Neural Space Mapping Methods for Device Modeling and Optimal Design

J.W. Bandler and J.E. Rayas-Sánchez

Simulation Optimization Systems Research Laboratory
McMaster University

Bandler Corporation, www.bandler.com
john@bandler.com

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Outline

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

statistical analysis and yield optimization using SM-based neuromodels

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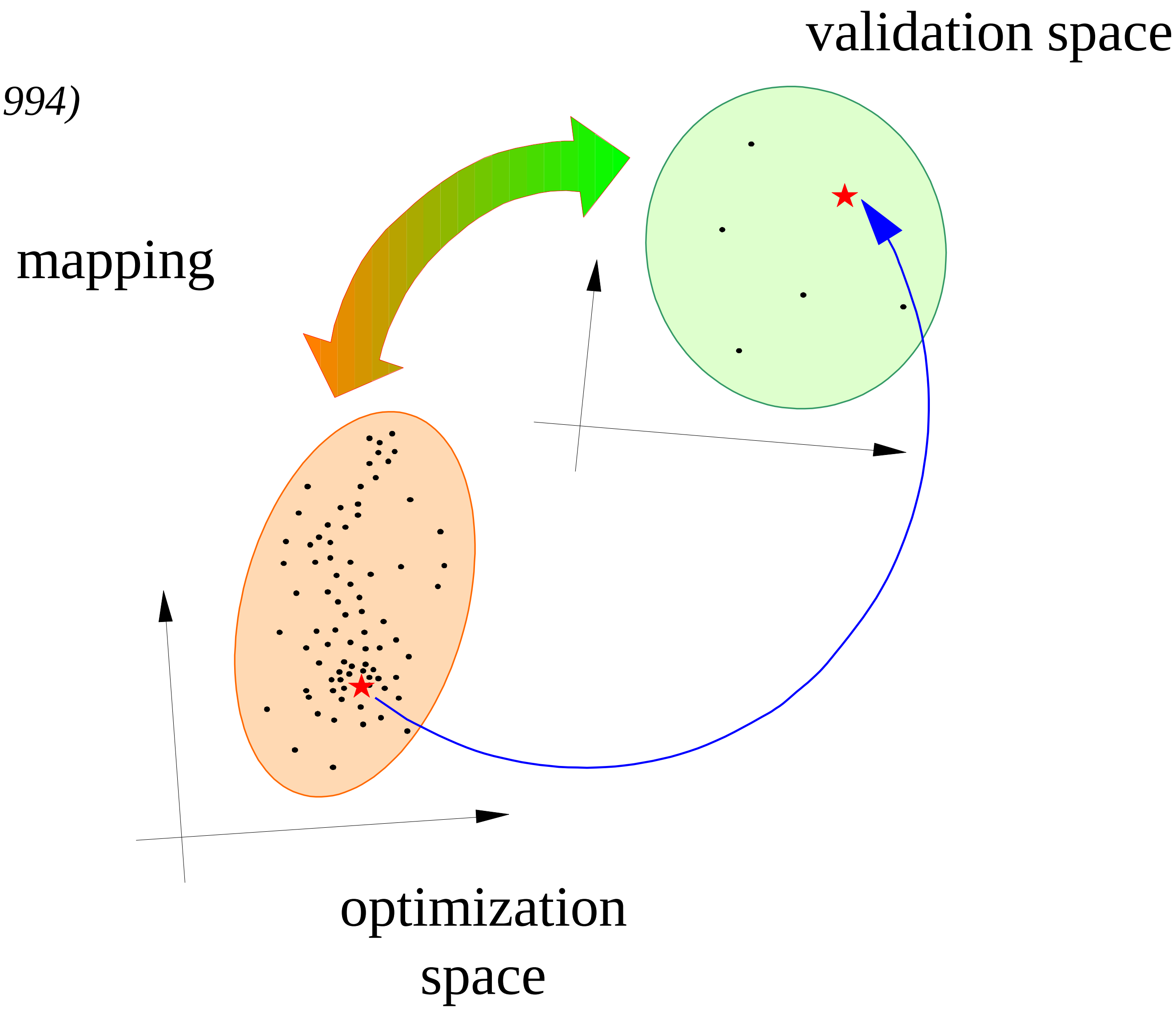
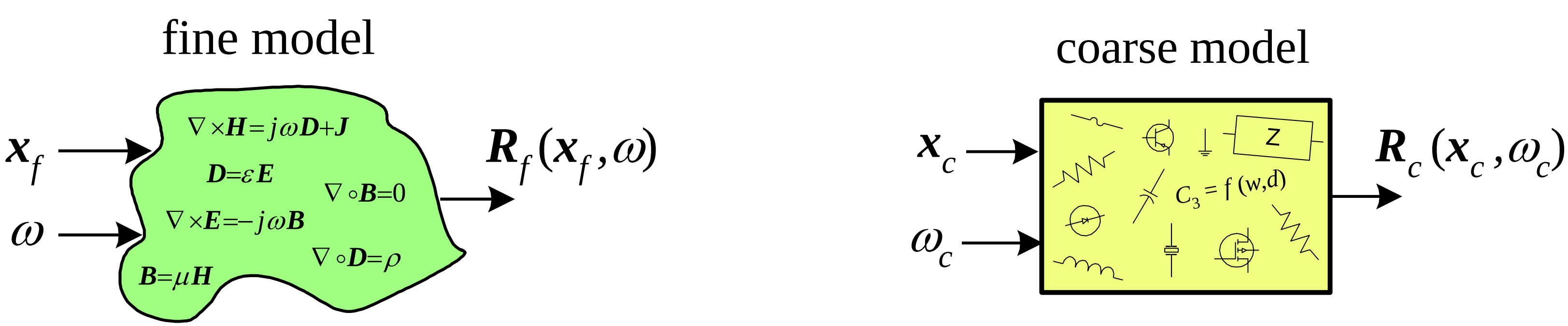
statistical analysis and yield optimization using SM-based neuromodels

Space Mapping
(Bandler et al., 1994)



Exploiting Space Mapping for Neuromodeling

(Bandler et. al., 1999)



find

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

such that

$$\boldsymbol{R}_c(\boldsymbol{x}_c,\omega_c) \approx \boldsymbol{R}_f(\boldsymbol{x}_f,\omega)$$

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)*

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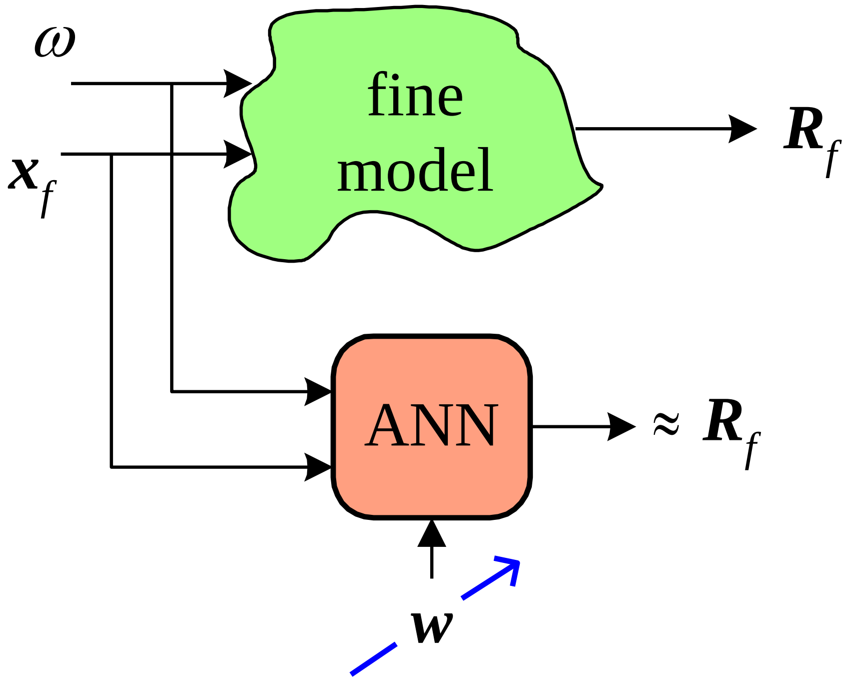
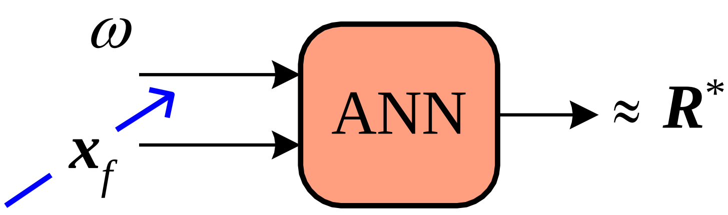
Conventional ANN Optimization Approach

