Stability and Passivity Enforcement of Parametric Macromodels in Time and Frequency Domain

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***Abstract*—This paper presents a robust technique for the macromodeling of time-domain and frequency-domain responses, which are parameterized by one or more design variables. The representation of the multivariate macromodel ensures that stability of the transfer function poles is enforced by construction. Passivity of the parametric macromodel can be enforced in a post-processing step by perturbation of barycentric weights.**

***Index Terms*—Interpolation, parametric macromodels, rational functions, time-domain fitting, vector fitting.**

I. Introduction

Robust parametric macromodeling is becoming increasingly important for the design, study, and optimization of microwave structures. Parametric macromodels approximate the variation of the complex electromagnetic (EM) behavior of a multiport system in terms of several design variables that describe physical properties of the structure. Such macromodels are frequently used for efficient design space exploration, design optimization, and sensitivity analysis [1]–[4].

Recently, a multivariate extension of the orthonormal vector fitting (OVF) technique was introduced in [5] and [6]. It was shown that the method is robust, and accurately models parameterized frequency responses with a highly dynamic behavior. Unfortunately, the algorithm is not directly applicable to the macromodeling of parameterized time-domain responses. The main difficulty lies in the representation of the multivariate transfer function, which does not guarantee an overall stability of the poles. Therefore, a direct evaluation of the multivariate macromodel for various parameter combinations may lead to unstable time-domain simulations, which is undesired. The analytical detection of unstable poles and the enforcement of stability is a topic which is still open for further research [7].

This paper resolves the stability problem by proposing a multivariate macromodel representation, which is guaranteed to be stable for all possible geometrical parameter combinations. The method starts by computing a univariate time-domain or frequency-domain macromodel with OVF [8] for various combinations of a design variable. Stability of each univariate macromodel can be ensured by means of a simple pole-flipping scheme [9]. These univariate macromodels (referred to as *nodes*) are then combined into a multivariate macromodel by means of barycentric Lagrange interpolation [10], [11]. Passivity of the parametric macromodel can be enforced by perturbation of the barycentric weights, provided that the occurring passivity violations are reasonably small.

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II. OVF

OVF is a robust macromodeling technique for the identification of a rational transfer function $R(s)$ from frequency-domain responses $(s, H(s))$. It minimizes a weighted linear cost function by iteratively relocating the transfer function poles using a Sanathanan–Koerner iteration [8], [12], [13]. Numerical ill conditioning is avoided by using a set of orthonormal rational basis functions, which are based on a prescribed set of poles. Such basis functions have the advantage that an implicit weighting scheme can be applied, which was found to give more reliable results than an explicit weighting scheme if the prescribed poles need to be relocated over long distances [14]. At the same time, it simplifies the enforcement of system stability by means of a pole flipping scheme. In [15], a time-domain generalization of OVF is presented, which allows the identification of a transfer function $r(t)$ based on univariate transient input-output port responses $(t, u(t), y(t))$. The idea is based on a time-domain implementation of the vector fitting technique, which is well described in the literature [16]. The passivity enforcement of univariate macromodels has been widely studied in the literature, and several robust techniques are available (see [17]–[19] for details).

III. Parametric Macromodeling

A. Bivariate Frequency-Domain Macromodeling

The goal of this section is to provide a bivariate extension of the OVF algorithm, which computes a stable parametric macromodel $R(s,\alpha)$ from simulated frequency responses $(s,\alpha,H(s,\alpha))$, which are parameterized by a certain design variable α over some predefined parameter range. The challenging task is to find a bivariate transfer function representation, which is general enough to model a dynamic response, while preserving a guaranteed stability of the poles for all possible values of α. Therefore, the frequency-domain representation of the bivariate transfer function is chosen as

$$R(s,\alpha)=\sum_{v=1}^{V} R(s,\alpha_v)\ell_v(\alpha) \tag{1}$$

where $\ell_v(\alpha)$ represents the fundamental Lagrange polynomial

$$\ell_v(\alpha) = \frac{\prod_{k=1,k\neq v}^{V} (\alpha - \alpha_k)}{\prod_{k=1,k\neq v}^{V} (\alpha_v - \alpha_k)} \tag{2}$$

and $R(s,\alpha_v)$ are stable 1-D fits for various choices of α, as computed in Section II (see [8] for details). Since the $\ell_v(\alpha)$ polynomial has the property that $\ell_v(\alpha_k) = \delta_{v,k}$ for $v,k = 1,\ldots,V$, it is guaranteed that the bivariate model $R(s,\alpha)$ is an exact interpolation of the univariate transfer function nodes $R(s,\alpha_v)$. If $\ell(\alpha)$ is defined as

