OPTIMIZATION TECHNOLOGY FOR MICROWAVE CIRCUIT MODELING AND DESIGN

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Invited Paper

Abstract

We review relevant concepts, formulations and algorithms for microwave circuit optimization. Emphasis is given to recent advances in the state of the art: automated electromagnetic design, Space Mapping, Huber optimization, integrated CAD environment and parallel computing. An example of statistical optimization utilizing electromagnetic simulation illustrates our approach.

I. INTRODUCTION

Microwave circuit designers have become more enthusiastic and at the same time more critical users of numerical optimization techniques in the strive for first-pass success [1]. Among their current needs and expectations for CAD tools are electromagnetic (EM) simulation (e.g., [2-9]), integrated and concurrent design environment, mixed-domain multi-level hierarchical optimization, physical and physics-based modeling, intelligent and robust optimizers, yield and cost optimization, and visualization.

The thrust for faster and smaller circuits has raised EM field-theoretical studies to new prominence in the simulation of MMICs, interconnects, component packaging and housings, etc. However, the prevailing use of EM simulators for validation of designs obtained through traditional techniques does not fully exploit their predictive power. Furthermore, the widespread use of EM simulators for ad hoc design is highly wasteful of human and computer resources. We pioneered [10-12] direct and automated EM optimization with successful applications to designing matching circuits, filters, attenuators and amplifiers, including statistical analysis and yield optimization.

Another challenge is to integrate optimization technology into a design environment with a diversified set of CAD tools, which may include digital, analog time-domain, analog frequency-domain, EM, mechanical and thermal simulators. Our success with Datapipe™ [10] demonstrates that this can be achieved without immensely complicated syntax and protocols, e.g., [13]. We have developed a novel approach to capturing design data from external simulators in their native format. One application of this approach is Geometry Capture™ [10], which automates the parameterization of arbitrary microstrip structures for EM optimization.

In EM optimization, the field solver, not the optimization algorithm, is the true bottleneck. This is especially significant when gradients are estimated by perturbations or when yield is estimated from many Monte Carlo outcomes. We promote parallel computing as an effective means of speeding up CPU intensive EM optimization.

Our recent exploitation of Space Mapping (SM) [14,15], a totally new concept in engineering optimization, roused great excitement. It opens new horizons of optimization linking engineering models of different types and levels of complexity, including empirical, EM-based, analytic, numerical, physics-based and even direct lab measurement, which represent the same physical design.

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The SM concept is founded on the computational expediency of empirical engineering models (which embody expert knowledge accumulated over many years) and the acclaimed accuracy of EM simulators. SM facilitates automated design optimization within a practical time frame. We extended SM to parameter extraction and introduced the concept of Frequency Space Mapping (FSM) [15]. It provides a powerful means of overcoming problems of local minima and data misalignment, especially at the starting point.

We introduced a novel approach to "robustizing" circuit optimization using Huber functions [16]. Robust handling of both large and small measurement errors, bad starting points and statistical uncertainties can now be automated, as validated by FET modeling from data contaminated with "wild points". We developed a statistical verification procedure for device models, using yield as the statistical estimator. Our new cumulative probability distribution fitting technique directly determines statistics such as the mean values and standard deviations in a single optimization.

II. DESIGN OPTIMIZATION

We start by briefly reviewing the concepts involved in design optimization, including yield optimization. We formulate design as an abstract optimization problem, regardless of the nature of the object being designed. We show how the error functions for design goals are typically defined and discuss ways of combining them into a single objective function.

Design optimization is a powerful computational tool enabling designers to adjust designable parameters in order to meet design specifications. The nature of the designed object is irrelevant to the optimizer. However, the computer simulation of the object must be available. The computer simulator should provide the means for processing a number of input parameters, some of which are (directly or indirectly) designable, into the corresponding set of responses.

Simulation, Specifications and Error Functions

The response functions that can be of interest to the designer may involve a combination of frequency domain responses, time domain responses, space domain responses, frequency spectra of periodic functions, and their functions such as power, etc. "Of interest" means that design specifications are imposed on the responses. A specification is typically imposed on a range of domain values. This leads to an infinite number of specifications and it becomes necessary to discretize the domain and consider only a finite subset of representative frequency, time or space points. After discretization, the jth specification can be denoted by S_{uj} or $S_{\ell j}$ if it is an upper or a lower specification, respectively.

