SPACE MAPPING BASED DEVICE MODELING AND CIRCUIT OPTIMIZATION

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presented at

WORKSHOP ON AUTOMATED CIRCUIT OPTIMIZATION USING ELECTROMAGNETIC SIMULATORS

2000 IEEE MTT-S International Microwave Symposium, Boston, MA, June 16, 2000

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Abstract

Electromagnetics (EM) based device modeling and circuit optimization through Artificial Neural Network (ANN) and Space Mapping (SM) technologies are reviewed. These two concepts continue to promise important benefits in the next generation of design optimization methodologies. ANNs can learn from and generalize patterns in data and model nonlinear relationships. On the other hand, Aggressive Space Mapping (ASM) optimization closely follows the traditional experience and intuition of designers, while being rigorously grounded mathematically. Current progress in the development of suitable algorithms and software engines are presented. The ANN and SM concepts address the contradictory challenge of exploitation of device models for CAD that are both accurate and fast.

Outline

Generalized Space Mapping (GSM) tableau approach to engineering device modeling is reviewed

new work on Space Mapping optimization exploiting surrogate models is described

a Neural Space Mapping (NSM) optimization approach exploiting our SM-based neuromodeling techniques is presented

Generalized Space Mapping (GSM)

GSM is a comprehensive framework for engineering device modeling

GSM exploits the Space Mapping (SM), the Frequency Space Mapping (FSM) *(Bandler et al., 1994)* and the Multiple Space Mapping (MSM) *(Bandler et al., 1998)* concepts to build a new engineering device modeling framework

two cases are considered:

the basic Space Mapping Super Model (SMSM) concept maps the device parameters

the Frequency-Space Mapping Super Model (FSMSM) concept maps the device parameters as well as frequency

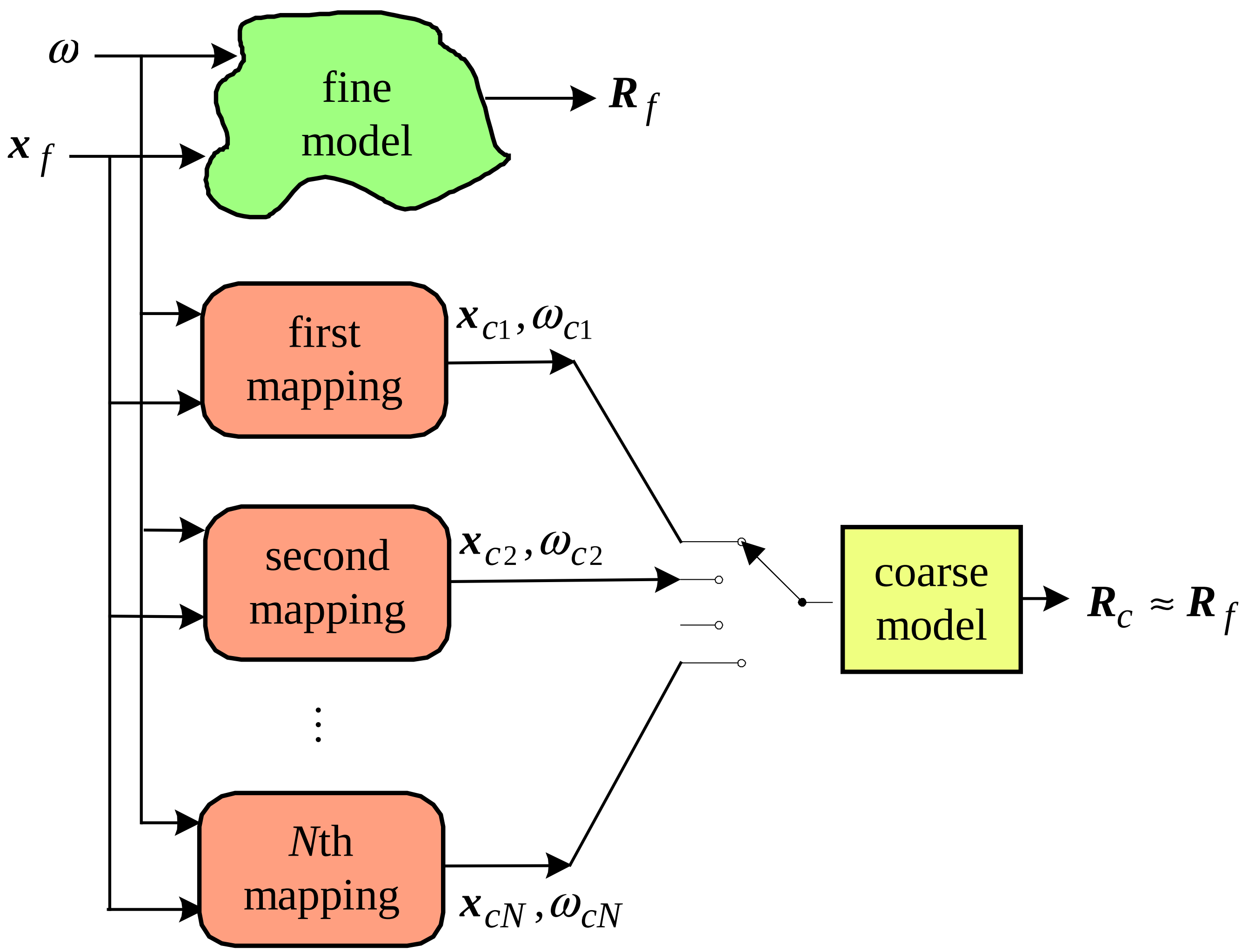
two variations of MSM are presented *(Bandler et al., 1999)*:

MSM for Device Responses (MSMDR) develops a different mapping for each subset of responses

MSM for Frequency Intervals (MSMFI) develops a different mapping for each frequency interval

Multiple Space Mapping (MSM) Concept

MSM for Frequency Intervals (MSMFI)



Mathematical Formulation for GSM

the kth mapping targeting the sub-response $\boldsymbol{R}_k$ or the response $\boldsymbol{R}$ in the kth frequency sub-range is given by

$$(\boldsymbol{x}_{ck}, \omega_{ck}) = \boldsymbol{P}_k(\boldsymbol{x}_f, \omega)$$

or, in matrix form, assuming a linear mapping,

$$\begin{bmatrix} \boldsymbol{x}_{ck} \\ \omega_{ck} \end{bmatrix} = \begin{bmatrix} \boldsymbol{c}_k \\ \delta_k \end{bmatrix} + \begin{bmatrix} \boldsymbol{B}_k & \boldsymbol{s}_k \\ \boldsymbol{t}_k^T & \sigma_k \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_f \\ \omega \end{bmatrix}$$

the mapping parameters $\{\boldsymbol{c}_k, \boldsymbol{B}_k, \boldsymbol{s}_k, \boldsymbol{t}_k, \sigma_k, \delta_k\}$ can be evaluated, directly or indirectly, by solving the optimization problem

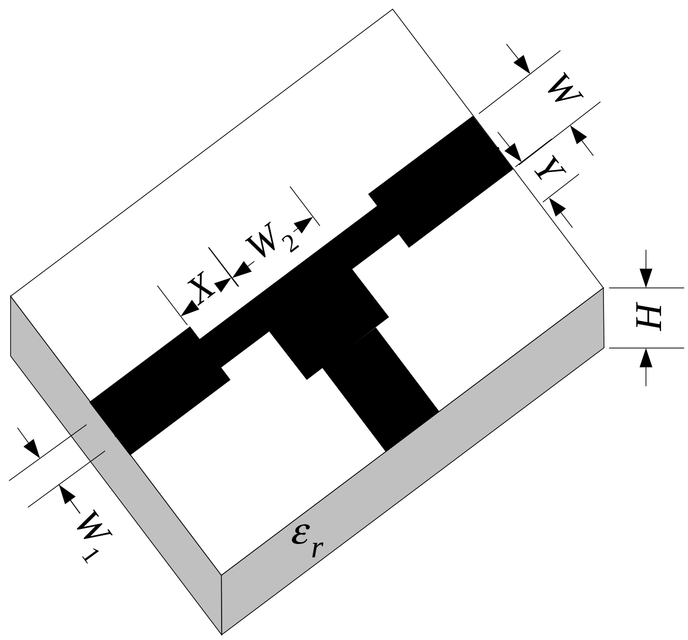
$$\min_{\boldsymbol{c}_k, \boldsymbol{B}_k, \boldsymbol{s}_k, \boldsymbol{t}_k, \sigma_k, \delta_k} \left\| \begin{bmatrix} \boldsymbol{e}_{k1}{}^T & \boldsymbol{e}_{k2}{}^T & \cdots & \boldsymbol{e}_{km}{}^T \end{bmatrix}^T \right\|$$

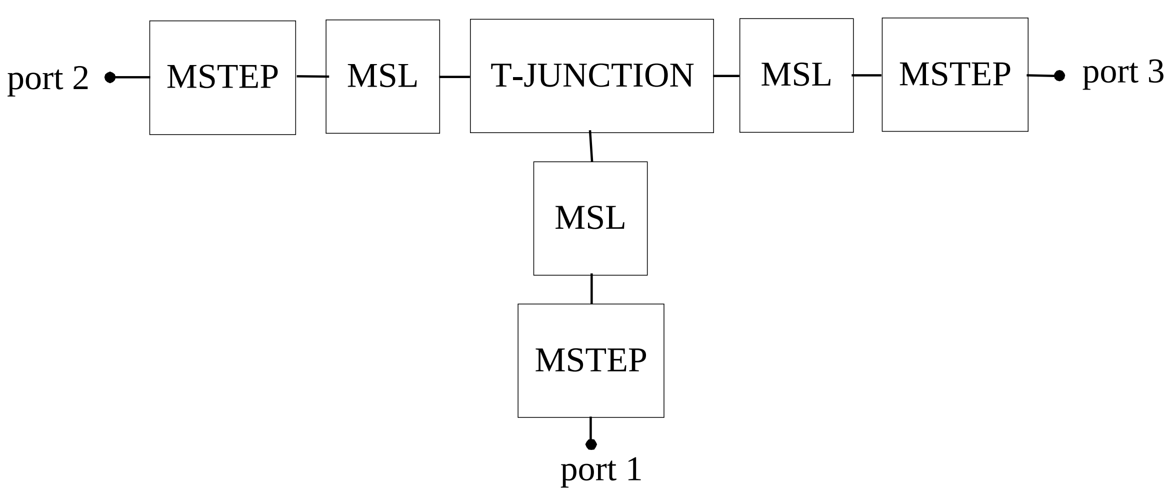
where m is the number of base points selected in the fine model space and $\boldsymbol{e}_{kj}$ is an error vector given by

$$\boldsymbol{e}_{kj} = \boldsymbol{R}_f(\boldsymbol{x}_f^{(j)}, \omega) - \boldsymbol{R}_c(\boldsymbol{x}_{ck}^{(j)}, \omega_{ck}), \quad j = 1,2,\ldots,m$$

