Extraction of Passive Device Model Parameters Using Genetic Algorithms

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The extraction of model parameters for embedded passive components is crucial for designing and characterizing the performance of multichip module (MCM) substrates. In this paper, a method for optimizing the extraction of these parameters using genetic algorithms is presented. The results of this method are compared with optimization using the Levenberg-Marquardt (LM) algorithm used in the HSPICE circuit modeling tool. A set of integrated resistor structures are fabricated, and their scattering parameters are measured for a range of frequencies from 45 MHz to 5 GHz. Optimal equivalent circuit models for these structures are derived from the s-parameter measurements using each algorithm. Predicted s-parameters for the optimized equivalent circuit are then obtained from HSPICE. The difference between the measured and predicted s-parameters in the frequency range of interest is used as a measure of the accuracy of the two optimization algorithms. It is determined that the LM method is extremely dependent upon the initial starting point of the parameter search and is thus prone to become trapped in local minima. This drawback is alleviated and the accuracy of the parameter values obtained is improved using genetic algorithms.

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I. INTRODUCTION

As electronics technology continues to develop, there is a continuous need for higher levels of system integration and miniaturization. For example, in many applications, it is desirable to package several integrated circuits (ICs) together in multichip modules (MCMs) to achieve further compactness and higher performance. Passive components (i.e., capacitors, resistors, and inductors) are an essential requirement for many MCM applications [1]. A significant advantage of MCM technology is the ability to embed large numbers of these passive components directly into the substrate at low cost. Such an arrangement provides further advantages in component miniaturization, power consumption, reliability, and performance.

It is common for high frequency systems to include filters with specifications into the gigahertz range. In order to successfully design passive filters at such high frequencies, the behavior of the passive components that comprise the filter must be modeled accurately up to those frequencies. Recently, computer-aided design tools such as HSPICE [2] have become indispensable in IC design. Accurate circuit simulation using HSPICE is dependent on both the validity of the device models and the accuracy of the values used as model parameters. Therefore, the extraction of an optimum set of device model parameter values is crucial to characterizing the precise relationship between the device model and the measured behavior. Even if the structure of a model is valid, it could lead to poor simulation results if model parameters are not extracted properly.

In this paper, a method for optimizing the extraction of these parameters using genetic algorithms (GAs) is presented [3]. GAs are a set of guided stochastic search procedures based loosely on the principles of genetics. To investigate the use of GAs for the optimization of parameter extraction in passive devices operated at high frequencies, a set of integrated passive structures were fabricated, and their scattering parameters were measured for a range of frequencies from 45 MHz to 5 GHz. Optimal equivalent circuit models for these structures were derived from the s-parameter measurements. Predicted s-parameters for the optimized equivalent circuit were then obtained from HSP ICE. The difference between the measured and predicted s-parameters in the frequency range of interest is used as the measure of the accuracy of the optimization results.

Conventional optimization techniques such as the Levenberg-Marquardt (LM) method [4], which is used by HSPICE for parameter extraction, are often subject to becoming trapped in local minima, leading to suboptimal parameter values. GAs represent an effective method for determining the global minimum and are less dependent upon the initial starting point of the search. Here, we compare optimization using the LM algorithm to optimization using GAs. It is determined that drawbacks of the LM method are alleviated, and the accuracy of the parameter values obtained is improved using GAs.

II. TEST STRUCTURE DESCRIPTION

Three different types of passive devices were considered in this study. These test structures are shown in Fig. 1. The first structure is simply a straight-line resistor with probe pads on its ends. This structure is needed to characterize basic uncoupled material parameters including self resistance, inductance, and capacitance. The second test structure is an interdigitated capacitor. This type of device is used in a wide variety of circuits, including resonators, oscillators, and filters to perform functions such as DC blocking, frequency filtering and impedance transformation. The final test structure is a three-dimensional solenoid inductor made using a low-temperature cofired ceramic (LTCC) process [1], [5].