In order to formulate an objective function for design optimization the object is simulated at the same frequency or time points at which the upper and/or lower specifications are selected by discretization. The corresponding responses are denoted by $R_j(\boldsymbol{x})$ and the error vector $\boldsymbol{e}(\boldsymbol{x})$ is defined as

$$\boldsymbol{e}(\boldsymbol{x}) = [e_1(\boldsymbol{x}) \;\; e_2(\boldsymbol{x}) \; \ldots \; e_M(\boldsymbol{x})]^T \tag{1}$$

where the individual errors $e_j(\boldsymbol{x})$ are

$$e_j(\boldsymbol{x}) = R_j(\boldsymbol{x}) - S_{uj} \quad \text{or} \quad e_j(\boldsymbol{x}) = S_{\ell j} - R_j(\boldsymbol{x}). \tag{2}$$

$\boldsymbol{x}$ is the vector of designable parameters and M is the total number of errors. The negative error values indicate that the corresponding specifications are satisfied. For positive error values the corresponding specifications are violated. The acceptability region $\boldsymbol{A}$ in the parameter space is defined as

$$\boldsymbol{A} = \left\{ \boldsymbol{x} \mid e_j(\boldsymbol{x}) < 0 \quad j = 1, 2, \ldots, M \right. \tag{3}$$

Clearly, all specifications are satisfied if the designable parameters fall into A, and at least one specification is violated if that point falls outside the acceptability region $\boldsymbol{A}$.

Objective Functions and Algorithms

For the purpose of optimization all the errors $e_j(\boldsymbol{x})$ have to be combined into a single objective function. The three important types of the objective function are minimax, ℓ_1 and ℓ_2 (least squares). The generalized ℓ_p function $U(\boldsymbol{x})$ from $\boldsymbol{e}(\boldsymbol{x})$ takes the form [17,18] (used, for example, in [19])

$$U(\boldsymbol{x}) = \begin{cases} \left[\sum_{j \in \boldsymbol{J}} e_j(\boldsymbol{x})^p\right]^{1/p} & \text{if } \boldsymbol{x} \notin \boldsymbol{A} \\ -\left[\sum_{j=1}^{M} (-e_j(\boldsymbol{x}))^{-p}\right]^{-1/p} & \text{if } \boldsymbol{x} \in \boldsymbol{A} \end{cases} \tag{4}$$

where $\boldsymbol{J} = \left\{ j \mid e_j(\boldsymbol{x}) \geq 0 \right\}$.

Some variations of this function include: (a) one-sided ℓ_p function where the lower expression in (4) is set to zero, and (b) the ℓ_p norm where only the upper expression in (4) is used and the summation is over the absolute values of e_j's for all $j = 1, 2, ..., M$. The minimax function corresponds to $p \rightarrow \infty$ and can simply be expressed as

$$U(\boldsymbol{x}) = \max_{j} \{e_j(\boldsymbol{x})\} \tag{5}$$

The novel Huber and one-sided Huber objectives combine respective advantages of ℓ_1 and ℓ_2. The Huber function is defined as [20]

$$\rho_k(e) = \begin{cases} e^2/2 & \text{if } |e| \leq k \\ k|e| - k^2/2 & \text{if } |e| > k \end{cases} \tag{6}$$

where k is a positive constant threshold value and e represents an error function. The one-sided Huber function $\rho_k^+(\boldsymbol{x})$ [16] is defined similarly to all other one-sided functions by setting it to zero for negative error values. The Huber (or one-sided Huber) objective is simply defined as a sum of all Huber (or one-sided Huber) functions for all M errors.

The minimax is the objective function of choice for performance driven design optimization and leads to equi-ripple solutions. The ℓ_2 norm or one-sided ℓ_2 function are also commonly used for performance driven design optimization. The ℓ_1 and Huber functions are uniquely useful in modeling and in yield optimization. Finally, it is worth mentioning that non-negative multiplicative weighting factors can be applied in (4) and (5) to individual errors. Specialized algorithms exist for minimization of each of the aforementioned objective functions (e.g., [21]).

Exploiting the Huber functions we "robustize" circuit optimization [16]. Similarly to the ℓ_1 norm, the Huber function filters out gross errors and thus it automatically ignores "wild" measurement data points. On the other hand it treats small statistical variations and measurement errors in the smooth, least-squares sense. The Huber function is well suited to handle analog fault diagnosis problems.

