This is the author's version of an article that has been published in this conference. Changes were made to this version by the publisher prior to publication. The final version is available at http://dx.doi.org/10.1109/LAMC63321.2025.10880508

Cognitive Parameter Extraction for Space Mapping Design Optimization

José E. Rayas-Sánchez

Department of Electronics, Systems, and Informatics, ITESO – The Jesuit University of Guadalajara, Tlaquepaque, Jalisco, 45604 Mexico
erayas@iteso.mx

(*Invited Paper*)

***Abstract*—Parameter extraction (PE) is a key subproblem of space mapping (SM) design optimization. It consists of a local alignment between the coarse and fine models at each SM iteration. In this work, cognition-driven PE is proposed for SM. In contrast to classical PE, where the full fine model responses are used as targets, the proposed cognitive PE focuses on key features of the fine model response selected from an engineering perspective. It is demonstrated that the proposed cognitive PE approach: 1) yields more accurate extracted parameters regardless of the type of PE objective function employed; and 2) achieves a more meaningful matching to the fine model target response and with less variability. To proof this with independence of the optimization method employed for PE, plots of the PE objective functions are presented over large regions of the coarse model design space. Two synthetic examples are used to support these findings.**

***Index Terms*—Broyden, Chebyshev, cognition, Euclidean, Kullback-Leibler, Manhattan, norm, objective function, optimization, parameter extraction, space mapping.**

I. Introduction

The concept of cognition driven design, as applied to CAD techniques for RF and microwave circuits, was first proposed by Prof. John Bandler [1]. The overall idea behind that general concept is to incorporate key engineering knowledge, intuition, and experience, in automated numerical techniques to make the modeling and design optimization processes more efficient and accurate [2].

A paradigmatic example of how the design optimization of computationally expensive models can be dramatically accelerated by exploiting prior engineering knowledge is space mapping (SM) [3],[4]. Deeply rooted in engineering expertise and intuition, SM emerged [5],[6] as a feasible technique to optimize computationally expensive EM models (known as fine models) by exploiting physics-based inaccurate but computationally cheap models (known as coarse models). SM techniques were soon adapted for addressing many other engineering problems [5], [7].

Most SM approaches require performing parameter extraction (PE) at each iteration [4]. In essence, PE consists of a local alignment between the coarse and fine model responses at each SM iteration. PE is also the most vulnerable aspect of SM, since inadequate PE solutions can make SM to diverge [7], which heavily depends on the coarse model properties [8].

Classical PE is formulated by matching the full fine model response of interest [3],[4],[7]. In this paper, a cognition-driven PE formulation is proposed for the first time, where instead of using the full fine model response as target, key features of fine model response are used to make a more meaningful local alignment from an engineering perspective. The selection of those key features depends on the engineering knowledge and experience about the problem at hand. It is demonstrated that the proposed cognitive PE formulation yields more accurate extracted parameters and achieves a more meaningful matching with less variability regardless of the type of PE objective function employed. To make these conclusions independent of the numerical optimization method employed for PE, plots of the PE objective functions are shown over a large region of the coarse model design space, which allows displaying the PE objective functions behavior and the exact minima (limited just by the plots resolution). A couple of synthetic examples confirm these observations.

II. The Role of Parameter Extraction in Space Mapping Design Optimization

In the SM context, PE is an optimization subproblem where the coarse model design parameters, $\boldsymbol{x}_c$, are found to make the coarse model response, $\boldsymbol{R}_c$, as close as possible to the fine model response, $\boldsymbol{R}_f$, at the i-th iterate, $\boldsymbol{x}_f^{(i)}$. This is typically done by solving

$$\boldsymbol{x}_c^{PE} = \arg\min_{\boldsymbol{x}_c} U_{PE}\left(\boldsymbol{R}_c(\boldsymbol{x}_c), \boldsymbol{R}^t\right) \tag{1}$$

where $\boldsymbol{x}_c^{PE}$ has the extracted parameters at the i-th SM iteration, $\boldsymbol{R}^t = \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)})$ is the current target response, and U_{PE} is a suitable objective function for PE, *e.g.*, Manhattan. Euclidean, Chebyshev, or Kullback-Leibler (K-L), as described in [9]. By solving (1), the coarse model design parameters $\boldsymbol{x}_c^{PE}$ achieve a local alignment with the current fine model response, $\boldsymbol{R}_c(\boldsymbol{x}_c^{PE}) \approx \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)})$.

