Microwave Modeling and Design Optimization: The Legacy of John Bandler

José E. Rayas-Sánchez, *Senior Member, IEEE*, Qi-Jun Zhang, *Fellow, IEEE*, James C. Rautio, *Life Fellow, IEEE*, Natalia K. Nikolova, *Fellow, IEEE*, Vicente E. Boria, *Fellow, IEEE*, Qingsha S. Cheng, *Senior Member, IEEE*, Ming Yu, *Fellow, IEEE*, and Wolfgang J. R. Hoefer, *Life Fellow, IEEE*

(Invited Paper)

***Abstract*— In this article, we honor Prof. John W. Bandler and his legacy in RF and microwave modeling and automated design optimization. We showcase his pioneering breakthroughs in minimax optimization, *p*th norm formulations, yield optimization, and nonlinear circuit design optimization. We highlight advances in direct electromagnetic (EM) microwave optimization, circuit response sensitivities, and efficient *S*-parameters sensitivity calculations. We explore the port-tuning version of space mapping (SM) for EM-based analysis, techniques for industrial microwave design of satellite systems, and post-manufacture hardware tuning. The integration of artificial neural networks (ANNs) with SM for enhanced EM-based design optimization and yield prediction, cognition-driven microwave filter design, and parallels between SM and artificial intelligence (AI) is examined. Finally, we speculate on the future integration of cognitive science with engineering design, leveraging the synergy of AI, machine learning (ML), and SM.**

***Index Terms*— Adjoint sensitivities, artificial intelligence (AI), circuit optimization, electromagnetic (EM) optimization, design centering, design optimization, frequency scaling, machine learning (ML), microwave circuits, minimax, neural networks, parameter extraction, port tuning, sensitivities, space mapping (SM), surrogate modeling, statistical analysis, yield.**

Manuscript received 28 June 2024; accepted 16 July 2024. Date of publication 12 August 2024; date of current version 7 January 2025. This article corresponds to an expanded version of the material presented by the authors at the Memorial Session honoring Prof. John W. Bandler, during the IEEE MTT-S International Microwave Symposium (IMS), June 16-21, 2024, Washington, DC, USA. *(Corresponding author: José E. Rayas-Sánchez.)*

José E. Rayas-Sánchez is with the Department of Electronics, Systems, and Informatics, ITESO, Jesuit University of Guadalajara, Tlaquepaque, Jalisco 45604, Mexico (e-mail: erayas@iteso.mx).

Qi-Jun Zhang is with the Department of Electronics, Carleton University, Ottawa, ON K1S5B6, Canada (e-mail: qjz@doe.carleton.ca).

James C. Rautio is with Sonnet Software, Syracuse, NY 13212 USA (e-mail: rautio@ieee.org).

Natalia K. Nikolova is with the Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON L8S 4K1, Canada (e-mail: talia@mcmaster.ca).

Vicente E. Boria is with the Departamento de Comunicaciones and ITEAM, Universitat Politècnica de València, 46022 Valencia, Spain (e-mail: vboria@dcom.upv.es).

Qingsha S. Cheng and Ming Yu are with the Department of Electronic and Electrical Engineering, Southern University of Science and Technology, Shenzhen 518055, China (e-mail: chengqs@sustech.edu.cn; ming.yu@ieee.org).

Wolfgang J. R. Hoefer is with the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC V8W 2Y2, Canada (e-mail: w.hoefer@ieee.org).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TMTT.2024.3437198.

Digital Object Identifier 10.1109/TMTT.2024.3437198

I. Introduction

THE early 1950s marked the advent of computer-aided analysis and design of high-frequency circuits and structures such as microwave and millimeter-wave waveguide components and antennas. Prof. John W. Bandler stands out among the pioneers who shaped this field of study early on with methodologies and techniques, which we use and build upon to this day. In this article, we wish to pay homage to him and his legacy, highlighting his groundbreaking contributions to RF and microwave modeling and his visionary insights into automated design optimization. We showcase his pivotal technical breakthroughs and their enduring impact.

In Section II, we recall Prof. Bandler's pioneering work on minimax optimization, *p*th norm formulations, yield optimization, and nonlinear circuit design optimization. In Section III, we discuss direct electromagnetic (EM) microwave optimization, first in the frequency domain and then in a hybrid frequency/time arrangement where a frequency-domain optimizer controls a time-domain EM simulator whose transient field response is Fourier-transformed and returned to the optimizer in the frequency domain. Section IV presents innovative analysis methods for microwave circuit response sensitivities, notably adjoint sensitivities, and efficient EM-based *S*-parameters sensitivity calculations for accurate design and image-reconstruction.

Section V is devoted to space mapping (SM), a breakthrough that dramatically reduces the computational burden of the direct optimization of fine or high-fidelity EM models, by iteratively mapping a coarse but fast low-fidelity physics-based model, such as an equivalent circuit, to the fine model accuracy. After a short introduction to the basics of SM, we present SM-based surrogates and make an initial comparison with artificial intelligence (AI), followed by a discussion of coarse EM models for SM, and an example of frequency SM between fine and coarse transmission-line matrix (TLM) models. In Section V-C, we explore the port-tuning version of SM for efficient EM-based analysis and design.

Section VI describes the contributions to SM-based post-manufacture tuning of microwave hardware, and Section VII reports industrial-scale applications of SM. Section VIII elaborates on the relationship between SM and AI, introduces neural SM as a pioneering AI approach, deals with cognition-driven design, and contrasts AI- and SM-based methods. It also projects potential new developments, envisioning a closer integration of cognitive science with engineering design, leveraging AI, machine learning (ML), and SM. Finally, Section IX concludes this article.

II. Foundations of Circuit Optimization

By 1969 [1], Bandler had already contributed the very first comprehensive review of microwave circuit design optimization [2]. In that foundational work [2], he explains the basic concepts and the state-of-the-art formulations in that early stage of CAD for network optimization [2].

A. Minimax Optimization

Bandler pioneered in 1969 a minimax formulation tailored for impedance transformers optimized by heuristic direct search methods [3], [4]. A few years later, in 1975, mathematically rigorous minimax formulations were published by Madsen [5], using gradient-free [6] and gradient-based [7] optimization algorithms. Madsen's work provided a solid foundation [1] for Bandler's robust gradient-based minimax methods for microwave circuit design optimization [8], [9].

B. Least pth Norm Formulations

Almost simultaneously with his initial work on minimax optimization, Bandler formulated in the early 1970s innovative least pth norm objective functions solved by gradient-based optimization methods [10], [11], resulting in effective and practical CAD tools for parameter extraction and active device modeling [12], [13].

C. Statistical Analysis and Yield-Driven Design

Bandler's work on generalized pth norm objectives, especially Huber norms [14], were also instrumental for his seminal contributions on statistical device modeling and analog fault location [15], as well as on circuit-based statistical analysis (Monte Carlo performance, worst case analysis, yield prediction, and so on) and yield-driven design (design with tolerances and uncertainties, design centering, yield maximization, and so on) [16], [17], [18], [19], [20], [21].

An excellent review of Bandler's work on the above three foundational aspects of circuit optimization is found in [22].

D. Nonlinear Circuit Design

The late 1980s' state of the art in nonlinear microwave circuit simulation techniques [23], mostly based on harmonic balance (HB), was enriched by Bandler's work on sensitivity analysis of nonlinear circuits [24]. A few years later, Bandler et al. [25] developed gradient-based yield optimization of nonlinear circuits, as well as a simultaneous small- and large-signal HB-based minimax optimization method to extend the dynamic range of power amplifiers [26]. A brief retrospective on Bandler's work on nonlinear circuit optimization is in [27].

III. Direct EM Optimization

Performing direct full-wave EM optimization of microwave physical structures was considered unfeasible in the 1980s and early 1990s [1]. Defeating the opinion of experts from academia and industry [1], Bandler demonstrated in 1993 the first direct EM optimization method applied to microwave filter design [28], where he used response surface modeling, database updates, and smooth gradient estimation to keep the computational cost reasonable.

A. Direct EM Optimization in Frequency-Domain

In the early 1990s, Bandler and his team had developed and commercialized a general-purpose CAD program called OSA90/hope[1] [29] that featured Datapipe[1] communication protocols, which allowed it to control external executable programs running on the same or on other remote computers. In particular, it could control EM field solvers running on various hardware platforms, with automated planar parameterization through Empipe[1] [30]. Sonnet Software's tool ***em***[2] [31] was the first commercial full-wave EM simulator employed in nominal [28] and yield-driven [32] direct EM optimization. Bandler soon extended his method to 3-D EM optimization in frequency-domain [33].

B. EM Optimization in Hybrid Time–Frequency Domain

Since microwave structures were traditionally analyzed and designed in the frequency domain, it seemed natural to use a frequency-domain simulator as the objective function server. However, this requires in each optimization cycle a number of field simulations equal to the number of required frequency points, while a time-domain simulator yields in a single analysis an arbitrary number of frequency points over a wide bandwidth using an impulse excitation. A collaborative project involving researchers from Bandler's and Hoefer's teams was initiated to connect for the first time the OSA90/hope program with time-domain TLM simulators developed at the University of Victoria, including a version running on a massively parallel DECmpp 12 000. The basic simulation technique is shown in Fig. 1. The TLM simulator takes input parameters from the OSA90/hope via an input pipe. The simulator then declares meshes of appropriate size, sets up boundary conditions, and performs one wideband TLM simulation. It then computes wideband S-parameters via Fourier transform and pipes them back to OSA90/hope.

The details of this hybrid time–frequency CAD system were presented in 1993 [34], illustrating the optimization of a Ka-band waveguide filter and comparing the CPU times of TLM simulations on various platforms available in the early 1990s. Further developments in hybrid time–frequency domain optimization using parallel TLM simulators are found in [35].

IV. Adjoint Sensitivities for Microwave Circuit and EM-Based Optimization

As an avid proponent and a developer of fast fully automated design approaches [2], Bandler was acutely aware of a

[1]Trademarked.
[2]Registered trademark.

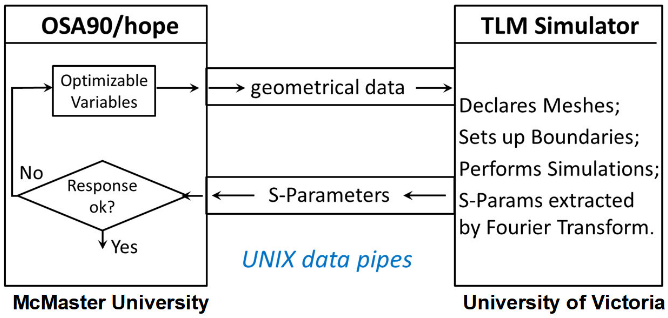


Fig. 1. Combination of OSA90/hope with a TLM simulator through UNIX high-speed data pipes. From [34].

major bottleneck: the gradients and Hessians of the microwave responses (network voltages, currents, and scattering parameters) in the design-variable space were not available. Thus, the potential of an entire category of powerful design-optimization methods relying on response gradients (or response sensitivities) remained largely unrealized. The response sensitivities had to be computed using response-level finite-difference approximations or parameter sweeps with multidimensional surface approximations. Not only is this approach prone to errors, but also it is extremely inefficient since it requires many system analyses, scaling with the number of design variables [36], [37]. Most microwave design problems aim at optimizing simultaneously many such variables: circuit component values, geometrical and shape attributes of structural components, EM properties, biasing, and so on. The response-level sensitivity approximations with so many design variables would often render the gradient-based design optimization impractical.

When the first adjoint-variable methods for circuit response sensitivity analysis emerged in the late 1960s [38], [39], [40], Bandler immediately grasped their significant potential in microwave design. These methods, commonly referred to as adjoint sensitivity analysis, offered two important advantages. First, all response sensitivities are computed with two circuit analyses at the most, regardless of the number of optimized variables. The first (original) analysis is the one that yields the circuit responses (voltages and currents). The second (adjoint) circuit analysis yields the so-called adjoint responses, which, too, are voltages and currents. However, if the circuit is reciprocal, the adjoint analysis is not needed since the adjoint responses are equal to response counterparts already calculated in the original analysis [36], [37]. Second, the sensitivity formula yielding the response gradient in the entire design-variable space is exact. Therefore, the result is far more accurate than any response-level approximation. Consider the adjoint formula for the derivatives of the voltage V_k at the kth port of a multiport network, where the kth port is excited by a current source of 1 A [36]

$$\frac{\partial V_k}{\partial x_n} = -\sum_{m=1}^{M} \widehat{\boldsymbol{X}}_m^T \frac{\partial \boldsymbol{H}_m}{\partial x_n} \boldsymbol{X}_m, \quad n = 1, \ldots, N \tag{1}$$

where x_n is the nth design variable (e.g., a circuit component value); N is the number of such variables; M is the number of subnetworks, from which the entire circuit is built; $\boldsymbol{H}_m$ is the mth subnetwork hybrid matrix; and $\boldsymbol{X}_m$ and $\widehat{\boldsymbol{X}}_m$ are the vectors of voltages/currents at the ports of the mth original and adjoint subnetworks, respectively. It is clear from (1) that as long as the voltage/current original and adjoint solutions are accurate, the derivatives' accuracy is also ensured.