Microstrip Shaped T-Junction

the fine and coarse models





Microstrip Shaped T-Junction

the region of interest

Parameter	Minimum value	Maximum value
H	15 mil	25 mil
X	5 mil	15 mil
Y	5 mil	15 mil
ε_r	8	10

the frequency range is 2 GHz to 20 GHz with a step of 2 GHz

the number of base points is 9 and the number of test points is 50

the width W of the input lines is determined in terms of H and ε_r so that the characteristic impedance of the input lines is 50 ohm

the width W_1 is taken as 1/3 of the width W

the width W_2 is obtained so that the characteristic impedance of the microstrip line after the step connected to port 2 is twice that of the microstrip line after the step connected to port 1

Microstrip Shaped T-Junction

MSM for Frequency Intervals (MSMFI) was developed to enhance the accuracy of the T-Junction coarse model

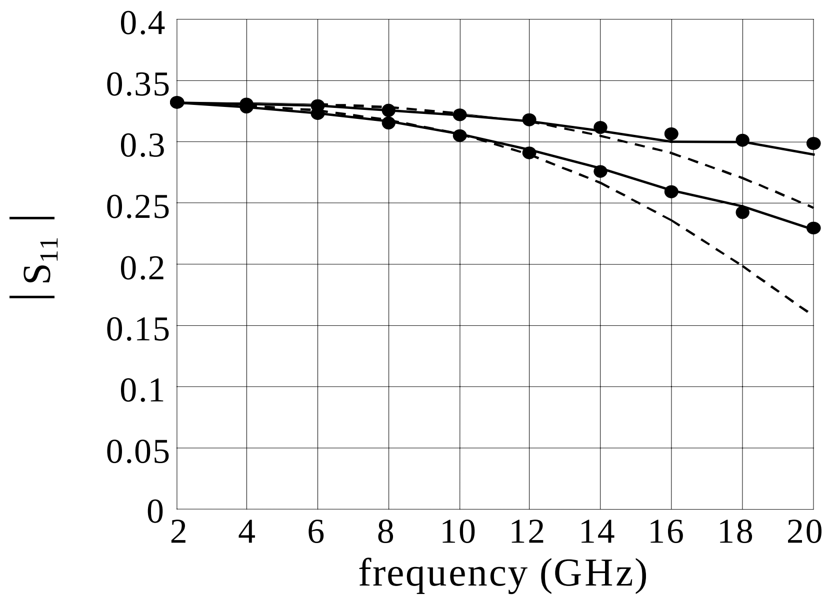
the total frequency range was divided into two intervals: 2 GHz to 16 GHz and 16 GHz to 20 GHz

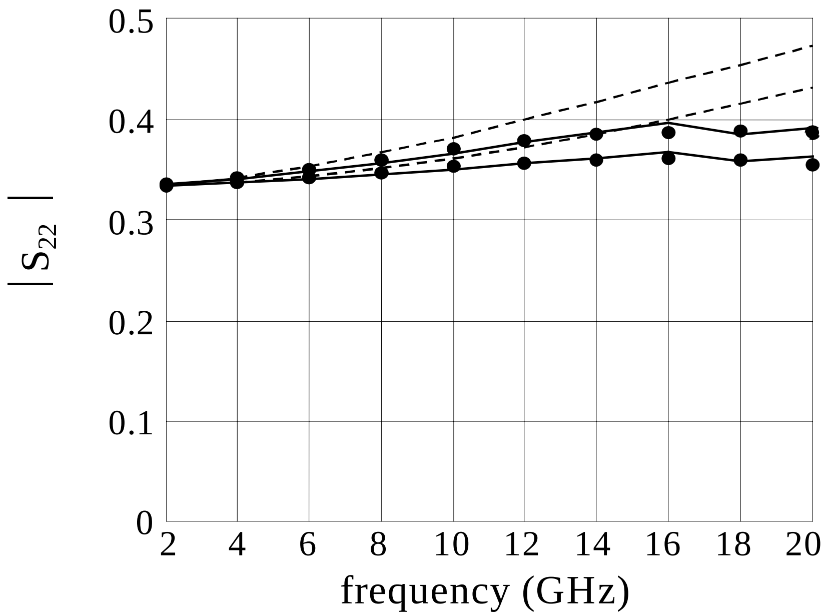
the mapping parameters are

	2 GHz to 16 GHz	16 GHz to 20 GHz
$\boldsymbol{B}$	$\begin{bmatrix} 1.04 & 0.07 & 0.01 & 0.08 & -0.06 & 0.00 & 0.22 \\ 0.00 & 0.89 & 0.00 & -0.07 & -0.20 & 0.06 & -0.03 \\ -0.00 & 0.07 & 0.99 & 0.04 & -0.12 & 0.01 & -0.06 \\ -0.04 & 0.00 & -0.01 & 0.97 & 0.10 & -0.06 & -0.27 \\ 0.01 & 0.04 & 0.00 & 0.03 & 0.99 & -0.05 & -0.03 \\ -0.13 & -0.05 & -0.04 & -0.16 & 0.12 & 0.99 & 0.62 \\ -0.08 & 0.12 & -0.03 & 0.00 & -0.07 & 0.03 & 0.83 \end{bmatrix}$	$\begin{bmatrix} 0.99 & 0.02 & -0.00 & 0.01 & -0.09 & -0.01 & 0.13 \\ 0.05 & 0.85 & 0.01 & -0.07 & -0.28 & 0.01 & -0.01 \\ -0.06 & 0.15 & 0.98 & 0.04 & -0.25 & 0.00 & 0.02 \\ -0.10 & -0.06 & -0.03 & 0.88 & 0.13 & -0.09 & -0.27 \\ 0.08 & 0.04 & 0.03 & 0.11 & 1.07 & -0.04 & -0.12 \\ -0.14 & -0.02 & -0.05 & -0.15 & 0.23 & 1.03 & 0.51 \\ -0.13 & 0.22 & -0.04 & 0.02 & -0.07 & 0.03 & 0.87 \end{bmatrix}$
$\boldsymbol{c}$	$[0.02 \;\; 0.01 \;\; -0.01 \;\; -0.03 \;\; -0.01 \;\; 0.07 \;\; -0.03]^T$	$[0.01 \;\; 0.01 \;\; -0.01 \;\; -0.03 \;\; -0.01 \;\; 0.05 \;\; -0.03]^T$
$\boldsymbol{s}$	$[-0.01 \;\; 0.09 \;\; -0.10 \;\; -0.02 \;\; 0.00 \;\; -0.02 \;\; -0.20]^T$	$[0.00 \;\; 0.01 \;\; -0.01 \;\; 0.00 \;\; 0.00 \;\; 0.00 \;\; -0.02]^T$
$\boldsymbol{t}$	$\boldsymbol{0}$	$[0.01 \;\; 0.00 \;\; -0.02 \;\; 0.00 \;\; 0.00 \;\; 0.00 \;\; 0.00]^T$
σ	0.851	0.957
δ	–0.003	0.008

Microstrip Shaped T-Junction

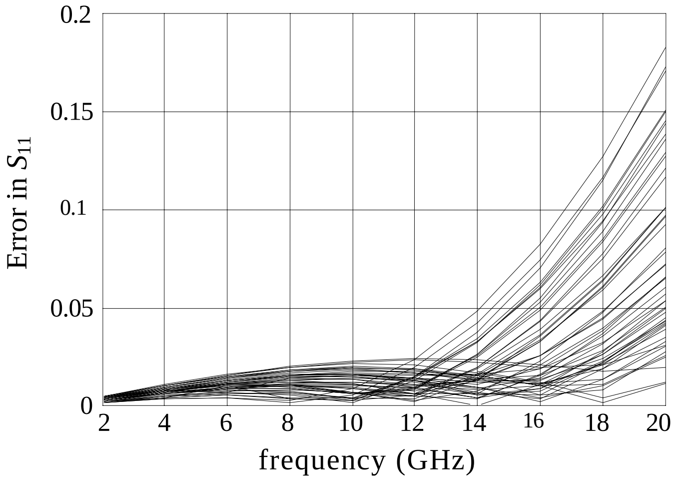
the responses of the shaped T-Junction at two test points in the region of interest by Sonnet's ***em*** (●), by the coarse model (---) and by the enhanced coarse model (—)

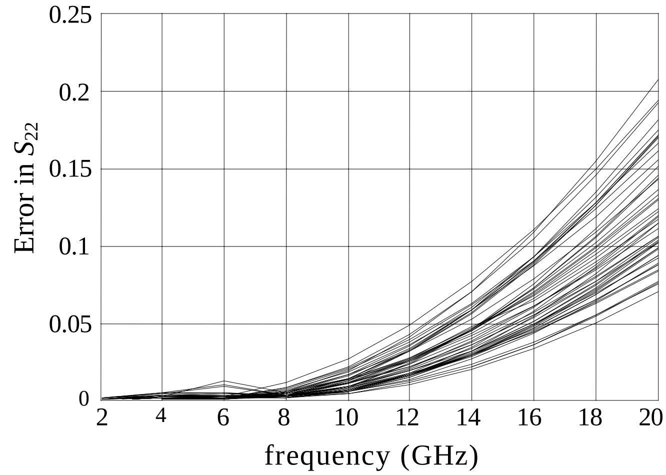




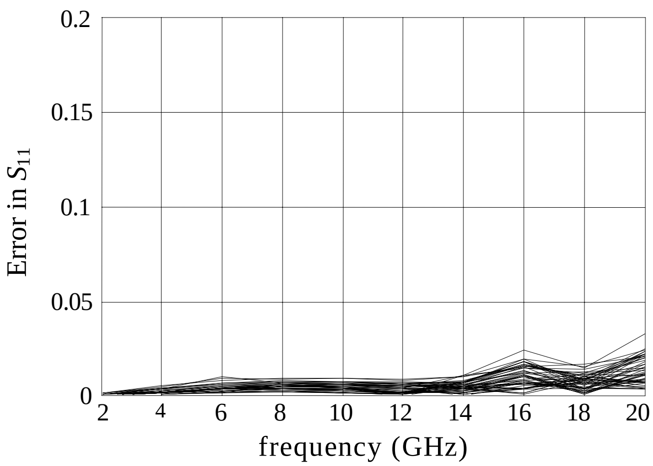
Microstrip Shaped T-Junction

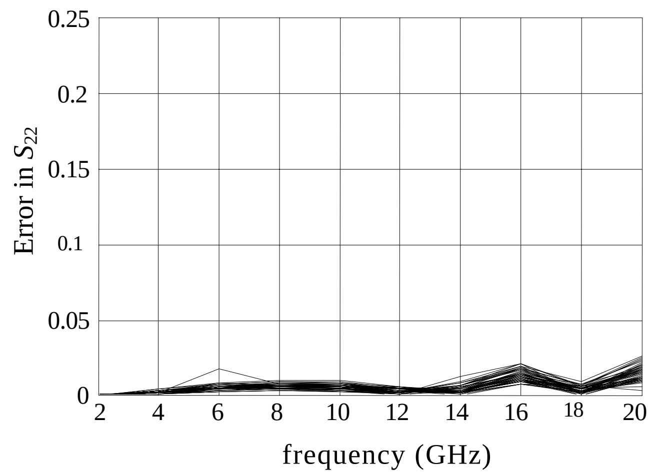
the error in S_{11} and in S_{22} of the shaped T-Junction coarse model at the test points





the error in S_{11} and in S_{22} of the shaped T-Junction enhanced coarse model at the test points





