Implicit Space Mapping Optimization Exploiting Preassigned Parameters

John W. Bandler, *Fellow, IEEE*, Qingsha S. Cheng, *Student Member, IEEE*, Natalia K. Nikolova, *Member, IEEE*, and Mostafa A. Ismail, *Member, IEEE*

Abstract—We introduce the idea of implicit space mapping (ISM) and show how it relates to the well-established (explicit) space mapping between coarse and fine device models. Through comparison, a general space mapping concept is proposed. A simple algorithm based on the novel ISM concept is implemented. It is illustrated on a contrived "cheese-cutting problem" and is applied to electromagnetics-based microwave modeling and design. An auxiliary set of parameters (selected preassigned parameters) is extracted to match the coarse model with the fine model. The calibrated coarse model (the surrogate) is then (re)optimized to predict a better fine model solution. This is an easy space mapping technique to implement since the mapping itself is embedded in the calibrated coarse model and updated automatically in the procedure of parameter extraction. We illustrate our approach through optimization of a high-temperature superconducting filter using Agilent ADS with Momentum and Agilent ADS with Sonnet's em.

Index Terms—Circuit design, computer-aided design (CAD), electromagnetics, microwave modeling, optimization, space mapping (SM), surrogate modeling.

I. INTRODUCTION

T HE space mapping (SM) [1] concept of using mapped "coarse" models (usually computationally fast circuit-based models) to align with "fine" models (typically CPU intensive full-wave electromagnetic (EM) simulations) has been exploited by a number of authors [2]–[5]. Several notable implementations and applications of SM have been reported. Pavio presented a companion approach [6]. Snel [7] derived mapped models for RF components. Swanson and Wenzel [8] used SM to optimize mechanical adjustments by iterating between a finite-element simulator and a circuit simulator. Wu *et al.* [9] applied SM to design low-temperature co-fired ceramic (LTCC) circuits. Choi *et al.* [10] applied it to magnetic systems, and Redhe [11] in vehicle crashworthiness design.

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J. W. Bandler is with the Simulation Optimization Systems Research Laboratory, Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON, Canada L8S 4K1 and also with Bandler Corporation, Dundas, ON, Canada L9H 5E7 (e-mail: bandler@mcmaster.ca).

Q. S. Cheng is with the Simulation Optimization Systems Research Laboratory, Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON, Canada L8S 4K1.

N. K. Nikolova is with the Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON, Canada L8S 4K1.

M. A. Ismail is with Com Dev International Ltd., Cambridge, ON, Canada N1R 7H6.

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In [2]–[5], a calibration is performed through a mapping between optimizable design parameters of the fine model and precisely corresponding parameters of the coarse model such that their responses match. This mapping is iteratively updated. In [12], the coarse model is calibrated against the fine model by adding circuit components to nonadjacent individual coarse model elements. The component values are updated iteratively. The expanded space mapping design framework (ESMDF) algorithm [13] calibrates the coarse model by extracting certain preassigned parameters such that corresponding responses match. It establishes an explicit mapping from the optimizable design parameters to preassigned (nonoptimized) parameters.

Our new approach does not establish an explicit mapping: instead we suggest an indirect approach. In each iteration, we extract selected preassigned parameters to match the coarse model with the fine model. With these preassigned parameters now fixed, we reoptimize the calibrated coarse model. We then assign its optimized design parameters to the fine model. We repeat this process until the fine model response is sufficiently close to the target response. The preassigned parameters, which are updated, calibrate the "mapping." It is an application of a new concept we call implicit space mapping (ISM) [14].

Examples of preassigned parameters are physical parameters such as dielectric constant in microstrip structures, geometrical parameters such as substrate height, or mathematical concepts such as frequency-transformation parameters. Typically, they are not optimized, but clearly they influence the responses. As in [13], we allow the preassigned parameters (of the coarse model) to change in some components and keep them intact in others. We implement our technique in Agilent ADS.¹

II. SM TECHNOLOGY

We categorize SM into: 1) the original or explicit SM and 2) ISM. Both share the concept of "coarse" and "fine" models. Both use an iterative approach to update the mapping and predict the new design.

