A CAD ENVIRONMENT FOR PERFORMANCE AND YIELD DRIVEN CIRCUIT DESIGN EMPLOYING ELECTROMAGNETIC FIELD SIMULATORS

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A CAD Environment for Performance and Yield Driven Circuit Design Employing Electromagnetic Field Simulators

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ABSTRACT

In this paper we describe a CAD environment for performance and yield driven circuit design with electromagnetic (EM) field simulations employed within the optimization loop. Microstrip structures are accurately simulated and their responses are incorporated into the overall circuit analysis. We unify the component level interpolation technique, devised to handle discretization of geometrical parameters, and the modeling technique used to lighten the computational burden of statistical design centering. We discuss the organization and utilization of our data base system integrated with the modeling technique. We demonstrate the feasibility and benefits of performance and yield optimization with EM simulations.

INTRODUCTION

Electromagnetic (EM) field simulators, though computationally intensive, are regarded as highly accurate at microwave frequencies. With the increasing availability of EM simulators it is very tempting to include them in performance-driven and even in yield-driven circuit optimization. Feasibility of such optimization has already been shown in our pioneering work [1,2].

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We unify our interpolation technique, devised to reconcile inherent discretization of geometrical parameters with continuously varying optimization variables, and our modeling technique used for computationally intensive statistical design centering.

We report new results on circuit design employing EM simulators. Simulation of a microstrip line demonstrates the flexibility of our interpolation and modeling technique. With a 3-section microstrip impedance transformer we illustrate nominal and yield-driven design optimization. These results were obtained using the CAD system OSA90/hope [3] interfaced to the *em* field simulator from Sonnet Software [4] through Empipe [3].

EFFICIENT INTERPOLATION/MODELING

Numerical EM simulation requires discretized, or on-the-grid, values of geometrical parameters. Gradient based optimizers, on the other hand, assume continuously varying parameters. To this end we interpolate responses for off-the-grid points. Our efficient quadratic modeling technique [2,5,6] is extended and unified to handle this geometrical interpolation.

The quadratic model (or the Q-model) of a generic response $f(x)$ is a quadratic polynomial of the form [5,6]

$$q(x) = a_0 + \sum_{i=1}^{n} a_i(x_i - r_i) + \sum_{\substack{i=1 \\ j \geq i}}^{n} a_{ij}(x_i - r_i)(x_j - r_j) \quad (1)$$

where $x = [x_1 \; x_2 \; \ldots \; x_n]^T$ is the vector of generic parameters and $r = [r_1 \; r_2 \; \ldots \; r_n]^T$ is a chosen reference point in the parameter space.

To build the Q-model we use $n + 1 \leq m \leq 2n + 1$ base points at which the function $f(\boldsymbol{x})$ is evaluated. The reference point $\boldsymbol{r}$ is selected as the first base point $\boldsymbol{x}^1$. The remaining $m - 1$ base points are selected by perturbing one variable at a time around $\boldsymbol{r}$ with a predetermined perturbation β_i. If a variable is perturbed twice the second perturbation is located symmetrically w.r.t. $\boldsymbol{r}$. Applying the Maximally Flat Quadratic Interpolation technique [5] to such a set of base points results in simple and efficient formulas for the Q-model $q(\boldsymbol{x})$ [2].

This formulation allows for a flexible choice of the number of base points starting at $m = n + 1$ which leads to the linear model (or the L-model), through linear/quadratic models w.r.t. selected variables, to the quadratic model w.r.t. all variables.

