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Automated Neural Network-Based Multiphysics Parametric Modeling of Microwave Components

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ABSTRACT This paper proposes a novel technique for automated neural network based multiphysics parametric modeling of microwave components. For the first time, we propose to utilize automated model generation (AMG) algorithm in the field of electromagnetic (EM) centric multiphysics parametric model development to improve the neural-based multiphysics modeling efficiency. All the subtasks in developing a neural network based multiphysics parametric model, including EM centric multiphysics data generation, neural network structure adaptation, training and testing, are integrated into one unified and automated framework, thus converting the conventional human-based manual modeling into an automated computational process. In the proposed algorithm, automated EM centric multiphysics data generation is realized by automatic driving of multiphysics simulation tools. Parallel computation technique is incorporated to further speedup the data generation process by driving multiple EM centric multiphysics simulations on parallel computers simultaneously. In addition, automated neural model structure adaptation algorithm for multiphysics parametric modeling is also proposed. In this way, the proposed technique automates the neural-based multiphysics model development process and significantly reduces the intensive human effort and modeling time demanded by the conventional manual multiphysics modeling methods. The achieved neural model can be used to provide accurate and fast prediction of the EM centric multiphysics responses of microwave components in high-level multiphysics design. Examples of multiphysics parametric modeling of two microwave filters are presented to show the advantage of this work.

INDEX TERMS Design automation, multiphysics modeling, neural networks, parallel computation, parametric modeling.

I. INTRODUCTION

With the increasing accuracy requirements, electromagnetic (EM) centric multiphysics parametric modeling is becoming more and more important and necessary for high performance microwave component and system design. Besides the EM domain, other physics domains such as thermal and structural mechanics are needed to be taken into consideration in EM centric multiphysics parametric modeling, to provide accurate EM behavior evaluation of microwave components and systems in a real-world multiphysics environment [1]–[3]. The multiphysics model representing not only EM domain but also other physics domains is essential for accurate microwave system analysis and design.

In recent years, many EM centric multiphysics modeling related researches have been done in microwave design area. An innovative multiphysics model of a microstrip line excited by high voltage is developed in [4]. The multiphysics phenomenon is analyzed with the intrinsic interaction between the electrical power and the heat dissipation, and the multiphysics model is generated with the electrical, temperature and microstrip line structure geometrical parameters. In [5], the electromagnetic-thermal characteristics of interconnects are investigated based on appropriate thermal

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models which represent the thermal effects. In [6], space mapping techniques are used to combine the computational efficiency of EM single physics simulation with the accuracy of the multiphysics simulation in microwave component modeling process. This technique can achieve good accuracy for multiphysics parametric modeling with fewer multiphysics data because of the embedded empirical models. However, in case when empirical models are not available for a multiphysics parametric modeling problem, the technique in [6] is not directly applicable and new methods need to be proposed.

In recent years, artificial neural networks (ANNs) have been recognized as powerful tools in microwave modeling and design [7]–[9], such as nonlinear microwave device modeling [10]–[12], EM optimization [13], [14] and parametric modeling [15]–[17]. In parametric modeling area, ANNs can represent general nonlinear relationship between EM behavior of microwave components and the geometrical parameters after a proper training process. The trained ANNs can be used for high-level microwave system design to provide fast and accurate solutions to the task they have learned. In [18], neural network modeling is introduced to multiphysics parametric modeling area. ANNs are trained to learn the nonlinear relationship between EM behaviors and multiphysics design variables, then provide effective and fast prediction of EM responses with respect to the multiphysics design parameters. The neural-based multiphysics parametric modeling in [18] is a step-by-step manual process, which involves sequential multiphysics data generation, neural network selection, training and testing. This multiphysics parametric modeling process is manually carried out and requires intensive human effort and experience. In addition, because a multiphysics simulation always includes multiple domains, coupling between domains and structure deformation, the sequential data generation process in [18] is computationally expensive and time-consuming.

