EM-based Multidimensional Parameterized Modeling of General Passive Planar Components

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***Abstract* — A new adaptive algorithm is presented for building multidimensional parameterized analytical models for general passive planar components. The component models are based on multiple full-wave electro-magnetic (EM) simulations. The modeling accuracy level is chosen by the user. Models can be generated for arbitrarily geometries and substrates, and they can be easily implemented and used in commercial circuit simulators. The adaptive model generation process is an up-front time investment and requires multiple EM simulations. The model extraction provides EM-accuracy and generality at traditional circuit simulation speed.**

I. Introduction

Precise characterization of high-frequency passive planar components is very important for circuit simulation and optimization purposes. Different numerical EM analysis techniques (e.g. the method of moments, the finite elements method, the finite difference time domain method) can be used to accurately simulate passive interconnection structures. Those numerical EM techniques might require a significant amount of computer resources, so that they are hardly being used for designing and optimizing huge and complex networks. Circuit simulators on the other hand are very fast, and offer a lot of different analysis possibilities. 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 made to build models for general interconnection structures based on full-wave simulations. Previously used techniques include look-up tables [1], curve fitting techniques [2] and neural networks [3]. A common drawback of these previous efforts is the lack of knowledge about the accuracy of the resulting models. The technique described here - in what follows, referred to as MAPS (*Multidimensional Adaptive Parameter Sampling*) [4] – selects a minimum number of EM simulations, and builds a global analytical fitting model for the scattering parameters of general planar structures as a function of the geometrical parameters and of the frequency, with a predefined accuracy. Data points are selected efficiently and model complexity is automatically adapted. The algorithm consists of an adaptive modeling loop (section II) and an adaptive sample selection loop (section III). Examples are given to illustrate the technique (section IV). The work presented in this paper is submitted for patenting in the US by Agilent Technologies.

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 multidimensional coordinates $\bar{x}$ in the parameter space R, while the weights C_m only depend on the frequency f:

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

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 $d = 1, \ldots, D$). The number of multinomials in the sum is adaptively increased until the error function:

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

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 are used, i.e. the multinomials $P_m(\bar{x})$ satisfy the condition:

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

III. Adaptive Data Selecting Algorithm

The modeling process starts with an initial set of data points. 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 often called *reflective exploration* [5]. Reflective exploration is useful when the process that provides the data is very costly, which is the case for full-wave electro-magnetic (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 equation (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 point is 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, 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, a new data point is chosen where the criteria are violated the most.

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

IV. EXAMPLES

A. Model Generation: microstrip components

The *MAPS (Multidimensional Adaptive Parameter Sampling*) algorithm was used to generate analytical models for an *open stub* and for a (symmetrical) *tee*, both on a 635 μm microstrip substrate, with $\varepsilon_r = 10.0$ (figures 2 and 3). Feedlines are connected to all ports (635 μm).

The *open stub* model has one variable geometrical parameter, namely the width of the stub (*W*). There is only one relevant S-parameter, S_{11}.

The *tee model* has two geometrical parameters: the width of the thru line (*W_thru*) and the width of the stub (*W_stub*). There are three relevant S-parameters, S_{11}, S_{12} and S_{13}. The ranges of the continuously varying geometrical parameters are given in tables 1 and 2.

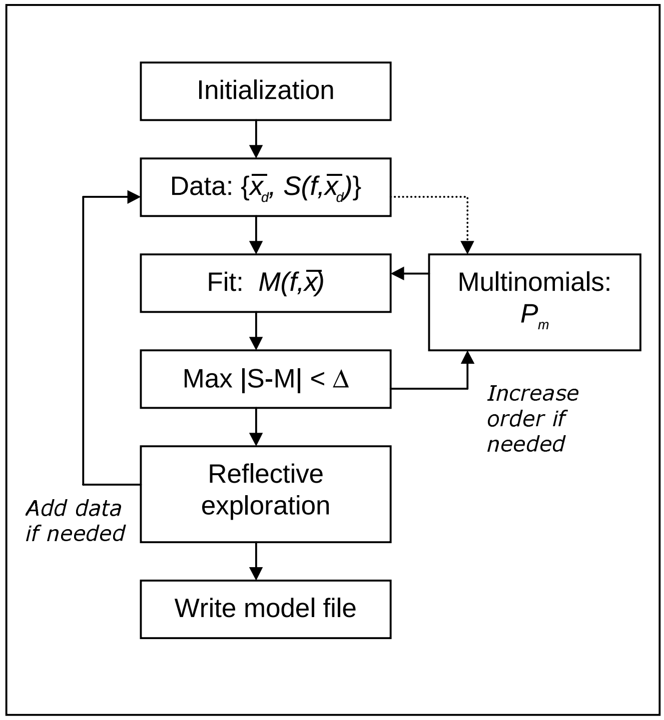

Fig. 1. Adaptive multidimensional modeling flowchart

Fig. 2. microstrip *open stub* component with variable width and fixed feedline length

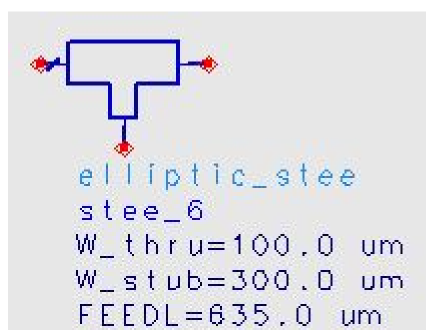

Fig. 3. microstrip *tee* with variable Thru-width and Stub-width, and fixed feedline length

variable	min	max
W	100 µm	1000 µm
f	1 GHz	20 GHz

Table 1. Parameter ranges for the microstrip *open stub*

variable	min	max
W_thru	100 µm	1000 µm
W_stub	300 µm	600 µm
f	1 GHz	20 GHz

Table 2. Parameter ranges for the microstrip *tee*

The scattering parameters are generated using the commercially available full-wave electro-magnetic simulator Momentum [6].

