Convolutional Neural Network for Coupling Matrix Extraction of Microwave Filters

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***Abstract* –** Tuning a microwave filter is a challenging problem due to its complexity. Extracting coupling matrix from given *S*-parameters is essential for ?lter tuning and design. In this paper, a deep-learning-based neural network namely, a convolutional neural network (CNN) is proposed to extract coupling matrix from *S*-parameters of microwave filters. The training of the proposed CNN is based on a circuit model. In order to exhibit the robustness of the new technique, it is applied on 5- and 8-pole filters and compared with a shallow neural network namely, radial basis function neural network (RBFNN). The results reveal that the CNN can extract the coupling matrix of target *S*-parameters with high accuracy and speed.

***Index Terms* –** convolutional neural network, coupling matrix, deep learning, microwave filters, parameters extraction.

I. INTRODUCTION

Microwave filters are widely used in all types of electronic systems [1, 2]. Tuning of microwave filter is an inevitable process in the design procedure of microwave filters. For the case of coupled resonator filter, extracting of the coupling matrix from the required *S*-parameters can be viewed as an inverse problem for microwave filters.

Therefore, accurate solution of the inverse problem (extraction of coupling matrix) is crucial. However, it is extremely difficult to solve this inverse problem directly [3, 4]. Traditionally, the coupling matrix of the microwave filter is extracted by adopting the Cauchy method [5] or vector fitting [6]. However, these methods need to be repeated for many iterations in different conditions. Consequently, the process of filter design suffers from the time-consuming and complicated parameters extraction.

Neural network (NN) has been recognized as a powerful tool in microwave modeling and design [7–10]. Some conventional (shallow) NN techniques have been developed to extract the coupling matrix [11–13]. However, these techniques are not suitable for high-dimensional (many input variables) problems because data generation and model training become too complicated. A deep NN is applied to the parameter extraction of microwave filter [14]. However, there are too many layers in the deep NN, which make the training process complicated.

On the other hand, convolutional neural network (CNN) is a variant of deep network framework and achieves remarkable success on image and face recognition [15, 16]. Recently, it has gained much attention in the microwave field [17, 18]. It has unique capabilities of extracting underlying nonlinear features of input data. Two main advantages, sparse connectivity and shared weights, enable CNNs to have small numbers of parameters during learning and, hence, high training speed. Motivated by the inherent advantages of the CNN, it has been incorporated into coupling matrix extraction [19, 20].

In all the above NN methods, the training data is generated using full-wave electromagnetic (EM) model through simulation or measurement which becomes impractical when large training data is needed. Furthermore, the cost of training data generation increases exponentially with the number of input variables. Therefore, collection of training data using EM-based model to cover the interested input parameter range over a frequency band can be an overwhelmingly time-consuming task. Different from EM models, circuit models are used for all kinds of electronic designs. They are usually straightforward to build, and fast to evaluate.

In this paper, a CNN is used to extract the coupling matrix of ideal (target) *S*-parameters based on a

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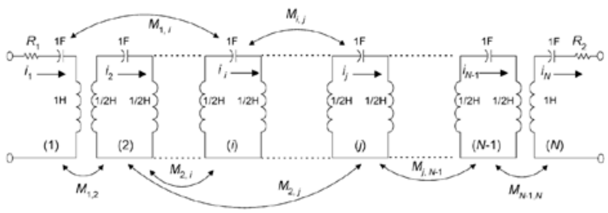


Fig. 1. Equivalent circuit of an N-coupled resonator filter [24].

