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***Abstract*— This paper presents an inverse model for the optimization of the geometrical parameters of a parallel coupled-line pass-band filter. Given the overall structure of the filter, the least square support vector machine is combined with the principal component analysis with the aim of constructing an inverse model able to estimate the geometrical parameters of the filter starting from a frequency-domain mask. Such model is trained via a set of scattering parameters computed via a 2D solver for few configurations of the filter geometrical parameters. The feasibility and the accuracy of the proposed optimization scheme is investigated by comparing its predictions with the corresponding optimal configuration estimated via a commercial tool.**

***Keywords*— Optimization, machine learning, inverse model, least-squares support vector machine, principal component analysis.**

I. INTRODUCTION

Due to their simple layout, broad-band behavior as well as their capability of providing structures with matched impedance, microstrip filters are widely used in microwave applications. Starting from the given specifications and selecting the filter type, the geometrical parameters of the microstrip filter can be estimated from prototype filter design and conventional formulas [1]. Such filter design can be further improved through optimization, as an example, by relying on the optimization algorithms available in most of the Electronic Design Automatic (EDA) tools.

Conventional optimization algorithms iteratively look for the optimal configurations of the system parameters by running, at each iteration, a new simulation with the computational model. However, especially for the case of a multi-objective optimization, such conventional optimization scheme can be rather expensive, since it may require many iterations to converge.

This paper presents a different approach for the optimization of a microwave filter based on an inverse model. The underlying idea is to construct an inverse model able to inexpensively estimate the filter geometry starting directly from the desired shape of the filter scattering parameters, without iterating. In this work, the inverse model is constructed by combining the least-square support-vector machine (LS-SVM) regression [2] with the principal component analysis (PCA) [3] from a set of training samples provided by the full-computational model implemented within the software Advanced Design System (ADS). The performance and the effectiveness of the proposed approach are then evaluated by comparing the results of a traditional optimization scheme available in ADS [4].

Table 1. Preliminar design of the proposed microwave filter.

W_1	1.09099 mm	S_1	0.977841 mm	L_1	11.9815 mm
W_2	1.19140 mm	S_2	3.41580 mm	L_2	11.8137 mm
W_3	1.19177 mm	S_3	3.94654 mm	L_3	11.8082 mm

II. PROBLEM STATEMENT & CONVENTIONAL FILTER OPTIMIZATION

Let us consider the design of a pass-band microstrip filter with the specifications: center frequency $F_C = 2400\,\text{MHz}$, bandwidth $BW = 100$ MHz, insertion loss $IL = -5$ dB, return loss $RL = -14$ dB, and out of band rejection $-60\,\text{dB}$ at $f = 2300\,\text{MHz}$. Without loss of generality, we will focus on 6 stages symmetric coupled-line microstrip filter structure inspired by [5]. The overall filter structure is characterized by 9 geometrical parameters, i.e., length L_i, width W_i and gap S_i, for $i = 1, \ldots, 3$. An initial design of the above parameters obtained via analytic formulas [1] is collected in Table 1. The obtained values of the filter geometry are then used as the initial guess for the gradient optimizer available in ADS by considering a variation range of 50% for the width and gap parameters (i.e., W_i, S_i with $i = 1, \ldots, 3$) and 10% for the lengths (L_i with $i = 1, \ldots, 3$) around their initial value collected in Tab. 1.

The ADS optimizer [4], has been run by considering three different optimization "goals": (i) $|S_{21}| \leq 5\,\text{dB}$ in the band pass; (ii) $|S_{21}| \geq 60\,\text{dB}$ @ 2300 MHz; (iii) $|S_{11}| \geq 14\,\text{dB}$ in the band pass. The solver converges after 125 iterations in 3 min and 24 s. The scattering parameters S_{11} and S_{21} for the optimized filter geometry shown in Fig. 1 (dashed black line) demonstrate the capability of the ADS optimizer of providing a filter design compliant with the design specifications. However, it is important to point out that a high number of iterations are required by the solver to converge to the optimal configuration of the filter parameters. Moreover, such optimization algorithms are usually not "tunable", i.e., if for some reason the design specifications change, the optimization algorithm must be completely re-run.

