REALIZATIONS OF SPACE MAPPING BASED NEUROMODELS OF MICROWAVE COMPONENTS

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INTRODUCTION

Artificial Neural Networks (ANN) are suitable in modeling high-dimensional and highly nonlinear elements, such as those found in the microwave arena. In modeling microwave components, the learning data is obtained from a detailed or "fine" model (typically an EM simulator), which is accurate but slow to evaluate. This is aggravated because simulations are needed for many combinations of input parameter values. This is the main drawback of conventional ANN modeling. We use available equivalent circuits or "coarse" models to overcome this limitation.

In the Space Mapping (SM) based neuromodeling techniques an ANN is used to implement a suitable mapping from the fine to the coarse input space. The implicit knowledge in the coarse model not only allows us to decrease significantly the number of learning points needed, but also to reduce the complexity of the ANN and to improve the generalization performance. We present novel realizations of SM based neuromodels of practical passive components using commercial software. An SM-based neuromodel of a microstrip right angle bend is developed using *NeuroModeler* [1], and entered into HP ADS [2] as a library component through an ADS plug-in module.

SPACE MAPPING CONCEPT

SM establishes a link between proposed coarse and fine models, and directs the bulk of CPU intensive evaluations to the coarse model, while preserving the accuracy of the fine model. Let the vectors $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ represent the design parameters of the coarse and fine models, respectively, and $\boldsymbol{R}_c(\boldsymbol{x}_c)$ and $\boldsymbol{R}_f(\boldsymbol{x}_f)$ the corresponding model responses. As illustrated in Fig. 1, the aim of SM is to find an appropriate mapping $\boldsymbol{P}$, valid in a parameter region of interest, from the fine model parameter space $\boldsymbol{x}_f$ to the coarse model parameter space $\boldsymbol{x}_c$

$$\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_f) \tag{1}$$

such that

$$\boldsymbol{R}_c(\boldsymbol{P}(\boldsymbol{x}_f)) \approx \boldsymbol{R}_f(\boldsymbol{x}_f) \tag{2}$$

Once the mapping is found, the coarse model can be used for fast and accurate simulations in the region of interest.

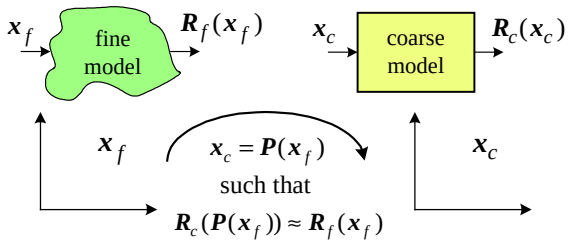

Fig. 1. Illustration of the aim of Space Mapping.

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SPACE-MAPPED NEUROMODELING

In the Space-Mapped Neuromodeling (SMN) approach an ANN implements the mapping from the fine to the coarse parameter space. It can be found by solving the optimization problem

$$\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^{\,T} \quad \boldsymbol{e}_2^{\,T} \quad \cdots \quad \boldsymbol{e}_l^{\,T}]^T \right\| \tag{3}$$

where $\boldsymbol{w}$ contains the internal parameters of the ANN, l is the number of learning samples, and $\boldsymbol{e}_j$ is the error given by

$$\boldsymbol{e}_j = \boldsymbol{R}_f(\boldsymbol{x}_{f\,j}) - \boldsymbol{R}_c(\boldsymbol{x}_{f\,j}, \boldsymbol{w}), \quad j = 1, 2, \ldots, l \tag{4}$$

Fig. 2 illustrates the SMN concept. Once the ANN is trained, an SMN model for fast, accurate evaluations is available.

Including Frequency in the Neuromapping

Many empirical models are based on quasi-static analysis: they usually yield good accuracy over low frequencies. We overcome this limitation through a frequency-sensitive mapping from the fine to the coarse parameter space. This is realized by considering frequency as an extra input variable of the ANN that implements the mapping. As illustrated in Fig. 3a, in the Frequency Dependent Space-Mapped Neuromodeling (FDSMN) approach both coarse and fine models are simulated at the same frequency, but the mapping from the coarse to the fine parameter space is dependent on the frequency. With a more comprehensive domain, the Frequency Space-Mapped Neuromodeling (FSMN) technique establishes a mapping not only for the design parameters but also for the frequency variable, such that the coarse model is simulated at a mapped frequency f_c to match the fine model response. This is realized by adding an extra output to the ANN that implements the mapping, as shown in Fig. 3b. Two additional techniques to efficiently create frequency-sensitive neuromappings are proposed in [3].

SM BASED NEUROMODEL OF A MICROSTRIP RIGHT ANGLE BEND

Consider a microstrip right angle bend with conductor width W, substrate height H, substrate dielectric constant ε_r, and operating frequency *freq*. An FSMN model is developed for the region of interest shown in Table I.