$$\ell(\alpha) = \prod_{k=1}^{V} (\alpha - \alpha_k) \tag{3}$$

and the barycentric weights w_v are chosen as

$$w_v = \prod_{k=1,k\neq v}^{V} (\alpha_v - \alpha_k)^{-1} \tag{4}$$

then the interpolant $R(s,\alpha)$ can be written in Rutishauser's first form of the barycentric interpolation formula [10], where $R(s,\alpha) = R(s,\alpha_v)$ for $\alpha = \alpha_v$, $v = 1,\ldots,V$, and

$$R(s,\alpha) = \ell(\alpha) \sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v} R(s,\alpha_v) \tag{5}$$

elsewhere. A more elegant formulation is obtained by dividing (5) by the corresponding interpolant for constant function 1 and simplifying $\ell(\alpha)$, which leads to the second "true" form of the barycentric interpolation formula

$$R(s,\alpha) = \frac{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v} R(s,\alpha_v)}{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v}}. \tag{6}$$

It is evident that the bivariate transfer function (6) is an α-weighted sum of stable univariate transfer functions, which, therefore, guarantees stability of the overall macromodel by construction. It is also observed that the interpolation property of (6) is preserved for an arbitrary choice of weights w, which results in a rational interpolating function. Since an interpolating function may fluctuate in between the nodes, the weight vector can be chosen in such way that the error vanishes at some judiciously chosen set of $V-1$ test points [20]. The weights can also be chosen such that the rational interpolant does not have real poles, which may occur on the parameter range of interest. The reader is referred to [21] for details.

B. Bivariate Time-Domain Macromodeling

A direct application of the inverse Laplace transform to the frequency-domain bivariate transfer function (6) yields an equivalent bivariate transfer function in the time domain

$$r(t,\alpha) = \mathcal{L}^{-1}\left(R(s,\alpha)\right) = \frac{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v} r(t,\alpha_v)}{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v}} \tag{7}$$

provided that $r(t,\alpha_v) = \mathcal{L}^{-1}(R(s,\alpha_v))$ is the inverse Laplace transform of the univariate frequency-domain transfer function nodes, and the time-domain relationship between the input signal and output signal is given by the following convolution:

$$y(t,\alpha) = \frac{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v} \left(r(t,\alpha_v) \star u(t)\right)}{\sum_{v=1}^{V} \frac{w_v}{\alpha - \alpha_v}}. \tag{8}$$

The output signal $y(t,\alpha)$ for an arbitrary choice of α can easily be computed by simulating the minimal state-space realization of all the univariate nodes $r(t,\alpha_v)$ with the input signal $u(t)$ using MATLAB's "lsim" function, and by evaluating (8).

The time-domain macromodel (7) can also be obtained directly from time-domain responses $(t, u(t), y(t,\alpha))$ in a completely analogous way. First, several stable univariate time-domain macromodels $r(t,\alpha_v)$ are computed with time-domain OVF (see [15]), which are then combined into a stable bivariate macromodel by barycentric interpolation.

C. Extension to Multivariate Macromodeling

The stable bivariate formulation can easily be generalized to the multivariate case by the barycentric interpolation of lower dimensional macromodels. Consider a set of frequency-domain responses $(s, H(s,\vec{\alpha}))$ [or time-domain responses $(t, u(t), y(t,\vec{\alpha}))$], which vary along N design variables $\vec{\alpha} = \{\alpha^{(i)}\}_{i=1}^{N}$. An $(n+1)$-dimensional model can then be obtained by the barycentric Lagrange interpolation of several n-dimensional models $R(s,\alpha^{(1)},\ldots,\alpha^{(n-1)})$ [or $r(t,\alpha^{(1)},\ldots,\alpha^{(n-1)})$], which are computed for all values of $\alpha_{v_n}^{(n)}$ for $v_n = 1,\ldots,V_n$, where V_n represents the number of nodes in terms of the design variable $\alpha^{(n)}$. This procedure is repeated in a recursive fashion for $n = 2,\ldots,N$ of which the bivariate formulation is the base case $(n = 2)$ [2], [22].

It is then clear that the multivariate parametric macromodel has a balanced tree-like structure, i.e., a tree of which no leaf is further away from the root than any other leaf. This implies that data samples should not be scattered in the design space, but 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. If it is inconvenient or impossible to structure the data samples this way, one can always resort to the multivariate OVF algorithm [6].