Yield Optimization

Yield optimization is an effective means of improving first-pass success in circuit design, e.g., [22-24]. Due to various fluctuations inherent in the manufacturing process, the circuit outcomes exhibit variations of their responses w.r.t the nominal design response. Manufacturing yield is simply the ratio of the number of circuit outcomes meeting all design specifications to the total number of outcomes. Formally, yield driven optimization is formulated as

$$\underset{\boldsymbol{x}^0}{maximize} \; \{ \; Y(\boldsymbol{x}^0) = \int_{\boldsymbol{R}^n} I_a(\boldsymbol{x}) f_x(\boldsymbol{x}^0, \boldsymbol{x}) \, d\boldsymbol{x} \; \} \tag{7}$$

where $\boldsymbol{x}^0 \in \boldsymbol{R}^n$ is the vector of nominal circuit parameters, $\boldsymbol{x}$ is the vector of actual circuit outcome parameters, $f_x(\boldsymbol{x}^0, \boldsymbol{x})$ is the probability density function (pdf) of $\boldsymbol{x}$ around $\boldsymbol{x}^0$, $I_a(\boldsymbol{x}) = 1$ if $\boldsymbol{x} \in \boldsymbol{A}$, the acceptability region in the $\boldsymbol{x}$-space where all design specifications are satisfied, and $I_a(\boldsymbol{x}) = 0$, otherwise.

Since $\boldsymbol{x}$ is a continuous random variable an infinite number of outcomes would be involved in evaluating yield $Y(\boldsymbol{x}^0)$ in (7) . Therefore, in practice a number of Monte Carlo outcomes, $\boldsymbol{x}^i$, $i = 1,2,...,K$, is sampled around $\boldsymbol{x}^0$ according to $f_x(\boldsymbol{x}^0, \boldsymbol{x})$ and yield is estimated by

$$Y(\boldsymbol{x}^0) \approx \frac{1}{K} \sum_{i=1}^{K} I_a(\boldsymbol{x}^i) \tag{8}$$

The one-sided ℓ_1 objective function for yield driven optimization is formulated as follows [1]. First, for each of K circuit outcomes $\boldsymbol{x}^i$ the corresponding error vector $\boldsymbol{e}(\boldsymbol{x}^i) = [e_1(\boldsymbol{x}^i) \;\; e_2(\boldsymbol{x}^i) \; . \; . \; . \; e_M(\boldsymbol{x}^i)]^T$ is determined from (2) with $\boldsymbol{x}$ replaced by $\boldsymbol{x}^i$ and the generalized ℓ_1 function (4), denoted here by $v(\boldsymbol{x}^i)$, is calculated. This function has the property that it is positive if at least one specification is violated, i.e., $\boldsymbol{x}^i \notin \boldsymbol{A}$, and it is negative if all design specifications are satisfied. Then, the final one-sided ℓ_1 objective function is defined from $v(\boldsymbol{x}^i)$ as

$$U(\boldsymbol{x}^0) = \sum_{i \in \boldsymbol{J}} \alpha_i v(\boldsymbol{x}^i) \tag{9}$$

where $\boldsymbol{J}$ is defined similarly to (4) but w.r.t. $v(\boldsymbol{x}^i)$. α_i are properly chosen non-zero multipliers. The function (9) naturally imitates the percentage of outcomes violating design specifications and, therefore, its minimization leads to yield improvement. An enhanced approach to yield optimization takes advantage of yield probability function which replaces $v(\boldsymbol{x}^i)$ in (9). A robust alternative to (9) is to formulate yield optimization as a one-sided Huber problem.

Statistical Modeling

The purpose of statistical modeling is to determine or approximate the probability density function $f_x(\boldsymbol{x}^0, \boldsymbol{x})$ in (7) from a sample of measurement data. Circuit simulation can be performed at different levels of primary parameters depending on available software tools or desired efficiency, e.g., timing analysis, cell or device simulations. Therefore, the vector $\boldsymbol{x}^0$ of designable parameters in (7) as well as the pdf must be considered at the same level as available or desired simulation. Physics-based and physical simulation (e.g., [24-26]) is the most suitable level for statistical device modeling.

We developed a statistical verification procedure for device models, using yield as the statistical estimator. Our new cumulative probability distribution fitting technique directly determines statistics such as the mean values and standard deviations in a single optimization.

Very recently Snowden [26] noted that the advent of more powerful computers has increased the drive in using physical models and physics-based models for microwave and mm-wave CAD to meet the requirement of predictability and economization. Physical and physics-based models permit statistical characterization at the geometrical/process parameter level, and also offer the opportunity of device optimization. A methodology of integrating EM analyses of passive structures and physical simulations of active devices will have a tremendous impact on reducing the cost and time required for design cycles.