The resistor and capacitor test structures were built using Ti/Au deposited on a 96 % alumina substrate. An electron beam evaporation system was used to deposit 0.04 um of titanium followed by a 0.2 um layer of gold. The thin layer of titanium was used to improve adhesion of the gold to the substrate. Following deposition, the resistors were defined using standard photolithography and etch back techniques. The photoresist was hard-baked for five minutes at 125 °C in order to stabilize it before etching. The gold was etched in a heated KCN solution for one minute, followed by a buffered oxide etch to remove the titanium. Due to the surface roughness of the substrate (approximately +/– 1.5 um), the edges of the resistor were jagged, but the lines were continuous. All processing was done at the Georgia Tech Microelectronics Research Center.

The LTCC inductor structure was designed within the Cadence Virtuoso design environment. A custom technology file for a 12-layer process was developed, and a process design rule compliant test structure coupon was fabricated at the National Semiconductor Corporation LTCC fabrication facility. The size of the completed coupon was approximately 2.25" × 2.25". Each layer of ceramic tape was specified to be 3.6 mils thick with a dielectric constant of 7.8. The metal lines were drawn to be 10 mils wide, and the vias were a diameter of 5.6 mils.

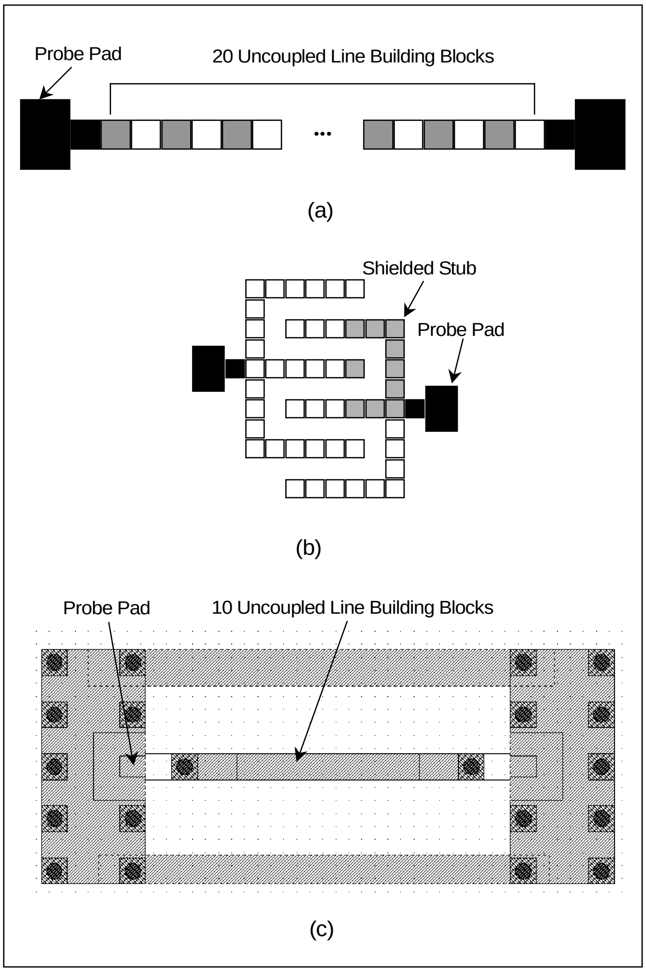

Fig. 1. Schematic three test structures: (a) straight-line resistor; (b) interdigitated capacitor; and (c) LTCC inductor.

III. MODELING SCHEME

High frequency analysis of complex geometrical structures is required to investigate their electrical performance in a frequency range of interest. This analysis is especially important to determine the effects of unwanted spurious couplings and resonances which can greatly affect the overall system response. Analysis such as this is usually only achievable through the use of electromagnetic or RF/microwave simulation tools. The derivation of equivalent circuit models is very useful to designers who would