IV. Multiport Systems

In the case of multiport systems, the presented methodology can be applied to model each element of the transfer matrix $\mathbf{R}(s,\vec{\alpha})$ separately. In most cases, it is preferable that all elements of the transfer matrix share a common set of transfer function poles if one evaluates the multivariate macromodel for fixed values of the parameters $\vec{\alpha}$. It can be seen from the model representation (6) that this condition is automatically satisfied if OVF considers all matrix elements simultaneously to identify the poles of the univariate macromodel nodes [23].

V. Passivity Enforcement

In the case of scattering parameters, the exact definition of passivity in the frequency-domain stipulates that the transfer matrix $\mathbf{R}(s)$ of a structure must be unitary bounded $(s=j\omega)$

$$\mathbf{I}-\mathbf{R}^*(s)\mathbf{R}(s)\geq 0 \qquad \forall\omega \tag{9}$$

which leads to the following equivalent condition:

$$\max_{m,\omega}\left(\sigma_m(s)\right)\leq 1 \qquad \forall\sigma_m(s)\in\sigma\left(\mathbf{R}(s)\right) \tag{10}$$

provided that $\sigma(\mathbf{R}(s))$ denotes the singular values of $\mathbf{R}(s)$. Passivity of univariate macromodels has been widely studied, and robust techniques for the detection and enforcement of passivity are available in the literature [18], [19]. The following sections describe a new passivity enforcement technique, which generalizes these concepts to parametric macromodels [24].

A. *Passive Multivariate Macromodels*

First, a stable bivariate macromodel $\mathbf{R}(s,\alpha)$ is computed by barycentric interpolation of several passive univariate macromodels $\mathbf{R}(s,\alpha_v)$ for various choices of α_v with $v=1,\ldots,V$. Since these univariate models are passive, it is certain that the bivariate macromodel is passive in the interpolation nodes. However, this does not guarantee passivity of the overall macromodel. In order to ensure stability of the time-domain simulations, it is necessary that condition (10) is satisfied for *all* values of α within a predefined parameter range $\alpha_{\min}\leq\alpha\leq\alpha_{\max}$. Therefore, it is necessary to detect possible passivity violations by a dense parameter sweep over α [25].

Let us assume that the bivariate macromodel is not passive, and that the largest passivity violation occurs at frequency $\hat{s}$ and parameter value $\hat{\alpha}$. To remove this passivity violation, one would like to perturb the barycentric weights of the macromodel in such way that the singular values of

$$\mathbf{R}(\hat{s},\hat{\alpha})=U\Sigma V^* \tag{11}$$

are unitary bounded. Truncating the diagonal elements of Σ to $\varepsilon=1$ yields a modified matrix Σ_{pass} such that

$$\mathbf{R}_{\text{pass}}(\hat{s},\hat{\alpha})=U\Sigma_{\text{pass}}V^*. \tag{12}$$

In order to compensate the passivity violation, it suffices that the following conditions hold for each element $R^{ij}_{\text{pass}}(\hat{s},\hat{\alpha})$ on row i and column j of the transfer matrix $\mathbf{R}_{\text{pass}}(\hat{s},\hat{\alpha})$:

$$R^{ij}_{\text{pass}}(\hat{s},\hat{\alpha})=\frac{\sum\limits_{v=1}^{V}\dfrac{w^{ij}_v+\Delta w^{ij}_v}{\hat{\alpha}-\alpha_v}R^{ij}(\hat{s},\alpha_v)}{\sum\limits_{v=1}^{V}\dfrac{w^{ij}_v+\Delta w^{ij}_v}{\hat{\alpha}-\alpha_v}}. \tag{13}$$

It is allowed to linearize (13) by reformulating it as

$$R^{ij}_{\text{pass}}(\hat{s},\hat{\alpha})\sum_{v=1}^{V}\frac{w^{ij}_v+\Delta w^{ij}_v}{\hat{\alpha}-\alpha_v}=\sum_{v=1}^{V}\frac{w^{ij}_v+\Delta w^{ij}_v}{\hat{\alpha}-\alpha_v}R^{ij}(\hat{s},\alpha_v). \tag{14}$$

Solving (14) for each matrix element of $\mathbf{R}_{\text{pass}}(\hat{s},\hat{\alpha})$ leads to an undetermined problem of the form $A^{ij}x^{ij}=b^{ij}$ with

$$A^{ij}_{1,v}=\left[\frac{R^{ij}_{\text{pass}}(\hat{s},\hat{\alpha})-R^{ij}(\hat{s},\alpha_v)}{\hat{\alpha}-\alpha_v}\right] \tag{15}$$

$$x^{ij}=\left[\Delta w^{ij}_1\ \ldots\ \Delta w^{ij}_V\right]^T \tag{16}$$

$$b^{ij}=\left[\sum_{v=1}^{V}\frac{\left(R^{ij}(\hat{s},\alpha_v)-R^{ij}_{\text{pass}}(\hat{s},\hat{\alpha})\right)w^{ij}_v}{\hat{\alpha}-\alpha_v}\right]. \tag{17}$$