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

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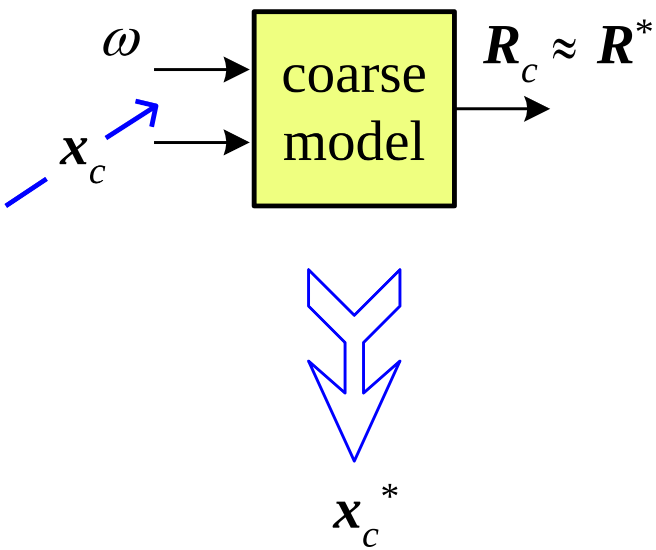
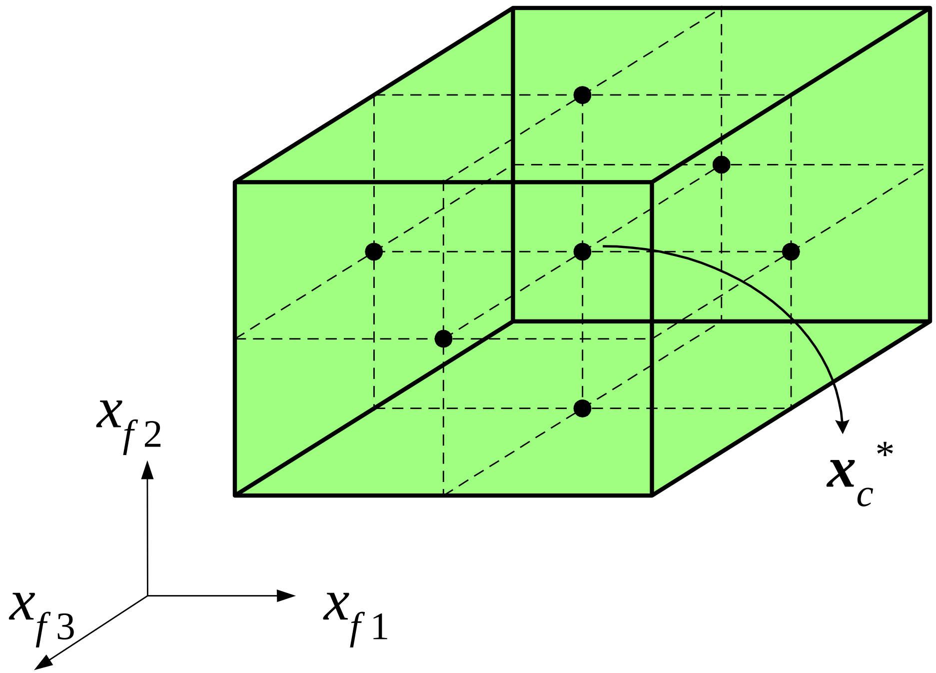
Neural Space Mapping (NSM) Optimization Concept

step 1



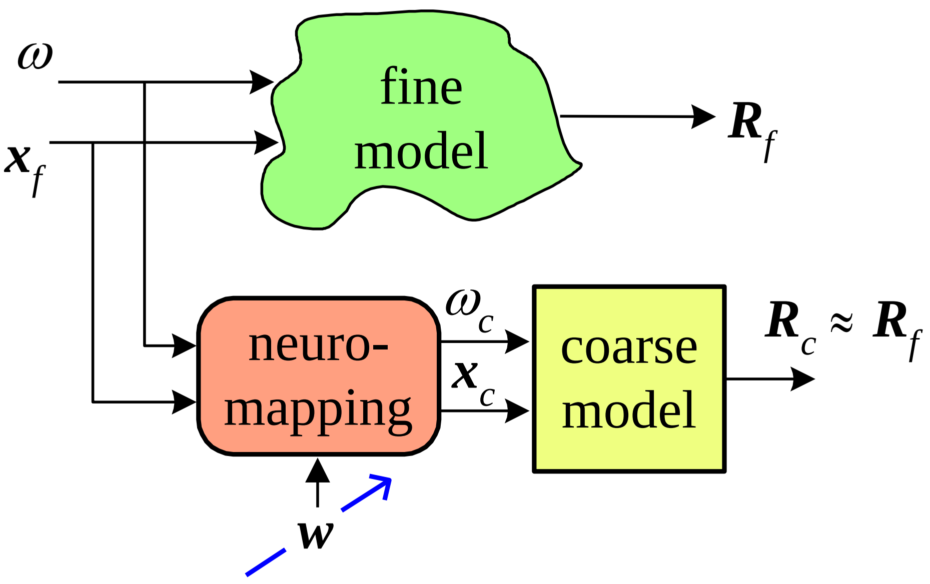
step 2



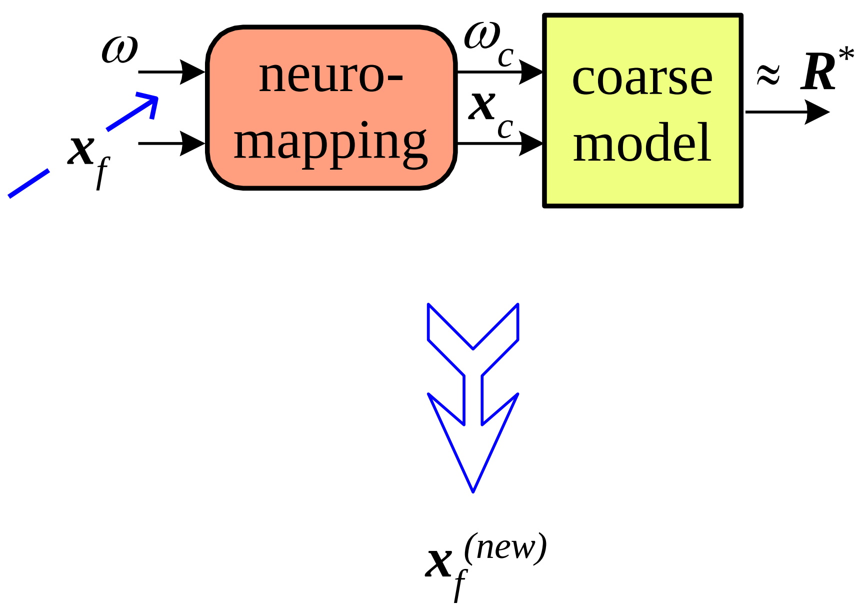
(2*n* + 1 learning base points for a microwave circuit with *n* design parameters)

Neural Space Mapping (NSM) Optimization Concept (continued)

