EM-based Statistical Analysis and Yield Optimization using Space Mapping Based Neuromodels

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, 1280 Main St. West, Hamilton, Canada L8S 4K1
Tel: 905 628 9671 E-mail: j.bandler@ieee.org

EM Yield-driven Design via SM-based Neuromodels

Accurate yield optimization and statistical analysis of microwave components are crucial in manufacturability-driven designs in a time-to-market development environment. Yield optimization requires intensive simulations to cover the entire statistic of possible outcomes of a given manufacturing process. Performing direct yield optimization using accurate full wave electromagnetic (EM) simulations does not appear feasible. Here, an efficient procedure to realize EM-based yield optimization and statistical analysis of microwave structures using space mapping-based neuromodels is proposed.

We have mathematically formulated the yield optimization problem using SM-based neuromodels. A general equation to express the relationship between the fine and coarse model sensitivities through a nonlinear, frequency-sensitive neuromapping has been found.

We illustrate our technique by the yield analysis and optimization of an HTS filter. Here we assume symmetric variations in the physical parameters due to tolerances. Efficient procedures have also been developed for the asymmetric case.

Yield Optimization of an HTS Filter

Consider a high-temperature superconducting (HTS) parallel coupled-line microstrip filter [1,2] (Fig. 1).

L_1, L_2 and L_3 are the lengths of the parallel coupled-line sections and S_1, S_2 and S_3 are the gaps. The width W is the same for all the sections as well as for the input and output lines, of length L_0. A lanthanum aluminate substrate with thickness H and dielectric constant ε_r is used.

The design specifications are as in [2].

OSA90/hope™ [3] built-in linear elements connected by circuit theory form the "coarse" model. Sonnet's ***em***™ [4] driven by Empipe™ [3] forms the fine model, using a high-resolution grid.

The SM-based neuromodel of the HTS filter of [1] is used. This model was obtained assuming that the design parameters are $\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$, and taking L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; the metalization was considered lossless. The corresponding SM-based neuromodel is illustrated in Fig. 2, which implements a frequency partial-space mapped neuromapping with 7 hidden neurons, mapping only L_1, S_1 and the frequency (3LP:7-7-3). L_{1c} and S_{1c} in Fig. 2 denote the corresponding physical dimensions used by the coarse model, i.e., after being transformed by the mapping. The coarse model is simulated at mapped frequency ω_c.

Applying direct minimax optimization to the coarse model, we obtain the optimal coarse solution $\boldsymbol{x}_c^* = [188.33\ \ 197.98\ \ 188.58\ \ 21.97\ \ 99.12\ \ 111.67]^T$ (mils).

We apply direct minimax optimization to the SM-based neuromodel, starting at $\boldsymbol{x}_c^*$, to obtain the optimal SM-based neuromodel nominal solution $\boldsymbol{x}_{SMBN}^* = [185.79\ \ 194.23\ \ 184.91\ \ 21.05\ \ 82.31\ \ 89.32]^T$ (mils).

For yield analysis, we consider 0.2% of variation for the dielectric constant and for the loss tangent, as well as 75 micron of variation for the physical dimensions, with uniform statistical distributions. We perform Monte Carlo yield analysis of the SM-based neuromodel around $\boldsymbol{x}_{SMBN}^*$ with 500 outcomes. The responses for 50 outcomes are shown in Fig. 3. The yield calculation is shown in Fig. 4. A yield of only 18.4% is obtained at $\boldsymbol{x}_{SMBN}^*$.

Performing yield analysis using 500 outcomes with the SM-based neuromodel of the HTS filter takes a few tens of seconds on a PC (AMD 640MHz, 256M RAM, Windows NT 4.0). A single outcome calculation for the same circuit using an EM simulation takes about 5 hours.

We then apply yield optimization to the SM-based neuromodel with 500 outcomes using the Yield-Huber optimizer available in OSA90/hope™ [3], obtaining the optimal yield solution: $\boldsymbol{x}_{SMBN}^{Y*} = [183.04\ \ 196.91\ \ 182.22\ \ 20.04\ \ 77.67\ \ 83.09]^T$ (mils). The corresponding responses for 50 outcomes are shown in Fig. 5. The yield is increased from 18.4% to 66%, as shown in Fig. 6. Excellent agreement between the EM responses and the SM-based neuromodel responses is found at both the optimal nominal solution and the optimal yield solution.

