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NEURAL SPACE MAPPING EM OPTIMIZATION OF MICROWAVE STRUCTURES

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ABSTRACT

We propose, for the first time, Neural Space Mapping optimization for EM-based design. It exploits our Space Mapping-based neuromodeling techniques, avoiding troublesome parameter extraction. Simple neuromodels are trained, without testing points, during each optimization iteration. Coarse model sensitivities are exploited to select suitable fine model base points for the initial mapping.

INTRODUCTION

Artificial Neural Networks (ANNs) are suitable models for microwave circuit yield optimization and statistical design. Neuromodels are computationally much more efficient than EM models. Once they are trained with reliable learning data, obtained from a “fine” model by either EM simulation or by measurement, the neuromodels can be used for efficient and accurate optimization within the region of training. This has been the conventional approach to microwave optimization using ANNs [1]. The principal drawback of this approach is the cost of generating sufficient learning samples, since the fine model must be evaluated for many combinations of different values of input parameters over a large region. Additionally, the extrapolation ability of neuromodels is poor, making unreliable any solution predicted outside the training region. Introducing knowledge, as in [2], can alleviate these limitations.

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A powerful new method for optimization of microwave circuits based on Space Mapping (SM) technology and Artificial Neural Networks (ANN) is presented. An innovative strategy is proposed to exploit our SM-based neuromodeling techniques [3] in an efficient Neural Space Mapping (NSM) optimization algorithm, including frequency. A “coarse” or empirical model is used not only as source of knowledge that reduces the amount of learning data and improves the generalization performance, but also as a means to select the initial learning base points through sensitivity analysis. A novel procedure that does not require parameter extraction to predict the next point is presented. Huber optimization is used to train the SM-based neuromodels at each iteration. The SM-based neuromodels are developed without using testing points: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons. NSM optimization is illustrated by an HTS microstrip filter.

NEURAL SPACE MAPPING (NSM) OPTIMIZATION: AN OVERVIEW

We start by finding the optimal solution $\boldsymbol{x}_c^*$ that yields the desired response using the coarse model. We select $2n$ additional points following an n-dimensional star distribution [3] centered at $\boldsymbol{x}_c^*$, where n is the number of design parameters

($\boldsymbol{x}_c$, $\boldsymbol{x}_f \in \Re^n$). The percentage of deviation from $\boldsymbol{x}_c^*$ for each design parameter is determined according to the coarse model sensitivity. The larger the sensitivity of the coarse model response w.r.t. a certain parameter, the smaller the percentage of variation of that parameter. We assume that the coarse model sensitivity is similar to that one of the fine model.

The fine model response $\boldsymbol{R}_f$ at the optimal coarse solution $\boldsymbol{x}_c^*$ is then calculated. If $\boldsymbol{R}_f$ is approximately equal to the desired response, the algorithm ends, otherwise we develop an SM-based neuromodel over the $2n$+1 fine model points.

Once an SM-based neuromodel with small learning errors is available, *we use it as an improved coarse model*, optimizing its parameters to generate the desired response. The solution to this problem becomes the next point in the fine model parameter space, and it is included in the learning set.

We calculate the fine model response at the new point, and compare it with the desired response. If it is still different, we re-train the SM-based neuromodel over the extended set of learning samples and the algorithm continues. If not, the algorithm terminates.

COARSE OPTIMIZATION

During the coarse optimization phase of NFSM optimization, we want to find the optimal coarse model solution $\boldsymbol{x}_c^*$ that generates the desired response over the frequency range of interest. The vector of coarse model responses $\boldsymbol{R}_c$ might contain m different responses (for example, $|S_{11}|$ and $|S_{21}|$),

$$\boldsymbol{R}_c(\boldsymbol{x}_c) = [\boldsymbol{R}_c^1(\boldsymbol{x}_c)^T \quad \ldots \quad \boldsymbol{R}_c^m(\boldsymbol{x}_c)^T]^T \tag{1}$$

where each individual response has been sampled at F_p frequency points,

$$\boldsymbol{R}_c^r(\boldsymbol{x}_c) = [R_c^r(\boldsymbol{x}_c, \omega_1) \quad \ldots \quad R_c^r(\boldsymbol{x}_c, \omega_{F_p})]^T \qquad r = 1, \ldots, m \tag{2}$$

The desired response $\boldsymbol{R}^*$ is expressed in terms of specifications. The problem of circuit design using the coarse model can be formulated as [4]

$$\boldsymbol{x}_c^* = \arg\min_{\boldsymbol{x}_c} U(\boldsymbol{R}_c(\boldsymbol{x}_c)) \tag{3}$$

where U is a suitable objective function. For example, U could be a minimax objective function expressed in terms of upper and lower specifications for each response and frequency sample. A rich collection of objective functions, for different design constraints, is in [4].