To discretize the model parameters we consider simulation and modeling grids. The first one is imposed by the EM simulator. Let the simulation grid $\boldsymbol{\delta}_S$ be defined as

$$\boldsymbol{\delta}_S = [\delta_{S1}\ \delta_{S2}\ \dots\ \delta_{Sn}]^T \tag{2}$$

The simulation grid sizes are floating point numbers and have the same units as the corresponding parameters. The modeling grid constitutes a subset of points defined by the simulation grid and is implied by the multipliers

$$\boldsymbol{\delta}_M = [\delta_{M1}\ \delta_{M2}\ \dots\ \delta_{Mn}]^T \tag{3}$$

The modeling grid multipliers are dimensionless integers. Both $\boldsymbol{\delta}_S$ and $\boldsymbol{\delta}_M$ are positive. The first modeling grid point is aligned with the first nonzero simulation grid point. For the ith parameter the distance between adjacent modeling grid points is the δ_{Mi} multiple of the simulation grid δ_{Si}, i.e., $\delta_{Mi}\delta_{Si}$. In our approach, EM simulations are performed at the modeling grid points only.

To utilize the Q-modeling technique for geometrical interpolation we first generate a set of m base points called the interpolation base $\boldsymbol{B}$. The reference point $\boldsymbol{r}$ is selected as the first base point $\boldsymbol{x}^1$ by snapping $\boldsymbol{x} = [x_1\ x_2\ \dots\ x_n]^T$ to the closest (in the ℓ_2 sense) modeling grid point. The vector

$$\boldsymbol{\theta} = [\theta_1\ \theta_2\ \dots\ \theta_n]^T \tag{4}$$

defines the relative deviation of $\boldsymbol{x}$ from $\boldsymbol{r}$ and is calculated as

$$\theta_i = (x_i - r_i)/(\delta_{Si}\delta_{Mi}), \quad i = 1, 2, \dots, n \tag{5}$$

The other base points are created by perturbing one variable at a time around $\boldsymbol{r}$. The magnitude of the perturbation β_i is $\delta_{Si}\delta_{Mi}$. These base points can then be expressed as

$$\boldsymbol{x}^{i+1} = \boldsymbol{r} + [0\dots0\ \ +\delta_{Si}\delta_{Mi}\ \ 0\dots0]^T,\ i = 1, \dots, n \tag{6a}$$

$$\boldsymbol{x}^{n+1+i} = \boldsymbol{r} + [0\dots0\ \ -\delta_{Si}\delta_{Mi}\ \ 0\dots0]^T,\quad i = 1, \dots, m - (n + 1) \tag{6b}$$

For each Q-model we define a validity region $\boldsymbol{V}$. If $\boldsymbol{x} \in \boldsymbol{V}$ than we assume that the model is valid and that $q(\boldsymbol{x}) \approx f(\boldsymbol{x})$. If $\boldsymbol{x} \notin \boldsymbol{V}$ the model $q(\boldsymbol{x})$ must be updated. One possible choice for $\boldsymbol{V}$ is given by

$$\boldsymbol{V} = \{\boldsymbol{x} \mid \frac{-\delta_{Si}\delta_{Mi}}{2} < (x_i - r_i) \leq \frac{\delta_{Si}\delta_{Mi}}{2}\},\ i = 1, 2, \dots, n \tag{7}$$

It is easy to see from (1) that if a certain x_i in $\boldsymbol{x}$ has the same value as the corresponding r_i in $\boldsymbol{r}$ then the contribution of x_i to $q(\boldsymbol{x})$ is zero. Therefore, the base points $\boldsymbol{x}^{i+1}$ and $\boldsymbol{x}^{n+1+i}$ need not be simulated and can be excluded from the interpolation base $\boldsymbol{B}$.

MULTILEVEL MODELING

The circuit under consideration may be divided into subcircuits, possibly in a hierarchical manner. At the lowest level we have circuit components, e.g., a lumped capacitor or a microstrip structure.

We can express the response of the circuit as a function of the subcircuit responses which are in turn functions of component responses.

We can create a single Q-model for the overall circuit or a hierarchy of Q-models to represent some or all of the subcircuits and components. By applying the Q-modeling technique to geometrical interpolation outlined in the preceding section we effectively unify the overall multilevel modeling approach and address it in a consistent manner at all levels of hierarchy.

