SIMULATION OPTIMIZATION SYSTEMS
Research Laboratory

MULTILEVEL MULTIDIMENSIONAL QUADRATIC MODELING FOR YIELD-DRIVEN ELECTROMAGNETIC OPTIMIZATION

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Abstract

Powerful multilevel multidimensional quadratic modeling has been developed for efficient yield-driven design. This approach makes it possible, for the first time, to perform direct yield optimization of circuits with components simulated by an electromagnetic simulator. Efficiency and accuracy of our technique are demonstrated by yield optimization of a small-signal amplifier.

Introduction

we extend our highly efficient quadratic approximation technique to multilevel modeling

it is particularly suitable for circuits containing complex subcircuits or components whose simulation requires significant computational effort

direct utilization of electromagnetic (EM) simulation for yield optimization might seem to be computationally prohibitive

our approach makes it possible to perform yield optimization of circuits with microstrip structures simulated by an EM simulator

by constructing local quadratic models for each component simulated by an EM simulator we effectively overcome the computational burden of repeated EM simulations

when the multilevel quadratic modeling technique is used together with expensive, but more accurate simulations at the component level, the results are more reliable than those obtained from traditional empirical component simulations

efficiency and accuracy of our technique are demonstrated by yield optimization of a small-signal amplifier

Yield Optimization

the problem of yield optimization can be formulated as

$$\underset{\phi^0}{\text{maximize}} \; \{ \; Y(\phi^0) = \int_{R^n} I_a(\phi) f_\phi(\phi^0, \phi) d\phi \; \}$$

where

ϕ^0	nominal circuit parameters
ϕ	actual circuit outcome parameters
$Y(\phi^0)$	design yield
$f_\phi(\phi^0, \phi)$	probability density function of ϕ around ϕ^0
A	acceptability region

in practice, the integral is approximated using K Monte Carlo circuit outcomes ϕ^i and yield is estimated by

the outcomes ϕ^i are generated by a random number generator according to $f_\phi(\phi^0, \phi)$

Error and Objective Functions

to estimate yield we create a set of multi-circuit error functions $e(\phi^1), e(\phi^2), ..., e(\phi^K)$

the error functions $e(\phi^i)$ are derived from the circuit responses R_j and lower specifications (S_l) and upper specifications (S_u) as

$$e_j(\phi^i) = R_j(\phi^i) - S_{uj} \quad \text{or} \quad e_j(\phi^i) = S_{lj} - R_j(\phi^i)$$

for yield optimization we use the one-sided ℓ_1 objective function

$$U(\phi^0) = \sum_{i \in J} \alpha_i v(\phi^i)$$

where

$J = \{i \mid v(\phi^i) > 0\}$

α_i suitably chosen positive multipliers

$v(\phi^i)$ generalized ℓ_1 function

consequently, $U(\phi^0)$ becomes an approximation to the percentage of outcomes violating design specifications and minimization of $U(\phi^0)$ leads to yield improvement

Efficient Q-Modeling - Concept
(*Biernacki et al., 1989*)

the *Q-model* to approximate a generic response $f(\boldsymbol{x})$ is a multidimensional quadratic polynomial of the form

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

where

$\boldsymbol{x} = [x_1\, x_2 \ldots x_n]^T$ vector of generic circuit parameters
$\boldsymbol{r} = [r_1\, r_2 \ldots r_n]^T$ chosen reference point

to build the model we use $n+1 < m \leq 2n+1$ 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 $\boldsymbol{\beta}_i$

$$\boldsymbol{x}^{i+1} = \boldsymbol{r} + [0 \ldots 0\ \boldsymbol{\beta}_i\ 0 \ldots 0]^T, \quad i = 1, 2, \ldots, n$$

$$\boldsymbol{x}^{n+1+i} = \boldsymbol{r} + [0 \ldots 0\ \text{-}\boldsymbol{\beta}_i\ 0 \ldots 0]^T, \quad i = 1, 2, \ldots, m\text{-}(n+1)$$

