NEURAL SPACE MAPPING EM OPTIMIZATION OF MICROWAVE STRUCTURES

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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 they are trained with reliable learning data, the neuromodel can be used for efficient and accurate optimization within the region of training

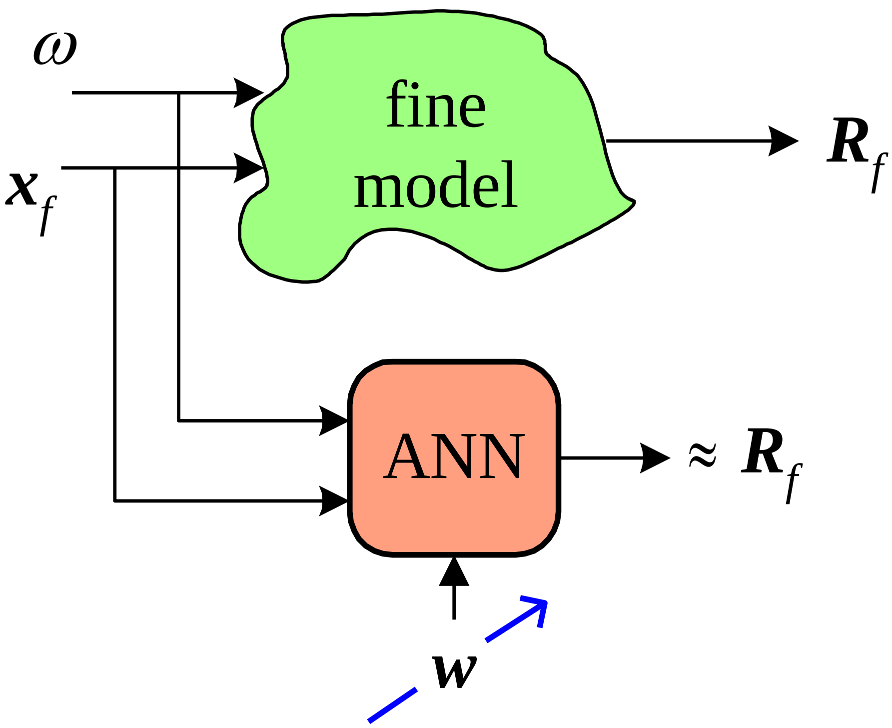
the principal drawback of this ANN optimization approach is the cost of generating sufficient learning samples

additionally, it is well known that the extrapolation ability of neuromodels is very poor, making unreliable any solution predicted outside the training region

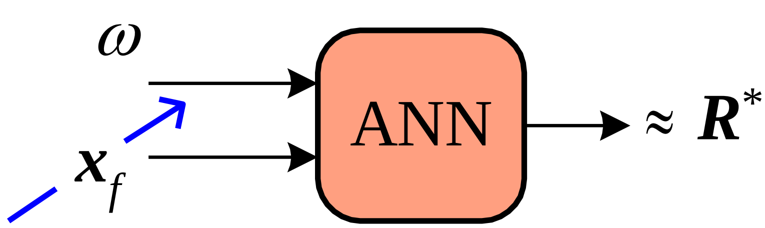
introducing knowledge can alleviate these limitations *(Gupta et al., 1999)*

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

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

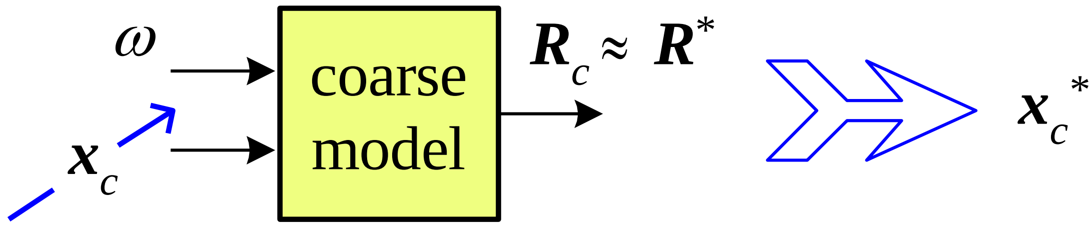
NSM requires a reduced set of upfront learning base points