Hence, it is possible to offset the given passivity violation by adding the perturbation of the barycentric weights Δw^{ij}_v in the solution vector x^{ij} to the individual weights w^{ij}_v of the corresponding matrix element [see (6)]. While solving the equations, one can impose additional nonlinear constraints, which minimize the deviation to the input–output port response of the macromodel (see [18] and [19] for details). This procedure can be repeated iteratively until all passivity violations are compensated. In a similar way, several passive bivariate macromodels can be combined into a trivariate (or multivariate) macromodel, which is subjected to the same procedure.

The main advantage of the perturbation of barycentric weights is that this enforcement scheme preserves the interpolation property in the nodes, which means that the accuracy of the macromodel in the simulated data samples remains unaffected. However, as opposed to residue perturbation techniques, a modification to the barycentric weights does not guarantee that the perturbation will be localized to a specific part of the parameter range [18]. In order to have a good convergence of the algorithm, this approach should only be applied if the occurring passivity violations are reasonably small. It is also noted that perturbed barycentric weights result in a rational interpolation instead of polynomial interpolation.

VI. Example 1: High-Speed Interconnect

In this example, the frequency response $(s,\alpha,S_{11}(s,\alpha))$ of a one-port passive lossy transmission line structure is simulated using Agilent Technologies' EEsof Momentum over the frequency range of 0.1–20 GHz for four different values of a normalized loss factor $\alpha=\{1,1.3,3,4\}$. Each response is

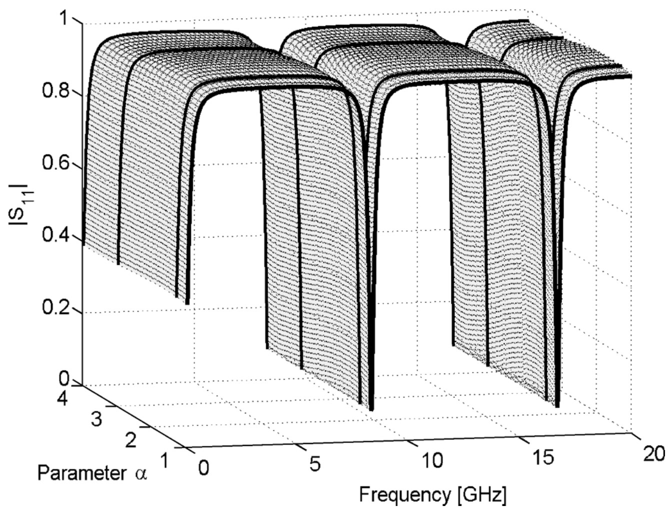

Fig. 1. Magnitude parametric frequency response of interconnect.

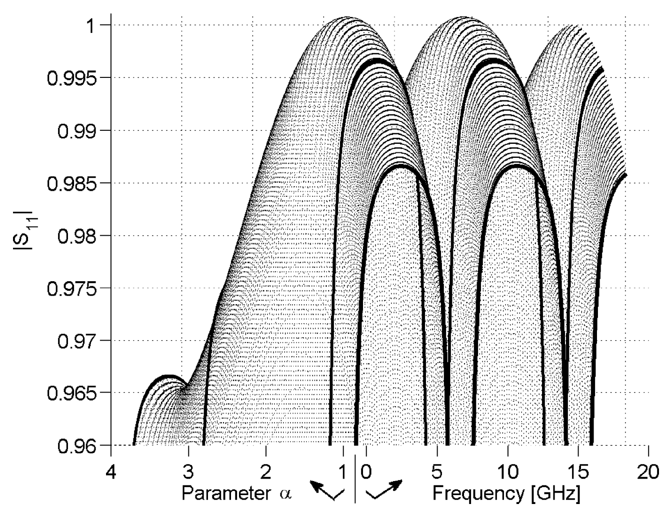

Fig. 2. Zoom Fig. 1 (rotated to right and tilted upward).

