Neuromodeling of Microwave Circuits Exploiting Space Mapping Technology

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Abstract—**For the first time, we present neuromodeling of microwave circuits based on Space Mapping (SM) technology. SM based neuromodels decrease the cost of training, improve generalization ability and reduce the complexity of the ANN topology w.r.t. classical neuromodeling. Three novel techniques are proposed to generate SM based neuromodels: Space-Mapped Neuromodeling (SMN), Frequency Dependent Space-Mapped Neuromodeling (FDSMN), and Frequency-Space-Mapped Neuromodeling (FSMN). Huber optimization is proposed to train the neuro-space-mapping (NSM). The techniques are illustrated by a microstrip right angle bend.**

I. INTRODUCTION

A powerful new concept in neuromodeling of microwave circuits based on Space Mapping technology is presented. The ability of Artificial Neural Networks (ANN) to model high-dimensional and highly nonlinear problems is exploited in the implementation of the Space Mapping concept. By taking advantage of the vast set of empirical models already available, Space Mapping based neuromodels decrease the number of EM simulations for training, improve generalization ability and reduce the complexity of the ANN topology with respect to the classical neuromodeling approach.

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Three innovative techniques are proposed to create Space Mapping based neuromodels for microwave circuits: Space-Mapped Neuromodeling (SMN), Frequency Dependent Space-Mapped Neuromodeling (FDSMN) and Frequency-Space-Mapped Neuromodeling (FSMN). In both the FDSMN and FSMN approaches, a frequency-sensitive neuromapping is established to expand the frequency region of accuracy of the empirical models already available for microwave components that were developed using quasi-static analysis.

For the first time, Huber optimization is proposed to efficiently train the neuro-space-mapping (NSM), as a powerful alternative to the popular backpropagation algorithm. The SM based neuromodeling techniques are illustrated by a microstrip right angle bend. We contrast our approach with classical neuromodeling as well as with other state-of-the-art neuromodeling techniques.

II. SPACE MAPPING CONCEPT

The Space Mapping (SM) technology [1] 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 often have a limited validity range for their parameters, beyond which the simulation results may become inaccurate. On the other hand, detailed or "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 and confidence offered by the fine model.

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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. As illustrated in Fig. 1, the aim of SM 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.

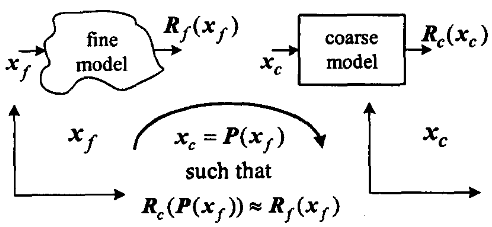

Fig. 1. Illustration of the aim of Space Mapping.

III. NEUROMODELING MICROWAVE CIRCUITS

The ability to learn and generalize from data, the non-linear processing nature, and the massively parallel structure make the ANN particularly suitable in modeling high-dimensional and highly nonlinear problems, as in the case of microwave circuits.

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 [2]. 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.

ANN models are computationally more efficient than EM or physics-based models and can be more accurate than empirical models. It has been demonstrated [3, 4] 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 very expensive since the simulation or measurements must be performed for many combinations of different values of geometrical, material, process and input signal parameters. This is the principal drawback of classical ANN modeling. Without sufficient learning samples, the neural models may not be very reliable.

Innovative strategies have been proposed to reduce the learning data needed and to improve the generalization capabilities of an ANN by incorporating empirical models. In the knowledge based ANN approach [5] (KBNN), a non fully connected network is used, with a layer assigned to the microwave knowledge in the form of single or multidimensional functions. In the hybrid EM-ANN modeling approach [6], the difference in S-parameters between the available coarse model and the fine model is used to train the corresponding ANN, reducing the number of fine model simulations due to a simpler input-output relationship.

IV. SPACE-MAPPED NEUROMODELING

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

$$\min_{w} \left\| [e_1^T \;\; e_2^T \;\; \cdots \;\; e_l^T]^T \right\| \tag{3}$$

where vector w 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

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

Fig. 2 illustrates the SMN concept. Once the mapping is found, i.e., once the ANN is trained, a space-mapped neuromodel for fast, accurate evaluations is immediately available.

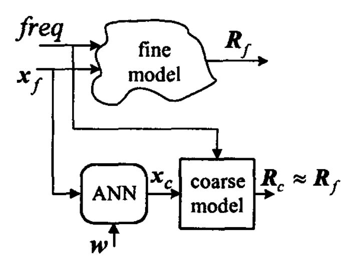

Fig. 2. Space-Mapped Neuromodeling concept.

V. INCLUDING FREQUENCY IN THE 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 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. We propose Frequency Dependent Space-Mapped Neuromodeling (FDSMN) and Frequency-Space-Mapped Neuromodeling (FSMN).

As illustrated in Fig. 3, in the 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.

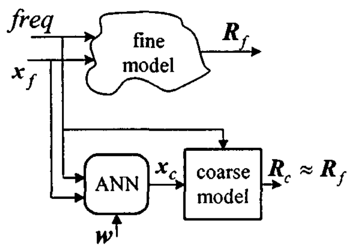

Fig. 3. Frequency Dependent SM Neuromodeling.

With a more comprehensive domain, the 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. 4.

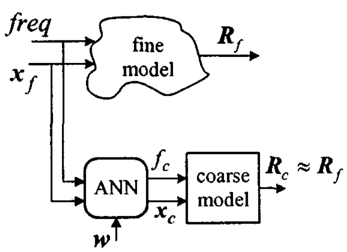

Fig. 4. Frequency-Space-Mapped Neuromodeling.

