Guaranteed Passive Parameterized Admittance-Based Macromodeling

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***Abstract*—We propose a novel parametric macromodeling technique for admittance and impedance input-output representations parameterized by design variables such as geometrical layout or substrate features. It is able to build accurate multivariate macromodels that are stable and passive in the entire design space. An efficient combination of rational identification and interpolation schemes based on a class of positive interpolation operators, ensures overall stability and passivity of the parametric macromodel. Numerical examples validate the proposed approach on practical application cases.**

***Index Terms*—Parametric macromodeling, rational approximation, interpolation, passivity.**

I. INTRODUCTION

Efficient design space exploration, design optimization and sensitivity analysis of microwaves structures call for the development of robust parametric macromodeling techniques. Parametric macromodels can take multiple design variables into account, such as geometrical layout or substrate features.

Recently, a multivariate extension of the orthonormal vector fitting (OVF) technique was presented in [1], [2]. This MOVF method is able to compute accurate parametric macromodels based on parameterized frequency responses which exhibit a highly dynamic behavior. Unfortunately, the algorithm does not guarantee stability and passivity of the parametric macromodel. In [3] the stability problem is addressed by computing a parametric macromodel with barycentric interpolation of univariate stable macromodels. It is shown that the overall stability of the parametric macromodel is guaranteed. An enforcement scheme for the passivity of the parametric macromodel is proposed by perturbation of the barycentric weights. This technique has some limitations: 1) the convergence of the passivity enforcement procedure is not guaranteed, 2) the passivity violations must be reasonably small, 3) a dense sweep in the design space is needed to detect possible passivity violations, with a computational cost that increases exponentially with the number of design variables, 4) the data samples cannot be scattered in the design space, but must be located on a fully filled, not necessarily equidistant, rectangular grid. A method that overcomes the restriction on the data samples ordering and uses the flexibility of least-squares fitting, while preserving stability was proposed in [4]. More recently, a novel technique that combines the advantages of [1] and [4] was presented in [5]. The hybrid technique is able to calculate more compact macromodels without compromising the accuracy of the results. It is less sensitive to the sample density and the overall stability of the poles is preserved.

This paper presents a novel technique to build accurate multivariate rational macromodels that are stable and passive in the entire design space, for admittance ($\mathbf{Y}$) and impedance ($\mathbf{Z}$) representations. It combines rational identification and interpolation schemes based on a class of positive interpolation operators [6], [7], to guarantee overall stability and passivity of the parametric macromodel. The technique starts by computing multiple univariate frequency domain macromodels using the (Orthonormal) Vector Fitting ((O)VF) technique [8], [9] for different combinations of design variables, as in [3]. In the paper we refer to these initial univariate macromodels as *root macromodels*. A simple pole-flipping scheme is used to enforce stability [8] for each *root macromodel* , while passivity is checked and enforced by means of standard techniques (see e.g. [10], [11], [12]). Next, a multivariate macromodel is obtained by combining all *root macromodels* using an interpolation scheme that preserves stability and passivity properties over the complete design space. The proposed technique is validated by some numerical application examples.

II. PARAMETRIC MACROMODELING

This section explains how the proposed technique builds a multivariate representation $\mathbf{R}(s,\vec{g})$ which models accurately a large set of K_{tot} data samples $\{(s,\vec{g})_k, \mathbf{H}(s,\vec{g})_k\}_{k=1}^{K_{tot}}$ and guarantees overall stability and passivity in the design space. These data samples depend on a complex frequency $s = j\omega$, and several design variables $\vec{g} = (g^{(n)})_{n=1}^{N}$. The design variables describe e.g. the metallizations in an EM-circuit (such as lengths, widths,...) or the substrate parameters (like thickness, dielectric constant, losses,...). Two data grids are used in the modeling process: an estimation grid and a validation grid. The first one is utilized to build the *root macromodels* which, combined with an interpolation scheme, provide the parametric macromodel. The second grid, more dense than the previous one, is utilized to assess the interpolation capability of the parametric macromodel, its capability of describing the system under study in points of the design space previously not used for the construction of the *root macromodels*.