III. Assessing a Parameter Extraction Solution for Space Mapping

Knowing in advanced what should be the exact correct value of $\boldsymbol{x}_c^{PE}$ when solving (1) is not possible, excepting at the

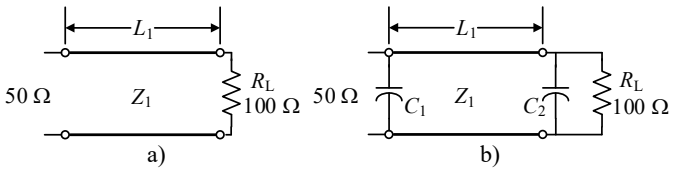


Fig. 1. Quarter-wave impedance transformer: a) ideal coarse model; b) "fine" model with parasitic capacitances C_1 and C_2.

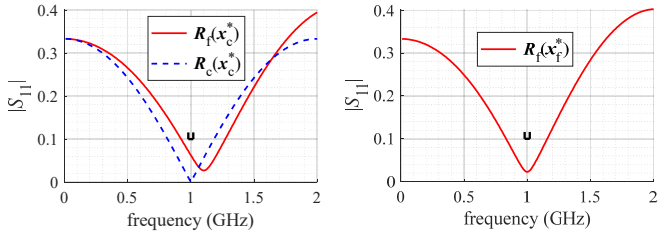


Fig. 2. Responses of the quarter-wave impedance transformer at: a) starting point for SM; b) ideal target for the last PE in SM.

very end of an ideal successful SM optimization. In that last SM iteration, the final fine model response should be equal or very close to its optimal response, $\boldsymbol{R}_f(\boldsymbol{x}_f^*)$. Ideally, when $\boldsymbol{R}^t = \boldsymbol{R}_f(\boldsymbol{x}_f^*)$ is used in (1), the extracted parameters $\boldsymbol{x}_c^{PE}$ should be equal to the optimal coarse model design $\boldsymbol{x}_c^*$, since that corresponds to the ideal ending criterion for SM [6],[7].

Assuming that the fine model optimal design $\boldsymbol{x}_f^*$ is known (obtained from directly optimizing the fine model), then the above condition can be used to assess the quality of the PE solution. For this reason, synthetic examples where the fine model can be directly optimized are considered here.

The following error metrics are used to assess the accuracy of the extracted parameters $\boldsymbol{x}_c^{PE}$ with respect to $\boldsymbol{x}_c^*$ (at the ideal last iteration of SM): the average absolute relative error (ε_{avg}^{PE}), the maximum absolute relative error (ε_{max}^{PE}), and the normalized mean square error (ε_{nms}^{PE}), defined as

$$\varepsilon_{avg}^{PE} = \frac{100}{n}\frac{\| \boldsymbol{x}_c^{PE} - \boldsymbol{x}_c^* \|_1}{\| \boldsymbol{x}_c^* \|_\infty} \ (\%) \tag{2a}$$

$$\varepsilon_{max}^{PE} = 100\frac{\| \boldsymbol{x}_c^{PE} - \boldsymbol{x}_c^* \|_\infty}{\| \boldsymbol{x}_c^* \|_\infty} \ (\%) \tag{2b}$$

$$\varepsilon_{nms}^{PE} = 100\frac{\| \boldsymbol{x}_c^{PE} - \boldsymbol{x}_c^* \|_2}{\| \boldsymbol{x}_c^* \|_2} \ (\%) \tag{2c}$$

To make fare graphical comparisons of the different PE objective functions U_{PE}, we plot all objectives normalized as

$$U_{PE}^n = \frac{U_{PE}\left(\boldsymbol{R}_c(\boldsymbol{x}_c^{(k)}), \boldsymbol{R}^t\right)}{\max_k \left\{ \ldots U_{PE}\left(\boldsymbol{R}_c(\boldsymbol{x}_c^{(k)}), \boldsymbol{R}^t\right) \ldots \right\}} \tag{3}$$

where $\boldsymbol{x}_c^{(k)}$ is the k-th evaluated base point varied to cover the whole design space of interest for plotting.