Microstrip Shaped T-Junction

the enhanced coarse model for the shaped T-Junction can be utilized in optimization

the optimization variables are X and Y

the other parameters are kept fixed (W = 24 mil, H = 25 mil and $\varepsilon_r = 9.9$)

the design specifications are

$$|S_{11}| \leq 1/3, \quad |S_{22}| \leq 1/3$$

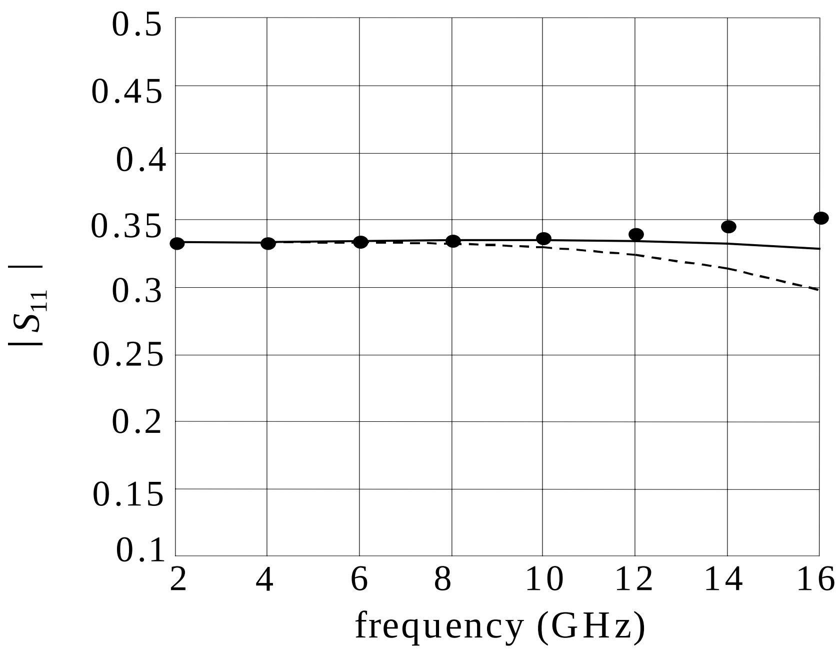
in the frequency range 2 GHz to 16 GHz

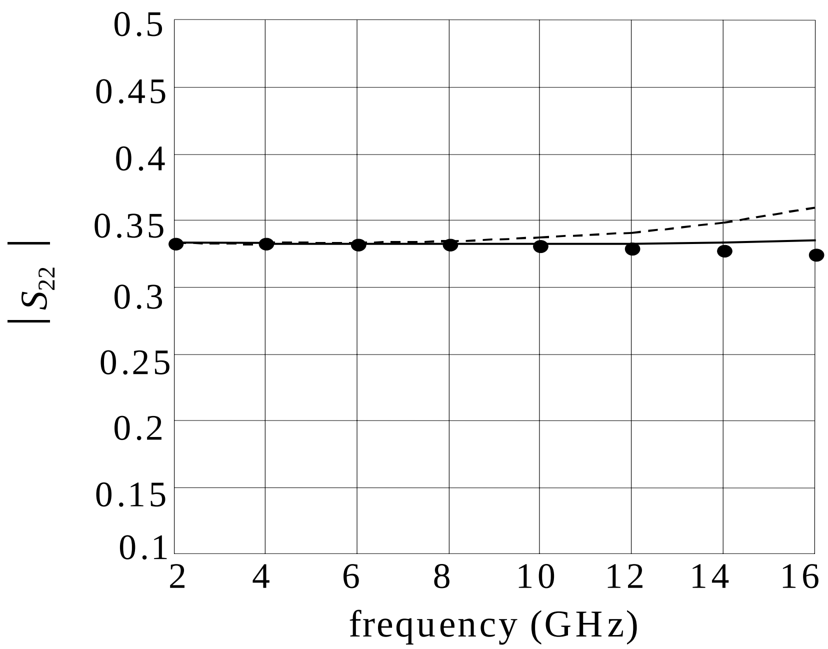
the minimax optimizer in OSA90/hope reached the solution

$$X = 2.1 \text{ mil and } Y = 21.1 \text{ mil}$$

Microstrip Shaped T-Junction

responses of the optimum shaped T-Junction by Sonnet's ***em*** (●), by the coarse model (---) and by the enhanced coarse model (—)





Space Mapping Optimization Exploiting Surrogates

a powerful new Space Mapping (SM) optimization algorithm is presented

it draws upon recent developments in both surrogate model-based optimization and modeling of microwave devices

SM optimization is formulated as a general optimization problem of a surrogate model

this model is a convex combination of a mapped coarse model and a linearized fine model

it exploits, in a novel way, a linear frequency-sensitive mapping

during the optimization iterates, the coarse and fine models are simulated at different sets of frequencies.

this approach is shown to be especially powerful if a significant response shift exists

SM Optimization vs. Surrogate Model Optimization

the optimal fine model design $\boldsymbol{x}_f^*$ is obtained by solving

$$\boldsymbol{x}_f^* = arg\left\{ \min_{\boldsymbol{x}_f} U(\boldsymbol{R}_f(\boldsymbol{x}_f)) \right\}$$

solving this problem using direct optimization methods can be prohibitive

SM optimization algorithms efficiently solve this design problem

they exploit the existence of a less accurate but fast coarse model of the circuit under consideration

a mapping $\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_f)$ is established between the two spaces such that $\boldsymbol{R}_f(\boldsymbol{x}_f) \approx \boldsymbol{R}_c(\boldsymbol{x}_c)$

the space-mapped design $\overline{\boldsymbol{x}}_f$ is a solution of the nonlinear system

$$\boldsymbol{f}(\boldsymbol{x}_f) = \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* = \boldsymbol{0}$$

the mapping $\boldsymbol{P}(\boldsymbol{x}_f)$ is approximated through Parameter Extraction (PE)

SM Optimization vs. Surrogate Model Optimization (continued)

the ASM algorithm solves this problem using a quasi-Newton method

the TRASM algorithm integrates a trust region methodology with the ASM technique

surrogate model optimization approximates the fine model at the ith iteration by a surrogate model $\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f) \in \Re^{m \times 1}$

the step suggested is obtained by solving

$$\boldsymbol{h}^{(i)} = arg \left\{ \min_{\boldsymbol{h}^{(i)}} \; U(\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)})) \right\}, \; \left\| \boldsymbol{h}^{(i)} \right\| \le \delta^{(i)}$$

$\boldsymbol{h}^{(i)}$ is validated using fine model simulation

the accuracy of the surrogate model is improved in every iteration using the simulated fine model points

The Surrogate Model

our surrogate model is a convex combination of a mapped coarse model and a linearized fine model

the *i*th iteration surrogate model is

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}_f) = \lambda^{(i)}\boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f) + (1-\lambda^{(i)})(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) + \boldsymbol{J}_f^{(i)}\Delta\boldsymbol{x}_f),\ \lambda^{(i)} \in [0,1]$$

the mapped coarse model utilizes the frequency-sensitive mapping

$$\boldsymbol{R}_f(\boldsymbol{x}_f,\omega_j) \approx \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f,\omega_j) = \boldsymbol{R}_c(\boldsymbol{P}^{(i)}(\boldsymbol{x}_f,\omega_j), P_\omega^{(i)}(\boldsymbol{x}_f,\omega_j))$$

where

$$\begin{bmatrix} \boldsymbol{P}^{(i)}(\boldsymbol{x}_f,\omega_j) \\ P_\omega^{(i)}(\boldsymbol{x}_f,\omega_j) \end{bmatrix} = \begin{bmatrix} \boldsymbol{B}^{(i)} & \boldsymbol{s}^{(i)} \\ \boldsymbol{t}^{(i)T} & \sigma^{(i)} \end{bmatrix} \begin{bmatrix} \Delta\boldsymbol{x}_f \\ \omega_j \end{bmatrix} + \begin{bmatrix} \boldsymbol{c}^{(i)} \\ \gamma^{(i)} \end{bmatrix}$$

the parameters $\boldsymbol{B}^{(i)} \in \Re^{n\times n}$, $\boldsymbol{s}^{(i)} \in \Re^{n\times 1}$, $\boldsymbol{t}^{(i)} \in \Re^{n\times 1}$, $\boldsymbol{c}^{(i)} \in \Re^{n\times 1}$, $\sigma^{(i)} \in \Re^{1\times 1}$ and $\gamma^{(i)} \in \Re^{1\times 1}$ are obtained such that the mapped coarse model approximates the fine model over a given set of fine model points $V^{(i)}$ and frequencies ω