This paper proposes a further advance over the work of [18]. For the first time, we propose to use automated model generation (AMG) techniques [17] in multiphysics parametric modeling area to automate the neural-based multiphysics parametric model development process and improve the multiphysics modeling efficiency. All the subtasks in developing a neural-based multiphysics parametric model, including EM centric multiphysics data generation, neural network structure adaptation, training and testing, are integrated into one unified and automated framework. Since the multiphysics simulations are typically computationally expensive and time-consuming, we propose to use parallel computation mechanism in the multiphysics data generation process by automatically driving multiple multiphysics simulations in multiple computers simultaneously. Thus, the proposed algorithm automatically develops neural-based multiphysics parametric models of microwave components, and effectively shortens the model development time over the existing manual neural modeling method in [18].

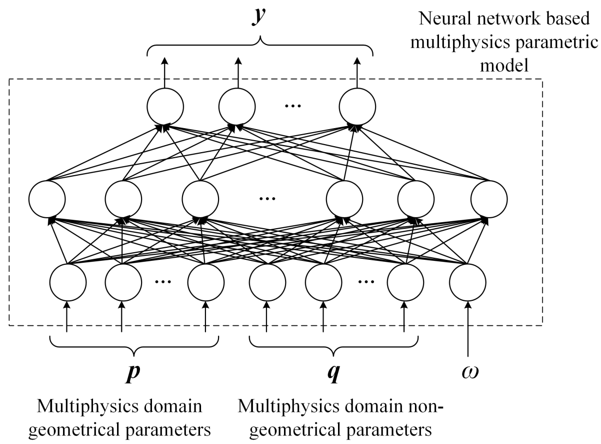

FIGURE 1. The proposed neural-based multiphysics parametric model structure with both geometrical and non-geometrical design parameters as input variables.

II. PROPOSED AUTOMATED NEURAL NETWORK BASED MULTIPHYSICS PARAMETRIC MODELING ALGORITHM

The proposed automated neural network based multiphysics parametric modeling algorithm proceeds in a stage-wise fashion. The proposed algorithm performs parallel multiphysics data generation in the first stage, then proceeds to ANN structure adaptation in the following stages. During parallel multiphysics data generation stage, the workload is distributed into multiple computers for parallel processing and the multiphysics simulator on every computer is driven by the proposed algorithm, thus speeding up the entire sampling process. During ANN structure adaptation stages, the neural network training and testing is carried out to determine the most suitable model structure for a multiphysics parametric modeling problem. Finally, a compact neural network model with good accuracy is automatically and efficiently achieved.

A. PROPOSED NEURAL-BASED MULTIPHYSICS PARAMETRIC MODEL STRUCTURE

The proposed neural-based multiphysics parametric model structure is shown in Fig. 1. While an EM single physics (EM only) domain parametric model has only geometrical parameters as input variables, a multiphysics domain parametric model has not only geometrical parameters but also other physics domain non-geometrical parameters (such as thermal and structure mechanics domain parameters). Let $\boldsymbol{p}$ represent a vector containing the multiphysics domain geometrical parameters, and $\boldsymbol{q}$ represent a vector containing multiphysics domain non-geometrical parameters. Both $\boldsymbol{p}$ and $\boldsymbol{q}$ are the inputs of the neural-based multiphysics model. We also define ω to represent the frequency parameter as an extra input of the neural-based multiphysics model, and $\boldsymbol{y}$ to represent a vector containing the outputs of the neural-based multiphysics model, i.e., the responses of multiphysics analysis for a microwave component. Let f_{ANN} be the neural network function. The input-output relationship of the neural-based multiphysics parametric model in the proposed algorithm is represented as

$$y = f_{ANN}\left(\left[p^T\ q^T\ \omega\right]^T, w\right) \tag{1}$$

where w is a vector containing the neural network weights.

B. AUTOMATED PARALLEL MULTIPHYSICS DATA GENERATION

The proposed automated neural-based multiphysics parametric modeling algorithm proceeds in a stage-by-stage manner. Let k represent the number of stages during multiphysics model development process. In the first stage (i.e., $k = 1$), multiphysics data is generated for training and testing the neural-based multiphysics model f_{ANN}. Let N represent the total number of multiphysics data to be generated, and d_i represent the response of the microwave component under consideration for the input sample $\left[p_i^T\ q_i^T\ \omega\right]^T$, $i = 1, 2, \cdots, N$. In the proposed algorithm, we use design of experiments (DoE) method [19] as the sampling method. Training and testing data are generated through multiphysics simulations to obtain the EM responses of the microwave component with respect to different values of geometrical and non-geometrical input parameters.

