

# Basic Space Mapping: A Retrospective and its Application to Design Optimization of Nonlinear RF and Microwave Circuits

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**Abstract** — Space mapping (SM) is one of the most powerful and computationally efficient design optimization methodologies in RF and microwave engineering. Its impressive evolution in terms of algorithmic variations and diverse engineering applications is well-documented. Most of the SM-based design optimization cases, including those solved by advanced and sophisticated space mapping formulations, have been demonstrated for linear frequency-domain microwave circuits. In this paper, we provide a brief retrospective on the emergence of space mapping, including its initial impression on a worldwide authority on nonlinear microwave circuit simulation and design: Prof. Vittorio Rizzoli. We briefly review some of the most fundamental space mapping optimization concepts and emphasize their applicability to nonlinear transient-domain microwave circuit design optimization. We illustrate this by a typical problem of high-speed digital signal conditioning: the physical design of a set of CMOS inverters driving an FR4 printed circuit board interconnect.

**Keywords** — Broyden, CAD, CMOS drivers, high-speed interconnects, Rizzoli, signal integrity, space mapping, transient-domain design optimization, design automation.

## I. INTRODUCTION

Surrogate-based optimization (SBO) algorithms are especially suitable for the efficient optimization of computationally expensive objective functions [1]. Space mapping (SM) [2], [3], that may be classified within the general class of SBO algorithms [4], is one of the most powerful and computationally efficient design optimization methodologies in RF and microwave engineering [5]. Its impressive evolution in terms of algorithmic variations and diverse engineering applications is well-documented [5], [6].

Before its first publication, introducing the space mapping concept in person to Prof. Vittorio Rizzoli [7], world renowned in nonlinear microwave circuit simulation [8], confirmed the natural connection of space mapping with engineering intuition. A fruitful Bandler-Rizzoli scientific synergy [9] had already been established in development of design automation tools<sup>1,2</sup>.

Most of the space mapping design optimization examples available in the literature, including those solved by advanced and sophisticated space mapping formulations, have been illustrated for the efficient optimization of linear frequency-domain microwave circuits. In this paper, we provide a retrospective on space mapping in the context of nonlinear

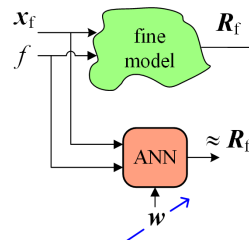


Fig. 1. Classical neuromodeling in frequency-domain, where the fine model is typically a full-wave EM simulator. Here the ANN is typically a feed-forward multilayer perceptron (MLP) or a radial basis function (RBF). From [10].

microwave circuit design optimization. In this brief review, we highlight interesting intersections between space mapping and Prof. Rizzoli's outstanding work on nonlinear microwave circuit simulation. We revisit basic space mapping optimization concepts, accentuating their simplicity and applicability to nonlinear transient-domain microwave circuit design optimization. We illustrate this by the physical design of a set of CMOS inverters driving an FR4 printed circuit board interconnect.

## II. COMPLEXITIES OF NEURAL MODELING IN NONLINEAR TRANSIENT-DOMAIN

Among surrogate modeling methods for RF and microwave circuits design [4], artificial neural networks (ANNs) offer well-established, flexible, and powerful alternatives for efficient EM-based design optimization [10], [11]. Most neural network approaches for microwave design have been developed either for frequency- or for time-domain circuits.

Conventional neuromodeling in the frequency-domain is illustrated in Fig. 1. Here the fine model responses  $R_f(x_f, f)$  are typically obtained from highly accurate full-wave EM simulations. Vector  $x_f$  has the design variables and  $f$  is the operating frequency. The most widely used ANN paradigms for frequency-domain neuromodeling are feed-forward multilayer perceptrons (MLP) and radial basis functions (RBF) [10]. The adjustable parameters (weighting factors, bias elements, etc.) of the ANN, contained in vector  $w$ , are optimized during training, such that the ANN best approximates the fine model responses in the region of interest for  $x_f$ .

Neural models in the time domain can be trained from

<sup>1</sup> Microwave Harmonica User's Manual, Compact Software Inc., Paterson, NJ 07504, 1987.

<sup>2</sup> OS490, Optimization Systems Associates, Dundas, Canada, L9H 5E7, Canada, 1990.