The Surrogate Model (continued)

the mapping parameters are obtained through the optimization process

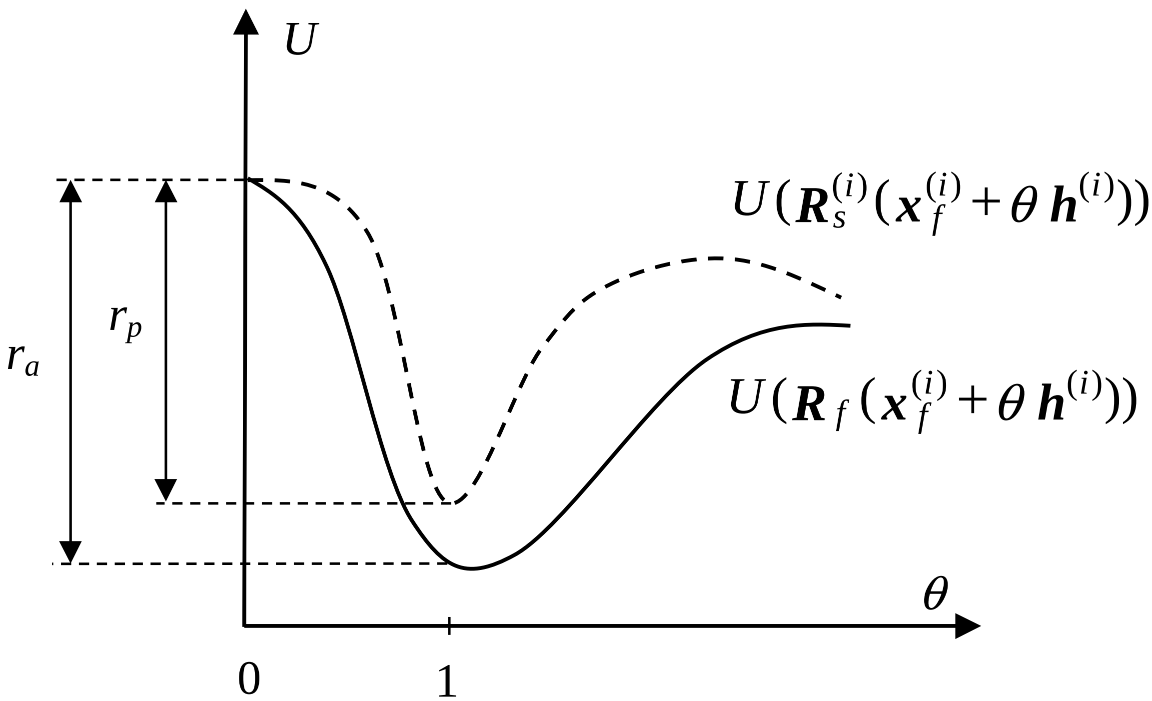
$$[\boldsymbol{B}^{(i)}, \boldsymbol{s}^{(i)}, \boldsymbol{t}^{(i)}, \sigma^{(i)}, \boldsymbol{c}^{(i)}, \gamma^{(i)}] =$$

$$arg\left\{ \min_{\boldsymbol{B}, \boldsymbol{s}, \boldsymbol{t}, \sigma, \boldsymbol{c}, \gamma} \left\| \begin{bmatrix} \boldsymbol{e}_1^T & \boldsymbol{e}_2^T & \cdots & \boldsymbol{e}_{N_p}^T \end{bmatrix}^T \right\| \right\}$$

where

$$\boldsymbol{e}_k = \boldsymbol{R}_m^{(i)}(\boldsymbol{x}_f^{(k)}) - \boldsymbol{R}_f(\boldsymbol{x}_f^{(k)}) \quad \forall\, \boldsymbol{x}_f^{(k)} \in V^{(i)}$$

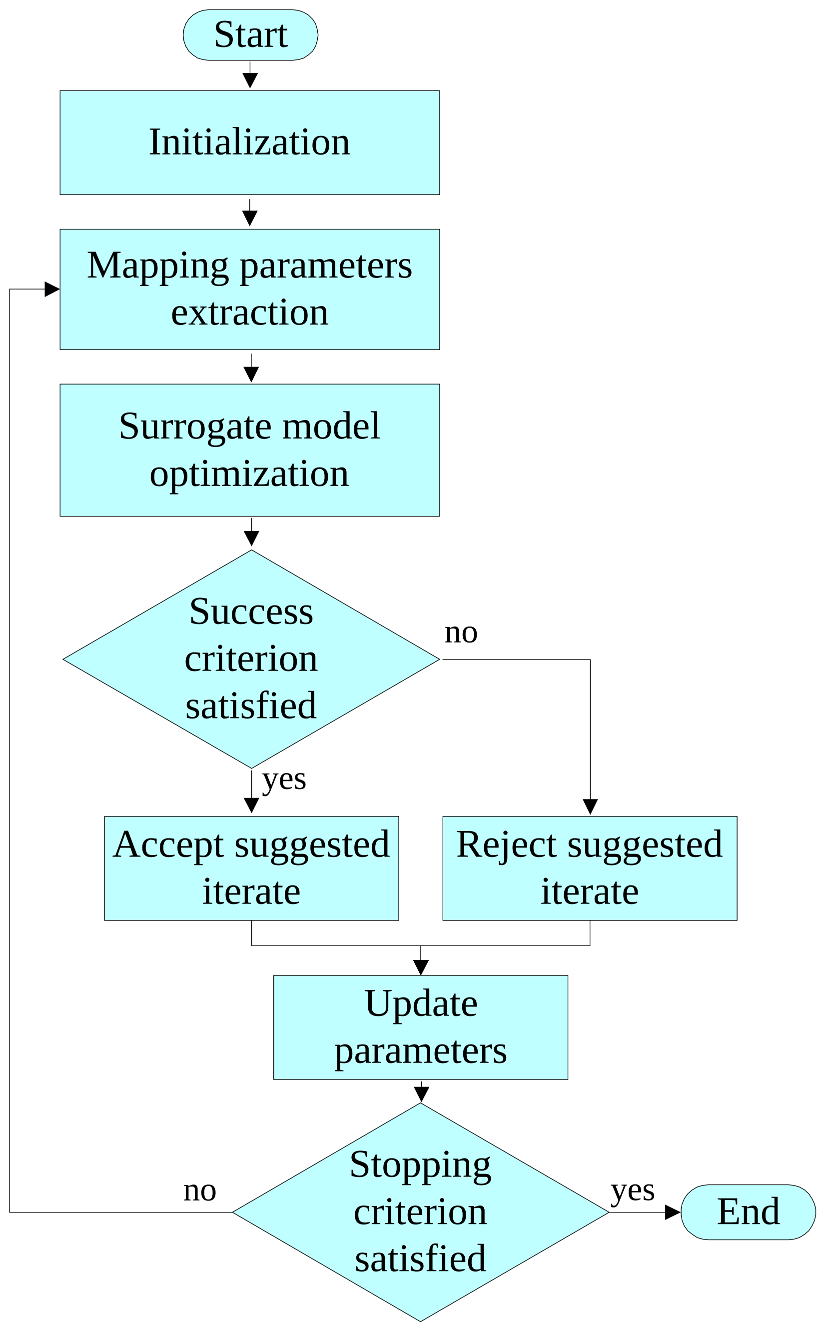
Illustration of One Iteration of the Algorithm



r_p = predicted reduction in the objective function using the surrogate model

r_a = actual reduction in the objective function

The Algorithm Flowchart



Neural Space Mapping (NSM) Optimization

exploits the SM-based neuromodeling techniques
(Bandler et al., 1999)

coarse models are used as source of knowledge that reduce the amount of learning data and improve the generalization and extrapolation performance

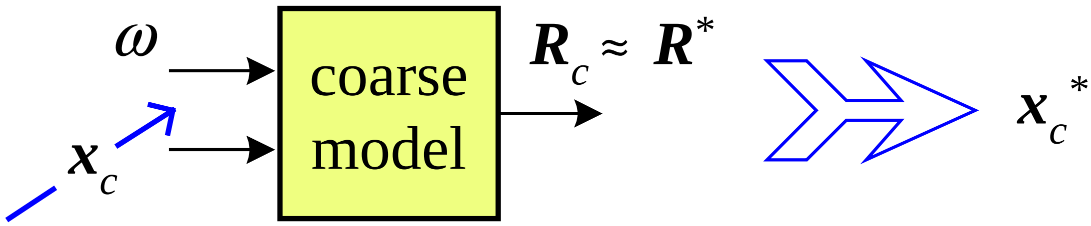
NSM requires a reduced set of upfront learning base points

the initial learning base points are selected through sensitivity analysis using the coarse model

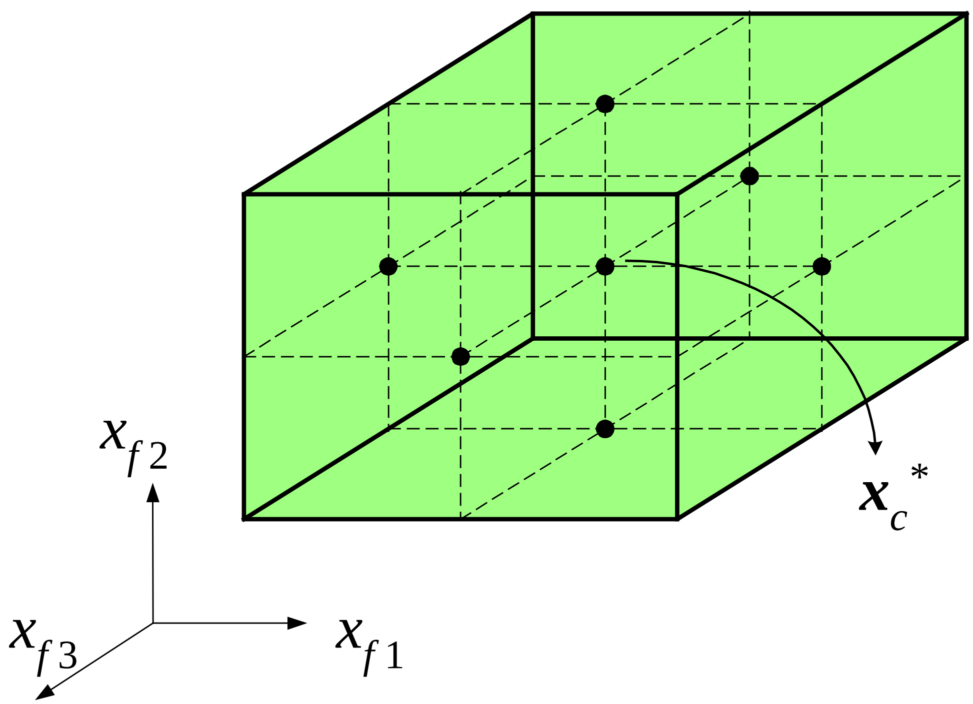
neuromappings are developed iteratively: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons

