Space Mapping Technology with Applications in EM-based Device Modeling and Statistical Design

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presented at

WORKSHOP ON STATISTICAL DESIGN AND MODELING TECHNIQUES FOR MICROWAVE CAD
2001 IEEE MTT-S International Microwave Symposium, Phoenix, AZ, May 21, 2001

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Abstract

The Space Mapping concept intelligently links companion "coarse" and "fine" engineering models of different complexities, e.g., full-wave electromagnetic (EM) simulations and empirical circuit-theory based models.

A comprehensive framework to engineering device modeling which we call Generalized Space Mapping (GSM) has been developed. GSM is a tableau-based approach. It permits many different practical implementations. As a result the accuracy of available empirical models of microwave devices can be significantly enhanced in selected regions of interest in the parameter space. We present two fundamental illustrations: a basic Space Mapping Super Model (SMSM) which maps designable device parameters and a Frequency-Space Mapping Super Model (FSMSM) which also maps the frequency variable. The SMSM and FSMSM concepts have been verified on several modeling problems, typically utilizing a few relevant full-wave EM simulations. We present several microstrip examples, yielding remarkable modeling improvement.

We consider the GSM technique to be very easy to implement. It has been reported to be very useful in the RF industry for development of new library models involving commercial software such as Agilent Momentum and ADS.

Accurate yield optimization and statistical analysis of microwave components are crucial for manufacturability-driven designs in a time-to-market development environment. Yield optimization requires intensive simulations to cover the entire statistic of possible outputs of a given manufacturing process. An efficient procedure to realize EM-based yield optimization and statistical analysis of microwave structures using space mapping based neuromodels will be presented. Several practical microwave components illustrate our technique using commercial EM simulators.

Outline

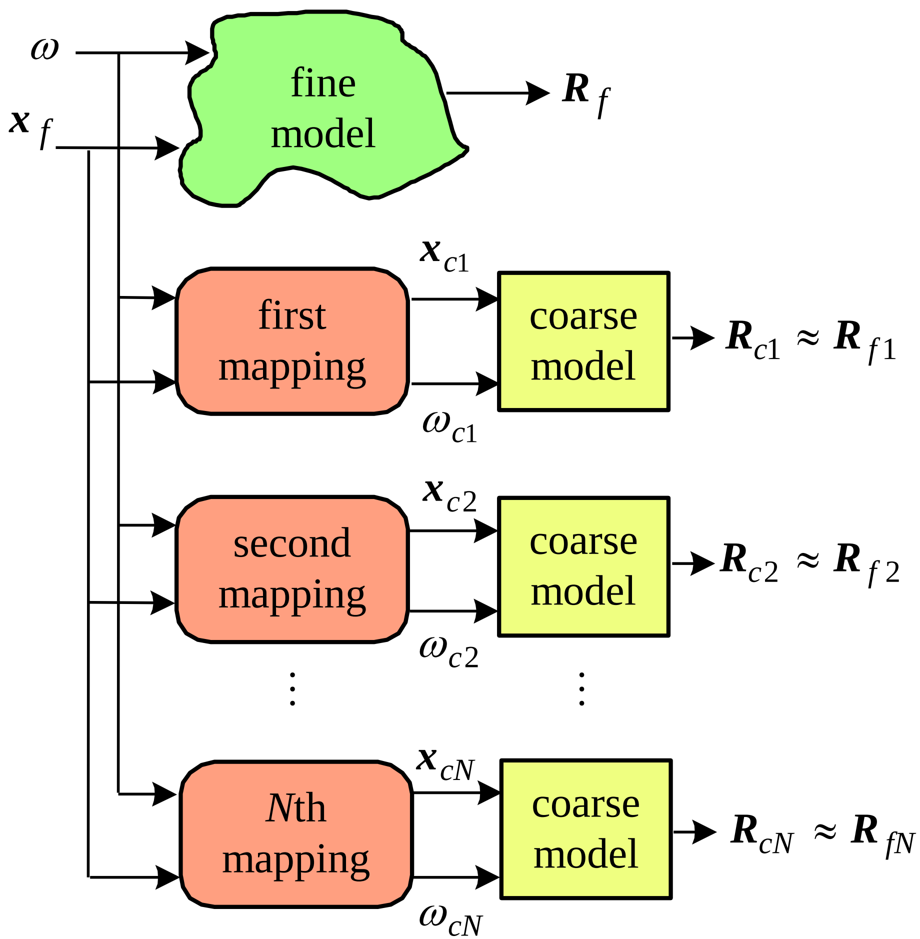
Generalized Space Mapping (GSM) tableau approach is a comprehensive framework for engineering device modeling *(Bandler et al., 2001)*

Neural Space Mapping (NSM) optimization exploiting SM-based neuromodeling techniques *(Bakr et al., 2000)*

statistical analysis and yield optimization using SM-based neuromodels *(Bandler et al., 2001)*

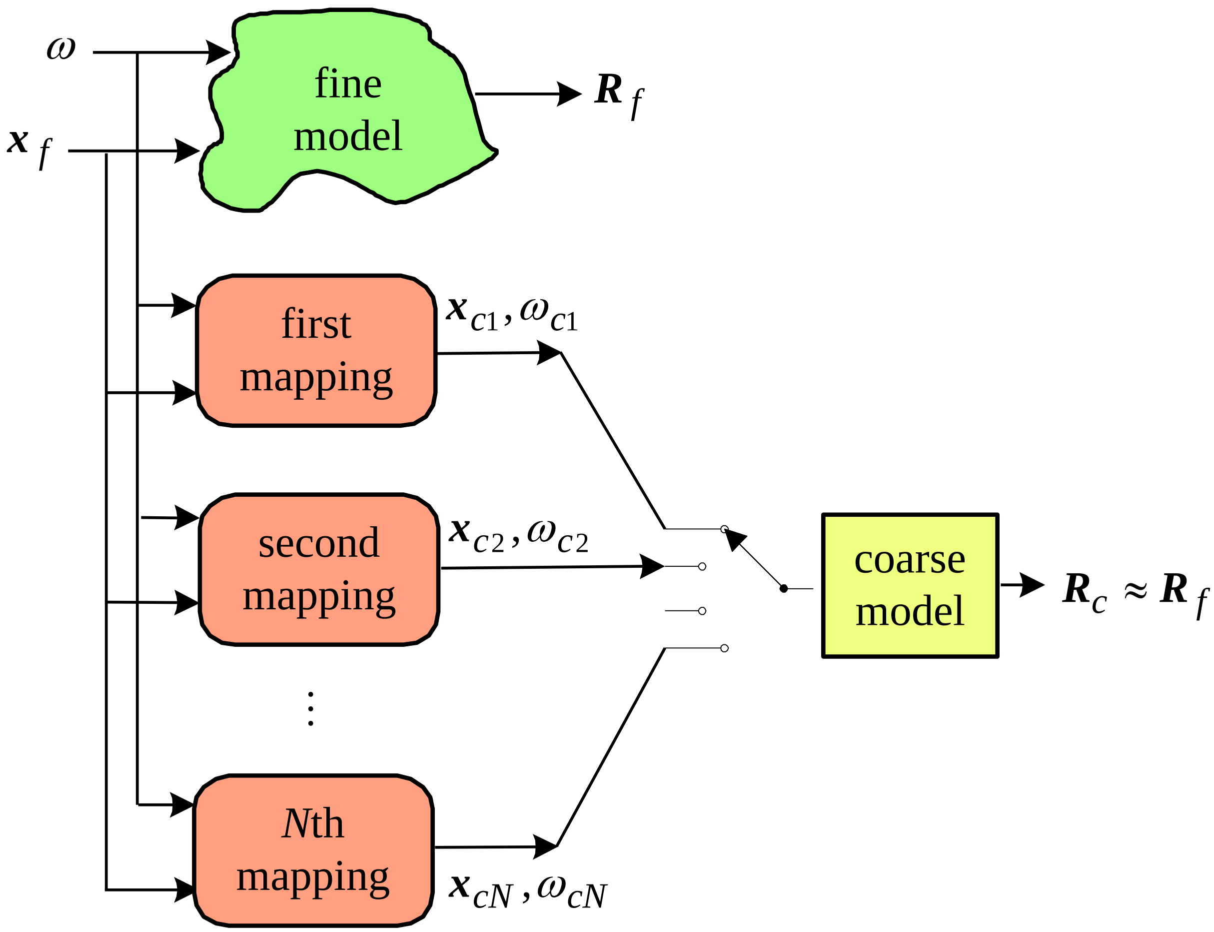
Multiple Space Mapping (MSM) Concept

MSM for Device Responses (MSMDR)



Multiple Space Mapping (MSM) Concept

MSM for Frequency Intervals (MSMFI)



Mathematical Formulation for GSM

the kth mapping is given by

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

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 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

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

Mathematical Formulation for GSM (continued)

we impose constraints on the mapping parameters such that they are as close as possible to those corresponding to a unit mapping

the objective function is modified as

$$\min_{\boldsymbol{c}_k, \boldsymbol{B}_k, \boldsymbol{s}_k, \boldsymbol{t}_k, \sigma_k, \delta_k} \; w_1 \left\| [\boldsymbol{e}_{k1}{}^T \quad \boldsymbol{e}_{k2}{}^T \quad \cdots \quad \boldsymbol{e}_{km}{}^T]^T \right\| + w_2 \, \|\boldsymbol{\beta}_k\|$$

where

$$\boldsymbol{\beta}_k = [\boldsymbol{c}_k^T \; \boldsymbol{s}_k^T \; \boldsymbol{t}_k^T \; \Delta\boldsymbol{b}_{k1}^T \cdots \Delta\boldsymbol{b}_{kn}^T \; \Delta\sigma_k \; \delta_k]^T$$

$$\Delta\boldsymbol{B}_k = \boldsymbol{B}_k - \boldsymbol{I}$$

$$\Delta\sigma_k = \sigma_k - 1$$

An Implementation of SMSM and FSMSM

select m base points $\{\boldsymbol{x}_f^{(j)},\ j = 1,2,\ldots,m\}$ in the region of interest (star distribution)

for SMSM apply direct optimization to solve

$$\min_{\boldsymbol{c}_k,\boldsymbol{B}_k} w_1 \left\| [\boldsymbol{e}_{k1}^T \quad \boldsymbol{e}_{k2}^T \quad \cdots \quad \boldsymbol{e}_{km}^T]^T \right\| + w_2 \left\| \boldsymbol{\beta}_k \right\|$$