Because multiphyscis simulations involve multiple domains and often deal with the deformed structure, multiphysics data generation is the most computationally expensive and time-consuming process in existing manual multiphysics modeling methods. To improve the efficiency of multiphysics data generation, we propose to use parallel processing mechanism by driving multiple multiphysics simulators simultaneously. Let M represent the number of parallel computers performing multiphysics simulations. The proposed parallel multiphysics data generation algorithm firstly initializes the parallel environment, then divides the N input samples into M subsets. Let L_j represent the number of input samples in the jth subset, $j = 1, 2, \cdots, M$, i.e.,

$$L_j = \begin{cases} \left\lfloor \dfrac{N}{M} \right\rfloor, & \text{if } 1 \leqslant j \leqslant M-1 \\ N \bmod M, & \text{otherwise} \end{cases} \tag{2}$$

These subsets are written into M files and distributed to M computers for multiphysics data generation, respectively. Then each computer reads the corresponding file containing the input samples, and drives multiphysics simulators to obtain the responses d_i of these samples, where $i = 1, 2, \cdots, N$. The proposed algorithm has built-in multiphysics simulation drivers for facilitating the automated multiphysics data generation process. After multiphysics simulations finish in each computer, the proposed algorithm collects all generated multiphysics data from all computers, finally obtaining the training and testing data for neural-based multiphysics model development.

We use the speedup factor S and the parallel efficiency η to measure the performance of the parallel multiphysics data generation process. Let S be the ratio between the multiphysics data generation time on one single computer and that on M computers, and let η be equal to the speedup factor divided by the number of the computers, i.e.,

$$S = \frac{t + N \cdot t_d}{t + \left(\max\limits_{1 \leqslant j \leqslant M} L_j\right) \cdot t_d} \tag{3}$$

and

$$\eta = \frac{S}{M} \times 100\% \tag{4}$$

where t represents the overhead time during multiphysics data generation process, and t_d represents the simulation time for each multiphysics data generation on a single computer. Since in multiphysics simulation, t is much smaller than t_d, a large speedup and high parallel efficiency of multiphysics data generation can be achieved.

C. AUTOMATED MULTIPHYSICS PARAMETRIC MODEL STRUCTURE ADAPTATION

After parallel multiphysics data generation, the proposed automated multiphysics parametric modeling algorithm proceeds to the model structure adaptation stages. For different multiphysics parametric modeling problems, the number of hidden neurons of the neural network is usually different and unknown in advance. Existing manual multiphysics modeling method of [18] uses a trial-and-error mechanism to manually train neural networks with different numbers of hidden neurons and determine the most suitable neural network structure with designer's experience. This process is time-consuming and requires intensive human efforts. Here, we propose an automated multiphysics parametric model structure adaptation algorithm to automatically determine the number of hidden neurons in the multiphysics parametric model based on neural-network learning phenomena (i.e., over-learning, under-learning and good-learning).

Let H^k represent the number of hidden neurons of the neural network in the kth stage of the proposed automated multiphysics parametric model development process. We define E^k_{train} and E^k_{test} to represent the training error and testing error of the neural-based multiphysics parametric model in the kth stage respectively, formulated as

$$E^k_{train} = \frac{1}{2}\sum_{i=1}^{N_1}\left\| f_{ANN}\left(\left[p_i^T\ q_i^T\ \omega\right]^T, w^k\right) - d_i\right\|^2 \tag{5}$$

and

$$E^k_{test} = \frac{1}{2}\sum_{i=1}^{N_2}\left\| f_{ANN}\left(\left[p_i^T\ q_i^T\ \omega\right]^T, w^k\right) - d_i\right\|^2 \tag{6}$$

where N_1 and N_2 represent the number of training data and the number of testing data respectively, and $N = N_1 + N_2$. w^k represents the vector containing the weights of the multiphysics parametric model in the kth stage during automated model development process. Besides, we define E_d to represent the user-desired neural-based multiphysics parametric model accuracy.