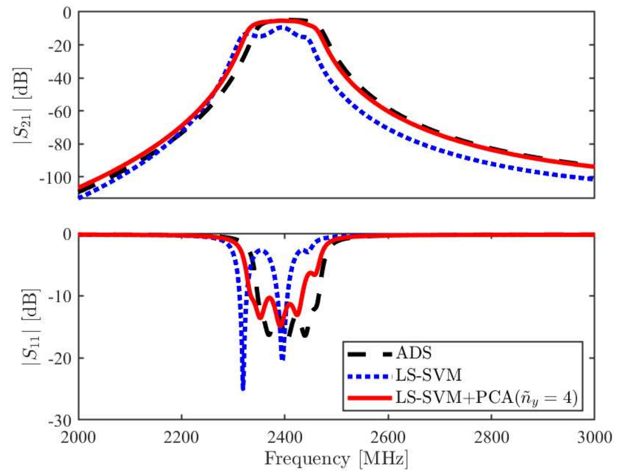

Figure 1. Frequency responses computed from the optimal filter design computed by the ADS optimizer (dashed black line), the LS-SVM-based inverse model (dotted blue line), and proposed inverse model combining LS-SVM and PCA (solid red line).

III. Inverse Model via LS-SVM Regression and PCA Compression

Different from the conventional optimization, our goal is to construct an inverse model $\mathbf{x} = \tilde{M}^{-1}(\mathbf{y})$ able to estimate the geometrical parameters of the filter $\mathbf{x} = [S_1, S_2, S_3, W_1, W_2, W_3, L_1, L_2, L_3]^T \in \mathbb{R}^{n_x=9}$ starting from the desired spectra of the scattering parameters S_{11} and S_{21} defined for $n_f = 1001$ frequency points, such that $\mathbf{y} = [|\mathbf{S}_{11}|, |\mathbf{S}_{21}|]^T \in \mathbb{R}^{n_y=2002}$, where $|\mathbf{S}_{ij}| = \left[|S_{ij}(f_1)|, \ldots, |S_{ij}(f_{n_f})|\right]$.

According to above definitions, the inverse model $\tilde{M}^{-1} : \mathbb{R}^{2002} \rightarrow \mathbb{R}^9$ defines an inverse mapping between a space with 2002 dimensions representing the absolute values of the scattering parameters $\mathbf{y}$ and a 9-dimensional space collecting the geometrical parameters $\mathbf{x}$. The construction of such kind of model is rather complex and challenging. First of all, the extremely large dimensionality of the input space (i.e., $n_y = 2002$) can lead to accuracy issue and to the infamous curse-of-dimensionality. On the other hand, an inverse model is generally ill-posed, in the sense that a given set of scattering parameters might be generated by more than one combinations of the filter geometry [6].

A. Inverse model via LS-SVM regression

Due to its simplicity and its capability of providing compact non-parametric models, the LS-SVM regression will be considered hereafter in this section to construct the advocated inverse model. The multioutput dual formulation of the LS-SVM allows approximating a set of L training samples $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^L$ via the following set of models:

$$x_k = \tilde{M}_k^{-1}(\mathbf{y}) = \sum_{i=1}^{L} \beta_i K(\mathbf{y}_i, \mathbf{y}) + b, \tag{1}$$

for $k = 1 \ldots, n_x = 9$, where K is the regression kernel, and β_i and b are the regression coefficients and bias, respectively [2].

The above dual formulation of the LS-SVM regression provides a non parametric model in which the number of regression coefficients is independent from the dimensionality of $\mathbf{y}$. Also, the regularizer used by the LS-SVM regression [2] allows to limit the detrimental effects introduced by the considered ill-posed problem.