A. Root Macromodels

Starting from a set of data samples $\{(s,\vec{g})_k, \mathbf{H}(s,\vec{g})_k\}_{k=1}^{K_{tot}}$ a frequency dependent rational model is built for all grid points in the design space by means of (O)VF. A pole-flipping scheme is used to enforce stability [8] and passivity enforcement can be accomplished using one of the robust

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standard techniques [10], [11], [12]. The result of this initial procedure is a set of rational univariate macromodels, stable and passive, that we call *root macromodels* being the starting points to build a parametric macromodel.

B. 2-D Macromodeling

First, we discuss the representation of a bivariate macromodel and afterwards the generalization to more dimensions. Once the *root macromodels* are built, the next step is to find a bivariate representation $\mathbf{R}(s,g)$ which models the set of K_{tot} data samples $\{(s,g)_k, \mathbf{H}(s,g)_k\}_{k=1}^{K_{tot}}$ and preserves stability and passivity over the entire design space. The bivariate macromodel we adopt can be written as:

$$\mathbf{R}(s,g) = \sum_{k=1}^{K_1} \mathbf{R}(s,g_k)\ell_k(g) \tag{1}$$

where each interpolation kernel $\ell_k(g)$ is a scalar function satisfying the following constraints:

$$\ell_k(g) \geq 0 \tag{2}$$
$$\ell_k(g_i) = \delta_{k,i} \tag{3}$$

The model in (1) is a linear combination of stable and passive univariate models by means of positive interpolation kernels [6], [7]. The positiveness of the interpolation kernels is fundamental to preserve passivity in the design space ,while stability is automatically preserved as (1) is a weighted sum of stable rational macromodels. The proof of the passivity preserving property of the proposed technique in the entire design space is given in Section II-D.

C. N-D Macromodeling

The bivariate formulation can easily be generalized to the multivariate case by using multivariate interpolation methods. Multivariate interpolation can be realized in different forms: by means of tensor product [13], [14] and algorithms for scattered data as well-known Shepard's method [6], [7], [15].

1) Tensor product multivariate interpolation: the tensor product multivariate interpolation suffers from the curse of dimensionality. The data samples have to be located on a fully filled, but not necessarily equidistant, rectangular grid. In many cases, this corresponds to the most practical way how multivariate data samples are organized and computed by a numerical simulation tool. The multivariate model can be written as:

$$\begin{aligned}&\mathbf{R}(s,g^{(1)},...,g^{(N)}) = \\ &= \sum_{k_1=1}^{K_1} \cdots \sum_{k_N=1}^{K_N} \mathbf{R}(s,g_{k_1}^{(1)},...,g_{k_N}^{(N)})\ell_{k_1}(g^{(1)})\cdots\ell_{k_N}(g^{(N)})\end{aligned} \tag{4}$$

where each $\ell_{k_i}(g^{(i)}),\ i=1,...,N$ respects both constraints (2) and (3). A suitable choice is to select each set $\ell_{k_i}(g^{(i)})$ as in piecewise linear interpolation:

$$\frac{g^{(i)} - g_{k_i-1}^{(i)}}{g_{k_i}^{(i)} - g_{k_i-1}^{(i)}},\ g^{(i)} \in \left[g_{k_i-1}^{(i)}, g_{k_i}^{(i)}\right],\ k_i = 2,...,K_i, \tag{5a}$$

$$\frac{g_{k_i+1}^{(i)} - g^{(i)}}{g_{k_i+1}^{(i)} - g_{k_i}^{(i)}},\ g^{(i)} \in \left[g_{k_i}^{(i)}, g_{k_i+1}^{(i)}\right],\ k_i = 1,...,K_i-1, \tag{5b}$$

$$0 \quad , \text{otherwise} \tag{5c}$$

that yields to an interpolation scheme in (4) called piecewise multilinear interpolation. It can be also seen as a recursive implementation of simple piecewise linear interpolation [16], [17].