Until the early 1970s, most microwave structures were modeled with equivalent circuits. Bandler and Seviora [41] formulated the adjoint sensitivities of the generalized incident and scattered waves at the network ports, not only relative to circuit component parameters but also relative to frequency. Moreover, they extended the theory to the Hessian of the wave state variables. These formulas then allowed for the accurate and efficient computation of the sensitivities and Hessians of the generalized S-parameters of microwave circuits. Applications followed in the sensitivity analysis of the group delay of microwave circuits [42] and the responses of cascaded networks (e.g., filters) [43], [44]. Later, Bandler et al. [24] developed exact sensitivities for HB analyses of nonlinear microwave circuits and used them to perform yield optimization of circuits operating under large-signal excitation [25], [45].

In the early 2000s, Bandler with Bakr and Nikolova [46], [47] developed methods for field-based adjoint sensitivity computations with full-wave EM simulators exploiting analytical and finite-difference system matrices, suitable for various numerical EM methods: the method of moments, the transmission-line matrix method [48], the finite-element method [49], and the finite-difference time-domain method [50]. Similar to the adjoint sensitivity analysis of circuits, the adjoint sensitivity formulas need only one additional (adjoint) full-port EM analysis. With reciprocal structures (e.g., passive and isotropic), there is no need for an adjoint analysis since the adjoint-field solution is equal to or obtained from the field solution given by the original EM simulation, whose simulation also provides the responses (e.g., S-parameters). Thus, only one full-port simulation provides both the responses and the field distributions needed to compute the response sensitivities.

In the 2010s, Bandler contributed to the development of analytical field-based S-parameter sensitivity formulas for shape and EM-property design variables of metallic and dielectric reciprocal structures [51], [52]. Similar to the earlier field-based adjoint sensitivities, these formulas employ the EM field distributions provided by the original full-port simulation that also provides the S-parameters. However, unlike the earlier approaches, the formulas are analytic, i.e., they are directly applicable with field solutions of any EM simulator, regardless of how the numerical method discretizes the structure or forms the system matrix to obtain the field solution.

The accuracy and efficiency of the adjoint-variable computations are now fully exploited in modern commercially available microwave CAD tools, accelerating design optimization, parameter extraction, modeling, and statistical analysis and design. The legacy of Bandler's work on sensitivity analysis lives in ongoing research that develops or uses adjoint sensitivity theories. This is an extensive subject, but a few glimpses are provided by applications in SM optimization [53],

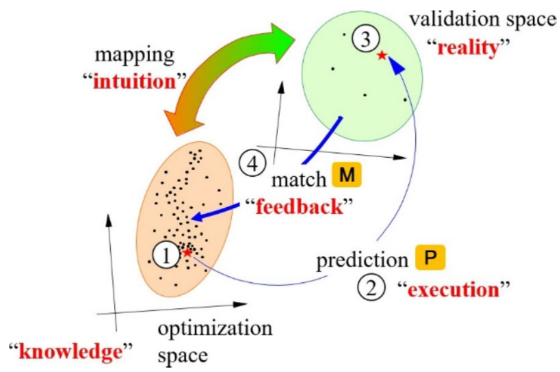


Fig. 2. SM general concept. From [62].

[54], ANN-based modeling and design [55], [56], [57], [58], and microwave and millimeter-wave imaging [59], [60].

V. SM: A Breakthrough in Optimizing Expensive Models

SM was invented by Bandler in 1993 [1] and first published in 1994 [61]. The inspiration for SM stems from the intuition that experienced engineers rely on to address complex problems, coupled with the cognitive process of relating or mapping objects between different experiences or realities [62].

SM avoids the direct optimization of computationally expensive models (also known as fine models or high-fidelity models, e.g., finely discretized full-wave EM models), by iteratively mapping a coarse model (fast low-fidelity physics-based model, e.g., equivalent circuits) to the fine model accuracy.

A. Basics of SM

The SM concept is illustrated in Fig. 2. The fine model is frugally used in the validation space ("reality check"), while the coarse model is intensively used in the optimization space (it provides "prior knowledge"). The relationship between them is established by a mapping ("intuition").

The essence of the SM methods is to establish a mapping $\boldsymbol{P}$ between the fine model design parameters, $\boldsymbol{x}_{\mathrm{f}}$, and those of the coarse model, $\boldsymbol{x}_{\mathrm{c}}$, simply by

$$\boldsymbol{x}_{\mathrm{c}} = \boldsymbol{P}(\boldsymbol{x}_{\mathrm{f}}) \tag{2}$$

such that the mapped coarse model responses, $\boldsymbol{R}_{\mathrm{c}}(\boldsymbol{P}(\boldsymbol{x}_{\mathrm{c}}))$, approximate the fine model responses, $\boldsymbol{R}_{\mathrm{f}}(\boldsymbol{x}_{\mathrm{f}})$, in a region of interest.

Starting from the coarse model optimal design $\boldsymbol{x}_{\mathrm{c}}^{*}$ (marked by ① in Fig. 2), the current (inverse) mapping is used to predict the next iterate in the fine model space (②), which is then validated by a fine model evaluation (③) to check if, in "reality," the design specifications are optimally met. If not, a "feedback" procedure (④, typically by parameter extraction) is implemented to enhance the mapping $\boldsymbol{P}$, from which the next fine model design is predicted. SM has been proven to efficiently solve complex microwave and other engineering problems within a few iterations [1], [63], [64], [65].

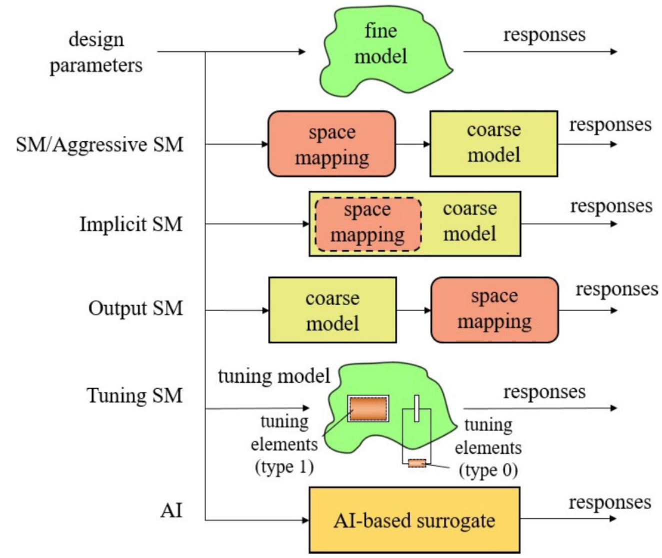


Fig. 3. Contrasting SM-based surrogates and AI-based surrogates.

B. SM-Based Surrogates and Initial Comparison With AI

SM-based surrogates have been proposed in a variety of schemes, as illustrated in Fig. 3. Both the original SM [61] and the aggressive SM (ASM) [66] are widely known, with ASM being notable for using Broyden's updates and quasi-Newton steps to achieve fast convergence [65]. Implicit SM (ISM) [67], [68] utilizes a set of preassigned parameters to establish an indirect mapping between the coarse and fine models. Output SM (OSM) [69], [70], [71] addresses residual misalignment between the coarse and the fine model responses by adjusting the output of the coarse model. Tuning SM (TSM) [72], [73], [74], [75] combines the port-tuning technique (see Section V-C) and the SM approach to create a "tunable" surrogate model allowing fast optimization.

For an initial comparison, classical AI-based surrogate modeling is represented in Fig. 3 alongside other SM-based surrogates. An AI-based surrogate [76] can be constructed by using ML methods to directly emulate the fine model behavior, e.g., by using neural networks and Gaussian processes [76].

C. Coarse Models for SM

Typically, a coarse model for SM consists of an equivalent circuit model or some physics-based analytical approximation [65], [77]. Less frequently, the coarse model is implemented by some metamodel (response surface model, ANN model, Kriging model, and so on) developed from fine model simulations [65] or from measurements [78]. The performance of SM heavily depends on the quality of the underlying coarse model used. Koziel et al. [79] developed formal methods to assess the quality of coarse models (equivalent circuits) based on convergence results for SM optimization.

Coarse models have also been implemented by simplified and coarsely discretized full-wave EM models [80], [81], [82], [83], which can be especially useful for microwave problems with no equivalent circuits, e.g., antenna structures in working environments [84]. Interpolated [85] and variable-resolution

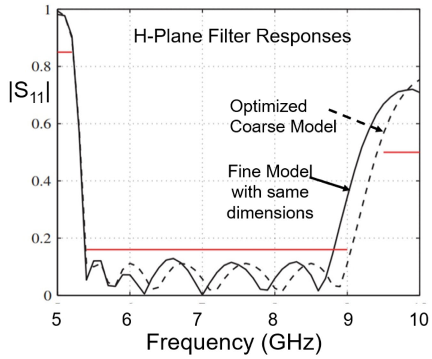


Fig. 4. Filter EM responses obtained with a fine and a coarse TLM grid. They can be mapped upon each other by frequency scaling. From [89].

coarsely discretized frequency-domain EM models [86], [87], [88] have also been successfully employed in SM optimization.

D. Frequency SM Between Fine and Coarse TLM Models

If TLM models of the same microwave structure with a fine and a coarse mesh discretization are used, it should be possible to accomplish the mapping between them through a simple frequency shift. Indeed, after Hoefer and Bandler discussed this hypothesis, the University of Victoria team provided its TLM simulator MEFiSTo to investigate and test this idea. Fig. 4 compares $|S_{11}|$ of a six-section H-plane waveguide filter computed using a coarse and a fine TLM mesh discretization. The study and results are described in [89]. Bandler's team confirmed [86] that the frequency-scaled model yielded a smaller specification error than other coarse model types.

VI. Port Tuning

EM analysis of microwave structures has revolutionized microwave design over the last four decades [90]. Correctly applied, it provides unprecedented analysis accuracy, often yielding success on first fabrication. However, a major impediment to successful application is long analysis times of hours or even days.

A methodology now known as "port tuning" provides a solution. After an initial EM analysis, we can optimize structure dimensions at circuit theory speed while also maintaining full EM accuracy. A short overview is provided in [91], which includes additional detailed references for the interested practitioner. Port tuning is a special case of SM [92], [93].

Fig. 5 shows an illustrative microstrip parallel connected open circuited stub laid out in an EM analysis tool (Sonnet[2]). Note that there is a narrow gap in the middle of the stub. Two internal ports, 3A and 4A, are placed in the gap, one on either edge of the gap. The "A" indicates that the two ports share the same ground reference, which in this case is the microstrip ground plane. These ports, along with the input and output ports, 1 and 2, are fully deembedded [94]. High accuracy deembedding of tuning ports is required for the specific port-tuning implementation shown here. This EM analysis results in four-port S-parameters.

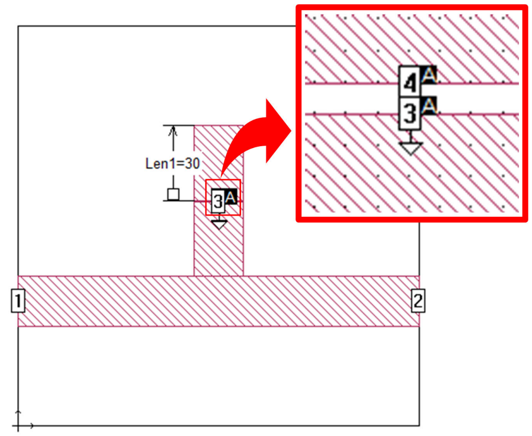


Fig. 5. Simple microstrip stub illustrates tuning ports, 3A and 4A, inserted into a microwave circuit.

