Design of Microwave Filter Using Segmentation, Coupling Matrix and Neural Network

Chahrazad Erredir, Mohamed Lhadi Riabi

Laboratory of electromagnetism and Telecommunications
Department of Electronic University Constantine1
Constantine, Algeria
cerredir@yahoo.fr

ml.riabi@yahoo.fr

***Abstract*—In this paper, neural network modeling techniques are applied for modeling and design of microwave filter, where neural networks and filter coupling matrix are combined in an innovative way to deliver speed and accuracy of the overall filter design. Filter structure is decomposed into sub-structures representing each coupling mechanism, where the decomposition is used to simplify the overall high-dimensional neural- network modeling problem into a set of low-dimensional-network problem. Generalized scattering matrices (GSM) of the modules are calculated using mode-matching method. Equivalent circuit parameters, such as coupling value and insertion phase lengths are then extracted from EM data. Neural network models are developed for each individual module, and are then combined to form a complete model. Good agreement is obtained between neural models and EM based data, where the proposed technique is very useful for neural-based microwave optimization and synthesis. Application of the method to a three cavity waveguide filter is presented.**

Keywords-Segmentation method; coupling matrix; equivalent circuit; microwave filter; neural networks

I. INTRODUCTION

The optimization of a microwave circuit is a problem where the differences between the circuit response and the desired response are minimized by adjusting the free parameters of the system. As a consequence, precise knowledge of the circuit response is needed to achieve a good design.

In recent years, there have been increased interests in applying neural network (NN) to microwave design problems due to its superior computation speed and accuracy. Applications of NN are also found in microwave filter design and optimization [1]. There are generally two types of approaches. In the first type, NN training data are based on full EM simulation of entire filter, which is only feasible for simple structures such as direct-coupled cavity filters. In the second type of approach, NN is used for direct modeling of the generalized scattering matrix (GSM) of each segment of the filter. For complex structures, large number of modes is required to ensure good accuracy. To model these EM data directly not only requires enormous amount of data, but also increases dimension of the NN output parameters, which increases training difficulty. Furthermore, reports are limited to relatively simple Tchebyscheff type of filters without cross couplings.

In this paper, NN modeling techniques are applied to advanced microwave filter design, where coupling matrix is used to correctly characterize complex filter function. We develop a method where neural network and filter equivalent circuits are combined in a special way to predict filter physical parameter quickly [2]. The following approaches are taken to ensure feasibility of NN model development and to ensure reliability of the trained neural model:

- The filter structure is decomposed into modules representing each coupling mechanism. Neural models are developed for each module instead of the entire filter. In doing so, it not only speeds up data generation but also reduces neural network size, which warrants better accuracy. Furthermore, the trained neural model may be applied to filters with any number of poles, as long as the filter configuration remains the same.
- In each region, the generalized scattering matrix (GSM) is computed by mode-matching. Instead of trying to model the GSM directly; equivalent circuit parameters, such as coupling value and insertion phase lengths are extracted from EM data first.
- In each region of the microwave circuit, the circuit parameters are approximated applying multi-layer perceptrons (MLPs). The expression of an MLP with two layers of weights can be written [3]:

$$y_k = f_k\left(\sum_{j=1}^{N_h} w_{kj}\ f_j\left(\sum_{i=1}^{N_i} w_{ji}\, x_i + w_{j0}\right) + w_{k0}\right), \quad k = 1, \dots, N_o \qquad (1)$$

Where x_i, is the *ith* input, y_k is the *kth* output, $f_k(.)$ and $f_j(.)$ are activation functions (typically: sigmoid, tanh ...), N_i, N_h and N_o are the numbers of neurons in the input, hidden and output layers respectively and the w are adjustable parameters called weights. The use of the MLPs is based on the universal approximation theorem, using which it can be deduced that an MLP with only two layers of weights is capable of modeling virtually any real function to any desired degree of accuracy if the number of neurons in the hidden layer is large enough.

II. FORMULATION OF PROBLEM

The main objective is to obtain fast parametric models for filters that hold many design variables. Let n and m represent the number of inputs and outputs, and $x=[x_1, x_2,\ldots,x_n]^T$ to be n-vector vector containing all the input variables of a model, $y=[y_1,y_2,\ldots,y_m]^T$ be m- vector containing output. For example x represent iris length, iris width, cavity length for a filter, and output y represent the S-parameter of the filter. A conventional neural-network model for the problem is defined as $y=f(x, w)$, where f defines the input- output relationship and w is a neural networks internal weight vector.