In the proposed automated multiphysics model structure adaptation algorithm, the initial guess of the number of hidden neurons can be flexible. In the kth stage, if $E_{train}^{k} > E_d$, under-learning is detected and the proposed algorithm will automatically add hidden neurons by $H^{k+1} = H^k + \delta$, where δ represents the number of newly added hidden neurons, and the suggested range for δ is 10%–20% of H^k. If $E_{train}^{k} \leqslant E_d$ and $E_{test}^{k} > E_d$, over-learning is detected and the proposed algorithm will automatically reduce hidden neurons by $H^{k+1} = H^k - \delta$ until good-learning (i.e., $E_{test}^{k} \leqslant E_d$) is achieved. When good-learning is detected, the proposed algorithm will continue to recursively reduce the number of hidden neurons until the testing error of the reduced neural network starts to increase again. The purpose of this additional procedure, after good-learning is detected, is to minimize the number of hidden neurons on the premise of satisfying the user-desire accuracy, thus making the final neural-based multiphysics parametric model as compact as possible.

In this way, the proposed multiphysics parametric modeling algorithm automatically determines the most suitable and compact neural model structure for a multiphysics parametric modeling problem, without any help of designer's experience and human efforts.

D. PROPOSED AUTOMATED MULTIPHYSICS PARAMETRIC MODELING ALGORITHM

The proposed algorithm can be summarized as follows:

Step 1) Set $k = 1$. Initialize H^1 and the parallel environment.

Step 2) Calculate L_j and divide the N input samples into M subsets, so that the jth subset ($j = 1, 2, \cdots, M$) contains L_j samples. Write these subsets into M files and distribute these files to M parallel computers, respectively.

Step 3) Perform multiphysics simulations to generate the responses of corresponding samples on M parallel computer simultaneously.

Step 4) Collect all N generated multiphysics data from all computers and divide these N multiphysics data into two sets, i.e., one set containing N_1 training data and the other set containing N_2 testing data.

Step 5) Set $k = k + 1$. Train the neural-based multiphysics parametric model with H^k hidden neurons.

Step 6) Test the model. If $E_{train}^{k} > E_d$ (i.e. under-learning is detected), add δ hidden neurons (i.e., $H^{k+1} = H^k + \delta$), and go back to Step 5). Else if $E_{train}^{k} \leqslant E_d$ and $E_{test}^{k} > E_d$ (i.e., over-learning is detected), reduce δ hidden neurons (i.e., $H^{k+1} = H^k - \delta$), and go back to Step 5). Else, good-learning is detected and go to Step 7).

Step 7) Reduce hidden neurons by $H^{k+1} = H^k - \delta$. If the model with H^{k+1} hidden neurons has not been trained before, go back to Step 5). Else, the trained model with H^k hidden neurons is the final multiphysics parametric model.