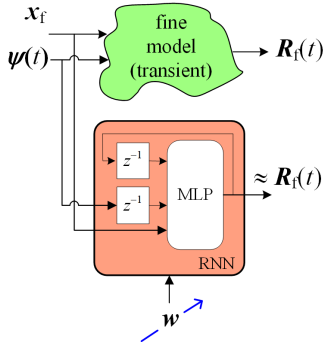


Fig. 2. Classical neuromodeling in transient-domain, where the fine model is either a time-domain full-wave EM simulator or a highly accurate nonlinear circuit model. Here the ANN is a recurrent neural network (RNN). From [10].

frequency-domain spectral data [12]; once trained, they can be efficiently used in accurate harmonic balance steady-state time-domain simulations of highly nonlinear circuits. These dynamic neural models, based on reduced-order state equations, can also be trained directly from steady-state time-domain simulations [13], from transient simulations [14], or even from time-domain measured samples [15], [16].

Conventional feed-forward perceptrons are unsuitable paradigms for transient neuromodeling. In contrast, recurrent neural networks (RNN) are more adequate to capture the dynamic behavior of nonlinear circuits [17]. Essentially, RNNs incorporate feedback loops with delay elements into static multilayer perceptrons with nonlinear activation functions, as illustrated in Fig. 2, where the process of developing a neurodynamic model of a microwave circuit in transient-domain is also illustrated. Vector function  $\psi(t)$  represents the excitation waveforms evaluated at time  $t$ , while  $R_f(t)$  contains the corresponding fine model transient output waveforms amplitudes. Banks of unit-delays are denoted by  $z^{-1}$ .

Neuromodeling RF and microwave circuits in transient-domain is particularly challenging. In addition to the typical issues that must be considered when developing static MLP neural models (space sampling, under-learning, overfitting, scaling, poor local minima during training, etc.), developing RNN dynamic models should carefully consider three additional issues: training, time sampling, and stability. Unconventional ANN training algorithms should be employed for training RNNs, such as [18]. The sampling cycle for generating training and testing data should also be carefully selected considering the input transient waveforms. Finally, the number of unit-delay elements in each bank of delays is perhaps the most critical and difficult to predict; it is usually determined heuristically [17] and is closely related to model stability [19].

### III. NONLINEAR RF AND MICROWAVE NEURAL MODELING EXPLOITING CO-SIMULATION

Another popular alternative for developing computationally efficient nonlinear models of RF and microwave circuits consists of combining available equivalent linear circuits with ANNs. In this scenario, the neural model is not trained to approximate the complete input-output relationship of the nonlinear microwave component, as in Section II. Here, neural

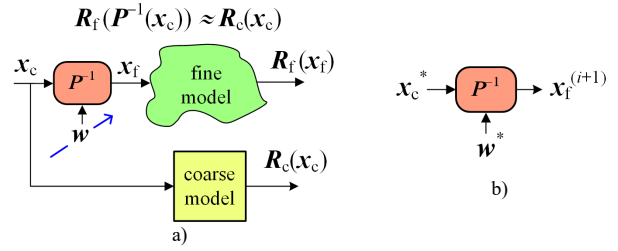


Fig. 3. Inverse space mapping design optimization: a) an inverse mapping  $P^{-1}(x_c) = x_f$  is “trained” to interpolate all the accumulated corresponding designs from previous parameter extractions; b) evaluating the already trained inverse mapping at  $x_c^*$  yields the next iterate  $x_f^{(i+1)}$ . From [33].

models are trained to approximate the empirical relationships between some linear sub-circuit responses and the actual nonlinear responses (neural mappings). This approach is more suitable for large system-level nonlinear simulations.

Interestingly, Prof. Rizzoli was a pioneer in the development of CAD methods for ANN-based behavioral modeling of nonlinear RF/microwave systems and subsystems [20]. In this approach, the training and testing data is obtained from standard harmonic balance simulations using highly accurate nonlinear circuit models. The resultant ANN-based co-simulation models effectively combine nonlinear techniques with linear circuit/EM simulations [21]. This methodology is amenable to massive nonlinear simulation tasks, such as those required in RF/microwave subsystems, *e.g.*, front ends of mobile communication equipment.

### IV. SPACE MAPPING FOR TRANSIENT-DOMAIN DESIGN OPTIMIZATION

Most of the algorithmic space mapping approaches to microwave design optimization have been demonstrated with linear frequency-domain steady-state design problems. Moreover, SM methods that intelligently manipulate the frequency variable to improve the parameter extraction process through frequency mappings, as some variations in [22]-[26], of course are restricted to frequency-domain problems. However, several formulations of space mapping can in principle be applied to transient-domain design.