The 9 inverse models in (1) have been built by using $L = 200$ training samples computed via a forward model implemented in ADS. The configurations of the geometrical parameters $\{\mathbf{x}_1, \ldots, \mathbf{x}_L\}$ in the training set are randomly generated via a latin hypercube sampling scheme by considering a uniform variation of 50% for W_i, S_i and 10% for L_i variables around the values specified in Tab. 1. The above configurations are then used as input for a set of parametric simulations in ADS to calculate the magnitude of the scattering parameters $\mathbf{S}_{11}$ and $\mathbf{S}_{21}$ used to get the training samples $\{\mathbf{y}_1, \ldots, \mathbf{y}_L\}$.

An ideal Chebyshev mask incorporating all the specification provided in Sec. II, has been used as input for the inverse models trained via the LS-SVM. Then, the filter geometry predicted by the inverse models has been used as input within an ADS simulation. The resulting scattering parameters $\mathbf{S}_{11}$ and $\mathbf{S}_{21}$ in Fig. 1(dotted blue line) clearly highlight the improved performances of the filter designed with the ADS optimizer with respect to the one obtained via the proposed inverse model. Such lack of accuracy is attributed to the high dimensionality of the input space (i.e., $n_y = 2002$) compared with the small number of training samples (i.e., $L = 200$).

B. PCA Compression

A data compression strategy based on the PCA can be seen as a promising approach to mitigate the above issue. PCA allows to exploit and to remove the redundant information from the scattering responses of the filter in the training set, thus leading to a compressed approximation of the training set with a lower dimensionality with respect to the original data [7]. To this aim the complete dataset of the training scattering responses $\{\mathbf{y}_i\}_{i=1}^L$ are collected in the matrix $\mathbf{Y} = [\mathbf{y}_1, \ldots, \mathbf{y}_L] \in \mathbb{R}^{n_y \times L}$. The matrix $\mathbf{Y}$ is used within the PCA algorithm to find out the smallest set of "principal components", approximating the training responses $\{\mathbf{y}_i\}_{i=1}^L$ as [3]:

$$\mathbf{y}_i \approx \boldsymbol{\mu} + \sum_{n=1}^{\tilde{n}_y} \tilde{y}_{n,i} \mathbf{u}_n, \tag{2}$$

for $i = 1, \ldots, L$. The PCA coefficients $\tilde{y}_{n,i}$ writes:

$$\tilde{y}_{n,i} = \mathbf{u}_n^T (\mathbf{y}_i - \boldsymbol{\mu}), \tag{3}$$

where $\boldsymbol{\mu}$ is the column-wise mean, and the principal components $\{\mathbf{u}_n\}_{n=1}^{\tilde{n}_y}$ are the left singular vectors calculated via singular value decomposition applied to the matrix $\mathbf{Y}$.

According to (2) and (3), the training samples $\{\mathbf{y}_i\}_{i=1}^L$ with $\mathbf{y}_i \in \mathbb{R}^{n_y}$ can be approximated (with a tunable accuracy) via a compressed training set $\{\tilde{\mathbf{y}}_i\}_{i=1}^{L}$, in which $\tilde{\mathbf{y}}_i = [\tilde{y}_{1,i}, \ldots, \tilde{y}_{\tilde{n}_y,i}]^T \in \mathbb{R}^{\tilde{n}_y}$, where $\tilde{n}_y \ll n_y$.

The number of PCA coefficients $\tilde{n}_y$ must be carefully tuned. It should be as small as possible, to reduce the dimensionality of the samples $\tilde{\mathbf{y}}_i$ used as input for the inverse model in (1), but at the same time the compressed set of training samples $\{\tilde{\mathbf{y}}_i\}_{i=1}^{L}$ should provide as much information as possible to avoid an ill-posed formulation of the inverse model. A wise strategy is to use only the PCA coefficients which provide the largest variability with respect to a variation in the geometrical parameters of the filter. The above analysis can be carried out numerically by looking at the variance of the PCA coefficients, which writes:

$$\sigma_n^2 = \frac{1}{L}\sum_{i=1}^{L}(\tilde{y}_{n,i} - \mu_n)^2, \tag{4}$$

for $n = 1, \ldots, \tilde{n}_y$, where $\mu_n = \frac{1}{L}\sum_{i=1}^{L}\tilde{y}_{n,i}$ is the mean computed on the L realizations of the n-th PCA coefficient available in the training set.

