**NEW DIRECTIONS IN MODEL DEVELOPMENT
FOR RF/MICROWAVE COMPONENTS UTILIZING
ARTIFICIAL NEURAL NETWORKS AND SPACE MAPPING**

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SOS-99-1-R

January 1999

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J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang
Simulation Optimization Systems Research Laboratory
and Department of Electrical and Computer Engineering
McMaster University, Hamilton, Canada L8S 4K1

Abstract   This paper presents recent advances in model development for RF/microwave components exploiting two powerful technologies: Artificial Neural Networks (ANN) and Space Mapping (SM). We survey the fundamental issues on classical neuromodeling. We review some state-of-the-art neuromodeling techniques, emphasizing SM based neuromodeling techniques. We show how SM based neuromodels decrease the cost of training, improve generalization ability and reduce the complexity of the ANN topology w.r.t. the classical neuromodeling approach. We illustrate these novel approaches through a practical microwave modeling problem. We conclude by proposing some possible exciting future applications of ANN and SM in microwave CAD.

A Brief Review of Neuromodeling of Microwave Components

ANNs are particularly suitable in modeling high-dimensional and highly nonlinear devices, as those found in the microwave area, due to their ability to learn and generalize from data, their non-linear processing nature, and their massively parallel structure.

The size of an ANN model does not grow exponentially with dimension and, in theory, can approximate any degree of nonlinearity to any desired level of accuracy, provided a deterministic relationship between input and target exists [1]. The most widely used ANN paradigm in the microwave arena is the multi-layer perceptron (MLP), which is usually trained by the well established backpropagation algorithm. It has been demonstrated [2, 3] that ANNs are suitable models for microwave circuit yield optimization and statistical design.

For microwave problems the learning data is usually obtained by either EM simulation or by measurement. This is expensive since the simulation/measurements must be performed for many combinations of different values of input parameters. This is the main drawback of classical ANN modeling. Without sufficient learning samples, the neural models may not be reliable.

Three innovative strategies have been proposed to reduce the learning data needed and to improve the generalization capabilities of an ANN by incorporating empirical models: the hybrid EM-ANN modeling approach, the knowledge based ANN (KBNN) approach, and the Space Mapping (SM) based neuromodeling approach.

In the hybrid EM-ANN modeling approach [4], the difference in *S*-parameters between the empirical model and the EM model is used to train the corresponding ANN, reducing the number of fine model simulations due to a simpler input-output relationship. In the knowledge based ANN approach [5] (KBNN) the empirical model is incorporated into the internal structure of the ANN. Knowledge Based ANNs are non fully connected networks, with a layer assigned to the microwave knowledge in the form of single or multidimensional functions.

By combining SM and ANN, three novel techniques are proposed in [6] to generate SM

based neuromodels: Space-Mapped Neuromodeling (SMN), Frequency-Dependent Space-Mapped Neuromodeling (FDSMN), and Frequency Space-Mapped Neuromodeling (FSMN).

Space Mapping Concept

The Space Mapping (SM) technique [7] combines the computational efficiency of coarse models with the accuracy of fine models. The coarse models are typically empirical functions or equivalent circuits, which are computationally very efficient but have a limited validity range for their parameters. Fine models can be provided by an electromagnetic (EM) simulator, or even by direct measurements: they are very accurate but CPU intensive. The SM technique establishes a mathematical link between the coarse and the fine models, and directs the bulk of CPU intensive evaluations to the coarse model, while preserving the accuracy offered by the fine model.