2) Shepard's multivariate interpolation: Shepard's method is a standard algorithm for interpolation at nodes having no exploitable pattern, referred to as scattered or irregularly distributed data. The corresponding multivariate model is written in a barycentric form as:

$$\mathbf{R}(s,\vec{g}) = \sum_{k=1}^{K_{tot}^{\vec{g}}} \mathbf{R}(s,\vec{g}_k)\ell_k(\vec{g}) \tag{6}$$

$$\ell_k(\vec{g}) = \frac{\|g-\vec{g}_k\|_2^{-p}}{\sum_{h=1}^{K_{tot}^{\vec{g}}} \|g-\vec{g}_h\|_2^{-p}} \tag{7}$$

where $p > 0$. The case $p = 2m,\ m \in \mathbb{N}$ is of particular importance, since the interpolation kernels are then infinitely differentiable. The interpolation kernels of Shepard's formula also respect both constraints (2) and (3) [7]. Unfortunately Shepard's scheme presents the occurrence of flat spots at the grid points when $p > 1$ since its gradient vanishes, and it is not differentiable if $p \leq 1$ giving a generally unsatisfactory internodal behavior [6], [18]. Shepard's method in one dimension can be also extended to more dimensions by using the tensor product formulation, leading to a different Shepard's multivariate interpolation scheme not related to scattered data.

In this paper we use the piecewise multilinear interpolation method based on a fully filled data grid in the design space, that, as mentioned before, in many cases represents the structure of multivariate data samples computed by a numerical simulation tool. It is a local method, because each interpolated value does not depend on all the data and it avoids unsatisfactory internodal oscillations as present in Shepard's method. The scheme is easy to implement and provides accurate results. It is clear that more data samples in the estimation grid are needed in the case of high dynamics induced by the design parameters on the frequency behavior of the system than in the case of low dynamics, leading to an increased computational cost to obtain the multivariate model $\mathbf{R}(s,g^{(1)},...,g^{(N)})$. We note that the kernel functions we propose only depend on the data grid points and their computation does not require the solution of a linear system to impose an interpolation constraint. The proposed technique is general and any interpolation scheme that leads to a parametric macromodel composed of a weighted sum of *root macromodels* with nonnegative weights can be utilized.

D. Passivity Preserving Interpolation

When performing transient analysis, stability and passivity must be guaranteed. It is known that, while a passive system is also stable, the reverse is not necessarily true [19], which is crucial when the macromodel is to be utilized in a general-purpose analysis-oriented nonlinear simulator. Passivity refers to the property of systems that cannot generate more energy than they absorb through their electrical ports. When the system is terminated on any arbitrary passive loads, none of them will cause the system to become unstable [20], [21]. A linear network described by admittance matrix $\mathbf{Y}(s)$ is passive if [22], [23]:

1) $\mathbf{Y}(s^*) = \mathbf{Y}^*(s)$ for all s, where "$*$" is the complex conjugate operator.
2) $\mathbf{Y}(s)$ is analytic in $\Re e(s) > 0$.
3) $\mathbf{Y}(s)$ is a positive-real matrix, i.e. : $\mathbf{z}^{*t}\left(\mathbf{Y}^t(s^*) + \mathbf{Y}(s)\right)\mathbf{z} \geq 0$; $\forall s : \Re e(s) > 0$ and any arbitrary vector $\mathbf{z}$.

Similar results are valid for a linear network described by impedance matrix $\mathbf{Z}(s)$.

Concerning the *root macromodels*, conditions 1) and 2) are always satisfied since all complex poles/residues are always considered along with their conjugates and strict stability is imposed by pole-flipping. Condition 1) is preserved in (1) and the proposed multivariate extensions, as they are weighted sums with real nonnegative weights of systems respecting this first condition. Condition 2) is preserved in (1) and the proposed multivariate extensions, as they are weighted sums of strictly stable rational macromodels. Condition 3) is enforced, if needed, on the *root macromodels* by using a standard passivity enforcement technique. To prove that our parameterized macromodeling technique preserves overall passivity, we refer to the following theorem [24]:

Theorem 1: Any nonnegative linear combination of positive real matrix is a positive real matrix.