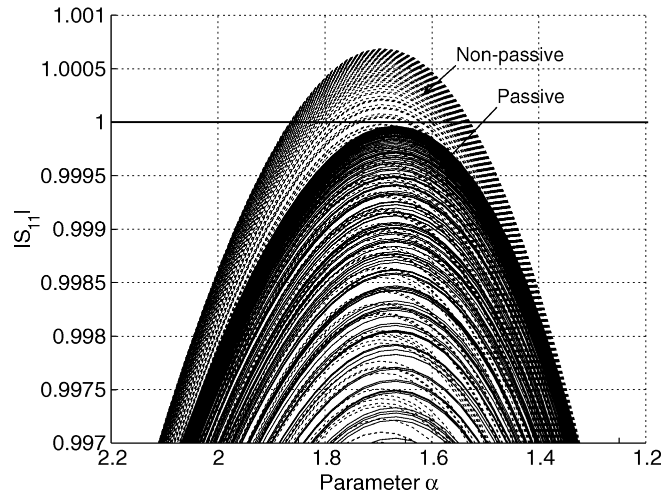

Fig. 3. Side view of Fig. 1 before/after passivity enforcement (zoom).

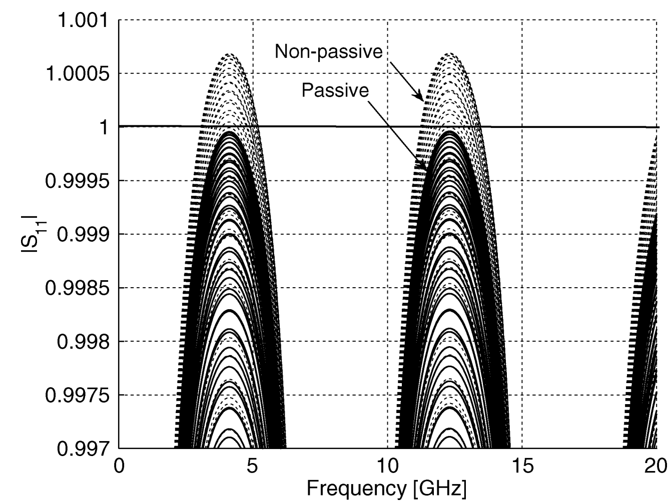

Fig. 4. Front view of Fig. 1 before/after passivity enforcement (zoom).

approximated by a stable six-pole macromodel using the univariate OVF technique, and passivity of each model is verified by checking the eigenvalues of a Hamiltonian matrix. A bivariate macromodel is obtained by barycentric Lagrange interpolation of each univariate macromodel. Since the response has a smooth variation in terms of the design variable, the barycentric weights are chosen as in (4), which yields a polynomial interpolating function in terms of α.

Fig. 1 shows the magnitude of the four frequency responses (solid lines), and the behavior of the bivariate macromodel at intermediate values of α (dotted lines). It can be seen that the magnitude of the bivariate model has a smooth continuous behavior over the parameter range, which is often close to one. Fig. 2 shows a zoom of Fig. 1, which is rotated to the right and tilted upward so that the frequency axis and parameter axis coincide (due to the viewing angle). It shows that there are some small passivity violations in between the nodes. A dense parameter sweep over α reveals that the maximum passivity violation occurs at $\hat{\alpha} = 1.697$ and $\hat{s} = 12.311$ GHz with a magnitude of 6.8821×10^{-4}. A perturbation of the barycentric weights (as described in Section V) was applied to compensate the violation, and the singular values threshold ε was set to 0.99995 (i.e., slightly below 1).

Fig. 3 shows the magnitude of the original and the perturbed macromodel as a function of α, where each line corresponds to a different frequency between dc and 20 GHz. Fig. 4 shows the magnitude of the original and perturbed macromodel as a function of frequency s, where each line corresponds to a different value of α with $1 \leq \alpha \leq 4$.

Figs. 3 and 4 are, in fact, a zoom of the side view (α axis) and the front view (frequency axis) of Fig. 1, respectively, which confirms that passivity is ensured for *all* frequencies (also outside the frequency band), provided that α is chosen within the predefined parameter range. Fig. 5 shows that the maximum deviation $|R_{\rm pass}(s,\alpha) - R(s,\alpha)|$, which is introduced by the enforcement, is well below -60 dB.

