

# Constrained EM-based Modeling of Passive Components

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**Abstract** — An adaptive algorithm is developed for constrained modeling of general passive components. The algorithm builds compact, multidimensional, analytical circuit models and represents the scattering parameters of the passive components as a function of its geometrical parameters and as a function of the frequency. Multiple constraints, or relationships between the geometrical parameters, may exist. The model generation algorithm combines iterative sampling and modeling techniques. It groups a number of full-wave electromagnetic (EM) simulations in one multidimensional analytic model. The modeling accuracy level is user-defined. The analytical circuit models can easily be implemented and used in commercial circuit simulators. The models provide EM-accuracy and generality at traditional circuit simulation speed.

## I. INTRODUCTION

Accurate models for arbitrary  $\mu$ W/RF components are very important for the design of high-speed electronic circuits. Several numerical EM analysis techniques can be used to accurately model passive components. However, most numerical EM techniques require a significant amount of expertise and computer resources, and are often only used for verification purposes. On the other hand circuit simulators are very fast, and offer a lot of different analysis possibilities (e.g. optimization, parameter sweeps, tuning). However, the number of available high-frequency models in circuit simulators is limited, and the accuracy is not always guaranteed up to high frequencies.

Numerous efforts have been spent to build models for general structures based on full-wave EM simulations. Previously used techniques include lookup tables, curve fitting techniques and neural networks [1-3]. A common drawback of these efforts is the lack of knowledge about the accuracy of the resulting models, and there are capacity issues with higher dimensional models.

We developed a new adaptive technique, called *MAPS* (*Multidimensional Adaptive Parameter Sampling*), for building parameterized analytical models of general passive  $\mu$ W/F components with a user-defined accuracy [4-6]. The MAPS models are based on full-wave EM simulations, and can be used in a circuit simulator. In this paper, the basic MAPS technique is extended to handle constrained parameter spaces, where multiple relations may exist between the different geometrical layout parameters.

## II. ADAPTIVE MODEL BUILDING ALGORITHM

The scattering parameters  $S$  are represented by a weighted sum of multidimensional orthonormal polynomials (*multinomials*)  $P_m$ . The multinomials only depend on the coordinates  $\bar{x}$  in the multidimensional parameter space  $R$ , while the weights  $C_m$  only depend on the frequency  $f$ :

$$S(f, \bar{x}) \approx M(f, \bar{x}) = \sum_{m=1}^M C_m(f) P_m(\bar{x}) \quad (1)$$

The weights  $C_m$  are calculated by fitting equation (1) on a set of  $D$  data points  $\{\bar{x}_d, S(f, \bar{x}_d)\}$  (with  $d = 1, \dots, D$ ). The number of multinomials in the sum is adaptively increased until the error function  $E(f, \bar{x}) = |S(f, \bar{x}) - A(f, \bar{x})|$  is lower than a given threshold (which is function of the desired accuracy of the model) in all the data points.

For numerical stability and efficiency reasons orthonormal multinomials  $P_m(\bar{x})$  are used [5].

## III. ADAPTIVE DATA SELECTING ALGORITHM

The modeling process starts with an initial set of data points. New data points are added adaptively until the user-defined accuracy level is guaranteed. The process of selecting data points and building models in an adaptive way is called *reflective exploration* [7]. Reflective exploration is useful when the process that provides the data is very costly, which is the case for full-wave EM simulators. Reflective exploration requires *reflective functions* that are used to select a new data point. The difference between 2 consecutive approximated models (with different order  $M$  in (1)) is used as a reflective function. A new data point is selected near the maximum of the reflective function. No new data points are added if the magnitude of the reflective function is smaller than the user-defined accuracy level (over whole parameter space).

Physical rules are also checked. If the approximate modeling function  $M(f, \bar{x})$  violates certain physical rules, a new data point is chosen where the criteria are violated the most.

Furthermore, at least one data point is chosen in the close vicinity of local minima and maxima of the modeling function  $M(f, \bar{x})$  over the parameter space of interest.