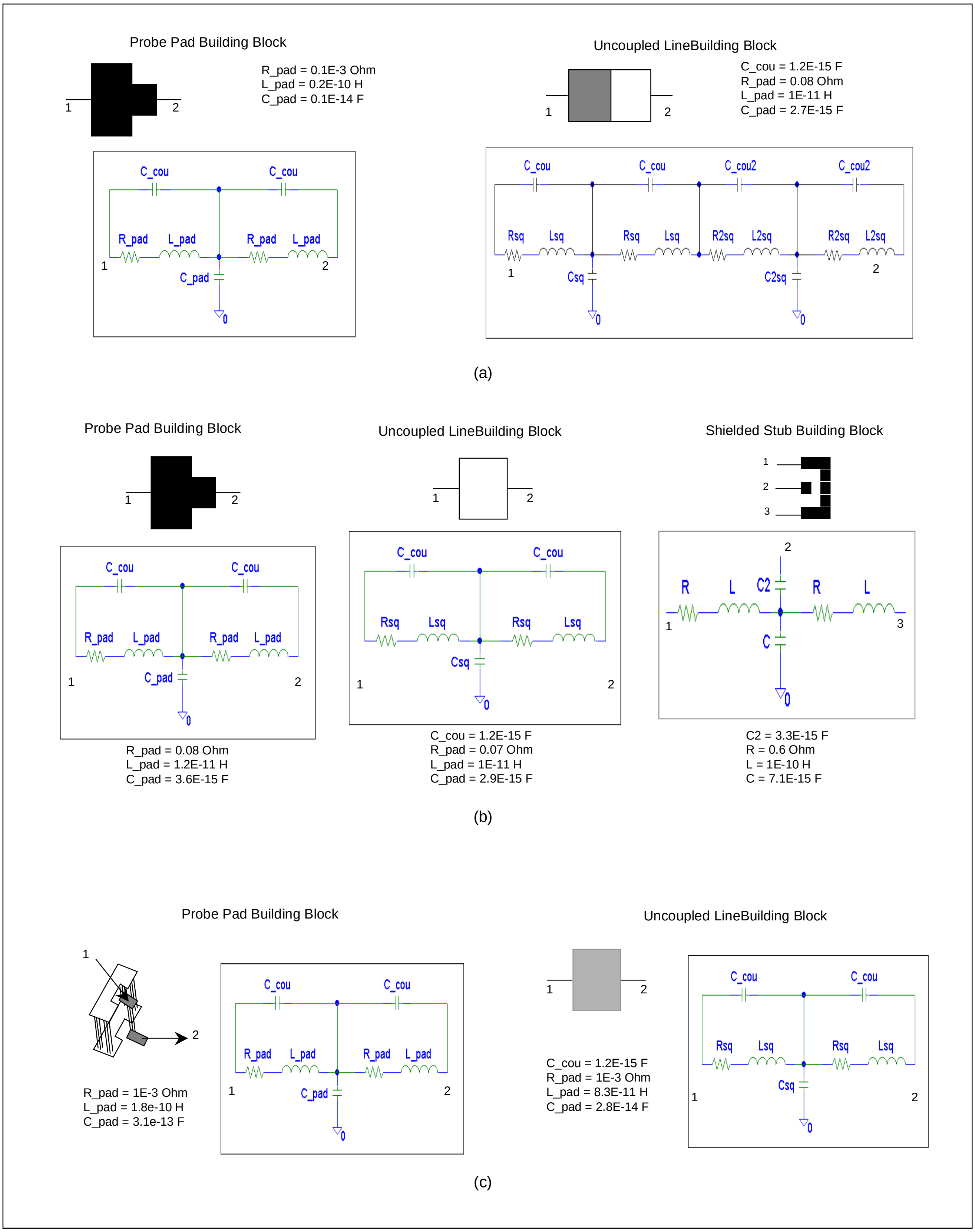

Fig. 2. Building blocks with associated circuit topologies and model parameters for (a) the straight-line resistor; (b) the interdigitated capacitor; and (c) the LTCC inductor.

like to incorporate the complex behavior of these structures in a system level circuit simulation. However, the process of obtaining lumped models from these simulators is a slow and computationally challenging task.

The modeling procedure implemented here involves determining a set of fundamental building blocks for the passive structures and then characterizing test structures comprised of combinations of those blocks [6]. The test structures are measured up to a desired frequency, and the electrical contribution to the overall response by the building blocks can then be determined. Equivalent circuits of each of the building blocks are then extracted using a hierarchical extraction procedure that will be described. Simulation of the derived circuit in a standard SPICE-compatible circuit simulator then provides the desired prediction of electrical behavior. Test structure models are verified experimentally by comparing the predicted electrical response with the measured response.