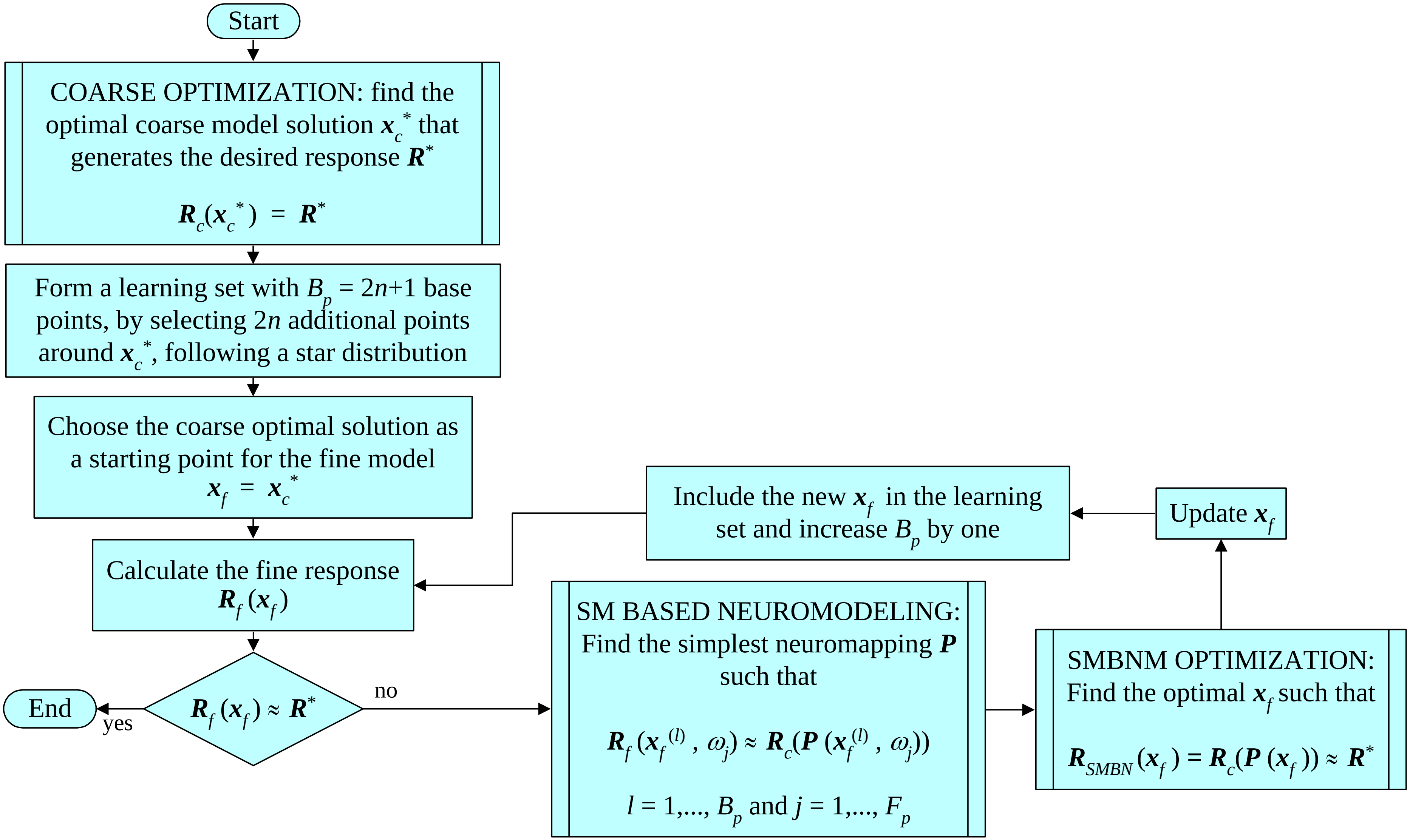
step 3



step 4

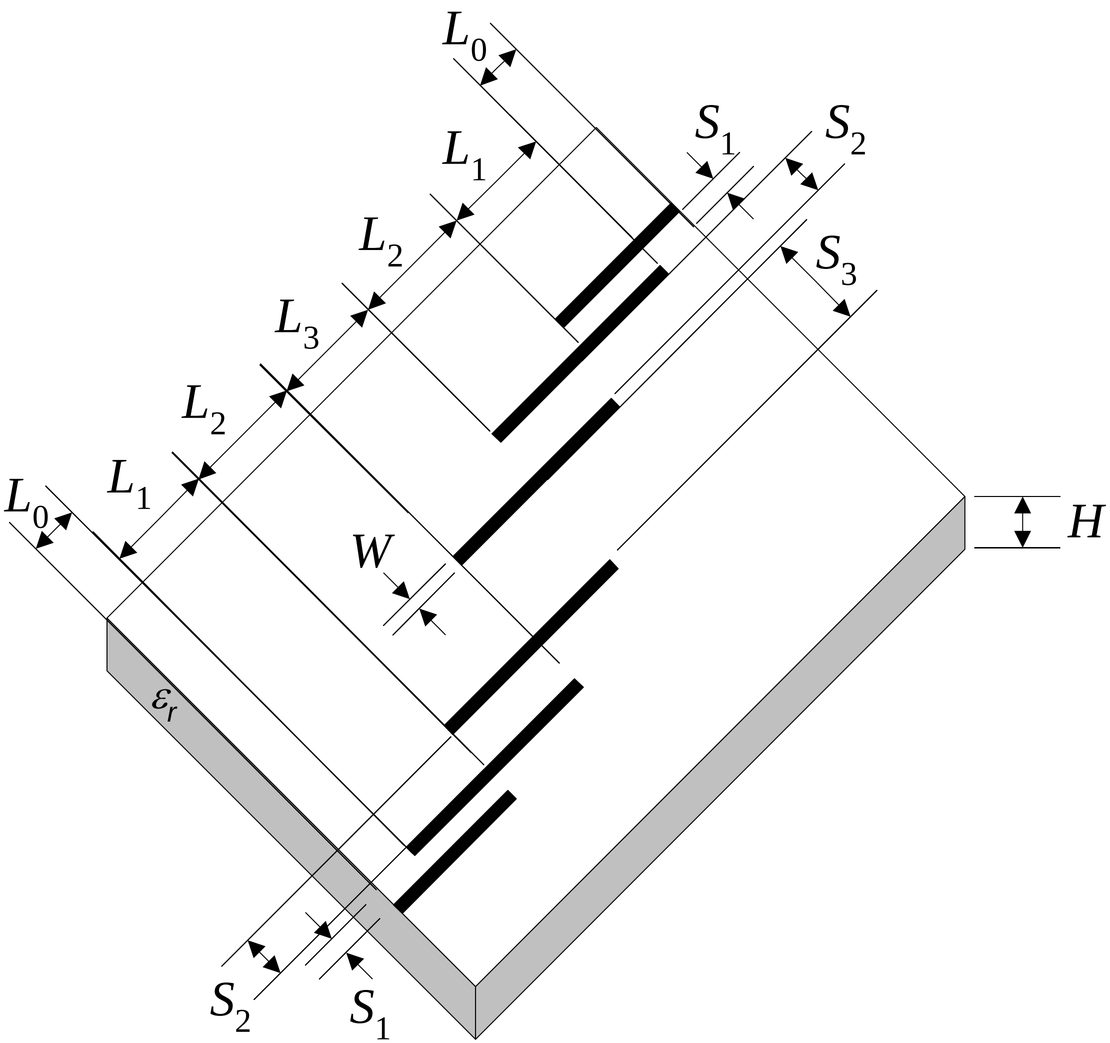


Neural Space Mapping (NSM) Optimization Algorithm



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

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

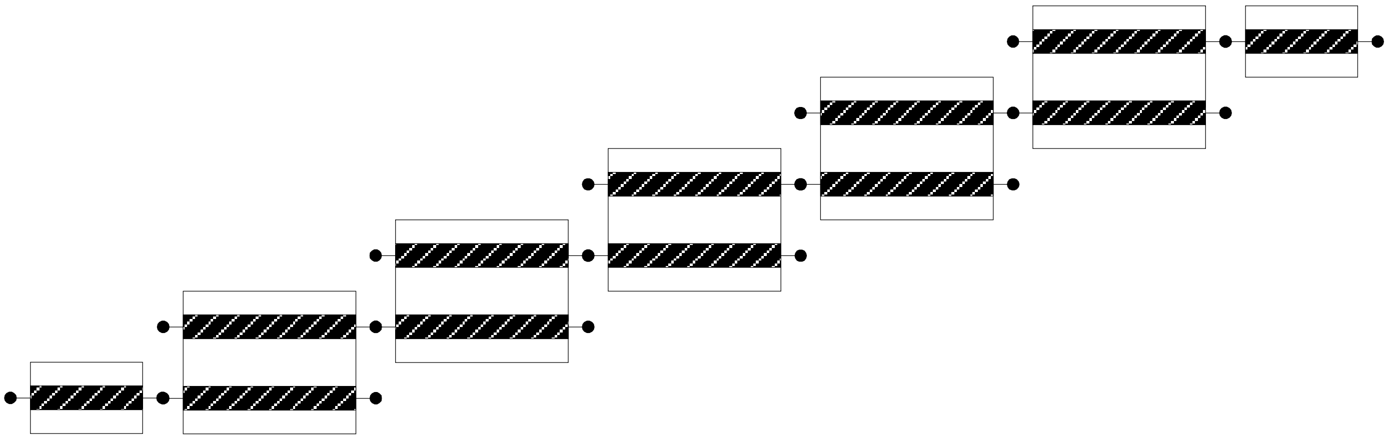
NSM Optimization of the HTS Microstrip Filter

specifications

$$|S_{21}| \geq 0.95 \text{ for } 4.008 \text{ GHz} \leq \omega \leq 4.058 \text{ GHz}$$