III. DIRECT EM OPTIMIZATION

We pioneered direct and automated EM optimization with successful applications to designing matching circuits, filters, attenuators and amplifiers, including statistical analysis and yield optimization.

To successfully interface optimizers with EM simulators we needed to address a number of challenges that either did not exist or were not as severe in traditional simulators. This included efficiency, discretization of geometrical dimensions, and continuity of optimization variables. To effectively carry out direct EM optimization we introduced: (1) efficient on-line response interpolation w.r.t. geometrical dimensions of microstrip structures simulated with fixed grid sizes, (2) smooth and accurate gradient evaluation for use in conjunction with "geometrical" interpolation, and (3) storing the results of expensive EM simulations in a dynamically updated data base. Design optimization of a double folded stub bandstop filter and of a millimeter-wave 26-40 GHz interdigital capacitor bandpass microstrip filter illustrated the first applications of those techniques.

Our initial approach to direct EM optimization was by creating an element library (Empipe, OSA, 1992). It was designed specifically to interact with Sonnet's ***em*** and followed the conventional approach of predefined, built-in elements (primitives) such as lines, bends, junctions, gaps, stubs. Each element was already parameterized and ready for optimization. The circuits were decomposed into those predefined primitives. Although that approach gained immediate acceptance by CAD users, it inherently omits possible couplings between the elements since they are connected by the circuit-level simulator. Furthermore, it does not accommodate structures which cannot be decomposed into library elements.

One of the most attractive advantages of EM simulators is the ability to analyze structures of arbitrary geometry. Naturally, EM simulator users wish to be able to designate optimizable parameters directly within the graphical layout representation. To satisfy their wish, we must be able to relate geometrical coordinates of the layout to the numerical parameters for optimization. To automate such a parameterization process is quite a challenge.

Our new approach is based on the breakthrough technique of Geometry Capture [10]. EM simulators deal directly with the layout representation of circuits in terms of absolute coordinates which are not directly designable parameters. Therefore, geometrical parameterization is needed for every new structure. Geometry Capture is a graphical tool for parameterizing arbitrary structures. It facilitates automatic translation of the values of user-defined designable parameters to the layout description in terms of absolute coordinates. During optimization, this translation is automatically performed for each new set of parameter values before the EM simulator is invoked.

IV. SPACE MAPPING OPTIMIZATION

Space Mapping is a totally new concept in engineering optimization linking engineering models of different types and levels of complexity, including empirical, EM-based, analytic, numerical, physics-based and even direct lab measurement, which represent the same physical design. A key step in SM is to determine pairs of corresponding EM and empirical models through parameter extraction. The "empirical" model can even be a coarse EM simulation!

In its basic form, the SM optimization technique [14] exploits a mathematical link between input parameters of two simulators (models). One is considered very accurate but computationally very intensive while the other one is fast but less accurate. The goal is to direct the bulk of CPU intensive optimization to the fast model in the optimization system (OS) parameter space X_{OS}. This model is referred to as the OS simulator. EM simulations serve as the accurate model and the EM simulator input parameter space is denoted by

X_{EM}. As a first step in SM optimization we carry out conventional design optimization entirely in the X_{OS} space. The resulting solution is denoted by x_{OS}^*. Then, we create and iteratively refine a mapping

$$x_{OS} = P(x_{EM}) \tag{10}$$

from X_{EM} to X_{OS} in order to align the two models.

In principle, the choice of the mathematical form of the mapping is an implementational issue. In [14] we only assume that the mapping can be expressed as a linear combination of some predefined and fixed fundamental functions. In the current implementation of SM we also assume that P is invertible. Once the mapping is established the inverse mapping P^{-1} is used to find the EM solution as the image of the optimal OS solution x_{OS}^*, namely,

$$\bar{x}_{EM} = P^{-1}(x_{OS}^*) \tag{11}$$

In other words, we map the optimal OS model parameters back into the EM parameters (e.g., physical layout).

P is established through an iterative process. The initial mapping $P^{(0)}$ is found using a preselected set B_{EM} of k points in X_{EM} and the set B_{OS} of corresponding points in X_{OS}. The number k of these base points should be sufficient to uniquely determine all the coefficients of the linear combination defining the mapping. Their selection is fairly arbitrary. However, it is advantageous to select these points on the grid. The points in B_{OS} are determined by k auxiliary optimizations to achieve

$$f_{OS}(x_{OS}^i) \approx f_{EM}(x_{EM}^i), \quad i = 1, 2, ..., k \tag{12}$$

where f_{OS} and f_{EM} are the circuit responses simulated by the OS and EM simulators, respectively. This may be referred to as a parameter extraction (fit). In other words, we optimize the OS model to fit its response to the EM simulator response calculated at x_{EM}^i. In this optimization the OS model parameters x_{OS} are the optimization variables. As a result we find the point x_{OS}^i. This process is repeated for all the base points.