If a filter model has many input variables, a massive amount of data are required for neural- network model training to achieve good accuracy. This massive data generation and model training become too expensive and impractical. To overcome this limitation, we propose to use the decomposition approach to simplify the high-dimensional problem into a set of small sub-problems [4].

A filter with many design variables is decomposed into several sub-strictures, each representing a specific part of the filter. The GSM for each sub-stricture is computed by mode-matching as

$$[S11]= ([YL] + [Y1])^{-1} ([Y1]-[YL])$$
$$[S12]=2([YL] + [Y1])^{-1} [M]^T [Y2]$$
$$[S21]= [Y2] [M] [Y1]^{-1}([I] + [S11])$$
$$[S22]= [Y2] [M] [Y1]^{-1} [S12] - [I] \qquad (2)$$

Yi are diagonal matrices of which the diagonal elements are the square roots of the admittances of the modes TE_{mn} and TM_{mn}. The elements of the matrices M are the scalar products of the transverse fields TE-TE, TM-TE, and TM-TM respectively on the level of discontinuity.

Neural network sub-models are then developed to represent the sub-structures. Let us assume that a filter is decomposed into N types of sub-structures. Let $\tilde{x}_i$ be a vector containing the design variables of the *ith* sub-structure and $\tilde{y}_i$ be a vector containing the output parameters of the *ith* sub-structure. A neural network sub-model for the sub-structure is defined as

$$\tilde{y}_i = f_i(\tilde{x}_i, w_i) \qquad (3)$$

Where f_i defines the geometrical to electrical relationship of the *ith* sub-model, w_i is a vector containing neural-network weight parameters for the *ith* sub-model, and $i=1, 2\ldots N$. Data generation for sub-models becomes less expensive than that for the overall filter model because the sub-models contain fewer input variables than the overall filter model and the input- output relationships of the sub-models become simpler than that of the overall filter model.

We need to combine the multiple sub-models to reproduce the overall model completely. For this purpose, a mechanism equivalent circuit is needed to obtain the solution of the overall filter by using the outputs from the neural network sub-modes. A big advantage of the proposed method is multiple use of sub-model, where some of the neural network sub-models may be used multiple times as the same junction my appear several times in the overall model. In this way, we can obtain all the sub-models needed for an overall filter model by training only a few neural network sub-models. The equivalent circuit model is expressed in term of the outputs of the neural network sub-models as

$$y^c = f^c(\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_{N_0}) \qquad (4)$$

Let N_0 be the number of neural network sub-models needed to form the overall filter model, y^c is a vector containing approximate values of the output of the overall filter, f^c represent the equivalent circuit function, and $\tilde{y}_1$ to $\tilde{y}_{N0}$ are electrical parameters obtained from N_0 sub-models.

III. EXEMPLE

The proposed method was applied to the design of a three cavity filter as shown in fig1. The filter model has nine variables as inputs, which include four geometrical variables: iris width a_1 and a_2, iris length $b1$ and $b2$, cavity lengths L_1 and L_2, and three electrical variables: bandwidth BW, center frequency f_0, and frequency f. The filter outputs are S-parameters S_{11} and S_{12}. Thus, the input and output vector of the filter model is

$$x = [a_1\ a_2\ b_1\ b_2 L_1\ L_2\ B\ f_0\ f]^T \qquad (5)$$

$$y = [S_{11}\ S_{12}]^T \qquad (6)$$

The first step was to segment the filter into four regions *(Si, i=1… 4)* connected through rectangular waveguide segments, as can be seen in the fig1. These waveguide segments are analytically included in the computations. It was assumed for simplicity that there were no losses in the filter and that the cavity lengths (L1, L2) were always large enough to connect the GSM of the irises, considering only the fundamental waveguide mode. Using this assumption and bearing in mind the geometrical symmetry.