IV. PE Graphical Example 1: Quarter-Wave Impedance Transformer

As a one-dimensional graphical study case, consider the

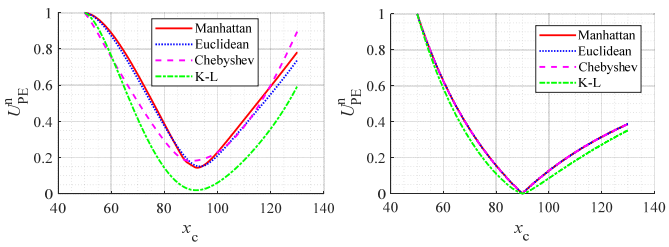


Fig. 3. Normalized PE objective function plots when $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$ for the quarter-wave transformer: a) classical PE by matching $|S_{11}|$ in the full frequency band; b) cognitive PE by matching just f_{min}, the frequency at which $|S_{11}|$ is minimum.

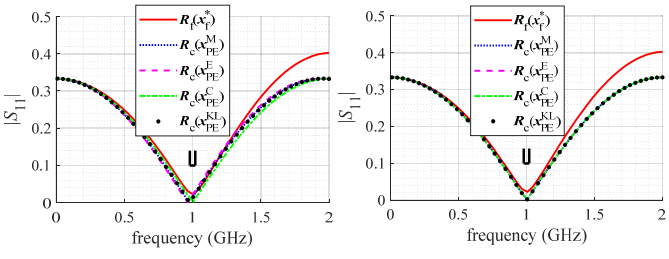


Fig. 4. Matching achieved by each PE solution when $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$ for the quarter-wave transformer: a) classical PE by matching $|S_{11}|$ in the full frequency band; b) cognitive PE by matching just f_{min}, the frequency at which $|S_{11}|$ is minimum.

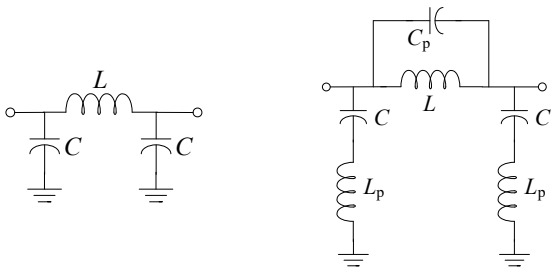
design optimization by SM of a simple quarter-wave one-section impedance transformer, with design specifications to achieve the best possible impedance matching at 1 GHz. The coarse and "fine" models are illustrated in Fig. 1. The reference impedance is $Z_0 = 50\ \Omega$, the load impedance is $R_L = 100\ \Omega$, and the transmission line characteristic impedance in both models is $Z_1 = (Z_0 R_L)^{1/2} = 70.7107\ \Omega$ [10]. The "fine" model has parasitic capacitances $C_1 = 0.5$ pF and $C_2 = 0.05$ pF. The design variable in both models is $x = L_1$ (electrical length in degrees). Of course, we know that $x_c^* = 90$ [10]. The starting point for SM is shown in Fig. 2a, confirming that the "fine" model does not achieve the best impedance matching at 1 GHz when evaluated at x_c^*.

Applying direct optimization to the "fine" model, its optimal design is found as $x_f^* = 98.6877$. The corresponding optimal fine model response $\boldsymbol{R}_f(x_f^*)$ is in Fig. 2b, which ideally

TABLE I. Comparing PE Results for the Quarter-Wave Transformer using Classical vs. Cognitive PE Formulations

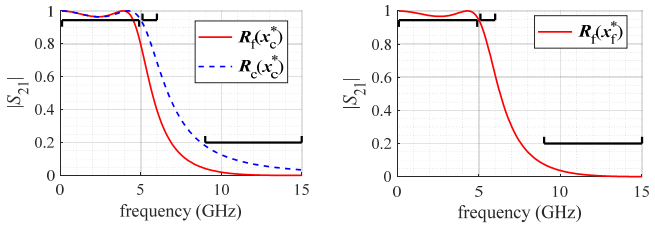
PE	OF	$\boldsymbol{x}_c^{PE}$	ε_{avg}^{PE}	ε_{max}^{PE}	ε_{nms}^{PE}
Classical	M	92.325	2.583	2.583	2.583
	E	93.447	3.830	3.830	3.830
	C	89.920	0.089	0.089	0.089
	K-L	92.004	2.227	2.227	2.227
Cognitive	M	89.920	0.089	0.089	0.089
	E	89.920	0.089	0.089	0.089
	C	89.920	0.089	0.089	0.089
	K-L	89.920	0.089	0.089	0.089

OF is the PE objective function: Manhattan (M), Euclidean (E), Chebyshev (C), or Kullback-Leibler (K-L).



a) b)

Fig. 5. Third-order low-pass lumped filter: a) ideal coarse model; b) "fine" model with parasitic elements L_p and C_p.



a) b)

Fig. 6. Responses of the third-order lumped filter at: a) starting point for SM; b) ideal target for the last PE in SM.

is the target response for PE in the last SM iteration, such that the extracted parameters $\boldsymbol{x}_c^{PE}$ must be equal to x_c^* and SM ends.