Let the vectors x_c and x_f represent the design parameters of the coarse and fine models, respectively, and $R_c(x_c)$ and $R_f(x_f)$ the corresponding model responses. The aim of SM optimization is to find an appropriate mapping P from the fine model parameter space x_f to the coarse model parameter space x_c

$$x_c = P(x_f) \tag{1}$$

such that

$$R_c(P(x_f)) \approx R_f(x_f) \tag{2}$$

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

Space Mapping Based Neuromodeling

In the Space-Mapped Neuromodeling (SMN) approach an ANN implements the mapping from the fine to the coarse parameter space, as illustrated in Fig. 1(a). The mapping can be found by solving the optimization problem

$$\min_N \left\| [e_1^T \quad e_2^T \quad \cdots \quad e_l^T]^T \right\| \tag{3}$$

where N contains the internal parameters of the neural network (weights, bias, etc.) selected as optimization variables, l is the total number of learning samples, and e_j is the error vector given by

$$e_j = R_f(x_{fj}) - R_c(x_{fj}, N), \quad j = 1, 2, \ldots, l \tag{4}$$

Once the mapping is found, i.e., once the ANN is trained, a space-mapped neuromodel for fast, accurate evaluations is immediately available.

Frequency-Sensitive Neuromapping

Many available empirical models are based on quasi-static analysis: they usually yield good accuracy over a limited low range of frequencies. We overcome this limitation through a frequency-sensitive mapping, which is realized by considering frequency as an extra input variable of the ANN. As illustrated in Fig. 1(*b*), 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 fine to the coarse parameter space is dependent on the frequency. With a more comprehensive domain, the Frequency Space Mapped Neuromodeling (FSMN) technique in Fig. 1(*c*) 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.

Illustration: A Microstrip Right Angle Bend

Consider a microstrip right angle bend, with the following input parameters: conductor width W, substrate height H, substrate dielectric constant e_r, and operating frequency *freq*. Several neuromodels exploiting SM technology have been developed for the following region of interest:

20mil $\leq W \leq$ 30mil, 8mil $\leq H \leq$ 16mil, 8 $\leq e_r \leq$ 10, and 1GHz $\leq freq \leq$ 41GHz.

Gupta's model [8], consisting of a lumped LC circuit whose parameter values are given by analytical functions of the physical quantities W, H and e_r is taken as the "coarse" model and implemented in *OSA90/hope™* [9]. Sonnet's *em™* [10] is used as the fine model.

The coarse and fine models before any neuromodeling are compared in Fig. 2(*a*) using 50 random test points with uniform statistical distribution in the region of interest. Gupta's model, in this region of physical parameters, yields acceptable results for frequencies less than 10 GHz.

Seven learning base points are used for the three SM neuromodels, and the corresponding ANNs were implemented and trained within *OSA90*. Huber optimization was employed as the training algorithm, exploiting its robust characteristics for data fitting [11].

Fig. 2(*b*) shows typical results for the SMN model implemented with a three layer perceptron with 3 input neurons, 6 hidden neurons, and 3 output neurons (3LP:3-6-3). A FDSMN model is developed using a 3LP:4-7-3, and the improved results are shown in Fig. 2(*c*). In Fig. 2(*d*) the results for the FSMN model with a 3LP:4-8-4 are shown, that are even better (as expected). It is seen that the FSMN model yields excellent results for the whole frequency range of interest, overcoming the frequency limitations of the empirical model by a factor of four.

Conclusions

We review fundamental advances in the microwave neuromodeling arena. We describe novel applications of Space Mapping technology and Artificial Neural Networks to the modeling of microwave components. SM based neuromodels 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. Frequency-sensitive neuromapping is demonstrated to be a clever strategy to expand the usefulness of empirical models that were developed using quasi-static analysis. As an original alternative to the classical backpropagation algorithm, Huber optimization is employed to efficiently train the neuromapping. Promising perspectives are open by the application of frequency-space neuromapping to the solution of complex yield optimization and statistical design problems.