1. Test Structure Characterization

The test structures described in Section II above were measured using standard network analysis techniques. For high frequency measurements, an HP 8,510 C network analyzer was used in conjunction with a Cascade Microtech probe station and ground-signal-ground configuration probes. Calibration was accomplished using a supplied substrate and the line-reflect-match (LRM) calibration method. After calibration was completed, s-parameters were obtained for each of the test structures at 201 frequency points between 45 MHz and 5 GHz. This data was stored with the aid of computer data acquisition software and equipment.

2. Device Model Parameter Extraction

For passive device structures, it is desirable to predict their electrical behavior in a standard circuit simulator. In order to accomplish this, circuit models for each of the defined building blocks need to be extracted. The fundamental circuit for the building blocks is based on the partial element equivalent circuit (PEEC) [7] which has been used extensively for interconnect analysis [8] and general three-dimensional high frequency structure simulation [9]. Coupling behavior is represented by the coupling capacitance between center nodes of the two PEEC circuits, as well as by mutual inductances between the left upper and left lower branch inductors in the model, and likewise for the right hand side. These circuits represent models for the building blocks only. The test structure circuits are comprised of many of the building block circuits connected in accordance with the structure geometry. The various circuit models and parameters for the different building blocks are shown in Fig. 2.

After the circuit models for the different building blocks were obtained, the extraction of the circuit model parameters was achieved using two different optimization techniques. The first method chosen was the Levenberg-Marquardt (LM) algorithm [10]. Since the LM algorithm is built into HSPICE, all LM-based optimization and simulations were done using the HSPICE simulator on a Sun Sparc 20 workstation. Since the starting point or initial guesses for the circuit parameters were crucial for achieving convergence, an initial optimization was done assuming that each test structure was comprised of just one building block, utilized repetitively across the length of the structure on a per square basis. The initial guesses for the circuit parameters were derived by converting the measured s-parameters to z-parameters, and then dividing by the number of blocks used in order to extract the valid R, L, and C, values for the circuit model. Figure 3 shows a flow chart for the s-parameter extraction procedure.

However, since small changes in the initial guesses often led to non-convergence or incorrect optimization results, another optimization method which used genetic algorithms (GAs) was investigated. GA optimization was performed by software written in ANSI standard C++, and was compiled for use in the UNIX environment. HSPICE circuit simulations were still needed to obtain s-parameter data to complete GA optimization. GAs represent a guided stochastic approach to optimization which establishes a parallel search of the solution space. Since GAs use a large population of trial solutions, they can explore many regions of the search space simultaneously. Therefore, GAs are insensitive to initial guesses, and they are less likely to become trapped in local optima compared to conventional optimization methods. Further details on both the LM algorithm and GAs are provided in the following section.

IV. PARAMETER OPTIMIZATION METHODS

The equivalent circuit model parameter values required by the HSPICE simulator are usually obtained by curve fitting the model equations to device measured data. This curve fitting is accomplished using nonlinear least squares optimization techniques. Optimization is the process by which the set of model parameter values which best fit the data are selected. This optimum parameter set is created by adjusting an initial estimate of model parameter values using an iterative process. The process continues until simulated output data matches the actual measured output data within specified tolerances. In short, given a set of measured data, the optimizer solves for a set of model parameters which produce simulated data that optimally approximates the measured data.