The complete flowchart of the algorithm is given in figure 1.

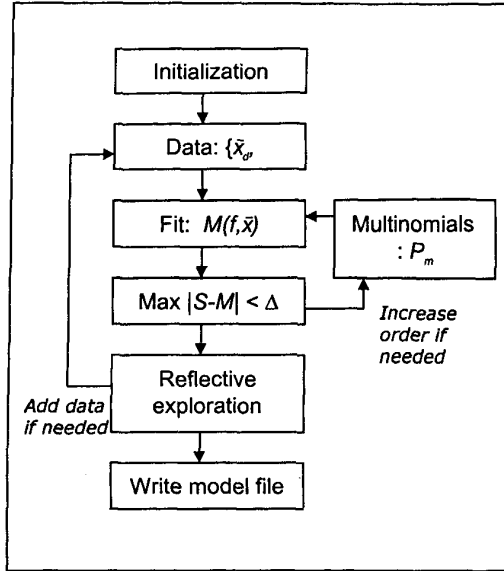


Fig. 1. Adaptive modeling and sampling flowchart

#### IV. CONSTRAINED MODELING

In the basic modeling algorithm it is assumed that the parameter space is a  $n$ -dimensional hypercube, where all of the geometrical parameters can be varied independently over their whole range. However, in certain structures the geometrical parameters must satisfy a number of constraints. Due to these conditions the parameter space is no longer rectangular. Certain parts of the parameter space are forbidden. This affects the way in which the initial one-dimensional models are built as well as the way in which the initial  $n$ -dimensional data point distribution is generated.

Figure 2 shows a two-dimensional normalized parameter space (the extension to more dimensions is straightforward). The two geometrical parameters  $x_1$  and  $x_2$  cannot be varied independently. They have to satisfy the condition  $g(x_1, x_2) \geq 0$ . Due to this condition the parameter space is divided in two parts: a valid part where  $g(x_1, x_2) \geq 0$  and a forbidden part where  $g(x_1, x_2) < 0$ . All data points must lie in the valid part of the parameter space.

The borders of the parameter space are assumed to be linear: a straight line in a two-dimensional parameter space, a plane in a three-dimensional parameter space or a hyperplane in a hypercube. In this way a border can be represented by an equation of the form:

$$g(x_1, \dots, x_n) = \sum_{i=1}^n \alpha_i x_i = 0 \quad (2)$$

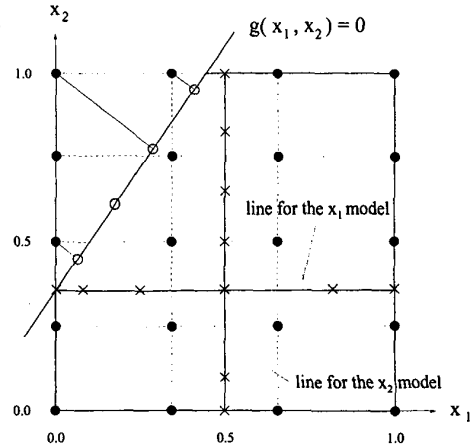


Fig. 2. Constrained two-dimensional parameter space

The first step in the modeling process is building the one-dimensional models. In the basic MAPS algorithm [5] these models would be built along lines through the center of the parameter space. Since the one-dimensional models are used to gain insight in the influence each of the geometrical parameters has on the modeled  $S$ -parameters, the models should be built along lines where the geometrical parameters have their maximum variation. In the case of figure 2,  $x_1$  doesn't have its maximum variation along the line  $x_2 = 0.5$ . Therefore, a first adaptation is made to the basic algorithm. The lines for the one-dimensional models are shown in figure 2.

