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Self-organizing multivariate constrained meta-modeling technique for passive microwave and RF components

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Abstract

A self-organizing algorithm is developed for multivariate constrained modeling of general passive components. The algorithm builds compact, 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 simulations in one multivariate analytic model. The modeling accuracy level is user-defined. The analytical circuit models can easily be implemented and used in commercial circuit simulators. The model extraction provides EM-accuracy and generality at traditional circuit simulation speed.

Keywords: Meta-modeling; Multivariate systems; Adaptive sampling; Electronic design automation; Circuit modelling; Electromagnetic modeling

1. Introduction

Accurate circuit models for arbitrary microwave and RF components are very important for the study and design of high-speed electronic circuits. Several numerical EM analysis techniques (e.g. method of moments, finite elements method, FDTD method) can be used to accurately model and simulate passive components. However, most numerical EM techniques require a significant amount of expertise and computer resources, so that they are often only used for analysis and verification purposes, but not for designing and optimizing complex layouts or schematics. 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 interconnection structures based on full-wave EM simulations. Previously used techniques

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include lookup tables [1], curve fitting techniques [2] and neural networks [3–5]. A common drawback of these previous efforts is the lack of knowledge about the accuracy of the resulting models.

We developed an adaptive technique, called *multidimensional adaptive parameter sampling* (MAPS), for building parameterized analytical models of general passive microwave and RF components with a user-defined accuracy [6,7]. We use mixed rational-multinomial functions (of frequency and geometrical parameters) to model the scattering parameters. In [8], multivariate rational functions are used instead.

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.

The MAPS models are based on full-wave EM simulations. The models can easily be incorporated in a circuit simulator. This brings EM-accuracy and generality in the circuit simulator, without sacrificing speed. The model generation process is fully automatic. Data points are selected efficiently and model complexity is automatically adapted. The algorithm consists of an adaptive modeling loop (Section 2) and an adaptive sample selection loop (Section 3). The constrained modeling requires some modifications (Section 4). Examples are given to illustrate the technique (Section 5).

2. Adaptive model building algorithm

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

$$S(f, \overline{x}) \approx M(f, \overline{x}) = \sum_{m=1}^{M} C_m(f) P_m(\overline{x}). \tag{1}$$

The weights C_m are calculated by fitting Eq. (1) on a set of D data points $\{\overline{x}_d, S(f, \overline{x}_d)\}$ (with $d = 1, \ldots, D$) [9]. The number of multinomials in the sum is adaptively increased until the error function:

$$E(f, \overline{x}) = |M(f, \overline{x}) - S(f, \overline{x})| \tag{2}$$

is lower than a given threshold (which is a function of the desired accuracy of the model) in all the data points.

For numerical stability and efficiency reasons orthonormal multinomials are used, i.e. the multinomials $P_m(\overline{x})$ satisfy the condition:

$$\sum_{d=1}^{D} P_k(\overline{x}_d) P_l(\overline{x}_d) = \begin{cases} 1 & \text{for } k = l, \\ 0 & \text{for } k \neq l. \end{cases} \tag{3}$$

The multinomials can be written as a sum of basis functions B_k:

$$P_m(\overline{x}) = \sum_{k=1}^{m} \beta_k B_k(\overline{x}) = \sum_{k=1}^{m} \beta_k x_1^{e_{k1}/E_1} \cdots x_n^{e_{kn}/E_n}. \tag{4}$$

The weights B_k are chosen in such a way that the multinomials P_m are orthonormal. The normalization factors E_i of the exponents e_{ki} (with $i = 1, \ldots, n$) are a measure for the influence each of the geometrical parameters has on the modeled scattering parameters. Making use of these normalization factors significantly speeds up the model generation process.

To get an idea about the influence each of the geometrical parameters has on the scattering parameters prior to building the n-dimensional model, n one-dimensional models are built. Each one-dimensional model is built along a line through the center of the parameter space: the ith model is a model for x_i varying from a_i to b_i and all x_j (with $i \neq j$) set to $(a_j + b_j)/2$. The power to which a parameter x_i is raised in the one-dimensional model determines the normalization factor E_i.

3. Adaptive data selecting algorithm

The n one-dimensional models determine the initial n-dimensional data point distribution. It consists of a uniform mesh of data points where the number of points in the ith direction is proportional to the number of data points required for the ith one-dimensional model. In this way, the geometrical parameters that have the most influence on the scattering parameters are sampled the most densely.

New data points are selected adaptively in such a way that a predefined accuracy Δ for the models is guaranteed. The process of selecting data points and building models in an adaptive way is called *reflective exploration* [10]. 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 reflective function used in the MAPS algorithm is the difference between two different models (different order M in Eq. (1)). A new data point is selected near the maximum of the reflective function. When the magnitude of the reflective function becomes smaller than Δ over the whole parameter space, no new data points are selected.

If one of the scattering parameters has a local minimum or maximum in the parameter space of interest, it is important to have at least one data point in the close vicinity of this extremum in order to get an accurate approximation. Therefore, if there is no data point close to a local maximum or minimum of $M(f, \bar{x})$, the local extremum is selected as a new data point. For resonant structures, the power loss has local maxima at the resonance frequencies. Again, to get an accurate approximation, a good knowledge of these local maxima is very important.