VI. EXAMPLE: 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 ε_r, and operating frequency *freq*. Several neuromodels exploiting SM technology are developed for the following region of interest: 20mil $\leq W \leq$ 30mil, 8mil $\leq H \leq$ 16mil, $8 \leq \varepsilon_r \leq 10$, and 1GHz $\leq$ *freq* $\leq$ 41GHz.

Gupta's model [7], consisting of a lumped LC circuit whose parameter values are given by analytical functions of the physical quantities W, H and ε_r is taken as the "coarse" model and implemented in *OSA90/hope*™ [8]. Sonnet's ***em***™ [9] is used as the fine model. To parameterize the structure, the Geometry Capture technique available in *Empipe*™ [10] is utilized.

The coarse and fine models before neuromodeling are compared in Fig. 5 using 50 random test base points with uniform statistical distribution in the region of interest. Gupta's model, in this region of physical parameters, yields excellent results for frequencies less than 10 GHz.

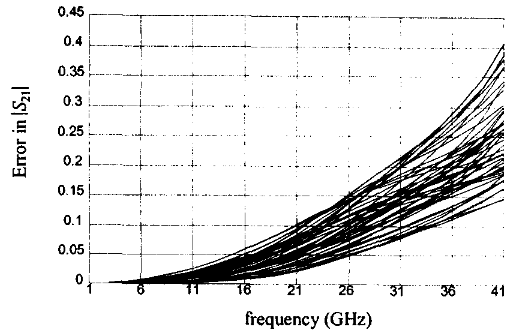

Fig. 5. Error in Gupta model with respect to Sonnet's ***em***.

Only seven learning base points (with 21 frequency points per base point) are used for the three SM based 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. 6 shows typical results for the SMN model implemented with a three layer perceptron with 3 inputs, 6 hidden neurons, and 3 outputs (3LP:3-6-3).

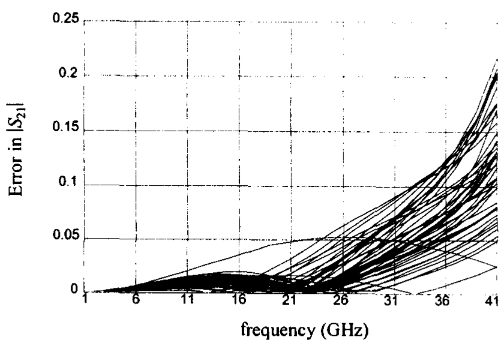

Fig. 6. Error in SMN model with respect to Sonnet's ***em***.

A FDSMN model is developed using a 3LP:4-7-3, and the improved results are shown in Fig. 7. In Fig. 8 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.

To compare these results with those from a classical neuromodeling approach, an ANN was developed using *NeuroModeler* [12]. Training the ANN with the same 147 learning samples, the best results were obtained for a 3LP:4-15-4 trained with the conjugate gradient and quasi-Newton methods. Due to the small number of learning samples, this approach did not provide good generalization capabilities, as illustrated in Fig. 9. To produce similar results to those in Fig. 8 using the same ANN size, the learning samples have to increase from

147 to 315.

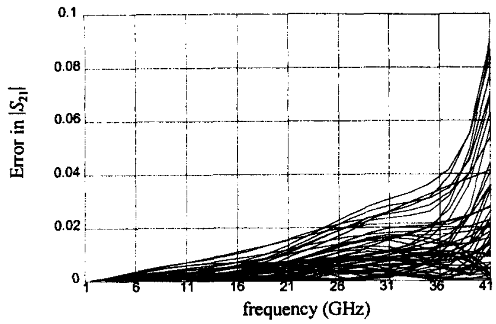

Fig. 7. Error in FDSMN model with respect to Sonnet's ***em***.

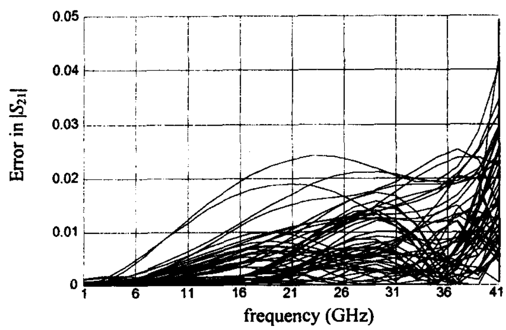

Fig. 8. Error in FSMN model with respect to Sonnet's ***em***.

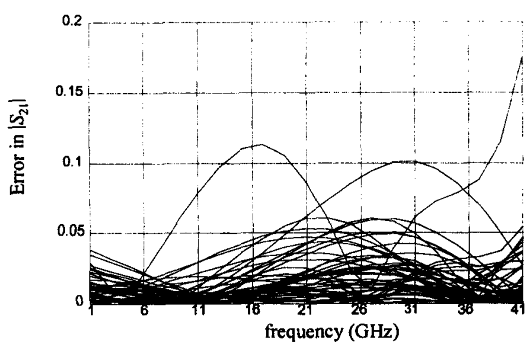

Fig. 9. Error in classical neuromodel w.r.t. Sonnet's ***em***.

VII. CONCLUSIONS

We present novel applications of Space Mapping technology to the neuromodeling of microwave circuits: Space-Mapped Neuromodeling (SMN), Frequency Dependent Space-Mapped Neuromodeling (FDSMN) and Frequency-Space-Mapped Neuromodeling (FSMN). These techniques can exploit the vast set of empirical models 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 (FDSMN and FSMN) is demonstrated to be a clever strategy to expand the usefulness of empirical models that were developed using quasi-static analysis. Huber optimization was employed to efficiently train the neuromapping, exploiting its robust characteristics for data fitting.

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