In a second step, the one-dimensional models are used to generate the initial two-dimensional data point distribution. In figure 2 these data points are represented by the black dots. Some of the data points lie in the forbidden part of the parameter space. These points have to be projected onto the border  $g(x_1, x_2) = 0$ . This is done as follows. A straight line through a point  $(x_{d1}, \dots, x_{dn})$  perpendicular to (2) is given by the equation:

$$x_i = x_{di} + \lambda \alpha_i \quad (3)$$

Substituting (3) in (2) results in an expression for  $\lambda$ :

$$\lambda = - \frac{\sum_{i=1}^n \alpha_i x_{di}}{\sum_{i=1}^n \alpha_i^2} \quad (4)$$

Substituting this expression in (3) yields the coordinates of the projected point. In figure 2, the projected points are represented by the circles on the border of the parameter space. The initial data point distribution then consists of

the points in the uniform mesh that lie in the valid part of the parameter space, the projected points and the data points used for the one-dimensional models.

Once the initial data point distribution is generated, the rest of the modeling process is almost the same as the basic modeling algorithm. New data points are selected by evaluating the selection criteria on a dense grid. This grid covers only the valid part of the parameter space. In this way it is made sure that no new data points are selected in the forbidden part of the parameter space.

### V. EXAMPLE

As an example consider the layout shown in figure 3. This is the layout of a spiral inductor on a microstrip substrate (with a thickness of 25 mil and a relative dielectric constant of 9.6). There are two ports,  $P_1$  and  $P_2$ . A model is built for the scattering parameters of this structure as a function of two geometrical parameters,  $W$  (the width of the strips) and  $S$  (the spacing between the strips), and of the frequency  $f$ . The ranges for  $W$ ,  $S$  and  $f$  are given in table 1. The S-parameters are calculated using the commercially available full-wave simulator ADS Momentum [8]. The desired accuracy of the model compared to the EM simulations is set to -55 dB.

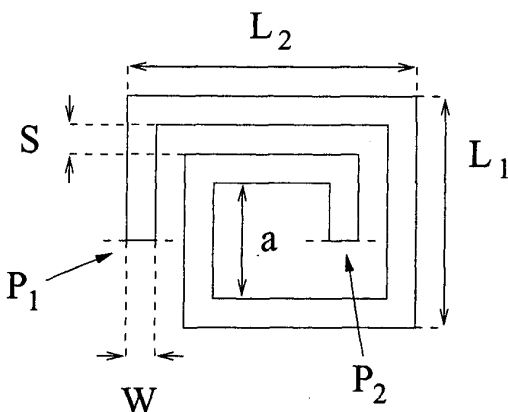


Fig. 3. Layout of spiral inductor

variable	min	max
$W$	10 mil	30 mil
$S$	5 mil	15 mil
$f$	1 GHz	5 GHz

Table 1. Parameter ranges for the spiral inductor

Suppose that embedding the inductor in a given design forces the total dimensions of the inductor to be restricted, e.g.:

$$\begin{aligned} L_1 &= 3W + S + a \leq 110 \\ L_2 &= 4W + 2S + a \leq 140 \end{aligned} \quad (5)$$

Due to these restrictions  $W$  and  $S$  cannot be varied independently ( $a = 40$  mil). Figure 4 shows the reduced parameter space along with the two borders  $G_1(W,S) = 70 - 3W - S = 0$  and  $G_2(W,S) = 100 - 4W - 2S = 0$ . The intersect of  $G_1$  and  $G_2$  is the point  $(W,S) = (20,10)$ . The forbidden part of the parameter space is grayed.

Due to the restrictions,  $W$  cannot reach the maximum of its range. For  $W > 21.667$  all points are in the forbidden part of the parameter space. The modeling algorithm must be able to detect this and adapt the original parameter ranges. To do this, interval arithmetic [9] is used in an iterative process:

- STEP 0: Set the initial interval values  $W^{(0)} = [10,30]$  and  $S^{(0)} = [5,15]$ . Set  $k=1$ .
- STEP 1: Solve both  $G_1(W, S^{(k-1)}) = [0, +\infty]$  and  $G_2(W, S^{(k-1)}) = [0, +\infty]$  for  $W$ . The results are  $W_1$  and  $W_2$ . Set  $W^{(k)} = \text{intersect}(W^{(k-1)}, W_1, W_2)$ . Do the same for  $S$ .
- STEP 2: If  $W^{(k)} = W^{(k-1)}$  and  $S^{(k)} = S^{(k-1)}$  stop the iteration, else set  $k=k+1$  and return to STEP 1.

