the overall multiphysics model are $\boldsymbol{q} = [V_1\ V_2]^T$ which are the tuning variables. The model has two outputs, i.e., $\boldsymbol{y} = [RS_{11}\ IS_{11}]^T$, which are the real and imaginary parts of the overall multiphysics model output S_{11} with respect to different values of geometrical and nongeometrical input parameters. For the coarse model construction, we consider only the EM single physics (EM only) simulation. The coarse model has four design variables $\boldsymbol{p}_c = [h_1\ h_2\ h_{c1}\ h_{c2}]^T$. Frequency f_c is an additional input of the EM domain (single physics) coarse model.

COMSOL MULTIPHYSICS 5.2 is used to perform the multiphysics simulation to generate the overall multiphysics model training and testing data, with respect to different geometrical and nongeometrical input parameters. The actual process of this multiphysics problem is shown in Fig. 8. The fine model actually uses the entire mesh information to calculate the multiphysics responses while our technique uses the mapping functions to represent the output response changes caused by other physics domains. Fig. 9 shows the deformation information of the cavity filter with the multiphysics design parameters $\boldsymbol{\phi} = [3.52\ 4.18\ 3.34\ 3.07\ 250\ -250]^T$ [mm mm mm mm V V]. We can see that with the positive voltage, the piezoactuator deflects toward the bottom while with negative voltage the piezoactuator deflects upward the bottom. These deformations make the outputs of the multiphysics simulation different from the outputs of the EM single physics (EM only) simulation. Fig. 10 shows the output responses using EM domain (single physics) simulation and multiphysics simulation for this cavity filter example, i.e., the coarse model response and overall model response using the same geometrical parameters. From the figure, we can see that the single physics analysis is not accurate enough to represent the multiphysics responses. Our multiphysics model is more accurate because we include other physics domain besides the EM domain effects into our model.

For EM domain (single physics) coarse model data generation with respect to different geometrical input parameters, the EM single physics (EM only) evaluation is performed by ANSYS HFSS EM simulator using the fast simulation

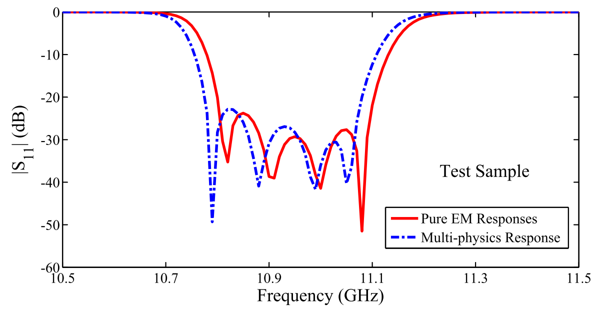


Fig. 10. Comparison of the magnitude (in decibels) of S_{11} of the EM single physics (EM only) responses and multiphysics analysis responses using the same geometrical parameters for the four-pole waveguide filter. From the figure, we can see that without mapping, the single physics analysis is not accurate enough to represent the multiphysics responses.

TABLE I

DEFINITION OF TRAINING AND TESTING DATA FOR EM DOMAIN (SINGLE PHYSICS) COARSE MODEL AND MULTIPHYSICS DOMAIN OVERALL MODEL FOR THE FOUR-POLE WAVEGUIDE FILTER EXAMPLE

Input Variables to the Model		Training Data Range			Testing Data Range		
		Min	Max	Step	Min	Max	Step
EM Data (Coarse Model)	h_1 (mm)	3.42	3.62	0.025	3.4325	3.6075	0.025
	h_2 (mm)	4.08	4.28	0.025	4.0925	4.2675	0.025
	h_{c1} (mm)	3.18	3.38	0.025	3.1925	3.3675	0.025
	h_{c2} (mm)	2.94	3.14	0.025	2.9525	3.1275	0.025
Multi-physics Data (Overall Model)	h_1 (mm)	3.44	3.60	0.04	3.45	3.59	0.02
	h_2 (mm)	4.10	4.26	0.04	4.11	4.25	0.02
	h_{c1} (mm)	3.22	3.34	0.03	3.2275	3.3325	0.015
	h_{c2} (mm)	2.98	3.10	0.03	2.9875	3.0925	0.015
	V_1 (V)	-400	400	200	-350	350	100
	V_2 (V)	-400	400	200	-350	350	100

feature. DOE method is used as the sampling method for both EM domain (single physics) coarse model and multiphysics domain overall model data generation.

The EM single physics (EM only) simulation data with geometrical parameters as variables used to construct the EM domain (single physics) coarse model uses nine levels of DOE for defining the samples of the training data, i.e., a total of 81 samples of EM domain (single physics) training data, and eight levels of DOE for defining the samples of the testing data, i.e., a total of 64 samples of testing data. While for the overall multiphysics model data, we only use five levels of DOE for defining samples of the training data, i.e., a total of 25 samples of multiphysics training data. The input ranges of geometrical parameters for the EM domain (single physics) coarse model should be larger than the overall multiphysics model to accommodate the mapping between the EM domain and multiphysics domain. The physical shape of the training and testing structure for this example is shown in Fig. 7 and the specific values of training and testing data for both EM domain (single physics) coarse model and multiphysics domain surrogate model are shown in Table I. The testing data are randomly selected within the training ranges and never used in the training process. The frequency range for model development is from 10.5 to 11.5 GHz.