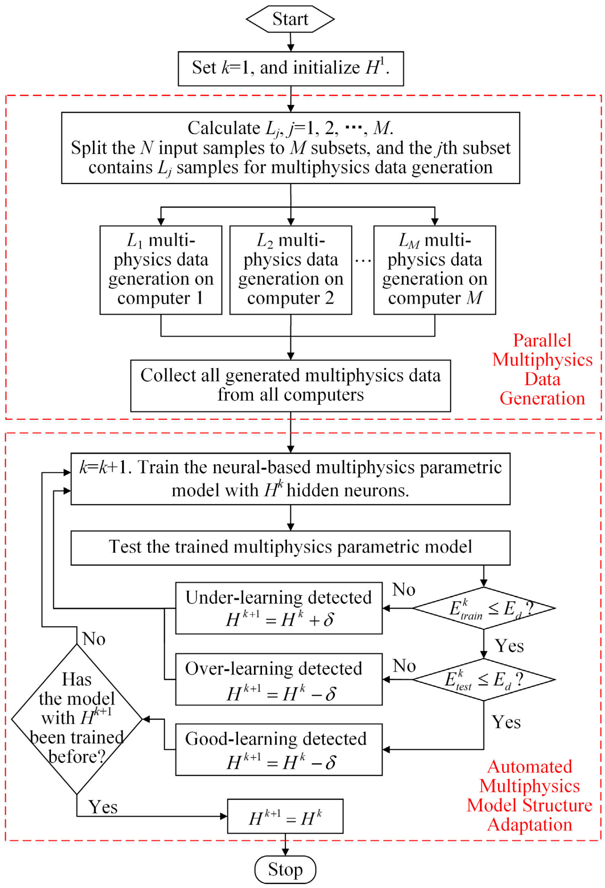

FIGURE 2. Flow diagram of the proposed automated neural-based multiphysics parametric modeling algorithm with parallel multiphysics data generation and multiphysics parametric model structure adaptation.

Step 8) Stop the neural-based multiphysics parametric modeling process.

The proposed automated neural-based multiphysics parametric modeling algorithm with parallel multiphysics data generation and multiphysics parametric model strcture adaptation is shown in Fig. 2. Using the proposed algorithm, the neural-based multiphysics model can be automatically produced with user-specified accuracy, without requiring the user's understanding of the neural-network issue, and the time of multiphysics parametric model development can be greatly shortened.

III. EXAMPLES

A. AUTOMATED MULTIPHYSICS PARAMETRIC MODEL DEVELOPMENT OF TUNABLE EVANESCENT-MODE CAVITY FILTER

In this example, we develop a multiphysics parametric model for a tunable evanescent-mode cavity filter [18], [20], as shown in Fig. 3. The displacement and deformation of the piezoactuator in the filter can change the magnitude of a small air gap which offers the tunability of the resonant frequency. In this example, the multiphysics domain geometrical input parameters of the model are $\boldsymbol{p} = [L\ W\ H]^T$ and the multiphysics domain non-geometrical input parameter is

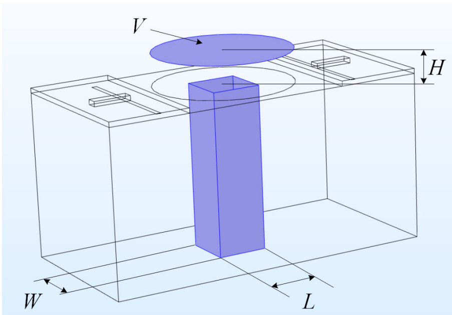

FIGURE 3. The tunable evanescent mode cavity filter example.

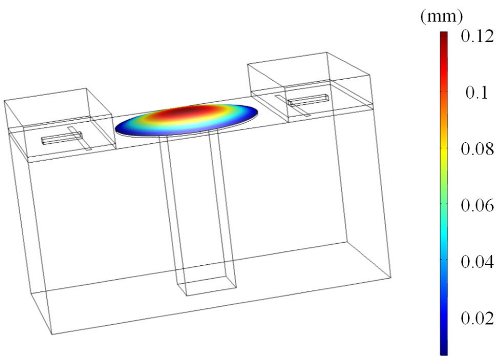

FIGURE 4. Structural deformation in the tunable evanescent-mode cavity filter caused by the input voltage.

TABLE 1. Training data and testing data for multiphysics parametric modeling of the tunable evanescent-mode cavity filter example.

Input	Training Data		Testing Data	
	Min	Max	Min	Max
L (mm)	12	18.4	12.4	18
W (mm)	10	16.4	10.4	16
H (um)	100	148	103	145
V (V)	-200	200	-175	175

$q = V$, where L and W are the length and width of the tuning post respectively, H is the gap between the top side of the tuning post and the bottom side of the piezoactuator, and V is the bias voltage applied across the piezoactuator, causing the structure deformation and changing the responses of the device. Fig. 4 shows the deformation information of the cavity filter with multiphysics design parameters $[\boldsymbol{p}^T\ q]^T = [15.2\ 14\ 124\ -200]^T$. We can see that with the negative voltage, the piezoactuator deflects upward to the bottom.