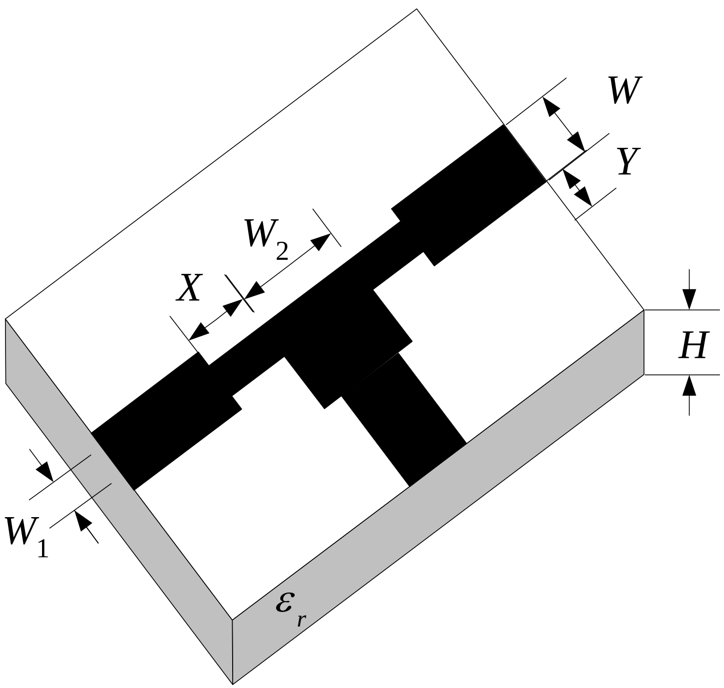
explicitly setting $\boldsymbol{s}_k = \boldsymbol{0},\ \boldsymbol{t}_k = \boldsymbol{0},\ \sigma_k = 1,\ \delta_k = 0$

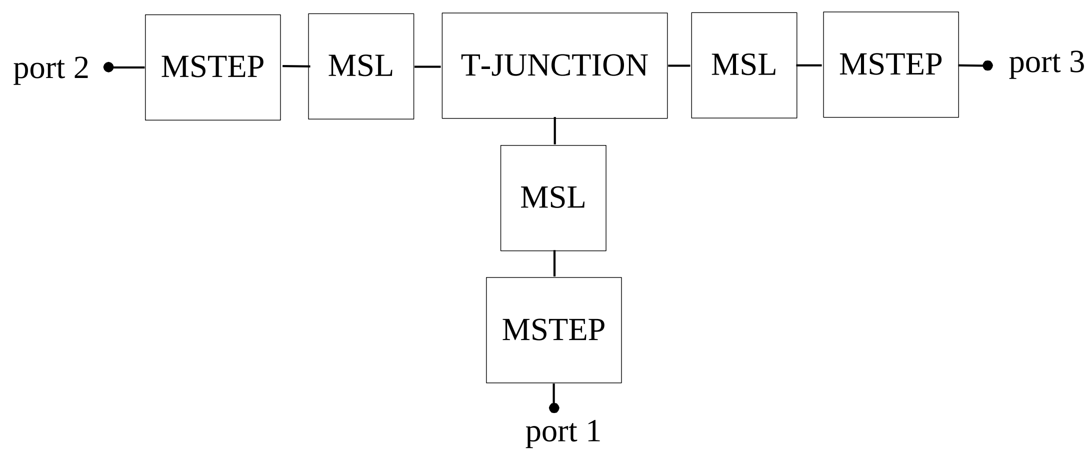
for FSMSM apply direct optimization to solve

$$\min_{\boldsymbol{c}_k,\boldsymbol{B}_k,\boldsymbol{s}_k,\boldsymbol{t}_k,\sigma_k,\delta_k} w_1 \left\| [\boldsymbol{e}_{k1}^T \quad \boldsymbol{e}_{k2}^T \quad \cdots \quad \boldsymbol{e}_{km}^T]^T \right\| + w_2 \left\| \boldsymbol{\beta}_k \right\|$$

Microstrip Shaped T-Junction

the fine and coarse models





Microstrip Shaped T-Junction

the region of interest

$$
\begin{aligned}
15 \text{ mil} \le\ & H \le 25 \text{ mil} \\
2 \text{ mil} \le\ & X \le 10 \text{ mil} \\
15 \text{ mil} \le\ & Y \le 25 \text{ mil} \\
8 \le\ & \varepsilon_r \le 10
\end{aligned}
$$

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

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

the widths W of the input lines track H so that their characteristic impedance is 50 ohm

$W_1 = W/3$

W_2 is suitably constrained

Microstrip Shaped T-Junction

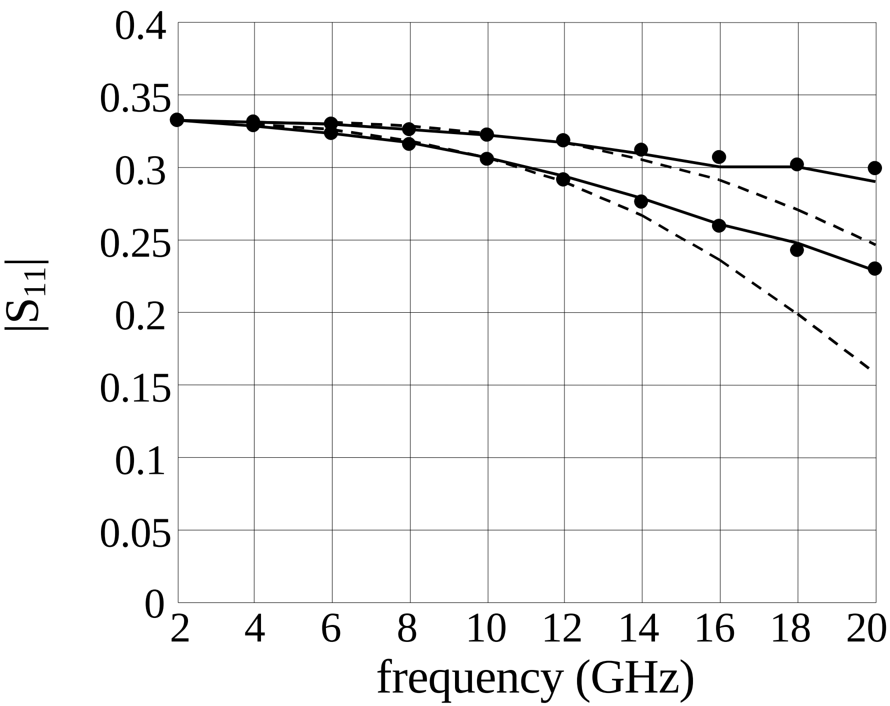
MSMFI is developed to enhance the accuracy of the coarse model

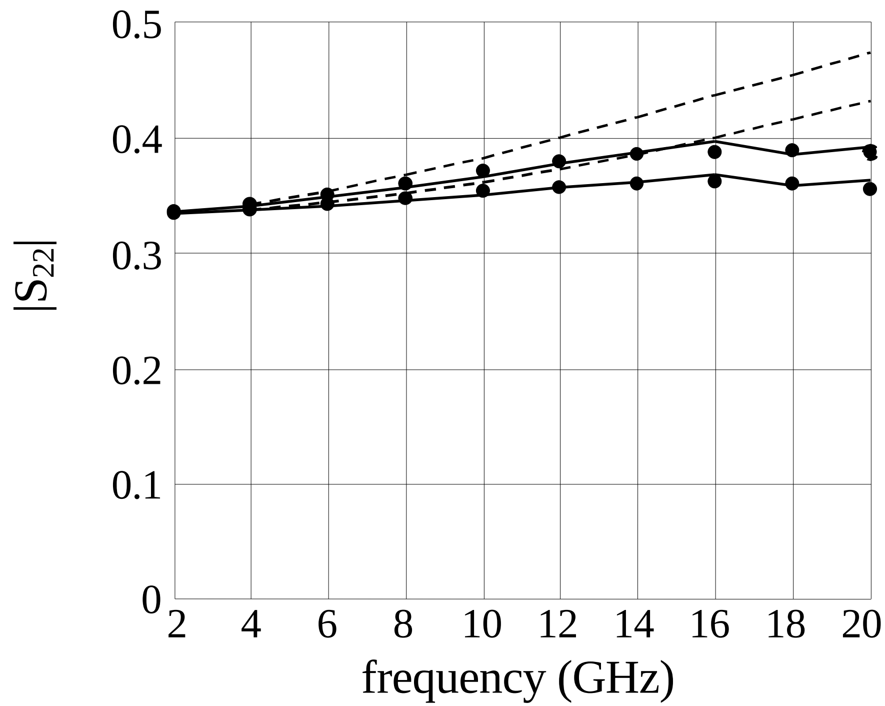
our algorithm determined two intervals: 2-16 GHz and 16-20 GHz

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

Microstrip Shaped T-Junction

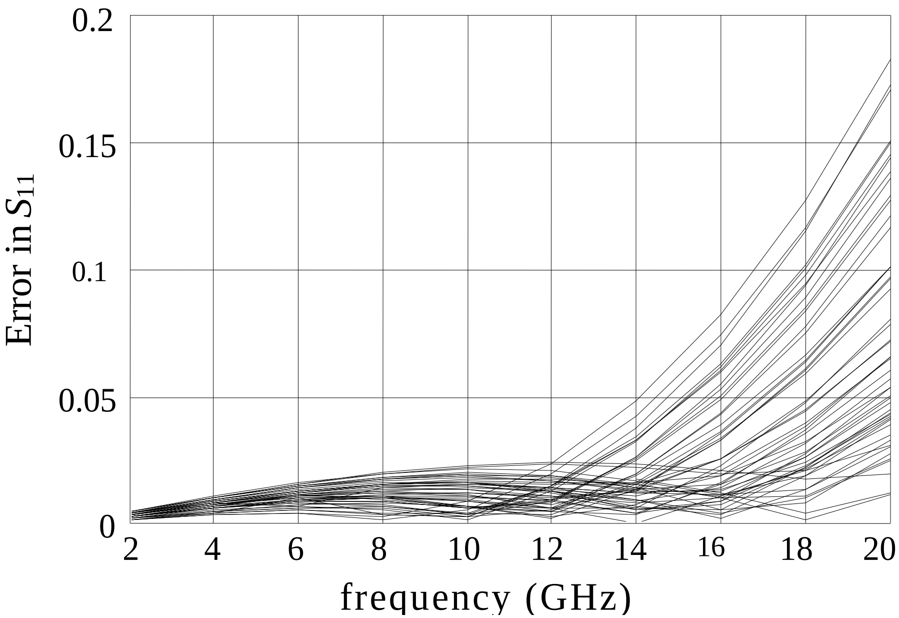
the responses at two test points in the region of interest by Sonnet's ***em*** (•):
the coarse model (---), the enhanced coarse model (—)