A. Explicit SM

In explicit SM, we should be able to draw a clear distinction between a physical coarse model and the mathematical mapping that links it to the fine model (see Fig. 1). Here, the mapping, together with the coarse model, constitute a "surrogate." In each iteration, only the mapping is updated, while the physical coarse model is kept fixed. If the inverse mapping is available at each

¹Agilent ADS, version 1.5, Agilent Technol., Santa Rosa, CA, 2000.



Fig. 1. Illustration of explicit SM.



Fig. 2. Illustration of ISM. (a) Implicit mapping within the surrogate. (b) With extra mapping and output mapping.

iteration, then the solution (best current prediction of the fine model) can be evaluated directly. Otherwise an optimization is performed on the mapping itself (not the mapped coarse model) to obtain the prediction. Examples of explicit SM are the original SM [2], aggressive SM [3], neural SM [4], etc.

B. ISM

Sometimes identifying the mapping is not obvious: it may be buried within the coarse model. If the "mapping" is integrated with the coarse model, the (mapped) coarse model becomes a calibrated coarse model or enhanced coarse model, which we also call a "surrogate," the rectangular box in Fig. 2(a). In the next step, the calibrated or enhanced coarse model is optimized to obtain an "inverse" mapped solution. If the implicitly mapped model is not sufficiently good after calibration, we may add an explicit mapping or output mapping [1], [15] [see Fig. 2(b)].

Both explicit and implicit SM iteratively calibrate the mapped model when approaching the fine model solution. Interestingly, the explicit mapping could be expressed in the form of ISM by using a simple mathematical substitution. We discuss this in Section III.

C. SM Optimization Steps

- Step 1) Select a mapping function (linear, nonlinear, neural).
- Step 2) Select an approach (implicit, explicit).

- Step 3) Optimize the coarse model with respect to design parameters.
- Step 4) Simulate the fine model at this solution.
- Step 5) Terminate if a stopping criterion (e.g., response meets specifications) is satisfied.
- Step 6) Apply parameter extraction using preassigned parameters [13], neuron weights [4], coarse space parameters, etc.
- Step 7) Rebuild the surrogate (update the mapping or surrogate if applicable).
- Step 8) Predict the next fine model solution by either:
 - a) inverting or optimizing the mapping with respect to the optimal coarse model design if possible, else,
 - b) reoptimizing the "mapped coarse model" with respect to design parameters.

Step 9) Go to Step 4).

Comments: Steps 6), 7) and 8) are separate steps in neural SM (training data is obtained by parameter extraction, the surrogate is rebuilt by the neural network training process, and prediction is obtained by evaluating the neural network). However, Step 7) may be implied in either the parameter-extraction process [Step 6)], e.g., ISM, where the surrogate is rebuilt by extracting preassigned parameters, or in the prediction [Step 8)], e.g., aggressive SM, where the surrogate is not explicitly rebuilt. Step 6) can be termed modeling for some cases.

III. ISM: CONCEPT

A. Original Design Problem

We denote the fine model responses at a point x_f by $R_f(x_f)$. The original design problem is to obtain

$$\boldsymbol{x}_{f}^{*} \triangleq \arg\min_{\boldsymbol{x}_{f}} U(\boldsymbol{R}_{f}(\boldsymbol{x}_{f}))$$
(1)

where U is the objective function and x_f^* is the optimal fine model design. Solving (1) using direct optimization methods may be prohibitive.

B. ISM

At the *j*th iteration, we denote by $\boldsymbol{x}_c^{*(j)}$ a coarse model optimum point (usually designable parameters) for given $\boldsymbol{x}^{(j)}$, a set of other (auxiliary) parameters, for example, preassigned parameters. The corresponding coarse model (the surrogate) response vector is $\boldsymbol{R}_c(\boldsymbol{x}_c^{*(j)}, \boldsymbol{x}^{(j)})$.

As indicated in Fig. 3, at the *j*th iteration, ISM aims at establishing an implicit mapping Q between the spaces x_f , x_c , and x. We solve

$$\boldsymbol{Q}(\boldsymbol{x}_f, \boldsymbol{x}_c, \boldsymbol{x}) = \boldsymbol{0} \tag{2}$$

with respect to \boldsymbol{x} to obtain $\boldsymbol{x}^{(j)}$ indirectly by an optimization algorithm, during which we set

$$\boldsymbol{x}_f = \boldsymbol{x}_c = \boldsymbol{x}_c^{*(j-1)} \tag{3}$$

such that

$$\boldsymbol{R}_f\left(\boldsymbol{x}_c^{*(j-1)}\right) \approx \boldsymbol{R}_c\left(\boldsymbol{x}_c^{*(j-1)}, \boldsymbol{x}^{(j)}\right) \tag{4}$$



Fig. 3. Illustration of ISM modeling. Here, Q = 0 is solved for x.