$$|S_{21}| \leq 0.05 \text{ for } \omega \leq 3.967 \text{ GHz and } \omega \geq 4.099 \text{ GHz}$$

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

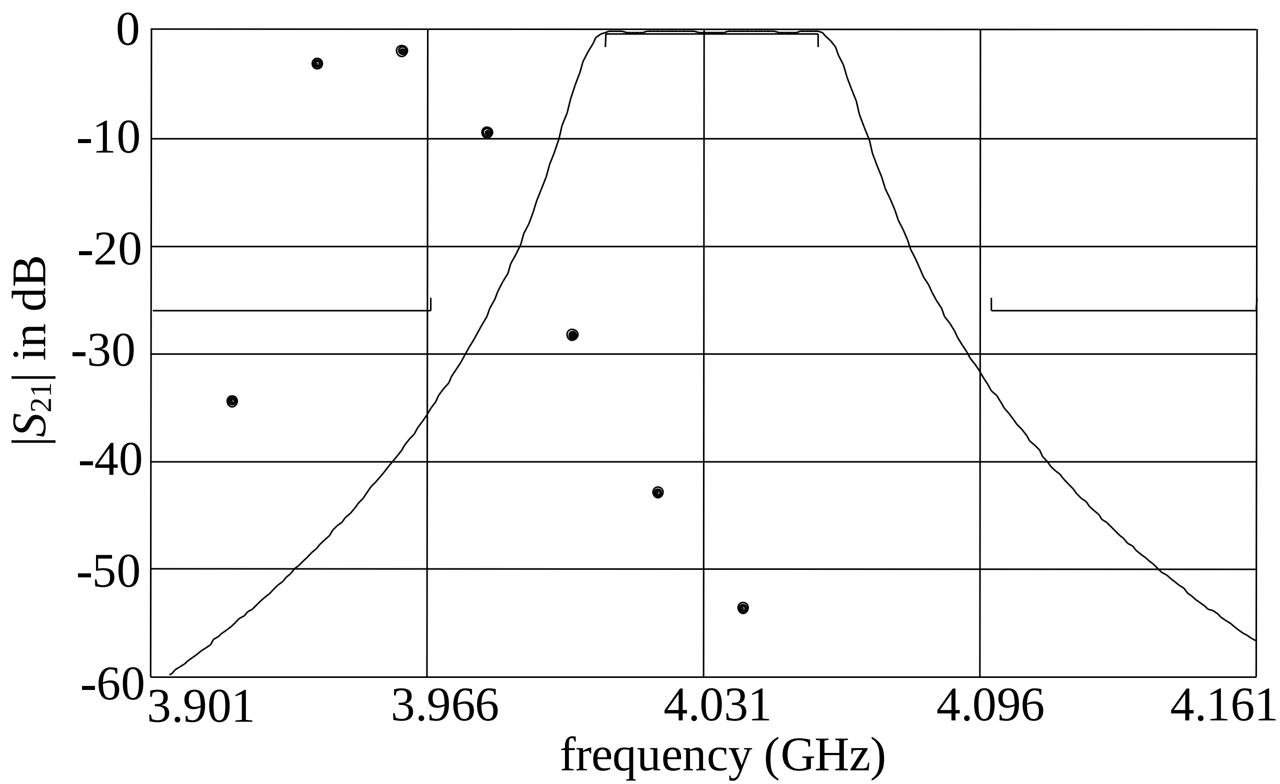
"coarse" model: OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines



NSM Optimization of the HTS Filter (continued)

coarse and fine model responses at the optimal coarse solution

OSA90/hope™ (–) and ***em***™ (•)

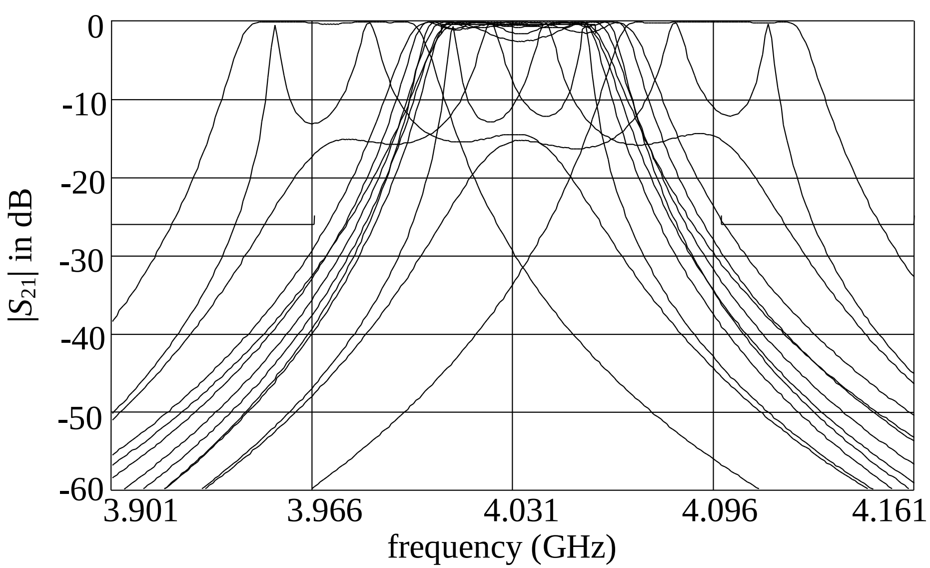


NSM Optimization of the HTS Filter (continued)