The modeling ranges of these multiphysics domain geometrical and non-geometrical input parameters are listed in Table 1. For this example, 81 training data and 64 testing data (i.e., $N_1 = 81$, $N_2 = 64$, $N = N_1 + N_2 = 145$) are used for multiphysics parametric modeling. Frequency ω is an additional input, and the model output is the magnitude of S_{11}. The training data and testing data are generated by *COMSOL Multiphysics* simulator at 25 frequency points between 3 and 3.06 GHz.

We perform the proposed automated multiphysics parametric modeling algorithm to develop a neural-based

TABLE 2. Modeling results of the proposed automated multiphysics parametric modeling algorithm using three neural networks with different initial number of hidden neurons for the tunable evanescent-mode cavity filter example.

	ANN1	ANN2	ANN3
Initial Hidden Neuron Number	30	50	44
Final Hidden Neuron Number	44	44	44
Number of Stages	8	5	2
Testing Error	1.49%	1.49%	1.49%
CPU Time (h)	0.15	0.095	0.04

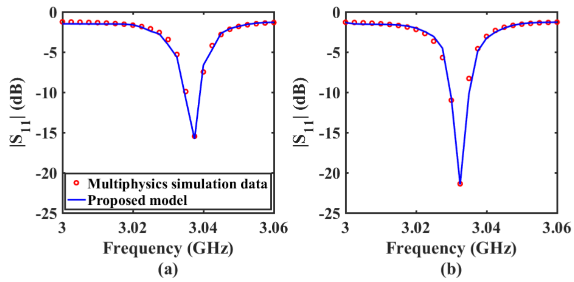

FIGURE 5. Tunable evanescent-mode cavity filter: modeling results at two different multiphysics geometrical and nongeometrical values (a) $[13.2\ 16\ 121\ \ -175]^T$ and (b) $[14.8\ 15.2\ 127\ \ -125]^T$. The solid line and "o" in the figures represent the proposed multiphysics parametric model response and the multiphysics simulation data, respectively.

multiphysics parametric model with 1.5% testing error for the tunable evanescent-mode cavity filter. For this example, $M = 4$ for parallel processing. We use C language to program the proposed automated multiphysics parametric modeling algorithm, including parallel multiphysics data generation by driving *COMSOL Multiphysics*, and multiphysics model structure adaptation by driving *NeuroModelerPlus* software for neural network training and testing. For comparison purpose, the proposed algorithm is performed 3 times by starting with different initial numbers of hidden neurons in a neural network. The modeling results are listed in Table 2 and shown in Fig. 5 to demonstrate the flexibility of our proposed automated multiphysics modeling algorithm. Whatever the initial guess of the number of hidden neurons, the proposed algorithm automatically adds or reduces the number of hidden neurons to finally achieve the most compact multiphysics model structure with user-desired accuracy.

For comparison purpose, we also perform the existing manual modeling method in [18] to manually develop multiphysics parametric model with 1.5% testing error for the same example. The comparison of the CPU time between our proposed automated modeling algorithm and the existing manual modeling method is listed in Table 3. With parallel multiphysics data generation and automated multiphysics model structure adaptation, the proposed automated modeling algorithm is about 3 times faster than existing manual method. The time for 145 multiphysics data generation in parallel is 0.84 h in the proposed automated modeling algorithm, and

TABLE 3. Comparison of the CPU time between proposed automated modeling algorithm and the existing manual modeling method [18] for the tunable evanescent-mode cavity filter example.

	Existing Manual Method [18]	Proposed Automated Algorithm
CPU Time of Multiphysics Data Generation (h)	2.75	0.84
CPU Time of Model Structure Adaptation (h)	0.3	0.15
Total CPU Time (h)	3.05	0.99

that for the sequential data generation is 2.75 h in existing manual modeling method, which results in a speedup (S) of 3.27 and a parallel efficiency (η) of about 81.75%. The time for automated multiphysics model structure adaptation is 0.15 h, and that for manual model structure selection is 0.3 h, which results in a speedup of 2. From the modeling results, it is observed that the proposed modeling algorithm can automatically develop multiphysics parametric model with user-desire accuracy, and is more efficient than existing manual modeling method.