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

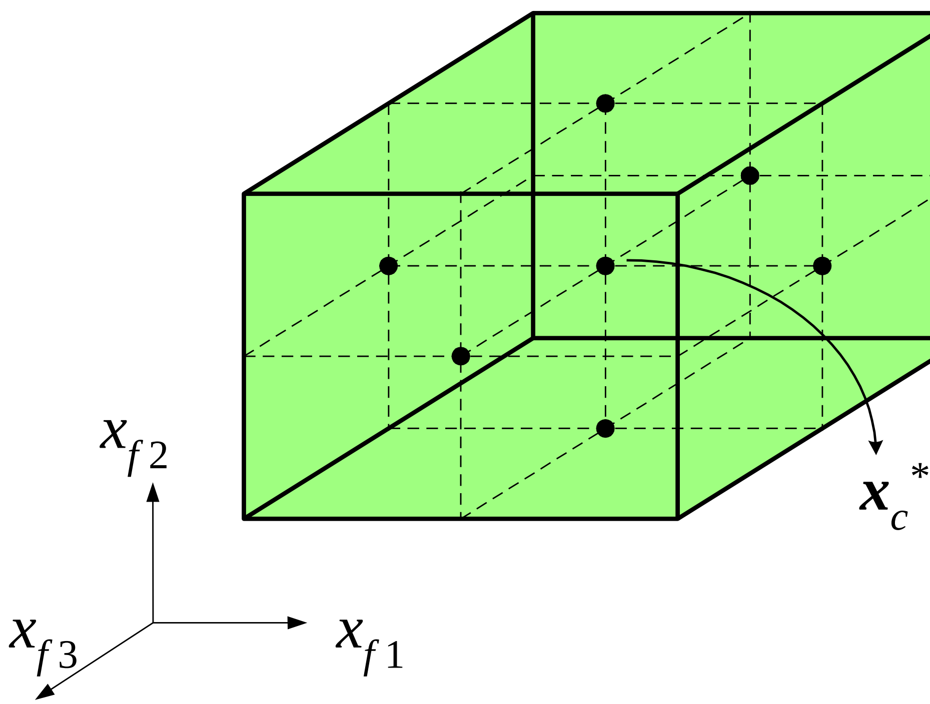
neuromappings are developed iteratively: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons

Neural Space Mapping (NSM) Optimization Concept

step 1



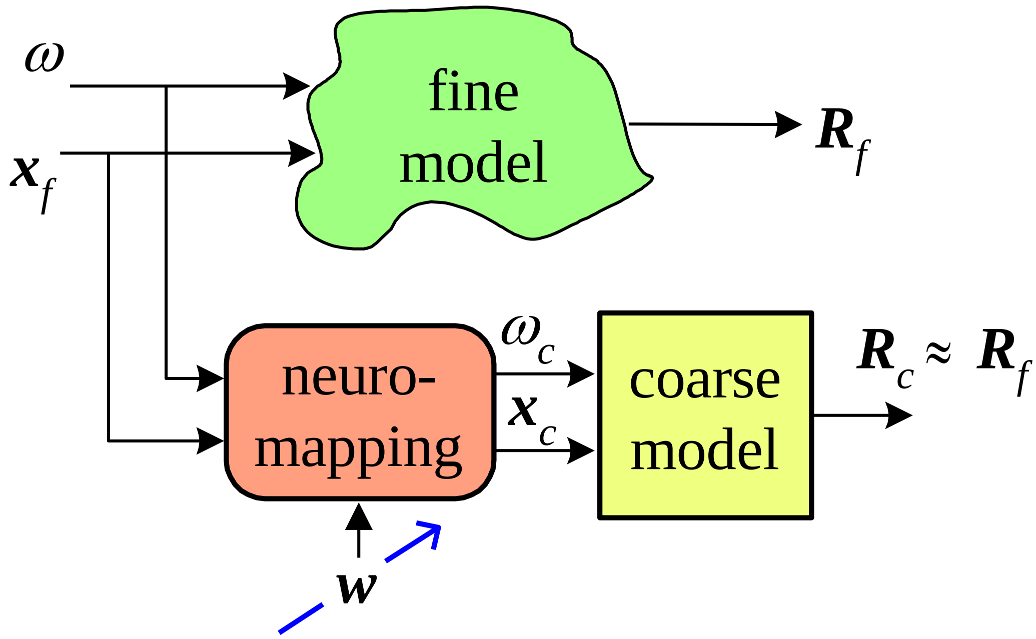
step 2



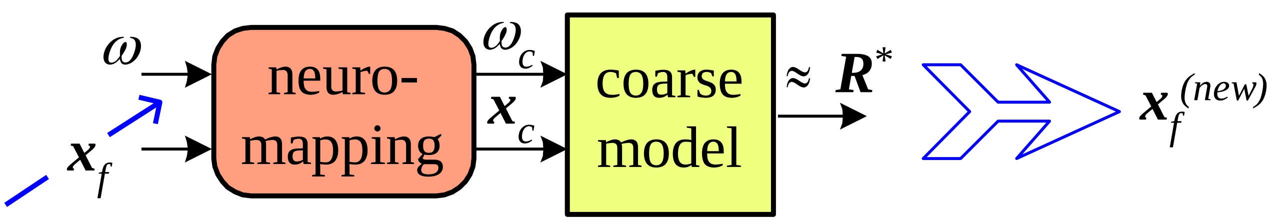
(2n + 1 learning base points for a microwave circuit with n design parameters)