Efficient Q-Modeling - Formulas

applying the Maximally Flat Quadratic Interpolation (MFQI) technique to the set of base points yields

$$q(\boldsymbol{x}) = f(\boldsymbol{r}) + \sum_{i=1}^{m-(n+1)} \Big\{ [f(\boldsymbol{x}^{i+1}) - f(\boldsymbol{x}^{n+1+i}) + (f(\boldsymbol{x}^{i+1}) + f(\boldsymbol{x}^{n+1+i}) - 2f(\boldsymbol{r}))(x_i - r_i)/\beta_i](x_i - r_i)/(2\beta_i) \Big\} + \sum_{i=m-n}^{n} \Big\{ [f(\boldsymbol{x}^{i+1}) - f(\boldsymbol{r})](x_i - r_i)/\beta_i \Big\}$$

to apply a gradient-based optimizer we need the gradient of $q(\boldsymbol{x})$

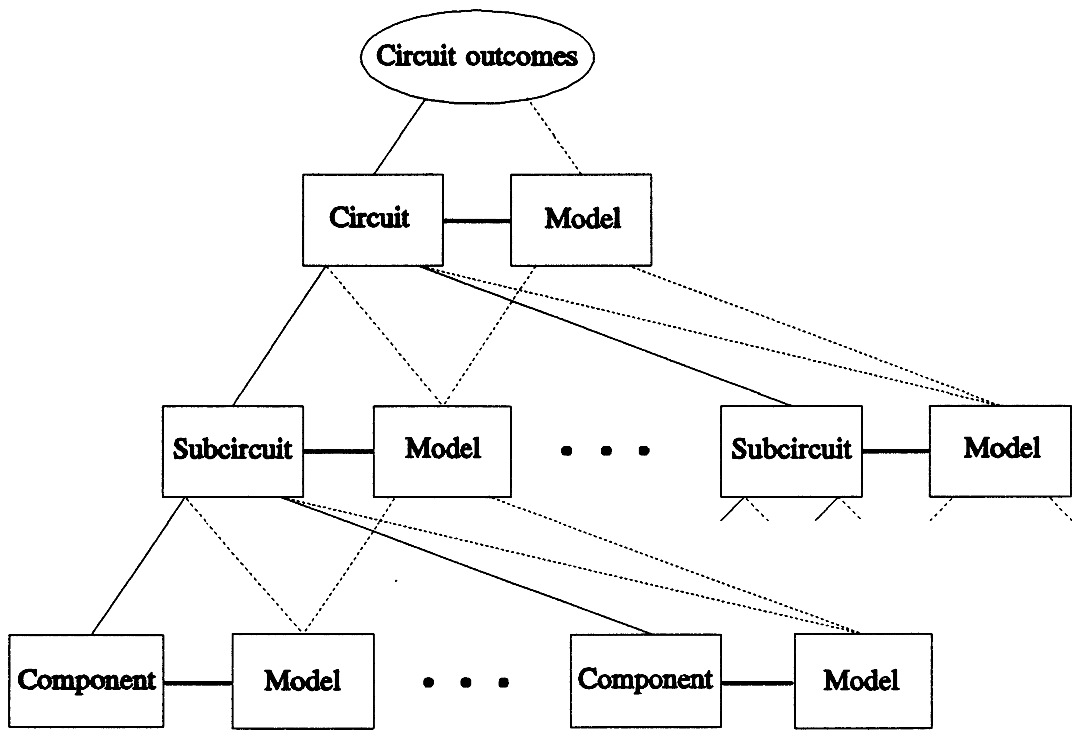
$$\partial q(\boldsymbol{x})/\partial x_i = [(f(\boldsymbol{x}^{i+1}) - f(\boldsymbol{x}^{n+1+i}))/2 + (f(\boldsymbol{x}^{i+1}) + f(\boldsymbol{x}^{n+1+i}) - 2f(\boldsymbol{r}))(x_i - r_i)/\beta_i]/\beta_i, \quad i = 1, \ldots, m-(n+1)$$

and, if $m<2n+1$,

$$\partial q(\boldsymbol{x})/\partial x_i = [f(\boldsymbol{x}^{i+1}) - f(\boldsymbol{r})]/\beta_i, \quad i=m-n, \ldots, n$$

the simplicity of these formulas results in unsurpassed efficiency

Multilevel Modeling



a Q-model can be established at any level for some or all subcircuits and components

the models are built from the results of exact simulations of the corresponding component, subcircuit, or the overall circuit