TRAINING THE SM-BASED NEUROMODEL DURING NSM OPTIMIZATION

At the ith iteration, we find the simplest neuromapping $\boldsymbol{P}^{(i)}$ such that the coarse model using that mapping approximates the fine model at all the learning points. This is realized by solving

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\cdots \quad \boldsymbol{e}_s^T \quad \cdots]^T \right\| \tag{4}$$

$$\boldsymbol{e}_s = \boldsymbol{R}_f(\boldsymbol{x}_f^{(l)}, \omega_j) - \boldsymbol{R}_c(\boldsymbol{x}_{c_j}^{(l)}, \omega_{c_j}) \tag{5a}$$

$$\begin{bmatrix} \boldsymbol{x}_{c_j}^{(l)} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f^{(l)}, \omega_j, \boldsymbol{w}) \tag{5b}$$

$$j = 1, \ldots, F_p \tag{5c}$$

$$l = 1, \ldots, 2n + i \tag{5d}$$

$$s = j + F_p(l-1) \tag{5e}$$

where $2n + i$ is the number of training base points and F_p is the number of frequency points per frequency sweep. The total number of learning samples at the ith iteration is $s = (2n + i)\ F_p$.

(5b) is the input-output relationship of the ANN that implements the mapping at the ith iteration. Vector $\boldsymbol{w}$ contains the internal parameters (weights, bias, etc.) of the ANN. The paradigm chosen to implement $\boldsymbol{P}^{(i)}$ is a 3-layer perceptron.

All the SM-based neuromodeling techniques proposed in [3] can be exploited to solve (4). The starting point for the first training is a unit mapping, i.e., $\boldsymbol{P}^{(0)}(\boldsymbol{x}_f^{(l)}, \omega_j, \boldsymbol{w}_u) = [\boldsymbol{x}_f^{(l)T}\ \omega_j]^T$, for $j = 1, \ldots, F_p$ and $l = 1, \ldots, 2n$+1, where $\boldsymbol{w}_u$ contains the internal parameters of the ANN for a unit mapping. The SM-based neuromodel is trained in the next iterations using the previous mapping as the starting point.

The complexity of the ANN is gradually increased according to the learning error ε_L, starting with a linear mapping (3-layer perceptron with 0 hidden neurons). In other words, we use the simplest ANN that yields an acceptable learning error, defined as

$$\varepsilon_L = \left\| [\cdots \quad \boldsymbol{e}_s^{\,T} \quad \cdots]^T \right\| \tag{6}$$

where $\boldsymbol{e}_s$ is obtained from (5) using the current optimal values for the ANN free parameters $\boldsymbol{w}^*$.

SM-BASED NEUROMODEL OPTIMIZATION

At the *i*th iteration of NSM optimization, we use an SM-based neuromodel with small learning error as an improved coarse model, optimizing its parameters to generate the desired response. We denote the SM-based neuromodel response as $\boldsymbol{R}_{SMBN}$, defined as

$$\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f) = [\boldsymbol{R}^1_{SMBN}(\boldsymbol{x}_f)^T \quad \ldots \quad \boldsymbol{R}^m_{SMBN}(\boldsymbol{x}_f) \tag{7}$$

where

$$\boldsymbol{R}^r_{SMBN}(\boldsymbol{x}_f) = [R^r_c(\boldsymbol{x}_{c1}, \omega_{c1}) \quad \ldots \quad R^r_c(\boldsymbol{x}_{cF_p}, \omega_{cF_p})]^T, \quad r = 1,\ldots,m \tag{8}$$

with

$$\begin{bmatrix} \boldsymbol{x}_{c_j} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j, \boldsymbol{w}^*) \tag{9}$$

and j defined in (5c). The solution to the following optimization problem becomes the next iterate:

$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f)) \tag{10}$$

If an SMN neuromapping is used to implement $\boldsymbol{P}^{(i)}$, the next iterate can be obtained in a simpler manner

$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} \left\| \boldsymbol{P}^{(i)}_{SM}(\boldsymbol{x}_f, \boldsymbol{w}^*) - \boldsymbol{x}_c^* \right\| \tag{11}$$

NSM ALGORITHM

Step 0. Find $\boldsymbol{x}_c^*$ by solving (3).

Step 1. Choose $\boldsymbol{x}_f^{(1)},\ldots,\ \boldsymbol{x}_f^{(2n)}$ following a star distribution around $\boldsymbol{x}_c^*$.

Step 2. Initialize $i = 1$, $\boldsymbol{x}_f^{(2n+i)} = \boldsymbol{x}_c^*$.