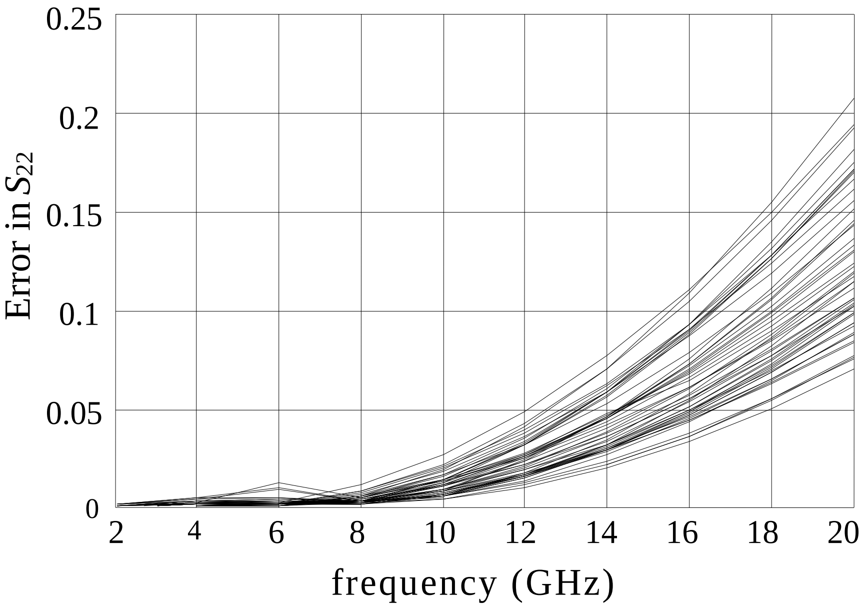




Microstrip Shaped T-Junction

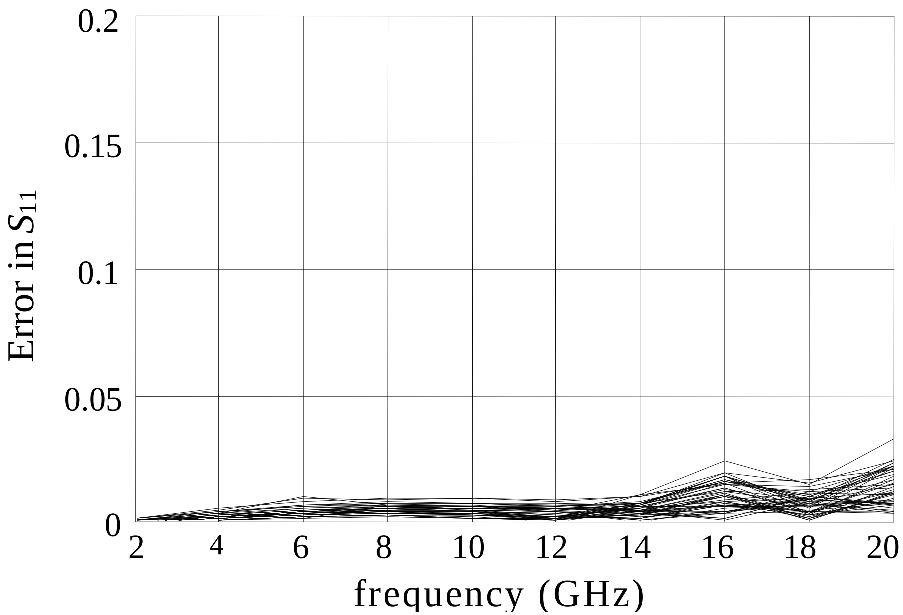
the errors of the coarse model responses at the test points

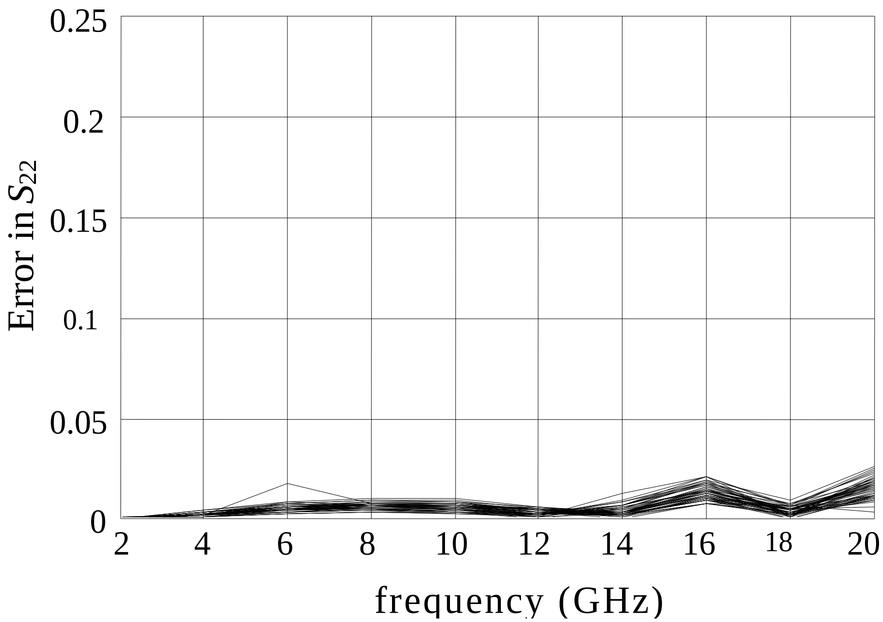




Microstrip Shaped T-Junction

the errors of the enhanced coarse model responses at the test points





Microstrip Shaped T-Junction Optimization

the enhanced coarse model is utilized

the optimization variables are X and Y

W = 24 mil, H = 25 mil and

specifications $\varepsilon_r = 9.9$

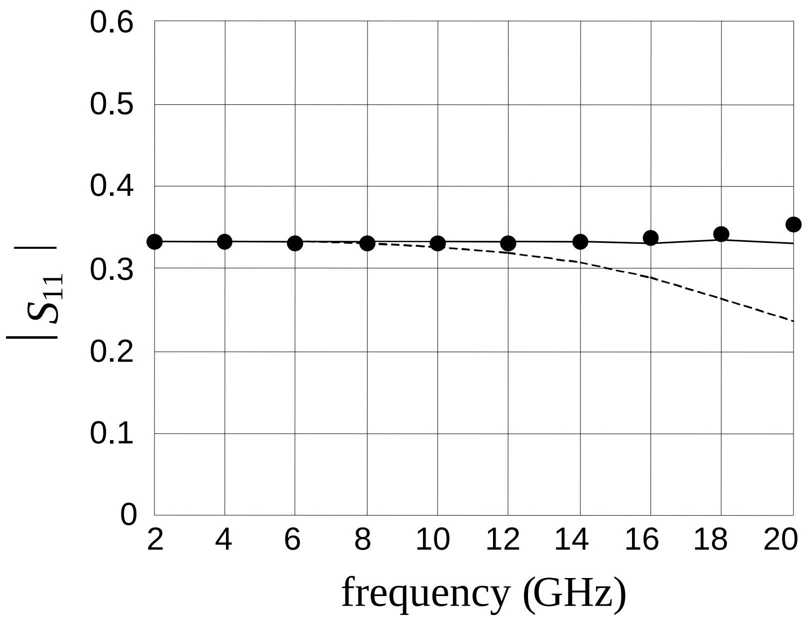
$|S_{11}| \leq 1/3, \quad |S_{22}| \leq 1/3$ in the frequency range 2 GHz to 20 GHz

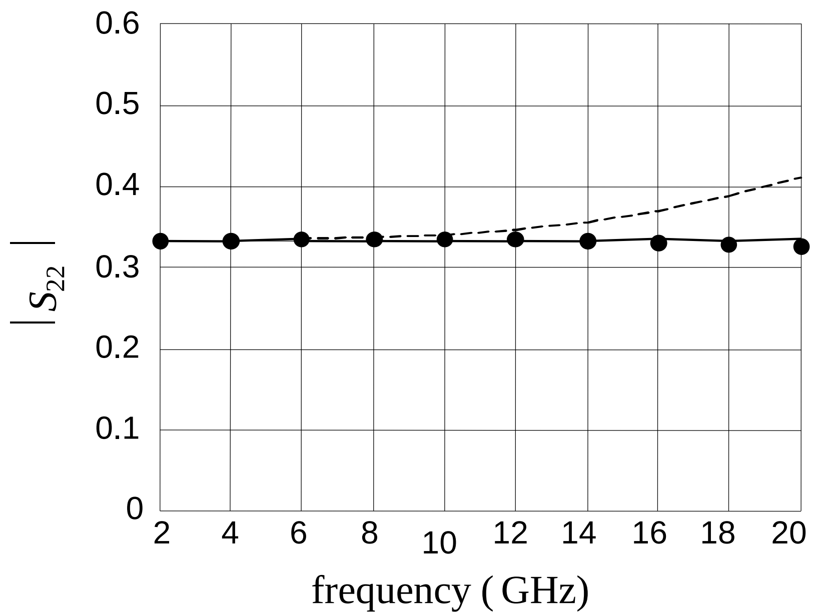
OSA90/hope minimax optimization reached

X = 4.31 mil and Y = 19.77 mil

Microstrip Shaped T-Junction Optimization

optimum responses by Sonnet's ***em*** (•):
the coarse model (**---**), the enhanced coarse model (—)





Artificial Neural Networks (ANN) in Microwave Design

ANNs are suitable models for microwave circuit optimization and statistical design *(Zaabab, Zhang and Nakhla, 1995, Gupta et al., 1996, Burrascano and Mongiardo, 1998, 1999)*

once trained, neuromodels can be used for optimization in the training region

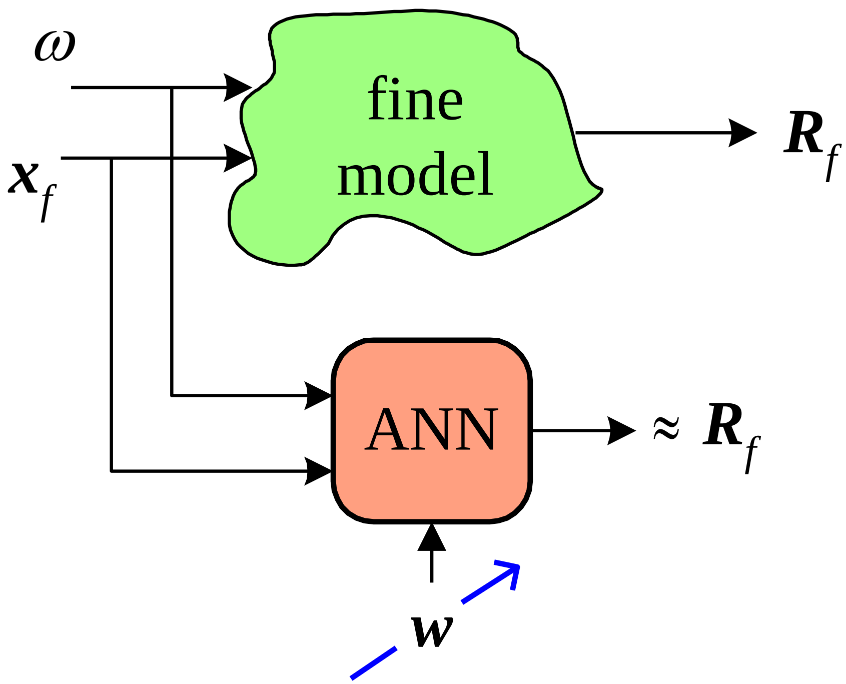
the principal drawback of this ANN optimization approach is the cost of generating sufficient learning samples

the extrapolation ability of neuromodels is poor, making unreliable any solution predicted outside the training region

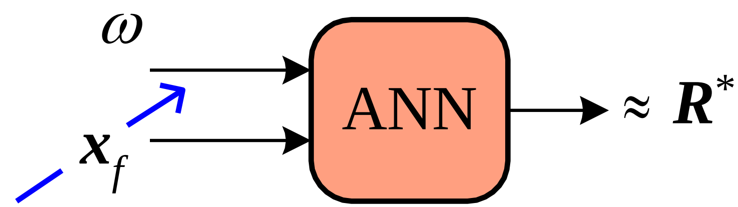
introducing knowledge can alleviate these limitations *(Gupta et al., 1999)*

Conventional ANN Optimization Approach

step 1



step 2



many fine model simulations are usually needed

solutions predicted outside the training region are unreliable

Neural Space Mapping (NSM) Optimization
(Bandler et al., 2000)

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

coarse models are used as sources of knowledge to reduce learning data and improve generalization and extrapolation