B. AUTOMATED MULTIPHYSICS PARAMETRIC MODEL DEVELOPMENT OF TUNABLE FOUR-POLE WAVEGUIDE FILTER

In this example, we consider the multiphysics parametric modeling of a tunable four-pole waveguide filter [6], [21] with tuning elements as the posts of the square cross section placed at the center of each cavity and each coupling window, as illustrated in Fig. 6. The piezoactuator will have a geometric strain proportional to an applied electric field through the piezoelectric effect. For this example, the multiphysics domain geometrical input parameters of the model are $\boldsymbol{p} = [H_1\ H_2\ H_{c1}\ H_{c2}]^T$ and the multiphysics domain non-geometrical input parameter is $\boldsymbol{q} = [V_1\ V_2]^T$, where H_1 and H_2 are the heights of the tuning posts in the coupling windows, H_{c1} and H_{c2} are the heights of the square cross section placed in the center of the resonator cavities, V_1 and V_2 are the voltages applied across the pieazoactuator, causing the structure deformation of the piezoactuator and further changing the responses of the device. Fig. 7 shows the deformation information of the filter with multiphysics design parameters $\left[\boldsymbol{p}^T\ \boldsymbol{q}^T\right]^T = [3.24\ 3.40\ 3.72\ 3.34\ -120\ 120]^T$. With the negative voltage, the piezoactuator deflects upward to the bottom, while with positive voltage the piezoactuator deflects toward the bottom.

The ranges of the training data and testing data are listed in Table 4. For this example, 81 training data and 64 testing data (i.e., $N_1 = 81$, $N_2 = 64$, $N = N_1 + N_2 = 145$) are used for multiphysics parametric modeling. Frequency ω is an additional input, and the model output is the magnitude of S_{11}. In this example, the training data and testing data are generated at 101 frequency points between 10 and 11 GHz.

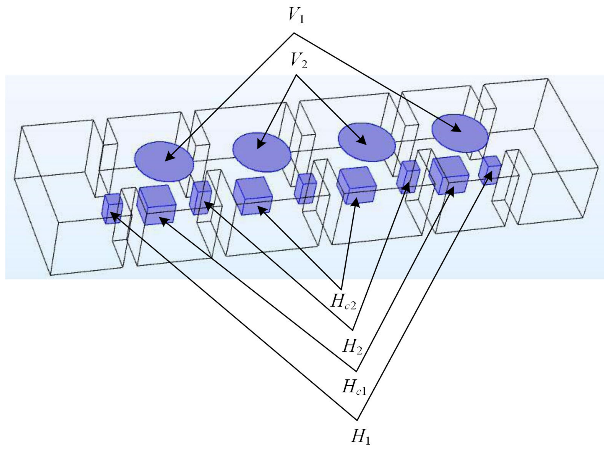

FIGURE 6. The tunable four-pole waveguide filter example.

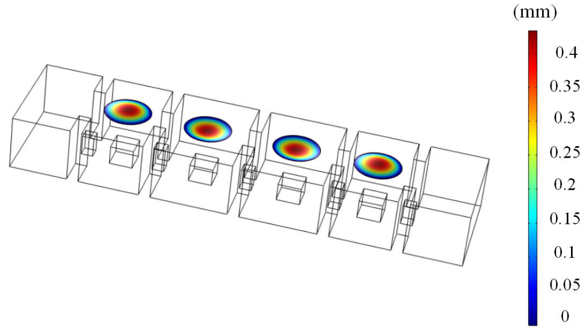

FIGURE 7. Structural deformation in the four-pole waveguide filter caused by the input voltages.

TABLE 4. Training data and testing data for multiphysics parametric modeling of the tunable four-pole waveguide filter example.