Figure 2 shows the normalized variances in (4) for the first 20 PCA coefficients. As expected, the blue bars show that the low order coefficients ($4 \leq \tilde{n}_y \leq 10$) are able of explaining most of the variability on the scattering parameters introduced by a variation on the geometrical parameters. Figure 1(solid red line) shows the optimized results computed via the proposed inverse model with $\tilde{n}_y = 4$, again starting from an ideal Chebyshev mask incorporating all the filter specifications. The results highlight the capability of the proposed inverse model of providing an accurate estimation of the optimal filter geometry. The obtained results are very similar to the ones provided by the ADS optimizer after 125 iterations. However, after the training phase, the proposed inverse model is able to *directly* estimate the optimal configuration of the filter parameters in less than 1 s, without requiring any iteration.

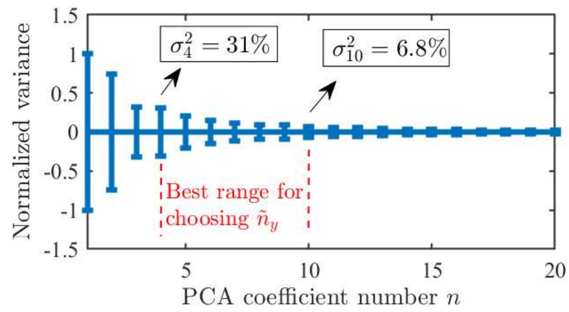

Figure 2. Normalized variances (blue bars) of the first 20 PCA coefficients ($\tilde{n}_y = 20$) in compressed training set.

It is important to remark that the obtained inverse model is tunable and can be suitably adopted to optimize the filter geometry for a generic set of filter specifications, just by changing the desired mask. To this aim, its performances have been assessed by using two new specifications: (i) $F_C = 2300$ MHz and $BW = 30$ MHz and (ii) $F_C = 2550$ MHz and $BW = 50$ MHz. Two new masks, generated according to the above specifications, have been used as input for the inverse model with $\tilde{n}_y = 4$. Obviously, the model tunability is limited to the range of $\mathbf{x}$ used during the model training. The scattering parameters obtained from the optimal parameters predicted via the inverse model are shown in Fig. 3. The results clearly highlight the capability of the proposed inverse model of optimizing structures for different specifications.

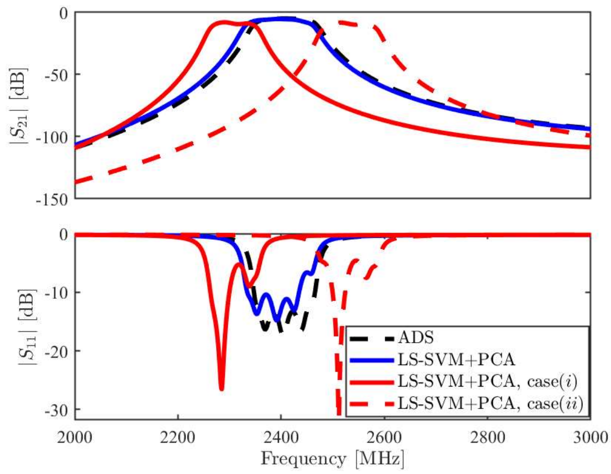

Figure 3. Tunability assessment of proposed inverse model with $\tilde{n}_y = 4$ (see text for additional details).

IV. Conclusions

This paper presented an efficient methodology for the optimization of the geometry of microwave filters based on an inverse model approach. The inverse model is constructed by combining the LS-SVM regression with the PCA. Such model is able to directly design the filter starting from the desired frequency-domain mask, without using computational expensive iterative optimization algorithms. The feasibility and the accuracy of the proposed optimization scheme have been investigated by comparing its predictions with the corresponding ones computed via a commercial solver.

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