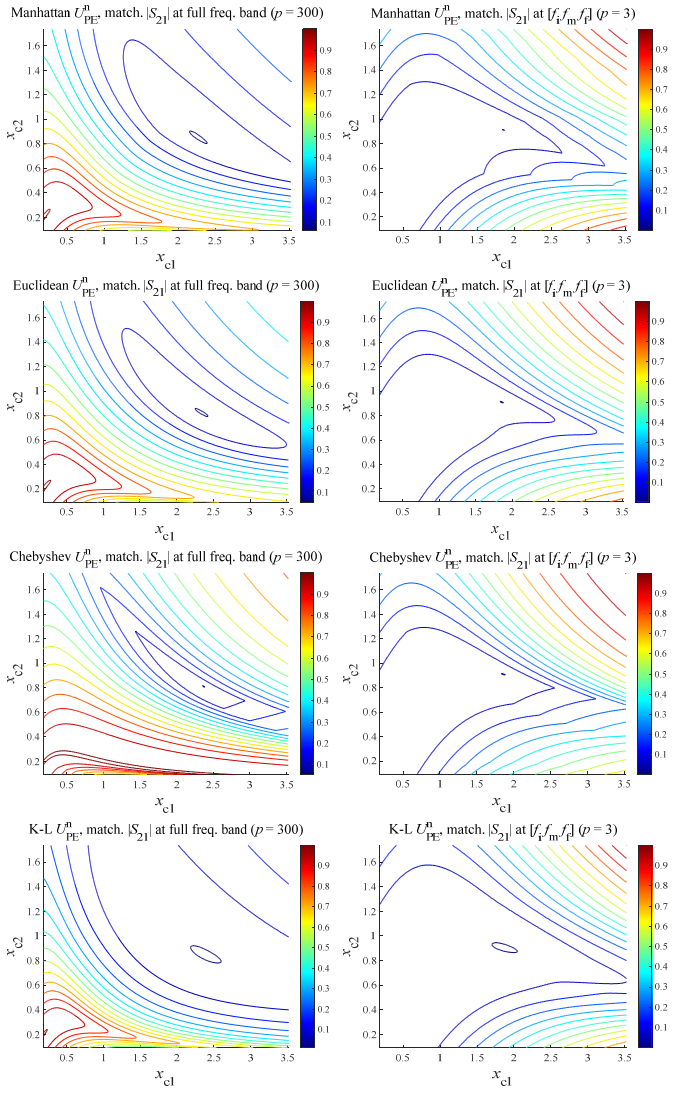
The classical formulation for PE based on full responses is first used, matching $\boldsymbol{R}_f(x_f^*) = |S_{11}|$ in the full frequency band (0.01-2 GHz). The normalized PE objective functions U_{PE} are plotted in a large region centered at x_c^* ($50 \le x_c \le 130$). The corresponding objective function plots are shown in Fig. 3a. It is seen that: 1) the Kulback-Leibler formulation yields a smoother PE objective function with larger dynamic range than the Manhattan, Euclidean, and Chebyshev formulations, reconfirming [9]; and 2) the minimizer notably varies around the expected solution $x_c^* = 90$, as also shown in Table I.

A cognitive PE formulation is now used by just matching the frequency f_{min} at which $|S_{11}|$ is minimum over the same full frequency band. The corresponding plots of the normalized PE objective functions in the same design space are shown in Fig. 3b. It is seen that: 1) Kulback-Leibler again yields smoother objectives [9]; and more importantly, 2) the minimizer is much more accurate regardless of the PE objective function used with practically no variability, as confirmed in Table I.

Finally, Fig. 4 illustrates the quality of the matching achieved by each of the extracted parameters when the target response is $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$. Clearly, cognition driven PE makes a more meaningful matching with the four objective functions.