Fig. 4. Illustration of ISM prediction. Here, Q = 0 is solved for x_c^* .

over a region in the parameter space. We think of this as a *modeling* procedure, also referred to as parameter extraction in this case.

As in Fig. 4, ISM then utilizes the mapping to obtain a *prediction* of \boldsymbol{x}_f by solving (2) again with respect to \boldsymbol{x}_c to obtain $\boldsymbol{x}_c^{*(j)}$. Here, we set

$$\boldsymbol{x} = \boldsymbol{x}^{(j)} \tag{5}$$

where $\boldsymbol{x}^{(j)}$ is obtained from the foregoing modeling procedure. Since the mapping is usually nonlinear and implicit, the prediction is obtainable by optimizing a mapped coarse model or surrogate, i.e., we find

$$\boldsymbol{x}_{c}^{*(j)} \triangleq \arg\min_{\boldsymbol{x}_{c}} U\Big(\boldsymbol{R}_{c}\big(\boldsymbol{x}_{c}, \boldsymbol{x}^{(j)}\big)\Big). \tag{6}$$

The fine model parameters are then assigned (predicted) as

$$\boldsymbol{x}_f = \boldsymbol{x}_c^{*(j)}.\tag{7}$$

In general, ISM optimization obtains a space-mapped design \bar{x}_f whose response approximates an optimized R_c target. \bar{x}_f is a solution, found iteratively, of the nonlinear system (2), which is enforced through parameter extraction (modeling) with respect to x, and subsequent prediction of the fine model solution (through optimization of the calibrated coarse model).

C. Interpretation and Insight

As mentioned before, the mapping is buried in the coarse model. However, we can synthesize examples to develop insight into ISM, i.e., we can construct and connect a known mapping to a physical coarse model to study the behavior of the mapping (see Fig. 5). A set of intermediate parameters \boldsymbol{x}_i is introduced for this purpose.



Fig. 5. Synthetic illustration of ISM optimization with intermediate parameters.

In a physically based simulation, design parameters such as physical length and width of a microstrip line can be mapped to intermediate parameters such as electrical length and characteristic impedance through empirical formulas [16]. The mapping may, in that case, be extractable (detachable), and the mapping can be (re)optimized to obtain an "inverse" mapped solution (the prediction). For a library of microstrip components, the transformation from circuit parameters to physical parameters may be implicit, and the intermediate parameters may not be directly accessible. The prediction is then obtained through optimizing suitably calibrated microstrip components (preassigned parameters).

Assuming the intermediate parameters x_i are accessible, a corresponding hidden mapping in the modeling procedure can be thought of as finding

$$\boldsymbol{x}_{i}^{(j)} = \boldsymbol{P}\left(\boldsymbol{x}_{c}^{*(j-1)}, \boldsymbol{x}\right)$$
(8)

to match the coarse and fine model responses.

Let \boldsymbol{x}_i^* be the intermediate solution producing coarse model optimum \boldsymbol{R}_c^* . Correspondingly, the prediction procedure can then be expressed as

$$\boldsymbol{x}_{c}^{*(j)} = \boldsymbol{P}^{-1} \Big(\boldsymbol{x}_{i}^{*}, \boldsymbol{x}^{(j)} \Big).$$
(9)

D. Relationship With Explicit SM

The first step in all SM-based algorithms results in an optimal coarse model design \boldsymbol{x}_c^* for given nominal preassigned parameters \boldsymbol{x} . The corresponding response is denoted by \boldsymbol{R}_c^* . Once obtained, \boldsymbol{x}_c^* is fixed, as seen in Fig. 6(a). In ISM, on the other hand, $\boldsymbol{x}_c^{*(j)}$ begins with \boldsymbol{x}_c^* , depends on the current value of \boldsymbol{x} , and will change from iteration to iteration through reoptimization, as in Fig. 6(b).