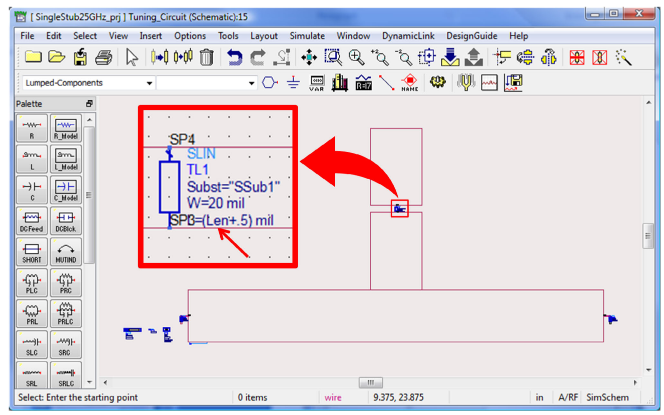


Fig. 6. Four-port EM analysis S-parameters are loaded into a circuit theory program and a circuit theory transmission line is attached to the tuning ports.

Fig. 6 shows the EM S-parameters loaded into a schematic of a circuit theory analysis tool (included in Keysight ADS[2]). A circuit theory transmission line is connected between the internal ports. Port tuning is now realized by tuning the length (the arrowed "Len" variable) of the circuit theory transmission line to optimize the overall length of the stub. The circuit theory transmission-line length can be varied over a wide range provided stub interaction with the rest of the circuit remains sufficiently constant. The stub may be shortened by specifying a negative length circuit theory transmission line.

If high accuracy deembedded internal EM ports are not available, then an infinitesimal gap port may be used even if it is not deembedded. Since the gap port does not use the microstrip ground as a ground reference, a circuit theory transmission line cannot be used to tune the circuit. Instead, a circuit theory inductor can be used provided only small changes are required.

A full 60-GHz filter with tuning ports added in the middle of resonators (Fig. 7) additionally requires tuning of the coupling between resonators. It is easiest to tune circuit theory capacitors connected, for example, between ports 8C and 10C, and so on. Alternatively, for broadband use, add appropriate lengths of circuit theory coupled line with even-mode characteristic impedance set to a large value and tune odd-mode characteristic impedance.

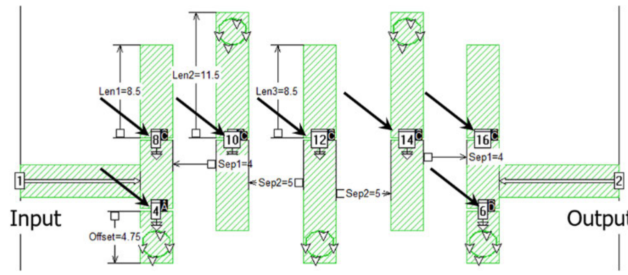


Fig. 7. 60-GHz filter with 14 tuning ports, arrowed. The resulting 16-port EM analysis is read into a circuit theory program and appropriate tuning components inserted.

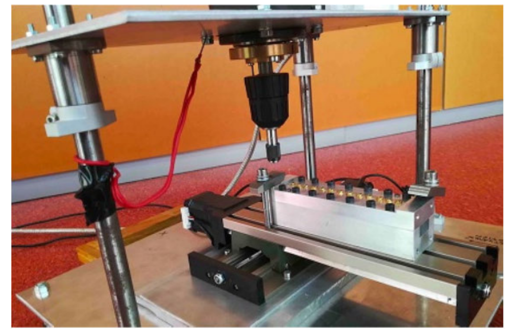


Fig. 8. Robotic tuner used in a high-precision tuning process (penetration accuracy of screws about 1 μm). From [103].

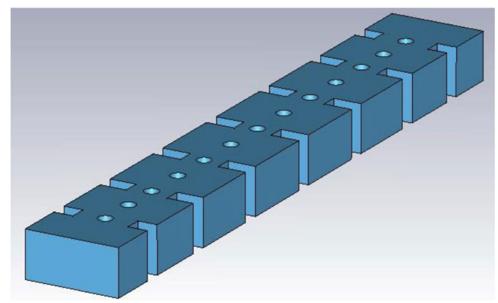


Fig. 9. RW filter (with tuning elements) used for accurate EM simulations in SM-based tuning techniques. The same structure but with no tuning elements is used as coarse model. From [103].

Once the initial EM analysis is complete and a tuning port model is constructed for a given type of filter or circuit, optimizing that type of filter or circuit for completely new requirements is performed at circuit theory speed and with EM accuracy, making EM analysis combined with port tuning an absolutely required part of modern microwave design methodology.

VII. SM-Based Post-Manufacture Tuning of Microwave Hardware

Microwave hardware must be designed and manufactured with high accuracy to meet the tough requirements of communication system front ends [95]. For satellite applications, where higher operational frequencies (K- and Ka-bands) are increasingly being used [96], and waveguide technology is the preferred choice for implementing low-loss filters, dimensional accuracies below 10 μs are often required in their fabrication processes. Such accuracy levels are not sufficient in some applications (e.g., very narrowband channel filters) or must be relaxed to reduce manufacturing costs. Thus, the inclusion of tuning elements (typically screws) becomes mandatory. As it is well known, the manual tuning of microwave filters is not a simple task, requiring significant effort, experience, and practical guidelines [97].

Recently, different computer-aided optimization strategies have been proposed to support post-manufacturing tuning of microwave filters [95, Ch. 19]. Among them, SM is one of the most efficient techniques [98]. The Technical University of Valencia, Spain, has contributed several SM-based tuning methods, many of them in fruitful and long-lasting collaboration with Prof. Bandler.

A. Tuning of Waveguide Filters Using ASM

In [99], the team from Valencia successfully applied ASM [66] to correct the fabrication errors of circular waveguide dual-mode filters, widely used in output multiplexers. For this purpose, a prototype was built with replaceable parts, including rectangular metal ridges as tuning elements. The measured response of the prototype was used as fine model results, whereas the coarse model was based on the efficient (but accurate) full-wave simulation of the real structure with FEST3D (now part of CST Studio Suite [100]). The optimal dimensions of the metal ridges were obtained, in just three iterations, using the Broyden update for the related mapping matrix [99]. The same procedure was also successful with the full tuning of a rectangular waveguide (RW) filter [101], but using this time real tuning screws driven by a high-precision robotic tuner (see Fig. 8).

Although this ASM-based tuning method performs very well, it requires a moderate (but relevant) computational effort. This is because, at the ith iteration of ASM, the penetration depths of the employed tuning elements (in $\boldsymbol{x}_\mathrm{f}$) are related to those of the simulated filter (in $\boldsymbol{x}_\mathrm{c}$) by

$$\boldsymbol{x}_\mathrm{f}^{(i+1)} = \boldsymbol{x}_\mathrm{f}^{(i)} - \left(\boldsymbol{B}^{(i)}\right)^{-1}\left(\boldsymbol{x}_\mathrm{c}^{(i)} - \boldsymbol{x}_\mathrm{c}^{*}\right) \tag{3}$$

where $\boldsymbol{B}^{(i)}$ is the Broyden-updated matrix [65], [66] of the local linear mapping at the ith iteration. For instance, in [101], the optimum ($\boldsymbol{x}_\mathrm{c}^{*}$) and extracted ($\boldsymbol{x}_\mathrm{c}^{(i)}$) depths in the coarse model were obtained through optimizations of an RW filter with tuning elements (see Fig. 9) using the commercial tool FEST3D, and this certainly requires a computational effort.

A very significant advance in the ASM technique for the design of microwave waveguide filters is reported in [102], where it is shown that when the physical structures of waveguide filters are identical, in both the coarse and fine models, matrix $\boldsymbol{B}$ is the identity matrix $\boldsymbol{I}$, so there is no need for any update, i.e., (3) converges in just one iteration. This is the so-called "One-Step ASM" method, providing convergent results in just one iteration. This approach is effective even if the structures in the coarse and fine models are not identical, but just very similar, as is the case for the real and simulated filters in our tuning procedure. In that case, however, one iteration is not enough, but a significantly faster convergence is achieved with respect to the classical ASM method. This alternative procedure was fully validated in [103], where the

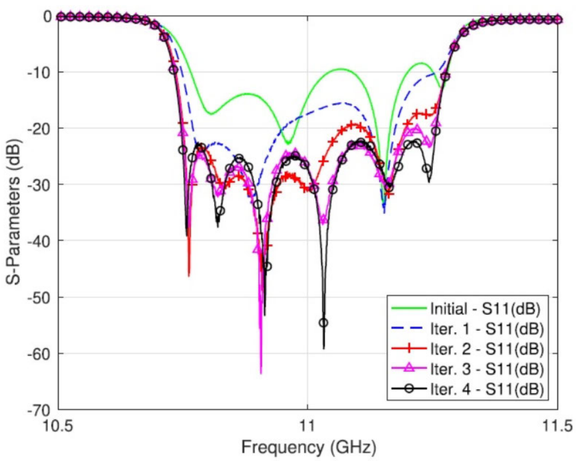


Fig. 10. Results (at different iterations) of the SM-based tuning procedure applied to the RW filter in Fig. 9. From [103].

tuning process of a sixth-order filter (see Fig. 9) was completed in just four iterations.

As mentioned before, applying this ASM-based tuning technique requires the intensive use of a detailed full-wave model, which can make the tuning process slow and unhandy.

B. Efficient ASM-Based Tuning Procedure

A more efficient approach consists of using a much simpler geometry as the coarse model structure (e.g., the filter shown in Fig. 9 but without tuning elements). In this case, FEST3D quickly provides accurate results for a faster optimization. Here, $\boldsymbol{x}_{\mathrm{c}}$ contains the lengths and widths of the resonators and coupling elements of the RW filter, whereas $\boldsymbol{x}_{\mathrm{f}}$ still contains the penetration depths of tuning elements. Thus, $\boldsymbol{B}$ cannot be chosen as $\boldsymbol{I}$ and must be properly initialized before starting the ASM iterations.

Matrix $\boldsymbol{B}$ (or its inverse) can be initialized by applying slight perturbations to all tuner depths in the filter and then extracting the corresponding coarse model parameters (with no tuners) that match those filter responses [103]. In this way, the initialized $\boldsymbol{B}$ is kept in (3) for all ASM iterations. By this method, the 6th-order RW filter of Fig. 9 is tuned, almost perfectly, in only four iterations (Fig. 10) and 21 min, saving 70% in time cost with respect to the previous ASM-based approach [103].

Initializing $\boldsymbol{B}$ can be done using a detailed highly accurate full-wave 3-D EM model (with tuners) or from measurements in the physical filter, in which case a robotic tuner can be employed (see Fig. 8). Details are given in [103] and [104].

Even though the previous SM-based tuning techniques were applied to RW filters, similar SM-based approaches have been successfully used to tune other hardware technologies with very different types of tuning elements [105], [106].

VIII. Industrial-Scale SM Applications

Practicing engineers have been applying optimization and inverse modeling techniques to industrial RF and microwave components exploiting CAD tools. To perform component design, the physical parameters of the component are determined to satisfy the required design specifications. EM simulations are usually compulsory in the microwave design process for verification. However, high-fidelity EM simulation can be computationally expensive. To address this issue, SM technologies have been applied in industry.

SM is widely used in the design of satellite payloads. One important satellite industry SM application is for designing multiplexers. A large-scale multiplexer has many channels, making the design optimization problem very complex, with a prohibitive computation cost if high-fidelity EM simulation is directly used. In [107] and [108], finite-element EM-based simulators and SM optimization are combined to produce an accurate design for manifold-coupled output multiplexers with dielectric resonator (DR) loaded filters. While the EM-based simulator serves as the fine model, a coupling matrix (CM) representation is used as a coarse model. As a result, a ten-channel multiplexer with 140 design variables was successfully designed and fabricated [108], as illustrated in Fig. 11. Also, a 15-channel multiplexer was designed using SM-based optimization. Fig. 12 shows that the corresponding measurement result agrees with the ideal curve, validating the effectiveness of SM.

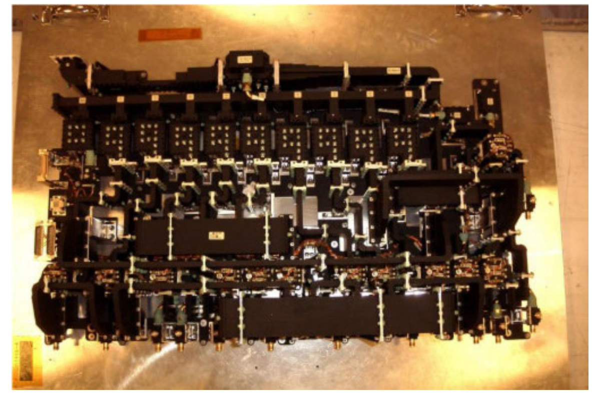


Fig. 11. Ten-channel multiplexer for satellite applications with 140 design variables.