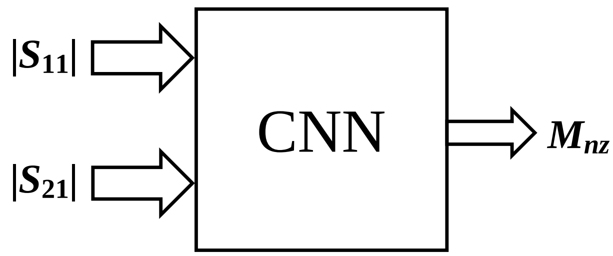


Fig. 2. The circuit model-based CNN for coupling matrix extraction.

circuit model. The CNN first extracts the features of S-parameters by using convolution layers and pooling layers, which are then mapped to the coupling matrix by full connection and output layers. To validate the effectiveness of the proposed CNN, it is applied on 5- and 8-pole microwave filters. The proposed CNN model is able to extract the coupling matrix of the ideal S-parameters with high accuracy and speed compared with a radial basis function neural network (RBFNN) [21–23] which is shallow (non-deep) NN.

II. CNN FOR CIRCUIT MODEL-BASED COUPLING MATRIX EXTRACTION

The circuit model-based equation that relates the coupling matrix $\mathbf{M}$ and filter S-parameters is given by [24]

$$S_{11} = 1 + 2jR_1[\gamma \mathrm{I} - j\mathrm{R} + \mathrm{M}]^{-1}_{11}$$
$$S_{21} = -2j\sqrt{R_1R_2}[\gamma \mathrm{I} - j\mathrm{R} + \mathrm{M}]^{-1}_{N1}, \qquad (1)$$

where $\gamma = (f_0/\mathrm{BW})((f/f_0) - (f_0/f)), f, f_0$, and BW are the frequency, filter center frequency, and filter bandwidth, respectively, N is the filter order, $\mathbf{I}$ is $N \times N$ identity matrix, $\mathbf{M}$ is the $N \times N$ symmetric coupling matrix, $\mathbf{R}$ is an $N \times N$ matrix with all entries being zero except $[\mathbf{R}]_{11} = R_1$ and $[\mathbf{R}]_{NN} = R_2$, and R_1 and R_2 are the filter's input and output coupling parameters, respectively, as shown in Fig. 1.

Figure 2 shows the CNN model for extracting the coupling matrix. The input to the CNN is the required vectors $|\boldsymbol{S}_{11}|$ and $|\boldsymbol{S}_{21}|$, representing the scalar magnitudes of the two S-parameters at $\mathscr{R}$ frequency points in the required frequency range. Therefore, the total number of inputs is $2\mathscr{R}$. In the present case, the number of the frequency points $\mathscr{R} = 2001$. The output of the CNN is the vector of *nonzero* coupling parameters $\boldsymbol{M}_{nz}$.

In order to generate the training and validation data of CNN, we assume a tolerance of ± 0.5 for every ideal nonzero coupling parameter. We then use 12,500 (10,000 for training and 2500 for validation) uniformly distributed random samples in this range for coupling parameters. For each sample of coupling parameters, eqn (1) is used to obtain the corresponding S-parameters. By swapping the data of coupling parameters and S-parameters, we can get the training and validation data for the coupling parameters extraction model. In the same way, the trained CNN is tested by the ideal set of S-parameters (corresponding to the ideal $\boldsymbol{M}_{nz}$ that is never used in the training), then the extracted $\boldsymbol{M}_{nz}$ is compared to the ideal one.

III. THE PROPOSED CNN STRUCTURE

CNNs have one or more convolutional and pooling layers to learn the discriminative features from the input data. After all the convolutional and pooling layers, these learned features are then aggregated to the vectors by the fully connected (FC) layers for the regression task [25].

After many simulation trials, it is found that the CNN structure that provides the best accuracy is detailed in Table 1. First, the total 4002 inputs are reshaped into a $2 \times 3 \times 667$ input image. Then, there are three convolutional (Conv) layers and three maximum pooling (MaxPool) layers. Each convolutional layer is followed by a pooling layer to reduce the dimension of network parameters. The first convolutional layer comprises eight feature maps. The number of feature maps at each convolutional layer is twice the previous layer, i.e., there are 16 and 32 feature maps in the second and third layers, respectively. The size of the feature map in each convolutional layer is fixed at 2×2. All convolutional layers have a stride of 1 and "same" padding. All pooling layers have a size of 2×2, stride 2, and "same" padding. After the sequence of convolutional and pooling layers, there is a single FC layer with 50 nodes followed by the output layer with a number of nodes equal to the number of nonzero coupling parameters. In order to avoid overfitting during training, a dropout operation with a rate of 50% is used at the end of the convolutional and pooling layers. The activation functions used in the convolutional layers and the FC layer are rectified linear unit (ReLU) and exponential linear unit (ELU), respectively. Since this is a regression problem instead of a classification problem, no activation is used at the output layer (linear activation).