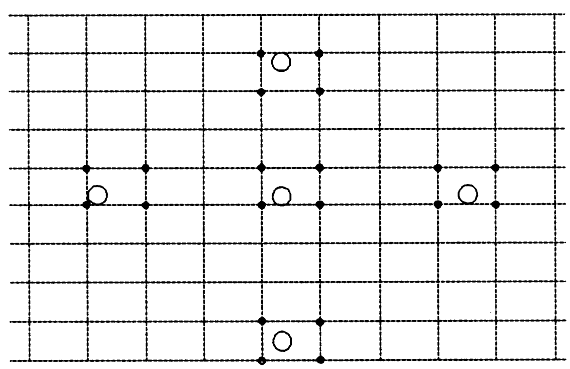
once the Q-model is established, it is used in place of the corresponding simulator

many Q-models may exist changing the path of calculations as indicated by different links in the figure

Model Variables

the vector $\boldsymbol{x}$ of circuit, subcircuit or component model variables may contain different combinations of designable $\boldsymbol{x}_D$, statistical $\boldsymbol{x}_S$, or discrete $\boldsymbol{x}_G$ parameters

the discrete parameters $\boldsymbol{x}_G$ are those for which simulation can only be performed at discrete values located on the grid as in EM simulation

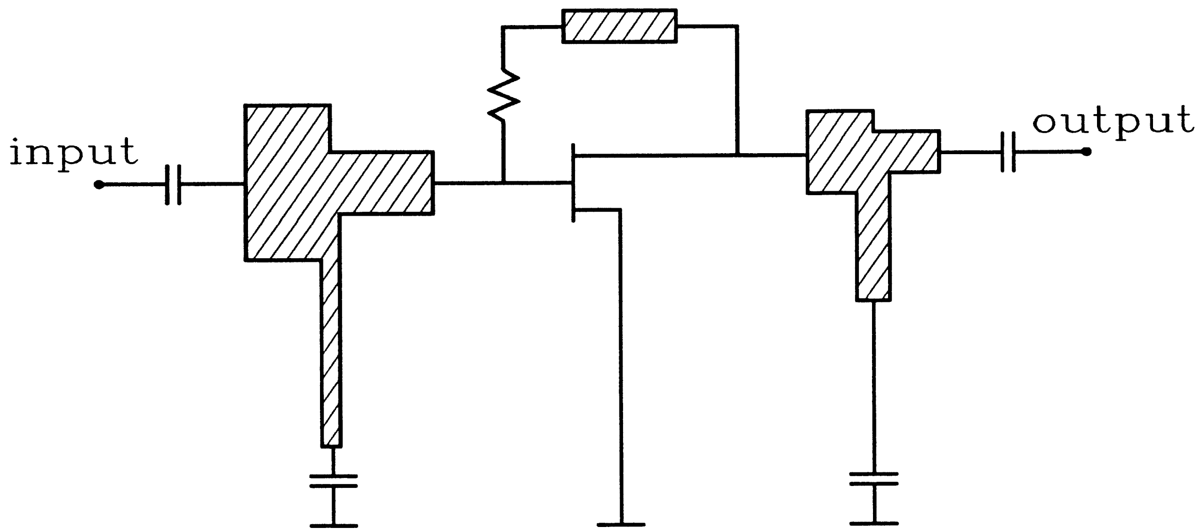


the reference vector and other base points are likely to be off-the-grid

local interpolation involving several simulations on the grid in the vicinity of each of the base points must then be performed

in order to avoid excessive simulations the base points are modified to snap to the grid

Optimization of a Small-Signal Amplifier



the specifications for yield optimization of the amplifier are

$$7 \text{ dB} \leq |S_{21}| \leq 8 \text{ dB} \qquad \text{for} \qquad 6 \text{ GHz} < f < 18 \text{ GHz}$$

the gate and drain circuit microstrip T-junctions and the feedback microstrip line are built on a 10 mil thick substrate with relative dielectric constant 9.9

the microstrip components of the amplifier are simulated using component level Q-models built from EM simulations