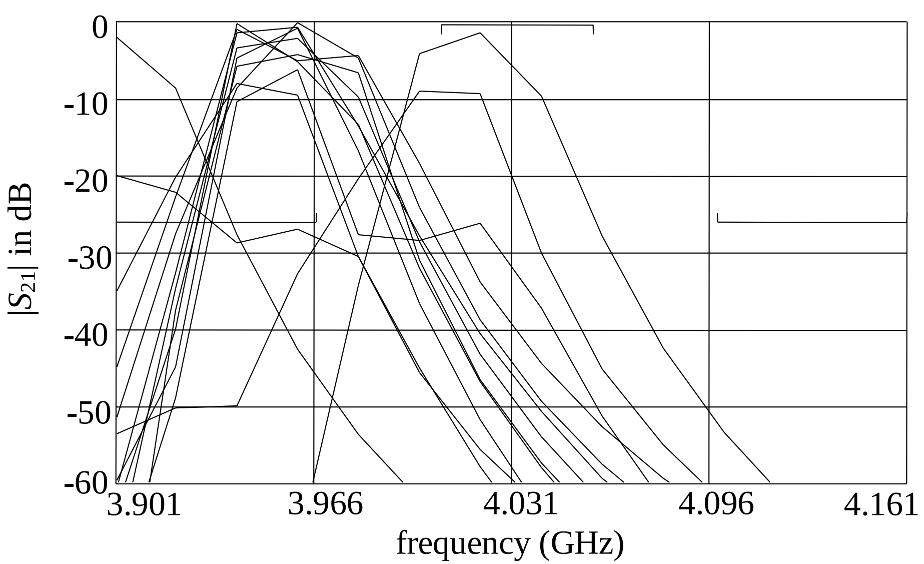
the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 3% deviation from $\boldsymbol{x}_c^*$ for L_1, L_2, and L_3 is used, while a 20% is used for S_1, S_2, and S_3

coarse and fine model responses at base points

OSA90/hope™



em™

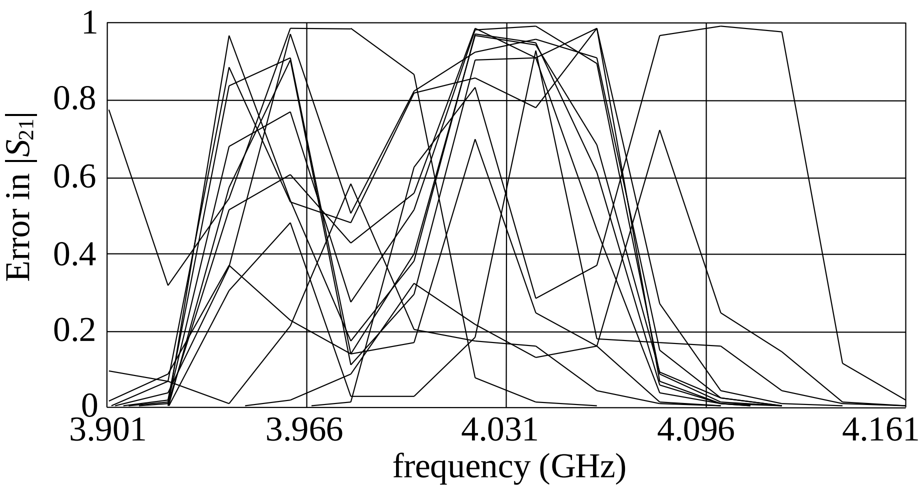


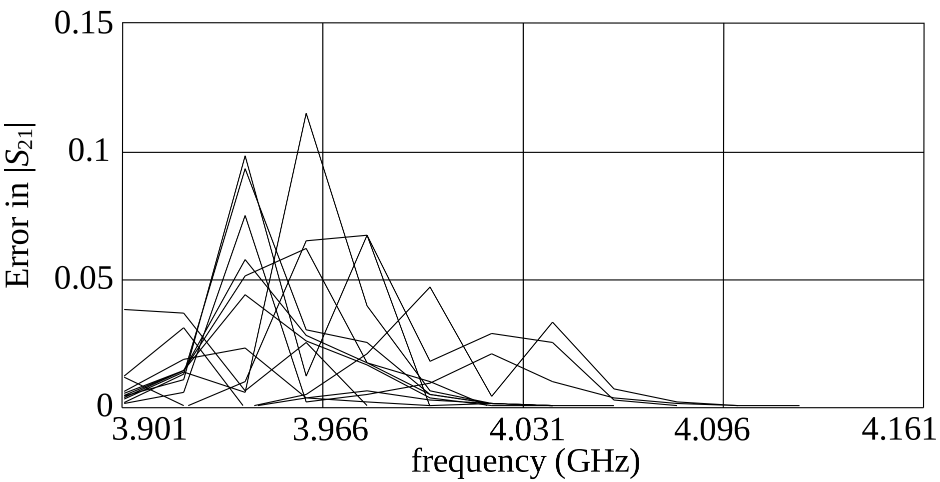
NSM Optimization of the HTS Filter (continued)