As a result of this iterative process the parameter ranges are adapted to  $W = [10,21.667]$  and  $S = [5,15]$ . The adapted parameter space is shown in figure 4.

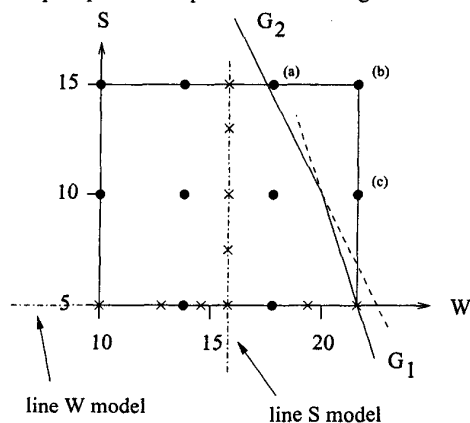


Fig. 4. Adapted parameter space

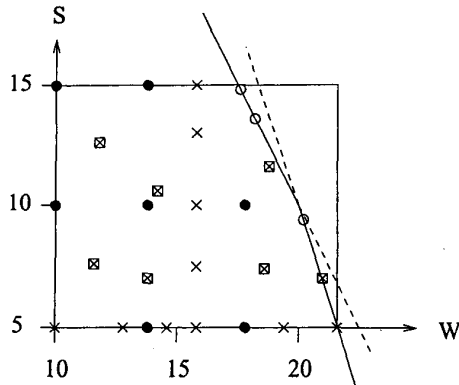


Fig. 6. Data points used during the modeling process

At this point the real modeling starts. The first step is building two one-dimensional models: one for  $W$  (with  $S=5$ ) and one for  $S$  (with  $W=15.833$ ). Based upon these models the initial two-dimensional data point distribution is generated. In figure 4 the crosses represent the data points used in the one-dimensional models, and the black dots represent the data points in the initial two-dimensional distribution. 3 of the points in the initial data point distribution lie in the forbidden part of the parameter space. These are projected onto the borders  $G_1$  and  $G_2$ .

Finally, 7 more data points are chosen using the selection criteria, resulting in a total of 27 data points for the whole modeling process. All data points used are shown in figure 6.

In figure 7, the scattering parameters of the spiral (in the constrained parameter space) are represented as a function of frequency  $f$ , and geometrical parameters  $W$  and  $S$ .

The accuracy of the model was tested in 4838 data points uniformly distributed over the parameter and frequency space. The maximum deviation that was found between the S-parameters calculated using the MAPS model and the results obtained with the EM simulator [8] was -54.3 dB. 99.9% of the test points had an accuracy level of -55 dB or better.

## VI. CONCLUSION

A new adaptive technique (MAPS) was presented for constrained parameterized model building of general passive components. Certain dependencies may exist between (some of) the geometrical parameters. The models are based on full-wave EM simulations, and have a predefined accuracy. Once generated, the analytical models can be grouped in a library, and incorporated in a circuit simulator where they can be used for simulation, design and optimization purposes.

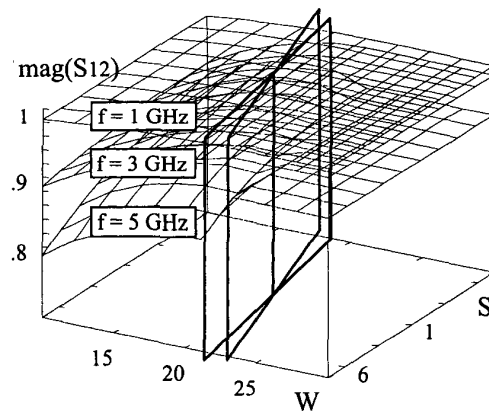


Fig. 7. S-data of spiral as a function of  $f$ ,  $W$ ,  $S$

An example was given to illustrate the technique.

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