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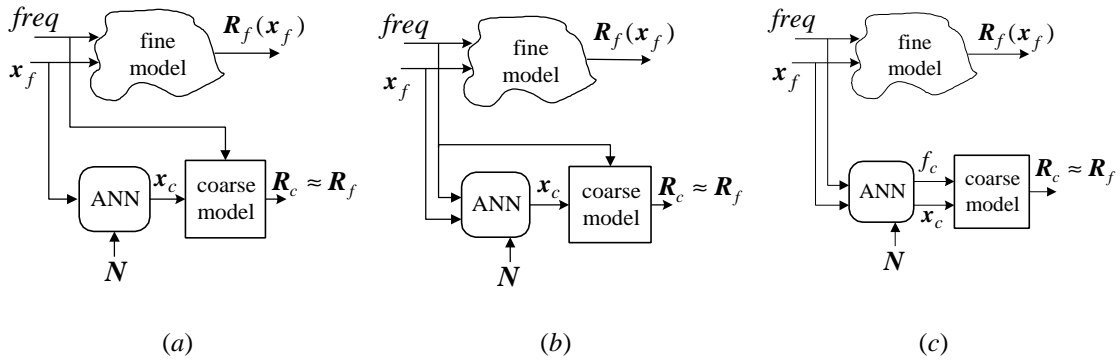
(*a*)   (*b*)   (*c*)

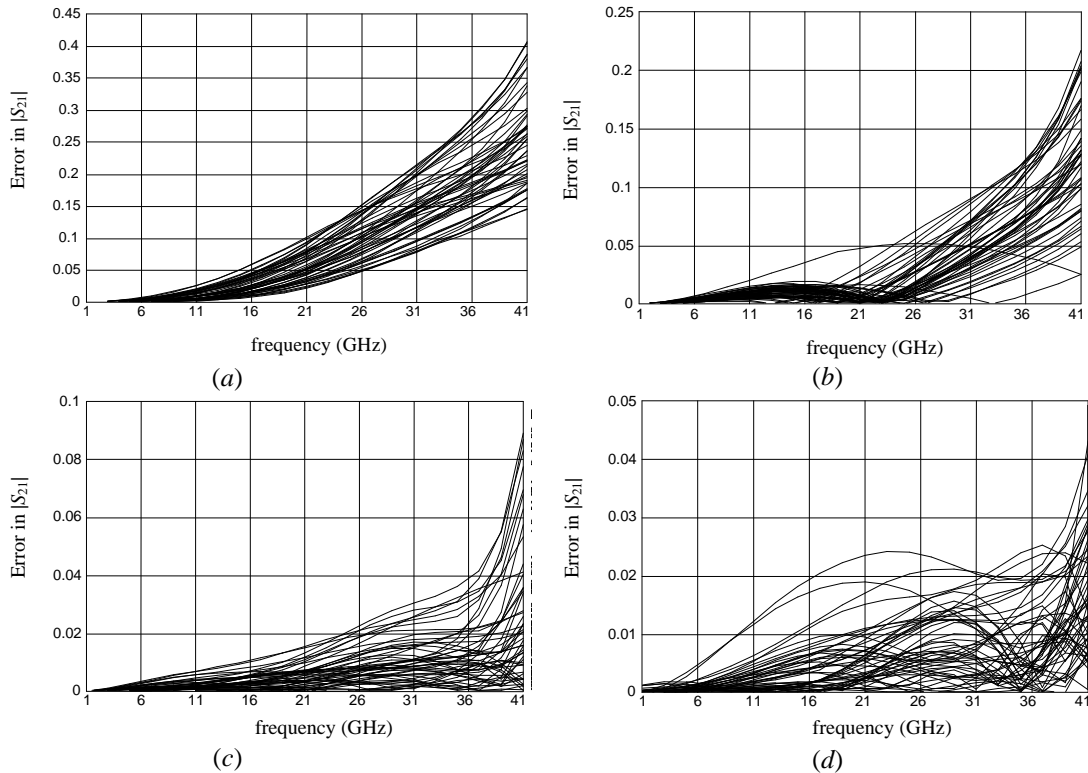Fig. 1. SM Neuromodeling techniques: (*a*) SMN, (*b*) FDSMN, (*c*) FSMN.

Fig. 2. Error in |S_{21}| with respect to *em* results for a right angle bend of: (*a*) Gupta model, (*b*) SMN model, (*c*) FDSMN model, (*d*) FSMN model.