**SPACE MAPPING BASED NEUROMODELING**
**OF HIGH FREQUENCY CIRCUITS**

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J.W. Bandler, 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
Tel: (905) 628 9671 E-mail: j.bandler@ieee.org

### Neuromodeling High Frequency Circuits

Artificial Neural Networks (ANN) are very convenient in modeling high-dimensional and highly nonlinear components, as those found in the microwave and high frequency arena, due to their ability to learn and generalize from data, their non-linear processing nature, and their massively parallel structure.

In modeling high frequency components the learning data is usually obtained from a detailed or "fine" model (EM simulator or measurements). This is generally very time consuming because 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.

Several innovative strategies to develop neuromodels take advantage of empirical or "coarse" models already available (circuit-equivalent models and analytical formulas): the hybrid EM-ANN modeling approach [1], the PKI modeling method [1], the knowledge based ANN [2] (KBNN) approach, and the Space Mapping (SM) based neuromodeling techniques [3].

### Space Mapping Based Neuromodeling

Let the vectors $x_f$ and $x_c$ represent the design parameters of the fine and coarse models, respectively, and $R_f(x_f)$ and $R_c(x_c)$ the corresponding model responses. $R_f$ is accurate but slow to evaluate while $R_c$ is fast but not very accurate.

In the Space-Mapping Neuromodeling (SMN) technique an ANN is used to implement the mapping from the fine to the coarse input parameter space. The mapping can be found by solving the optimization problem

$$\min_{w} \left\| [e_1^T \quad e_2^T \quad \cdots \quad e_l^T]^T \right\| \qquad (1)$$

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

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

The implicit knowledge in the coarse model, that can be considered as an "expert", not only allows us to decrease the number of learning points needed, but also to reduce the complexity of the ANN and to improve the generalization performance. Fig. 1 illustrates the SMN concept.

Many available empirical models are based on quasi-static analysis: they usually yield good accuracy over a limited low range of frequencies. To overcome this limitation a frequency-sensitive mapping can be established. Frequency Dependent Space-Mapping Neuromodeling (FDSMN) and Frequency-Space-Mapping Neuromodeling (FSMN) are two other variations of SM based neuromodeling techniques that implement this strategy [3].

### Example: A Microstrip Line with High Dielectric Constant

Fig. 2 illustrates a microstrip line to be modeled in the following region of interest: 5mil ≤ $W$ ≤ 9mil, 15mil ≤ $H$ ≤ 25mil, 40mil ≤ $L$ ≤ 60mil, 20 ≤ $e_r$ ≤ 25, 27GHz ≤ $freq$ ≤ 30GHz.

The coarse model, implemented in OSA90/hope™ [4], consists of Pozar's formulas [5] applied to a simple transmission line. Sonnet's em™ [6] is used as the fine model. The coarse and fine models before any neuromodeling are compared in Fig. 3 using 50 random test base points with uniform statistical distribution in the region of interest, with 7 points per frequency sweep.

Fig. 4 shows excellent results for a SMN model implemented with a three layer perceptron with 4 input neurons, 3 hidden neurons, and 4 output neurons. The ANN was implemented and trained within OSA90/hope™, using only 9 learning base points with Huber optimization.

### Conclusions

We describe innovative schemes to combine SM technology and ANN for the modeling of high frequency 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.

### Acknowledgements

### References

[1] P. Watson and K.C. Gupta, "EM-ANN models for microstrip vias and interconnects in multilayer circuits," *IEEE Trans. Microwave Theory Tech.*, vol. 44, 1996, pp. 2495-2503.

[2] F. Wang and Q.J. Zhang, "Knowledge based neuromodels for microwave design," *IEEE Trans. Microwave Theory Tech.*, vol. 45, 1997, pp. 2333-2343.

[3] J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE MTT-S Int. Microwave Symp.* (Anaheim, CA), June 1999.

[4] OSA90/hope™ Version 4.0, formerly Optimization Systems Associates Inc., P.O. Box 8083, Dundas, Ontario, Canada L9H 5E7, 1997, now HP EEsof Division, Hewlett-Packard Company, 1400 Fountaingrove Parkway, Santa Rosa, CA 95403-1799.

[5] M. Pozar, *Microwave Engineering*. Amherst, MA: John Wiley and Sons, 1998.