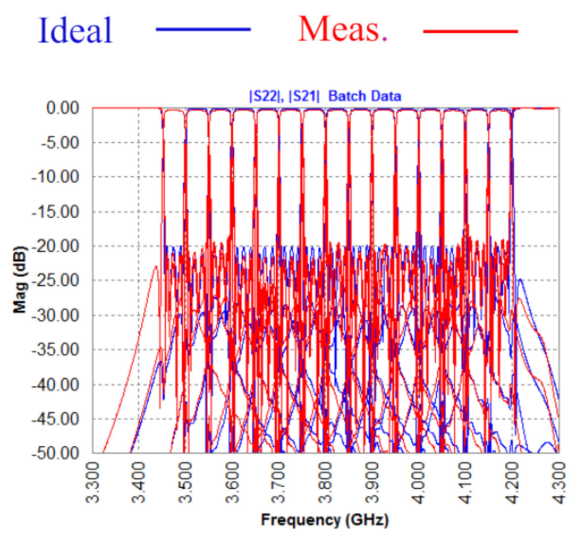


Fig. 12. Frequency response of the 15-channel multiplexer designed by SM.

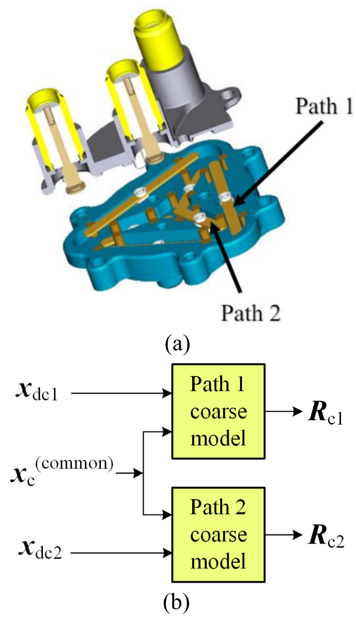


Fig. 13. Coaxial T-switch designed by SM [109]. (a) Three-dimensional layout and (b) coarse model block diagram for the two paths (x_{dc1} and x_{dc2} contain distinct coarse model parameters for each path).

Another significant industrial application of SM is in the design process of switches. In [109], a six-path coaxial T-switch is designed by SM. Only two paths are considered based on the symmetry, as shown in Fig. 13(a). A multiple SM algorithm is developed to evaluate each switch path parameter. As suggested in Fig. 13(b), the algorithm iteratively enhances the coarse model of each path. Then, the enhanced mapped coarse models are optimized to meet the required specifications.

It is well known that ANN and SM can be combined to optimize microwave filters [110]. Inverse ANN models can also be developed to facilitate microwave filter design. For that application, the nonuniqueness [111] and high dimensionality [112] challenges of training ANNs have been addressed. In [113], the homotopy continuation (HC) is applied to expedite the database construction for an ANN inverse model. ANNs can also be exploited to model large-scale multiplexers [114], leading to improved performance and reduced design cycles.

In addition to filters and multiplexers, SM and ANN are industrially applied to other components. For example, an ANN-based inverse model is used in [115] to design multiple directional couplers automatically and efficiently, which is promising to be generalized for a variety of components.

IX. SM and AI: Relationship and Potential New Developments

A. Neural SM as a Pioneering AI Approach to Microwave Modeling and Design

Artificial neural networks (ANNs), inspired from rudimentary biological neural networks, are nowadays a well-established, powerful, and general-purpose fundamental technique of AI [116]. Initial applications of ANN to RF and microwave engineering started in 1993 [117], [118]. On a totally separated track, Bandler published SM in 1994 [61], inspired from engineering intuition [62], to intelligently exploit the computational efficiency of inaccurate simplified physics-based coarse models to optimally design highly accurate but computationally expensive fine models in a very efficient manner. Starting in 1999, Bandler et al. pioneered the smart combination of ANN and SM to formulate EM-based modeling [119] and design optimization [120] algorithms.

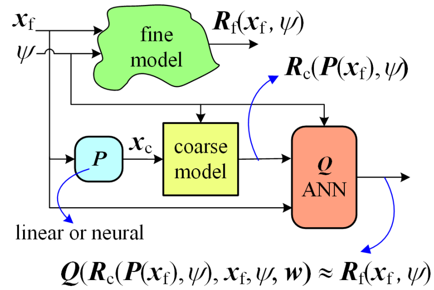


Fig. 14. NSM for accurate statistical analysis and yield prediction [122].

Neural SM (NSM) can be used for efficient statistical design [121]. Highly accurate yield prediction based on NSM [122] is illustrated in Fig. 14. It exploits the classical input SM function $\boldsymbol{P}$ in (2), which can be implemented linearly or by an ANN [123]. Variable ψ in Fig. 14 represents the independent variable (frequency, time, biasing voltages, and so on). The output mapping $\boldsymbol{Q}$ is intended to eliminate the inherent error in the responses of any SM-based coarse model, $\boldsymbol{R}_c(\boldsymbol{P}(\boldsymbol{x}_f), \psi)$, with respect to the actual fine model responses, $\boldsymbol{R}_f(\boldsymbol{x}_f)$. The ANN implementing $\boldsymbol{Q}$ is sensitive not only to the design parameters $\boldsymbol{x}_f$ but also to the independent variable ψ (see Fig. 14), achieving a highly accurate approximation of the fine model responses within the design space where the statistical analysis is performed [122]. NSM has also been applied to statistical nonlinear device modeling [124], [125].

The basic steps in neural inverse SM (NISM) for nominal design optimization [126] are illustrated in Fig. 15. The starting point is parameter extraction (step 1 in Fig. 15), where the best coarse model design $\boldsymbol{x}_c$ is found to make $\boldsymbol{R}_c$ as close as possible to the fine model response at the current iterate, $\boldsymbol{R}_f(\boldsymbol{x}_f)$. In step 2, a regularized ANN is trained to approximate the current inverse mapping between all the accumulated corresponding designs [127] ($\boldsymbol{w}$ has all the weighting factors and other free parameters in the ANN). The next iterate, $\boldsymbol{x}_f^{(new)}$, is predicted in step 3 by simply evaluating the current already trained inverse neuro-mapping at the optimal coarse model design $\boldsymbol{x}_c^*$. The whole cycle is repeated for additional refinements. Applications to linear frequency-domain [127] and nonlinear transient [128] problems have been reported.

Neural SM approaches [129], [130] naturally invite speculation on future developments to capitalize on the current full capacity of other AI and ML techniques in combination with SM.

Fig. 16 illustrates a feasible future development where SM and other AI techniques are exploited. This approach can be especially suitable to develop fast and accurate SM-based models valid over very large regions in the design space. It is inspired by the work by Burrascano and Mongiardo [131],

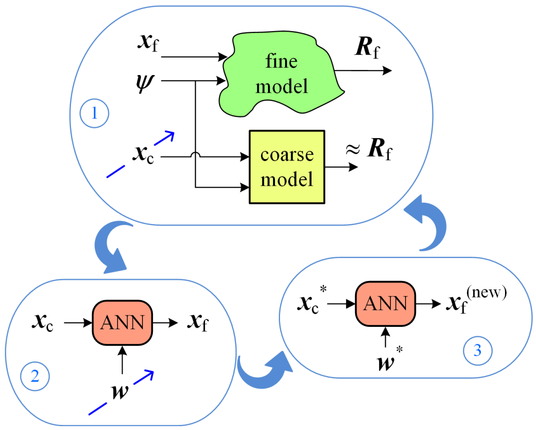


Fig. 15. NISM for nominal design optimization [127].

where self-organizing feature maps (SOMs) are used to identify clusters of similar responses, for which a specialized ANN model is developed following a "black-box" approach [132]. In contrast, the approach in Fig. 16 uses other AI clustering techniques (k-means, k-medoids, k-nearest neighbor, and so on), exploits the inherent knowledge available in the physics-based simplified coarse models, and implements each input mapping ($\mathrm{iML}_1, \ldots, \mathrm{iML}_k$) by any appropriate ML technique, such as support vector machines, Bayesian or Gaussian process regression, conventional ANN, generalized regression neural networks, and Kriging. Furthermore, the accuracy of the resultant SM-based model in Fig. 16 can be enhanced by implementing output mappings ($\mathrm{oML}_1, \ldots, \mathrm{oML}_k$) to eliminate possible residuals of the mapped coarse models.

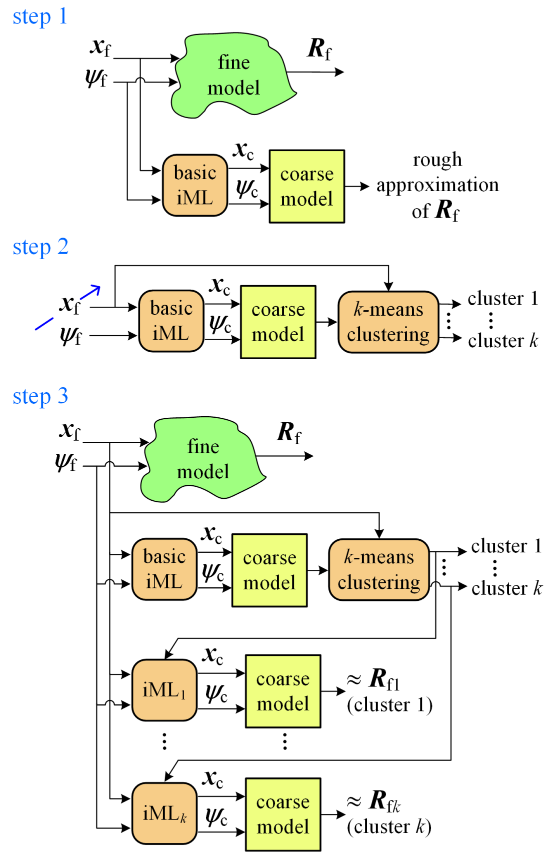


Fig. 16. Potential future development on AI and SM to address large design spaces.

B. Cognition-Driven Design

Cognition-driven design is a phrase introduced by Prof. Bandler while exploring future directions of microwave CAD. Bandler emphasized the need of fusion between advanced neuroscience and engineering design [133].

A cognition-driven formulation for optimization is an effort to address the challenge of SM when explicit coarse models are not available [134], [135], [136]. It exploits the concept of feature parameters to assist SM, as opposed to using coarse-mesh EM models. Several works have investigated possible feature parameters in model responses, e.g., [137], [138], [139], [140]. The cognition-driven formulation aims to explore the use of intermediate feature-space parameters in SM. A cognition-driven SM formulation for EM-based optimization of equal-ripple microwave filters is described in [134]. This optimization can proceed with neither explicit coarse models nor explicit surrogate models. In [134], intermediate feature-space parameters, including the feature frequency parameters and ripple height parameters, are used to set up two new kinds of SM. The design variables are mapped to feature frequency parameters, which are further mapped to the ripple height parameters, thus the concept of SM in our optimization. By formulating the cognition-driven optimization directly in the feature space, the method can increase optimization efficiency as well as the ability to avoid being trapped in local minima. This technique is regarded as "cognitive" [62] in the sense that a meaningful coarse or surrogate model is implied by the engineer's knowledge, intuition, and experience [133].

For instance, in a filter design optimization process, an experienced designer could first adjust the frequency locations of reflection zeros relative to the passband, rather than trying to push the S-parameter values in the initial design stage. In the subsequent design stages, the designer could adjust the ripple height using the fact that making two frequency locations of reflection zeros closer (further apart) will reduce (increase) the height of the passband ripple in the frequency response curve. By adopting such strategy, the design optimization can be reformulated by introducing new feature parameters, i.e., by exploiting a new feature parameter space, called the feature frequency space, as explained next.

For an equal-ripple bandpass filter, a filter response curve (e.g., $|S_{11}|$ versus frequency) has several minimizers, which are referred to as feature frequencies, and several maxima, which are referred to as ripples. The feature frequencies correspond to the reflection zeros at which the filter has maximum transmission. In a cognition-driven SM formulation, the feature frequencies are used to establish a mapping. For example, Fig. 17 shows $|S_{11}|$ in dB of a microwave filter, where the feature frequencies $\boldsymbol{f} = [f_1 \;\; f_2 \;\; f_3 \;\; f_4]^T$ are used as intermediate design parameters of the feature space to establishing a mapping between the physical or geometrical design variables $\boldsymbol{x}_f$ (i.e., the original optimization variables) and the feature frequency parameters $\boldsymbol{f}$.