Since (1) and the proposed multivariate extensions are weighted sums with real nonnegative weights of passive macromodels (*root macromodels*), condition 3) is satisfied by construction. We have proven that all the three passivity conditions for admittance and impedance representations are preserved in our parametric macromodeling algorithm.

III. Numerical examples

This section presents two numerical examples related to interconnection systems that validate the proposed approach on application cases. During the construction of the *root macromodels* a weighting function equal to:

$$w_{Y_i}(s, \vec{g}) = \left|(Y_i(s, \vec{g}))^{-1}\right| \tag{8}$$

is used in the VF fitting process for each entry of the admittance or impedance matrix. $i = 1, ..., P^2$ where P is the number of system ports. This approach gives increased weight to small function values [25], thus tending to provide a fitting with a high relative accuracy rather than a high absolute accuracy.

The weighted RMS-error for the parametric macromodels is defined as:

$$Err(\vec{g}) = \\ = \sqrt{\frac{\sum_{i=1}^{P^2}\sum_{k=1}^{K_s}\left|w_{Y_i}(s_k,\vec{g})\Big(R_i(s_k,\vec{g}) - Y_i(s_k,\vec{g})\Big)\right|^2}{P^2 K_s}} \tag{9}$$

The worst case RMS-error over the validation grid is chosen to assess the accuracy and the quality of parametric macromodels:

$$\vec{g}_{max} = \underset{\vec{g}}{\operatorname{argmax}}\, Err(\vec{g}),\ \ \vec{g} \in validation\ grid \tag{10}$$

$$Err_{max} = Err(\vec{g}_{max}) \tag{11}$$

and it is used in the numerical examples. The number of poles for each *root macromodel* is selected adaptively in VF by a bottom-up approach, in such a way that the corresponding weighted RMS-error is smaller than 10^{-2}.

A. One stripline with variable width and height substrate

In this example a microstrip transmission line (length $\ell = 3$ cm) has been modeled. The cross section is shown in Fig. 1. A trivariate macromodel is built as a function of the width W of the strip and the height h of the substrate in addition to frequency. Their corresponding ranges are shown in Table I.

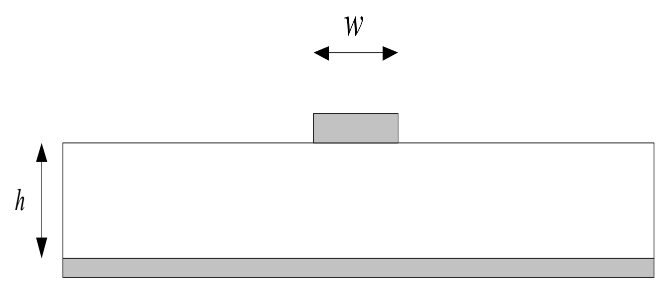

Fig. 1. Cross section of the microstrip.

TABLE I
PARAMETERS OF THE MICROSTRIP STRUCTURE.

Parameter	Min	Max
Frequency (freq)	1 MHz	10 GHz
Width (W)	100 μm	600 μm
Height (h)	500 μm	1200 μm

The admittance matrix $\mathbf{Y}(s, W, h)$ has been computed based on the quasi-TEM model discussed in [26] over a validation grid of $250 \times 70 \times 40$ samples $(freq, W, h)$. We have built *root macromodels* for 24 values of the width and 14 values of the height substrate by means of VF. The passivity of each model has been verified by checking the eigenvalues of the Hamiltonian matrix [27] and enforced if needed. A trivariate macromodel is obtained by piecewise multilinear interpolation of the *root macromodels*. The passivity of the parametric macromodel has been checked by the Hamiltonian test on a dense sweep over the design space and the theoretical claim of overall passivity has been confirmed. Figs. 2-3 show the magnitude of the parametric macromodel of $\mathbf{Y}_{12}(s, W, h)$ for $h = 841\ \mu m$ and $W = 346\ \mu m$ respectively. The worst case RMS-error defined in (11) is equal to $1.4 \cdot 10^{-2}$ and it occurs for $\vec{g}_{max} = \{W = 506\ \mu m, h = 518\ \mu m\}$. Figs. 4-7 compare $\mathbf{Y}_{12}(s, W, h)$, $\mathbf{Y}_{11}(s, W, h)$ and their macromodels for the width and height substrate values corresponding to $\vec{g}_{max}$. As clearly seen, a very good agreement is obtained between the the original data and the proposed passivity preserving macromodeling technique. The parametric macromodel captures very accurately the behavior of the system, preserving stability and passivity properties over the entire design space.