There is tow types *(N=2)* of sub-structures: input-output iris and internal coupling iris, each substructure is composed of a rectangular iris and connecting waveguide sections. It can be rigorously analyzed since it only contains two rectangular-to-rectangular waveguide junctions. We will develop two neural network sub-models; each sub-model contains three input variables: width of iris a, length of iris b and center frequency f_0. The inputs of the sub-models are

$$\tilde{x}_i = (a_i \; bi \; f_0)^T \tag{7}$$

The GSM of the iris can be described with only three independent real parameters. The behavior of these parameters was modeled over the range 0.9 to 2cm for a_i, 1.8 to 2.8 for b_i and 38to 40 GHz (frequency) by using tow MLPs with two layers of weight and 10 neurons in the hidden layer. Each MLP had three inputs, a_i, b_i and frequency f, and one output. We generate 64000 samples, which cover a large range of iris width, iris length, and center frequency for each sub-model. As an example, the module of the parameter S_{11}, at a fixed frequency of 39GHz, and iris length of 2.524cm, computed using both the MLPs neural network and EM method (mode-matching), are depicted in fig2. GSM of each junction is subsequently transformed to equivalent circuit parameters, and the output vector of the sub-model are a coupling parameter and phase

$$\tilde{y}_i = (M_i \; \theta_i)^T \tag{8}$$

For the internal coupling iris the equivalent circuit is an impedance inverter having a shunt reactance X_p and series reactance X_s and insertion phase length θ. The following equations relate the *S*-parameter from EM simulation to circuit parameters [5]:

$$jX_s = \frac{1 - S_{12} + S_{11}}{1 - S_{11} + S_{12}}$$

$$jX_p = \frac{2S_{12}}{(1 - S_{11})^2 - S_{12}^2} \tag{9}$$

Coupling coefficients and insertion phase length are then calculated through.

$$\theta = -tan^{-1}(2X_p + X_s) - tan^{-1} X_s$$

$$K = |tan^{-1}(\theta/2 + tan^{-1} X_s)|$$

$$M = 2/\pi \, (\lambda/\lambda_g)^2 \frac{f_0}{BW} K \tag{10}$$

Where K is the impedance value of the inverter, f_0 and BW are the filter center frequency and bandwidth, λ and λ_g are the free-space and guided wavelength and M is the coupling value.

We combine the neural-network sub-models and filter equivalent-circuit model, as shown in Fig. 3, to obtain the approximate ***S***-parameter of the filter.

The two types of neural-network sub-models are concatenated to represent the three-pole filter. The IO iris 1 produces R_1 and IO iris 2 produces R_2. The two coupling iris models produce M_{12} and M_{23}. These coupling parameters are then used for producing approximate parameters of the three-pole filter using the filter equivalent-circuit equation of (11) [6]. Note that the input–output iris model is used twice and the internal coupling iris model is used twice times to represent the overall three-pole filter, i.e., N_0=4. In other words, the four sub-models required in the filter are obtained by training only two sub-models.

$$S_{11}^c = 1 + 2jR_1^c[\eta I - R^c + M^c]_{11}^{-1}$$

$$S_{12}^c = -2j\sqrt{R_1^c R_2^c}[\eta I - jR^c + M^c]_{p1}^{-1} \tag{11}$$

In which $\eta = (f_0/B)((f/f_0) - (f_0/f))$, p is the filter order, and p=3 in this case, I is a $p \times p$ identity matrix, M^c is the $p \times p$ approximate coupling matrix, R^c is a $p \times p$ matrix with all entries zero, except $[R^c]_{11}$= R_1^c and $[R^c]_{pp}$= R_2^c, and R_1^c and R_2^c are approximate values of the filter's input and output coupling parameters, respectively.

To the combined neural-network sub-models and filter equivalent model and obtain approximate *S* –parameter by sweeping frequency from 36 to 42 GHz with a 0.25-MHz step. The center frequency is held constant at 38.5 GHz. The model outputs are

$$y^c = (S_{11}^c \; S_{12}^c) \tag{12}$$

The approximate S-parameter of filter with its accurate S –parameter are compared in fig 4, showing good correlation. Filter geometry: a1=1.932cm, b1=2.524cm, a2=1.032cm, b2=1.934cm, L1=4.340cm, L2=4.494cm.