The scattering parameters of a linear time invariant (LTI) passive circuit satisfy certain physical conditions. If the model fails these physical conditions, it cannot accurately model the scattering parameters. The physical conditions act as additional reflective functions: if they are not satisfied, new data points are chosen where the criteria are violated the most.

The flowchart of the adaptive algorithm is shown in Fig. 1.

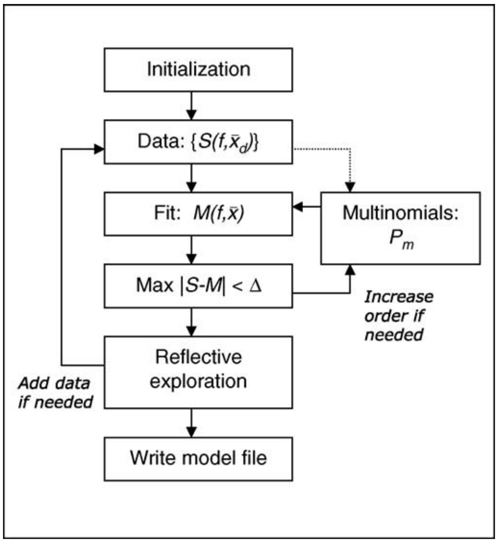

Fig. 1. Adaptive modeling and sampling flowchart.

4. 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.

Fig. 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 into two parts: a valid part

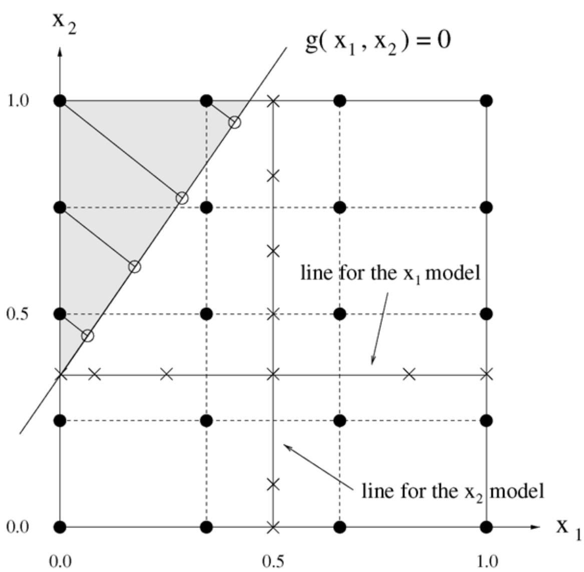

Fig. 2. Constrained two-dimensional parameter space.

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

$$g(x_1, \ldots, x_n) = \sum_{i=1}^{n} \alpha_i x_i = 0. \tag{5}$$

The first step in the modeling process is building the one-dimensional models. In the basic MAPS algorithm 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 Fig. 2, x_1 does not 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 Fig. 2.

In a second step, the one-dimensional models are used to generate the initial two-dimensional data point distribution. In Fig. 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 $(x_{d1}, \ldots, x_{dn})$ perpendicular to (5) is given by the equation:

$$x_i = x_{di} + \lambda \alpha_i. \tag{6}$$

Substituting (6) in (5) results in an expression for λ:

$$\lambda = -\frac{\sum_{i=1}^{n} \alpha_i x_{di}}{\sum_{i=1}^{n} \alpha_i^2}. \tag{7}$$

Substituting this expression in (6) yields the coordinates of the projected point. In Fig. 2, the circles on the border of the parameter space represent the projected points. 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.

5. Example

As an example consider the layout shown in Fig. 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 [11]. The desired accuracy of the model compared to the EM simulations is set to −55 dB.

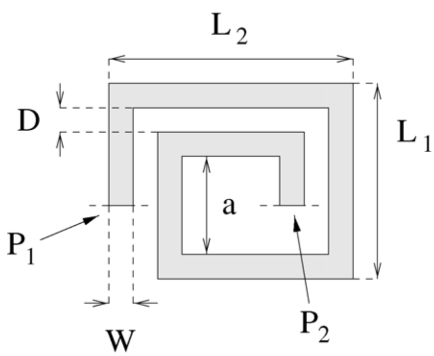

Fig. 3. Layout of spiral inductor.

Table 1
Parameter ranges for the spiral inductor

Variable	Minimum	Maximum
W (mil)	10	30
S (mil)	5	15
f (GHz)	1	5

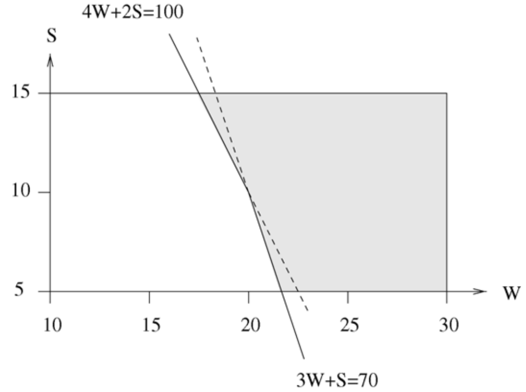

Fig. 4. Parameter space for the spiral inductor model.