learning errors at base points

before any neuromapping

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

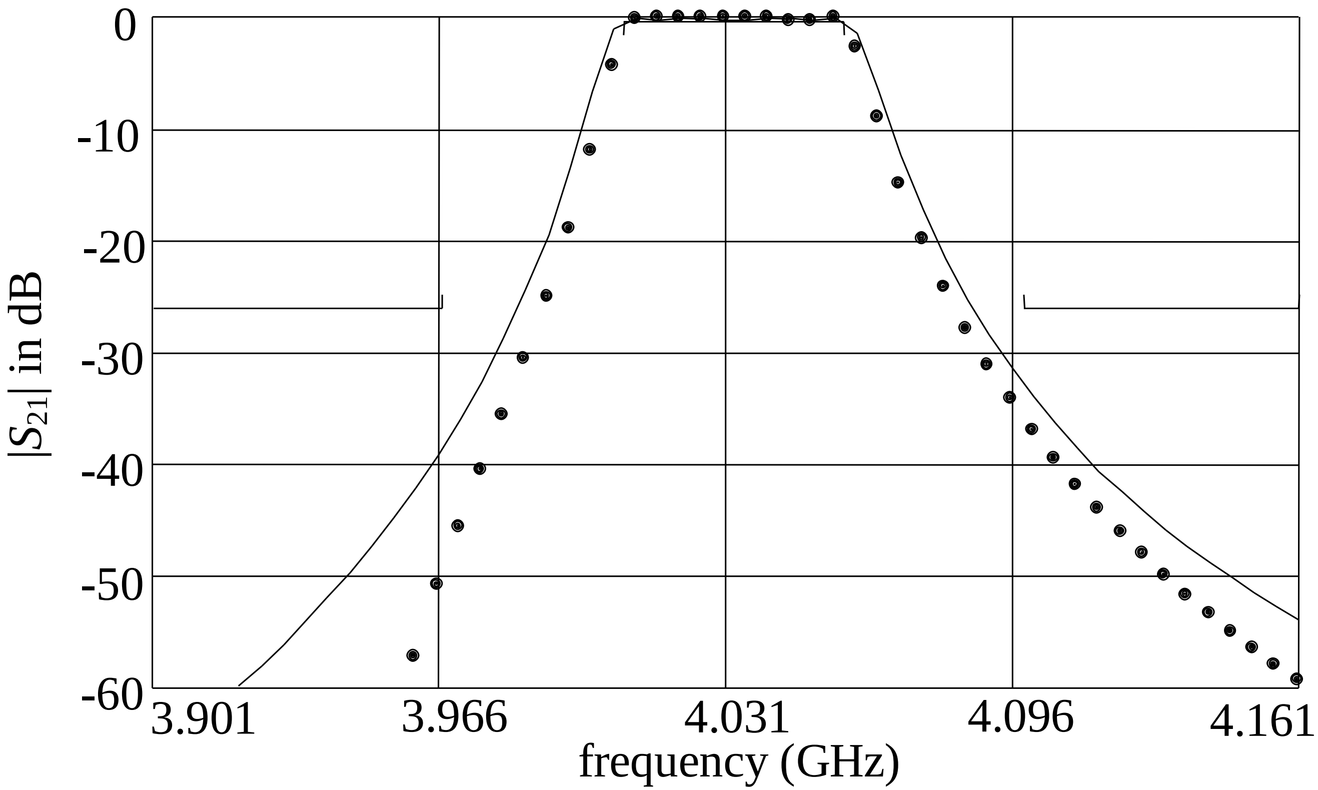




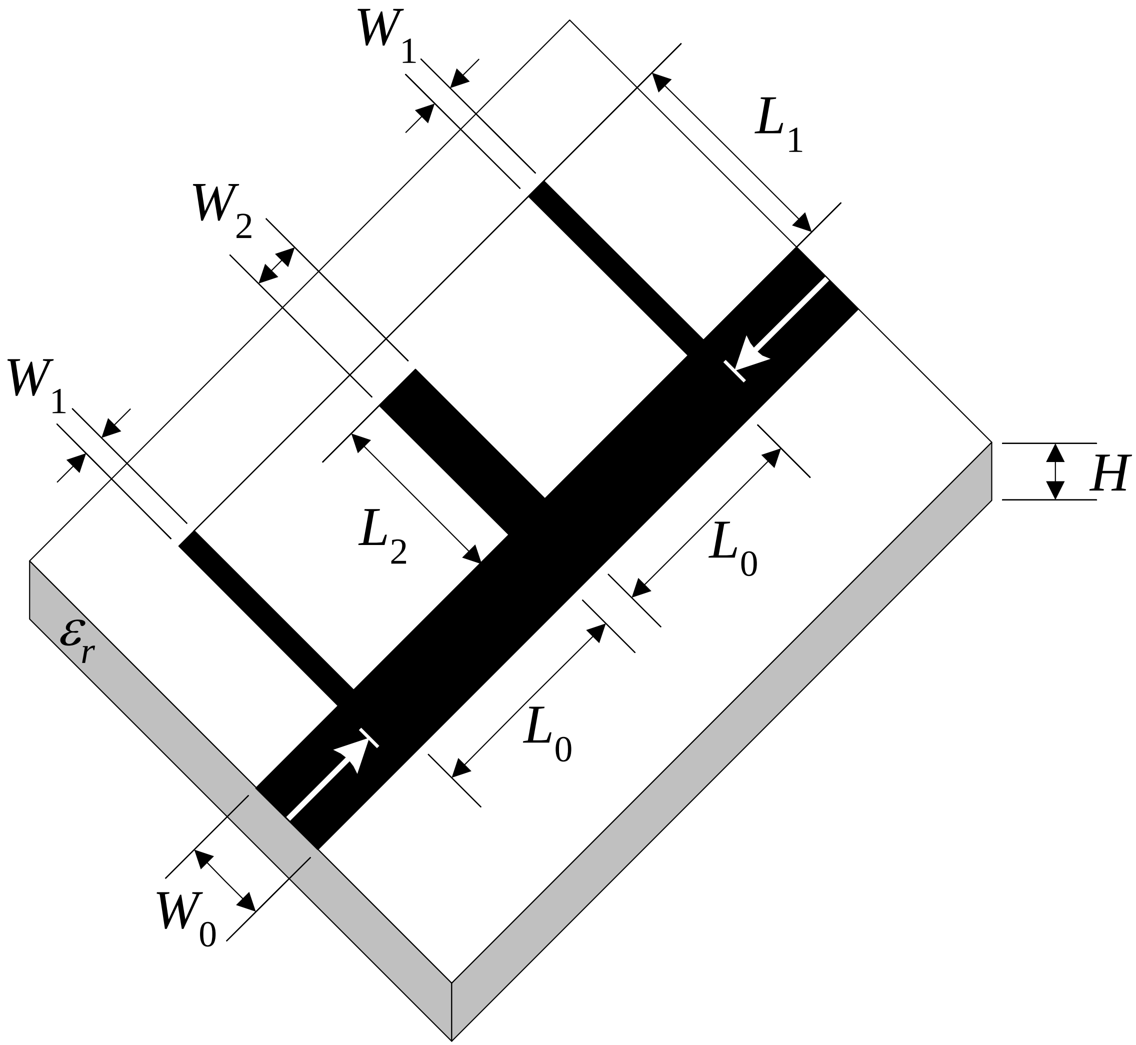
NSM Optimization of the HTS Filter (continued)

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

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

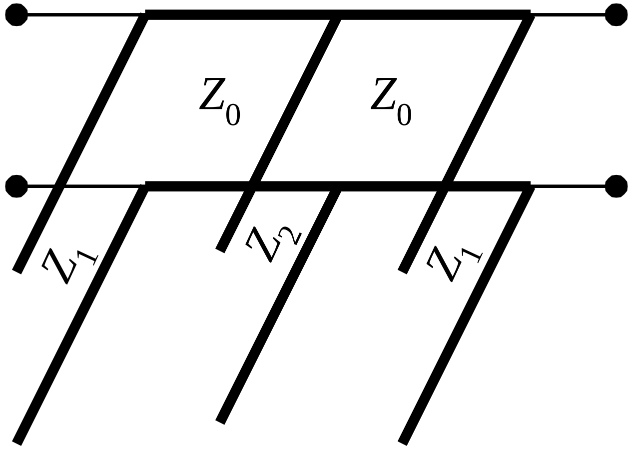
NSM Optimization of the Bandstop Filter

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

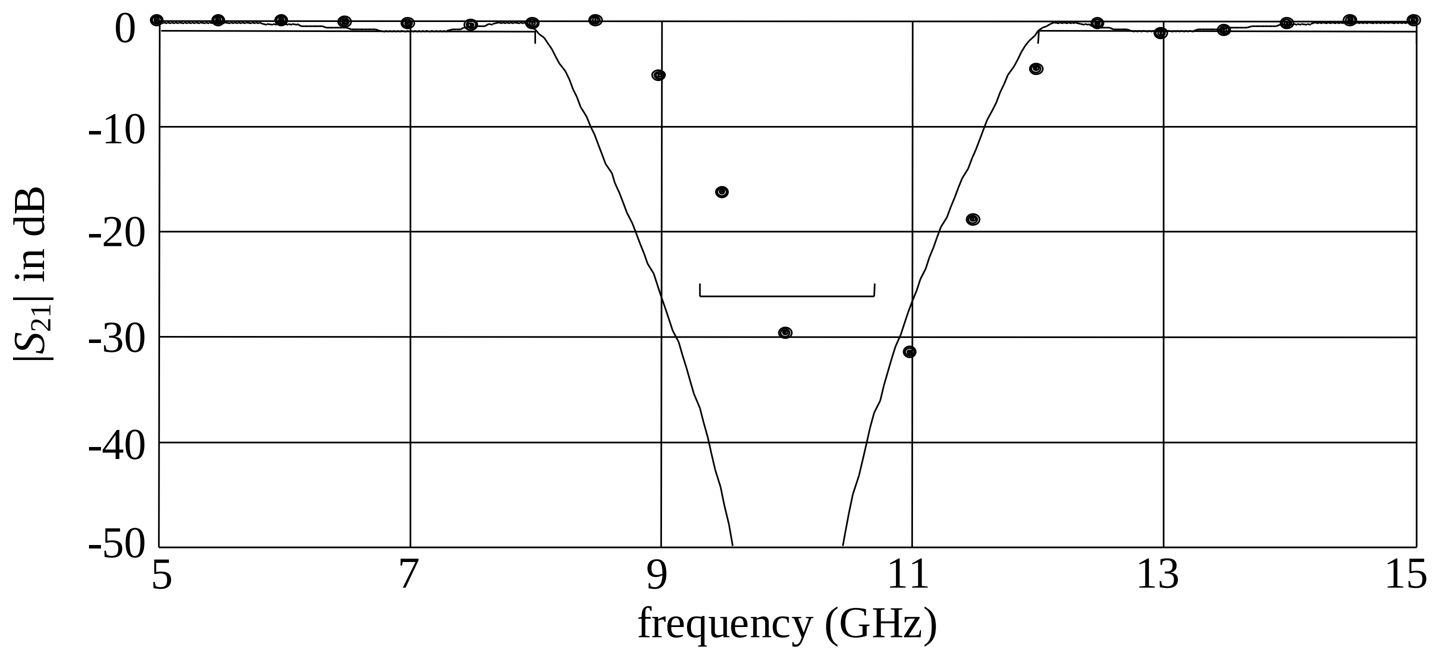
"coarse" model: transmission line sections and empirical formulas