An interesting point that relates the ISM to the explicit mapping is when we set the preassigned parameters at the jth iteration

$$\boldsymbol{x}^{(j)} = \Delta \boldsymbol{x}_c^{(j)} \triangleq \boldsymbol{x}_c^{(j)} - \boldsymbol{x}_c^{*(j-1)}$$
(10)

where $\boldsymbol{x}_{c}^{(j)}$ is obtained through parameter extraction. We can show that, after the modeling procedure, the prediction is

$$\boldsymbol{x}_{f}^{(j)} = \boldsymbol{x}_{f}^{(j-1)} + \boldsymbol{x}_{c}^{*} - \boldsymbol{x}_{c}^{(j)}.$$
(11)

This agrees with the steps of aggressive SM [3] using a unit mapping. The ISM, in this case, is consistent with the original



Fig. 6. When we set the preassigned parameters $\boldsymbol{x} = \Delta \boldsymbol{x}_c$, ISM is consistent with the explicit SM process. (a) Original SM. (b) ISM process interpreted in the same spaces.

SM with the difference, highlighted in Fig. 6, that ISM extracts Δx_c rather than x_c during parameter extraction.

In the case of neuro-SM [4], if we set

$$\boldsymbol{x} = \boldsymbol{w} \tag{12}$$

where w represents the weights of the neurons, then by associating the artificial neural networks (ANNs) with the coarse model, neuro-SM is representable by ISM. Preassigned parameters \boldsymbol{x} could also represent other variables such as the SM parameters $\boldsymbol{B}, \boldsymbol{c}, \sigma$, and δ in the SM-based surrogate approach [5], in frequency SM [3], etc.

E. Cheese-Cutting Illustration

The ISM process can be demonstrated by a simple example, i.e., the cheese-cutting problem, depicted in Fig. 7. The goal is to deliver a segment of cheese of *weight* 30 units (target "response"). The "coarse" model is a cuboidal block (top block in Fig. 7). A unity density and a cross section of 3×1 units are assumed. The "fine" model has a corresponding cuboidal shape with a defect of six missing units of *weight* (the second block from top).

A *length* of 10 units will give 30 units of *weight* for the coarse model (top block in Fig. 7). An unbiased cut of the same length in the fine model weighs 24 units (fine model evaluation). The *width* (preassigned parameter) of the (coarse) model is shrunk to 2.4 units to match the fine model weight (parameter extraction). A reoptimization of the *length* of the calibrated coarse model (the surrogate) is performed to achieve the goal. The new *length* of 12.5 units is then assigned to the irregular block (fine model). The procedure continues in this manner until the irregular block is sufficiently close to the desired *weight* of 30 units. From the illustration, we see that the error reaches 1% after three iterations.

ISM, in this case, is an *indirect* approach. A *direct* approach would extract the *length* in the parameter-extraction process.

The weight of the coarse cheese model can be written as

$$R_c(l,w) = l \times w \times h$$



Fig. 7. Cheese-cutting problem: a demonstration of the ISM algorithm.



Fig. 8. Cheese-cutting problem: illustration of an intermediate parameter $x_i = w \times l$.

where l, w, and h are the length, width, and height, respectively, as in Fig. 8. An intermediate variable x_i is the area

$$x_i = w \times l.$$

We can see that each prediction procedure returns x_i to a fixed $x_i^* = 30$, which produces the optimal coarse model design.

IV. ISM: ALGORITHM

In Fig. 9, we represent a microwave circuit whose coarse model is decomposed. We catalog the preassigned parameters into two sets, as in [13]. In Set A, we vary certain preassigned parameters \boldsymbol{x} . In Set B, we keep preassigned parameters \boldsymbol{x}_0 fixed. We can follow the sensitivity approach of [13] to formally select components for Sets A and B.

As implied in Fig. 9(b), in each iteration of the parameterextraction process, we set

$$\boldsymbol{x}_c = \boldsymbol{x}_f^{(j)}.\tag{13}$$

Notice also that we do not explicitly establish a mapping between the optimizable parameters and the preassigned parameters. This contrasts with [13], where the mapping is explicit [see Fig. 9(c)]. Therefore, our proposed approach will be easier to implement in commercial microwave simulators.



Fig. 9. Calibrating (optimizing) the preassigned parameters \boldsymbol{x} in Set A results in aligning the coarse model (b) or (c) with the fine model (a). In (c), we illustrate the ESMDF approach [13], where $\boldsymbol{P}(\cdot)$ is a mapping from optimizable design parameters to preassigned parameters.