At the jth iteration B_{EM} is expanded by the new image of x_{OS}^* computed using $(P^{(j)})^{-1}$ and snapped to the grid. B_{OS} is expanded accordingly. The iterations continue until

$$\| f_{EM}(\bar{x}_{EM}) - f_{OS}(x_{OS}^*) \| \leq \epsilon \tag{13}$$

where $\|\cdot\|$ indicates a suitable norm and ϵ is a small positive constant. In the process of finding the mapping an overdetermined system of equations may need to be solved. In such situations, optimization techniques, such as least-squares, can be used.

Recently, we proposed a new aggressive SM strategy [15]. Instead of waiting for upfront EM analyses at several base points, it exploits every available EM analysis, producing dramatic results right from the first step. We assume that the mapping P can be linearized locally, such that at the jth step we have

$$P(x_{EM}^j + h) \approx P(x_{EM}^j) + A_j h. \tag{14}$$

We target every EM analysis at the optimal design in the sense that x_{EM}^j is generated not merely as a base point for establishing the mapping, but as our current best estimate of the mapped solution as defined by (11). The mapping $\boldsymbol{P}$ is found iteratively starting from $\boldsymbol{P}_0(\boldsymbol{x}) = \boldsymbol{x}$.

At the starting point we let $x_{EM}^1 = x_{OS}^*$ and $A_1 = 1$. At the jth step, we obtain x_{EM}^j by applying (11) using the current estimate of $\boldsymbol{P}$, namely $\boldsymbol{P}_j$. If the EM analysis at x_{EM}^j produces the desired responses, then our mission is accomplished. Otherwise, we find x_{OS}^j which corresponds to x_{EM}^j by parameter extraction, i.e., we extract x_{OS}^j through optimization in X_{OS} from the data provided by the EM analysis at x_{EM}^j.

Adapting the Broyden formula [27], we update the SM transformation by

$$A_{j+1} = A_j + \frac{[x_{OS}^{j+1} - x_{OS}^*]\boldsymbol{h}_j^T}{\boldsymbol{h}_j^T \boldsymbol{h}_j} \tag{15}$$

where $\boldsymbol{h}_j = x_{EM}^{j+1} - x_{EM}^j$.

Frequency Space Mapping

As one of the key steps of SM we need to extract the parameter values of the corresponding empirical model such that it would match the EM simulation results. The uniqueness of the parameter extraction phase is of utmost importance to the success of SM. This can be a serious challenge, especially at the starting point, when the responses produced by EM analysis and by the empirical model may be severely misaligned, such as the case shown in Fig. 1. If we perform straightforward optimization from such a starting point, the extraction process can be trapped by a local minimum, as illustrated in Fig. 2.

We discovered a method for applying SM to parameter extraction and introduced the concept of automated Frequency Space Mapping (FSM) [15]. It leads to a powerful means of overcoming problems of local minima and data misalignment.

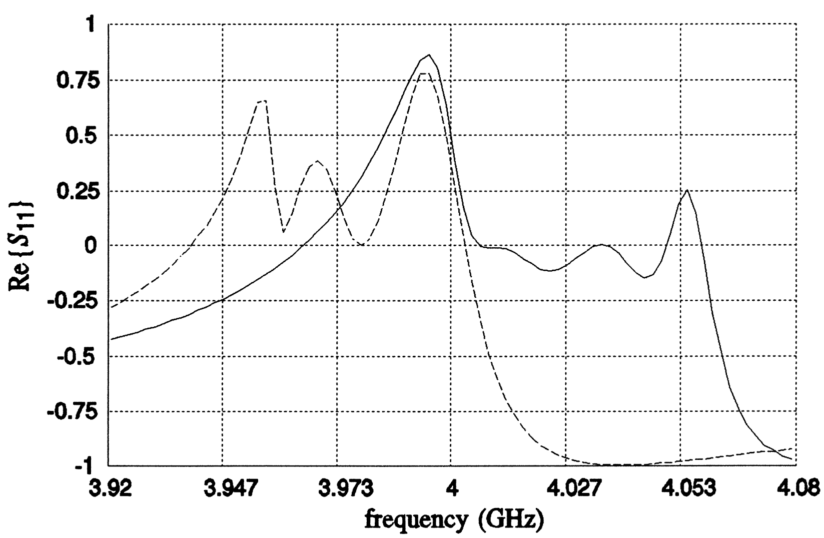

Fig. 1. Re$\{S_{11}\}$ simulated using the empirical model (——) and *em* (- - -) at the starting point for parameter extraction.