The desired accuracy for the *open stub* model was set to -60 dB. Building this model required 10 data points (adaptively selected). The accuracy of the model was checked in 71 points randomly chosen along the *W*-axis. The maximum deviation found between the MAPS model and Momentum was -60.6 dB.

The desired accuracy for the *tee* model was set to -55 dB. Here there were 31 data points needed (adaptively selected) during model generation. The accuracy of the tee model was checked in 208 points randomly chosen in the parameter space. The maximum deviation found between the MAPS model and Momentum was -54.3 dB.

B. Model extraction: Lowpass filter

The adaptively generated models were used to simulate a lowpass elliptic filter on a 635 µm microstrip substrate (ε_r = 10.0). The layout is given in figure 4 [7].

Figures 5 and 6 show the magnitude of S_{11} and S_{12} simulated *(a)* with Momentum, *(b)* with a commercial circuit simulator, and *(c)* with the MAPS models for the *open end* and the *tee* components. The results using the multiple MAPS models correspond very well to the global full-wave results, and yet the simulation using the MAPS models only took a fraction of the time required for the full-wave simulation (due to the divide and conquer technique used). On a 450 MHz PC the full-wave simulation took 5037 seconds, while the simulation using the MAPS models was virtually instantaneous. The results obtained with the 'classic' analytical models of the circuit simulator differ significantly from the full-wave results.

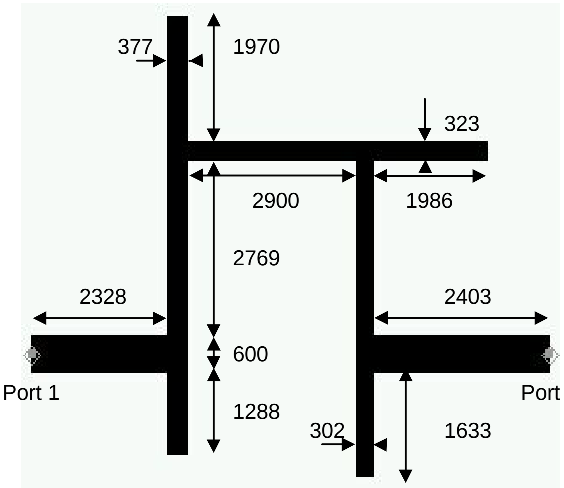

Fig. 4. Layout of elliptic lowpass filter (all lengths are in µm)

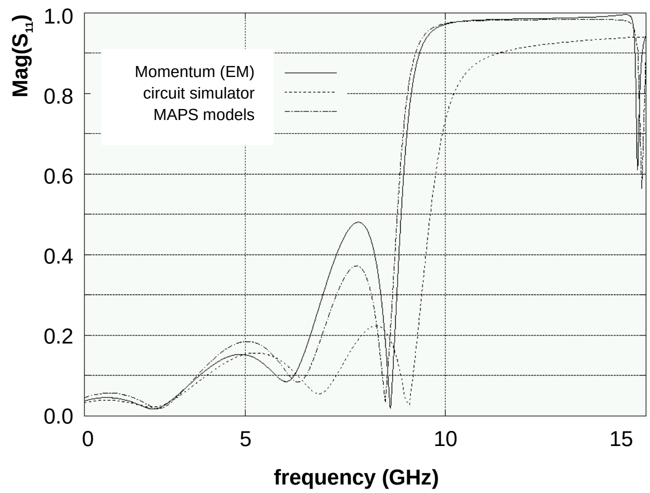

Fig. 5. S_{11} of elliptic lowpass filter

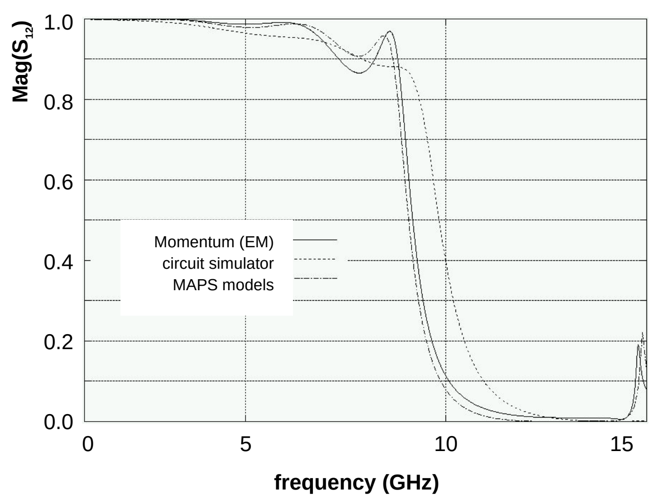

Fig. 6. S_{12} of elliptic lowpass filter

V. CONCLUSION

A new adaptive technique (MAPS) was presented for building parameterized models for general passive planar interconnection structures. The models are based on full-wave EM simulations, and have a pre-defined 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 elliptic filter example was given to illustrate the technique. The results based on the parameterized models correspond very well with the global full-wave simulations. However, the time required for a simulation using the compact analytical MAPS models was only a fraction of the time required for a global full-wave simulation. The generality and accuracy of the new parameterized models are far better than the traditional analytical models.

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