A. Summary of the Algorithm

- Step 1) Select candidate preassigned parameters x, as in [13] or through experience.
- Step 2) Set j = 0 and initialize $\boldsymbol{x}^{(0)}$.
- Step 3) Obtain the optimal (calibrated) *coarse model* parameters by solving (6).
- Step 4) Predict $\boldsymbol{x}_{f}^{(j)}$ from (7).
- Step 5) Simulate the fine model at $\boldsymbol{x}_{f}^{(j)}$.
- Step 6) Terminate if a stopping criterion (e.g., response meets specifications) is satisfied.
- Step 7) Calibrate the coarse model by extracting (parameter-extraction step) the preassigned parameters \boldsymbol{x} [noting (13)]

$$\boldsymbol{x}^{(j+1)} = \arg\min_{\boldsymbol{x}} \left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(j)}) - \boldsymbol{R}_c(\boldsymbol{x}_f^{(j)}, \boldsymbol{x}) \right\|.$$
(14)

Step 8) Increment j and go to Step 3).

V. HTS FILTER EXAMPLE

We consider the high-temperature superconducting (HTS) bandpass filter of [17]. The physical structure is shown in Fig. 10(a). Design variables are the lengths of the coupled lines and the separation between them, namely,

$$\boldsymbol{x}_f = \begin{bmatrix} S_1 & S_2 & S_3 & L_1 & L_2 & L_3 \end{bmatrix}^T$$

The substrate used is lanthanum aluminate with $\varepsilon_r = 23.425$, H = 20 mil and substrate dielectric loss tangent of 0.00003. The



Fig. 10. HTS filter [17]. (a) Physical structure and (b) coarse model as implemented in Agilent ADS .

length of the input and output lines is $L_0 = 50$ mil and the lines are of width W = 7 mil. We choose ε_r and H as the preassigned parameters of interest, thus, $x_0 = [20 \text{ mil } 23.425]^T$. The design specifications are

 $|S_{21}| \le 0.05$ for $\omega \ge 4.099$ GHz and for $\omega \le 3.967$ GHz $|S_{21}| \ge 0.95$ for 4.008 GHz $\le \omega \le 4.058$ GHz.

This corresponds to 1.25% bandwidth.

Our Agilent ADS coarse model consists of empirical models for single and coupled microstrip transmission lines with ideal open stubs [see Fig. 10(b)]. Set A [see Fig. 9(b)] consists of the three coupled microstrip lines. Notice the symmetry in the HTS structure, i.e., coupled lines "CLin5" are identical to "CLin1" and "CLin4" to "CLin2." Here, Set B [see Fig. 9(b)] is empty. The preassigned parameter vector is

$$oldsymbol{x} = egin{bmatrix} arepsilon_{r1} & H_1 & arepsilon_{r2} & H_2 & arepsilon_{r3} & H_3 \end{bmatrix}^T$$



Fig. 11. Momentum fine (\circ) and optimal coarse ADS model (—) responses at: (a) the initial solution. (b) The final iteration after two iterations (three fine model evaluations).



Fig. 12. Sonnet *em* fine (\circ) and optimal coarse ADS model (—) responses at: (a) the initial solution. (b) The final iteration after one iteration (two fine model evaluations).

TABLE I AGILENT MOMENTUM/SONNET *em* OPTIMIZABLE PARAMETER VALUES OF THE HTS FILTER

Parameter	Initial solution (mil)	Solution (mil) Agilent Momentum	Solution (mil) Sonnet <i>em</i>
L_1	189.65	187.10	186.80
L_2	196.03	191.30	192.68
L_3	189.50	186.97	185.86
S_1	23.02	22.79	22.19
S_2	95.53	93.56	88.12
S_3	104.95	104.86	103.42

TABLE II INITIAL AND FINAL PREASSIGNED PARAMETERS OF THE CALIBRATED COARSE MODEL OF THE HTS FILTER

Preassigned parameters	Original values	Final iteration Momentum	Final iteration <i>em</i>
H_1	20 mil	19.80 mil	18.79 mil
H_2	20 mil	19.05 mil	17.42 mil
H_3	20 mil	19.00 mil	17.67 mil
\mathcal{E}_{r1}	23.425	24.404	23.81
\mathcal{E}_{r2}	23.425	24.245	24.45
\mathcal{E}_{r3}	23.425	24.334	23.94