Neural Space Mapping (NSM) Optimization Concept

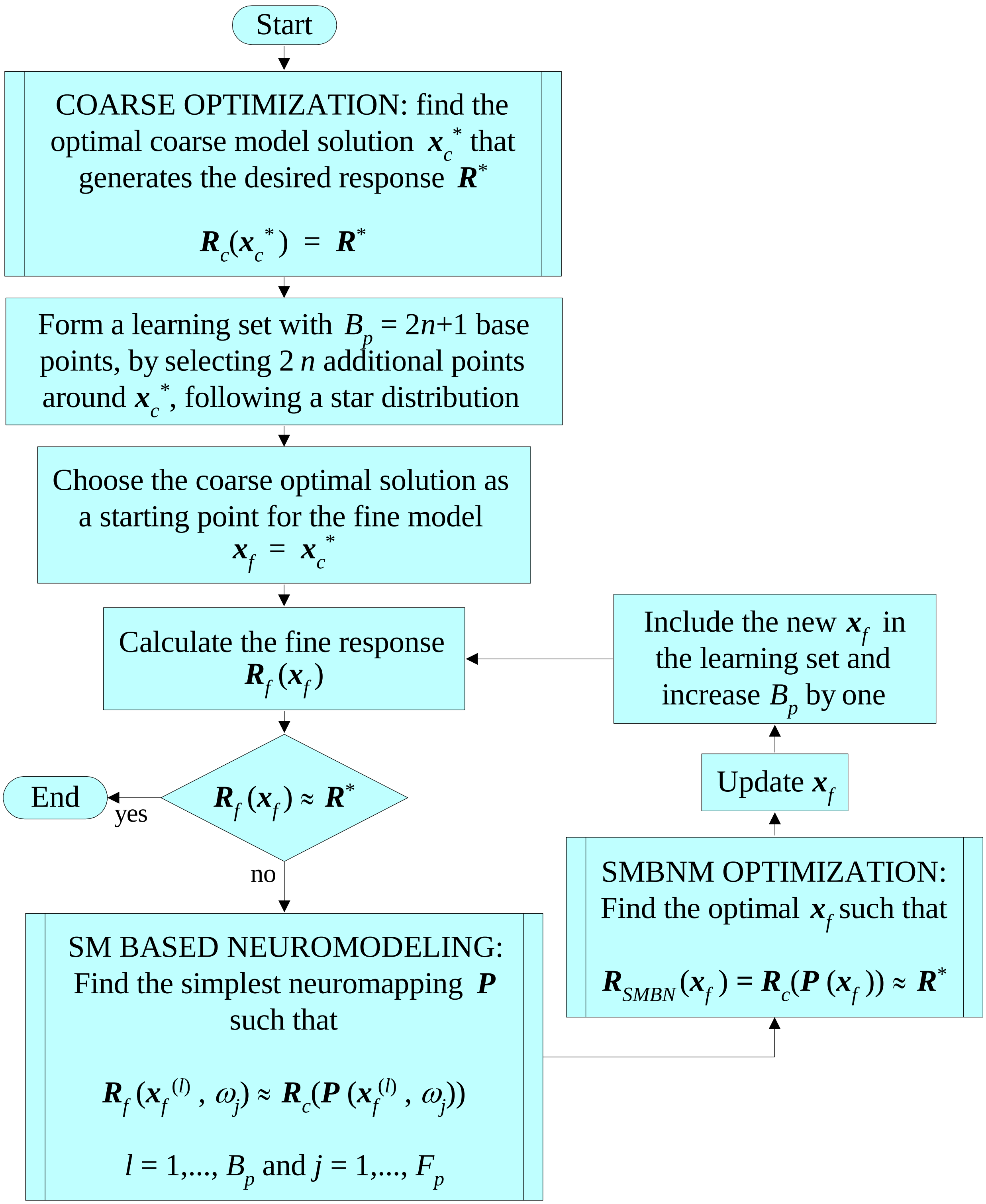
step 3



step 4

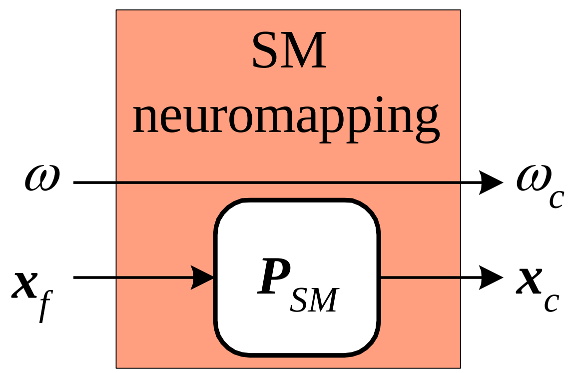


Neural Space Mapping (NSM) Optimization Algorithm

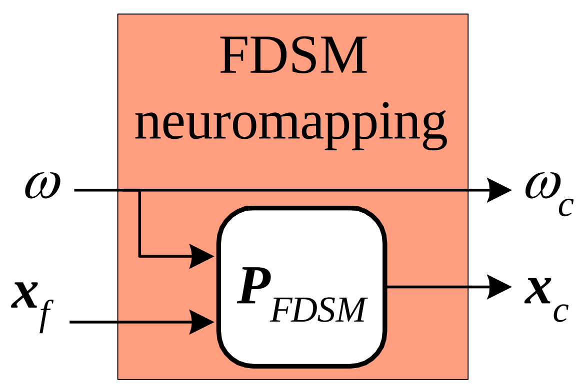


Neuromappings

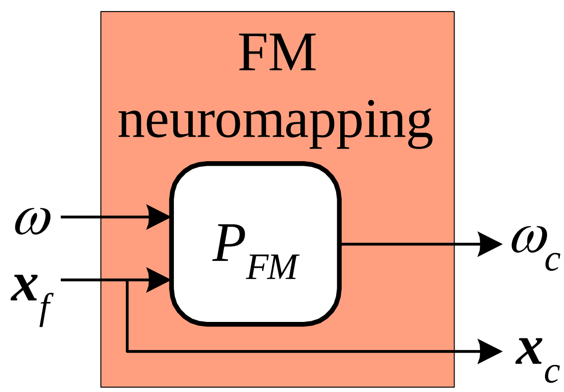
Space Mapped neuromapping



Frequency-Dependent Space Mapped neuromapping

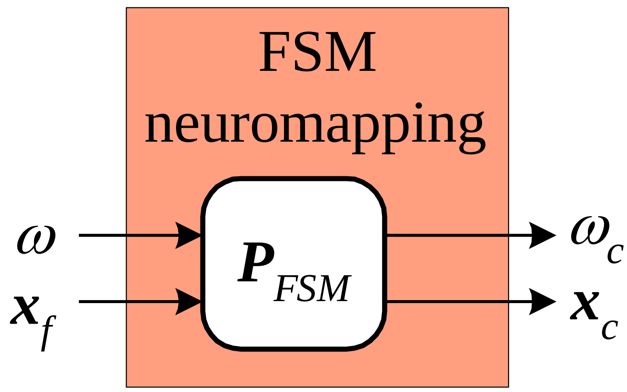


Frequency Mapped neuromapping

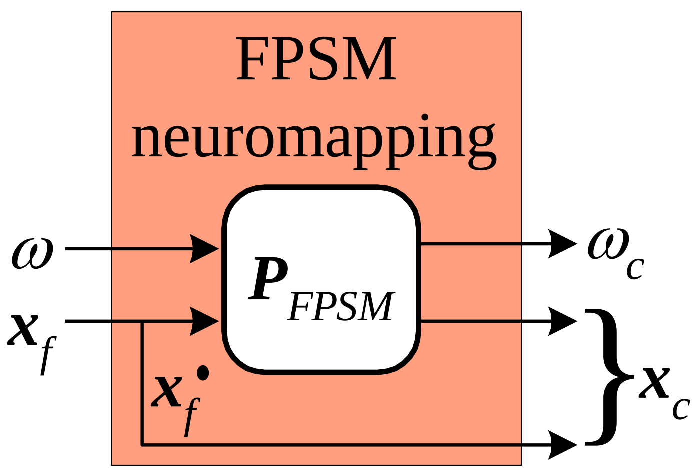


Neuromappings (continued)

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

Coarse Optimization Phase

we want to find the optimal coarse model solution $\boldsymbol{x}_c^*$ that generates the desired response over the frequency range of interest

vector of coarse model responses $\boldsymbol{R}_c$ might contain r different responses of the circuit

$$\boldsymbol{R}_c(\boldsymbol{x}_c) = [\boldsymbol{R}_c^1(\boldsymbol{x}_c)^T \quad \ldots \quad \boldsymbol{R}_c^r(\boldsymbol{x}_c)^T]^T$$

where each individual response has been sampled at F_p frequency points

$$\boldsymbol{R}_c^k(\boldsymbol{x}_c) = [R_c^k(\boldsymbol{x}_c, \omega_1) \quad \ldots \quad R_c^k(\boldsymbol{x}_c, \omega_{F_p})]^T, \; k = 1, \ldots, r$$

the problem of circuit design using the coarse model can be formulated as

$$\boldsymbol{x}_c^* = \arg\min_{\boldsymbol{x}_c} U(\boldsymbol{R}_c(\boldsymbol{x}_c))$$