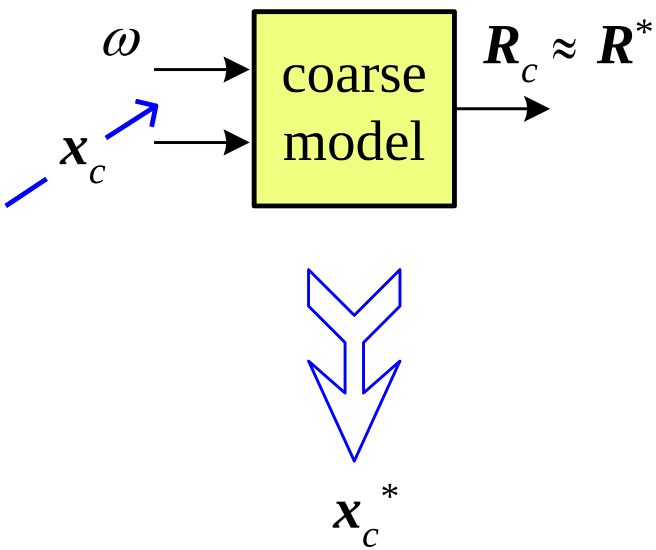
NSM requires a reduced set of upfront learning base points

initial learning base points are selected through coarse model sensitivity analysis

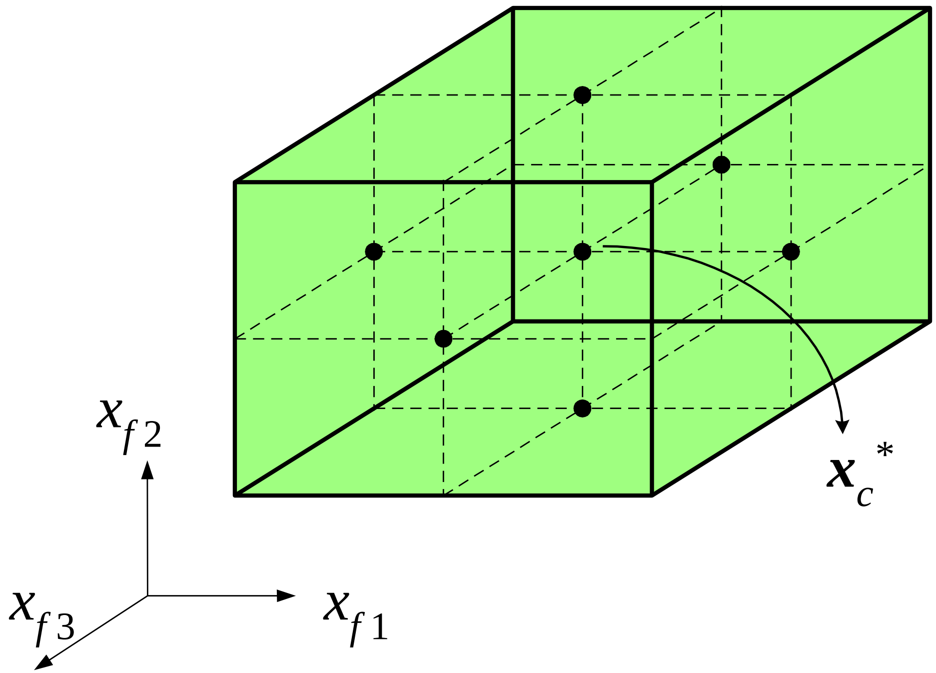
neuromappings are developed iteratively: generalization is controlled by gradually increasing complexity from a 3-layer perceptron with 0 hidden neurons

Neural Space Mapping (NSM) Optimization Concept

step 1



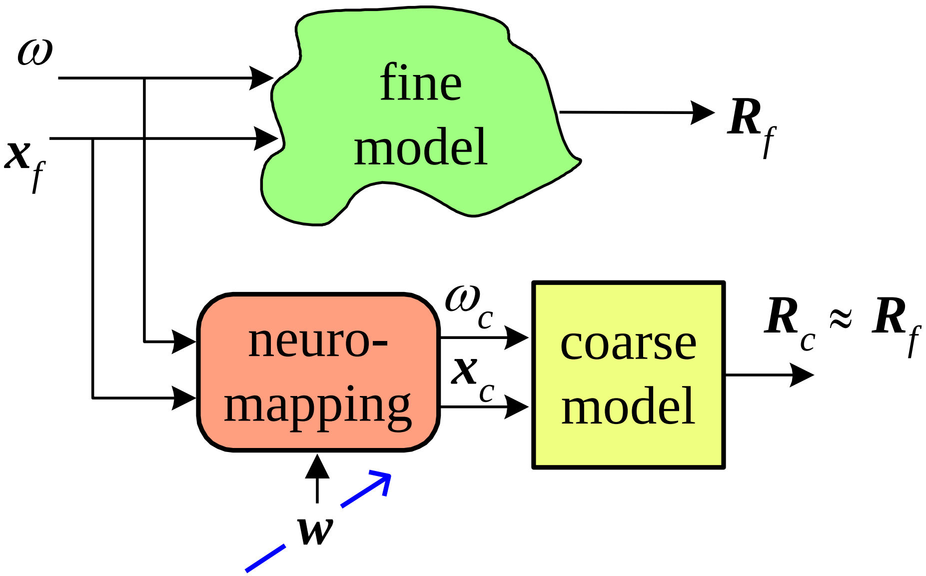
step 2



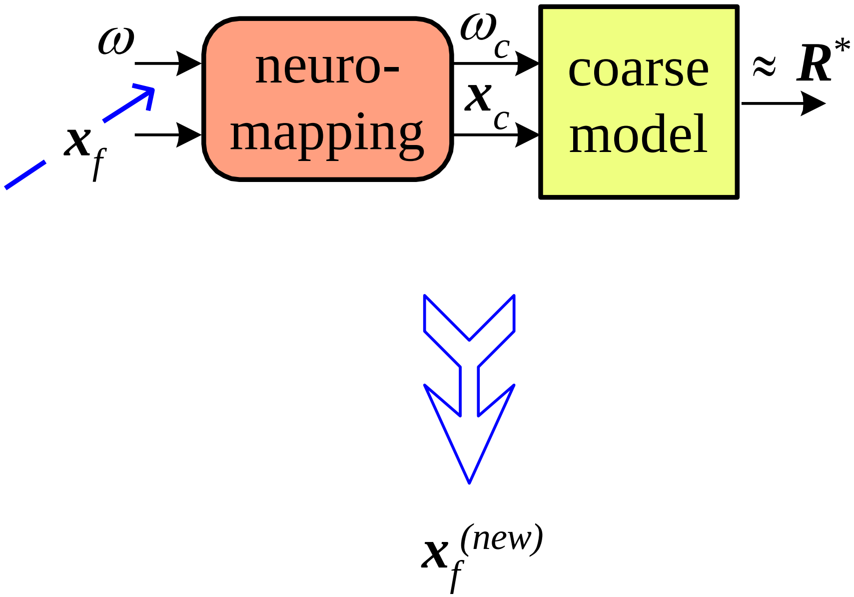
(2n + 1 learning base points for a microwave circuit with n design parameters)

Neural Space Mapping (NSM) Optimization Concept (continued)