For this example, the pole-residue-based Neuro-TF technique [25] is used to construct the EM domain coarse model with geometrical parameters as variables. The number of hidden neurons of the neural networks that represent the relationships between the geometrical parameters and poles/residues is 10. The EM domain (single physics) coarse model using the Neuro-TF techniques is trained using the NeuroModelerPlus software. The average training error for the EM domain coarse model development is 1.11%, while the average testing error is 1.38%. After an accurate EM domain coarse model is developed, we can continue to set up the proposed multiphysics model which can accurately represent the multiphysics data with different values of geometrical and nongeometrical design parameters as variables. The overall model including the Neuro-TF coarse model and two mapping neural networks is also constructed and trained using the NeuroModelerPlus software which is shown in Fig. 8. Numbers of hidden neurons for the two mapping neural network modules are 4 and 2, respectively. The average training error for the multiphysics domain overall model development is 1.56%, while the average testing error is 1.63%. The overall multiphysics model training process takes about 10 min including the parameter extraction, EM domain coarse model construction, and overall multiphysics domain model development.

For comparison purpose, ANN model (i.e., without mapping) is directly trained to learn multiphysics data for two cases, case 1 being with fewer multiphysics training data (25 sets of data) and case 2 being with more multiphysics training data (81 sets of data). We also train the model using the Neuro-TF modeling method with correlating mapping, i.e., the method of [31] to learn multiphysics data for two cases, case 1 being with fewer multiphysics training data (25 sets of data) and case 2 being with more multiphysics training data (81 sets of data). In this example, since the geometrical parameters (h_{c1} and h_{c2}) are influenced by (or correlated with) the nongeometrical parameters (V_1 and V_2), the correlating mapping between the geometrical parameters (h_{c1} and h_{c2}) and the nongeometrical parameters (V_1 and V_2) is established using the method of [31]. The multiphysics data are directly used for the training of Neuro-TF model with correlating mapping. Table II compares the different parametric modeling methods in terms of ANN structures, average training and testing error, and CPU time. From the table, we can see that when fewer multiphysics data are used, our proposed model is more accurate than the other two parametric models because our model has the knowledge of the coarse model trained with many inexpensive EM (single-physics) data. With the similar accuracy requirement, our proposed model uses fewer multiphysics data and less computation cost than the other two parametric models. The proposed multiphysics model provides accurate and fast prediction of multiphysics responses for high-level multiphysics design. Table III compares the computation time between the pure multiphysics nonparametric simulation (using COMSOL MULTIPHYSICS) and the proposed multiphysics parametric model with respect to different number of multiphysics simulations. From the table, we can see that since the training is a one-time investment, the benefit of using the proposed

TABLE II
COMPARISONS OF DIFFERENT METHODS FOR PARAMETRIC MODELING OF THE FOUR-POLE WAVEGUIDE FILTER EXAMPLE

Training Method	No. of EM Data	No. of Multi-Physics Data	Average Training Error	Average Testing Error	Multi-Physics Data Gene -ration Time	EM Single Physics Data Generation Time	Model Training Time	Total CPU Time
ANN Model Using Less Multi-Physics Training Data	0	25	1.47%	13.3%	12.1 h	0	0.1 h	12.2 h
ANN Model Using More Multi-Physics Training Data	0	81	1.86%	1.96%	39.8 h	0	0.1 h	39.9 h
Neuro-TF Model With Correlating Mapping Using Less Multi-Physics Training Data	0	25	1.56%	11.6%	12.1 h	0	0.2 h	12.3 h
Neuro-TF Model With Correlating Mapping Using More Multi-Physics Training Data	0	81	1.53%	1.67%	39.8 h	0	0.2 h	40 h
Proposed Model Using Less Multi-Physics Training Data	81	25	1.56%	1.63%	12.1 h	2.4 h	0.2 h	14.7 h

TABLE III
COMPARISON OF COMPUTATION TIME BETWEEN THE MULTIPHYSICS NONPARAMETRIC SIMULATION AND PROPOSED MULTIPHYSICS PARAMETRIC MODEL OF THE FOUR-POLE WAVEGUIDE FILTER EXAMPLE

No. of Changes of Physical/Geome -trical Parameters	CPU Time	
	Proposed Multi -physics Model	Simulation Using Multi-physics Software
1	14.7 h (model development) + 0.008 s	0.51 h
100	14.7 h (model development) + 0.8 s	approx. 50 h
500	14.7 h (model development) + 4 s	approx. 250 h

multiphysics model accumulates when the model is used over and over again with repetitive changes in physical/geometrical parameters.

The comparison of the magnitude (in decibels) of S_{11} of the proposed multiphysics model trained with less data (25 sets of data), the Neuro-TF model with correlating mapping trained with less data (25 sets of data), and the Neuro-TF model with correlating mapping trained with more data (81 sets of data) for two different filter geometries which are from testing data and have never been used in training process are shown in Fig. 11. The values of the input variables to our model for the two samples of the tunable cavity filter are as follows.