Finally, it is noted that perturbation of the barycentric weights should not be seen as a modification of the bivariate model at a single data point in the design space, as this would lead to discontinuous behavior in the model response. It is easy to see from (6) that passivity compensation will also affect the response at

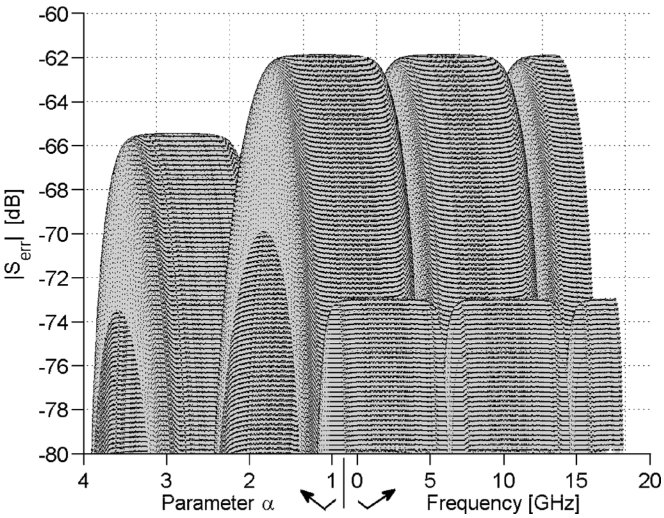

Fig. 5. Absolute error of interconnect introduced by passivity enforcement.

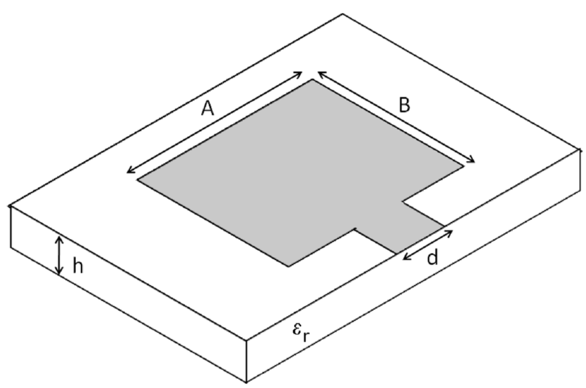

Fig. 6. Rectangular microstrip patch antenna.

other frequencies. This is the reason why a single perturbation of the weights also resolved the other passivity violations (such as the one at 4 GHz) at the same time.

VII. Example 2: Patch Antenna

In this example, the time-domain behavior of a rectangular microstrip patch antenna structure is simulated using Agilent Technologies' EMDS 3-D simulator. The rectangular patch antenna with length $A = 2.2951$ cm and width $B = 2$ cm is fed by a microstrip feedline of width $d = 0.2934$ cm, and lays on a substrate with thickness $h = 0.0795$ cm and varying relative permittivity $\varepsilon_r = [4 - 5.8]$, as shown in Fig. 6.

The time-domain response of the structure is computed for six different values of ε_r, which are equidistantly spread over the parameter range of interest. Each node is approximated by a 48-pole univariate macromodel using the time-domain OVF algorithm, as described in [15]. Fig. 7 shows the initial transient behavior of the currents induced to an injected voltage pulse for different values of ε_r. A good correspondence is observed between the simulated data (dotted lines) and the univariate rational OVF macromodels (solid lines). All the stable univariate macromodels are then combined into a bivariate macromodel by means of barycentric interpolation. As can be seen from Fig. 8,

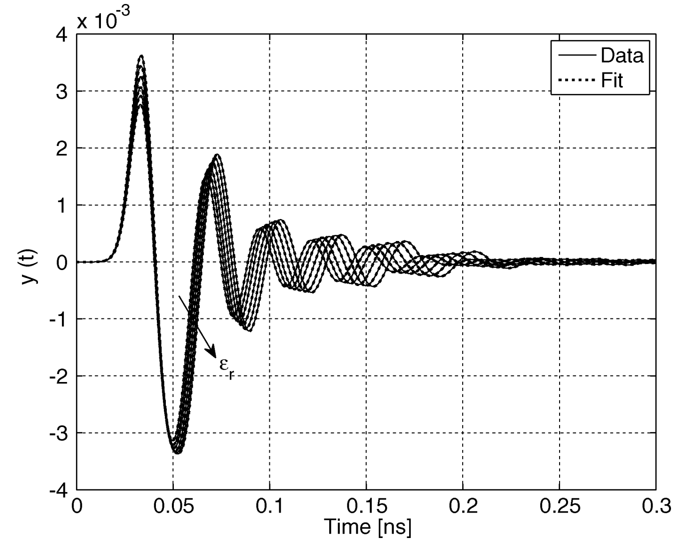

Fig. 7. OVF approximation of six univariates nodes of patch antenna.