(a) (b)

Fig. 2. Space-Mapped Neuromodeling concept: (a) SM neuromodeling, (b) SMN model.

(a) (b)

Fig. 3. Frequency-sensitive mappings: (a) Frequency Dependent Space-Mapped Neuromodeling (FDSMN), (b) Frequency Space-Mapped Neuromodeling (FSMN).

TABLE I
REGION OF INTEREST FOR THE MICROSTRIP RIGHT ANGLE BEND

Parameter	Minimum value	Maximum value
W	20 mil	30 mil
H	8 mil	16 mil
ε_r	8	10
freq	1 GHz	41 GHz

Sonnet's ***em***™ [4] is used as the fine model. To generate the learning and testing data, the bend is parameterized using the Geometry Capture [5] technique available in Empipe™ [6]. To evaluate the generalization performance of our neuromodel, 50 random test base-points with uniform statistical distribution within the region of interest shown in Table I are generated using a frequency step of 2 GHz (1050 test samples). Following a star distribution for the learning points [3], only 7 base points are used for learning (147 learning samples) since we have 3 design parameters.

Gupta's model [7], consisting of a lumped LC equivalent circuit whose parameter values are given by analytical functions of the physical quantities W, H and ε_r is taken as the "coarse" model. Fig. 4a illustrates the FSMN neuromodeling strategy for the microstrip bend, which was implemented using *NeuroModeler* as shown in Fig. 4b. The FSMN model as implemented in *NeuroModeler* consists of a total of 6 layers. The first layer, shown in green color, has the input parameters of the neuromapping (W, H, ε_r, and *freq*), which are scaled to ±1 to improve the numerical behavior during training. The second layer from bottom to top corresponds to the hidden layer of the ANN implementing the mapping (see Fig. 4b): optimal generalization performance is achieved with 8 hidden neurons with sigmoid nonlinearities. The third layer is linear and contains the coarse design parameters $\boldsymbol{x}_c$ and the mapped frequency f_c before descaling. The fourth layer is added to simply de-scale the parameters. Gupta's formulas to calculate L and C are programmed as the internal analytical functions of the fifth hidden layer, using the built-in MultiSymbolicFixed function. Finally, the output layer, shown in blue color, contains a simple internal circuit simulator that computes the real and imaginary parts of S_{11} and S_{21} for the lumped LC equivalent circuit. This layer uses the built-in CktSimulatorPS function.

Fig. 5 shows the learning and testing errors of the bend FSMN model after training using *NeuroModeler*. Conjugate Gradient and Quasi Newton built-in training methods are used. The average and worst case learning errors are 0.43% and 1.00%, while the average and worst-case testing errors are 1.04% and 10.94%. Excellent generalization performance is achieved. Plots in Fig. 5 were produced using the export-to-*MatLab*™ [8] capability available in *Neuromodeler*.