where U is a suitable objective function

Training the SM-Based Neuromodel During NSM Optimization

we solve the problem

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\cdots \quad \boldsymbol{e}_s{}^T \quad \cdots]^T \right\|$$

with

$$\boldsymbol{e}_s = \boldsymbol{R}_f(\boldsymbol{x}_f{}^{(l)}, \omega_j) - \boldsymbol{R}_c(\boldsymbol{x}_{c_j}{}^{(l)}, \omega_{c_j}) \;,\;\; \boldsymbol{e}_s \in \Re^r$$

$$\begin{bmatrix} \boldsymbol{x}_{c_j}{}^{(l)} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f{}^{(l)}, \omega_j, \boldsymbol{w})$$

$$j = 1, \ldots, F_p$$

$$l = 1, \ldots, 2n + i$$

$$s = j + F_p(l-1)$$

$\boldsymbol{P}^{(i)}$ is the input-output relationship of the ANN at the ith iteration

$\boldsymbol{w}$ contains the free parameters of the current ANN

$2n+i$ is the number of training base points and F_p is the number of frequency points per frequency sweep

the complexity of the ANN (the number of hidden neurons and the SM-based neuromodeling technique) is gradually increased according to the learning error, starting with a linear mapping (3-layer perceptron with 0 hidden neurons)

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:

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

where

$$\boldsymbol{R}_{SMBN}^k(\boldsymbol{x}_f) = [R_c^k(\boldsymbol{x}_{c1}, \omega_{c1}) \quad \dots \quad R_c^k(\boldsymbol{x}_{cF_p}, \omega_{cF_p})]^T, \; k = 1, \dots, r$$

with

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

the next iterate is obtained by solving

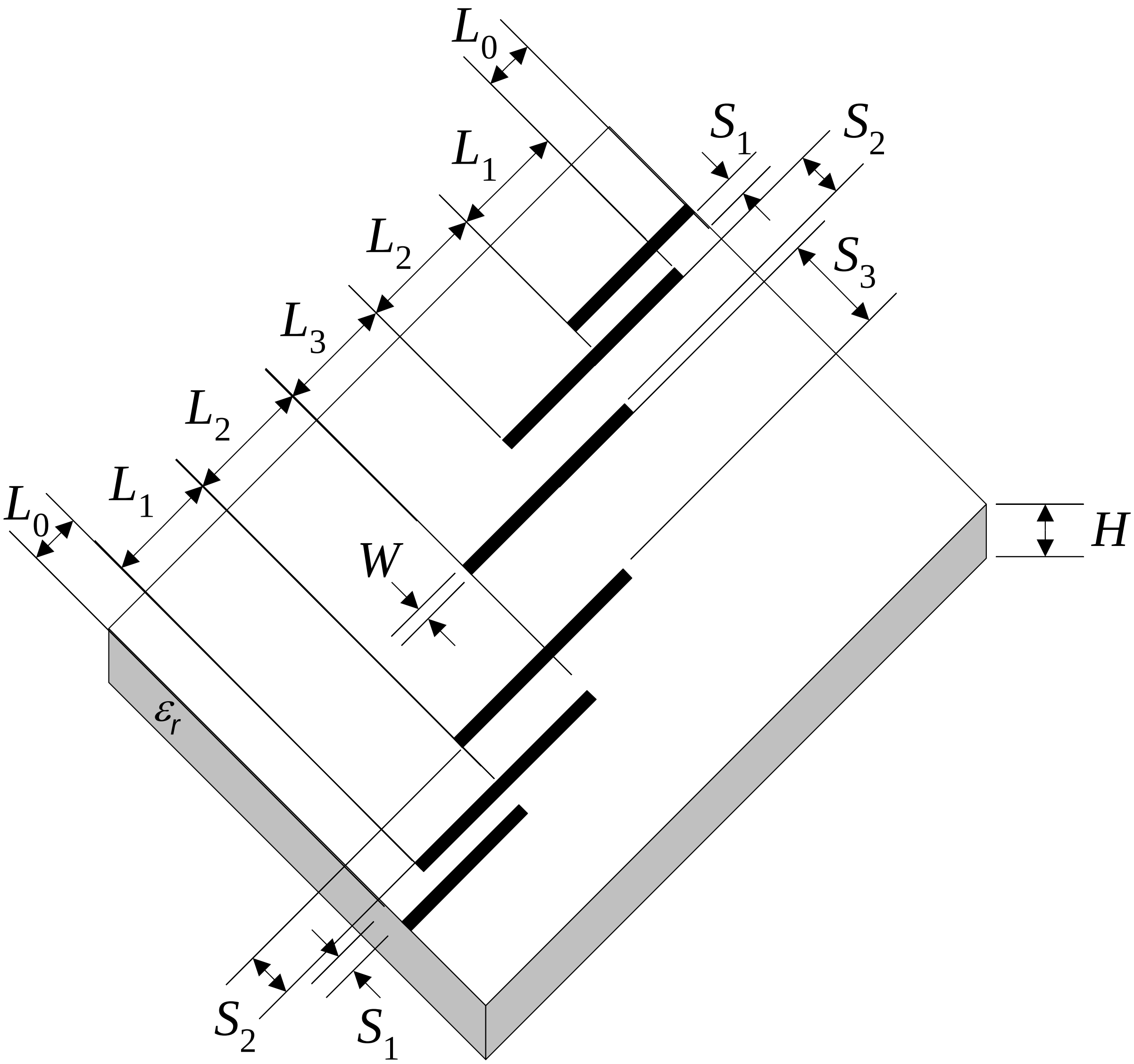
$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f))$$