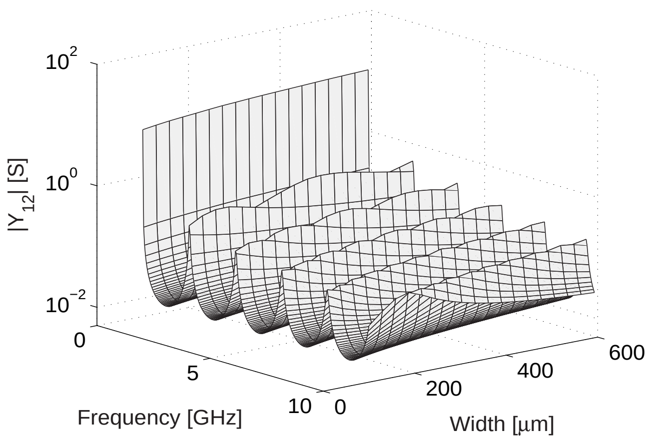

Fig. 2. Magnitude of the parametric macromodel of $\mathbf{Y}_{12}(s, W, h)$ ($h = 841\ \mu m$).

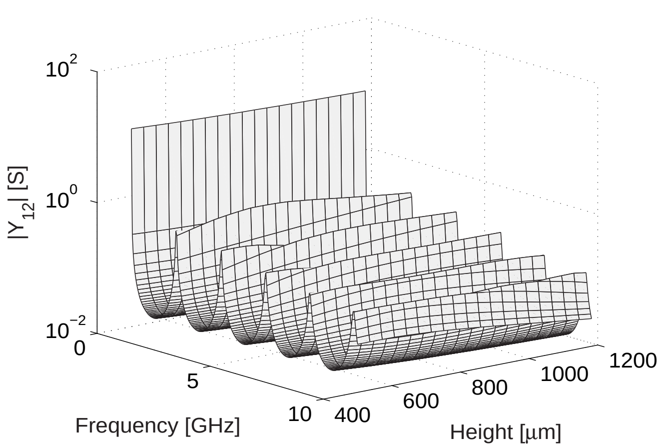

Fig. 3. Magnitude of the parametric macromodel of $\mathbf{Y}_{12}(s, W, h)$ ($W = 346\ \mu m$).

B. Two coupled microstrips with variable spacing

A three-conductor transmission line (length $\ell = 5$ cm) with frequency-dependent per-unit-length parameters has been

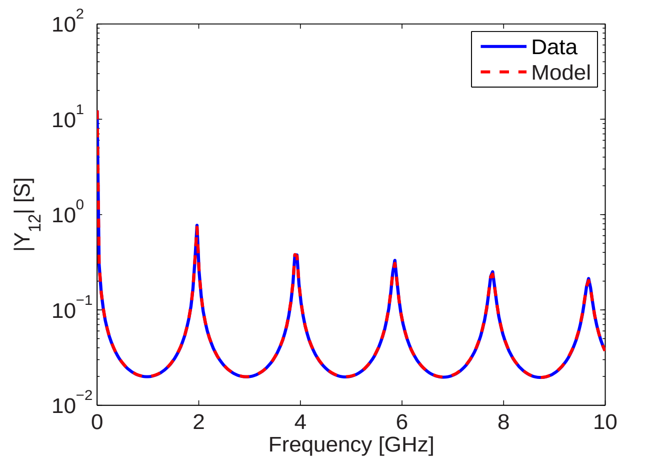

Fig. 4. Magnitude of the parametric macromodel of $\mathbf{Y}_{12}(s, W, h)$ ($W = 506\ \mu m$, $h = 518\ \mu m$).