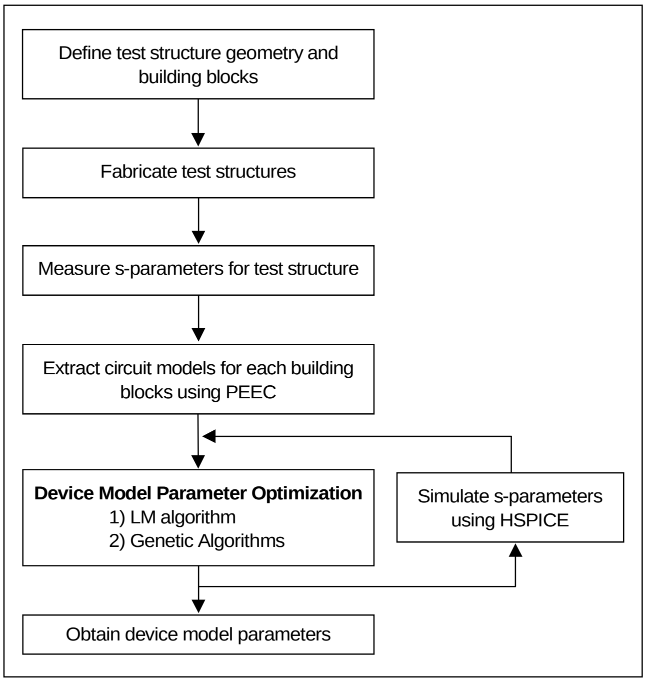

Fig. 3. Flow chart for s-parameter extraction.

1. Levenberg-Marquardt Algorithm

The optimization method used in the HSPICE simulator is the well-known Levenberg-Marquardt (LM) algorithm implemented with the Marquardt scaling parameter to prevent unexpected deviation of the parameter values. The LM search method is a combination of steepest descent and the Gauss-Newton method.

Gradient descent is a commonly used search method where parameters are moved in the opposite direction to the error gradient. Each step down the gradient results in smaller errors until minimum error is achieved. However, simple gradient descent suffers from slow convergence, in particular when a minimum is approached. Another commonly used method is the gradient with momentum that updates parameters proportionally to a running average of the gradient. In general, this technique can decrease the probability of becoming trapped in local minima. Nevertheless, the final iterations of the gradient with momentum method are still not effective when approaching a solution. The Gauss-Newton method provides better convergence properties near the solution. However, at a point away from the solution, this method suffers from the fact that prescribed the direction may not be a descent direction, and the associated inverted Hessian matrix may not exist.

In the LM algorithm, steepest descent is used initially to approach the solution, and then the Gauss-Newton method is used to refine the solution. During this search, the Marquardt scaling parameter becomes very small, but increases if the solution starts to deviate. If this happens, the LM technique optimizer becomes purely gradient descent when the Marquardt scaling parameter is very large, whereas the LM method is equivalent to the Gauss-Newton method when the Marquardt scaling parameter is zero.

The objective function of LM algorithm is

$$F_o(X)\Big|_{X=(x_1,x_2,\ldots,x_n)} = \sum_{i=1}^{m}\left[w_i \frac{f_i(X)-F^i_{meas}}{F^i_{meas}} \right]^2 \qquad (1)$$

where X = (x_1, x_2, ..., x_n) are the model parameters to be extracted, n is the total number of the model parameters, F^i_{meas} is the measured value of the ith model parameter, m is the total number of measurements, f_i(X) is the simulated value of the ith point, and w_i is a weight factor for the ith measured data point (used for giving higher significance to a given data point). Therefore, the HSPICE optimizer finds the vector X of the device model parameters that minimizes F_o(X).

2. Genetic Algorithms

Genetic algorithms (GAs) refer to a family of computational models inspired by evolution. In the last few years, GAs have started to be explored for several applications in industry [11], [12]. These algorithms encode a potential solution to a specific problem on a simple chromosome-like binary data structure and apply recombination operators to these structures so as to preserve critical information. An implementation of a genetic algorithm begins with a population of (typically random) chromosomes. To implement a GA, the set of parameters to be optimized are first mapped onto a set of binary strings, with each string representing a potential solution. The GA then manipulates the most promising strings in searching for improved solutions. A GA typically operates iteratively through a simple cycle of four stages: 1) creation of a population of strings, 2) evaluation of each string, 3) selection of the best strings, and 4) genetic manipulation to create a new population of strings. The process for optimizing passive device model parameters using GAs is shown in Fig. 4.

The genetic manipulation includes three genetic operations —reproduction, crossover, and mutation—to search the optimal solution in the entire search space. Using these operations, GAs can search through large, irregularly shaped spaces effectively, requiring only the information of the objective function. This is a desirable characteristic, considering that the majority of commonly used search techniques require not only the complete information of the objective function but also derivative information, continuity of the search space.