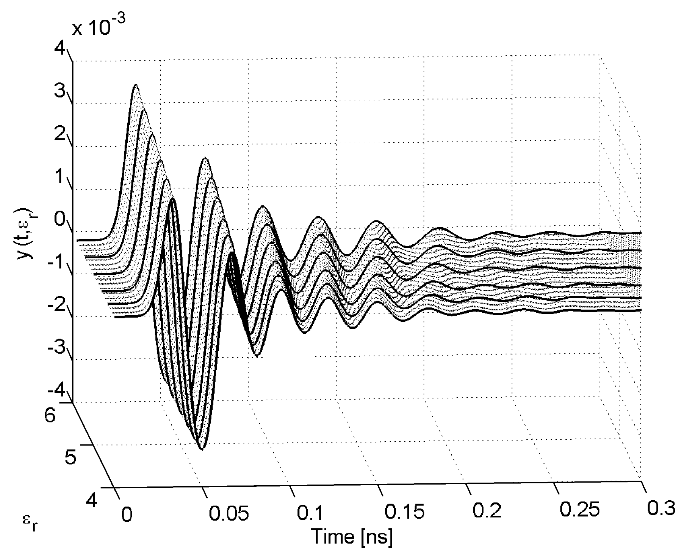

Fig. 8. Bivariate time-domain macromodel of patch antenna.

the macromodels exhibits a smooth continuous behavior for arbitrary values of ε_r, which are selected in between the nodes. Fig. 9 shows that the time-domain macromodel can also be evaluated in the frequency domain by computing the spectral response of each univariate node, and evaluating the barycentric interpolation formula (6).

VIII. Example 3: 3-D Transmission Line

The presented technique is used to model the reflection coefficient S_{11} of a lossless exponential tapered transmission line [26], [27] that is terminated with a matched load, as shown in Fig. 10, where $Z_0 = 50\,\Omega$ and $Z_L = 100\,\Omega$ represent the reference impedance and the load impedance, respectively. A multivariate macromodel is computed as a function of the varying relative dielectric constant $\varepsilon_r \in [3 - 5]$ and varying line length $L \in [1 \text{ cm} - 10 \text{ cm}]$ over the frequency range of 1 kHz–3 GHz. Fig. 11 shows the frequency response of the trivariate structure for a fixed value of $\varepsilon_r = 5$, while Fig. 12 shows the variation of

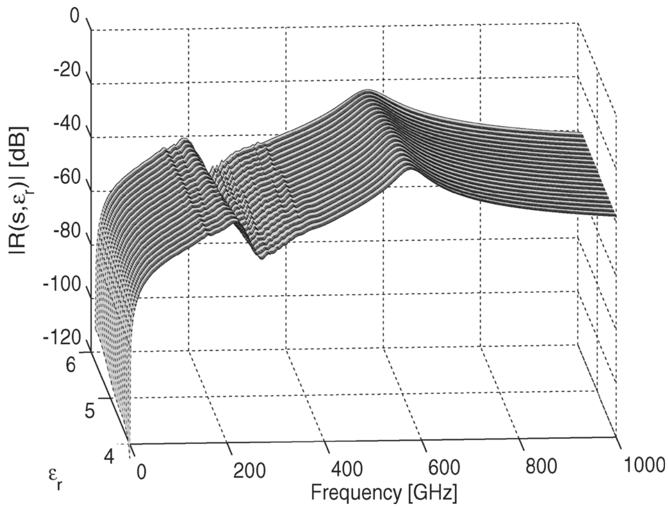

Fig. 9. Bivariate frequency-domain macromodel of patch antenna.

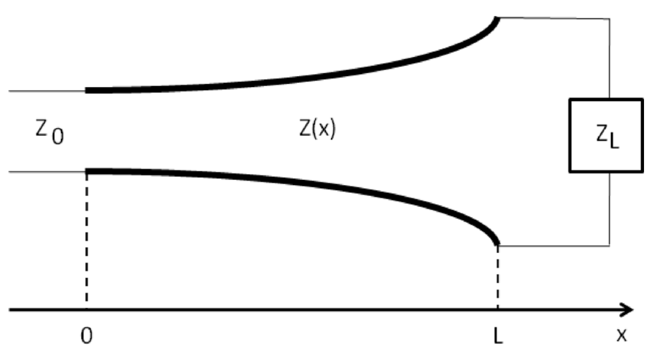

Fig. 10. Exponential tapered microstrip transmission line [27].