Test sample #1:

$\boldsymbol{\phi} = [3.49\ 4.23\ 3.3325\ 3.0775\ 25\ -175]^T$ [mm mm mm mm V V]

Test sample #2:

$\boldsymbol{\phi} = [3.59\ \ 4.25\ \ 3.2275\ \ 3.0325\ \ 125\ \ -125]^T$ [mm mm mm mm V V]

It is observed that compared to the simulation results performed with the COMSOL MULTIPHYSICS, our proposed multiphysics model can achieve good accuracy for different input samples even though these samples are never used in training. Once the overall model training is completed, we can implement the trained model into the design optimization where the design parameters can be repetitively adjusted during optimization. As an example of using the trained model with different values of geometrical and nongeometrical input

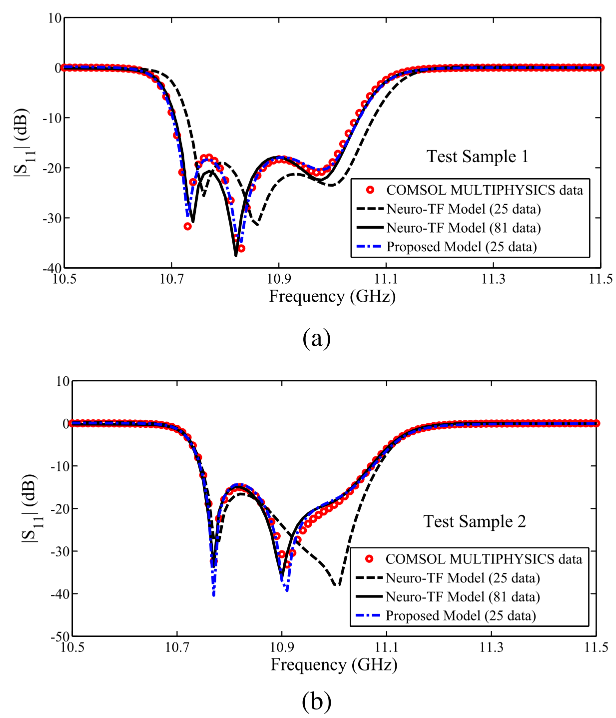
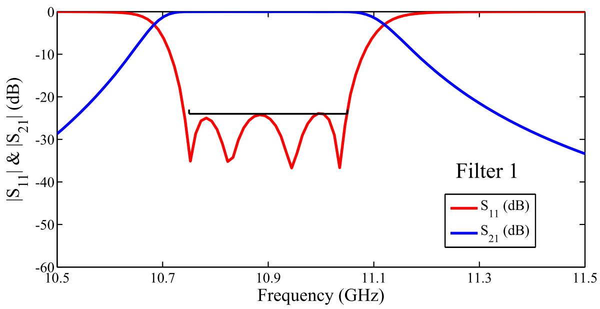
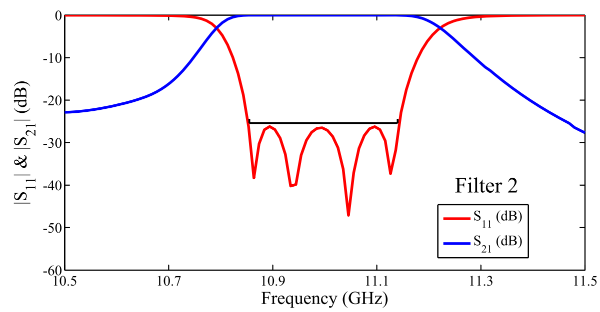


Fig. 11. Comparison of the magnitude (in decibels) of S_{11} of the overall multiphysics models developed using different modeling methods and COMSOL MULTIPHYSICS data. (a) Test sample #1 and (b) Test sample #2 for the four-pole waveguide example. In the figure, Neuro-TF model (less data) means the Neuro-TF model with correlating mapping trained with less multiphysics data. Neuro-TF model (more data) means the Neuro-TF model with correlating mapping trained with more multiphysics data. Proposed model (less data) means the proposed model trained with less multiphysics data.



(a)



(b)

Fig. 12. Proposed parametric model is used for optimization with respect to two separate cavity filters with two different specifications for the four-pole waveguide filter. The optimal solution is found by our model and verified by the COMSOL MULTIPHYSICS. The magnitude (in decibels) of S_{11} and S_{21} of COMSOL MULTIPHYSICS data at (a) optimized design solution for filter 1 and (b) optimized design solution for filter 2. As shown in the figure, the proposed model behaves well in design optimization with different specifications.

parameters for the four-pole waveguide filter, we perform the multiphysics optimization of two separate cavity filters with two different design specifications:

$$\text{Specifications for cavity filter \#1: } |S_{11}| \leq -24 \text{ dB at frequency range from 10.75 to 11.05 GHz.} \tag{17}$$

$$\text{Specifications for cavity filter \#2: } |S_{11}| \leq -25 \text{ dB at frequency range from 10.85 to 11.15 GHz.} \tag{18}$$

The initial values are $\boldsymbol{\phi} = [3.45 \quad 4.13 \quad 3.2425 \quad 3.0175 \quad -25 \quad 25]^T$ [mm mm mm mm V V]. The design optimization using the proposed overall multiphysics model took only about 20 s to achieve the optimal design solution for each cavity filter. The optimized design parameter values for these two separate cavity filters are:

Filter #1:

$\boldsymbol{\phi} = [3.48373\ 4.17073\ 3.25362\ 2.98028\ 397.636\ 235.752]^T$ [mm mm mm mm V V].