Step 3. Stop if
$$\left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(2n+i)}, \omega_j) - \boldsymbol{R}_c(\boldsymbol{x}_c^*, \omega_j) \right\| \le \varepsilon_R, \quad j = 1,\ldots,F_p.$$

Step 4. Initialize $\boldsymbol{P}^{(i)} = \boldsymbol{P}^{(i-1)}$, where
$$\boldsymbol{P}^{(0)}(\boldsymbol{x}_f^{(l)}, \omega_j, \boldsymbol{w}_u) = \begin{bmatrix} \boldsymbol{x}_f^{(l)} \\ \omega_j \end{bmatrix}, \quad j = 1,\ldots,F_p;\ \ l = 1,\ldots,2n+i.$$

Step 5. Find $\boldsymbol{w}^*$ by solving (4).

Step 6. Calculate ε_L using (6).

Step 7. If $\varepsilon_L > \varepsilon_{\min}$, increase the complexity of $\boldsymbol{P}^{(i)}$ and go to Step 5.

Step 8. If an SM neuromapping is used to implement $\boldsymbol{P}^{(i)}$, solve (11), otherwise solve (10).

Step 9. Set $i = i + 1$; go to Step 3.

HTS MICROSTRIP FILTER

We apply NSM optimization to a high-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter. 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 between the sections. The width W is the same for all the sections as well as for the input and output microstrip lines, of length L_0. A lanthanum aluminate substrate with thickness H and dielectric constant ε_r is used.

The specifications are $|S_{21}| \ge 0.95$ in the passband and $|S_{21}| \le 0.05$ in the stopband, where the stopband includes frequencies below 3.967 GHz and above 4.099 GHz, and the passband lies in the range [4.008GHz, 4.058GHz]. The design parameters are $\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$. We take L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; the metalization is considered lossless.

Sonnet's ***em***™ driven by Empipe™ was employed as the fine model, using a high-resolution grid. OSA90/hope™ built-in linear elements MSL (microstrip line), MSCL (two-conductor symmetrical coupled microstrip lines) and OPEN (open circuit) connected by circuit theory over the same MSUB (microstrip substrate definition) are taken as the "coarse" model.

The coarse and fine model responses at the optimal coarse model solution x_c^* are shown in Fig. 1(a). The initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: 3% deviation from x_c^* for L_1, L_2, and L_3 is used, while 20% is used for S_1, S_2, and S_3.

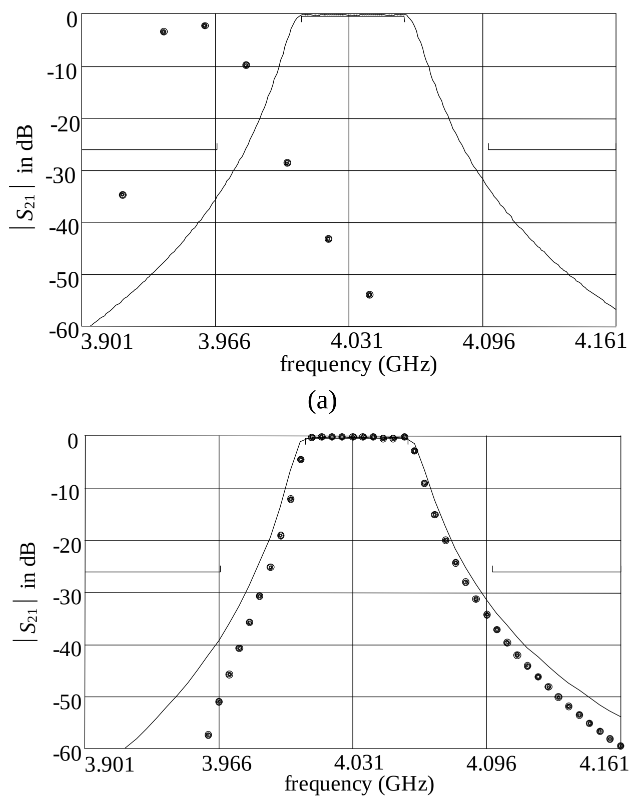

Fig. 1. Responses from Sonnet's ***em***™ (•) compared with desired response (–): (a) at the starting point, (b) at the point predicted by the first NSM iteration.

The final mapping follows a FPSM approach [3] using a 3-layer perceptron with 7 inputs (6 design parameters and the frequency), 5 hidden neurons, and 3 output neurons (ω, L_1, and S_1).

The next point predicted by optimizing the coarse model with the mapping found matches the desired response with excellent accuracy, as seen in Fig. 1(b), where a fine frequency sweep is used. The NFSM solution satisfies the specifications. The HTS filter is optimized in only one NSM iteration.

CONCLUSIONS

We propose EM optimization exploiting Space Mapping technology and Artificial Neural Networks. Our Neural Space Mapping (NSM) optimization algorithm exploits SM-based neuromodeling techniques to efficiently approximate mappings from the fine to the coarse input space. NSM does not require parameter extraction to predict the next point. An initial mapping is established by performing upfront fine model analysis at a number of base points. Coarse model sensitivities are exploited to select the base points. Huber optimization trains simple SM-based neuromodels at each iteration without using testing points. Their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons. An HTS filter is optimized in only one NSM iteration.

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