NSM Optimization of the Bandstop Filter (continued)

coarse and fine model responses at the optimal coarse solution

coarse model (–) and ***em***™ (•)

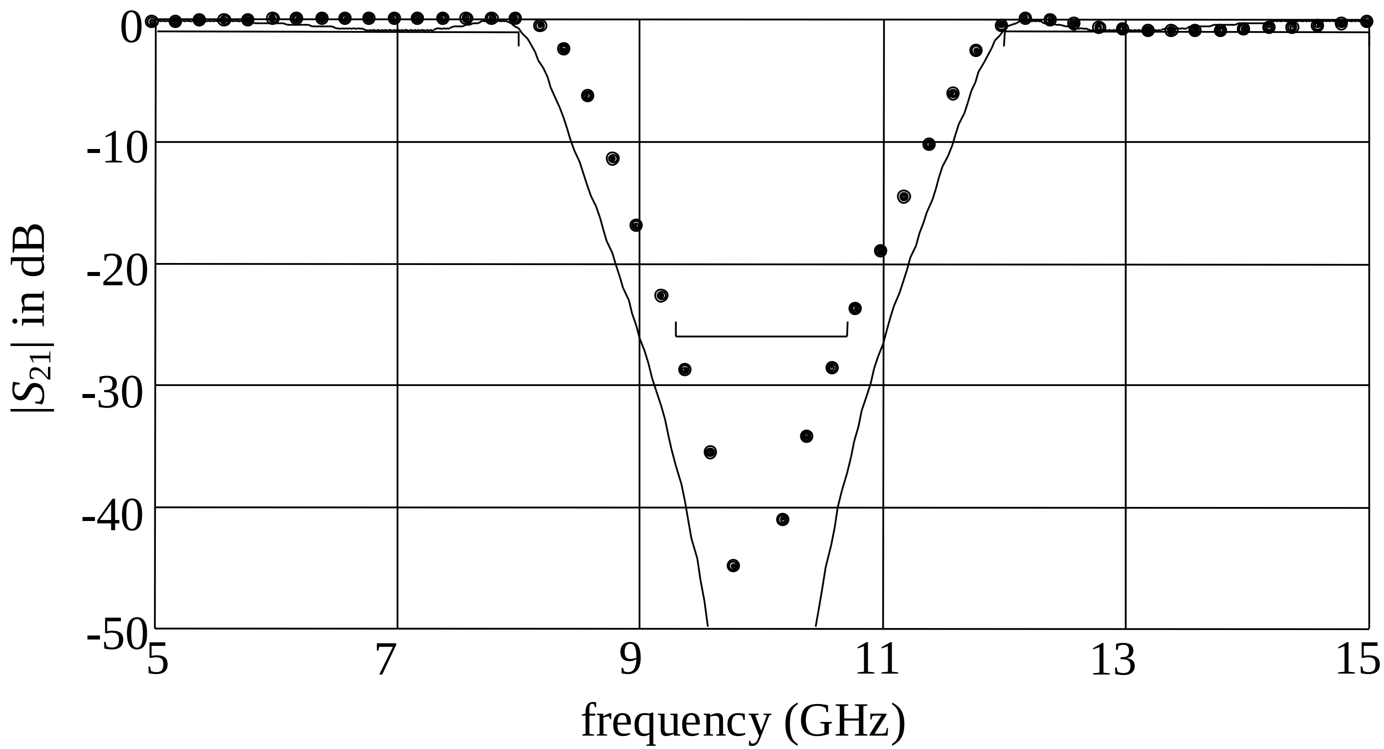


the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 50% deviation from $\boldsymbol{x}_c^*$ for W_1, W_2, and L_0 is used, while a 15% is used for L_1, and L_2

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)

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

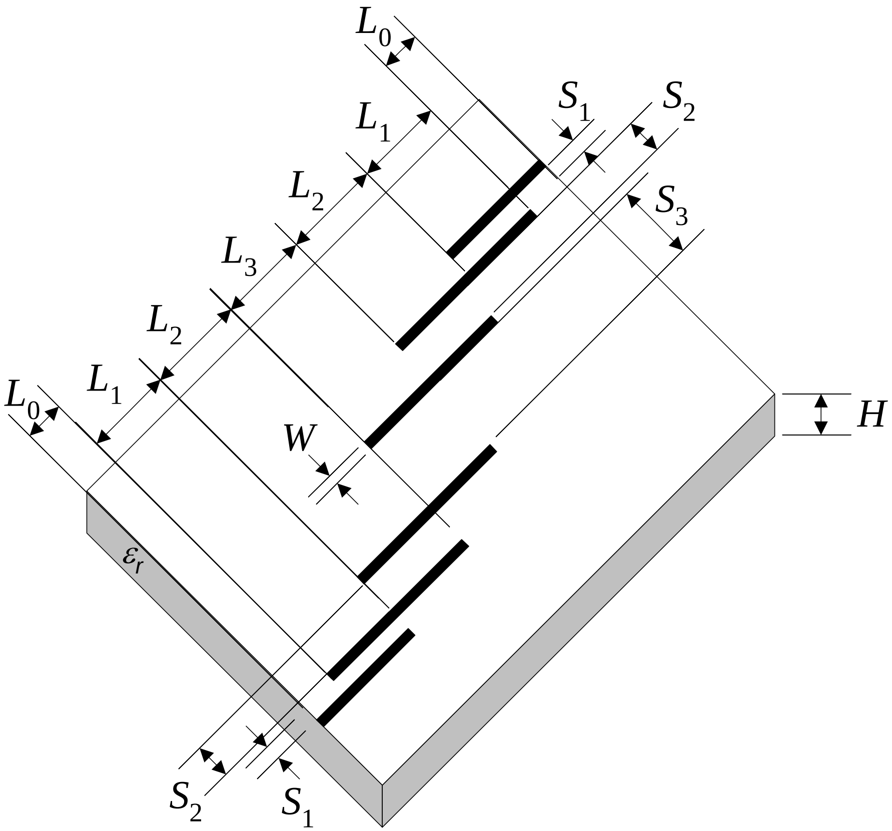
for all $\boldsymbol{x}_f$ and ω in the training region

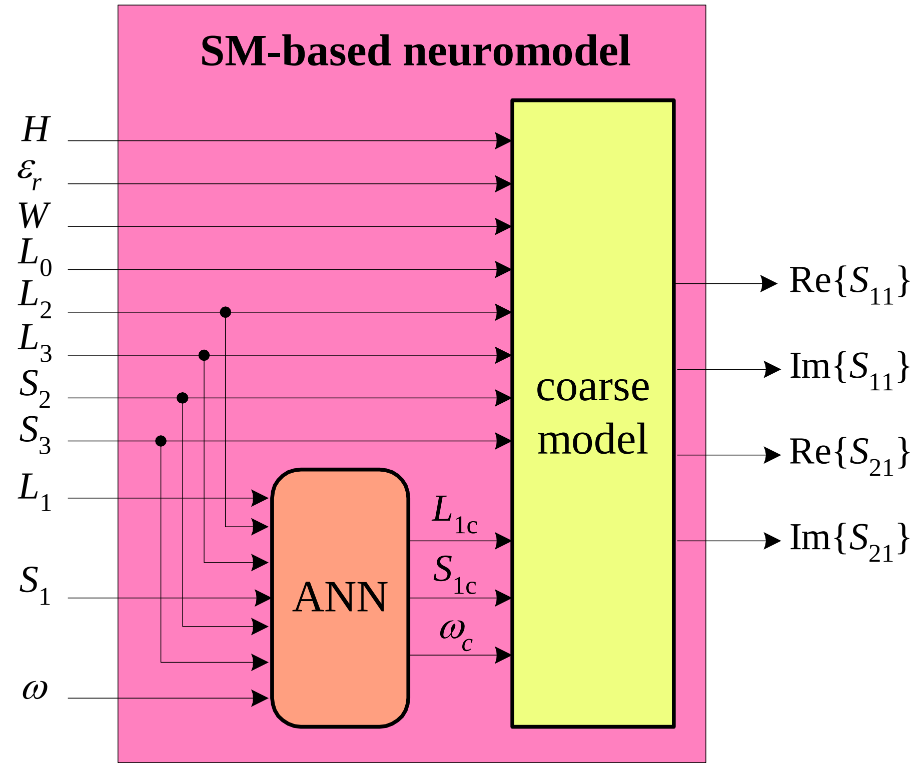
we can show that

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

$\boldsymbol{J}_f \in \Re^{r\times n}$	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