[6] *em*™ Version 4.0b, Sonnet Software, Inc., 1020 Seventh North Street, Suite 210, Liverpool, NY 13088, 1997.
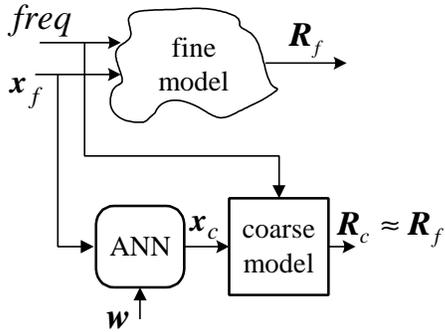
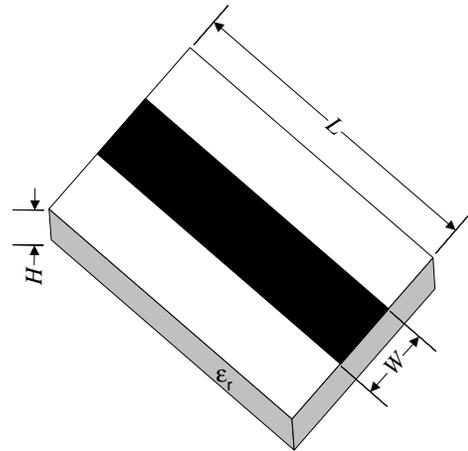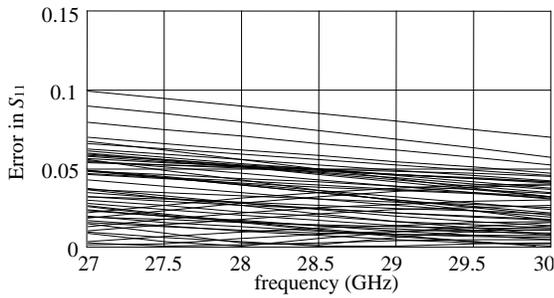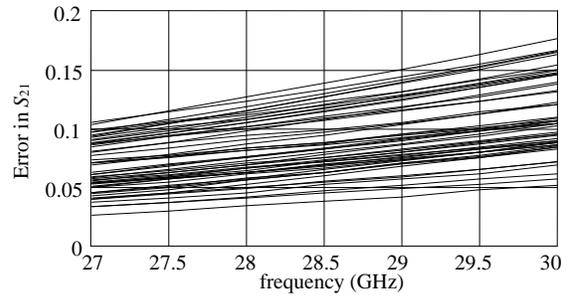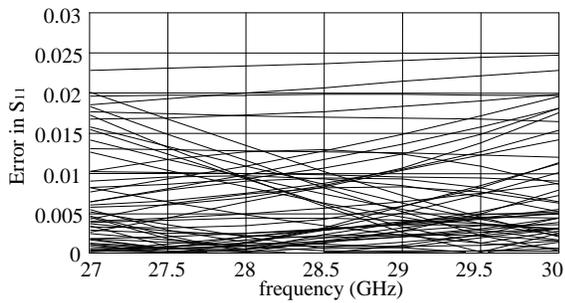Fig. 1. Space-Mapped Neuromodeling concept.



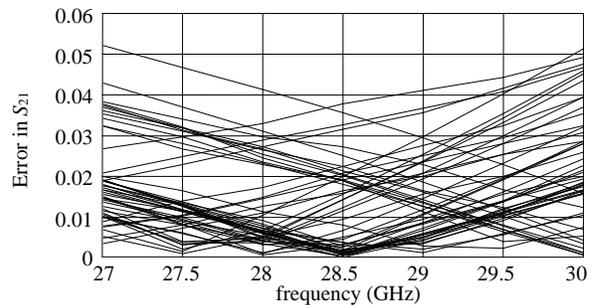Fig. 2. Microstrip line.



(*a*)



(*b*)

Fig. 3. Error in coarse model with respect to Sonnet's *em* before any neuromodeling:
(*a*) modulus of the complex $S_{11}$ error, (*b*) modulus of the complex $S_{21}$ error.



(*a*)



(*b*)

Fig. 4. Error in SMN model with respect to Sonnet's *em*: (*a*) modulus of
the complex $S_{11}$ error, (*b*) modulus of the complex $S_{21}$ error.