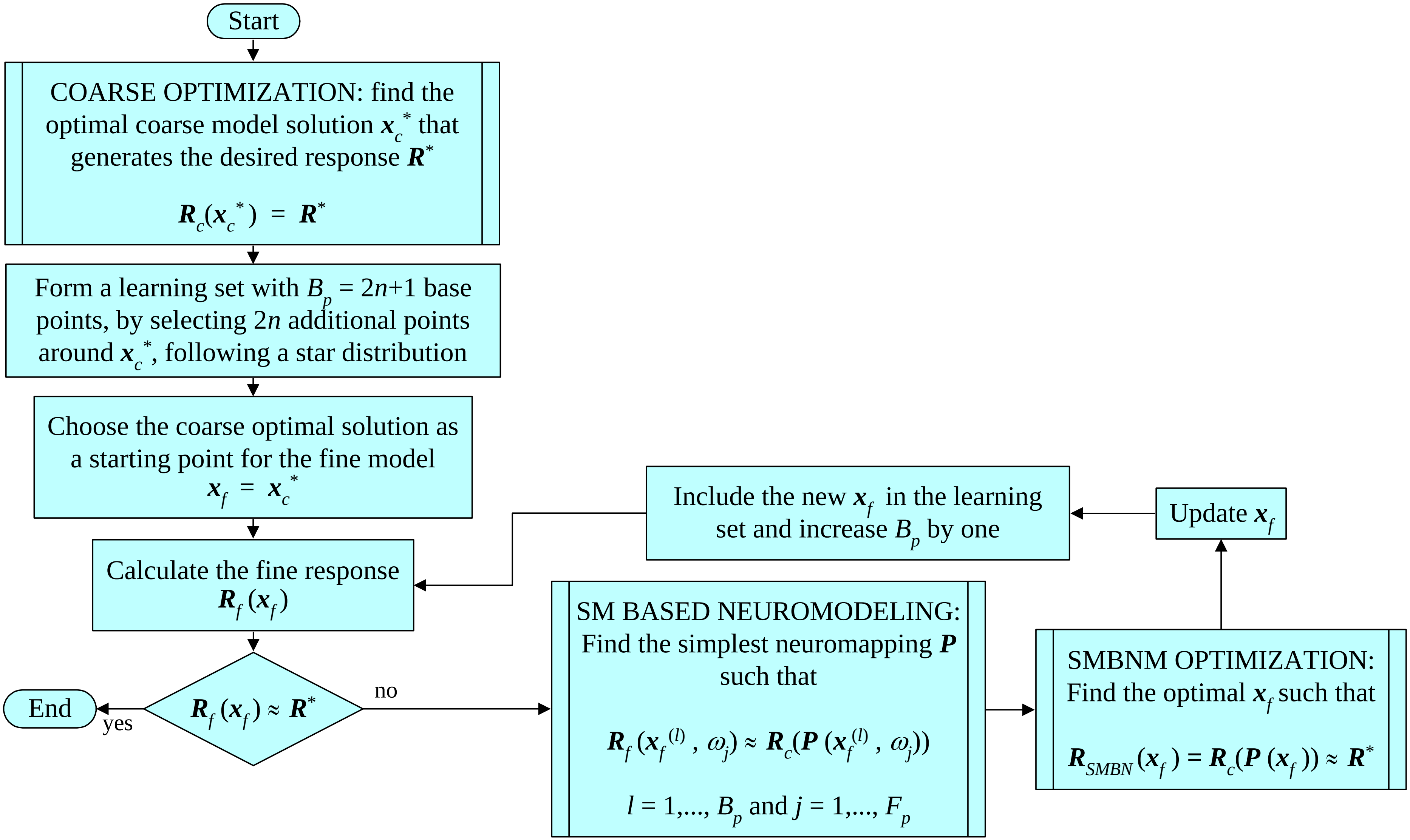
step 3



step 4

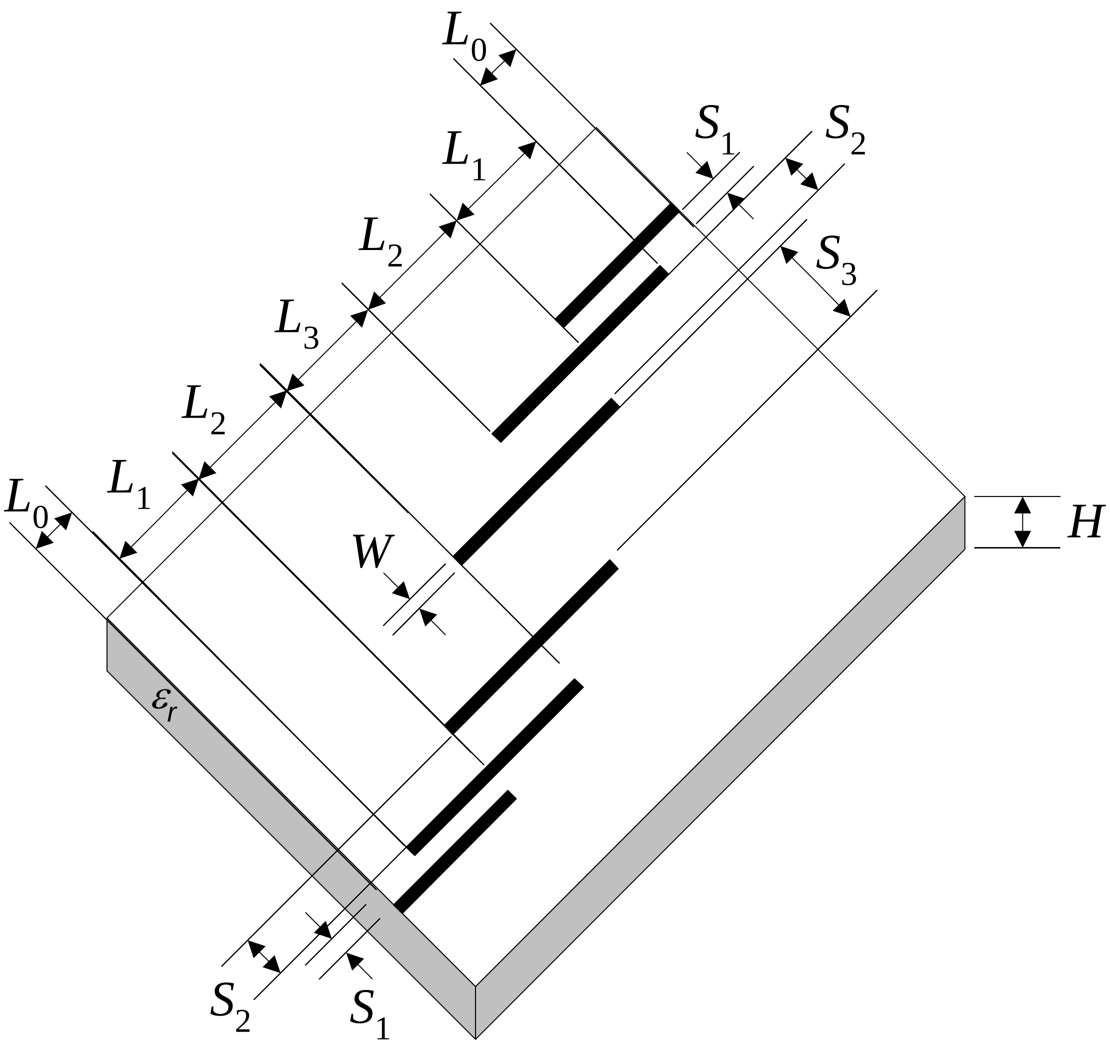


Neural Space Mapping (NSM) Optimization Algorithm



HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(Westinghouse, 1993)



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 Microstrip Filter

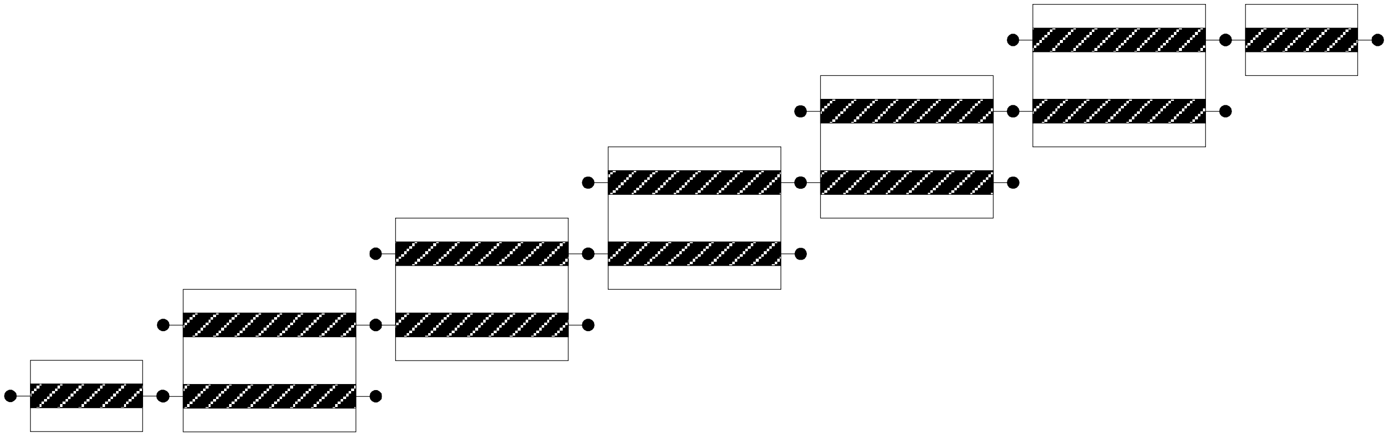
specifications

$|S_{21}| \geq 0.95$ for $4.008 \text{ GHz} \leq \omega \leq 4.058 \text{ GHz}$

$|S_{21}| \leq 0.05$ for $\omega \leq 3.967 \text{ GHz}$ and $\omega \geq 4.099 \text{ GHz}$

"fine" model: Sonnet's ***em***™ with high resolution grid

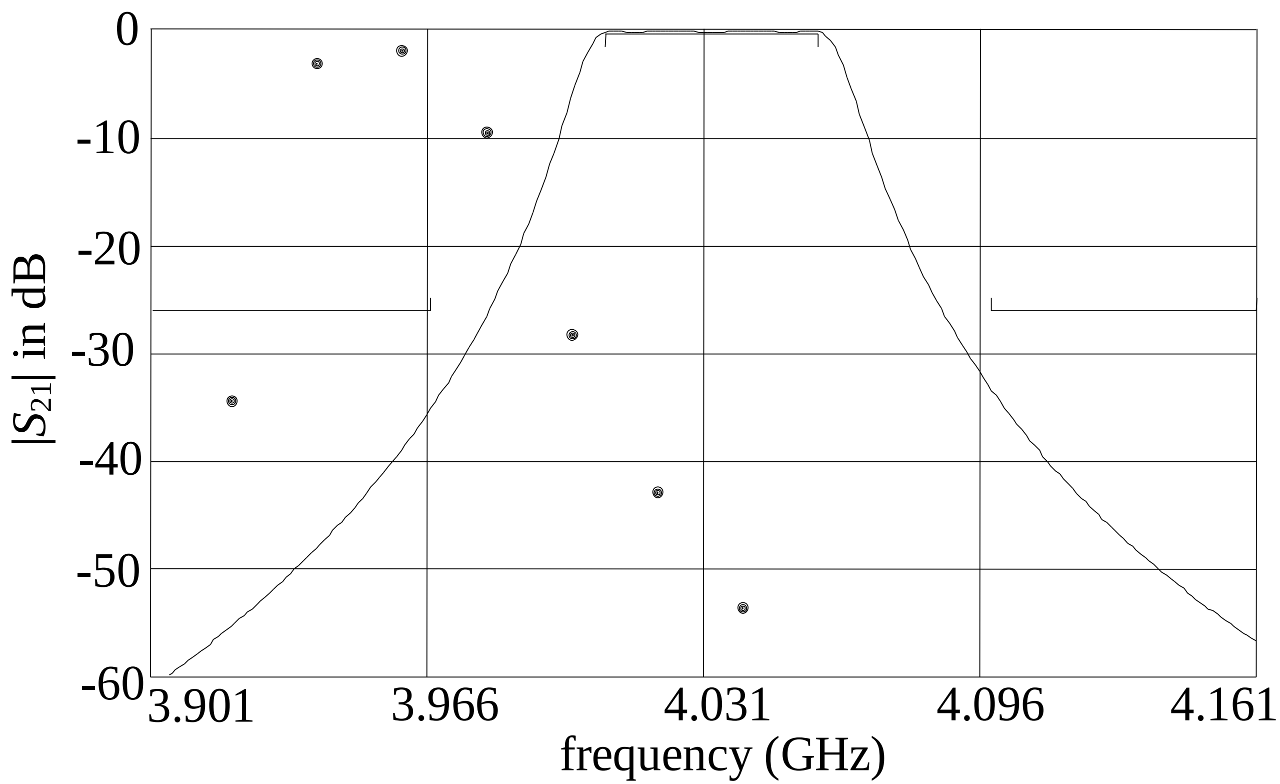
"coarse" model: OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines



NSM Optimization of the HTS Filter (continued)

coarse and fine model responses at the optimal coarse solution

OSA90/hope™ (–) and ***em***™ (•)

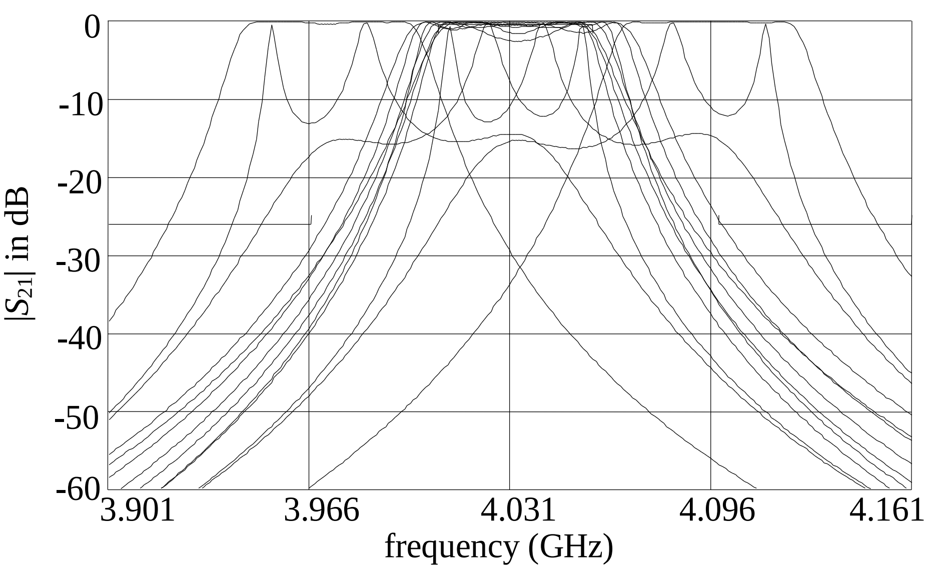


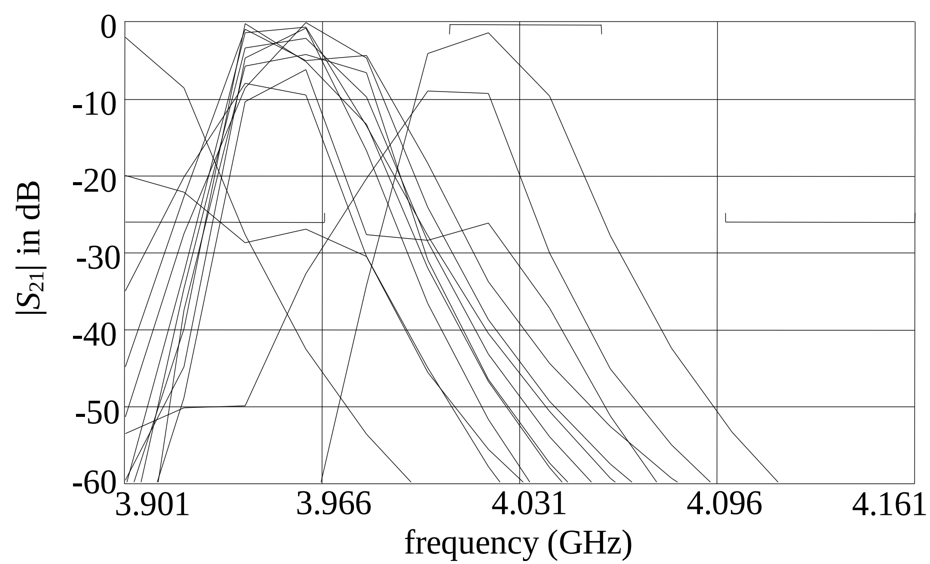
NSM Optimization of the HTS Filter (continued)