The fine model is simulated first by Agilent Momentum.² The relevant responses at the initial solution are shown in Fig. 11(a), where we notice severe misalignment. The algorithm requires two iterations (three fine model simulations). The total time taken is 26 min (one fine model simulation takes approximately 9 min on an Athlon 1100-MHz PC). Responses at the final iteration are shown in Fig. 11(b). Sonnet *em*³ has also been used as a fine model. It takes 74 min to complete a sweep on an Intel P4 2200-MHz PC. The initial solution and the final result in one iteration (two fine model simulations) are shown in Fig. 12(a) and (b), respectively. Table I shows initial and final designs. Table II shows the variation in the preassigned (coarse model) parameters.

The parameter-extraction process uses real and imaginary S-parameters and the ADS quasi-Newton optimization algorithm, while coarse model optima are obtained by the ADS minimax optimization algorithm.

VI. CONCLUSIONS

Based on a general concept, we have presented an effective technique for microwave circuit modeling and design with respect to full-wave EM simulations. We vary preassigned parameters in a coarse model to align it with the EM (fine) model. We believe this is the easiest to implement "SM" technique offered to date. The HTS filter design is entirely carried out by Agilent ADS and Momentum (three frequency sweeps) or Sonnet *em* (only two frequency sweeps) with no matrices to keep track of. A general SM concept has been presented, which enables us to verify that our implementation is correct and that no redundant steps are used.

²Momentum, version 4.0, Agilent Technol., Santa Rosa, CA, 2000.

³Sonnet *em*, version 7.0b, Sonnet Software, North Syracuse, NY, 2001.

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REFERENCES

- J. W. Bandler, Q. S. Cheng, S. A. Dakroury, A. S. Mohamed, M. H. Bakr, K. Madsen, and J. Søndergaard, "Space mapping: The state of the art," *IEEE Trans. Microwave Theory Tech.*, vol. 52, pp. 337–361, Jan. 2004.
- [2] J. W. Bandler, R. M. Biernacki, S. H. Chen, P. A. Grobelny, and R. H. Hemmers, "Space mapping technique for electromagnetic optimization," *IEEE Trans. Microwave Theory Tech.*, vol. 42, pp. 2536–2544, 1994.
- [3] J. W. Bandler, R. M. Biernacki, S. H. Chen, R. H. Hemmers, and K. Madsen, "Electromagnetic optimization exploiting aggressive space mapping," *IEEE Trans. Microwave Theory Tech.*, vol. 43, pp. 2874–2882, Dec. 1995.
- [4] J. W. Bandler, M. A. Ismail, J. E. Rayas-Sánchez, and Q. J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE Trans. Microwave Theory Tech.*, vol. 47, pp. 2417–2427, Dec. 1999.
- [5] M. H. Bakr, J. W. Bandler, K. Madsen, J. E. Rayas-Sánchez, and J. Søndergaard, "Space-mapping optimization of microwave circuits exploiting surrogate models," *IEEE Trans. Microwave Theory Tech.*, vol. 48, pp. 2297–2306, Dec. 2000.
- [6] A. M. Pavio, "The electromagnetic optimization of microwave circuits using companion models," presented at the IEEE MTT-S Int. Microwave Symp. Workshop, Anaheim, CA, 1999.
- [7] J. Snel, "Space mapping models for RF components," presented at the IEEE MTT-S Int. Microwave Symp. Workshop, Phoenix, AZ, 2001.
- [8] D. G. Swanson, Jr. and R. J. Wenzel, "Fast analysis and optimization of combline filters using FEM," in *IEEE MTT-S Int. Microwave Symp. Dig.*, Phoenix, AZ, 2001, pp. 1159–1162.
- [9] K.-L. Wu, M. Ehlert, and C. Barratt, "An explicit knowledge-embedded space mapping scheme for design of LTCC RF passive circuits," presented at the IEEE MTT-S Int. Microwave Symp. Workshop, Seattle, WA, 2002.
- [10] H.-S. Choi, D. H. Kim, I. H. Park, and S. Y. Hahn, "A new design technique of magnetic systems using space mapping algorithm," *IEEE Trans. Magn.*, vol. 37, pp. 3627–3630, Sept. 2001.
- [11] M. Redhe, "Simulation based design-structural optimization at the early design stages," Master's thesis 922, Dept. Mech. Eng., Div. Solid Mech., Linköping Univ., Linköping, Sweden, 2001.
- [12] S. Ye and R. R. Mansour, "An innovative CAD technique for microstrip filter design," *IEEE Trans. Microwave Theory Tech.*, vol. 45, pp. 780–786, May 1997.
- [13] J. W. Bandler, M. A. Ismail, and J. E. Rayas-Sánchez, "Expanded space mapping EM-based design framework exploiting preassigned parameters," *IEEE Trans. Circuits Syst. I*, vol. 49, pp. 1833–1838, Dec. 2002.
- [14] J. W. Bandler, Q. S. Cheng, N. Georgieva, and M. A. Ismail, "Implicit space mapping EM-based modeling and design using preassigned parameters," in *IEEE MTT-S Int. Microwave Symp. Dig.*, Seattle, WA, 2002, pp. 713–716.
- [15] J. W. Bandler, Q. S. Cheng, D. H. Gebre-Mariam, K. Madsen, F. Pedersen, and J. Søndergaard, "EM-based surrogate modeling and design exploiting implicit, frequency and output space mappings," in *IEEE MTT-S Int. Microwave Symp. Dig.*, Philadelphia, PA, 2003, pp. 1003–1006.