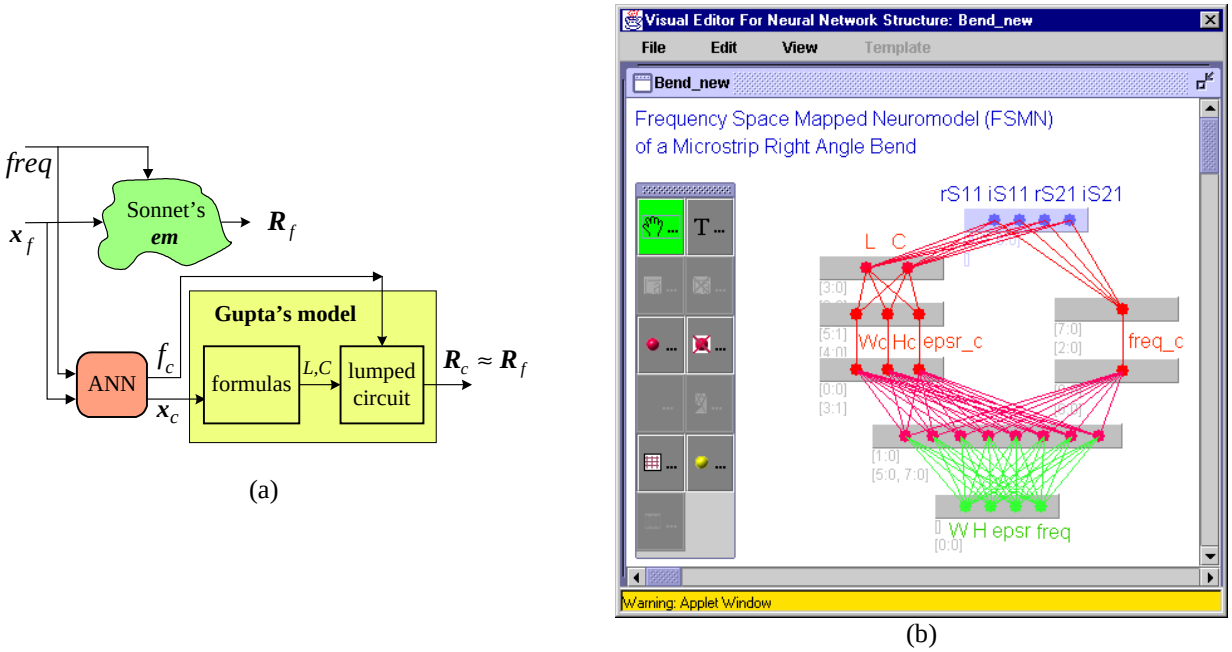

Fig. 4. Frequency Space-Mapped Neuromodel (FSMN) of microstrip right angle bend: (a) strategy, (b) implementation in *NeuroModeler*.

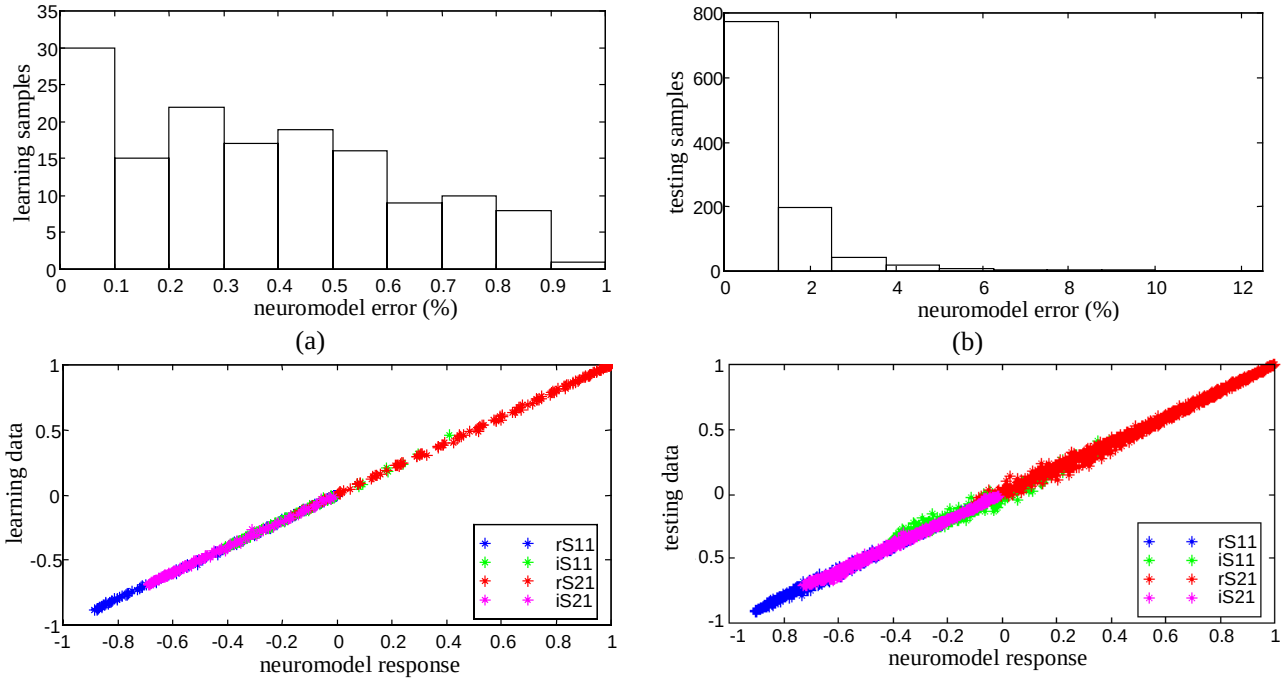

Fig. 5. Learning and testing errors of the FSMN model after training: (a) histogram of learning errors, (b) histogram of testing errors, (c) correlation to learning data, and (d) correlation to testing data.

The FSMN model of the right angle bend can now be used in HP ADS for fast and accurate simulations within the region of operation shown in Table I: it can be entered as a user-defined model through the plug-in module *NeuroADS* [1].

CONCLUSIONS

We present novel realizations of SM based neuromodels of practical passive components using commercial software. Three powerful techniques to generate SM based neuromodels are described and illustrated: Space-Mapped Neuromodeling (SMN), Frequency-Dependent Space-Mapped Neuromodeling (FDSMN) and Frequency Space-Mapped Neuromodeling (FSMN). These techniques exploit the vast set of empirical models already available, decrease the number of fine model evaluations needed for training, improve generalization ability and reduce the complexity of the ANN topology w.r.t. the classical neuromodeling approach. An SM-based neuromodel of a microstrip right angle bend is implemented using *NeuroModeler*, and entered into HP ADS as a library component through an ADS plug-in module.

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