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*™

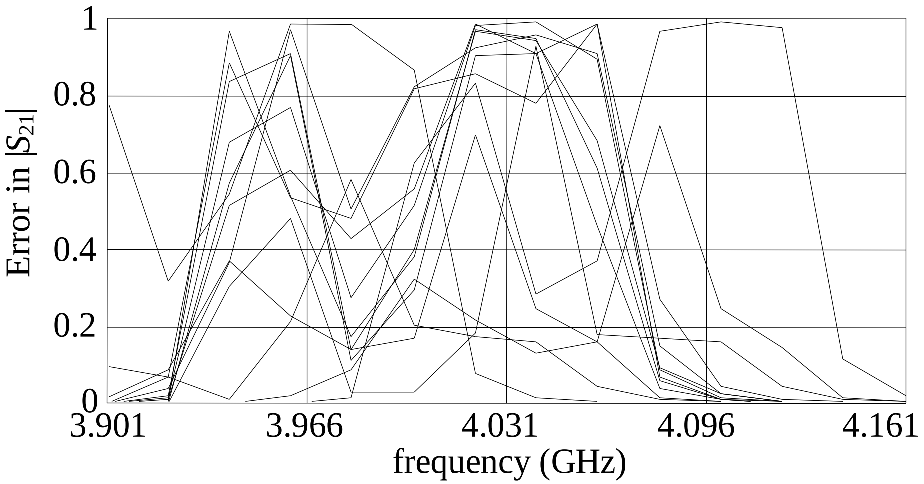




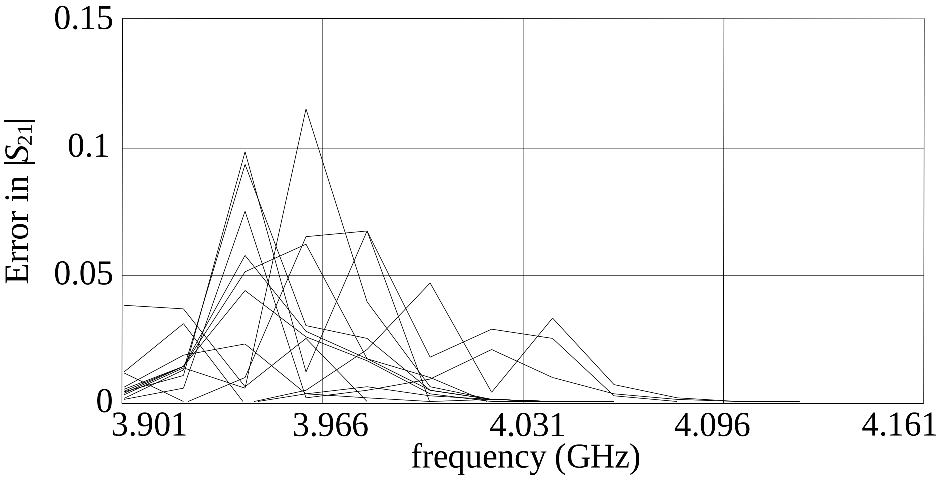
NSM Optimization of the HTS Filter (continued)

learning errors at base points

before any neuromapping



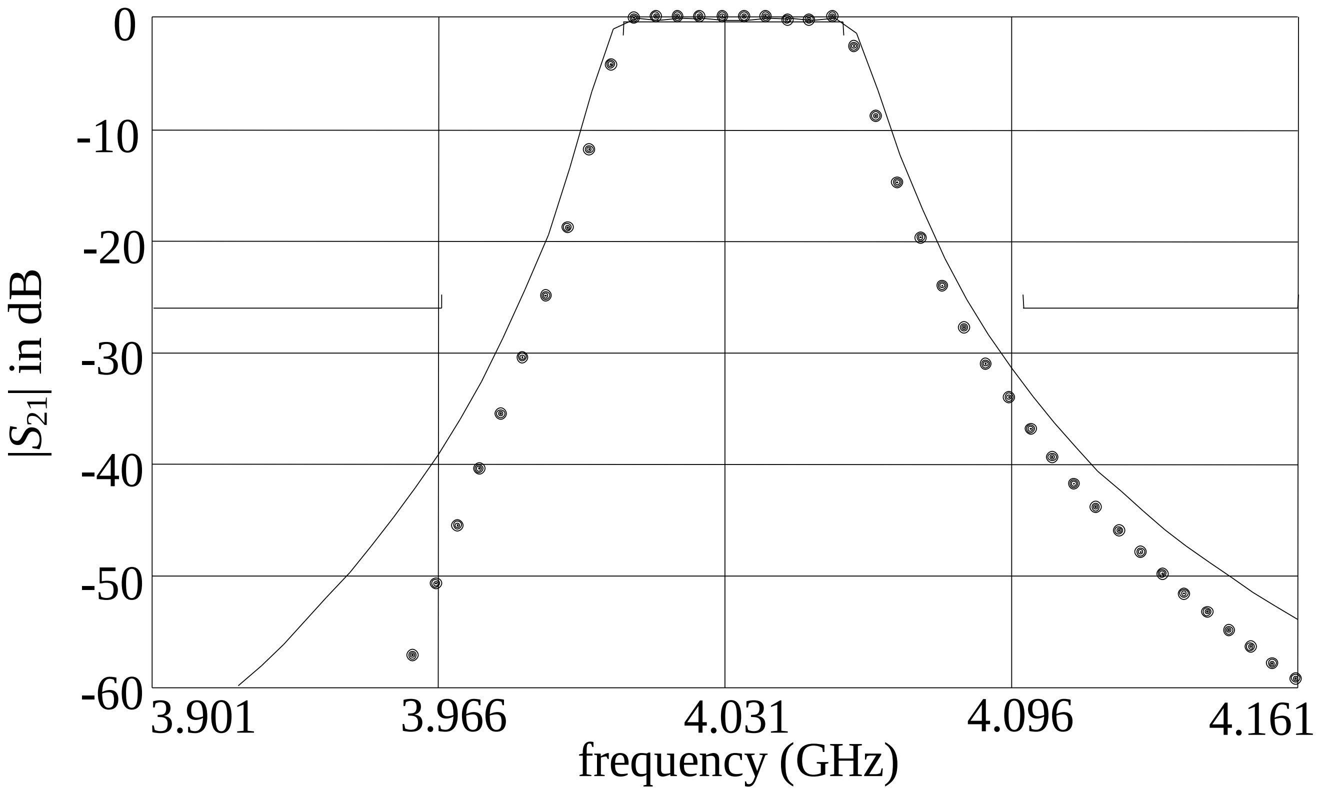
mapping ω, L_1 and S_1 with a 3LP:-7-5-3



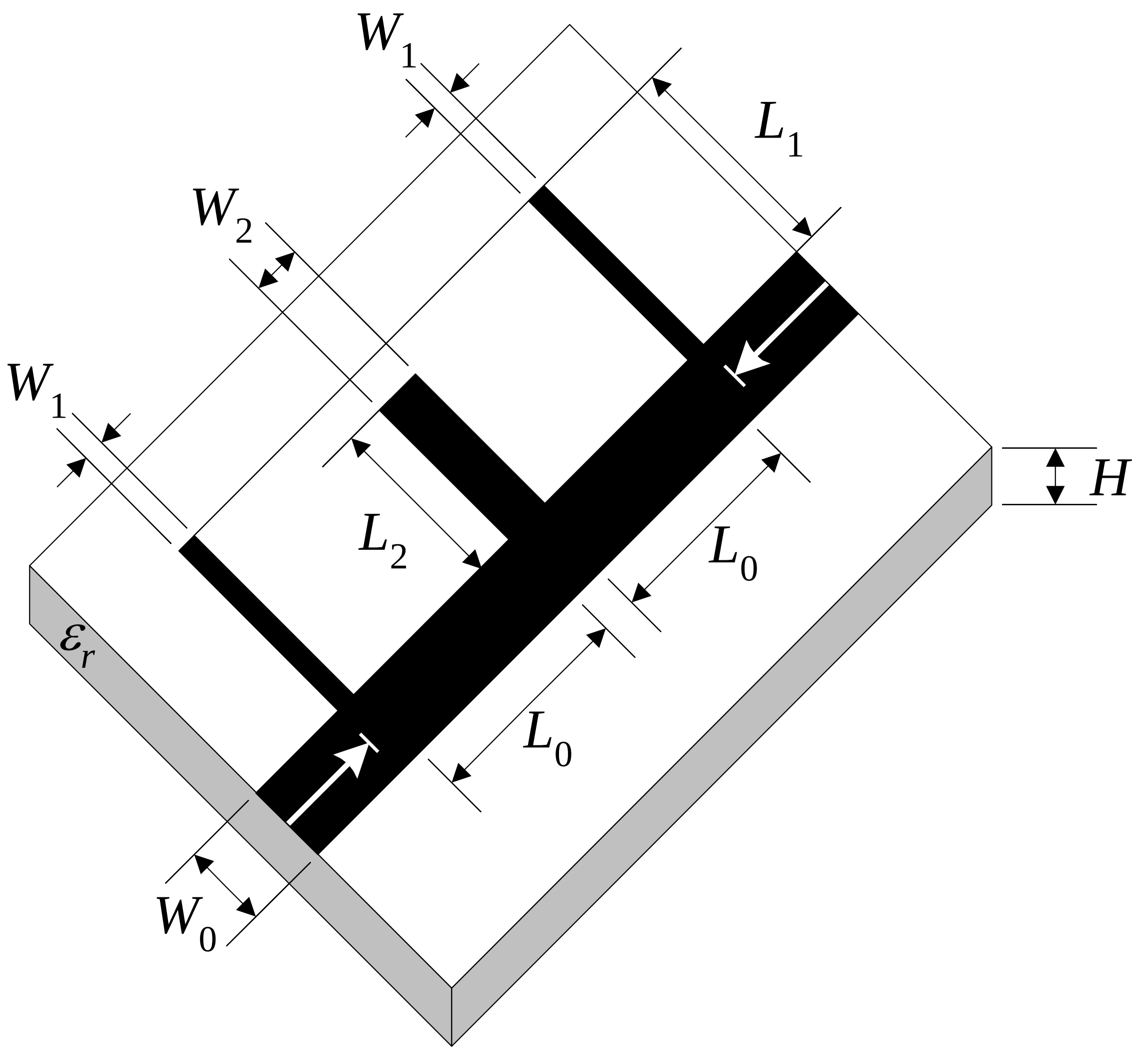
NSM Optimization of the HTS Filter (continued)

fine model response (•) at the next point predicted by the first NSM iteration and optimal coarse response (–)