Neural Space Mapping (NSM) Optimization Concept

step 1



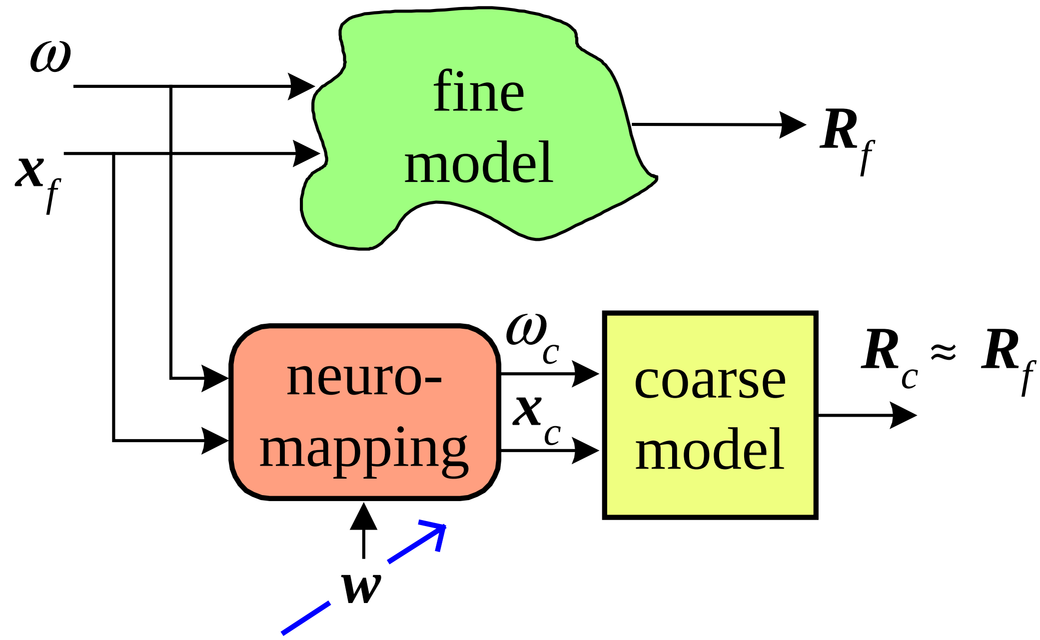
step 2



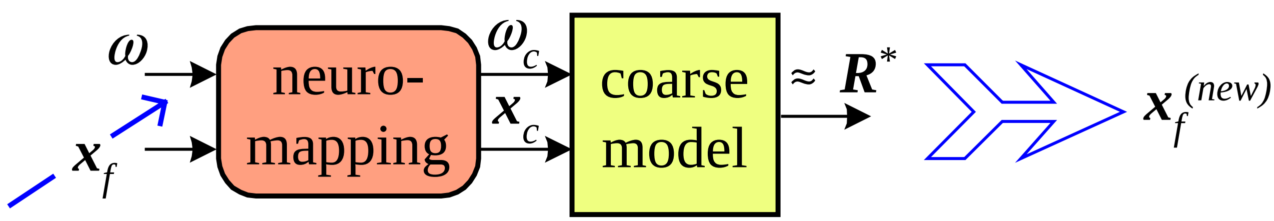
(2n + 1 learning base points for a microwave circuit with n design parameters)

Neural Space Mapping (NSM) Optimization Concept

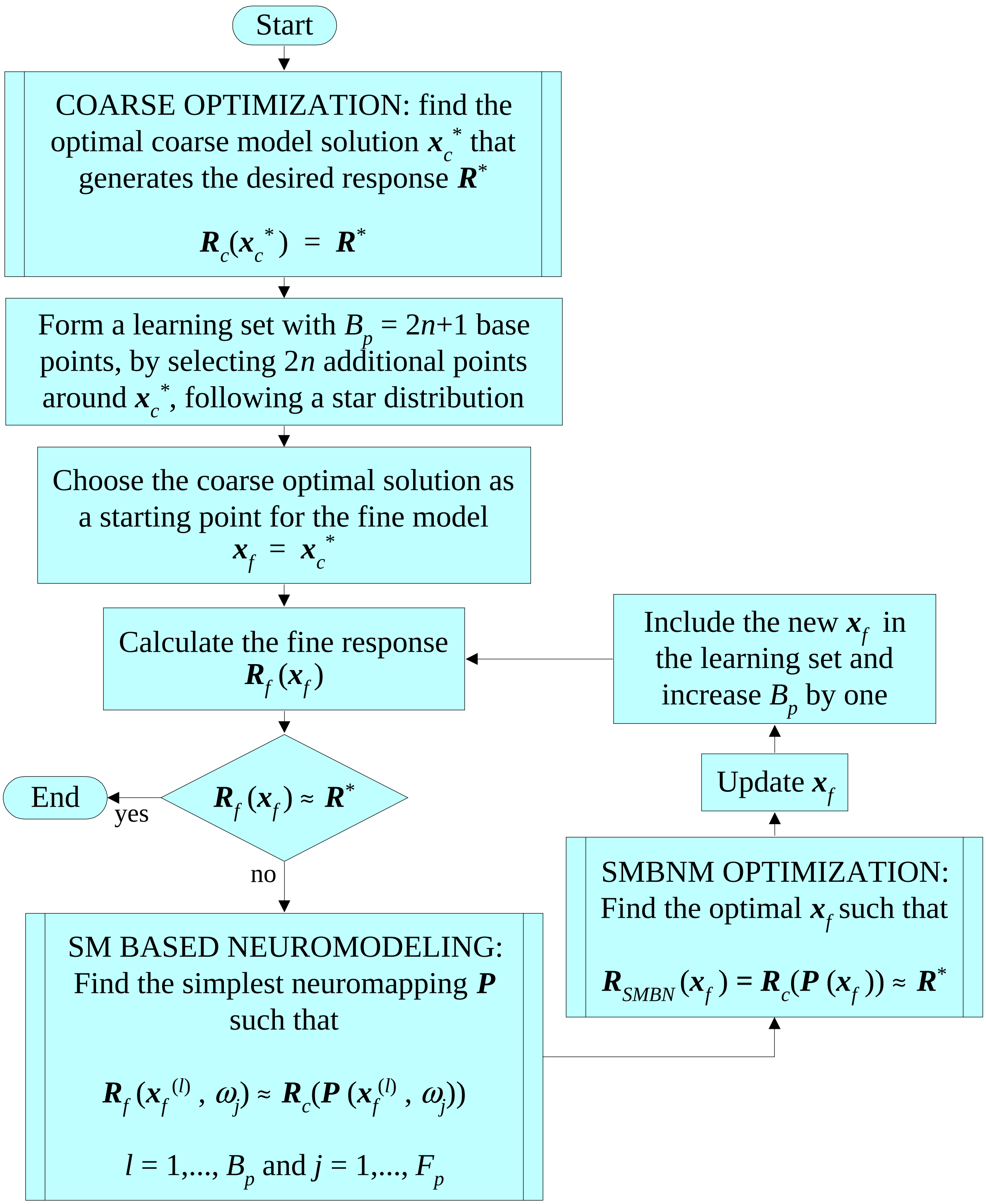
step 3



step 4

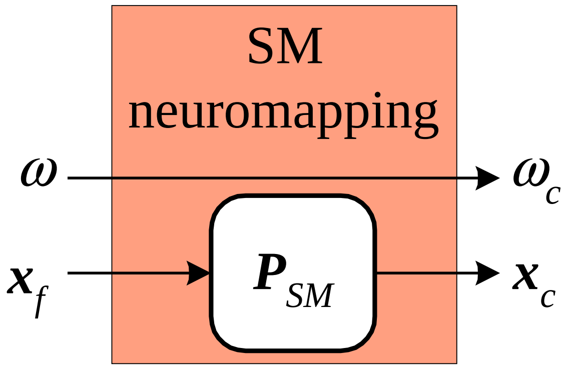


Neural Space Mapping (NSM) Optimization Algorithm

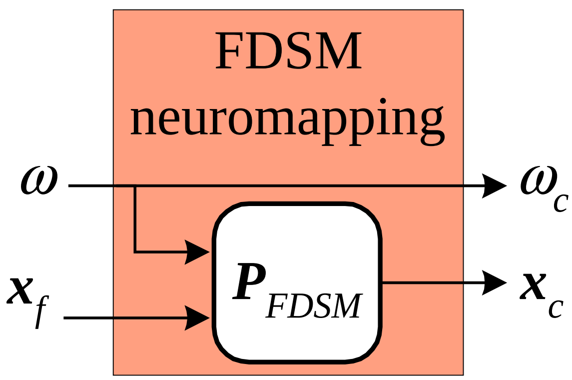


Neuromappings

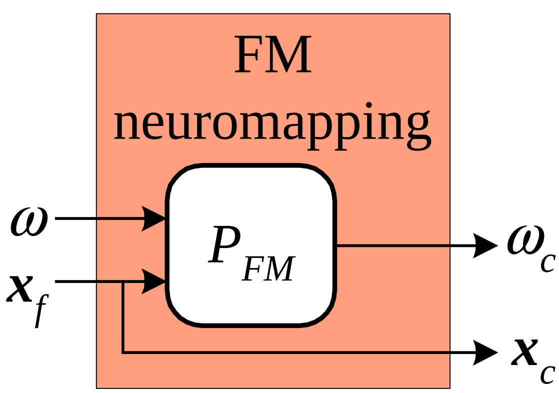
Space Mapped neuromapping



Frequency-Dependent Space Mapped neuromapping

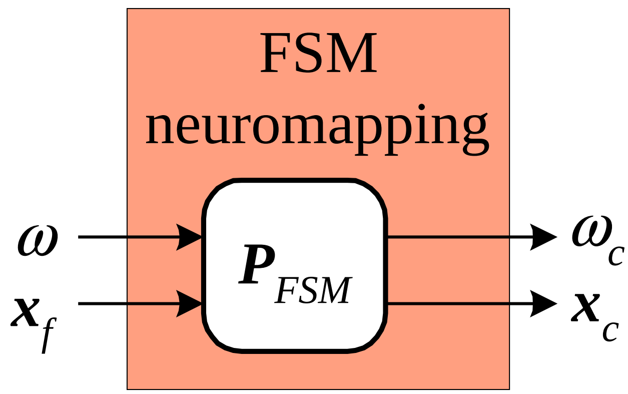


Frequency Mapped neuromapping

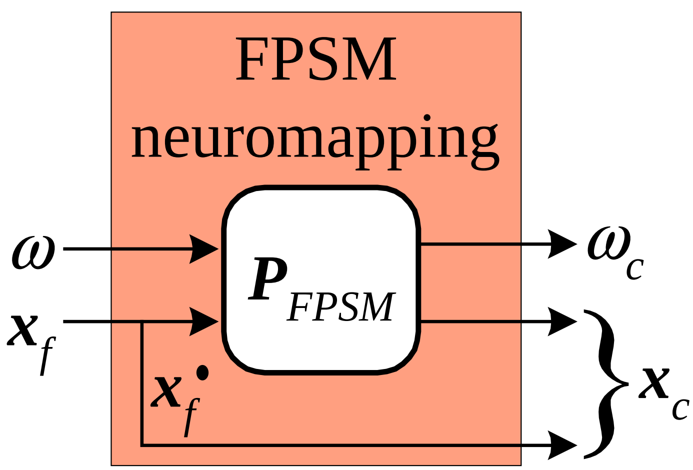


Neuromappings (continued)