Innovative formulations to nonlinear design optimization exploiting space mapping were developed by Prof. Rizzoli *et al.* [27], [28], where the mapping inversion process is combined with harmonic balance analysis to solve the inherent nonlinear system of equations coupled to full-wave EM analysis.

Inverse space mapping approaches have proved to be suitable for nonlinear transient-domain design optimization [29]. The inverse input mapping between the coarse and fine models,  $P^{-1}(x_c) = x_f$ , can be iteratively built to interpolate all the accumulated corresponding designs,  $x_f^{(i)}$  and  $x_c^{(i)}$  for  $i = 1, 2, \dots$ , obtained from previous parameter extractions, either using a neuronal mapping [30] or a linear mapping [31], [32]. In any case, the next iterate  $x_f^{(i+1)}$  is obtained by simply evaluating the current best inverse mapping at the optimal coarse model solution  $x_c^*$ . Inverse space mapping design optimization is conceptually illustrated in Fig. 3 [33]; it can be implemented in both frequency- and transient-domain [29].

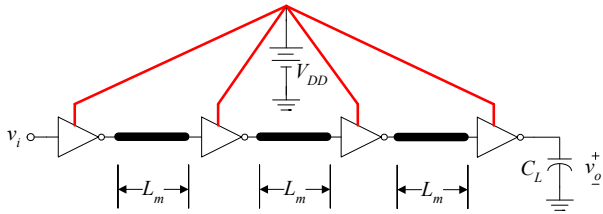


Fig. 4. CMOS inverters driving a capacitive load  $C_L$  through an electrically long microstrip line. Each segment of microstrip line has a length  $L_m$ . A single DC voltage source  $V_{DD}$  biases the four buffers using completely different interconnects (in red) than those used for the signal microstrip paths. From [29].

## V. EXAMPLE OF TRANSIENT-DOMAIN INVERSE SPACE MAPPING DESIGN OPTIMIZATION

Here we illustrate linear-inverse space mapping in transient-domain by a typical problem of high-speed digital signal conditioning: the physical design of a set of CMOS buffers to drive an electrically long microstrip line [29].

Although frequency-domain techniques can be applied to simulate and optimize similar high-speed interconnects [34], the use of nonlinear transient simulation and optimization is required since inserting nonlinear buffer stages at different locations along such long lines is a common practice to reduce delay and other signal integrity issues [30]. In this example, two intermediate buffers are inserted between the initial and final drivers on a long microstrip line terminated with a capacitive load  $C_L$ , as shown in Fig. 4, where the DC power lines biasing each inverter (in red color) are also considered, since they significantly affect the propagated signal.

The input voltage  $v_i(t)$  in Fig. 4 is a trapezoidal pulse with a 3 V amplitude, 2.5 ns duration, and 100-ps rise- and fall-time. The microstrip lines are on an FR4 dielectric substrate with height  $H = 10$  mil, loss tangent 0.025, and relative permittivity  $\epsilon_r = 4.5$ ; they use a width  $W = 19$  mil (50- $\Omega$  lines). The segments of microstrip lines for the signal paths have a length  $L_m = 200$  mil. The DC power biasing lines are also modelled as 50- $\Omega$  microstrip lines with a 500-mil length each. A typical 0.5  $\mu\text{m}$  CMOS process technology is assumed for all the inverters.

The transient design specifications are:  $v_{out} < 0.3\text{V}$  from 0 to 1ns;  $v_{out} > 2.7\text{V}$  from 3ns to 4.5ns; and  $v_{out} < 0.3\text{V}$  from 6.5ns to 8.5ns. The optimization variables are the channel widths for all the MOSFETs (assuming symmetric inverters),  $\mathbf{x}_t = [W_1 W_2 W_3 W_4]^T$ .

This problem is solved in [29] by using a linear inverse space mapping (see Fig. 3). The fine model is shown in Fig. 5a; it uses the BSIM model for each MOSFET as well as lossy microstrip components. The coarse model is shown in Fig. 5b; it uses Level 1 MOSFET models, ideal lossless transmission lines for the signal paths, and it neglects biasing lines. Both models are implemented in APLAC AWR.

Direct optimization of the coarse model yields  $\mathbf{x}_c^* = [11.0 \ 11.5 \ 11.0 \ 10.5]^T$  ( $\mu\text{m}$ ). The starting point for space mapping is shown in Fig. 6a. After only six iterations, a space mapped solution  $\mathbf{x}_t^{\text{SM}} = [23 \ 18 \ 21 \ 19.5]^T$  ( $\mu\text{m}$ ) is found. The final results are shown in Fig. 6b, requiring only seven fine model transient simulations to solve this problem.