Table 1: The proposed CNN structure

<table>
<tr><th>Layer</th><th>Size</th><th>Nodes</th><th>Stride</th><th>Padding</th><th>Activation</th></tr>
<tr><td>Input (image)</td><td>–</td><td>(2×3×667) = 4002</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td>Conv1</td><td rowspan="6">2×2</td><td>8</td><td>1</td><td rowspan="6">Same</td><td>ReLU</td></tr>
<tr><td>MaxPool1</td><td>–</td><td>2</td><td>–</td></tr>
<tr><td>Conv2</td><td>16</td><td>1</td><td>ReLU</td></tr>
<tr><td>MaxPool2</td><td>–</td><td>2</td><td>–</td></tr>
<tr><td>Conv3</td><td>32</td><td>1</td><td>ReLU</td></tr>
<tr><td>MaxPool3</td><td>–</td><td>2</td><td>–</td></tr>
<tr><td colspan="6">50% Dropout</td></tr>
<tr><td>FC</td><td>–</td><td>50</td><td>–</td><td>–</td><td>ELU</td></tr>
<tr><td>Output</td><td>–</td><td>Length{$\boldsymbol{M}_{nz}$}</td><td>–</td><td>–</td><td>Linear</td></tr>
</table>

IV. EXAMPLES

To verify the performance of the CNN-based coupling matrix extraction, it is applied on 5- and 8-pole microwave filters. The Adam (adaptive momentum) optimization algorithm [26] is used to update the network weights and the loss function used for this network is the mean squared error. The initial value of the learning rate is 0.001. During the training, the learning rate is decreased by a rate of 0.1 each 40% of number of epochs. The batch size is 40 and number of epochs is 10. To further verify the performance of the CNN, it is compared to that of the RBFNN. Both NNs have the same number of inputs (4002) and outputs (Length{$\boldsymbol{M}_{nz}$}) as well as the same size of training and validation datasets (10,000 and 2500, respectively). In all examples, the filter's input and output coupling parameters are assumed to be equal, i.e., $R_1 = R_2$.

A. 5-Pole filter

In this example, we use the proposed CNN to develop a parameter-extraction model for a 5-pole dielectric resonator filter with a 3.4-GHz center frequency and a 54-MHz bandwidth [24]. The nonzero coupling parameters are $\boldsymbol{M}_{nz} = [R_1\ M_{12}\ M_{14}\ M_{23}\ M_{34}\ M_{45}]^T$ with their ideal values shown in Table 2. Table 2 also shows the extracted coupling values by RBFNN and CNN. It can be seen that the values of CNN are much closer to the ideal ones than those of RBFNN. The used shallow RBFNN has only one hidden layer with 300 neurons and cannot represent this high-dimensional input–output relationship effectively. Our proposed CNN modeling technique is suitable for this high-dimensional modeling problem.

Figure 3 shows the *S*-parameters corresponding to the coupling values in Table 2. As can be seen, there is a perfect agreement between the responses from the ideal and extracted coupling matrix of CNN compared with RBFNN, that is, owing to the capability of CNN to extract the hidden features in the input data, *S*-parameters, automatically. On the other hand, because the RBFNN is shallow, it cannot strengthen the network training process by reconstructing the input *S*-parameters.