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

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

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

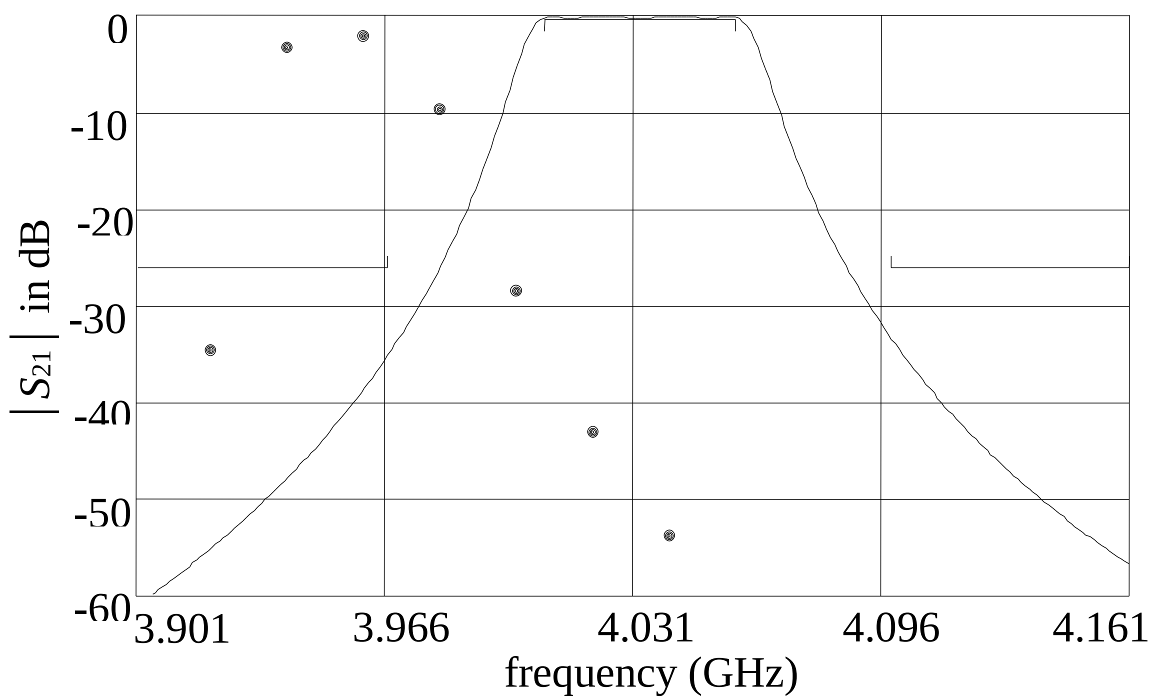
the design parameters are $\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$

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***™ (•)

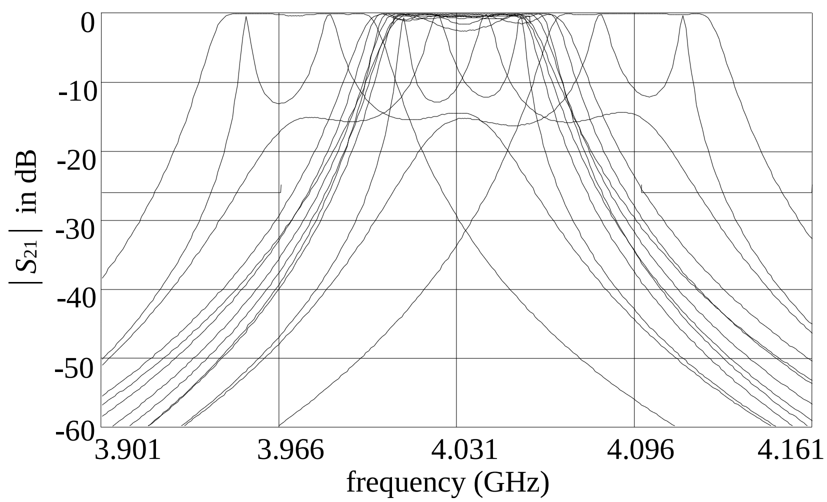


NSM Optimization of the HTS Filter (continued)