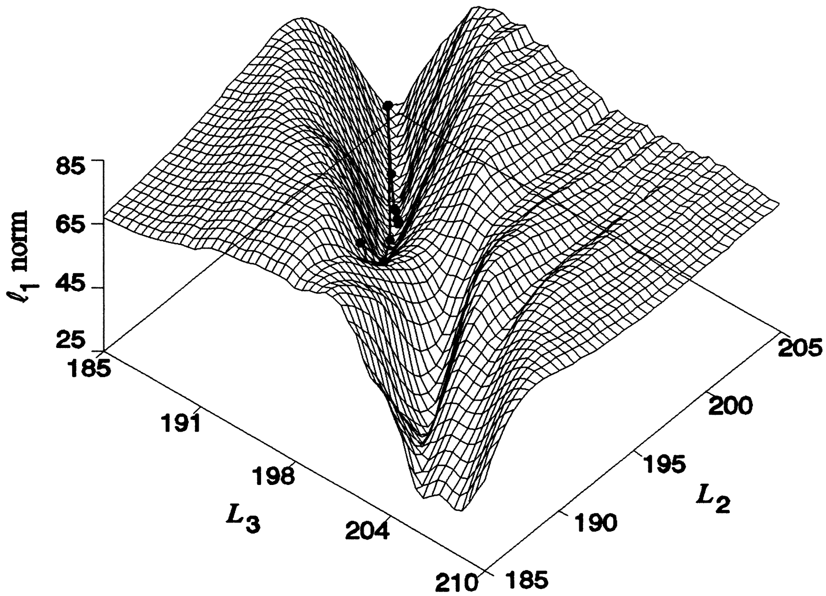

Fig. 2. Visualization of the ℓ_1 norm versus two of the model parameters L_2 and L_3, superimposed by the trace of the straightforward ℓ_1 optimization. The optimization converged to a local minimum instead of the true solution represented by the valley near the front of the graph.

The mapping can be as simple as frequency shift and scaling. We proposed two algorithms for FSM: a sequential FSM algorithm (SFSM) and an exact penalty function (EPF) algorithm [15]. The initial mapping is determined by optimizing the mapping coefficients while the circuit parameters are kept fixed. In SFSM, we perform a sequence of parameter extraction optimizations in which the FSM is gradually reduced to the identity mapping. In the EPF algorithm, we perform only one optimization, but a sensible selection of the weighting factors is needed.

V. CAD DESIGN ENVIRONMENT

For advances in optimization technology to benefit a large number of CAD users, such advances have to be integrated into a design environment with a diversified set of CAD tools, which may include digital, analog time-domain, analog frequency-domain, EM, mechanical and thermal simulators. Efficiency of the algorithms as well as organization of software are of utmost importance. Software modularity must be facilitated and modules of different origin need to be accommodated. For example, advanced, state-of-the-art optimization routines must interact with field simulators, developed separately, possibly in a different language and without optimization as the objective.

Our Datapipe makes such integration easy and flexible. It is based on the technique called IPPC (inter-program pipe communication) which allows for high speed numerical interaction between independent programs. Datapipe consists of a number of ready-to-use communication protocols, and only a small file server needs to be attached to an external module in order to make it pipe-ready, thus becoming integrated into the CAD design environment. For encapsulated external simulators we have developed a novel approach to capturing design data in their native format.

Parallel Computing

We promote parallel computing as an effective means of speeding up CPU intensive EM optimization. The general concept of parallel computing can be realized in many different ways, including multiprocessor computers and specialized compilers. However, parallel computing does not necessarily require an expensive multiprocessor system. It can be realized by distributing the computational load over a network of heterogeneous computers. We rely on standard UNIX protocols (remote shell and equivalent hosts) instead of any platform specific mechanisms. This allows us to apply the concept to both local and wide area networks of heterogeneous workstations.