Conclusions

An efficient procedure to realize EM-based statistical analysis and yield optimization of microwave structures using space mapping-based neuromodels is described.

Acknowledgement

The authors thank Dr. J.C. Rautio, President, Sonnet Software, Inc., Liverpool, NY, for making ***em***™ available.

References

[1] J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE Trans. Microwave Theory Tech.*, vol. 47, 1999, pp. 2417-2427.

[2] M.H. Bakr, J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neural space mapping optimization for EM-based design," *IEEE Trans. Microwave Theory Tech.*, vol. 48, 2000, pp. 2307-2315.

[3] OSA90/hope™ and Empipe™, Version 4.0, formerly Optimization Systems Associates Inc., P.O. Box 8083, Dundas, ON, Canada, L9H 5E7, 1997, now Agilent Technologies, 1400 Fountaingrove Parkway, Santa Rosa, CA 95403-1799.

[4] ***em***™ Version 4.0b, Sonnet Software, Inc., 1020 Seventh North Street, Suite 210, Liverpool, NY 13088, 1997.

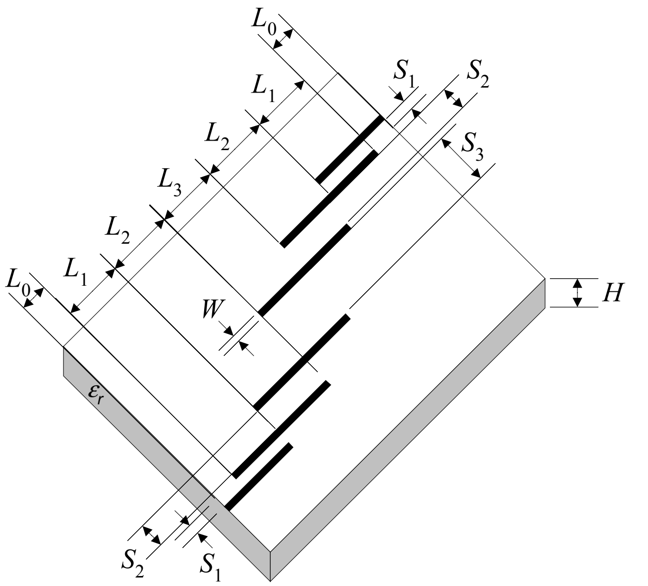

Fig. 1. HTS quarter-wave parallel coupled-line microstrip filter.

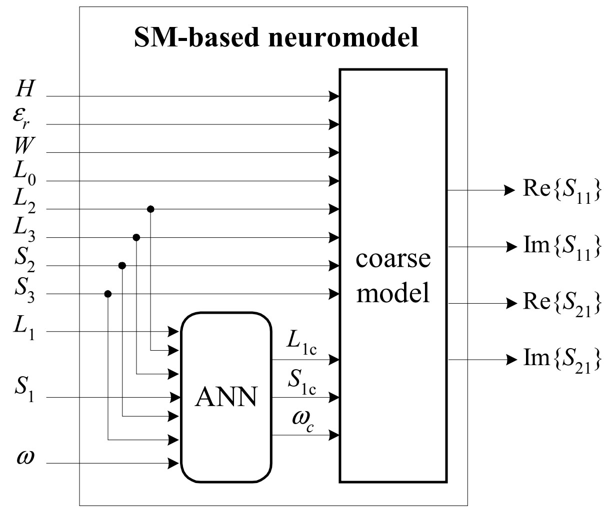

Fig. 2. SM-based neuromodel of the HTS filter for yield analysis assuming symmetry (L_{1c} and S_{1c} correspond to L_1 and S_1 as used by the coarse model).