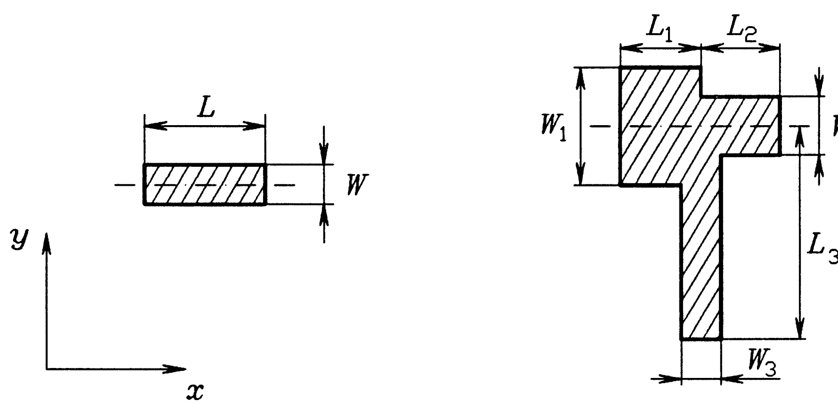
we used ***em***™ from *Sonnet Software* for EM simulations

Optimization Variables

W_{g1}, L_{g1}, W_{g2}, L_{g2} of the gate circuit T-junction and W_{d1}, L_{d1}, W_{d2}, L_{d2} of the drain circuit T-junction are the optimization variables

W_{g3}, L_{g3}, W_{d3} and L_{d3} of the T-junctions, W and L of the feedback microstrip line, as well as the FET parameters are not optimized

parameters of the microstrip line (a) and the T-junctions (b)



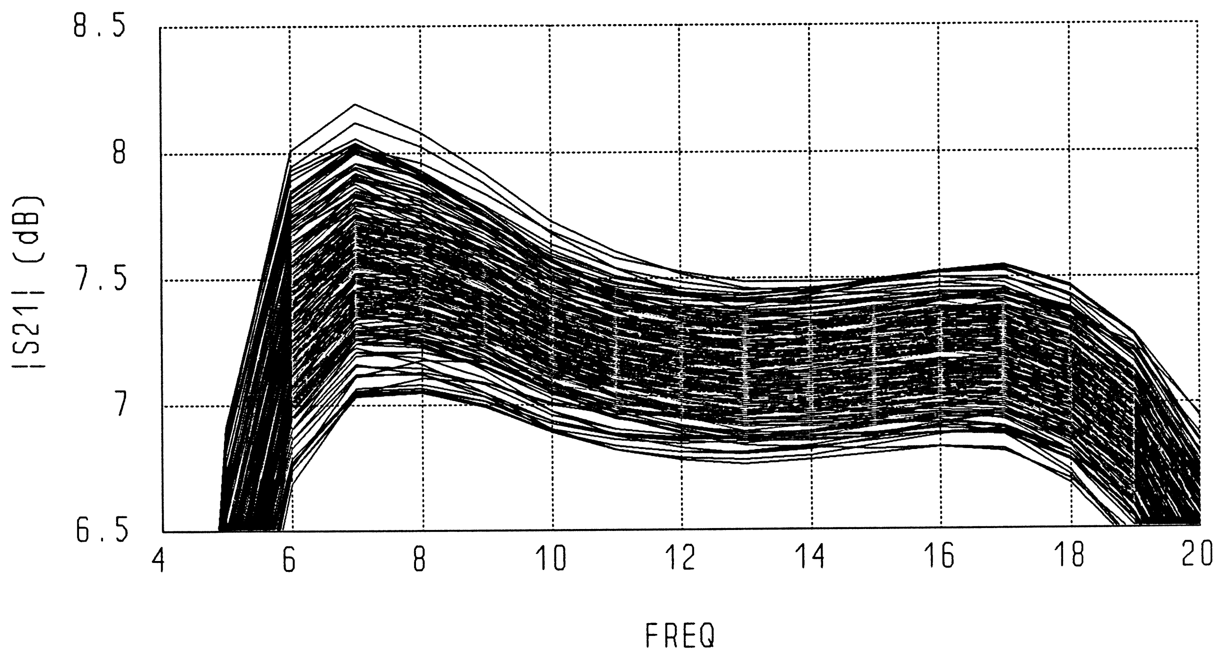
(a) (b)

we assumed 0.5 mil tolerance and uniform distribution for all geometrical parameters of the microstrip components

the statistics of the small-signal FET model were extracted from measurement data

Small-Signal Amplifier Yield Before Optimization

the starting point for yield optimization was obtained by nominal minimax optimization using analytical/empirical microstrip component models