We chose to split the load of EM analyses on the component/subcircuit level for two reasons: to reduce the complexity of implementation and to best suit the operational flow of interpolation, optimization and statistical analysis. For instance, if the parameter values are off the mesh grid imposed by the EM simulator, a number of EM analyses are needed at adjacent on-grid points for interpolation. In order to estimate the gradients for optimization, a number of perturbed analyses are required in addition to the analysis at the nominal point. For statistical analysis, EM analyses are to be performed at many Monte Carlo outcomes. By carrying out these analyses in parallel, the overall simulation time can be reduced by a factor of n, where n denotes the ratio between the combined effective computing power of the networked computers and that of a single computer (assuming that the overhead of parallelization is negligible compared with the CPU-intensive EM analyses).

The distribution of computational load is organized on one of the networked computers (master host). Using the UNIX remote shell command, an EM analysis is started on each of the available hosts. When the analysis is finished on a host, the next job, if any, is dispatched to that host. We can further improve the efficiency by combining parallelization with data interpolation and response function modeling. The EM simulation results are gathered from all the hosts and stored in a data base created on the master host. Fig. 3 illustrates this mechanism.

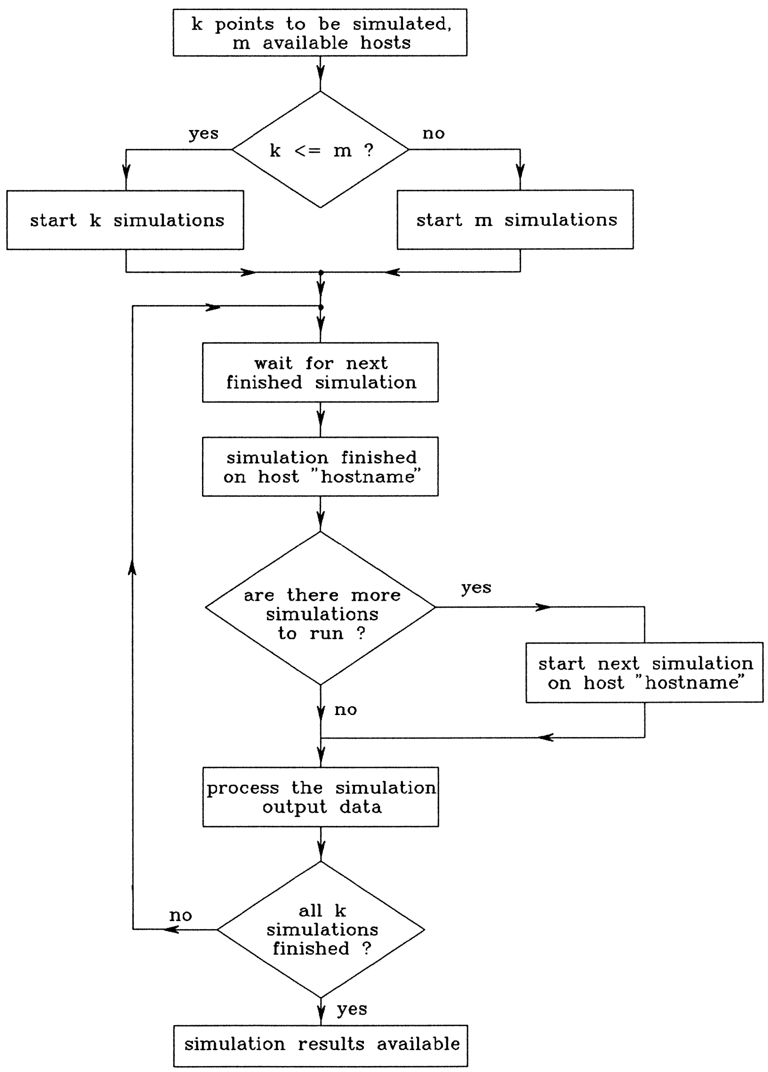

Fig. 3. Parallel computing by distributing EM analyses over a network of computers.

VI. STATISTICAL DESIGN OF A 10 DB DISTRIBUTED ATTENUATOR

Consider the distributed attenuator depicted in Fig. 4. The 15 mil substrate has a relative dielectric constant of 9.8. It exemplifies structures which are difficult, if not impossible, to be decomposed into library primitives. We treat the attenuator as one piece and define 8 geometrical parameters for Geometry Capture, namely P_1, P_2, ..., P_8. P_1, P_2, P_3 and P_4 are assumed to be designable parameters. EM simulation of the attenuator at a single frequency requires about 7 CPU minutes on a Sun SPARCstation 1+. The design specifications are given as

$$9.5 \text{ dB} \le \text{insertion loss} \le 10.5 \text{ dB from 2 GHz to 18 GHz}$$
$$\text{return loss} \ge 10 \text{ dB from 2 GHz to 18 GHz}$$

The error functions are calculated at three frequencies: 2, 10 and 18 GHz.