Table 2: The ideal and extracted coupling values by RBFNN and CNN for a 5-pole filter

$\boldsymbol{M}_{nz}$	**RBFNN**	**CNN**	**Ideal**
R_1	1.1098	1.1345	1.1330
M_{12}	0.8138	0.8659	0.8660
M_{14}	−0.1450	−0.2525	−0.2520
M_{23}	0.7389	0.7942	0.7920
M_{34}	0.5287	0.5946	0.5950
M_{45}	0.8594	0.9006	0.9010

Table 3: The ideal and extracted coupling values by RBFNN and CNN for 8-pole filter

$\boldsymbol{M}_{nz}$	**RBFNN**	**CNN**	**Ideal**
R_1	1.2206	1.2415	1.2420
M_{12}	0.8977	0.9387	0.9380
M_{23}	0.5882	0.6300	0.6310
M_{27}	−0.0110	−0.0172	−0.0180
M_{34}	0.5313	0.5729	0.5760
M_{36}	0.0034	0.0637	0.0660
M_{45}	0.4549	0.5193	0.5190

B. 8-Pole filter

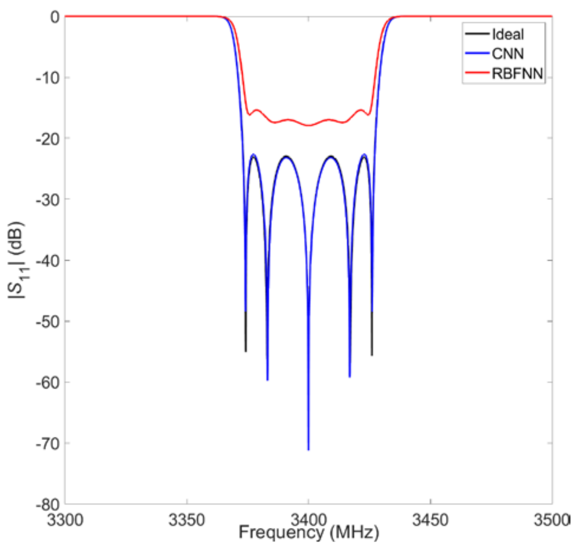
The second example involves the parameter-extraction of an 8-pole elliptic-function filter with 30-MHz bandwidth centered at 3 GHz [27]. The nonzero couplings are R_1, M_{12}, M_{23}, M_{27}, M_{34}, M_{36}, M_{45}, M_{56}, M_{67}, and M_{78}. However, the coupling matrix of this filter is dual-symmetrical meaning that it is symmetrical w.r.t. its anti-diagonal as well as its diagonal [28]. Therefore, $M_{12} = M_{78}$, $M_{23} = M_{67}$, and $M_{34} = M_{56}$. Consequently, the output of NNs is $\boldsymbol{M}_{nz} = [R_1\ M_{12}\ M_{23}\ M_{27}\ M_{34}\ M_{36}\ M_{45}]^T$. Table 3 shows the ideal as well as the extracted coupling values by both NNs with their corresponding *S*-parameters shown in Fig. 4.

According to Table 3 and Fig. 4, a very good match between the ideal and extracted coupling parameters by CNN along with an excellent agreement between the responses from the ideal and extracted coupling matrix by CNN have been achieved, compared to RBFNN. This again proves that the CNN is much more accurate than the RBFNN for coupling matrix extraction.

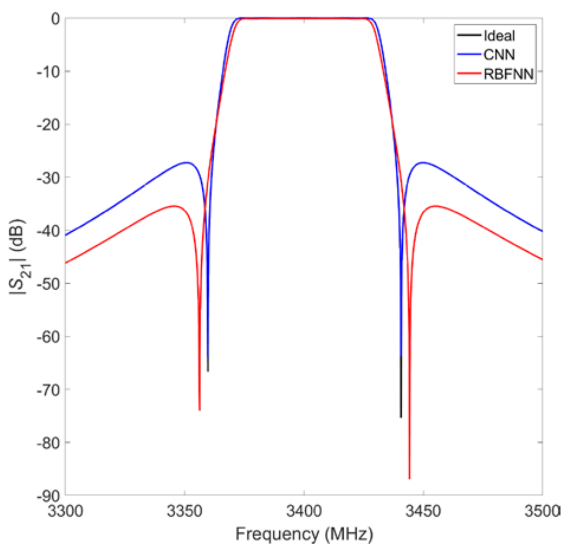
Table 4 shows the training time as well as the percentage root mean square error (RMSE) between ideal and extracted couplings by NNs for 5- and 8-pole filters. It can be seen that the CNN modeling for the extraction of coupling matrix is with much higher accuracy and shorter training time than the RBFNN modeling.

