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J.W. Bandler, R.M. Biernacki, S.H. Chen, M.L. Renault, J. Song and Q.J. Zhang

Optimization Systems Associates Inc.
163 Watson's Lane
Dundas, Ontario, Canada L9H 6L1

SUMMARY

Introduction

Yield driven design is becoming an indispensible tool in the microwave CAD area [1]. A real challenge is to apply the concepts of yield optimization to large scale circuits. There are two main difficulties: (1) the cost and time of simulation increases with the size of the circuit, and (2) algorithms capable of handling large optimization problems are needed.

In this paper we demonstrate for the first time the feasibility of yield optimization of large scale microwave circuits, both tunable and nontunable. We attack this difficult problem here by: (1) the use of supercomputers, (2) efficient approximation to the circuit responses, and (3) the use of fast, dedicated simulation techniques. We have successfully accomplished the yield optimization of a 5 channel multiplexer with 75 design and toleranced variables, 124 constraints and up to 200 statistically perturbed circuits. No microwave circuit design of this type and on this scale has ever been reported.

Statistical Design

Manufacturing yield is simply the ratio

$$N_{pass} / N_t , \tag{1}$$

where N_{pass} is the number of circuit outcomes meeting the design specifications and N_t is the total number of circuit outcomes. The same formula is used to estimate the design yield based on Monte-Carlo simulations where the statistical outcomes are sampled according to the probability density function (pdf) modeling the manufacturing spreads of the parameters.

This paper addresses the problem of yield optimization of large microwave circuits for both tunable and nontunable realizations. In both cases, if uniform distributions are assumed then the pdf is uniquely determined by the tolerances.

Formal definition of the problem will be given in the full paper. In this summary we point out the differences between the tolerances for tunable and nontunable circuits. Let x^0 denote the nominal design parameter vector. A statistical outcome x^k is given by

$$x^k = x^0 + r^k , \quad r^k = s^k + t^k + s_t^k \quad , \tag{2}$$

where s^k represents changes due to the model uncertainties and tolerances, t^k denotes post-production tuning adjustments and s_t^k represents tuning imprecisions in the form of residual tolerances which may remain after actual tuning. Usually we use x^k as equivalent circuit or model parameters, which are actually controlled by physical parameters. Model uncertainties, therefore, are accommodated by $\mathbf{s}_t^k$ also.

For nontunable circuits we have $\mathbf{r}^k = \mathbf{s}^k$ only. For ideally accurate tuning ($\mathbf{s}_t^k = \mathbf{0}$) we can obtain $\mathbf{r}^k = \mathbf{0}$ provided that the tuning ranges are large enough to accommodate the spreads due to the manufacturing tolerances. Then, for a realistic (imprecise) tuning we obtain $\mathbf{r}^k = \mathbf{s}_t^k$. Therefore, for both tunable and nontunable circuits the statistical spreads are determined by means of tolerances. The values of the tolerances, however, will differ for the two cases.

Our approach to yield optimization follows a novel multi-circuit approach [2] where a number of outcomes sampled according to the pdf are simultaneously optimized to meet the design specifications. The one-sided ℓ_1 objective function is used to perform the proper centering of these circuit outcomes.

Approximation to the Circuit Responses

In order to facilitate rapid statistical evaluations for the multiple circuits involved we use quadratic approximation to the circuit responses as proposed in [3]. A quadratic polynomial to approximate a given response $f(x)$, $x = [x_1 \; x_2 \; \ldots \; x_n]^T$, can be written as

$$q(x) = a_0 + \sum_{i=1}^{n} a_i(x_i - x_i^0) + \sum_{\substack{i,j=1 \\ i \geq j}}^{n} a_{ij}(x_i - x_i^0)(x_j - x_j^0). \tag{3}$$

Using the function values at m (m>n+1) base points, $f_k = f(x^k)$, k=0,1,2,...,m-1, we set up a system of linear equations

$$\begin{bmatrix} \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \mathbf{Q}_{21} & \mathbf{Q}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{a} \\ \mathbf{v} \end{bmatrix} = \begin{bmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \end{bmatrix}, \tag{4}$$

where the vectors $\mathbf{a}$ and $\mathbf{v}$ contain a_i and a_{ij}, respectively, and the vectors $\mathbf{f}_1$ and $\mathbf{f}_2$ contain f_k. The model coefficients can be solved as

$$\mathbf{v} = \mathbf{C}^T(\mathbf{C}\mathbf{C}^T)^{-1}\mathbf{e} \tag{5a}$$

and

$$\mathbf{a} = \mathbf{Q}_{11}^{-1}\mathbf{f}_1 - \mathbf{Q}_{11}^{-1}\mathbf{Q}_{12}\mathbf{v}, \tag{5b}$$

where

$$\mathbf{C} = \mathbf{Q}_{22} - \mathbf{Q}_{21}\mathbf{Q}_{11}^{-1}\mathbf{Q}_{12} \quad \text{and} \quad \mathbf{e} = \mathbf{f}_2 - \mathbf{Q}_{21}\mathbf{Q}_{11}^{-1}\mathbf{f}_1. \tag{6}$$