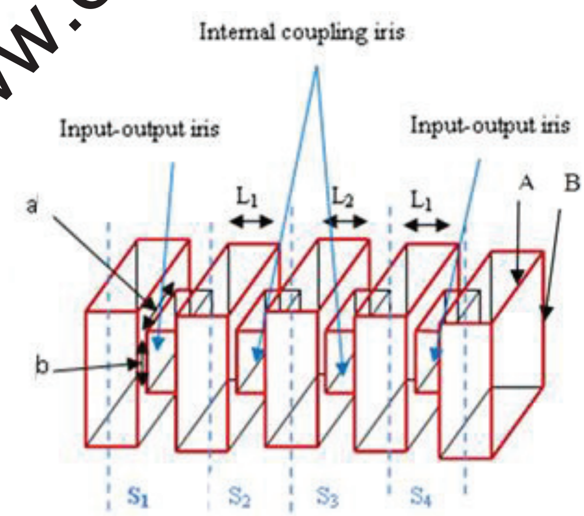

Figure 1. Geometry and segmentation of rectangular waveguide three cavities.

Dimensions (in cm) are: A=7.112, B=3.556.a1, b1, a2, b2, L1, and L2 are free parameter of system.

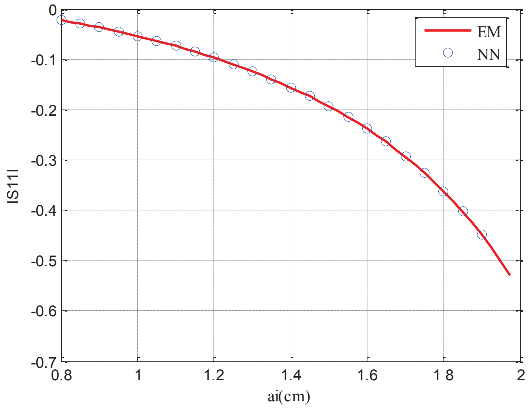

Figure 2. Variation of iris response against ai at fixed frequency and iris length

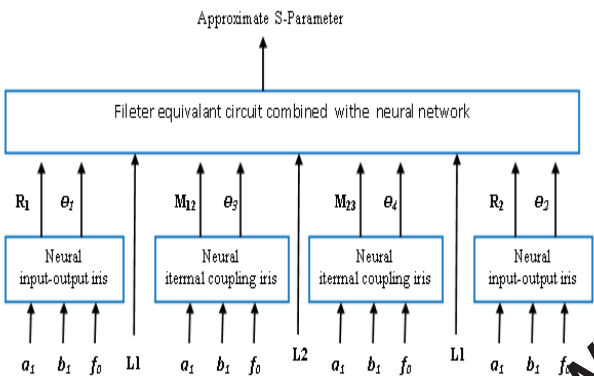

Figure 3. Structure for the three cavity waveguide filter, with tow neural-network sub-models.

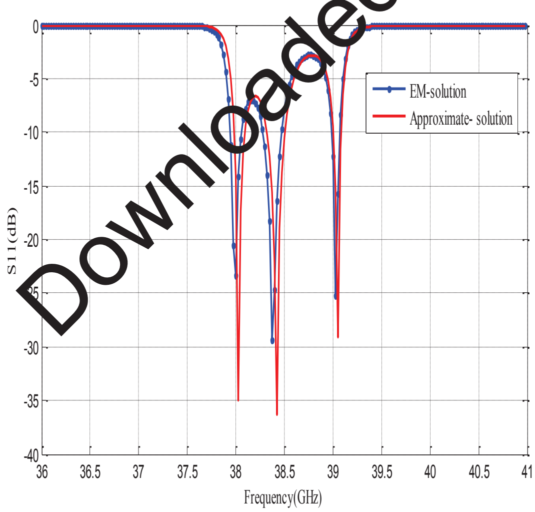

Figure 4. Comparison of approximate solution with accurate EM solution of a three cavity waveguide filter

IV. CONCLUSION

Efficient neural network modeling techniques have been presented and applied to microwave filter modeling and design. The proposed method based of decomposed the filter stricture into sub-structures, which reduces the number of variables input of sub-model neural network. Each sub-stricture are representing coupling mechanism. GSM of each junction is calculated using mode-matching method and subsequently transformed to equivalent circuit parameters. Neural models are then developed for each of the substructures. Equivalent-circuit models are combined with neural-network sub-models to produce an approximate solution of the overall filter. Good agreement is obtained between neural models and EM based data.

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