Table 4: Percentage RMSE and training time of RBFNN and CNN for 5- and 8-pole filters

NN	**5-Pole filter**		**8-Pole filter**	
	Training Time	*RMSE (%)*	*Training Time*	*RMSE (%)*
CNN	39 s	0.1413	38 s	0.2260
RBFNN	19.6 min	7.7997	17.7 min	6.3894



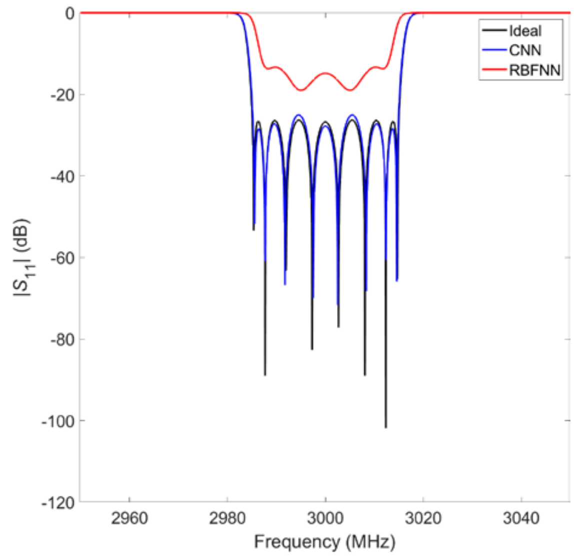
(a)



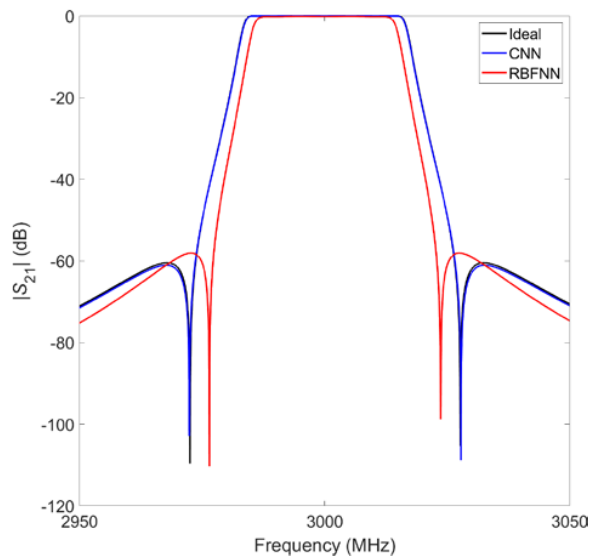
(b)

Fig. 3. The responses calculated by the coupling values in Table 2: (a) Return loss and (b) insertion loss.

Moreover, our proposed circuit model-based CNN can provide parameter-extraction solutions instantly, while the full-wave EM model-based methods can take hours to extract the solutions by repetitively simulating/measuring the filter during optimization iterations.



(a)



(b)

Fig. 4. The responses calculated by the coupling values in Table 3: (a) Return loss and (b) insertion loss.

V. CONCLUSION

A circuit model-based CNN is proposed to extract coupling matrix from *S*-parameters. The results show that the proposed CNN method can be used reliably to perform the parameter extraction for microwave filters. Compared to the shallow NN, the deep-learning-based CNN is much more accurate and faster in extracting the coupling parameters. Unlike the full-wave EM model-based methods, our proposed CNN model does not need to simulate and/or measure the filter iteratively. Once the CNN model is developed, it can be used to quickly extract the coupling parameters of microwave filters.

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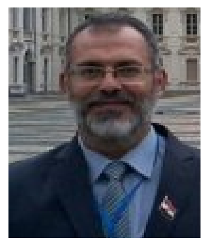

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