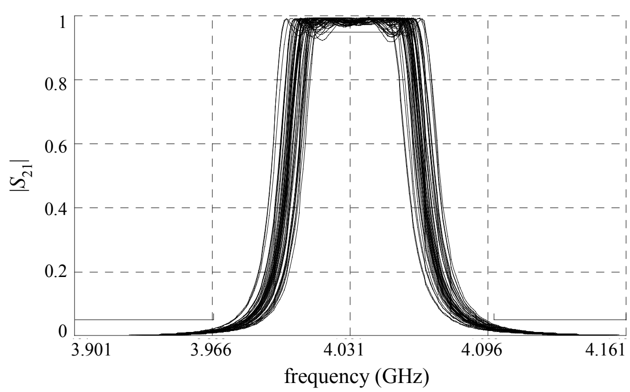

Fig. 3. Monte Carlo yield analysis of the SM-based neuromodel responses around the optimal nominal solution $\boldsymbol{x}_{SMBN}{}^{*}$ with 50 outcomes.

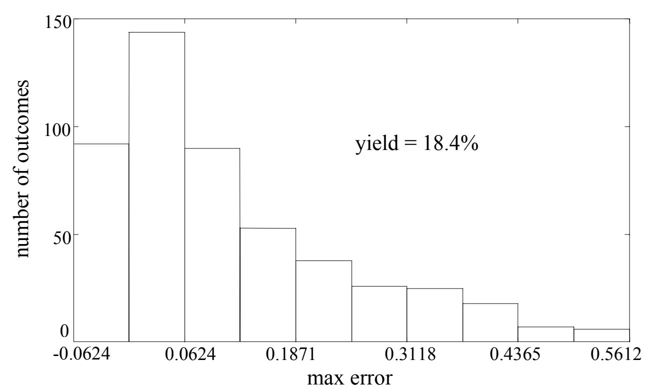

Fig. 4. Histogram of the yield analysis of the SM-based neuromodel around the optimal nominal solution $\boldsymbol{x}_{SMBN}{}^{*}$ with 500 outcomes.

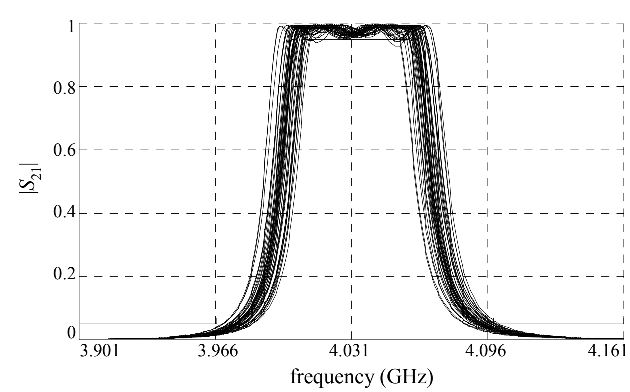

Fig. 5. Monte Carlo yield analysis of the SM-based neuromodel responses around the optimal yield solution $\boldsymbol{x}_{SMBN}{}^{Y*}$ with 50 outcomes.

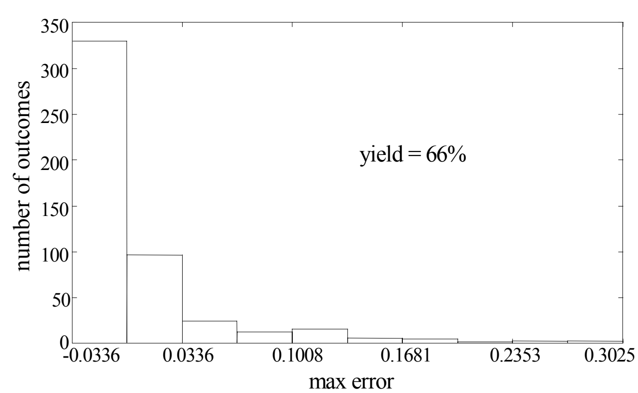

Fig. 6. Histogram of the yield analysis of the SM-based neuromodel around the optimal yield solution $\boldsymbol{x}_{SMBN}{}^{Y*}$ with 500 outcomes (considering symmetry).