In coding genetic searches, binary strings are typically used. One successful method for coding multiparameter optimization problems is concatenated, multiparameter, mapped, fixed-point

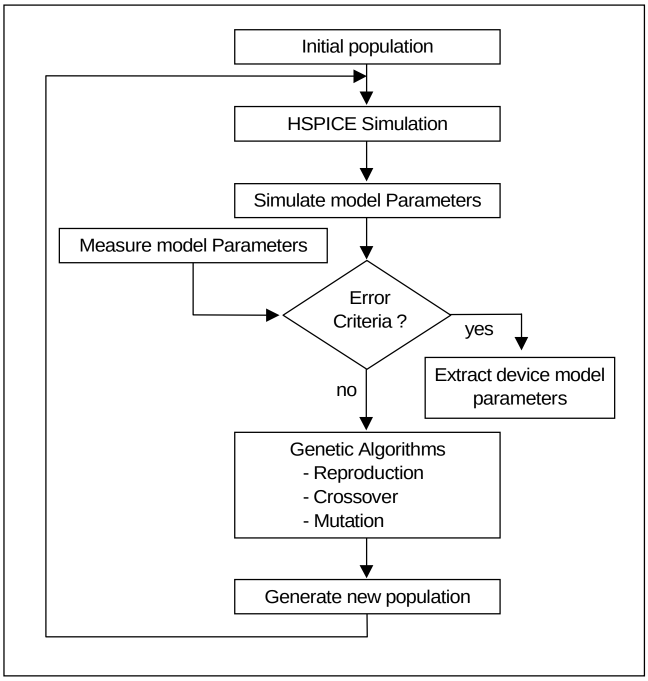

Fig. 4. Optimization process for device model parameters using GAs.

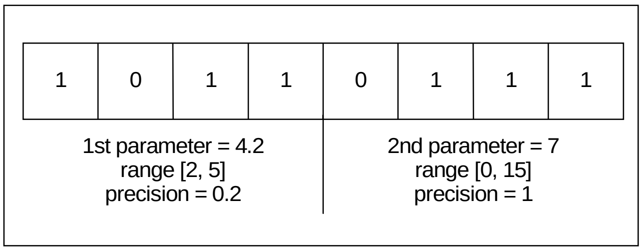

Fig. 5. Example of multiparameter coding.

coding [3]. If $x \in [0, 2^b]$ is the parameter of interest (where b is the number of bits in the string), the decoded unsigned integer x can be mapped linearly from $[0,2^b]$ to a specified interval $[U_{min}, U_{max}]$. In this way, both the range and precision of the decision variables can be controlled. To construct a multi-parameter coding, required single parameters can simply be concatenated. Each coding may have its own sub-length (i.e., its own U_{min} and U_{max}). Figure 5 shows an example of a 2-parameter coding with four bits in each parameter. The ranges of the first and second parameters are 2-5 and 0-15, respectively.

The string manipulation process employs the aforementioned genetic operators to produce a new population of individuals (called offspring) by modifying the genetic code possessed by members of the current population (called parents). Reproduction is the process by which strings with high fitness values (i.e., good solutions to the optimization problem under consideration) receive larger numbers of copies in the new population. A popular method of reproduction is elitist roulette wheel selection [13]. In this method, those strings with large

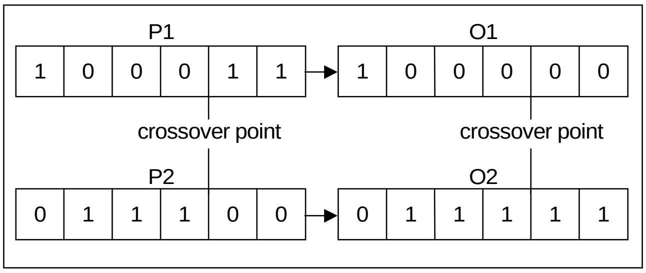

Fig. 6. Illustration of the crossover operation.