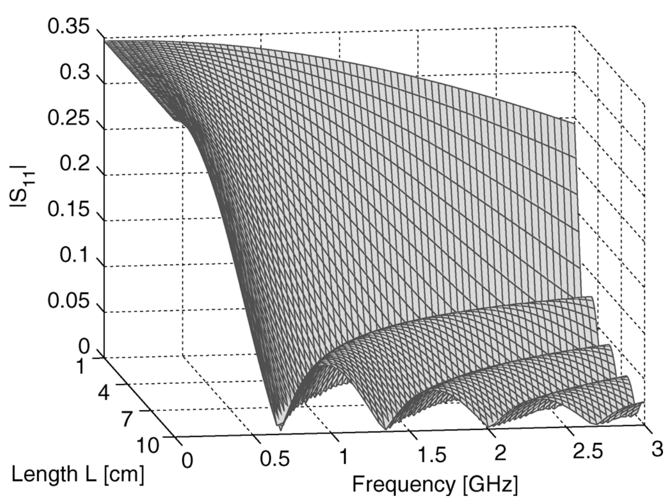

Fig. 11. Reflection coefficient S_{11} for $\varepsilon_r = 5$.

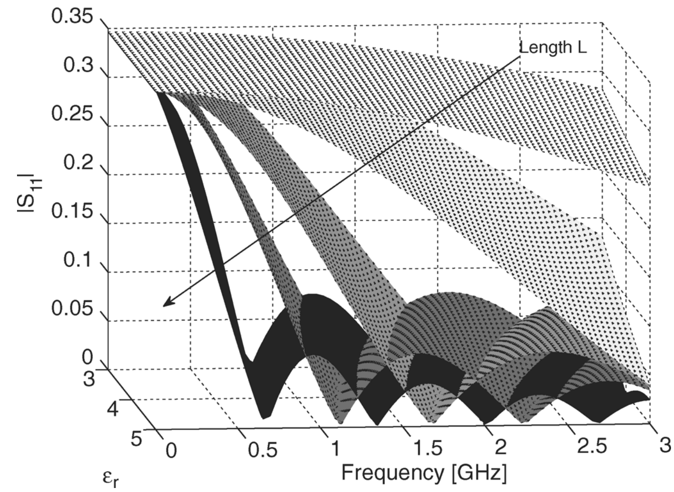

Fig. 12. Reflection coefficient S_{11} for $L = 1, 2, 4, 6, 10$ cm.

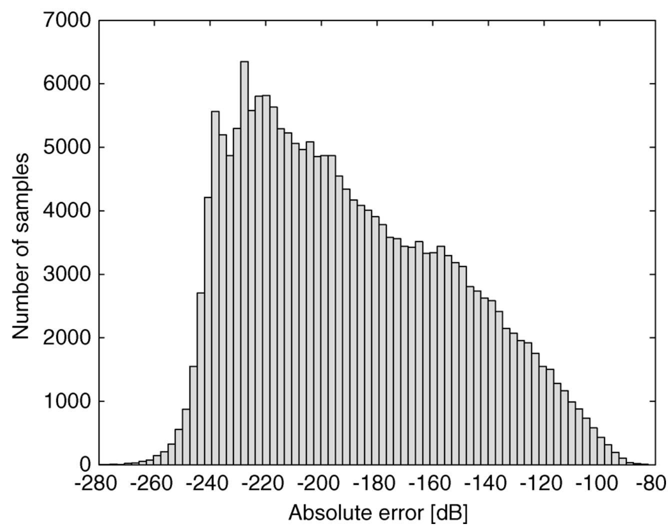

Fig. 13. Histogram: error distribution over 200 000 validation samples.

the response for an increasing line length L. The initial data is computed over a sparse grid of $10(\varepsilon_r) \times 25(L) \times 30(f)$ samples, and a set of 250 frequency-dependent univariate macromodels $R(s)$ is calculated by vector fitting. All the models that correspond to the same value of ε_r are interpolated as a function of L into a bivariate macromodel $R(s, L)$, and these bivariate macromodels are consecutively interpolated as a function of ε_r into a trivariate macromodel $R(s, L, \varepsilon_r)$. The overall macromodel is evaluated and compared over a dense set of 20 × 100 × 100 validation samples, and the distribution of the absolute error is shown by a histogram in Fig. 13. It is confirmed that an overall good approximation is obtained, as the maximum error is bounded by −82.64 dB. These results illustrate that the proposed method is accurate and applicable to model dynamical responses, which depend on multiple design parameters.

IX. Conclusions

A new multivariate macromodeling technique has been presented, which computes accurate parametric macromodels from time-domain and frequency-domain responses. The method starts by computing stable univariate macromodels using OVF for various combinations of a design variable. These univariate macromodels are then combined into a multivariate macromodel by means of barycentric Lagrange interpolation. Stability of the transfer function poles is always guaranteed, and a fast post-processing algorithm is introduced for passivity enforcement.

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