Filter #2:

$\boldsymbol{\phi} = [3.44 \quad 4.13458 \quad 3.22 \quad 2.98 \quad 173.039 \quad -211.601]^T$ [mm mm mm mm V V].

The magnitudes (in decibels) of S_{11} and S_{21} of COMSOL MULTIPHYSICS data at the model optimal solutions are shown in Fig. 12. Our multiphysics model can behave well in design optimization with different specifications. If we eliminate the effects of the other physics domains and consider only the EM single physics (EM only) simulation, in this example that means $V_1 = 0$ and $V_2 = 0$, we can get the EM response with other four geometrical parameters. We can still use our proposed model to do the optimization with only the four geometrical parameters. Fig. 13(a) shows the optimization result with the specifications for the cavity filter $|S_{11}| \leq -25$ dB at frequency range from 10.80 to 11.10 GHz. The optimized geometrical values are $\boldsymbol{\phi}_{\text{opt}}$: $\boldsymbol{\phi} = [3.48671\ 4.16753\ 3.28595\ 2.98005\ 0\ 0]^T$ [mm mm mm mm V V]. In order to show the multiphysics effects and its tunability, we perform the optimization using only the two nongeometrical variables as the tuning variables, i.e., V_1 and V_2 while the other four geometrical variables are fixed during the tuning optimization process. With the same starting point as shown in Fig. 13 (a), we perform the multiphysics optimization to determine the values of tuning parameters to match the two different design specifications as in (17) and (18).

The initial point of the tuning optimization is $V_1 = 0$ V and $V_2 = 0$ V and the optimized tuning design parameter values for the two different specifications are:

Specification #1: $V_1 = 230.429$ V and $V_2 = 233.428$ V.

Specification #2: $V_1 = -244.46$ V and $V_2 = -236.589$ V.

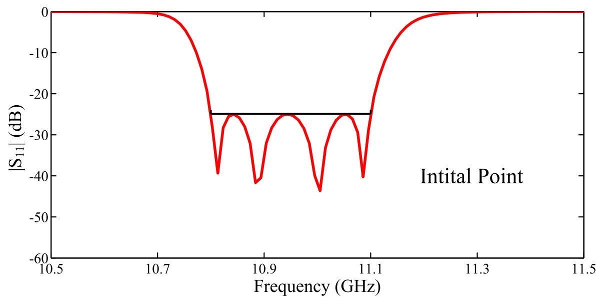
The COMSOL MULTIPHYSICS simulations at the optimal tuning solutions are shown in Fig. 13(b) and (c). From the figure, we can see that the nongeometrical parameters are used for tuning the cavity filter to obtain the desired response.

Our proposed multiphysics parametric model can provide similar results to those simulated with the commercial multiphysics tools within the training ranges as shown in Table II. If the multiphysics design parameters are slightly beyond the training ranges, our proposed model can still be used to get approximate results. Fig. 14 shows the extrapolation results of the test sample $\boldsymbol{\phi} = [3.42 \quad 4.08 \quad 3.20 \quad 2.96\ -450\ -450]^T$ [mm mm mm mm V V]. From the figure, we can see that the results become approximate since the design parameters are slightly beyond the training ranges. If the multiphysics design parameters are far beyond the training ranges, our model cannot guarantee the reliability of the results.

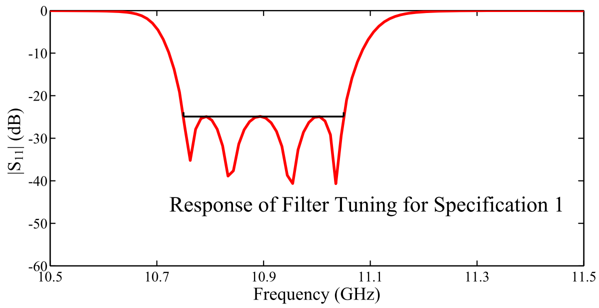
Similarly, for the frequency extrapolation, if the frequency is slightly beyond the training frequency ranges, our proposed model can still be used to get approximate results. If the frequency is far beyond the training frequency ranges, our model cannot provide reliable results. Fig. 15 shows the frequency extrapolation results of the test sample $\boldsymbol{\phi} = [3.49\ \ 4.23\ \ 3.3325\ \ 3.0775\ \ 25\ -175]^T$ [mm mm mm mm V V] in the frequency range from 9.5 to 12 GHz. The training frequency in this four-pole waveguide filter example ranges from 10.5 to 11.5 GHz. From the figure, we can see that our proposed model becomes less accurate in the frequency range from 9.5 to 10.1 GHz.