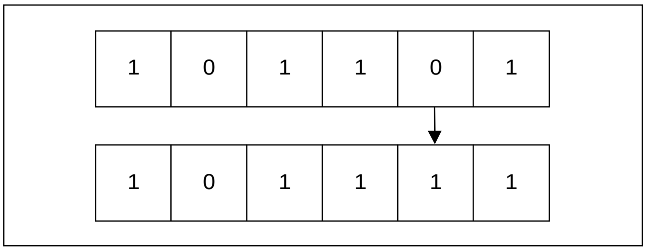

Fig.7. Illustration of the mutation operation.

fitness values F_i are assigned a proportionately higher probability of survival into the next generation. This probability distribution is determined according to

$$P_{select_i} = \frac{F_i}{\sum_{j=1}^{n} F} \tag{2}$$

Thus, an individual string whose fitness is n times better than another will produce n times the number of offspring in the subsequent generation. Once the strings have reproduced, they are stored in a mating pool awaiting the actions of the crossover and mutation operators.

The crossover operator takes two chromosomes and interchanges part of their genetic information to produce two new chromosomes (Fig. 6). After the crossover point has been randomly chosen, portions of the parent strings (P1 and P2) are swapped to produce the new offspring (O1 and O2) based upon a specified crossover probability. Mutation is motivated by the possibility that the initially defined population might not contain all of the information necessary to solve the problem. This operation is implemented by randomly changing a fixed number of bits every generation based upon a specified mutation probability (Fig. 7). Typical values for the probabilities of crossover and bit mutation range from 0.6 to 0.95 and 0.001 to 0.01, respectively. Higher mutation and crossover rates disrupt good “building blocks” (schemata) more often, and for smaller populations, sampling errors tend to wash out the predictions. For this reason, the greater the mutation and crossover rates and the smaller the population size, the less frequently predicted

Table 1. Genetic algorithm parameters.

Parameters	Value
Crossover Probability	0.9
Mutation Probability	0.01
Population Size	8
Chromosome Length	80 bits

solutions are confirmed.

In this study, the genetic algorithms have been implemented to extract the passive device circuit model parameters for the test structures described above using the following fitness function (F_{fit}):

$$F_{fit} = \frac{1}{1+\sum_{n}\left(y_{meas} - y_{sim}\right)^2} \tag{3}$$

where n is the number of s-parameter measurements taken, y_{meas} are the actual s-parameter measurements, and y_{sim} are the simulated s-parameters found using HSPICE. The probabilities of crossover and mutation were set to 0.9 and 0.01, respectively (see Table 1). A population size of 8 was used in each generation. Each of the eight device model parameters were encoded as a 10-bit string, resulting in a total chromosome length of 80 bits. The optimization procedure was stopped after 100 iterations or when F_{fit} was within a predefined tolerance.

V. RESULTS AND DISCUSSION

The optimization results using the LM algorithm in the HSPICE optimizer and GAs for the three test structures described in Section II are presented here. Each structure requires the extraction of eight passive device values from s-parameter measurements. The root mean square error (RMSE) between the measured and simulated s-parameters has been calculated for each optimization method.

For the extraction of the passive device model parameters in the straight-line resistor, 20 different sets of parameters were used as the initial starting points for the LM algorithm. These initial sets of parameters were randomly selected using 10% deviation from a previously analyzed set of parameters which had converged to a solution. Among the 20 simulations, only three converged to a solution. Table 2 shows the results of extracting the passive device model parameters for the straight line resistor using the LM algorithm and GAs. The results illustrate that the LM algorithm can be trapped in local minima, and the use of GAs can improve the accuracy of the model parameter values.

Table 2. Optimization results for the straight-line resistor.

	HSPICE Optimizer results			GA result
Parameter	run1	run2	run3	GA_run
C_cou	1.52E–14	1.63E–13	5.15E–14	2.19E–14
Rsq	5.38E–02	1.00E–02	3.04E–02	4.83E–02
Lsq	1.13E–15	9.36E–12	9.36E–12	9.32E–12
Csq	2.72E–15	2.59E–16	2.61E–15	2.70E–15
C_cou2	1.00E–15	6.23E–11	7.75E–11	9.22E–11
R2sq	9.85E–02	1.37E–01	1.15E–01	9.80E–02
L2sq	8.88E–12	1.15E–12	1.03E–12	9.32E–13
C2sq	3.35E–17	2.46E–15	8.98E–17	1.20E–17
RMSE	1.50E–03	1.40E–03	1.40E–03	1.20E–03

Table 3. Optimization results for the interdigitated capacitor.