INTEGRATED DATA BASE/MODELING SYSTEM

Let the set of base points for a Q-model be defined by $[\boldsymbol{x}^1\ \boldsymbol{x}^2\ \dots\ \boldsymbol{x}^m]^T$, where $\boldsymbol{x}^1$ is the reference point $\boldsymbol{r}$, $n + 1 \leq m \leq 2n + 1$, and n is the number of model parameters. Then we can express the simulation results at these base points as

$$[f(\boldsymbol{x}^1)\ f(\boldsymbol{x}^2)\ \dots\ f(\boldsymbol{x}^m)] \tag{8}$$

with

$$f(\boldsymbol{x}^i) = [f_1(\boldsymbol{x}^i)\ \dots\ f_k(\boldsymbol{x}^i)]^T,\ i = 1, 2, \dots, m \tag{9}$$

where k is the total number of different responses. f can be a response of the overall circuit, a subcircuit or a component. Then

$$f(x) \approx q(x) = [q_1(x)\ q_2(x)\ \dots\ q_k(x)]^T \qquad (10)$$

The Q-models in (10) approximate $f(x)$ for x belonging to the Q-model validity region V centered around the reference point $r = x^1$.

The nominal point moves during optimization, and so does, in the case of yield optimization, the set of associated statistical outcomes. This may result in parameter values of the nominal point as well as of some or even all the statistical outcomes to be outside of the validity region V for the current Q-models. When this happens, the Q-models are automatically updated. That is, a new set of base points is formed, the responses at these base points are simulated *but only if they have not been simulated previously*, and the updated Q-models are generated.

In order to avoid repeated simulations, we maintain a data base of the already simulated base points together with the corresponding responses. These results are stored and accessed when necessary. Each time simulation is requested the corresponding interpolation base B is generated and checked against the existing data base. Actual simulation is invoked only for the base points not present in the data base. The data base and the Q-models are automatically updated whenever new simulation results become available.

A MICROSTRIP LINE EXAMPLE

To illustrate the benefits and flexibility of the Q-modeling technique we simulate a microstrip line with different simulation and modeling grids. The substrate is 25 mil thick and the relative dielectric constant is 9.8. The width of the line is 25 mil and the length is varied from 100 to 202.5 mils with a 2.5 mil step. There are two geometrical parameters: the line width W and length L.

To establish reference data we use a fine simulation grid set to 2.5 mil for both parameters. Setting the modeling grid multipliers to 1 and using the sweep step of 2.5 mil, all simulations are performed for on-the-grid points. No interpolation is needed.

We perform two experiments. In the first one we increase both simulation and modeling grids to a coarse 25 mil grid. In the second one we use the original fine simulation grid but change the modeling grid multiplier for the line length to 10. In both cases we build and examine the L-models as well as the Q-models. On a Sun SPARCstation 10 it takes 0.3 and 5 CPU seconds to simulate the line at a single frequency using the coarse and fine simulation grids, respectively.

All curves in Fig. 1 show the $|S_{11}|$ response vs. the line length L at 10 GHz for different grids and models. The curves form two groups. Each group contains responses of both the L- (solid lines) and the Q-models (dashed lines). Solid dots indicate EM simulations needed to build the models. The upper group of curves is formed by the reference data and by the responses of the models built using the fine simulation and coarse modeling grids. The lower group of curves is formed by the responses of the models built using the coarse simulation grid. Clearly, responses of the models built using the fine simulation grid are much closer to the reference data, even if the modeling grid is coarse. This is because the accuracy of the EM simulations and hence of the models is much better when the fine simulation grid is used.