B. *Multiphysics Parametric Modeling of an Iris Coupled Microwave Cavity Filter*

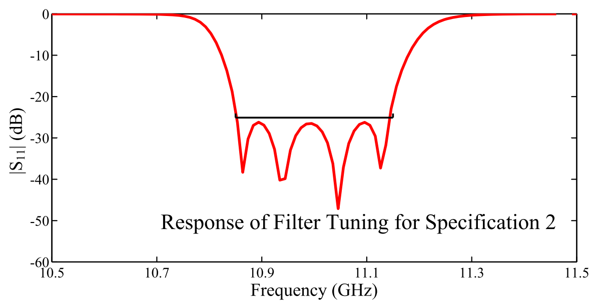
In this example, we apply the proposed space-mapped multiphysics model technique to an iris coupled cavity filter [36] shown in Fig. 16(a). The filter has four geometrical design parameters, i.e., the iris widths w_1, w_2, w_3, and w_4. A large power P_{in} is supplied to the cavity filter as an additional design parameter which can change the EM single physics



(a)



(b)



(c)

Fig. 13. Proposed parametric model is used for filter tuning with respect to two different specifications for the four-pole waveguide filter. The optimal tuning solution is found by our model and verified by the COMSOL MULTIPHYSICS. The magnitude (in decibels) of S_{11} of COMSOL MULTIPHYSICS data at (a) initial point: $V_1 = 0$ V and $V_2 = 0$ V, (b) optimized tuning solution for specification 1: $V_1 = 230.429$ V and $V_2 = 233.428$ V, and (c) optimized tuning solution for specification 2: $V_1 = -244.4$ V and $V_2 = -236.589$ V. As shown in the figure, the proposed model behaves well in tuning optimization with different specifications.

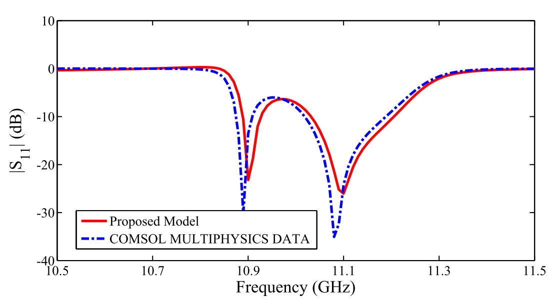


Fig. 14. Extrapolation results of the test sample slightly beyond the training ranges for the four-pole waveguide filter example. We can see that the approximate results can be obtained by our proposed model.

(EM only) responses due to the thermal effects and mechanical deformation as described in Section II. Frequency f is an additional input. For this multiphysics problem, the design parameter includes five variables $\boldsymbol{\phi} = [w_1\ w_2\ w_3\ w_4\ P_{\text{in}}]^T$.

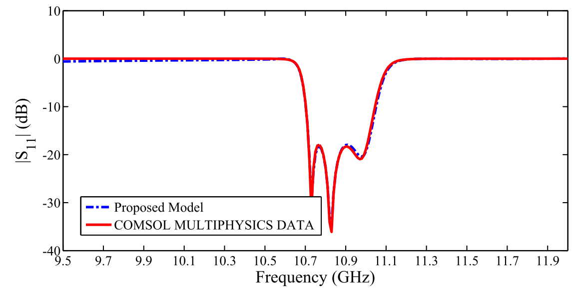
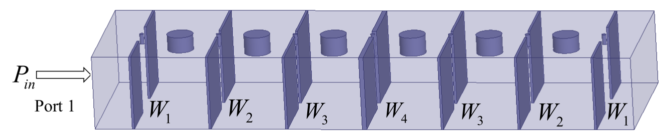
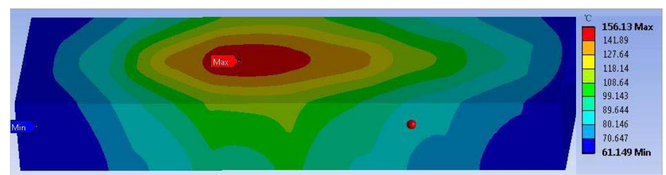


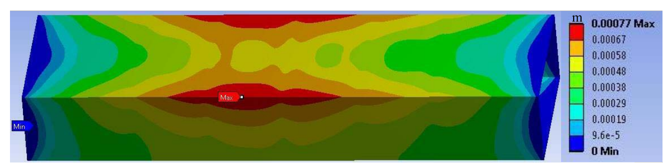
Fig. 15. Frequency extrapolation results of the test sample in the frequency range from 9.5 to 12 GHz for the four-pole waveguide filter example.



(a)



(b)



(c)

Fig. 16. (a) Structure of the iris coupled waveguide filter where a high input power is supplied to port 1. The design variables are $\boldsymbol{\phi} = [w_1\ w_2\ w_3\ w_4\ P_{\text{in}}]^T$. (b) Temperature distribution in the iris coupled waveguide filter caused by the large input power. (c) Structural deformation in the iris coupled waveguide filter caused by the temperature distribution.