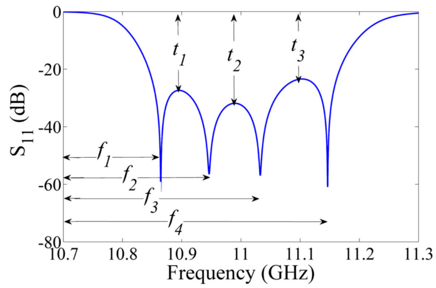


Fig. 17. Illustration of feature parameters $\boldsymbol{t}$ and $\boldsymbol{f}$ in the response of a microwave filter. From [134].

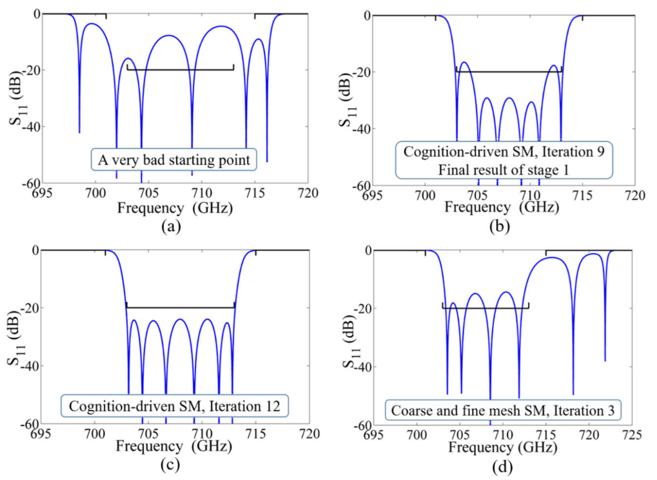


Fig. 18. Results comparison for three different optimization methods for a cavity filter with bad starting point. From [134]. (a) Very bad starting point for all three methods. Using cognition-driven SM method, (b) all the feature frequencies move to the passband after the first stage, and (c) good equal-ripple response is obtained after 12 iterations, avoiding being trapped in a local minimum. (d) Using coarse–fine mesh SM, the optimization process falls into a local minimum. Using direct EM optimization, a final response similar to that one in (d) is obtained after 300 iterations.

The maximum values of $|S_{11}|$ in dB between these feature frequency points are also important features of the $|S_{11}|$ response curve and are represented by a new set of feature parameters, called ripple height parameters $\boldsymbol{t} = [t_1 \ t_2 \ t_3]^{\mathrm{T}}$ (see Fig. 17), similar to those used in [139] and [140]. In general, the cognition-driven SM formulation for equal-ripple filter design uses the feature frequency parameters $\boldsymbol{f} = [f_1, f_2, f_3, \ldots, f_M]^{\mathrm{T}}$ and the ripple parameters $\boldsymbol{t} = [t_1, t_2, \ldots, t_M]^{\mathrm{T}}$ from the EM simulation response, where M is the number of poles of the filter.

The optimization proceeds in two stages. In the first stage, a mapping is built from the design variables $\boldsymbol{x}_{\mathrm{f}}$ to the feature frequency parameters $\boldsymbol{f}$ as

$$\boldsymbol{f} = \boldsymbol{F}(\boldsymbol{x}_{\mathrm{f}}) \tag{4}$$

where $\boldsymbol{F}$ represents the corresponding mapping. Through this stage, the locations of feature frequencies $\boldsymbol{f}$ are adjusted in terms of the frequency band specifications. In the second stage, an additional mapping is created from the feature frequency parameters to the ripple height parameters as

$$\boldsymbol{B}^{(i)}\left(\boldsymbol{f}_d^{(i)} - \boldsymbol{f}^{(i)}\right) + \boldsymbol{c}^{(i)} = \boldsymbol{t}_a - \boldsymbol{t}^{(i)} \tag{5}$$

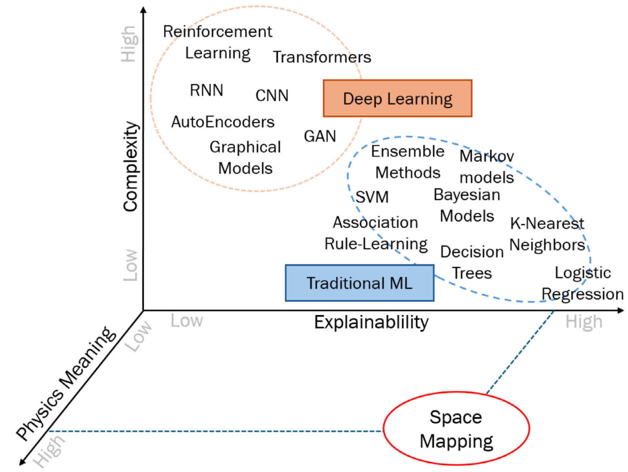


Fig. 19. Comparison between AI models and SM. The classification of AI models is inspired by [141].

where matrix $\boldsymbol{B}^{(i)}$ and vector $\boldsymbol{c}^{(i)}$ together represent the linear mapping parameters at the ith iteration between the $\boldsymbol{f}$ and $\boldsymbol{t}$ spaces, vector $\boldsymbol{t}_a$ contains the desired ripple height parameters, and vector $\boldsymbol{f}_{\mathrm{d}}^{(i)}$ has the desired feature frequency parameters at the current iteration [134]. To ensure convergence, a trust region method is applied while updating the design parameters at both stages [134].

Fig. 18 illustrates the optimization process of a waveguide cavity bandpass filter [134]. Using conventional direct EM optimization (150 h) or using a coarse–fine mesh EM-based SM (24 h), optimal solutions are highly dependent on starting values, and in the case of Fig. 18, the final solution by those methods is trapped in a local minimum where the design specifications are violated. With the cognition-driven SM optimization, an EM optimal design is achieved from that same starting point (11 h), exceeding the design specifications. The cognition-driven SM formulation increases optimization efficiency and finds a better result in less time compared to coarse–fine mesh EM SM and direct EM optimization.

C. Contrasting AI and SM

AI models excel at handling extensive datasets and high-dimensional design spaces. AI-based surrogate optimization (AISO) is predominantly executed in two steps: the training of the model and the prediction, similar to the mapping and prediction steps in the SM process. This procedural resemblance suggests the feasibility of integrating the two methodologies.

As depicted in Fig. 19, deep learning methods are characterized by high complexity and low explainability [141]. Their black-box nature can obscure the principles behind specific outcomes, making it challenging for engineers to understand and refine their outputs. Conversely, SM with embedded physics-based knowledge offers a simple but highly explainable approach. The complementary nature of these two approaches suggests that integrating SM with AI could potentially enhance the AI model.

An emerging and promising application of AI is the effective incorporation of large language models (LLM) into electronic design automation (EDA) [142]. LLM tools, such as ChatGPT, Gemini, and Llama, combined with state-of-the-art SM and ML approaches, might offer a breakthrough to streamline interoperability of different EDA tools to address highly complex design tasks with stringent specifications in record time-to-market. Microwave study cases and theoretical frameworks in this arena are yet to be developed.

X. Conclusion

We have endeavored to provide a comprehensive overview of John W. Bandler's seminal and pioneering contributions to the art and science of microwave circuit design and optimization. His creative concepts transcend the purely technical and mathematical aspects of engineering to enter the realm of the cognitive, imaginative, and intuitive capabilities of the design engineer. The resulting concept of SM has become a cornerstone of present and future design optimization in microwave engineering and beyond. Its affinity with ML and AI is rapidly expanding its potential as a ubiquitous and indispensable engineering paradigm.

John's accomplishments as the godfather of SM extend beyond his own original and pioneering contributions. He has mentored and inspired his students, associates, and colleagues to leverage his ideas and to promote his legacy through their own creativity. He will be remembered and appreciated by many future generations of engineers.

Acknowledgment

The authors thank Dr. Marco Guglielmi for his contribution and advice on space mapping techniques for post-manufacture tuning of microwave filters. They also thank Yu Deng for his assistance in drafting the space mapping section. They acknowledge the plethora of Prof. Bandler's co-authors and collaborators [1] who contributed to his extraordinary research legacy.

References

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

[2] J. W. Bandler, "Optimization methods for computer-aided design," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-17, no. 8, pp. 533–552, Aug. 1969.

[3] J. W. Bandler and P. A. Macdonald, "Optimization of microwave networks by Razor search," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-17, no. 8, pp. 552–562, Aug. 1969.

[4] J. W. Bandler, "Computer optimization of inhomogeneous waveguide transformers," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-17, no. 8, pp. 563–571, Aug. 1969.

[5] K. Madsen, "An algorithm for minimax solution of overdetermined systems of non-linear equations," *IMA J. Appl. Math.*, vol. 16, no. 3, pp. 321–328, 1975.

[6] K. Madsen, O. Nielsen, H. Schjaer-Jacobsen, and L. Thrane, "Efficient minimax design of networks without using derivatives," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-23, no. 10, pp. 803–809, Oct. 1975.

[7] K. Madsen, H. Schjaer-Jacobsen, and J. Voldby, "Automated minimax design of networks," *IEEE Trans. Circuits Syst.*, vol. CS-22, no. 10, pp. 791–795, Oct. 1975.

[8] J. W. Bandler, W. Kellermann, and K. Madsen, "A superlinearly convergent minimax algorithm for microwave circuit design," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-33, no. 12, pp. 1519–1530, Dec. 1985.

[9] J. W. Bandler, S. H. Chen, S. Daijavad, and K. Madsen, "Efficient optimization with integrated gradient approximations," *IEEE Trans. Microw. Theory Techn.*, vol. 36, no. 2, pp. 444–455, Feb. 1988.

[10] J. W. Bandler and C. Charalambous, "Practical least pth optimization of networks," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-20, no. 12, pp. 834–840, Dec. 1972.

[11] J. W. Bandler and C. Charalambous, "On conditions for optimality in least pth approximation with $p \to \infty$," *J. Optim. Theory Appl.*, vol. 11, no. 5, pp. 556–566, May 1973.

[12] J. W. Bandler, S. H. Chen, and S. Daijavad, "Microwave device modeling using efficient l_1 optimization: A novel approach," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-34, no. 12, pp. 1282–1293, Dec. 1986.

[13] Optim. Syst. Associates (OSA), Dundas, ON, Canada. (1989). *RoMPE™ User's Manual Version 1.2*. [Online]. Available: https://macsphere.mcmaster.ca/handle/11375/27782

[14] J. W. Bandler, S. H. Chen, R. M. Biernacki, L. Gao, K. Madsen, and H. Yu, "Huber optimization of circuits: A robust approach," *IEEE Trans. Microw. Theory Techn.*, vol. 41, no. 12, pp. 2279–2287, Dec. 1993.

[15] J. W. Bandler, S. H. Chen, R. M. Biernacki, and K. Madsen, "The Huber concept in device modeling, circuit diagnosis and design centering," in *Proc. IEEE Int. Symp. Circuits Syst.*, London, U.K., Jun. 1994, pp. 129–132.

[16] J. W. Bandler, P. C. Liu, and J. H. K. Chen, "Worst case network tolerance optimization," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-23, no. 8, pp. 630–641, Aug. 1975.

[17] J. Bandler, P. Liu, and H. Tromp, "A nonlinear programming approach to optimal design centering, tolerancing, and tuning," *IEEE Trans. Circuits Syst.*, vol. CS-23, no. 3, pp. 155–165, Mar. 1976.

[18] J. W. Bandler, P. C. Liu, and H. Tromp, "Integrated approach to microwave design," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-24, no. 9, pp. 584–591, Sep. 1976.

[19] H. Abdel-Malek and J. Bandler, "Yield optimization for arbitrary statistical distributions: Part I—Theory," *IEEE Trans. Circuits Syst.*, vol. CS-27, no. 4, pp. 245–253, Apr. 1980.

[20] H. Abdel-Malek and J. Bandler, "Yield optimization for arbitrary statistical distributions: Part II—Implementation," *IEEE Trans. Circuits Syst.*, vol. CS-27, no. 4, pp. 253–262, Apr. 1980.

[21] R. M. Biernacki, J. W. Bandler, J. Song, and Q.-J. Zhang, "Efficient quadratic approximation for statistical design," *IEEE Trans. Circuits Syst.*, vol. 36, no. 11, pp. 1449–1454, Nov. 1989.

[22] J. W. Bandler and S. H. Chen, "Circuit optimization: The state of the art," *IEEE Trans. Microw. Theory Techn.*, vol. 36, no. 2, pp. 424–443, Feb. 1988.

[23] V. Rizzoli and A. Neri, "State of the art and present trends in nonlinear microwave CAD techniques," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-36, no. 2, pp. 343–365, Feb. 1988.