- [16] D. M. Pozar, *Microwave Engineering*, 2nd ed. New York: Addison-Wesley, 1998, pp. 162–163.
- [17] J. W. Bandler, R. M. Biernacki, S. H. Chen, W. J. Getsinger, P. A. Grobelny, C. Moskowitz, and S. H. Talisa, "Electromagnetic design of hightemperature superconducting microwave filters," *Int. J. RF Microwave Computer-Aided Eng.*, vol. 5, pp. 331–343, 1995.



John W. Bandler (S'66–M'66–SM'74–F'78) was born in Jerusalem, on November 9, 1941. He studied at Imperial College of Science and Technology, London, U.K., from 1960 to 1966. He received the B.Sc. (Eng.), Ph.D., and D.Sc. (Eng.) degrees from the University of London, London, U.K., in 1963, 1967, and 1976, respectively.

In 1966, he joined Mullard Research Laboratories, Redhill, Surrey, U.K. From 1967 to 1969, he was a Post-Doctorate Fellow and Sessional Lecturer with the University of Manitoba, Winnipeg, MB, Canada.

In 1969, he joined McMaster University, Hamilton, ON, Canada, where he has served as Chairman of the Department of Electrical Engineering and Dean of the Faculty of Engineering. He is currently Professor Emeritus in Electrical and Computer Engineering, and directs research in the Simulation Optimization Systems Research Laboratory. He was President of Optimization Systems Associates Inc. (OSA), which he founded in 1983, until November 20, 1997, the date of acquisition of OSA by the Hewlett-Packard Company (HP). OSA implemented a first-generation yield-driven microwave CAD capability for Raytheon in 1985, followed by further innovations in linear and nonlinear microwave CAD technology for the Raytheon/Texas Instruments Joint Venture MIMIC Program. OSA introduced the computer-aided engineering (CAE) systems RoMPE in 1988, HarPE in 1989, OSA90 and OSA90/hope in 1991, Empipe in 1992, and Empipe3D and EmpipeExpress in 1996. OSA created empath in 1996, marketed by Sonnet Software Inc. He is currently President of Bandler Corporation, Dundas, ON, Canada, which he founded in 1997. He has authored or coauthored over 350 papers from 1965 to 2003. He contributed to Modern Filter Theory and Design (New York: Wiley-Interscience, 1973) and Analog Methods for Computer-aided Analysis and Diagnosis (New York: Marcel Dekker Inc., 1988). Four of his papers have been reprinted in Computer-Aided Filter Design (New York: IEEE Press, 1973), one in each of Microwave Integrated Circuits (Norwood, MA: Artech House, 1975), Low-Noise Microwave Transistors and Amplifiers (New York: IEEE Press, 1981), Microwave Integrated Circuits, 2nd ed. (Norwood, MA: Artech House, 1985), Statistical Design of Integrated Circuits (New York: IEEE Press, 1987), and Analog Fault Diagnosis (New York: IEEE Press, 1987). He joined the Editorial Boards of the International Journal of Numerical Modeling (1987), the International Journal of Microwave and Millimeterwave Computer-Aided Engineering (1989), and Optimization Eng. in 1998. He was Guest Editor of the International Journal of Microwave and Millimeter-Wave Computer-Aided Engineering Special Issue on Optimization-Oriented Microwave CAD (1997). He was Guest Co-Editor of the Optimization Eng. Special Issue on Surrogate Modelling and Space Mapping for Engineering Optimization (2001).