The geometrical inputs of the overall multiphysics model are $\boldsymbol{p} = [w_1\ w_2\ w_3\ w_4]^T$. The nongeometrical input variable is $\boldsymbol{q} = P_{\text{in}}$. The model has two outputs, i.e., $\boldsymbol{y} = [RS_{11}\ IS_{11}]^T$, which are the real and imaginary parts of the overall multiphysics model output S_{11} with different values of geometrical and nongeometrical parameters as variables. For the EM single physics (EM only) domain coarse model, we construct the coarse model which has the four input parameters $\boldsymbol{p}_c = [w_1\ w_2\ w_3\ w_4]^T$. Frequency f_c is an additional input of the EM domain coarse model.

ANSYS WORKBENCH 17.1 including HFSS, Steady-State Thermal and Static Structural is used to perform the multiphysics simulation to generate the overall multiphysics model training and testing data with respect to different geometrical and nongeometrical design parameters. The actual process of this multiphysics problem is shown in Fig. 17. Three physics domains (EM, thermal, and structural mechanics) are considered in this example, and different domains are coupled affecting each other as described in Section II. The actual fine model using the entire mesh information to calculate the

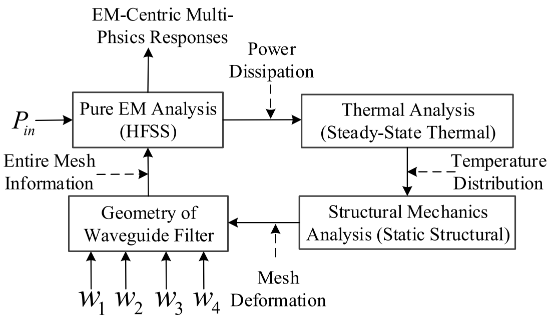


Fig. 17. Actual process of the multiphysics simulation for the iris coupled waveguide filter example using the ANSYS WORKBENCH software.

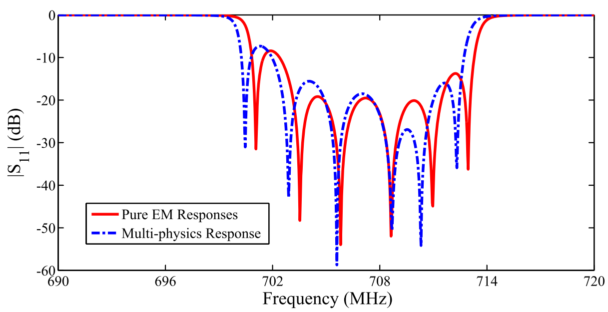


Fig. 18. Comparison of the magnitude (in decibels) of S_{11} of the EM single physics (EM only) response and multiphysics analysis response using the same geometrical parameters for the iris coupled waveguide filter. From the figure, we can see that without mapping, the single physics analysis is not accurate enough to represent the multiphysics responses.

multiphysics responses while our technique uses the mapping functions to represent the output response changes caused by other physics domains. After the multiphysics simulation, the temperature information and structural deformation information of the cavity filter with the design parameter $\boldsymbol{\phi} = [116.5\ 49.735\ 43.445\ 48.995\ 36.25]^T$ [mm mm mm mm kW] are shown in Fig. 16(b) and (c) respectively. We can see that due to the large input power, the power loss generates the heat in the cavity filter and causes the deformation of the filter structure. These deformations make the outputs of the multiphysics simulation different from the EM single physics (EM only) simulation. Fig. 18 shows the output responses using EM single physics (EM only) simulation and multiphysics simulation for this cavity filter example, i.e., the EM domain coarse model response and overall multiphysics overall model response using the same geometrical parameters. From the figure, we can see the single physics analysis is not accurate enough to represent the multiphysics responses. Our multiphysics model is more accurate because we include other physics domain besides the EM domain effects into our model.

For EM domain coarse model data generation with respect to different geometrical parameters as variables, the EM single physics (EM only) evaluation is performed by ANSYS HFSS EM simulator using the fast simulation feature. DOE method is used as the sampling method for both EM domain coarse and overall multiphysics model data generation.

The EM single physics (EM only) simulation data used to construct the EM domain coarse model with geometrical

TABLE IV
DEFINITION OF TRAINING AND TESTING DATA FOR EM DOMAIN COARSE MODEL AND OVERALL MULTIPHYSICS FINE MODEL FOR THE IRIS COUPLED WAVEGUIDE FILTER