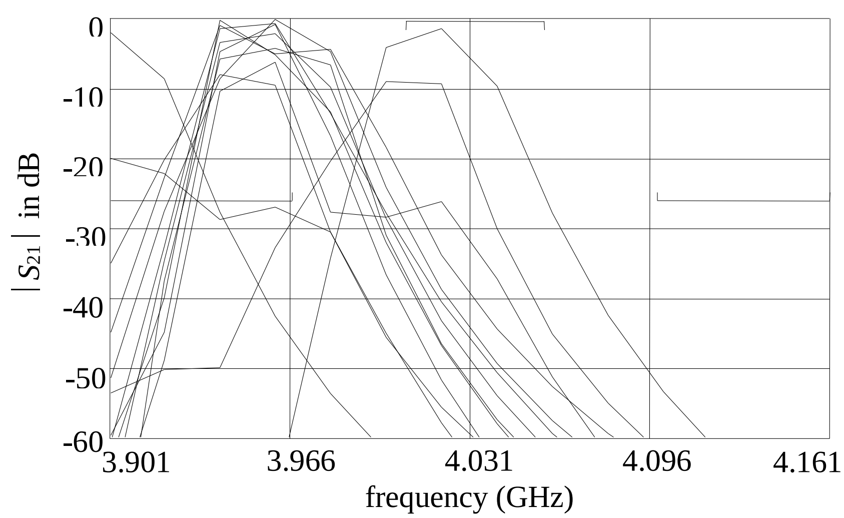
the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 3% deviation from $\boldsymbol{x}_c^*$ for L_1, L_2, and L_3 is used, while a 20% is used for S_1, S_2, and S_3

coarse and fine model responses at base points:

OSA90/hope™



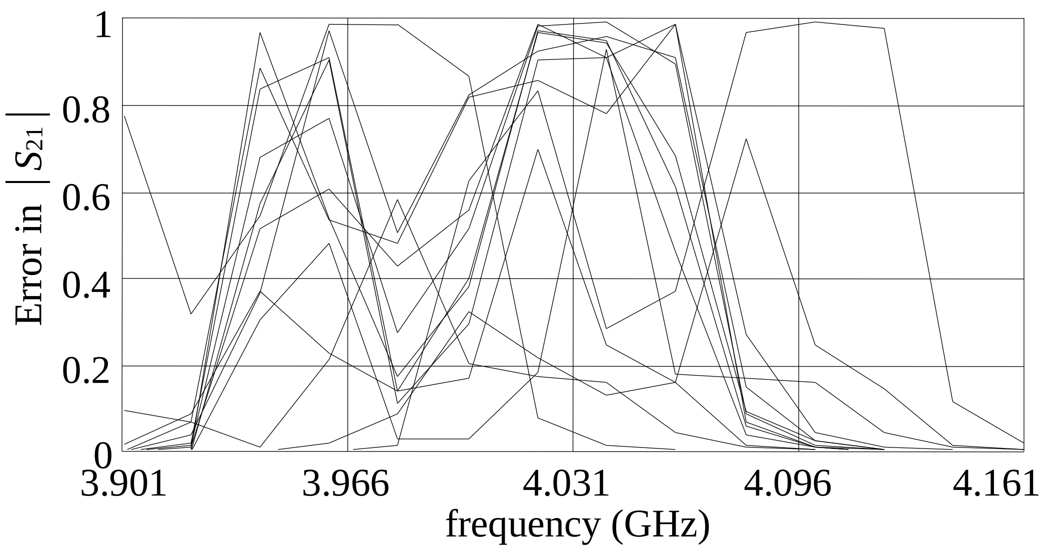
em™



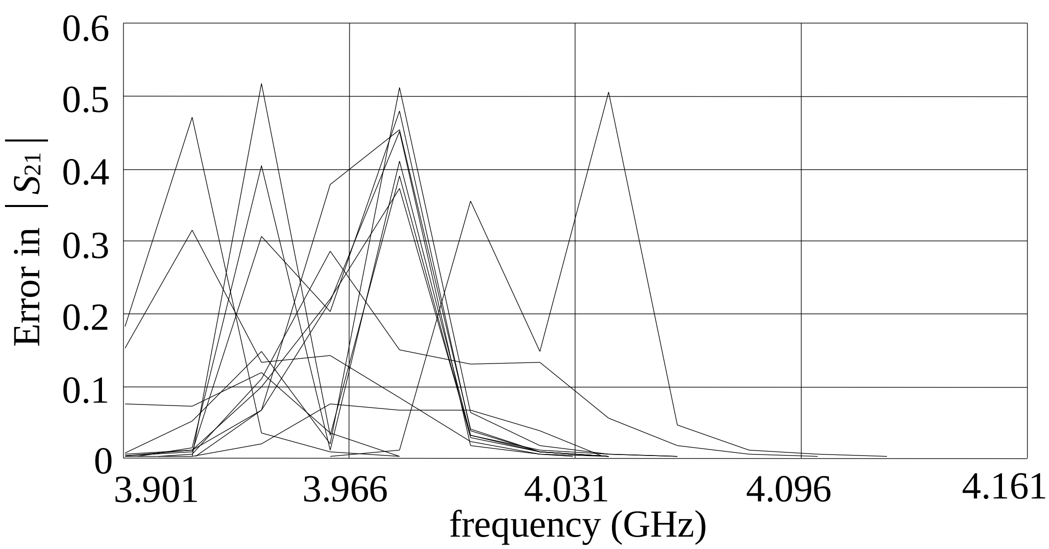
NSM Optimization of the HTS Filter (continued)