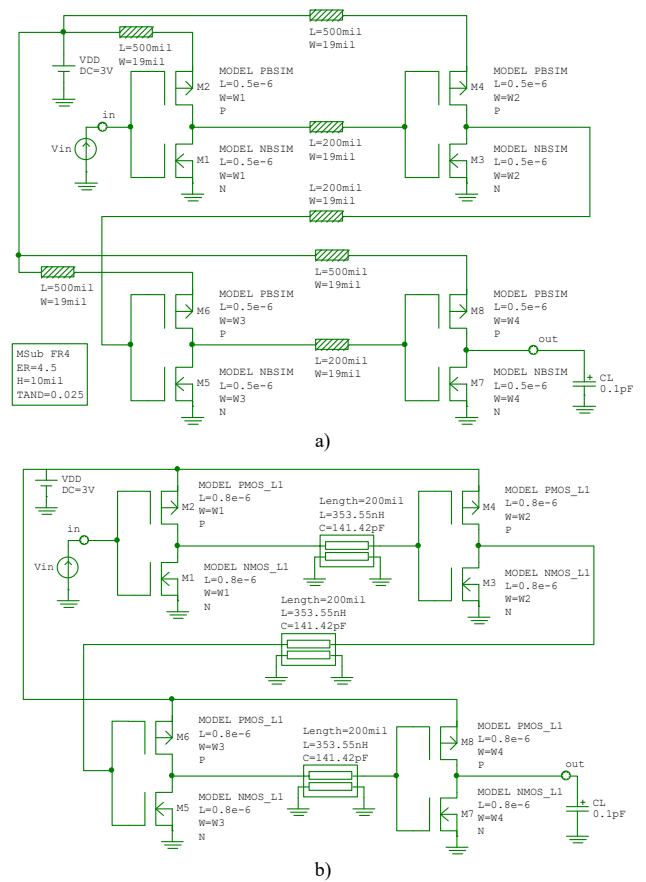


Fig. 5. Models used for the set of CMOS buffers driving the FR4 printed circuit board interconnect in Fig. 4: a) fine model; b) coarse model. From [29].

## VI. CONCLUSION

A retrospective on space mapping in the context of nonlinear microwave circuit design optimization has been provided. In our analysis, we emphasized the intersection between space mapping and Prof. Rizzoli's outstanding work on nonlinear microwave circuit simulation. We revisited basic space mapping optimization approaches, highlighting their simplicity and applicability to nonlinear transient-domain microwave circuit design optimization. The latter is illustrated by the physical design optimization of a set of CMOS buffers driving an FR4 printed circuit board interconnect.

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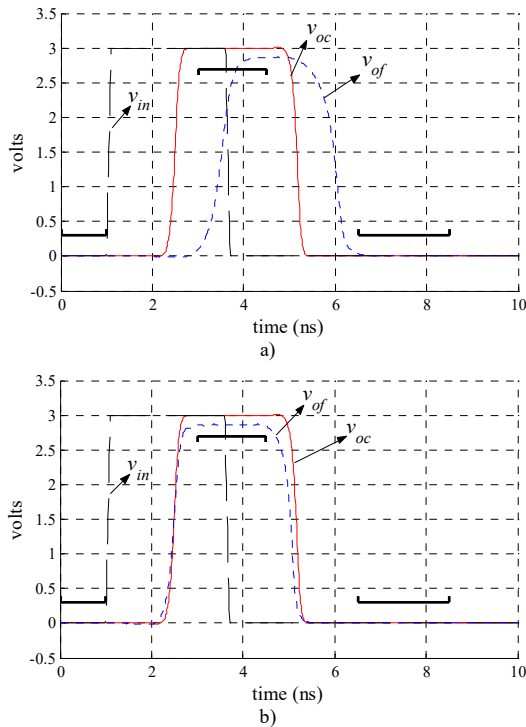


Fig. 6. Main transient waveforms for the circuits in Fig. 5; input trapezoidal voltage ( $v_{in}$ ), optimal coarse model output voltage ( $v_{oc}$ ), and fine model output voltage ( $v_{of}$ ): a) starting point ( $v_{of}$  at  $x_c^*$ ); b) after SM ( $v_{of}$  at  $x_r^{SM}$ ). From [29].

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