(3LP:7-5-3, ω, L_1, S_1)



Bandstop Microstrip Filter with Quarter-Wave Open Stubs



we take H = 25 mil, W_0 = 25 mil, ε_r = 9.4 (alumina)

the design parameters are

$\boldsymbol{x}_f = [W_1\ W_2\ L_0\ L_1\ L_2]^T$

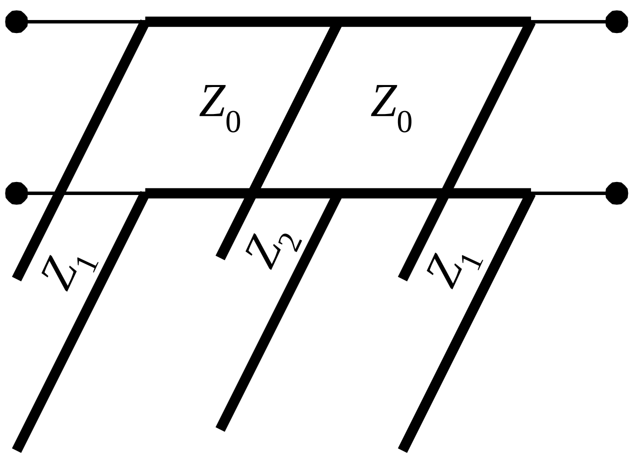
NSM Optimization of the Bandstop Filter

specifications

$$|S_{21}| \leq 0.05 \text{ for } 9.3 \text{ GHz} \leq \omega \leq 10.7 \text{ GHz}$$
$$|S_{21}| \geq 0.9 \text{ for } \omega \leq 8 \text{ GHz and } \omega \geq 12 \text{ GHz}$$

"fine" model: Sonnet's ***em***™ with high resolution grid

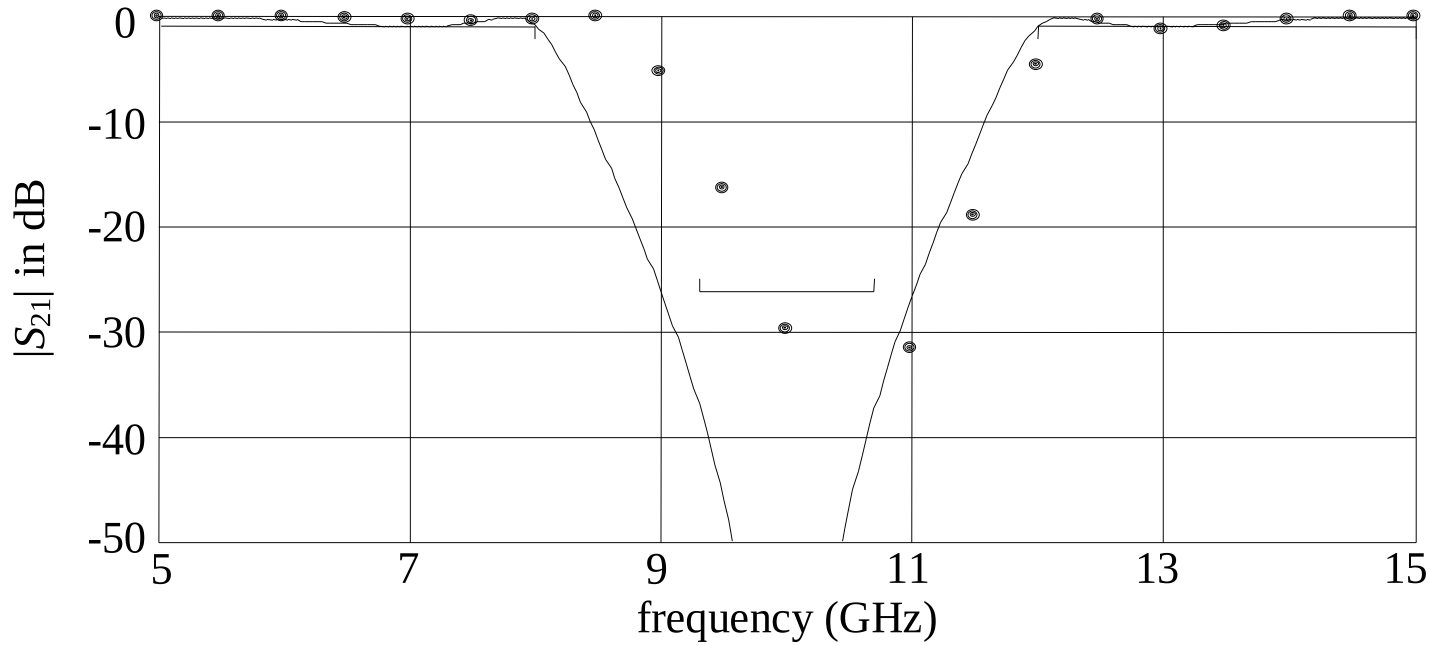
"coarse" model: transmission line sections and empirical formulas



NSM Optimization of the Bandstop Filter (continued)

coarse and fine model responses at the optimal coarse solution

coarse model (–) and ***em***™ (•)

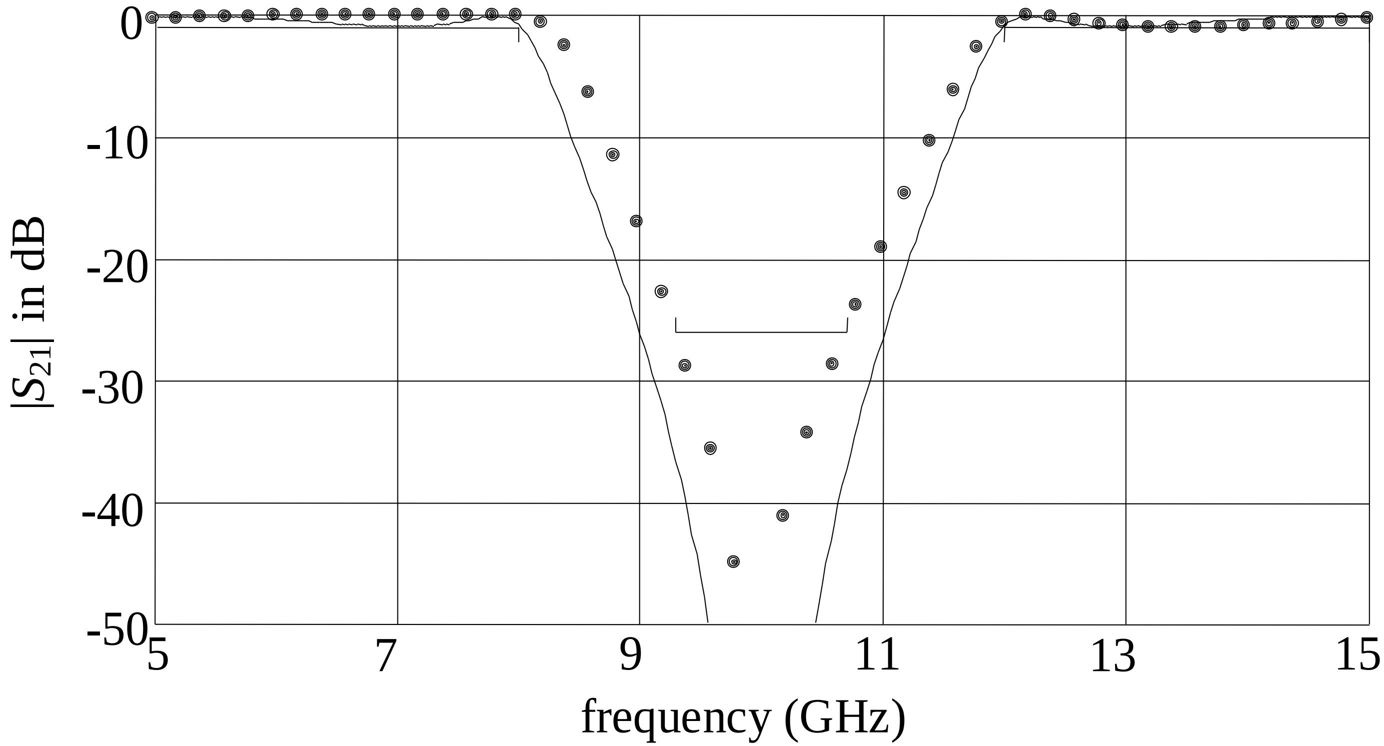


the initial $2n$+1 points are chosen by performing sensitivity analysis on the coarse model: a 50% deviation from $\boldsymbol{x}_c^*$ for W_1, W_2, and L_0 is used, while a 15% is used for L_1, and L_2

NSM Optimization of the Bandstop Filter (continued)

fine model response (•) at the point predicted by the second NSM iteration and optimal coarse response (–)

(3LP:6-3-2,ω,W_2)



EM-based Yield Optimization Via SM-Based Neuromodels
(Bandler et. al., 2001)

the SM-based neuromodel responses are given by

$$\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f,\omega)=\boldsymbol{R}_c(\boldsymbol{x}_c,\omega_c)$$

with

$$\begin{bmatrix}\boldsymbol{x}_c\\ \omega_c\end{bmatrix}=\boldsymbol{P}(\boldsymbol{x}_f,\omega)$$

where the mapping function $\boldsymbol{P}$ is implemented by a neuromapping variation (SM, FDSM, FSM, FM or FPSM)