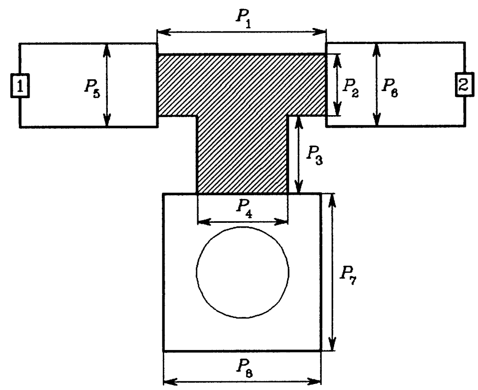

Fig. 4. 10 dB distributed attenuator. The shaded *T* area corresponds to metallization of a high resistivity (50 Ω/sq) and the feed lines and the grounding pad are assumed to be lossless.

First, we obtain a nominal design by minimax optimization. It requires 30 EM analyses. The nominal design took about 168 minutes on the network of Sun SPARCstations 1+.

For statistical design we assume normal distributions with a standard deviation of 0.25 mil for all 8 geometrical parameters. Estimated from 250 Monte Carlo outcomes, the yield is 82% at the minimax nominal solution. The yield is increased to 97% after design centering. The statistical simulation and optimization called for 113 additional EM analyses. Fig. 5 shows the Monte Carlo sweep of the attenuator responses.

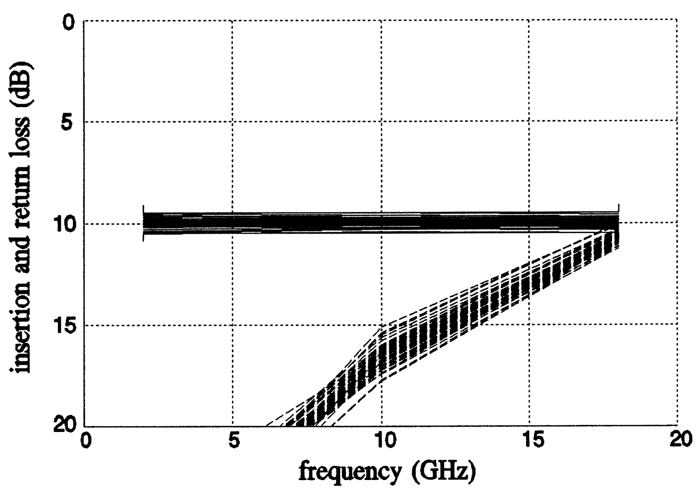

Fig. 5. Monte Carlo sweeps of the attenuator insertion loss (——) and return loss (---) after yield optimization.

VII. CONCLUSIONS

We have reviewed a number of concepts which are critical to the successful application of optimization technology to microwave circuit modeling and design. Space Mapping is one of the most exciting concepts we have ever discovered. SM has already had a tremendous impact on automated EM optimization. The expansion of SM to hierarchically structured, optimization-oriented, CAD systems promises to integrate optimization technology with field theory, circuit theory and system theory based simulators for process-oriented linear, nonlinear and statistical CAD. We are convinced that CAD and modeling of engineering devices, circuits and systems will reach a level of precision and computational efficiency previously undreamed of.

The importance of automated EM optimization has been confirmed by two recent events at the MTT-S International Microwave Symposia: a panel session in San Diego in 1994 [28] and a full-day workshop in Orlando in 1995 [29]. Also, two special journal issues (Bandler, Guest Editor) dedicated to microwave optimization are coming up: on Automated Circuit Design Using Electromagnetic Simulators (IEEE Trans. MTT, 1997) and on Optimization-Oriented Microwave CAD (Int. J. MMWCAE, 1996).

The limited space for this presentation does not permit us to discuss many other promising developments in microwave circuit optimization, e.g., [30]. Also, recent advances reported by Cendes [31] promise substantial acceleration of frequency sweeps by a 3D EM solver, motivating us to further intensify the work on automated 3D EM optimization.

One aspect in urgent need of attention is an accepted set of benchmark standards for comparing the accuracy, efficiency and robustness of different optimization techniques and methods. The establishment of such standards will contribute greatly to the understanding of the strength and weakness of optimization technology by microwave engineers at large.

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