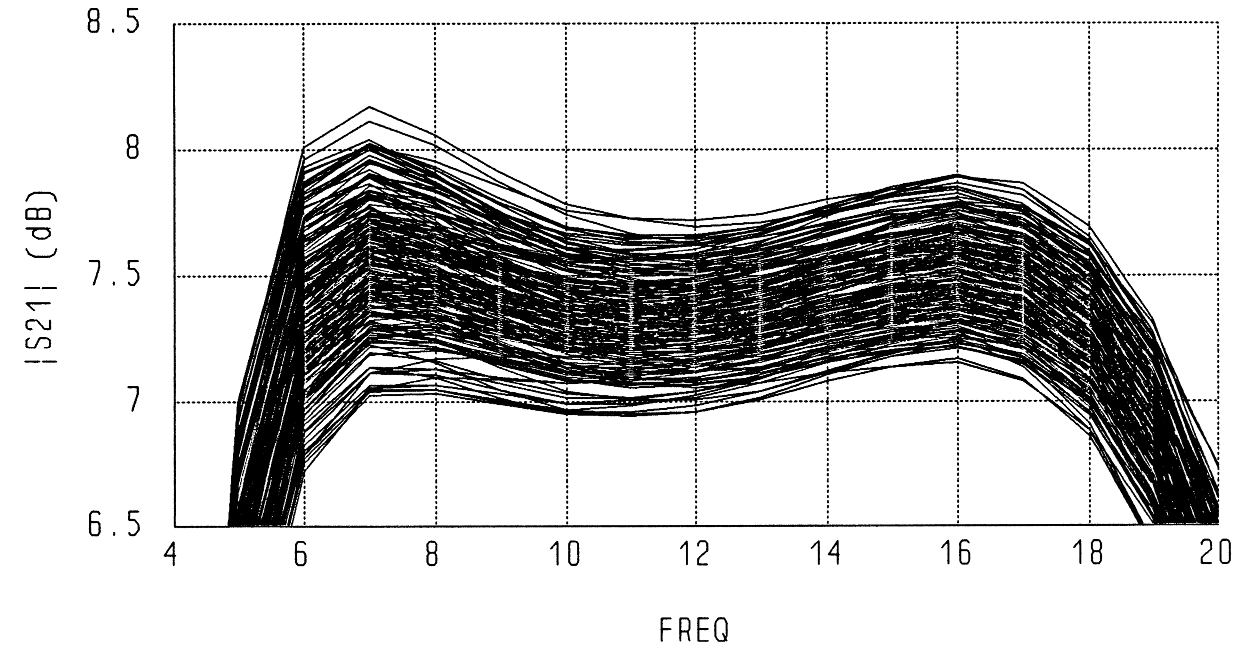
Monte Carlo simulation

250 outcomes

55% yield

Small-Signal Amplifier Yield After Optimization

the component level Q-models were used in yield optimization



yield estimated by 250 Monte Carlo simulations increased to 82%

optimization was performed by OSA90/hope™ with Empipe™ driving *em*™

Optimization Results

MICROSTRIP PARAMETERS OF THE AMPLIFIER

Parameters	Nominal design	Centered design
W_{g1}	17.45	19.0
L_{g1}	35.54	34.53
W_{g2}	9.01	8.611
L_{g2}	30.97	32.0
W_{g3}	3.0*	3.0*
L_{g3}	107.0*	107.0*
W_{d1}	8.562	7.0
L_{d1}	4.668	6.0
W_{d2}	3.926	3.628
L_{d2}	9.902	11.0
W_{d3}	3.5*	3.5*
L_{d3}	50.0*	50.0*
W	2.0*	2.0*
L	10.0*	10.0*
Yield (250 outcomes)	55%	82%

* Parameters not optimized.
Dimensions of the parameters are in mils. 50 outcomes were used for yield optimization. 0.5 mil tolerance and uniform distribution were assumed for all the parameters.

Conclusions

we have presented a new multilevel quadratic modeling technique suitable for effective and efficient yield-driven design optimization

this approach is particularly useful for circuits containing complex subcircuits or components whose simulation requires significant computational effort

the efficiency of this technique allowed us to perform yield-driven design of circuits containing microstrip structures accurately simulated by *em*™

our approach, illustrated by yield optimization of a small-signal amplifier, significantly extends the microwave CAD applicability of yield optimization techniques