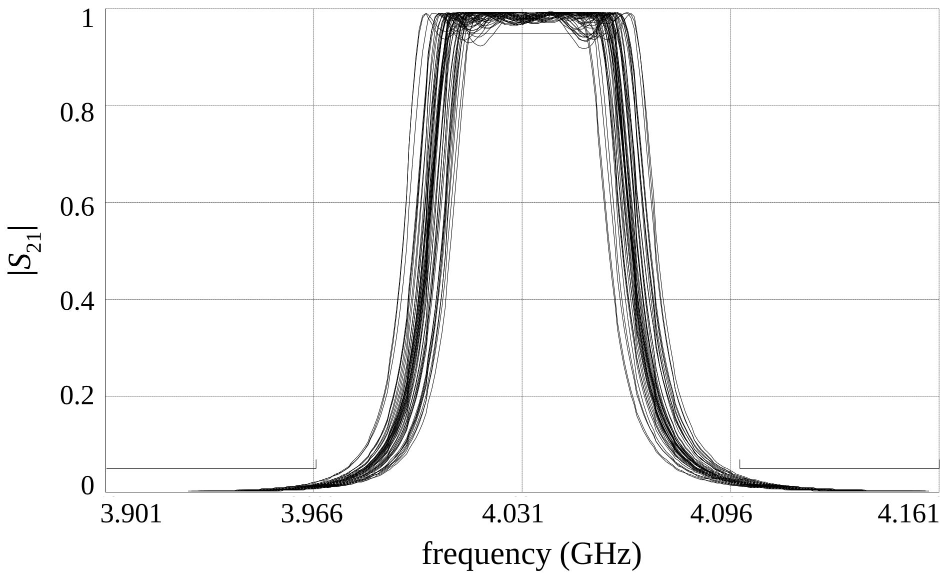
Yield Optimization of the HTS Filter

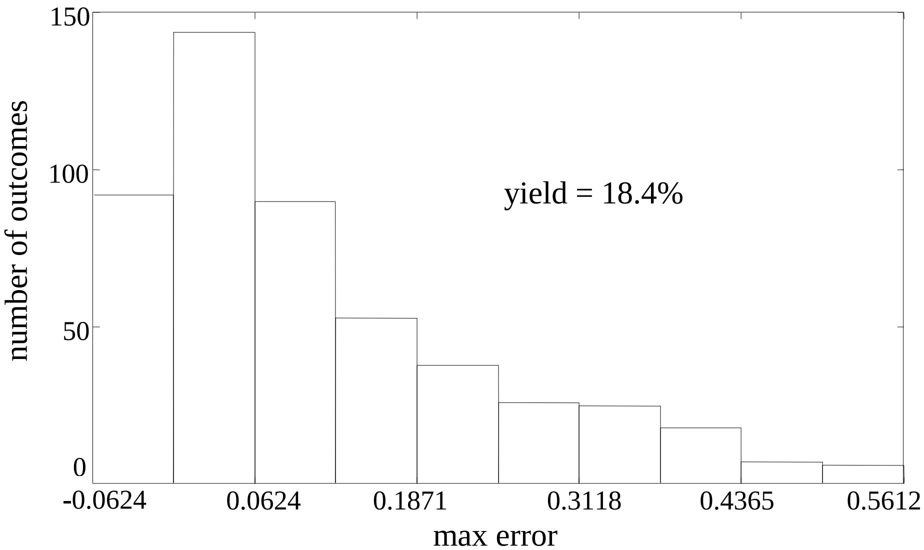




Yield Optimization of the HTS Filter

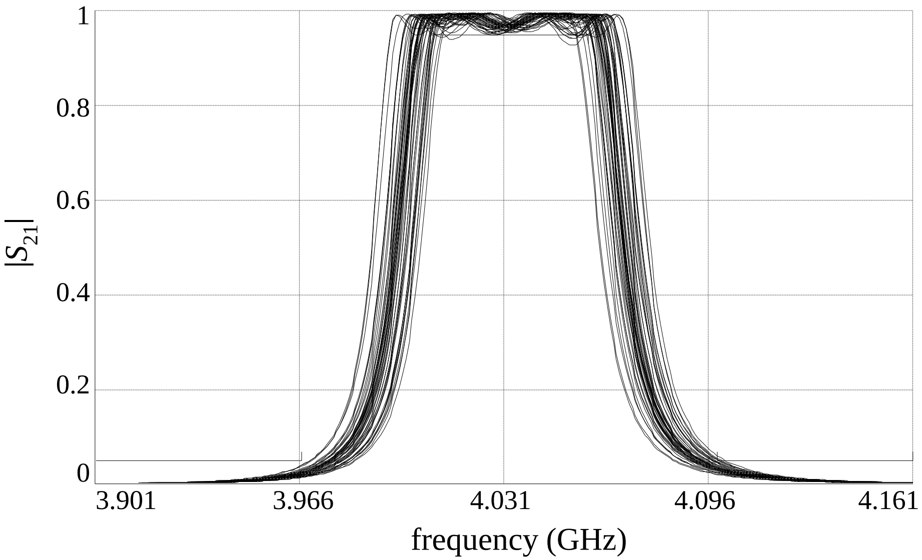
at the nominal solution (starting point): yield = 18.4%

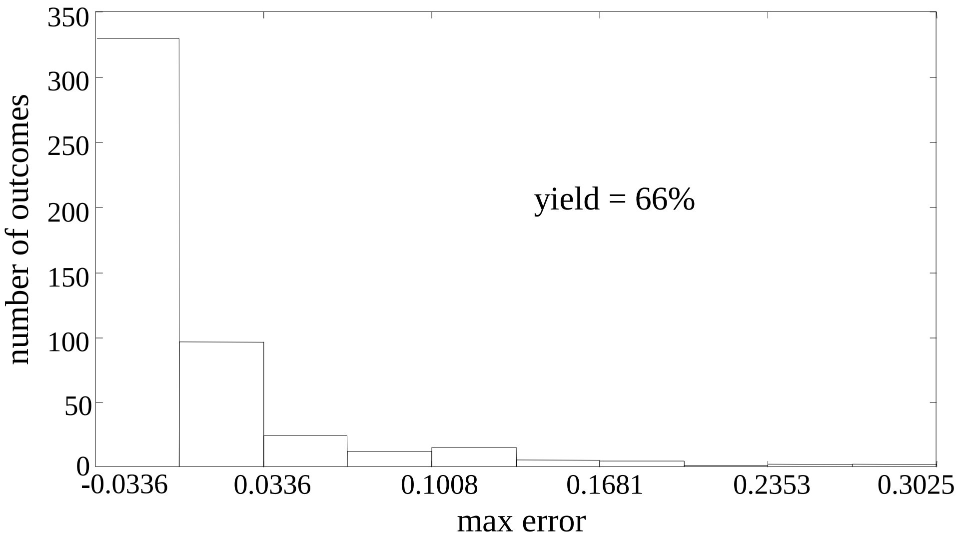




Yield Optimization of the HTS Filter (continued)

at the optimal yield solution: yield = 66%





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