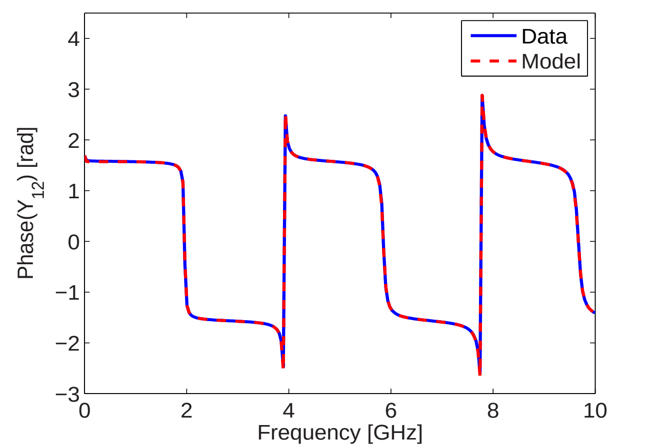

Fig. 5. Phase of the parametric macromodel of $\mathbf{Y}_{12}(s, W, h)$ ($W = 506\ \mu m$, $h = 518\ \mu m$).

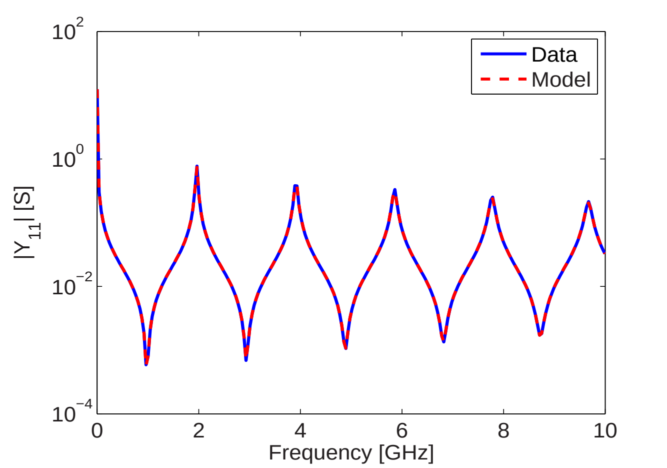

Fig. 6. Magnitude of the parametric macromodel of $\mathbf{Y}_{11}(s, W, h)$ ($W = 506\ \mu m$, $h = 518\ \mu m$).

modeled. It consists of two coplanar microstrips over a ground

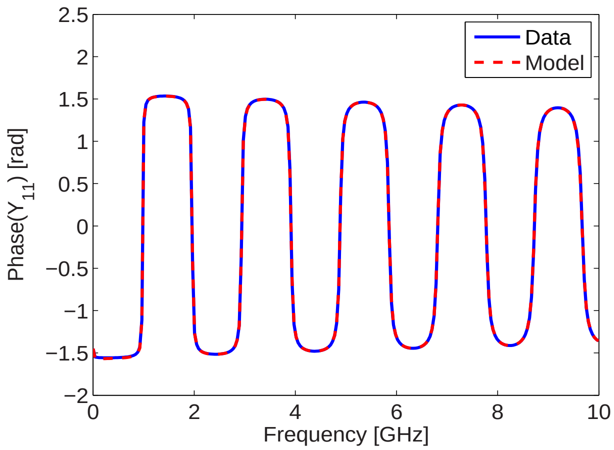

Fig. 7. Phase of the parametric macromodel of $\mathbf{Y}_{11}(s, W, h)$ ($W = 506\ \mu m$, $h = 518\ \mu m$).

plane. The cross sections is shown in Fig. 8. The conductors have width $W = 100\ \mu$m and thickness $t = 50\ \mu$m. The dielectric is 300 μm thick and characterized by a dispersive and lossy permittivity which has been modeled by the wide-band Debye model [28]. A bivariate macromodel is built as a function of the spacing S between the microstrips in addition to frequency. The ranges of frequency and spacing are shown in Table II.