Here, we arrange the first n+1 base points as x^0 and

$$x^i = x^0 + [0 \; 0 \; \ldots \; 0 \; \beta_i \; 0 \; \ldots \; 0]^T, \quad i=1, 2, \ldots, n, \tag{7}$$

where x^0 is the reference point and β_i is a certain length of perturbation. This arrangement results in very simple forms of $\mathbf{Q}_{11}$ and $\mathbf{Q}_{11}^{-1}\mathbf{Q}_{12}$ so that they do not have to be evaluated and stored. After these first (n+1) base points, a sequence of other base points follows with no particular restriction on their locations. When x^k (k>n) is added as a new point, the components of the (k-n)th row of $\mathbf{C}$ are simply either

$$c_{k-n,(ii)} = (x_i^k - x_i^0)^2 - \beta_i(x_i^k - x_i^0) \tag{8a}$$

or

$$c_{k-n,(ij)} = (x_i^k - x_i^0)(x_j^k - x_j^0), \quad \text{for} \quad i \neq j, \tag{8b}$$

Using these formulas, the computational effort required by the original approach of [3] can be substantially reduced, thus making this kind of approximation even more attractive.

Yield Optimization of a 5-channel Multiplexer

A 5-channel 12 GHz contiguous band microwave multiplexer, consisting of multi-cavity filters distributed along a waveguide manifold, has been designed by applying yield optimization. The ultimate specifications, after complete tuning, were 20dB for the common port return loss and 20dB for the individual channel insertion losses, resulting in 124 nonlinear constraint functions. Design variables for each channel include 12 couplings, input and output transformer ratios and the waveguide spacings.

Careful and time-consuming tuning is essential for multiplexers. Any adjustments involving physical disconnection of the structure is particulary expensive. For the sake of illustration we focus attention in this summary on the waveguide spacings as being expensive adjustments to make. Therefore, the larger tuning tolerances are assumed for the spacings.

The goals of yield enhancement for this design are: (1) to drive up the probability of those circuit outcomes presenting good initial responses for the tuning process, and (2) to increase the possibility of the circuits satisfying specifications after tuning a smaller number of variables, consisting mostly of couplings and transformer ratios. This should have an impact on the overall effort of tuning.

We considered tolerances of 5% for the spacings, 0.5% for the couplings and the transformer ratios, and relaxed the specifications from 20dB to 10dB for the return and insertion losses. The starting point was the solution of the conventional minimax nominal design. The corresponding responses are shown in Fig. 1. The estimated yield at this point turned out to be 75%.

Yield optimization was carried out on the CRAY X-MP/22 using the generalized ℓ_p centering algorithm [2], the approximation scheme described in this paper and utilizing a dedicated multiplexer simulation program [5]. The entire process consisted of 4 phases as shown in Table I. At the beginning of each phase a set of quadratic models were constructed by exact simulation of the circuit at 151 base points. Then the models were used in the optimization to evaluate the approximate circuit responses and their gradients. This approach allowed us to handle this extremely large optimization problem (75 toleranced variables, 124 constraints and up to 200 statistically perturbed circuits at each iteration) in acceptable cpu time.

After yield optimization the estimated yield increased to 90%. The statistical properties at the final solution are illustrated by two envelopes containing all the statistically perturbed responses and the acceptable responses, shown in Fig. 2 and Fig. 3, respectively.

References

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TABLE I

STATISTICAL DESIGN OF A 5-CHANNEL MULTIPLEXER
USING QUADRATIC APPROXIMATION

		PHASE 1	PHASE 2	PHASE 3	PHASE 4
Initial Yield	+	56.33%	69.00%	69.33%	92.00%
	++	75.00%	(81.00%)	(84.33%)	(90.00%)
Final Yield	+	77.33%	77.33%	91.33%	94.00%
	++	81.00%	84.33%	90.00%	90.33%
No. of Outcomes		50	100	150	200
No. of Iterations		4	6	6	4
CPU Time (CRAY X-MP/22)		16.5sec	17.6sec	17.8sec	17.6sec

CPU times do not include yield estimation based on exact simulations. All yields are estimated based on 300 samples.

\+ quadratic approximation used to evaluate responses

++ exact simulation used to evaluate responses

Figure Captions

Fig 1. Optimized return and insertion loss vs. frequency for the 5-channel multiplexer.

Fig 2. The envelope containing all statistically perturbed return loss responses for 3000 Monte-Carlo samples.

Fig 3. The envelope containing acceptable statistically perturbed return loss responses for 3000 Monte-Carlo samples.