V. PE Graphical Example 2: Third-Order Low-Pass Lumped Filter

As a two-dimensional graphical study case, consider a 3rd-order low-pass π symmetrical lumped filter. The coarse and "fine" models are illustrated in Fig. 5. The design variables are $\boldsymbol{x} = [L(\text{nH}) \quad C(\text{pF})]^T$. The "fine" model has parasitic elements $L_p = 0.11$ nH and $C_p = 0.07$ pF. Boths models use a reference



a) b)

Fig. 7. Normalized PE objective function contour plots when $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$ for the low-pass filter: a) classical PE by matching $|S_{21}|$ in the full frequency band; b) cognitive PE by matching just 3 frequency points (3, 4 and 5 GHz).

impedance $Z_0 = 50\ \Omega$. The design specifications are:

$$|S_{21}| \ge 0.9441 \text{ for } 0.1 \text{ GHz} \le f \le 4.9 \text{ GHz} \quad (4a)$$

$$|S_{21}| \le 0.9441 \text{ for } 5.1 \text{ GHz} \le f \le 6.0 \text{ GHz} \quad (4b)$$

$$|S_{21}| \le 0.2 \text{ for } 9 \text{ GHz} \le f \le 15 \text{ GHz} \quad (4c)$$

The optimal coarse model design, obtained from direct minimax optimization, is $\boldsymbol{x}_c^* = [1.8538 \quad 0.9136]^T$. The starting point for SM is shown in Fig. 6a, confirming that the "fine" model violates the design specifications when evaluated at $\boldsymbol{x}_c^*$. Since the "fine" model is computationally cheap, we can directly optimize it to get $\boldsymbol{x}_f^* = [1.6703 \quad 0.8031]^T$, whose optimal response $\boldsymbol{R}_f(x_f^*)$, shown in Fig. 6b, corresponds to the ideal target response for PE in a last SM iteration, for which the extracted parameters $\boldsymbol{x}_c^{PE}$ should be equal to $\boldsymbol{x}_c^*$.

The classical PE based on full responses is first used, matching $\boldsymbol{R}_f(x_f^*) = |S_{21}|$ in the full frequency band (0.01-15 GHz, with $p = 300$ frequency points). The contours of the

TABLE II. COMPARING PE RESULTS FOR THE LOW-PASS FILTER USING CLASSICAL VS. COGNITIVE PE FORMULATIONS

PE	OF	$\boldsymbol{x}_c^{PE}$	ε_{avg}^{PE}	ε_{max}^{PE}	ε_{nms}^{PE}
Classical	M	$[2.2609\ \ 0.8544]^T$	12.58	21.96	19.91
	E	$[2.3343\ \ 0.8248]^T$	15.36	25.92	23.64
	C	$[2.3743\ \ 0.8083]^T$	16.88	28.08	25.70
	K-L	$[2.3877\ \ 0.8478]^T$	16.17	28.80	26.03
Cognitive	M	$[1.8471\ \ 0.9136]^T$	0.18	0.36	0.32
	E	$[1.8605\ \ 0.9103]^T$	0.27	0.36	0.36
	C	$[1.8671\ \ 0.9070]^T$	0.54	0.72	0.72
	K-L	$[1.8738\ \ 0.9037]^T$	0.81	1.08	1.08

OF is the PE objective function: Manhattan (M), Euclidean (E), Chebyshev (C), or Kullback-Leibler (K-L).

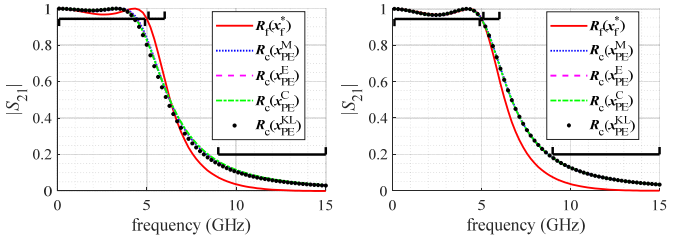


Fig. 8. Matching achieved by each PE solution when $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$ for the third-order low-pass filter: a) classical PE by matching $|S_{21}|$ in the full frequency band; b) cognitive PE by matching $|S_{21}|$ at just 3 suitable frequency points, $[f_i\ f_m\ f_f]$.

normalized U_{PE} are plotted over a large region centered at $\boldsymbol{x}_c^*$ ($0.1\boldsymbol{x}_c^* \prec \boldsymbol{x}_c \prec 1.9\boldsymbol{x}_c^*$, with 501 uniformly distributed base points per direction). The corresponding contours are shown in Fig. 7a. It is again seen that: 1) the Kulback-Leibler formulation yields a smoother PE objective function than Manhattan, Euclidean, and Chebyshev formulations, reconfirming [9]; and 2) the minimizers notably deviate from the plots center, where the expected solution $\boldsymbol{x}_c^*$ is located (also see Table II).