	HSPICE Optimizer results				GA result
Parameter	run1	run2	run3	run4	GA_run
C_cou	1.00E–15	1.00E–15	1.00E–15	1.00E–09	4.40E–16
R_pad	1.54E–01	1.50E–01	1.59E–01	1.70E–01	5.67E–02
L_pad	1.54E–11	1.50E–11	1.59E–11	1.20E–11	8.99E–11
C_pad	3.54E–15	3.50E–15	3.59E–15	3.20E–15	3.59E–15
Rsq	1.55E–01	1.55E–01	1.55E–01	1.39E–01	1.88E–01
Lsq	8.87E–12	8.87E–12	8.87E–12	9.15E–12	9.42E–12
Csq	2.76E–15	2.76E–15	2.76E–15	2.25E–15	2.51E–15
RMSE	1.13E–03	1.58E–03	1.29E–03	2.03E–03	5.81E–04

Similar results were found for the interdigitated capacitor test structure (see Table 3). In this case, 30 sets of randomly generated initial model parameters were used for the LM algorithm, and a solution was found for only four of these. The model parameter values found using GAs were much more accurate compared those found by means of the LM method.

Table 4 shows the results of extracting the passive device model parameters for the LTCC inductor. In this case, 20 sets of randomly generated initial model parameters were used for the LM algorithm, and a solution was found for ten of these cases. From these results, it was found that the LM algorithm yields a large variation in the extracted model parameters. For example, C_cou varies from 10^{-15} to 10^{-10} F, and Rsq varies from 10^{-3} to 10^{-6} ohms. However, since GAs can explore the search space more effectively, a single solution representing the global optimum is found using this method.

Table 4. Optimization results for the LTCC inductor.

	HSPICE Optimizer results										GA result
Parameter	run1	run2	run3	run4	run5	run6	run7	run8	run9	run10	GA_run
C_cou	1.36E–10	1.00E–15	1.00E–15	1.00E–15	5.75E–10	1.28E–10	8.36E–11	8.98E–11	1.00E–15	9.23E–11	6.90E–10
R_pad	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.03E–16
L_pad	5.68E–10	2.80E–10	3.01E–10	2.96E–10	5.99E–10	5.67E–10	5.52E–10	5.53E–10	2.95E–10	5.54E–10	6.45E–10
C_pad	4.03E–13	4.31E–13	4.35E–13	4.29E–13	4.06E–13	4.04E–13	4.05E–13	4.04E–13	4.20E–13	4.04E–13	3.11E–13
Rsq	1.00E–06	3.18E–03	1.00E–06	1.00E–06	1.83E–03	1.00E–06	1.00E–06	1.00E–06	1.00E–06	1.00E–06	3.40E–03
Lsq	5.94E–12	6.56E–11	6.25E–11	6.37E–11	1.74E–12	6.21E–12	8.72E–12	8.28E–12	6.40E–11	8.11E–12	8.64E–12
Csq	1.00E–17	2.90E–15	1.46E–15	2.90E–15	1.00E–17	1.00E–17	1.00E–17	1.00E–17	4.80E–15	1.00E–17	2.35E–17
RMSE	1.70E–03	1.49E–03	1.31E–03	1.32E–03	1.33E–03	2.49E–03	1.32E–03	1.31E–03	1.32E–03	1.66E–03	8.98E–04

VI. CONCLUSION

The extraction of circuit model parameters for the three passive device test structures using genetic algorithms has been investigated and compared with optimization using the Levenberg-Marquardt algorithm used in the HSPICE circuit simulation program. Results indicate that GAs tend to provide improved accuracy and are better in finding global optima, whereas the LM method is extremely sensitive to the initial starting point of the parameter search and easily trapped in local optima. However, GAs are generally slower and the number of GA iterations and the optimum set of GA parameters must be ascertained empirically. Thus, a trade-off exists between computational time and achieving acceptable accuracy in optimizing model parameters. Nevertheless, GAs appear to show much promise in this area.

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