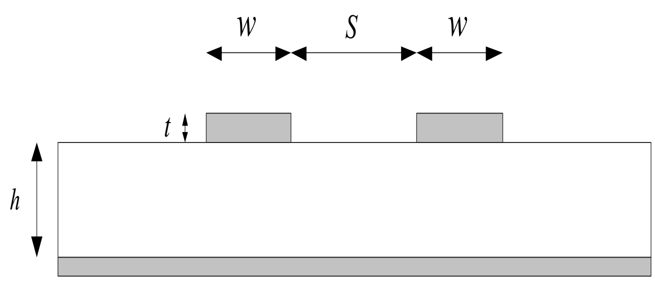

Fig. 8. Cross section of the two coupled microstrips.

TABLE II
PARAMETERS OF THE TWO COUPLED MICROSTRIPS STRUCTURE.

Parameter	Min	Max
Frequency (freq)	100 KHz	15 GHz
Spacing (S)	100 μm	500 μm

The frequency-dependent per-unit-length parameters have been evaluated using a commercial tool [29] over a validation grid of 250×80 samples, for frequency and spacing respectively. Then, the admittance matrix $\mathbf{Y}(s, S)$ has been computed using transmission line theory (TLT) [30]. We have built *root macromodels* for 30 values of the spacing by means of VF. The passivity of each model has been verified by checking the eigenvalues of the Hamiltonian matrix and enforced if needed. A bivariate macromodel is obtained by piecewise multilinear interpolation of the *root macromodels*. The passivity test on a dense sweep over S has confirmed the theoretical claim of overall passivity. Fig. 9 shows the magnitude of the parametric macromodel of $\mathbf{Y}_{14}(s, S)$. The worst case RMS-error defined in (11) is equal to $4 \cdot 10^{-2}$ and it occurs for $g_{max} = \{S = 490\ \mu m\}$. Figs. 10-13 compare $\mathbf{Y}_{14}(s, S)$, $\mathbf{Y}_{11}(s, S)$ and their macromodels for the spacing value corresponding to g_{max}. As in the previous example, the parametric macromodel describes very accurately the behavior of the system, guaranteeing stability and passivity properties over the entire design space.

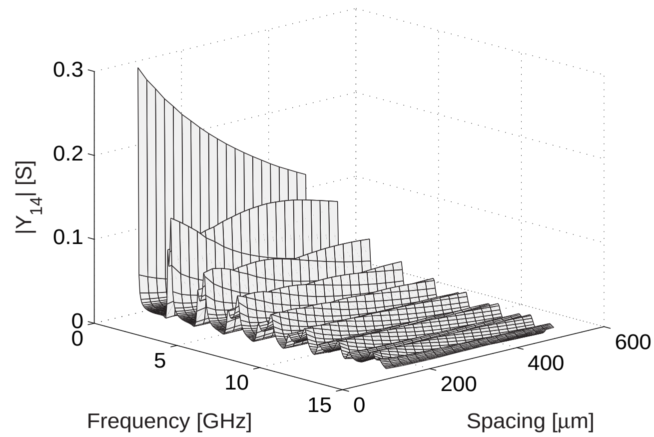

Fig. 9. Magnitude of the parametric macromodel of $\mathbf{Y}_{14}(s, S)$.

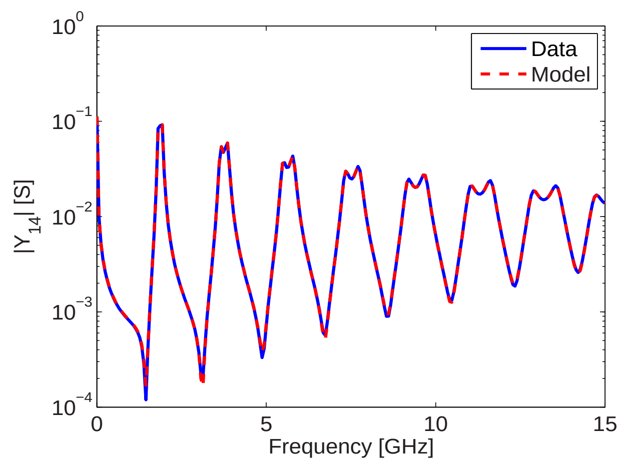

Fig. 10. Magnitude of the parametric macromodel of $\mathbf{Y}_{14}(s, S)$ ($S = 490\ \mu m$).