A cognitive PE formulation is next employed by matching $|S_{21}|$ at just three suitable frequency points, $[f_i\ f_m\ f_f]$, selected as 3, 4 and 5 GHz, respectively (see Fig. 6b). The corresponding plots of the PE objective functions U_{PE} in the same design space are shown in Fig. 7b. It is again seen that: 1) Kulback-Leibler yields smoother objectives, which reconfirms [9]; and more importantly, 2) the minimizer is much more accurate regardless of the PE objective function employed, as numerically confirmed in Table II. Notice that other key frequency points could have been selected, yielding similar results.

The matching achieved by each of the extracted parameters when the target response is $\boldsymbol{R}^t = \boldsymbol{R}_f(x_f^*)$ is shown in Fig. 8. Again, cognition driven PE makes a more meaningful matching with the four objective functions than the classical PE formulation based on matching the target response $\boldsymbol{R}^t$ at the full frequency band.

VI. CONCLUSION

Cognition-driven parameters extraction for space mapping optimization problems was presented in this paper. The proposed cognitive approach focuses on key features of the fine model response, which are problem-dependent and selected from engineering knowledge, in contrast to classical parameter extraction that uses the full fine model response as target. It was shown that the proposed cognitive approach yields more accurate extracted parameters regardless of the objective function used and achieves a more meaningful matching to the fine model response and with less variability.

REFERENCES

[1] J. E. Rayas-Sánchez, Q. J. Zhang, J. W. Rautio, N. K. Nikolova, V. E. Boria, Q. S. Cheng, M. Yu, and W. J. R. Hoefer, "Microwave modeling and design optimization: The legacy of John Bandler," *IEEE Trans. Microwave Theory Techn.*, early access ver., 2024.

[2] J. E. Rayas-Sánchez, S. Koziel, and J. W. Bandler, "Advanced RF and microwave design optimization: a journey and a vision of future trends," *IEEE J. of Microwaves*, vol. 1, no. 1, pp. 481-493, Jan. 2021.

[3] J. W. Bandler, Q. Cheng, S. A. Dakroury, A. S. Mohamed, M. H. Bakr, K. Madsen and J. Søndergaard, "Space mapping: the state of the art," *IEEE Trans. Microwave Theory Techn.*, vol. 52, no. 1, pp. 337-361, Jan. 2004.

[4] S. Koziel, Q. S. Cheng, and J. W. Bandler, "Space mapping," *IEEE Microwave Magazine*, vol. 9, no. 6, pp. 105-122, Dec. 2008.

[5] J. W. Bandler and J. E. Rayas-Sánchez, "An early history of optimization technology for automated design of microwave circuits," *IEEE J. of Microwaves*, vol. 3, no. 1, pp. 319-337, Jan. 2023.

[6] J. W. Bandler, R. M. Biernacki, S. H. Chen, P. A. Grobelny, and R. H. Hemmers, "Space mapping technique for electromagnetic optimization," *IEEE Trans. Microwave Theory Tech.*, vol. 42, no. 12, pp. 2536–2544, Dec. 1994.

[7] J. E. Rayas-Sánchez, "Power in simplicity with ASM: tracing the aggressive space mapping algorithm over two decades of development and engineering applications," *IEEE Microwave Magazine*, vol. 17, no. 4, pp. 64-76, Apr. 2016.

[8] S. Koziel, J. W. Bandler, and K. Madsen. "Quality assessment of coarse models and surrogates for space mapping optimization," *Optim. Eng.*, vol. 9, no. 4, pp. 375-391, Dec. 2008.

[9] R. Loera-Díaz and J. E. Rayas-Sánchez, "An objective function formulation for circuit parameter extraction based on the Kullback-Leibler distance," in *IEEE MTT-S Int. Microwave Symp. Dig.*, Los Angeles, CA, Jun. 2020, pp. 80-82.

[10] D. M. Pozar, *Microwave Engineering*. Amherst, MA: Wiley, 1998.