Input Variables to the Model		Training Data Range			Testing Data Range		
		Min	Max	Step	Min	Max	Step
EM Data (Coarse Model)	w_1 (mm)	111.93	118.73	0.85	112.355	118.305	0.85
	w_2 (mm)	48.66	51.86	0.4	48.86	51.66	0.4
	w_3 (mm)	43.13	45.93	0.35	43.305	45.755	0.35
	w_4 (mm)	46.65	49.69	0.38	46.84	49.5	0.38
Multi-physics Data (Fine Mdodel)	w_1 (mm)	112.21	118.45	1.56	112.6	118.06	0.78
	w_2 (mm)	48.86	51.26	0.7	49.035	51.485	0.35
	w_3 (mm)	43.29	45.77	0.62	43.445	45.615	0.31
	w_4 (mm)	46.85	49.49	0.66	47.015	49.325	0.33
	P_{in} (kW)	20	40	5	21.25	38.75	2.5

parameters as variables uses nine levels of DOE for defining samples of the training data, i.e., a total of 81 samples of training data, and eight levels of DOE for defining samples of the testing data, i.e., a total of 64 samples of testing data. While for the overall multiphysics model data, we only use five levels of DOE for defining samples of the multiphysics training data, i.e., a total of 25 samples of training data. The input ranges of the geometrical variables for the EM domain coarse model should be larger than the overall multiphysics model to accommodate the mapping between the EM domain and multiphysics domain. The physical shape of the training and testing structure for this example is shown in Fig. 16(a) and the specific values of training data and testing data for both coarse model and overall model are shown in Table IV. The testing data are randomly selected within the training ranges and never used in the training process. The frequency range for model development is from 690 to 720 MHz.

For this example, the three-layer perception neural network [18] is used to construct the EM domain coarse model with geometrical parameters as variables. The number of hidden neurons of the neural networks that represent the relationships between the geometrical parameters and EM single physics (EM only) responses is 40. The coarse model is trained using the NeuroModelerPlus software. The average training error for the EM domain (single physics) coarse model development is 1.65%, while the average testing error is 1.58%. After an accurate EM domain coarse model is developed, we can continue to set up the overall multiphysics model which can accurately represent the multiphysics data. The overall multiphysics model including ANN coarse model and two mapping neural networks is also constructed and trained using the NeuroModelerPlus software. Numbers of hidden neurons for the two mapping neural network modules are 6 and 2 respectively. The average training error for the overall multiphysics model development is 1.83%, while the average testing error is 1.92%. The overall multiphysics model training process takes about 8 min including EM domain (single physics) coarse model and overall multiphysics model developments.

TABLE V
COMPARISONS OF DIFFERENT METHODS FOR PARAMETRIC MODELING OF THE IRIS COUPLED WAVEGUIDE FILTER

Training Method	No. of EM Data	No. of Multi-Physics Data	Average Training Error	Average Testing Error	Multi-Physics Data Gene -ration Time	EM Single Physics Data Gene -ration Time	Model Training Time	Total CPU Time
ANN Model Using Less Multi-Physics Training Data	0	25	1.86%	9.56%	50 h	0	0.1 h	50.1 h
ANN Model Using More Multi-Physics Training Data	0	81	1.78%	1.86%	162 h	0	0.1 h	162.1 h
Proposed Model Using Less Multi-Physics Training data	81	25	1.83%	1.92%	50 h	28.8 h	0.2 h	79 h

In this example, the correlating information between the nongeometrical parameter P_{in} and geometrical parameters $\boldsymbol{p}$ is not available. Therefore, the method in [31] is not applicable. Our proposed technique can work well even when the correlating information needed in [31] is not available. We perform the parametric modeling using the direct method without correlating mapping for comparison purpose. ANN model (i.e., without mapping) is directly trained to learn multiphysics data for two cases, case 1 being with fewer multiphysics training data (25 sets of data) and case 2 being with more multiphysics training data (81 sets of data). Table V compares different parametric modeling methods in terms of ANN structures, average training and testing error, and CPU time. From the table, we can see that when fewer multiphysics data are used, our proposed model is more accurate than the direct method because our model has the knowledge of the coarse model trained with many inexpensive EM (single physics) data. With the similar accuracy requirement, our proposed model uses fewer multiphysics data and less computation cost than direct multiphysics modeling methods. The proposed multiphysics model provides accurate and fast prediction of multiphysics responses for high-level design. Table VI compares the computation time between the pure multiphysics nonparametric simulation (using ANSYS WORKBENCH) and the proposed multiphysics parametric model with respect to different number of testing samples. From the table, we can see that since the training is a one-time investment, the benefit of using the proposed multiphysics model accumulates when the model is used over and over again with repetitive changes in physical/geometrical parameters.

The comparison of the magnitude (in decibels) of $\boldsymbol{S}_{11}$ of the proposed model trained with less data (25 sets of data), direct ANN model trained with less data (25 sets of data), and direct ANN model trained with more data (81 sets of data) for two different filter geometries which are from testing data and have never been used in training process are shown in Fig. 19. The values of the input variables to our model for two samples of the high power cavity filter are as follows.

Test sample #1:

$\boldsymbol{\phi} = [118.06\ 49.385\ 44.685\ 48.995\ 28.75]^T$ [mm mm mm mm kW].

Test sample #2:

$\boldsymbol{\phi} = [117.28\ 50.435\ 43.755\ 48.9925\ 33.75]^T$ [mm mm mm mm kW].