Dr. Bandler is a Fellow of the Canadian Academy of Engineering, the Royal Society of Canada, the Institution of Electrical Engineers (U.K.), and the Engineering Institute of Canada. He is a member of the Association of Professional Engineers of the Province of Ontario (Canada) and a member of the Massachusetts Institute of Technology (MIT) Electromagnetics Academy. He was an associate editor of the IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES (1969-1974), and has continued serving as a member of the Editorial Board. He was guest editor of the IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES Special Issue on Computer-Oriented Microwave Practices (1974) and guest co-editor of the IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES Special Issue on Process-Oriented Microwave CAD and Modeling (1992). He was guest editor of the IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES Special Issue on Automated Circuit Design Using Electromagnetic Simulators (1997). He is guest co-editor of the IEEE TRANSACTIONS ON MICROWAVE THEORY AND TECHNIQUES Special Issue on Electromagnetics-Based Optimization of Microwave Components and Circuits (2004). He has served as chair of the MTT-1 Technical Committee on Computer-Aided Design. He was the recipient of the 1994 Automatic Radio Frequency Techniques Group (ARFTG) Automated Measurements Career Award.



Qingsha S. Cheng (S'00) was born in Chongqing, China. He received the B.Eng. and M.Eng. degrees in automation from Chongqing University, Chongqing, China, in 1995 and 1998, respectively, and is currently working toward the Ph.D. degree at McMaster University, Hamilton, ON, Canada.

In September 1998, he joined the Department of Computer Science and Technology, Peking University, Beijing, China. In September 1999, he joined the Simulation Optimization Systems Research Laboratory, Department of Electrical and Computer Engi-

neering, McMaster University. He has served as a Teaching and Research Assistant. His research interests are CAD, modeling of microwave circuits, software design technology and methodologies for microwave CAD.

Mr. Cheng was the recipient of a one-year Nortel Networks Ontario Graduate Scholarship in Science and Technology (OGSST) for the 2001–2002 academic year.



Natalia K. Nikolova (S'93–M'97) received the Ph.D. degree from the University of Electro-Communications, Tokyo, Japan, in 1997.

From 1998 to 1999, she was with the Natural Sciences and Engineering Research Council of Canada (NSERC), during which time she was initially with the Microwave and Electromagnetics Laboratory, DalTech, Dalhousie University, Halifax, NS, Canada. For a year, she was then with the Simulation Optimization Systems Research Laboratory, McMaster University, Hamilton, ON, Canada. In

July 1999, she joined the Department of Electrical and Computer Engineering, McMaster University, where she is currently an Assistant Professor. Her research interests include theoretical and computational electromagnetism, high-frequency analysis techniques, as well as computer-aided design (CAD) methods for high-frequency structures and antennas.

Dr. Nikolova was the recipient of an NSERC Post-Doctoral Fellowship from 1998 to 1999. She currently holds the 2000 NSERC University Faculty Award.



Mostafa A. Ismail (S'98–M'02) was born in Cairo, Egypt, on May 21, 1968. He received the B.Sc. degree in electronics and communications engineering and the Master's degree in engineering mathematics from Cairo University, Cairo, Egypt, in 1991 and 1995, respectively, and the Ph.D. degree from McMaster University, Hamilton, ON, Canada, in 2001.

From October 1991 to August 1997, he was a Teaching Assistant with the Department of Engineering Mathematics and Physics, Faculty of

Engineering, Cairo University. In 1997, he joined the Simulation Optimization Systems Research Laboratory and the Department of Electrical and Computer Engineering, McMaster University. In 2001, he joined Com Dev Ltd., Cambridge, ON, Canada, where he is currently an Advanced Member of Technical Staff in the Research and Development Department. His research includes computer-aided design and modeling of microwave circuits, EM optimization, efficient optimization of waveguide circuits, computer-aided tuning, device modeling, and parameter extraction.

Dr. Ismail was the recipient of a one-year Nortel Networks Ontario Graduate Scholarship in Science and Technology (OGSST) for the 2000–2001 academic year.