Frequency Space Mapped neuromapping



Frequency Partial-Space Mapped neuromapping



we chose a unit mapping ($\boldsymbol{x}_c = \boldsymbol{x}_f$ and $\omega_c = \omega$) as the starting point for the optimization problem

SM-Based Neuromodel Optimization

we use an SM-based neuromodel as an improved coarse model, optimizing its parameters to generate the desired response

$\boldsymbol{R}_{SMBN}$ is the SM-based neuromodel response:

$$\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f) = [\boldsymbol{R}^1_{SMBN}(\boldsymbol{x}_f)^T \quad \ldots \quad \boldsymbol{R}^m_{SMBN}(\boldsymbol{x}_f)^T]^T$$

where

$$\boldsymbol{R}^r_{SMBN}(\boldsymbol{x}_f) = [R^r_c(\boldsymbol{x}_{c1}, \omega_{c1}) \quad \ldots \quad R^r_c(\boldsymbol{x}_{cF_p}, \omega_{cF_p})]^T, \; r = 1, \ldots, m$$

with

$$\begin{bmatrix} \boldsymbol{x}_{c_j} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j, \boldsymbol{w}^*) \quad , \quad j = 1, \ldots, F_p$$

the next iterate is obtained by solving

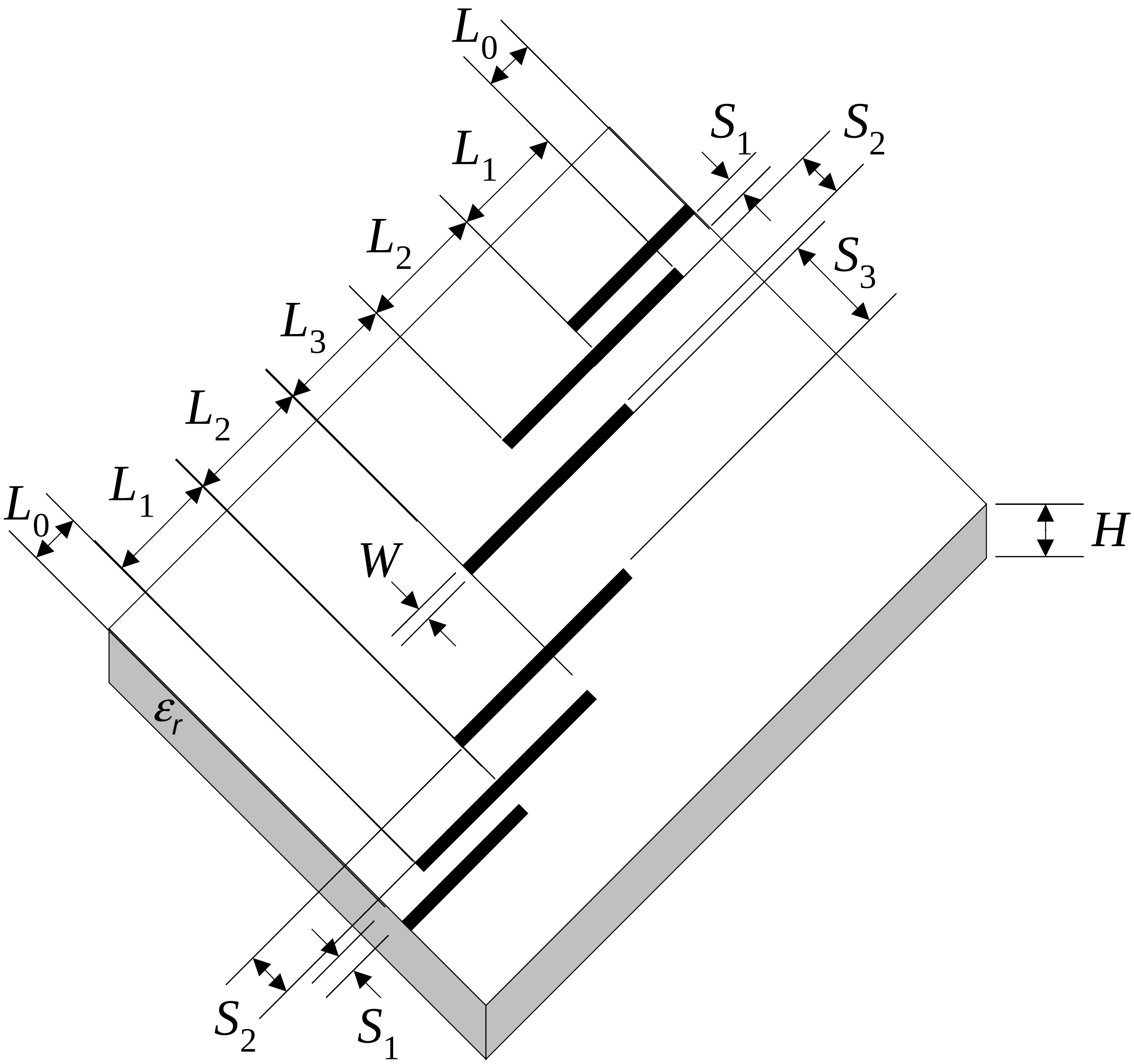
$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f))$$

if an SMN neuromapping is used to implement $\boldsymbol{P}^{(i)}$, the next iterate can be obtained in a simpler manner by solving

$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} \left\| \boldsymbol{P}^{(i)}_{SM}(\boldsymbol{x}_f, \boldsymbol{w}^*) - \boldsymbol{x}^*_c \right\|$$

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(Westinghouse, 1993)



NSM Optimization of the HTS Microstrip Filter

specifications

$|S_{21}| \geq 0.95$ in the passband and $|S_{21}| \leq 0.05$ in the stopband,

where the stopband includes frequencies below 3.967 GHz and above 4.099 GHz, and the passband lies in the range [4.008GHz, 4.058GHz]

“coarse” model: OSA90/hope™ empirical models

“fine” model: Sonnet’s ***em***™ with high resolution grid

we take L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; the metalization is considered lossless

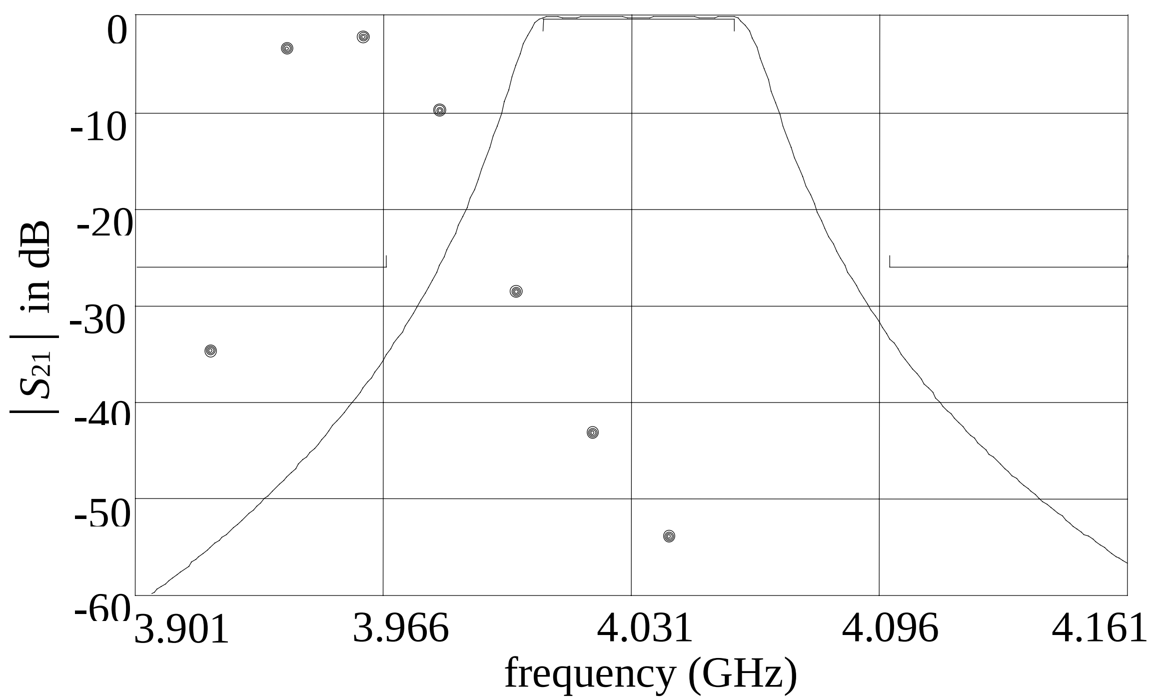
the design parameters are $\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$

NSM Optimization of the HTS Filter (continued)

coarse and fine model responses at the optimal coarse solution,

$\boldsymbol{x}_c^* = [188.33 \;\; 197.98 \;\; 188.58 \;\; 21.97 \;\; 99.12 \;\; 111.67]^T$ (mils)

OSA90/hope™ (–) and ***em***™ (•)

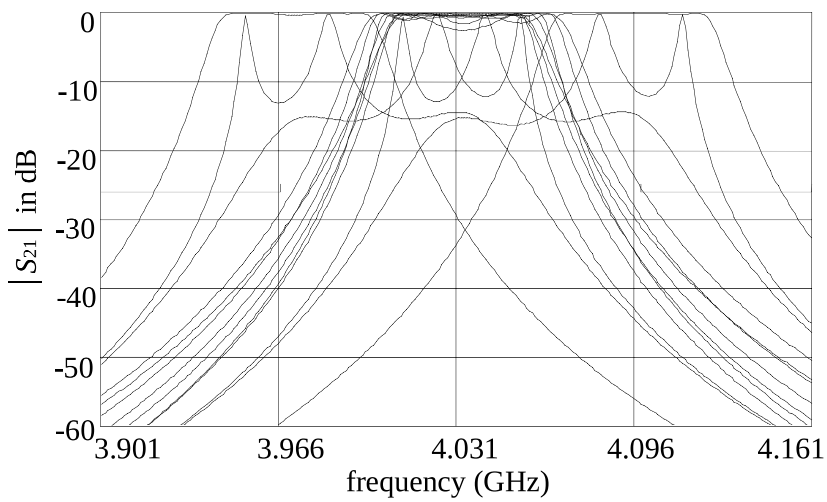


NSM Optimization of the HTS Filter (continued)