TABLE VI
COMPARISON OF COMPUTATION TIME BETWEEN THE MULTIPHYSICS NONPARAMETRIC SIMULATION AND PROPOSED MULTIPHYSICS PARAMETRIC MODEL OF THE IRIS COUPLED WAVEGUIDE FILTER

No. of Changes of Physical/Geome -trical Parameters	CPU Time	
	Proposed Multi -physics Model	Simulation Using Multi-physics Software
1	79 h (model development) + 0.008 s	2.03 h
100	79 h (model development) + 0.8 s	approx. 200 h
500	79 h (model development) + 4 s	approx. 1000 h

It is observed that compared to the simulation results performed with the ANSYS WORKBENCH, our proposed multiphysics model can achieve good accuracy for different input samples even though these samples are never used in training. Once the overall model training is completed, we can implement the trained multiphysics model into the design optimization where the design parameters can be repetitively adjusted during optimization. As an example of using the trained model for the iris waveguide filter, we perform multiphysics optimization of two separate cavity filters using two different starting points:

Initial values for cavity filter #1: $\boldsymbol{\phi} = [113.21\ 48.96\ 43.35\ 46.85\ 25.25]^T$ [mm mm mm mm kW].

Initial values for cavity filter #2: $\boldsymbol{\phi} = [116.45\ 50.66\ 45.97\ 49.65\ 35.5]^T$ [mm mm mm mm kW].

The specification for these two filters is $|S_{11}| \leq -20$ dB at frequency range from 702 to 712 MHz. The design optimization using the proposed overall multiphysics model took only about 20 s to achieve the optimal design solution for each cavity filter. The optimized design parameter values for these two separate cavity filters are:

Filter #1:

$\boldsymbol{\phi} = [115.699\ 50.915\ 45.0664\ 48.6048\ 21.25]^T$ [mm mm mm mm kW].

Filter #2:

$\boldsymbol{\phi} = [115.95\ 50.5348\ 44.3769\ 48.0035\ 38.25]^T$ [mm mm mm mm kW].

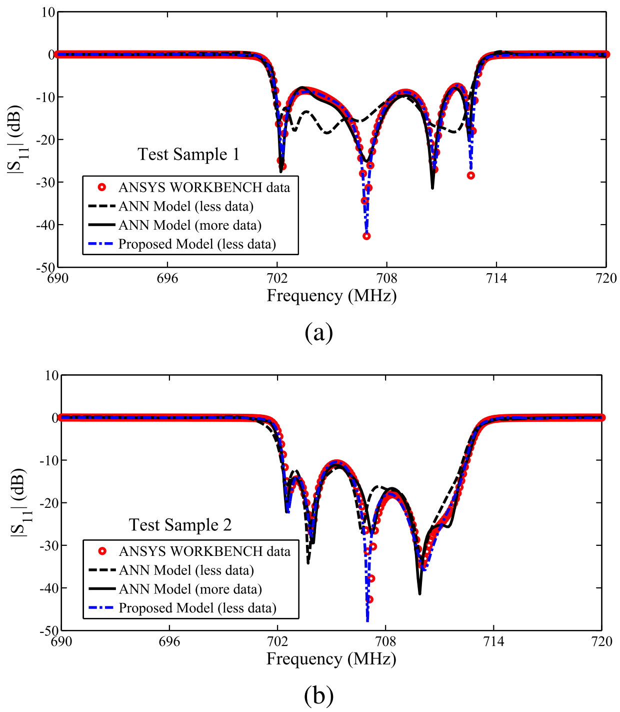


Fig. 19. Comparison of the magnitude (in decibels) of S_{11} of the models developed using different modeling methods and ANSYS WORKBENCH data. (a) Test sample #1 and (b) Test sample #2 for the iris waveguide filter. In the figure, ANN model (less data) means the ANN model trained with less multiphysics data. ANN model (more data) means the ANN model trained with more multiphysics data. Proposed model (less data) means the proposed model trained with less multiphysics data.

The ANSYS WORKBENCH performs the multiphysics simulations at the model optimal solutions and the multiphysics responses meet the required specifications. Our proposed EM centric multiphysics model can behave well in design optimization.

V. Conclusion

In this paper, a space-mapped multiphysics parametric modeling technique is proposed to develop an efficient multiphysics parametric model for microwave components. In the proposed method, we use the EM single physics (EM only) behaviors with respect to different values of geometrical parameters in nondeformed structure of microwave components as the coarse model. Two mapping module functions are formulated to map the EM domain responses to the multiphysics domain responses. Our proposed technique can achieve good accuracy of the multiphysics model with fewer multiphysics training data and less computational cost than direct multiphysics parametric modeling. After the proposed multiphysics modeling process, the trained multiphysics model can be used to provide accurate and fast prediction of multiphysics analysis responses of microwave components with geometrical and nongeometrical design parameters as variables. The developed overall model can be also used for high-level EM centric multiphysics design and optimization. We have used two microwave waveguide filter examples to illustrate our proposed method in the paper. The proposed technique for multiphysics parametric model can be applied to other passive microwave component modeling with physical parameters as variables. Possible future directions are to explore extrapolation techniques and also consider measurement data for training and testing of the multiphysics parametric model.

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