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

$$L_1 = 3W + S + a \leq 110,$$
$$L_2 = 4W + 2S + a \leq 140. \quad (8)$$

Due to these restrictions *W* and *S* cannot be varied independently, but have to satisfy the conditions (in this example we take $a = 40$ mil):

$$70 - 3W - S \geq 0, \qquad 100 - 4W - 2S \geq 0. \quad (9)$$

Fig. 4 shows the 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.

The first thing to notice is that 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 [12,13] 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.

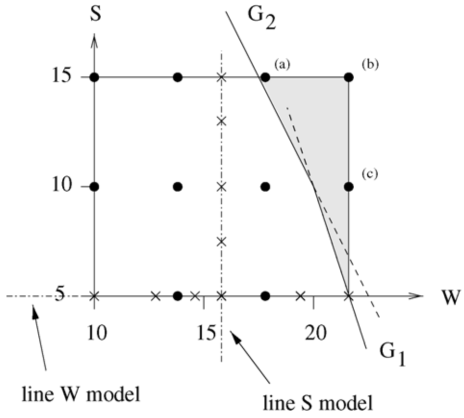

Fig. 5. Adapted parameter space.

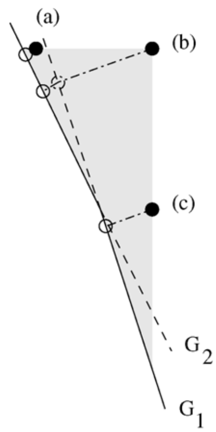

Fig. 6. Projection on the borders of the parameter space.

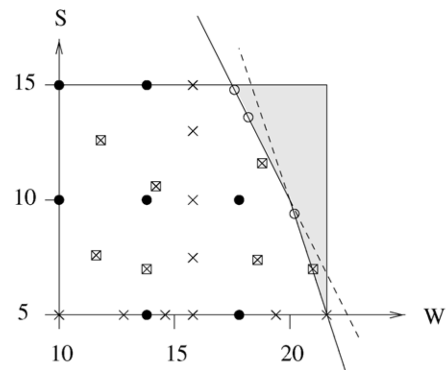

Fig. 7. Data points used during the modeling process.

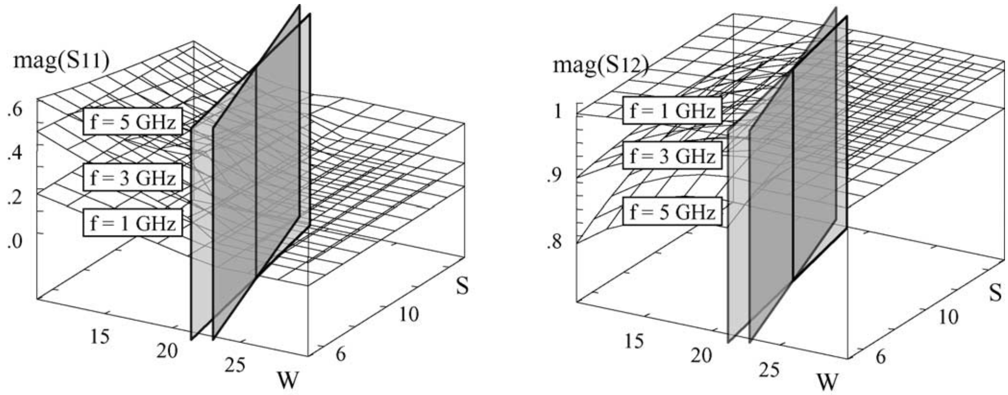

Fig. 8. *S*-data of spiral as a function of *f*, *W* and *S*.

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 Fig. 5.

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 Fig. 5 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. Three of the points in the initial data point distribution lie in the forbidden part of the parameter space (*a*, *b* and *c*). These are projected onto the borders G_1 and G_2 (as shown in Fig. 6). First, points *b* and *c* are projected onto G_1. Next, point *a* and the projection of point *b* on G_1 are projected onto G_2.

Finally, seven 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 Fig. 7.

In Fig. 8, 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 found between the *S*-parameters calculated using the MAPS model and the results obtained with the EM simulator [11] was −54.3 dB. 99.9% of the test points had an accuracy level of −55 dB or better.

6. Conclusion

A new adaptive technique (MAPS) was presented for constrained parameterized model building of general passive microwave and RF 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.

An example was given to illustrate the technique. Excellent agreement was found between the *S*-parameters obtained with the parameterized models and the *S*-parameters obtained from full-wave EM simulations.

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Jan De Geest received his degree in electrical engineering from the University of Ghent, Belgium, in 1994 and the degree in supplementary studies in aerospace techniques from the University of Brussels, Belgium, in 1995. From September 1995 to December 1999 he worked as a research assistant at the Department of Information Technology (INTEC) of the University of Ghent, where he received the PhD degree in electrical engineering in 2000. Since January 2000 he has been working for FCI in s-Hertogenbosch, The Netherlands. His work focuses on the modeling and simulation of high-speed interconnection links.