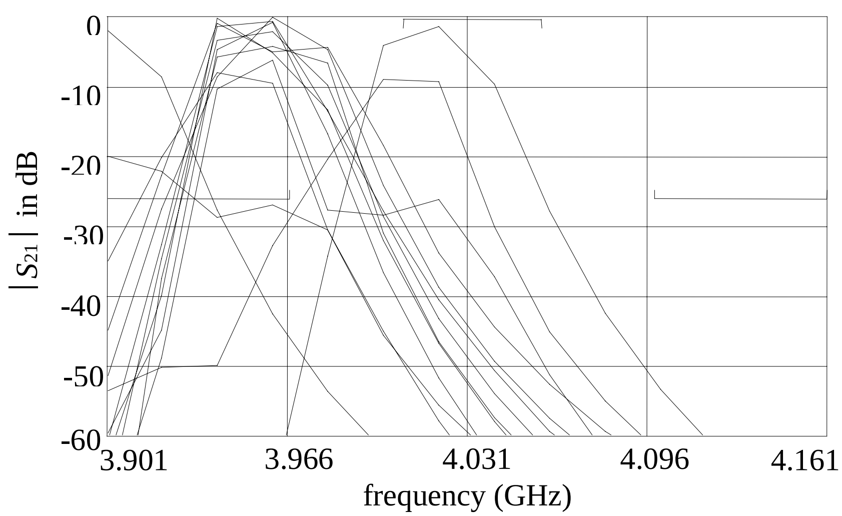
the initial $2n$+1 points are chosen by performing sensitivity analysis on the coarse model: a 3% deviation from $\boldsymbol{x}_c^*$ for L_1, L_2, and L_3 is used, while a 20% is used for S_1, S_2, and S_3

coarse and fine model responses at base points:

OSA90/hope™



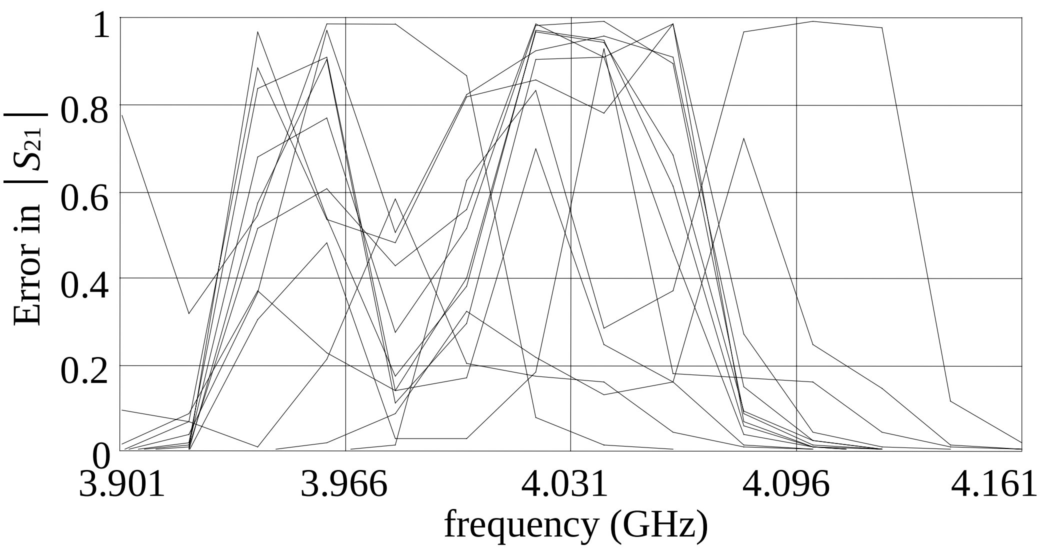
em™



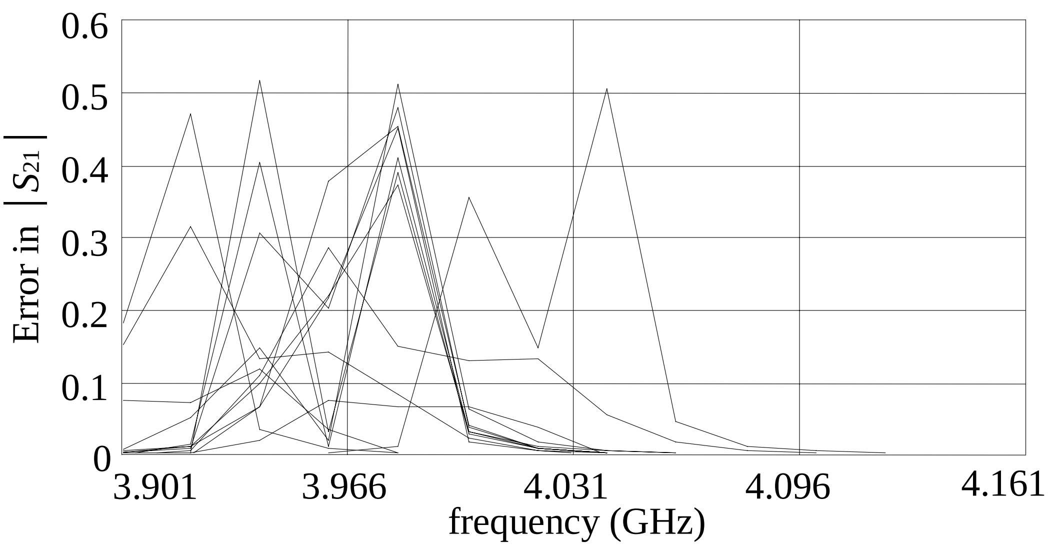
NSM Optimization of the HTS Filter (continued)

Learning errors at base points:

before any neuromapping



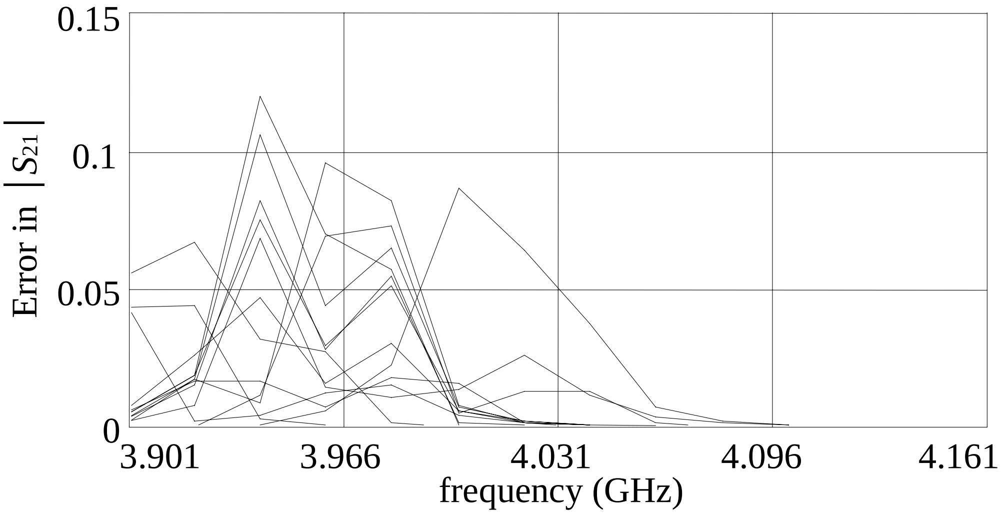
mapping ω with a 3LP:7-3-1



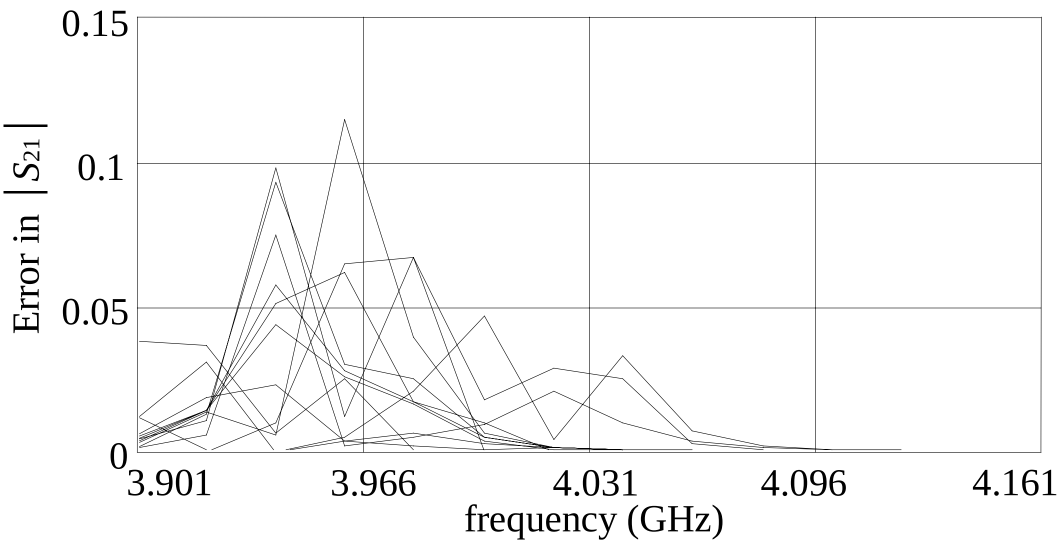
NSM Optimization of the HTS Filter (continued)

Learning errors at base points:

mapping ω and L_1 with a 3LP:7-4-2



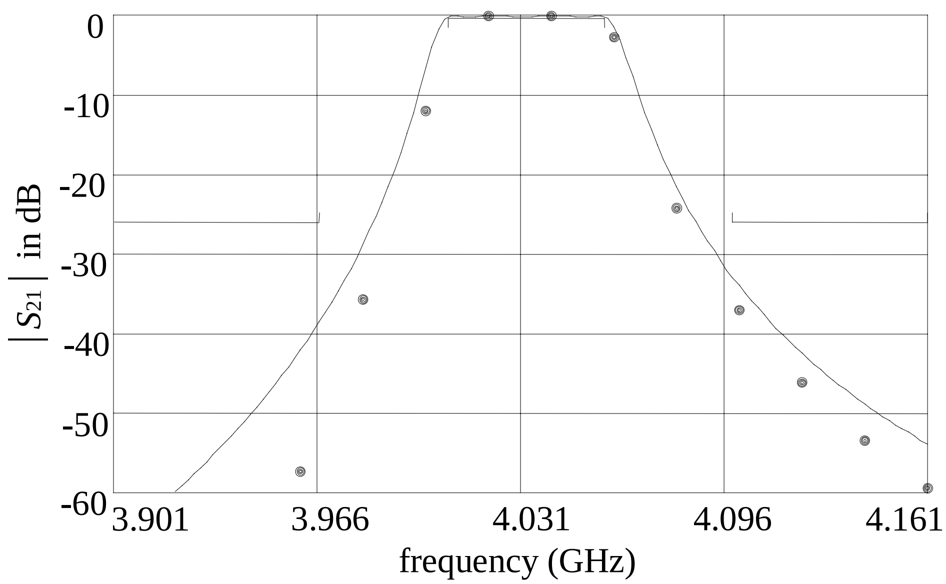
mapping ω, L_1 and S_1 with a 3LP:-7-5-3