Yield Optimization Via SM-Based Neuromodels (continued)

$$\boldsymbol{R}_f(\boldsymbol{x}_f, \omega) \approx \boldsymbol{R}_{SMBN}(\boldsymbol{x}_f, \omega)$$

for all $\boldsymbol{x}_f$ and ω in the training region

we can show that

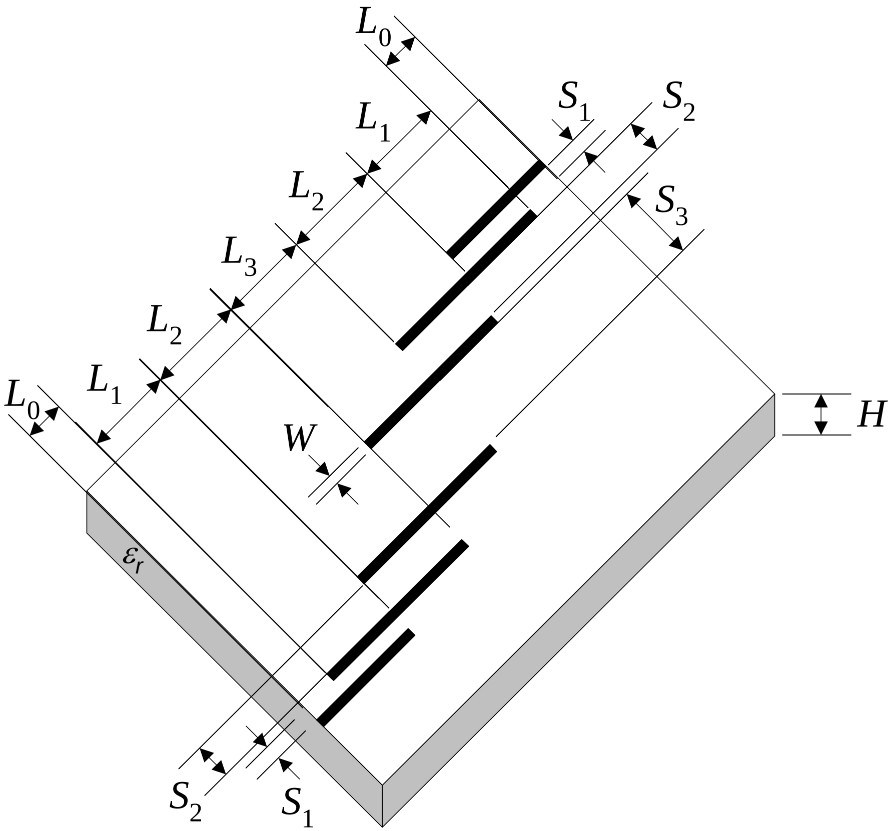
$$\boldsymbol{J}_f \approx \boldsymbol{J}_c \boldsymbol{J}_P$$

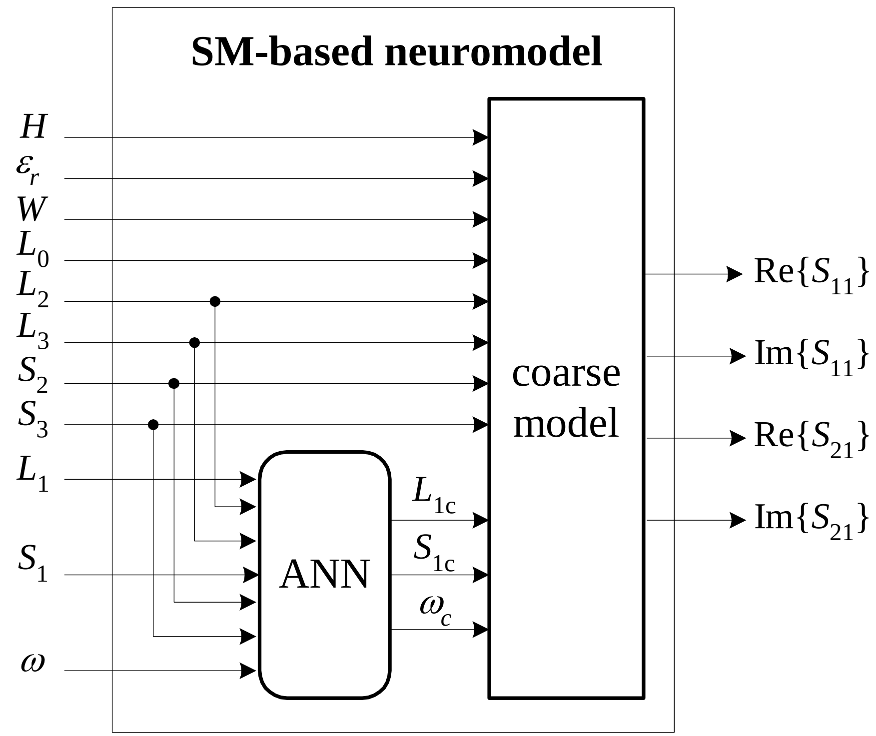
$\boldsymbol{J}_f \in \Re^{r \times n}$ Jacobian of the fine model responses w.r.t. the fine model parameters

$\boldsymbol{J}_c \in \Re^{r \times (n+1)}$ Jacobian of the coarse model responses w.r.t. the coarse model parameters and mapped frequency

$\boldsymbol{J}_P \in \Re^{(n+1) \times n}$ Jacobian of the mapping function w.r.t. the fine model parameters

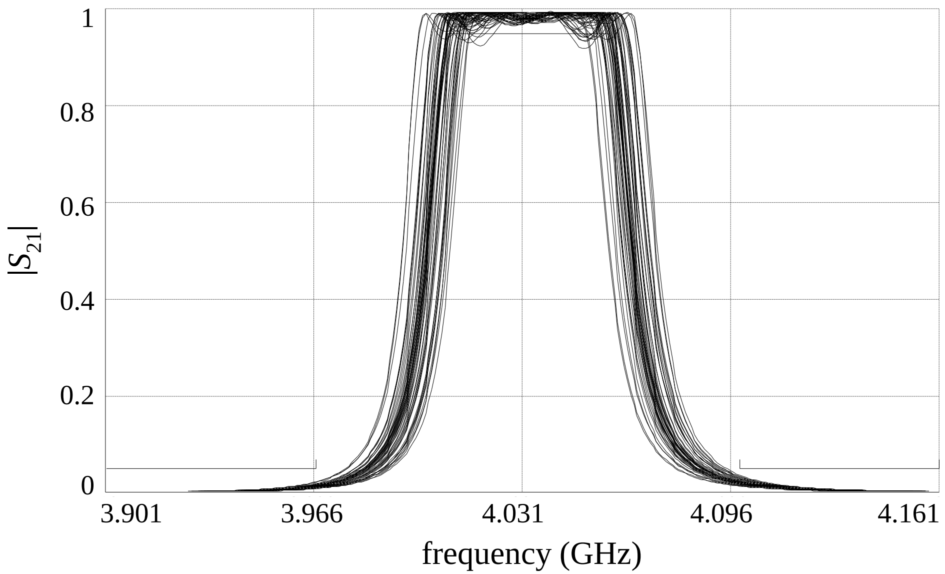
Yield Optimization of the HTS Filter

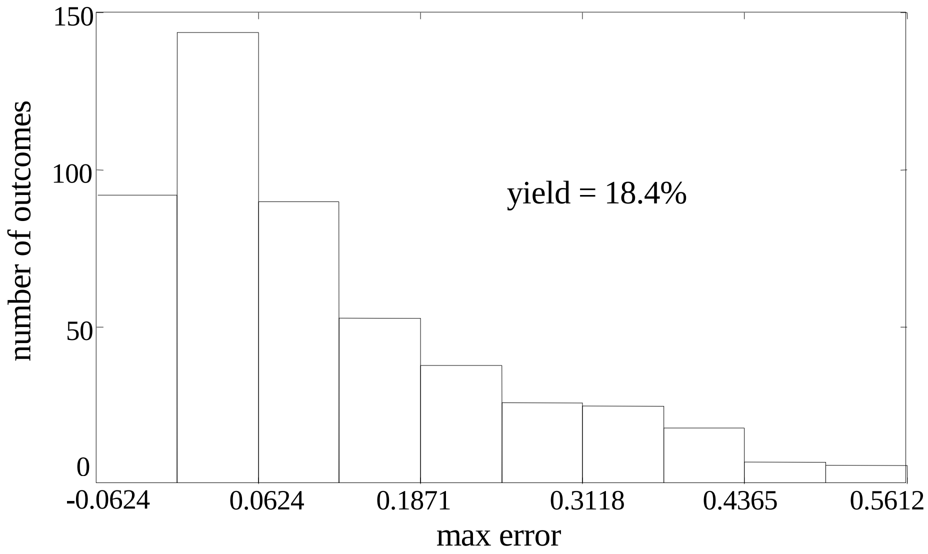




Yield Optimization of the HTS Filter

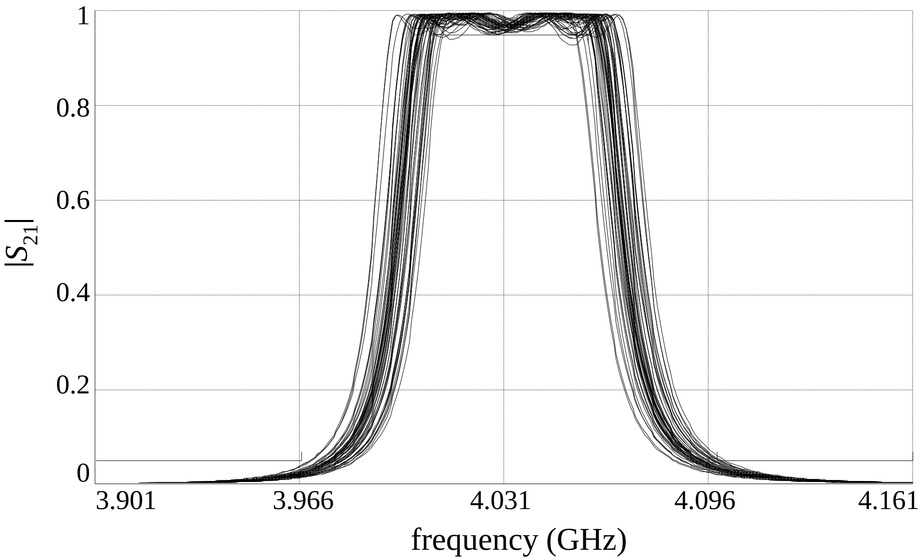
at the nominal solution (starting point): yield = 18.4%

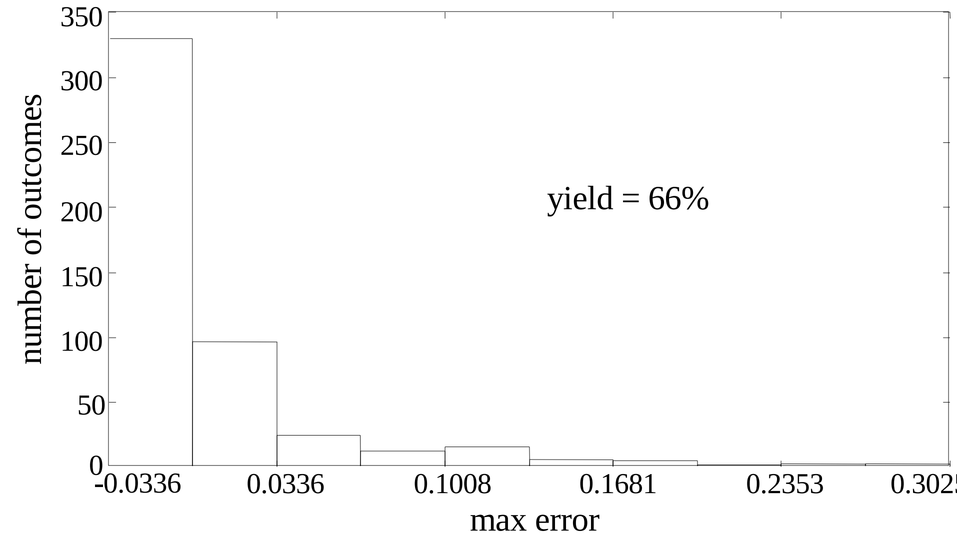




Yield Optimization of the HTS Filter (continued)

at the optimal yield solution: yield = 66%





Conclusions

Generalized Space Mapping (GSM) is an engineering device modeling framework that exploits Frequency Space Mapping (FSM) and Multiple Space Mapping (MSM)

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

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

we exploit SM-based neuromodels for EM statistical analysis and yield optimization

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