[24] J. W. Bandler, Q.-J. Zhang, and R. M. Biernacki, "A unified theory for frequency-domain simulation and sensitivity analysis of linear and nonlinear circuits," *IEEE Trans. Microw. Theory Techn.*, vol. 36, no. 12, pp. 1661–1669, Dec. 1988.

[25] J. W. Bandler, Q. J. Zhang, J. Song, and R. M. Biernacki, "FAST gradient based yield optimization of nonlinear circuits," *IEEE Trans. Microw. Theory Techn.*, vol. 38, no. 11, pp. 1701–1710, Nov. 1990.

[26] J. W. Bandler, R. M. Biernacki, S. H. Chen, J. Song, S. Ye, and Q.-J. Zhang, "Analytically unified DC/small-signal/large-signal circuit design," *IEEE Trans. Microw. Theory Techn.*, vol. 39, no. 7, pp. 1076–1082, Jul. 1991.

[27] J. E. Rayas-Sánchez and J. W. Bandler, "Basic space mapping: A retrospective and its application to design optimization of nonlinear RF and microwave circuits," in *Proc. 52nd Eur. Microw. Conf. (EuMC)*, Milan, Italy, Sep. 2022, pp. 12–15.

[28] J. W. Bandler, S. Ye, R. M. Biernacki, S. H. Chen, and D. G. Swanson, "Minimax microstrip filter design using direct EM field simulation," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Atlanta, GA, USA, Jun. 1993, pp. 889–892.

[29] Optim. Syst. Associates, Dundas, ON, Canada. (1997). *OSA90/Hope™ Version 4.0 User's Manual*. [Online]. Available: https://macsphere.mcmaster.ca/handle/11375/27835

[30] Optim. Syst. Associates, Dundas, ON, Canada. (1997). *Empipe™ Version 4.0 User's Manual*. [Online]. Available: https://macsphere.mcmaster.ca/handle/11375/27790

[31] *em® User's Manual*, Sonnet Softw., Liverpool, NY, USA, May 1992.

[32] J. W. Bandler, R. M. Biernacki, S. Hua Chen, P. A. Grobelny, and S. Ye, "Yield-driven electromagnetic optimization via multilevel multidimensional models," *IEEE Trans. Microw. Theory Techn.*, vol. 41, no. 12, pp. 2269–2278, Dec. 1993.

[33] J. W. Bandler, R. M. Biernacki, S. H. Chen, L. W. Hendrick, and D. Omeragić, "Electromagnetic optimization of 3-D structures," *IEEE Trans. Microw. Theory Techn.*, vol. 45, no. 5, pp. 770–779, May 1997.

[34] P. P. M. So, W. J. R. Hoefer, J. W. Bandler, R. M. Biernacki, and S. H. Chen, "Hybrid frequency/time domain field theory based CAD of microwave circuits," in *Proc. 23rd Eur. Microw. Conf.*, Madrid, Spain, Oct. 1993, pp. 218–219.

[35] P. P. M. So and W. J. R. Hoefer, "3D-TLM techniques for field-based optimization of electromagnetic structures," in *Proc. IEEE Antennas Propag. Soc. Int. Symp. URSI Nat. Radio Sci. Meeting*, Seattle, WA, USA, Jun. 1994, pp. 1116–1119.

[36] N. K. Nikolova, J. W. Bandler, and M. H. Bakr, "Adjoint techniques for sensitivity analysis in high-frequency structure CAD," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 403–419, Jan. 2004.

[37] J. W. Bandler and R. E. Seviora, "Current trends in network optimization," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-18, no. 12, pp. 1159–1170, Dec. 1970.

[38] S. Director and R. Rohrer, "The generalized adjoint network and network sensitivities," *IEEE Trans. Circuit Theory*, vol. CT-16, no. 3, pp. 318–323, Aug. 1969.

[39] S. Director, "LU factorization in network sensitivity computations," *IEEE Trans. Circuit Theory*, vol. CT-18, no. 1, pp. 184–185, Jan. 1971.

[40] F. Branin, "Network sensitivity and noise analysis simplified," *IEEE Trans. Circuit Theory*, vol. CT-20, no. 3, pp. 285–288, May 1973.

[41] J. W. Bandler and R. E. Seviora, "Wave sensitivities of networks," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-20, no. 2, pp. 138–147, Feb. 1972.

[42] J. W. Bandler, M. R. M. Rizk, and H. Tromp, "Efficient calculation of exact group delay sensitivities," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-24, no. 4, pp. 188–194, Apr. 1976.

[43] J. W. Bandler, M. R. M. Rizk, and H. L. Abdel-Malek, "New results in network simulation, sensitivity, and tolerance analysis for cascaded structures," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-26, no. 12, pp. 963–972, Dec. 1978.

[44] J. W. Bandler and M. R. M. Rizk, "Analysis and sensitivity evaluation of 2p-port cascaded networks," *IEEE Trans. Microw. Theory Techn.*, vol. MTT-29, no. 7, pp. 719–723, Jul. 1981.

[45] J. W. Bandler, R. M. Biernacki, Q. Cai, S. H. Chen, S. Ye, and Q.-J. Zhang, "Integrated physics-oriented statistical modeling, simulation, and optimization (MESFETs)," *IEEE Trans. Microw. Theory Techn.*, vol. 40, no. 7, pp. 1374–1400, Jul. 1992.

[46] N. K. Georgieva, S. Glavic, M. H. Bakr, and J. W. Bandler, "Feasible adjoint sensitivity technique for EM design optimization," *IEEE Trans. Microw. Theory Techn.*, vol. 50, no. 12, pp. 2751–2758, Dec. 2002.

[47] E. A. Soliman, M. H. Bakr, and N. K. Nikolova, "An adjoint variable method for sensitivity calculations of multiport devices," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 2, pp. 589–599, Feb. 2004.

[48] M. H. Bakr and N. K. Nikolova, "An adjoint variable method for time-domain transmission-line modeling with fixed structured grids," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 2, pp. 554–559, Feb. 2004.

[49] N. K. Nikolova, J. Zhu, D. Li, M. H. Bakr, and J. W. Bandler, "Sensitivity analysis of network parameters with electromagnetic frequency-domain simulators," *IEEE Trans. Microw. Theory Techn.*, vol. 54, no. 2, pp. 670–681, Feb. 2006.

[50] N. K. Nikolova, Y. Li, Y. Li, and M. H. Bakr, "Sensitivity analysis of scattering parameters with electromagnetic time-domain simulators," *IEEE Trans. Microw. Theory Techn.*, vol. 54, no. 4, pp. 1598–1610, Jun. 2006.

[51] M. S. Dadash, N. K. Nikolova, and J. W. Bandler, "Analytical adjoint sensitivity formula for the scattering parameters of metallic structures," *IEEE Trans. Microw. Theory Techn.*, vol. 60, no. 9, pp. 2713–2722, Sep. 2012.

[52] M. S. Dadash and N. K. Nikolova, "Analytical *S*-parameter sensitivity formula for the shape parameters of dielectric objects," *IEEE Microw. Wireless Compon. Lett.*, vol. 24, no. 5, pp. 291–293, May 2014.

[53] M. H. Bakr, *Nonlinear Optimization in Electrical Engineering With Applications in MATLAB*. Herts, U.K.: IET, 2013, pp. 261–301.

[54] S. Koziel and A. Bekasiewicz, "Fast EM-driven optimization using variable-fidelity EM models and adjoint sensitivities," *IEEE Microw. Wireless Compon. Lett.*, vol. 26, no. 2, pp. 80–82, Feb. 2016.

[55] S. A. Sadrossadat, Y. Cao, and Q.-J. Zhang, "Parametric modeling of microwave passive components using sensitivity-analysis-based adjoint neural-network technique," *IEEE Trans. Microw. Theory Techn.*, vol. 61, no. 5, pp. 1733–1747, May 2013.

[56] Y. Zhang, L. Dong, Y. Li, and Y. Li, "Sensitivity analysis of process parameters based on adjoint partial derivative network," in *Proc. 23rd Int. Conf. Electron. Packag. Technol. (ICEPT)*, Dalian, China, Aug. 2022, pp. 1–6.

[57] W. Na et al., "Advanced EM optimization using adjoint-sensitivity-based multifeature surrogate for microwave filter design," *IEEE Microw. Wireless Technol. Lett.*, vol. 34, no. 1, pp. 1–4, Jan. 2024.

[58] W. Na et al., "Automated model generation for microwave components using adjoint neural network and EM sensitivity analysis," *IEEE Microw. Wireless Technol. Lett.*, early access, May 28, 2024, doi: 10.1109/LMWT.2024.3391656.

[59] N. K. Nikolova, *Introduction to Microwave Imaging*. Cambridge, U.K.: Cambridge Univ. Press, 2017.

[60] D. S. Shumakov and N. K. Nikolova, "Fast quantitative microwave imaging with scattered-power maps," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 1, pp. 439–449, Jan. 2018.

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

[62] J. W. Bandler, "Have you ever wondered about the engineer's mysterious 'feel' for a problem?" *IEEE Microw. Mag.*, vol. 19, no. 2, pp. 112–122, Mar./Apr. 2018.

[63] J. W. Bandler et al., "Space mapping: The state of the art," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 337–361, Jan. 2004.

[64] S. Koziel, Q. S. Cheng, and J. W. Bandler, "Space mapping," *IEEE Microw. Mag.*, vol. 9, no. 6, pp. 105–122, Dec. 2008.

[65] J. E. Rayas-Sanchez, "Power in simplicity with ASM: Tracing the aggressive space mapping algorithm over two decades of development and engineering applications," *IEEE Microw. Mag.*, vol. 17, no. 4, pp. 64–76, Apr. 2016.

[66] J. W. Bandler, R. M. Biernacki, S. H. Chen, R. H. Hemmers, and K. Madsen, "Electromagnetic optimization exploiting aggressive space mapping," *IEEE Trans. Microw. Theory Techn.*, vol. 43, no. 12, pp. 2874–2882, Dec. 1995.

[67] J. W. Bandler, Q. S. Cheng, N. K. Nikolova, and M. A. Ismail, "Implicit space mapping optimization exploiting preassigned parameters," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 378–385, Jan. 2004.

[68] Q. S. Cheng, J. W. Bandler, and J. E. Rayas-Sánchez, "Tuning-aided implicit space mapping," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 18, no. 5, pp. 445–453, Sep. 2008.

[69] J. W. Bandler, Q. Cheng, D. H. Gebre-Mariam, K. Madsen, F. Pedersen, and J. Sondergaard, "EM-based surrogate modeling and design exploiting implicit, frequency and output space mappings," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Philadelphia, PA, USA, Jun. 2003, pp. 1003–1006.

[70] J. E. Rayas-Sanchez and J. A. Jasso-Urzua, "EM-based optimization of a single layer SIW with microstrip transitions using linear output space mapping," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Boston, MA, USA, Jun. 2009, pp. 525–528.

[71] S. Koziel, J. W. Bandler, and K. Madsen, "Space mapping with adaptive response correction for microwave design optimization," *IEEE Trans. Microw. Theory Techn.*, vol. 57, no. 2, pp. 478–486, Feb. 2009.

[72] S. Koziel, J. Meng, J. W. Bandler, M. H. Bakr, and Q. S. Cheng, "Accelerated microwave design optimization with tuning space mapping," *IEEE Trans. Microw. Theory Techn.*, vol. 57, no. 2, pp. 383–394, Feb. 2009.

[73] Q. S. Cheng, J. W. Bandler, and S. Koziel, "Space mapping design framework exploiting tuning elements," *IEEE Trans. Microw. Theory Techn.*, vol. 58, no. 1, pp. 136–144, Jan. 2010.

[74] S. Koziel, J. W. Bandler, and Q. S. Cheng, "Tuning space mapping design framework exploiting reduced electromagnetic models," *IET Microw., Antennas Propag.*, vol. 5, no. 10, pp. 1219–1226, Aug. 2011.

[75] Q. S. Cheng, J. W. Bandler, and S. Koziel, "Tuning space mapping: The state of the art," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 22, no. 6, pp. 639–651, Mar. 2012.

[76] Y. Yu et al., "State-of-the-art: AI-assisted surrogate modeling and optimization for microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 70, no. 11, pp. 4635–4651, Nov. 2022.

[77] Q. S. Cheng, J. W. Bandler, and S. Koziel, "Combining coarse and fine models for optimal design," *IEEE Microw. Mag.*, vol. 9, no. 1, pp. 79–88, Feb. 2008.

[78] J. E. Rayas-Sánchez and J. W. Bandler, "System-level measurement-based design optimization by space mapping technology," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Denver, CO, USA, Jun. 2022, pp. 118–120.