Input	Training Data		Testing Data	
	Min	Max	Min	Max
H_1 (mm)	3.04	3.44	3.065	3.415
H_2 (mm)	3.10	3.50	3.125	3.475
H_{c1} (mm)	3.52	3.84	3.54	3.82
H_{c2} (mm)	3.28	3.52	3.295	3.505
V_1 (V)	-120	120	-105	105
V_2 (V)	-120	120	-105	105

For comparison purpose, we perform the proposed automated multiphysics parametric modeling algorithm using 3 neural networks with different initial number of hidden neurons to develop multiphysics parametric model for the waveguide filter. The user-desired testing error of the model is 2%. The modeling results are listed in Table 5 and shown in Fig. 8 to demonstrate the flexibility of our proposed automated multiphysics modeling algorithm. Whatever the initial guess of the number of hidden neurons, the proposed algorithm can automatically adjust the number of hidden neurons to achieve the most compact multiphysics model structure with user-desired accuracy. In this way, the proposed automated multiphysics parametric modeling algorithm is more flexible than existing manual multiphysics modeling method.

TABLE 5. **Modeling results of the proposed automated multiphysics parametric modeling algorithm using three neural networks with different initial number of hidden neurons for the tunable four-pole waveguide filter example.**

	ANN1	ANN2	ANN3
Initial Hidden Neuron Number	30	70	52
Final Hidden Neuron Number	52	52	52
Number of Stages	12	11	2
Testing Error	1.95%	1.95%	1.95%
CPU Time (h)	0.36	0.3	0.07

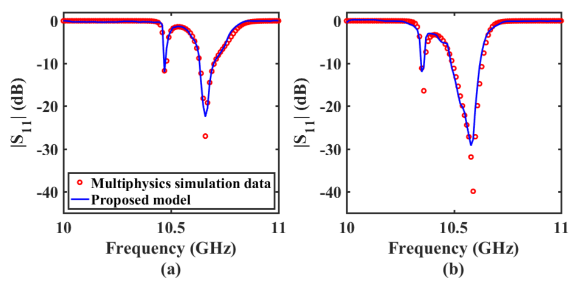

FIGURE 8. **Tunable four-pole waveguide filter: modeling results at two different multiphysics geometrical and nongeometrical values (a) $[3.115\ 3.125\ 3.58\ 3.325\ \ -75\ \ -75]^T$ and (b) $[3.265\ 3.125\ 3.7\ 3.415\ 15\ 15]^T$. The solid line and "o" in the figures represent the proposed multiphysics parametric model response and the multiphysics simulation data, respectively.**

TABLE 6. **Comparison of the CPU time between proposed automated modeling algorithm and the existing manual modeling method [18] for the tunable four-pole waveguide filter example.**

	Existing Manual Method [18]	Proposed Automated Algorithm
CPU Time of Multiphysics Data Generation (h)	41.75	13.6
CPU Time of Model Structure Adaptation (h)	1.2	0.36
Total CPU Time (h)	42.95	13.96

We also compare the modeling results between the proposed automated modeling algorithm and the existing manual modeling method in [18] for this waveguide filter example, as shown in Table 6. For this example, $M = 4$ for parallel processing during multiphysics data generation in the proposed method. The time for 145 multiphysics data generation in parallel is 13.6 h in the proposed automated modeling algorithm, and that for the sequential data generation is 41.75 h in existing manual modeling method, which results in a speedup (S) of 3.07 and a parallel efficiency (η) of about 76.74%. The time for automated multiphysics model structure adaptation is 0.36 h, and that for manual model structure selection is 1.2 h, which results in a speedup of 3.3. Therefore, the proposed automated multiphysics modeling process is benefited from the parallel multiphysics data generation and automated multiphysics model structure adaptation. From Table 6, it is observed the proposed automated modeling algorithm is more efficient for multiphysics parametric model development than existing manual modeling method.

IV. CONCLUSION

In this paper, an automated neural network based multiphysics parametric modeling algorithm has been proposed to automate the multiphysics parametric modeling process for the first time. The proposed algorithm can automatically produce a neural-based multiphysics parametric model with user-specified accuracy. Therefore, the intensive human effort in existing manual multiphysics modeling method is effectively reduced and the neural-based mutliphysics modeling efficiency is greatly improved. Parallel processing technique has been applied in the EM centric multiphysics data generation process by driving multiple multiphysics simulators in parallel. In this way, the proposed algorithm can greatly reduce the multiphysics parametric model development time than existing manual multiphysics modeling methods. The proposed technique provides a systematic framework for automated neural-based multiphysics modeling approach and can be incorporated into the overall microwave computer aided design environment.

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