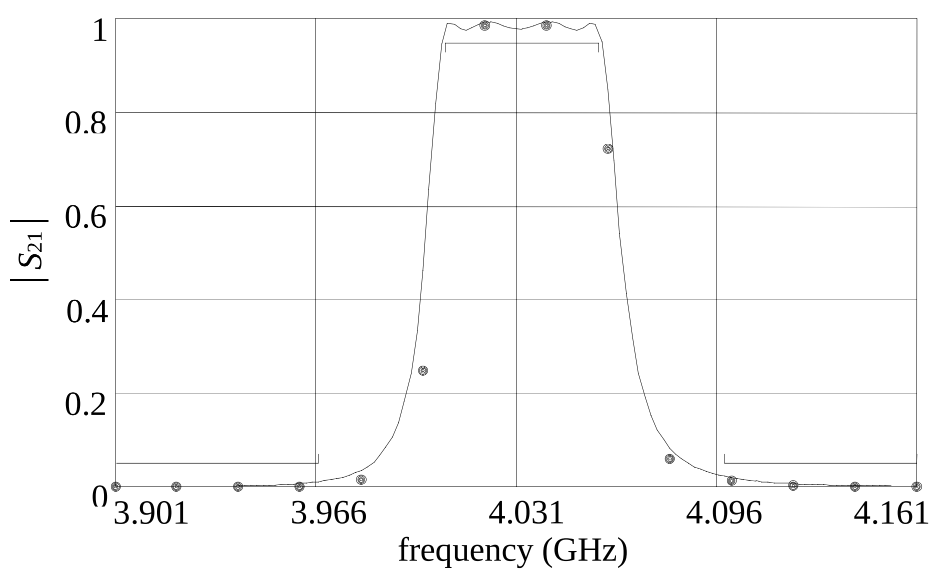


NSM Optimization of the HTS Filter (continued)

em™ (•) and FPSM 7-5-3 (–) model responses at the next point predicted after the first NSM iteration

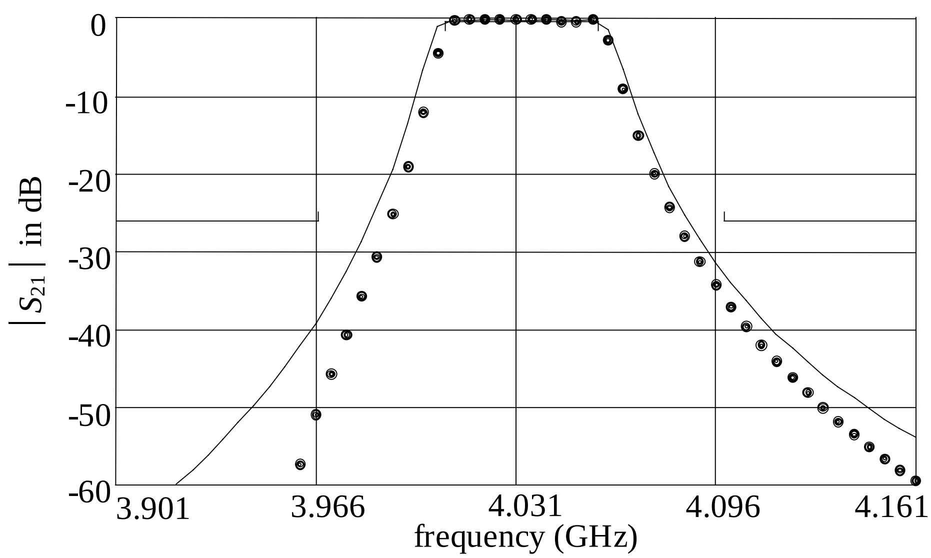
$\boldsymbol{x}_f^{(14)} = [185.37 \;\; 195.01 \;\; 184.24 \;\; 21.04 \;\; 86.36 \;\; 91.39]^T$ (mils)

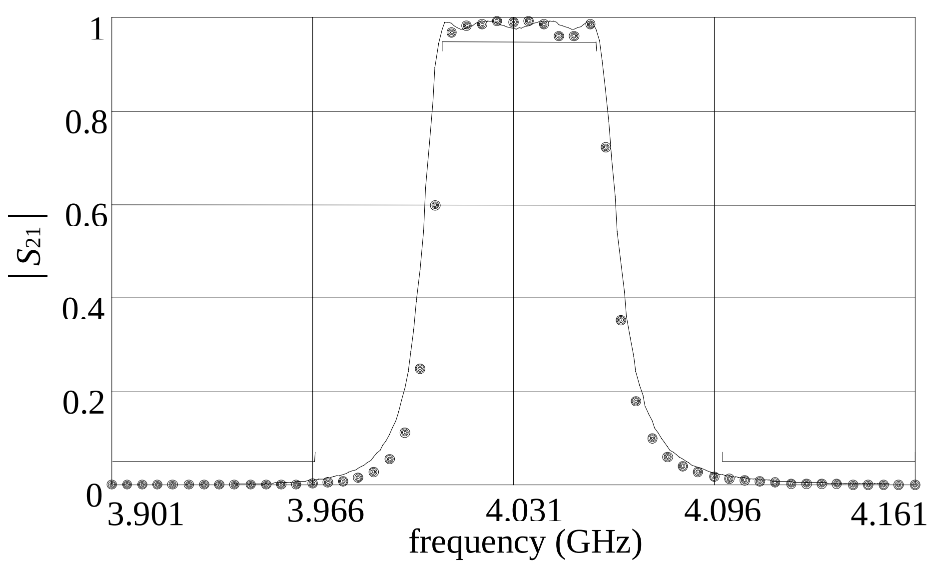




NSM Optimization of the HTS Filter (continued)

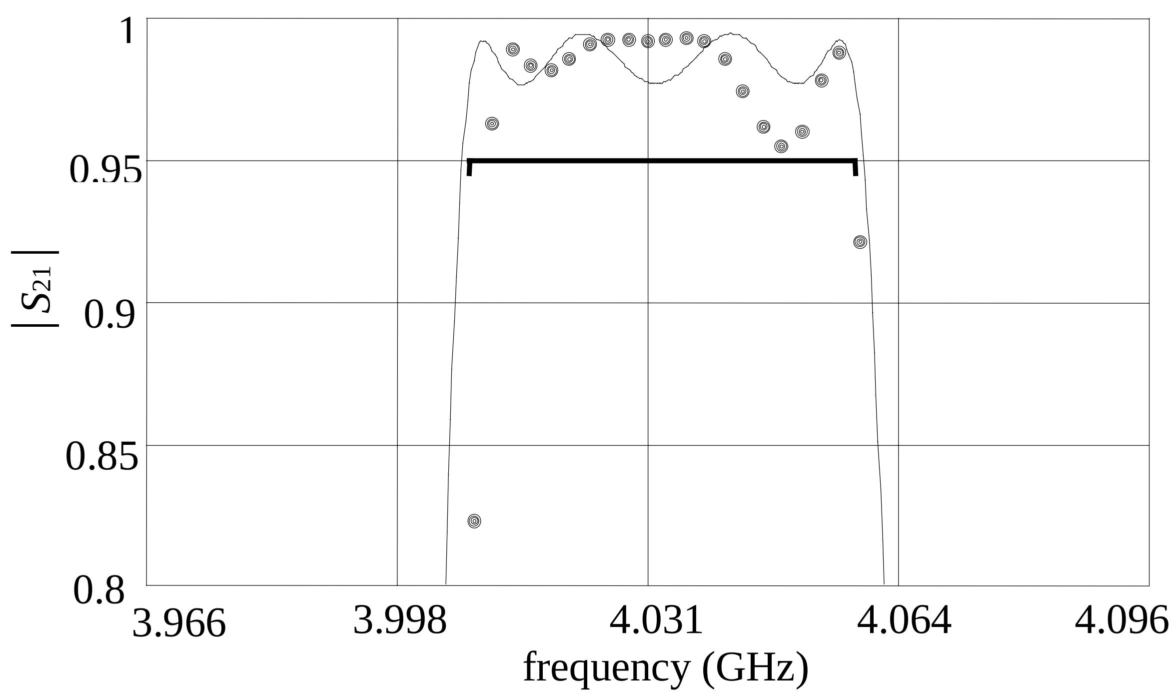
em™ (•) and FPSM 7-5-3 (–) model responses at the NSM solution using a fine frequency sweep





NSM Optimization of the HTS Filter (continued)

em™ (•) and FPSM 7-5-3 (–) model responses at the NSM solution in the passband using a fine frequency sweep



Conclusions

we review a comprehensive framework called Generalized Space mapping (GSM) to engineering device modeling

in GSM we utilize a few relevant full-wave EM simulations to match the responses of the fine model and the coarse model over a designable region of parameters and frequency

GSM generalizes the Space Mapping (SM), the Frequency Space Mapping (FSM) and the Multiple Space Mapping (MSM) concepts to build a new engineering device modeling framework

two fundamental concepts are presented: one is a basic Space Mapping Super Model (SMSM) and the other is a basic Frequency-Space Mapping Super Model (FSMSM)

MSM can be combined with SMSM and FSMSM to provide a powerful and reliable modeling tool for microwave devices

a novel SM optimization algorithm based on surrogate models is presented

SM optimization is formulated as a general optimization problem of a surrogate model

the surrogate model is a convex combination of a mapped coarse model and a linearized fine model

Conclusions (continued)

it exploits, in a novel way, a linearized frequency-sensitive mapping

we present an innovative algorithm for EM optimization based on Space Mapping technology and Artificial Neural Networks

Neural Space Mapping (NSM) optimization exploits our SM-based neuromodeling techniques

NSM does not require parameter extraction to predict the next point

an initial mapping is established by performing upfront fine model analysis at a reduced number of base points

coarse model sensitivity is exploited to select those base points

Huber optimization is used to train simple SM-based neuromodels at each iteration

the SM-based neuromodels are developed without using testing points: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons

an HTS filter illustrate our NSM optimization technique

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