[79] 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.

[80] J. W. Bandler, R. M. Biernacki, S. H. Chen, and Y. F. Huang, "Design optimization of interdigital filters using aggressive space mapping and decomposition," *IEEE Trans. Microw. Theory Techn.*, vol. 45, no. 5, pp. 761–769, May 1997.

[81] J. V. M. Ros et al., "Fast automated design of waveguide filters using aggressive space mapping with a new segmentation strategy and a hybrid optimization algorithm," *IEEE Trans. Microw. Theory Techn.*, vol. 53, no. 4, pp. 1130–1142, Apr. 2005.

[82] S. Koziel, "On space mapping optimization with coarsely-discretized EM coarse models," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Baltimore, MD, USA, Jun. 2011, pp. 1–4.

[83] C. Zhang, F. Feng, and Q. J. Zhang, "EM optimization using coarse and fine mesh space mapping," in *Proc. Asia–Pacific Microw. Conf. (APMC)*, Nov. 2013, pp. 824–826.

[84] J. C. Cervantes-González, J. E. Rayas-Sánchez, C. A. López, J. R. Camacho-Pérez, Z. Brito-Brito, and J. L. Chávez-Hurtado, "Space mapping optimization of handset antennas considering EM effects of mobile phone components and human body," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 26, no. 2, pp. 121–128, Feb. 2016.

[85] S. Koziel and J. W. Bandler, "Interpolated coarse models for microwave design optimization with space mapping," *IEEE Trans. Microw. Theory Techn.*, vol. 55, no. 8, pp. 1739–1746, Aug. 2007.

[86] S. Koziel and J. W. Bandler, "Multi-fidelity space mapping modeling of microwave devices with double coarse model processing and functional approximation," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Boston, MA, USA, Jun. 2009, pp. 969–972.

[87] S. Koziel and J. W. Bandler, "Knowledge-based variable-fidelity optimization of expensive objective functions through space mapping," in *Computational Intelligence in Expensive Optimization Problems*, Y. Tenne and C.-K. Goh, Eds., Berlin, Germany: Springer, 2010, ch. 4, pp. 85–109.

[88] S. Koziel, A. Pietrenko-Dabrowska, and P. Plotka, "Reduced-cost microwave design closure by multi-resolution EM simulations and knowledge-based model management," *IEEE Access*, vol. 9, pp. 116326–116337, 2021.

[89] S. Koziel and J. W. Bandler, "Space mapping optimization and modeling of microwave devices with MEFiSTo," in *Time Domain Methods in Electrodynamics*, P. Russer and U. Siart, Eds., Berlin, Germany: Springer, 2008, pp. 393–407.

[90] W. J. R. Hoefer, "A brief history of computational electromagnetics in microwave engineering—A personal retrospective," *IEEE J. Microw.*, vol. 3, no. 1, pp. 338–348, Jan. 2023.

[91] J. C. Rautio, "Port tuning: Optimization with EM accuracy and circuit theory speed," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Winnipeg, MB, Canada, Jun. 2023, pp. 58–61.

[92] Q. S. Cheng, J. C. Rautio, J. W. Bandler, and S. Koziel, "Progress in simulator-based tuning—The art of tuning space mapping [application notes]," *IEEE Microw. Mag.*, vol. 11, no. 4, pp. 96–110, Jun. 2010.

[93] G. Wang, Z. Zhang, and Q. S. Cheng, "Port tuning and tuning space mapping," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Winnipeg, MB, Canada, Jun. 2023, pp. 62–65.

[94] J. C. Rautio, "Deembedding the effect of a local ground plane in electromagnetic analysis," *IEEE Trans. Microw. Theory Techn.*, vol. 53, no. 2, pp. 770–776, Feb. 2005.

[95] R. J. Cameron, C. M. Kudsia, and R. R. Mansour, *Microwave Filters for Communication Systems: Fundamentals, Design, and Applications*, 2nd ed., Hoboken, NJ, USA: Wiley, 2018.

[96] R. De Gaudenzi, P. Angeletti, D. Petrolati, and E. Re, "Future technologies for very high throughput satellite systems," *Int. J. Satell. Commun. Netw.*, vol. 38, no. 2, pp. 141–161, Mar. 2020.

[97] R. V. Snyder, "Practical aspects of microwave filter development," *IEEE Microw. Mag.*, vol. 8, no. 2, pp. 42–54, Apr. 2007.

[98] S. Li, X. Fan, P. D. Laforge, and S. C. Qingsha, "Space mapping post-fabrication tuning of 3D printed air-filled waveguide filter," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Honololu, HI, USA, Jun. 2017, pp. 1635–1637.

[99] M. Brumos, V. E. Boria, M. Guglielmi, and S. Cogollos, "Correction of manufacturing deviations in circular-waveguide dual-mode filters using aggressive space mapping," in *Proc. 44th Eur. Microw. Conf.*, Rome, Italy, Oct. 2014, pp. 624–627.

[100] *SIMULIA CST Studio Suite*, Dassault Systèmes, Velizy Villacoublay Cedex, France, 2022.

[101] A. Rodriguez et al., "Robust optimization and tuning of microwave filters and artificial transmission lines using aggressive space mapping techniques," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Jun. 2017, pp. 1501–1504.

[102] J. Ossorio, J. C. Melgarejo, V. E. Boria, M. Guglielmi, and J. W. Bandler, "On the alignment of low-fidelity and high- fidelity simulation spaces for the design of microwave waveguide filters," *IEEE Trans. Microw. Theory Techn.*, vol. 66, no. 12, pp. 5183–5196, Dec. 2018.

[103] J. C. Melgarejo, J. Ossorio, S. Cogollos, M. Guglielmi, V. E. Boria, and J. W. Bandler, "On space mapping techniques for microwave filter tuning," *IEEE Trans. Microw. Theory Techn.*, vol. 67, no. 12, pp. 4860–4870, Dec. 2019.

[104] J. C. Melgarejo, J. Ossorio, A. A. San-Blas, M. Guglielmi, and V. E. Boria, "Space mapping filter design and tuning techniques," *Int. J. Microw. Wireless Technol.*, vol. 14, no. 3, pp. 387–396, Apr. 2022.

[105] F. E. Rangel-Patiño, J. E. Rayas-Sánchez, A. Viveros-Wacher, E. A. Vega-Ochoa, and N. Hakim, "High-speed links receiver optimization in post-silicon validation exploiting broyden-based input space mapping," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Reykjavik, Iceland, Aug. 2018, pp. 1–3.

[106] S. Li, X. Fan, P. D. Laforge, and Q. S. Cheng, "Surrogate model-based space mapping in postfabrication bandpass filters' tuning," *IEEE Trans. Microw. Theory Techn.*, vol. 68, no. 6, pp. 2172–2182, Jun. 2020.

[107] M. A. Ismail, D. Smith, A. Panariello, Y. Wang, and M. Yu, "EM based design of large-scale dielectric resonator multiplexers by space mapping," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Philadelphia, PA, USA, Jun. 2003, pp. 291–294.

[108] M. A. Ismail, D. Smith, A. Panariello, Y. Wang, and M. Yu, "EM based design of large-scale dielectric resonator multiplexers by space mapping," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 386–392, Jan. 2004.

[109] M. A. Ismail, K. G. Engel, and M. Yu, "Multiple space mapping for RF T-switch design," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Fort Worth, TX, USA, Jun. 2004, pp. 1569–1572.

[110] Y. Wang, M. Yu, H. Kabir, and Q.-J. Zhang, "Application of neural networks in space-mapping optimization of microwave filters," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 22, no. 2, pp. 159–166, Dec. 2011.

[111] H. Kabir, Y. Wang, M. Yu, and Q.-J. Zhang, "Neural network inverse modeling and applications to microwave filter design," *IEEE Trans. Microw. Theory Techn.*, vol. 56, no. 4, pp. 867–879, Apr. 2008.

[112] Y. Wu, G. Pan, D. Lu, and M. Yu, "Artificial neural network for dimensionality reduction and its application to microwave filters inverse modeling," *IEEE Trans. Microw. Theory Techn.*, vol. 70, no. 11, pp. 4683–4693, Nov. 2022.

[113] A. Liu, Y. Wu, M. Leng, Y. Zeng, and M. Yu, "Adaptive homotopy-based inverse model for the geometry scaling of microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 72, no. 1, pp. 680–695, Jan. 2024.

[114] Y. Wang, S. Li, and M. Yu, "Hybrid models for effective design and optimization of large-scale multiplexing networks," *IEEE Trans. Microw. Theory Techn.*, vol. 61, no. 5, pp. 1839–1849, May 2013.

[115] A. Liu, M. Leng, G. Pan, and M. Yu, "Automatic coupler design based on artificial neural network with self-adaptive local surrogates," *IEEE Trans. Microw. Theory Techn.*, vol. 70, no. 11, pp. 4711–4725, Nov. 2022.

[116] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Upper Saddle River, NJ, USA: Prentice-Hall, 1999.

[117] T.-S. Horng, C.-C. Wang, and N. G. Alexopoulos, "Microstrip circuit design using neural networks," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Atlanta, GA, USA, Jun. 1993, pp. 413–416.

[118] Q. J. Zhang and K. C. Gupta, *Neural Networks for RF and Microwave Design*. Norwood, MA, USA: Artech House, 2000.

[119] J. W. Bandler, M. A. Ismail, J. E. Rayas-Sánchez, and Q. J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE Trans. Microw. Theory Techn.*, vol. 47, no. 12, pp. 2417–2427, Dec. 1999.

[120] M. H. Bakr, J. W. Bandler, M. A. Ismail, J. E. Rayas-Sánchez, and Q. J. Zhang, "Neural space mapping optimization for EM-based design," *IEEE Trans. Microw. Theory Techn.*, vol. 48, no. 12, pp. 2307–2315, Dec. 2000.

[121] J. W. Bandler, J. E. Rayas-Sánchez, and Q.-J. Zhang, "Yield-driven electromagnetic optimization via space mapping-based neuromodels," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 12, no. 1, pp. 79–89, Jan. 2002.

[122] J. E. Rayas-Sanchez and V. Gutierrez-Ayala, "EM-based Monte Carlo analysis and yield prediction of microwave circuits using linear-input neural-output space mapping," *IEEE Trans. Microw. Theory Techn.*, vol. 54, no. 12, pp. 4528–4537, Dec. 2006.

[123] V. Gutiérrez-Ayala and J. E. Rayas-Sánchez, "Neural input space mapping optimization based on nonlinear two-layer perceptrons with optimized nonlinearity," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 20, no. 5, pp. 512–526, Sep. 2010.

[124] L. Zhang, J. Xu, M. C. E. Yagoub, R. Ding, and Q.-J. Zhang, "Efficient analytical formulation and sensitivity analysis of neuro-space mapping for nonlinear microwave device modeling," *IEEE Trans. Microw. Theory Techn.*, vol. 53, no. 9, pp. 2752–2767, Sep. 2005.

[125] L. Zhang, Q.-J. Zhang, and J. Wood, "Statistical neuro-space mapping technique for large-signal modeling of nonlinear devices," *IEEE Trans. Microw. Theory Techn.*, vol. 56, no. 11, pp. 2453–2467, Nov. 2008.

[126] J. W. Bandler, M. A. Ismail, J. E. Rayas-Sanchez, and Q. J. Zhang, "Neural inverse space mapping EM-optimization," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Phoenix, AZ, USA, May 2001, pp. 1007–1010.

[127] J. W. Bandler, M. A. Ismail, J. E. Rayas-Sánchez, and Q.-J. Zhang, "Neural inverse space mapping (NISM) optimization for EM-based microwave design," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 13, no. 2, pp. 136–147, Mar. 2003.

[128] J. E. Rayas-Sanchez, F. Lara-Rojo, and E. Martinez-Guerrero, "A linear inverse space-mapping (LISM) algorithm to design linear and nonlinear RF and microwave circuits," *IEEE Trans. Microw. Theory Techn.*, vol. 53, no. 3, pp. 960–968, Mar. 2005.

[129] J. E. Rayas-Sánchez, "Neural space mapping methods for modeling and design of microwave circuits," Ph.D. thesis, Dept. Elect. Comp. Eng., McMaster Univ., Hamilton, ON, Canada, 2001.

[130] J. E. Rayas-Sánchez and Q. J. Zhang, "On knowledge-based neural networks and neuro-space mapping," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Montreal, QC, Canada, Jun. 2012, pp. 1–3.

[131] P. Burrascano and M. Mongiardo, "A review of artificial neural networks applications in microwave CAD," *Int. J. RF Microw. CAE*, vol. 9, pp. 158–174, May 1999.