YIELD OPTIMIZATION OF A 3-SECTION MICROSTRIP IMPEDANCE TRANSFORMER

We consider a 3-section microstrip impedance transformer [2]. The source and load impedances are 50 and 150 Ω, respectively. The design specification is set for input reflection coefficient as

$$|S_{11}| \leq 0.11, \text{ from 5 GHz to 15 GHz}$$

The error functions for yield optimization are calculated at frequencies from 5 GHz to 15 GHz with a 0.5 GHz step. The substrate is 0.635 mm thick with relative dielectric constant of 9.7. The

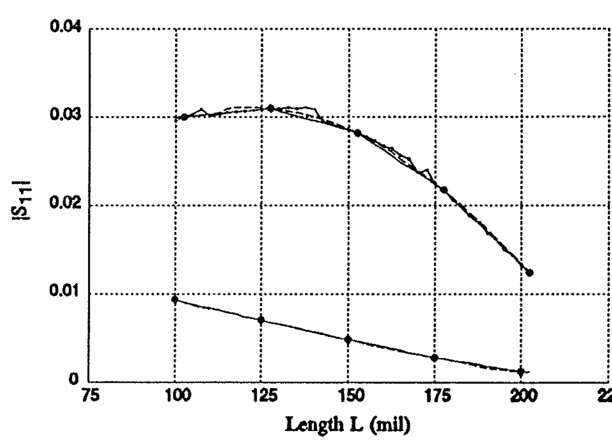

Figure 1

widths of the transformer sections, W_1, W_2 and W_3, are considered as optimization variables. The lengths, L_1, L_2 and L_3, are kept fixed. To obtain a good starting point for yield optimization we first perform minimax design. The maximum of $|S_{11}|$ is decreased from 0.28 to 0.09.

For all six geometrical parameters we assume normal distributions. Standard deviations are 0.005 mm and 2% for the lengths and widths, respectively. Yield estimated from 250 outcomes at the starting point (minimax solution) is 61%. It is increased to 77% after yield optimization. We used 100 outcomes in yield optimization. The Monte Carlo sweep at the centered design is shown in Fig. 2. The starting point, minimax and centered solutions are listed in Table I.

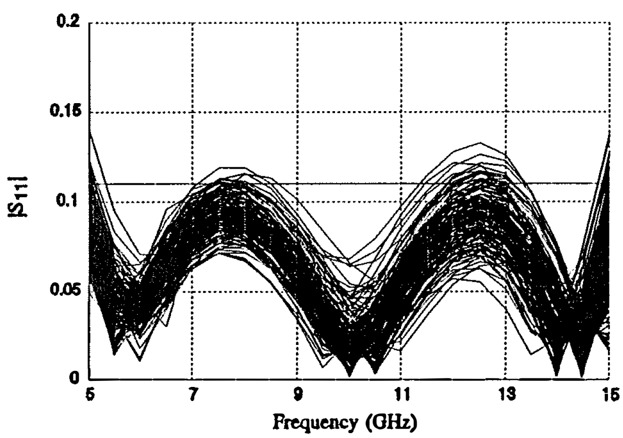

Figure 2

TABLE I
NOMINAL AND YIELD OPTIMIZATION OF A 3-SECTION MICROSTRIP TRANSFORMER

Parameter	Starting point (mm)	Minimax solution (mm)	Centered solution (mm)
W_1	0.65	0.349	0.373
W_2	0.35	0.139	0.165
W_3	0.15	0.039	0.049

L_1, L_2 and L_3 are fixed at 3 mm.

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CONCLUSIONS

In this paper we have described a CAD environment for performance and yield-driven design of circuits employing accurate EM field simulations. We have unified an efficient modeling technique used to decrease the computational burden of statistical design centering with geometrical interpolation needed to overcome problems related to the discrete nature of EM simulation. We have outlined the organization and utilization of our data base system integrated with the modeling technique. We have also outlined the concept of multilevel modeling. Simulation of a microstrip line demonstrates the flexibility of our unified interpolation/modeling technique. It also shows possible trade-offs between efficiency of EM simulations and accuracy of the models. We used a 3-section microstrip impedance transformer to exemplify the feasibility and benefits of both performance and yield-driven design with EM simulations invoked within the optimization loop.

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