IV. CONCLUSIONS

We have presented a new method for the generation of parameterized macromodels of admittance and impedance representations. The overall stability and passivity of the parametric macromodel is guaranteed by an efficient and reliable combination of rational identification and interpolation schemes based on a class of positive interpolation operators. Numerical examples have validated the proposed approach on practical application cases, showing that it is able to build very

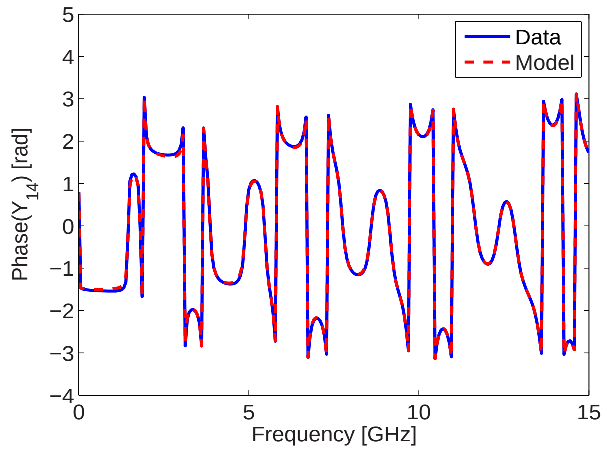

Fig. 11. Phase of the parametric macromodel of $\mathbf{Y}_{14}(s, S)$ ($S = 490\ \mu m$).

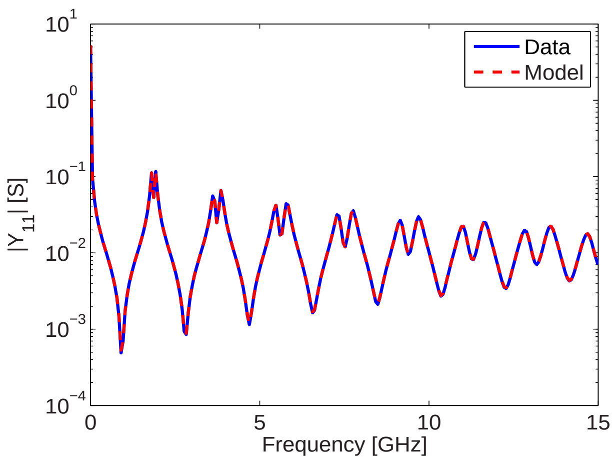

Fig. 12. Magnitude of the parametric macromodel of $\mathbf{Y}_{11}(s, S)$ ($S = 490\ \mu m$).

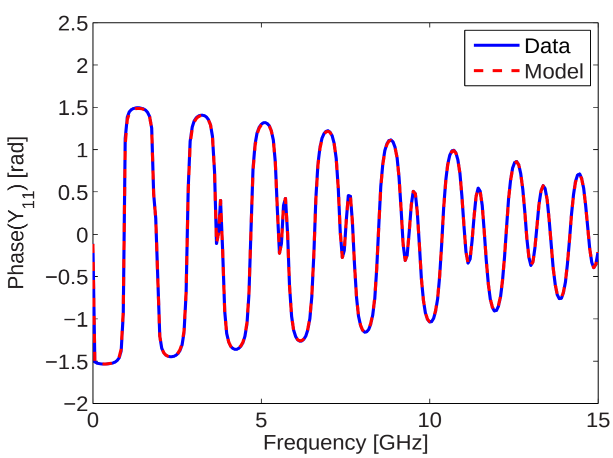

Fig. 13. Phase of the parametric macromodel of $\mathbf{Y}_{11}(s, S)$ ($S = 490\ \mu m$).

accurate parametric macromodels, while guaranteeing stability and passivity over the complete design space.

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