[132] J. E. Rayas-Sanchez, "EM-based optimization of microwave circuits using artificial neural networks: The state-of-the-art," *IEEE Trans. Microw. Theory Techn.*, vol. 52, no. 1, pp. 420–435, Jan. 2004.

[133] 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. Microw.*, vol. 1, no. 1, pp. 481–493, Jan. 2021.

[134] C. Zhang, F. Feng, V.-M.-R. Gongal-Reddy, Q. J. Zhang, and J. W. Bandler, "Cognition-driven formulation of space mapping for equal-ripple optimization of microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 63, no. 7, pp. 2154–2165, Jul. 2015.

[135] C. Zhang, F. Feng, Q. J. Zhang, and J. W. Bandler, "An enhanced cognition-driven formulation of space mapping for equal-ripple optimization of microwave filters," *IET Microw., Antennas Propag.*, vol. 12, no. 1, pp. 82–91, Jan. 2018.

[136] J. Jin et al., "Advanced cognition-driven EM optimization incorporating transfer function-based feature surrogate for microwave filters," *IEEE Trans. Microw. Theory Techn.*, vol. 69, no. 1, pp. 15–28, Jan. 2021.

[137] N. Leszczynska, L. Szydlowski, and M. Mrozowski, "Zero-pole space mapping for CAD of filters," *IEEE Microw. Wireless Compon. Lett.*, vol. 24, no. 9, pp. 581–583, Sep. 2014.

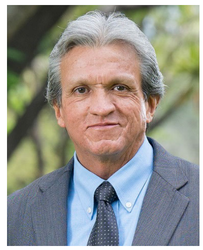
[138] P. Kozakowski and M. Mrozowski, "Automated CAD of coupled resonator filters," *IEEE Microw. Wireless Compon. Lett.*, vol. 12, no. 12, pp. 470–472, Dec. 2002.

[139] O. Glubokov and S. Koziel, "EM-driven tuning of substrate integrated waveguide filters exploiting feature-space surrogates," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Tampa, FL, USA, Jun. 2014, pp. 1–3.

[140] S. Koziel and J. W. Bandler, "Feature-based statistical analysis for rapid yield estimation of microwave structures," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Tampa, FL, USA, Jun. 2014, pp. 1–3.

[141] T. Clement, N. Kemmerzell, M. Abdelaal, and M. Amberg, "XAIR: A systematic metareview of explainable AI (XAI) aligned to the software development process," *Mach. Learn. Knowl. Extraction*, vol. 5, no. 1, pp. 78–108, Jan. 2023.

[142] H. Wu et al., "ChatEDA: A large language model powered autonomous agent for EDA," *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, early access, Mar. 29, 2024, doi: 10.1109/TCAD.2024.3383347.



José E. Rayas-Sánchez (Senior Member, IEEE) received the B.Sc. degree in electronics engineering from ITESO, Guadalajara, Mexico, in 1984, the M.Sc. degree in electrical engineering from ITESM, Monterrey, Mexico, in 1989, and the Ph.D. degree in electrical engineering from McMaster University, Hamilton, Ontario, Canada, in 2001.

He is a Profesor Numerario (Hons.) and a Emeritus Professor with ITESO, Jesuit University of Guadalajara, where he leads the Research Group on Computer-Aided Engineering of Circuits and Systems (CAECAS). He is a member of the Mexican National System of Researchers (SNI), Level III. His research focuses on computer-aided and knowledge-based modeling and design optimization of high-frequency circuits.

Dr. Rayas-Sánchez has been an Elected AdCom Member of the IEEE MTT-S for the years 2016–2024. He is the IEEE Microwave Theory and Technology Society (MTT-S) Representative for the IEEE EDA Council since 2019. Since 2013, he has been the IEEE MTT-S Regional Coordinator for Latin America. He was the General Chair of the First IEEE MTT-S Int. Microwave Workshop Series in Region 9 (IMWS2009-R9) on Signal Integrity and High-Speed Interconnects (Guadalajara, Mexico, February 2009) and the General Chair of the First IEEE MTT-S Latin America Microwave Conference (LAMC-2016, Puerto Vallarta, Mexico, December 2016).

Qi-Jun Zhang (Fellow, IEEE) received the Ph.D. degree in electrical engineering from McMaster University, Hamilton, ON, Canada, in 1987.

He was a Research Engineer with Optimization Systems Associates Inc., Dundas, ON, Canada, from 1988 to 1990. In 1990, he joined the Department of Electronics, Carleton University, Ottawa, ON, Canada, where he is currently a Chancellor's Professor. His research interests include AI/machine learning, modeling, and optimization for high-speed/high-frequency electronic design. He is the author of *Neural Networks for RF and Microwave Design* (Boston: Artech House, 2000), the Guest Co-Editor of the Special Issue on Machine Learning in Microwave Engineering for *IEEE Microwave Magazine* (2021), and the Guest Editor of the Special Issue of AI and Machine Learning Based Technologies for Microwaves in IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES (2022).

Dr. Zhang is a Fellow of Canadian Academy of Engineering and the Engineering Institute of Canada. He is the Topic Editor of IEEE JOURNAL OF MICROWAVES. He is the Co-Chair of the Working Group on AI and Machine Learning Based Technologies for Microwaves in the Future Directions Committee of the IEEE Microwave Theory and Technology Society.

James C. Rautio (Life Fellow, IEEE) received the B.S.E.E. degree from Cornell University, Ithaca, NY, USA, in 1978, the M.S. degree in systems engineering from the University of Pennsylvania, Philadelphia, PA, USA, in 1981, and the Ph.D. degree in electrical engineering from Syracuse University, Syracuse, NY, USA, in 1986, under the supervision of Dr. Roger Harrington.

From 1978 to 1986, he was with General Electric, initially with the Valley Forge Space Division, and then with Syracuse Electronics Laboratory, Syracuse. During this time, he developed microwave design and measurement software and designed microwave circuits on alumina and on GaAs. From 1986 to 1988, he was a Visiting Professor with Syracuse University and Cornell University. In 1988, he took Sonnet Software, North Syracuse, NY, USA, full time, a company he had founded in 1983. In 1995, Sonnet Software was listed on the Inc., 500 list of the fastest growing privately held U.S. companies, the only microwave software company ever to be so listed. Today, Sonnet Software is the leading vendor of high accuracy three-dimensional planar high-frequency electromagnetic analysis software.

Natalia K. Nikolova (Fellow, IEEE) received the Dipl.-Eng. Degree in radioelectronics degree from the Technical University of Varna, Varna, Bulgaria, in 1989, and the Ph.D. degree from the University of Electro-Communications, Tokyo, Japan, in 1997.

From 1998 to 1999, she held a Post-Doctoral Fellowship of the Natural Sciences and Engineering Research Council of Canada (NSERC), Ottawa, ON, USA. In 1999, she joined the Department of Electrical and Computer Engineering at McMaster University, Hamilton, ON, Canada, where she is currently a Professor. Her research interests include inverse scattering, microwave imaging, and computer-aided analysis and design of high-frequency structures and antennas. She has authored more than 300 refereed manuscripts, seven book chapters, and two books. She has delivered 56 invited lectures, webinars, and short courses.

Prof. Nikolova is a Fellow of Canadian Academy of Engineering and the Engineering Institute of Canada. From 2008 to 2018, she was the Canada Research Chair in High-frequency Electromagnetics. She served as an Associate Editor for IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES in 2014 and 2015 and the Track Editor for Microwave Instrumentation and Measurement Techniques from 2019 to 2022. She was appointed IEEE MTT-S Distinguished Microwave Lecturer from 2011 to 2013.

Vicente E. Boria (Fellow, IEEE) was born in Valencia, Spain, in May 1970. He received the "Ingeniero de Telecomunicación" degree (Hons.) and the "Doctor Ingeniero de Telecomunicación" degree from the Universidad Politécnica de Valencia, Valencia, Spain, in 1993 and 1997, respectively.

In 1993, he joined the "Departamento de Comunicaciones," Universidad Politécnica de Valencia, where he has been a Full Professor since 2003. From 1995 to 1996, he was a Spanish Traineeposition with European Space Agency (ESTEC-ESA), Noordwijk, The Netherlands. He has co-authored 15 chapters in technical textbooks, 200 articles in refereed technical journals, and 250 papers in conference proceedings. His research interests are focused on the analysis and design of high-frequency passive components (filters and multiplexers) in several technologies, and on simulation and measurement of power effects.

Dr. Boria is a member of the Technical Committees of IEEE-MTT International Microwave Symposium and European Microwave Conference. He has been the Chair of the 48th European Microwave Conference. He was an Associate Editor of IEEE MICROWAVE AND WIRELESS COMPONENTS LETTERS from 2013 to 2018 and *IET Electronics Letters* from 2015 to 2018. Presently, he is the Subject Editor *(Microwaves) of IET Electronics Letters* and an Editorial Board Member of *International Journal of RF and MiCAE*.

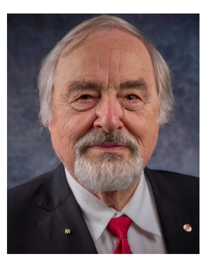
Qingsha S. Cheng (Senior Member, IEEE) received the B.Eng. and M.Eng. degrees from Chongqing University, Chongqing, China, in 1995 and 1998, respectively, and the Ph.D. degree from McMaster University, Hamilton, ON, Canada, in 2004.

In 1998, he joined the Department of Computer Science and Technology, Peking University, Beijing, China. In 2004, he became a Post-Doctoral Fellow and then a Research Engineer in 2007 with the Department of Electrical and Computer Engineering, McMaster University. In 2014, he joined the Department of Electrical and Electronic Engineering, Southern University of Science and Technology (SUSTech), Shenzhen, China, where he is currently an Associate Professor. He has authored or co-authored more than 200 publications in technical book chapters, refereed international technical journals, refereed international conference proceedings, and international workshops. His current research interests include smart modeling and optimization of microwave components and antennas, surrogate modeling and optimization, multiobjective optimization, and neural networks.

Ming Yu (Fellow, IEEE) received the Ph.D. degree in electrical engineering from the University of Victoria, Victoria, BC, Canada, in 1995.

In 1993, he joined COM DEV, Cambridge, ON, Canada, while finishing his Ph.D. part time. He was a Principal Developer and a Team Leader of a variety of COM DEV's core design and tuning software for microwave filters and multiplexers, including computer-aided tuning software in 1994 and a fully automated robotic diplexer tuning system in 1999. In 2003, he demonstrated the world's first robotic filter/diplexer tuning system at an IEEE IMS conference workshop. Until 2017, he was a COM DEV (Honeywell)'s Chief Scientist, Cambridge, ON, Canada, and the Director of Research and Development. He joined the Electronics Engineering Department, Chinese University of Hong Kong (CUHK), Hong Kong, as a tenured Full Professor in 2017. He has authored or co-authored over 200 publications and 30 patents worldwide. He is currently a Chair Professor at Southern University of Science and Technology, Shenzhen, China.

Prof. Yu is a Fellow of Canadian Academy of Engineering. He was a recipient of 2020 IEEE Microwave Application Award. He was an IEEE Distinguished Microwave Lecturer from 2010 to 2012. He is the IEEE MTT Filter Committee (TC-5) Chair and served as the Chair of TPC-11 multiple times.



Wolfgang J. R. Hoefer (Life Fellow, IEEE) received the Dipl.-Ing. degree from RWTH Aachen, Germany, in 1965, the D.-Ing. degree from the University of Grenoble, Grenoble, France, in 1968, and the Honorary Dr.-Ing. h.c. degree from the Technical University of Munich, Munich, Germany, in 2007.

He was a Faculty Member at the University of Ottawa, ON, Canada, from 1969 to 1992, and the Chair of Electrical Engineering from 1978 to 1981. In 1992, he joined the University of Victoria, Victoria, BC, Canada, as a Professor and the NSERC Industrial Research Chair in RF Engineering in 2006. From 2009 to 2012, he was a Principal Scientist at the Institute of High-Performance Computing, A*STAR, Singapore. He also held visiting and adjunct appointments in Academia, Research Institutions, and Industry in North America, Europe, and Asia.

Dr. Hoefer is a Fellow of several academies, including the Royal Society of Canada, Canadian Academy of Engineering, and German Academy of Science and Engineering. He received several prestigious honors, notably the Distinguished Educator, Pioneer, and Career Awards from the IEEE MTT-Society, the McNaughton Gold Medal from IEEE Canada, and the Most Inspiring Mentor Award from A*STAR Singapore.