Learning errors at base points:

before any neuromapping



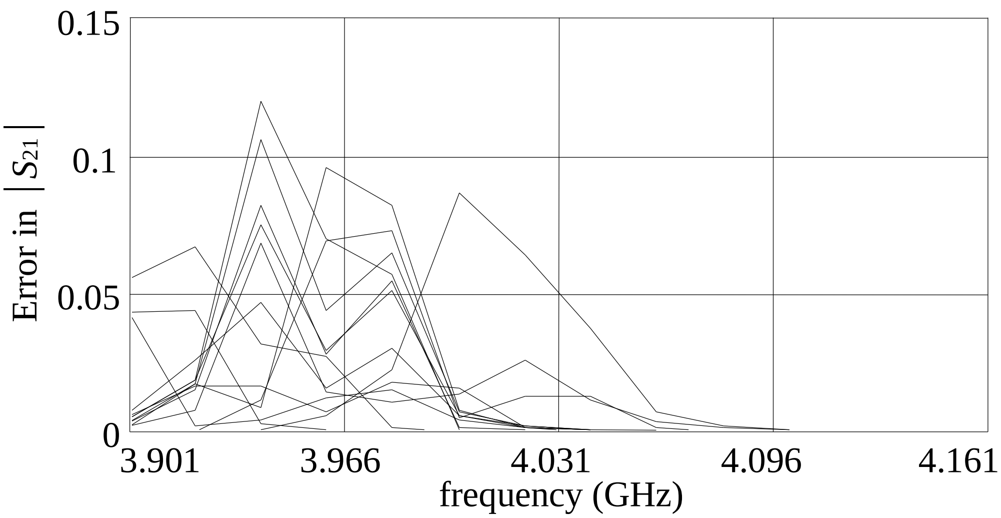
mapping ω with a 3LP:7-3-1



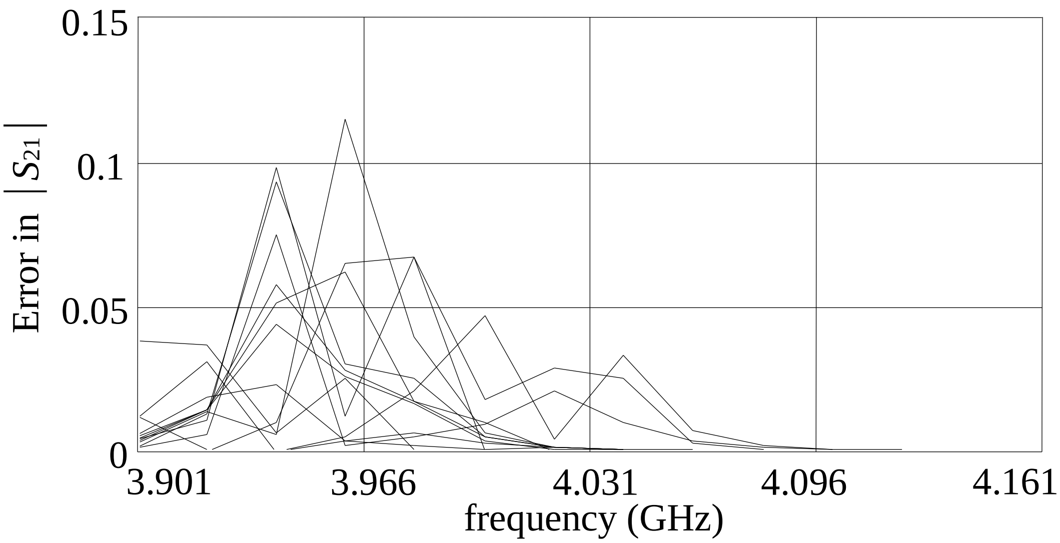
NSM Optimization of the HTS Filter (continued)

Learning errors at base points:

mapping ω and L_1 with a 3LP:7-4-2



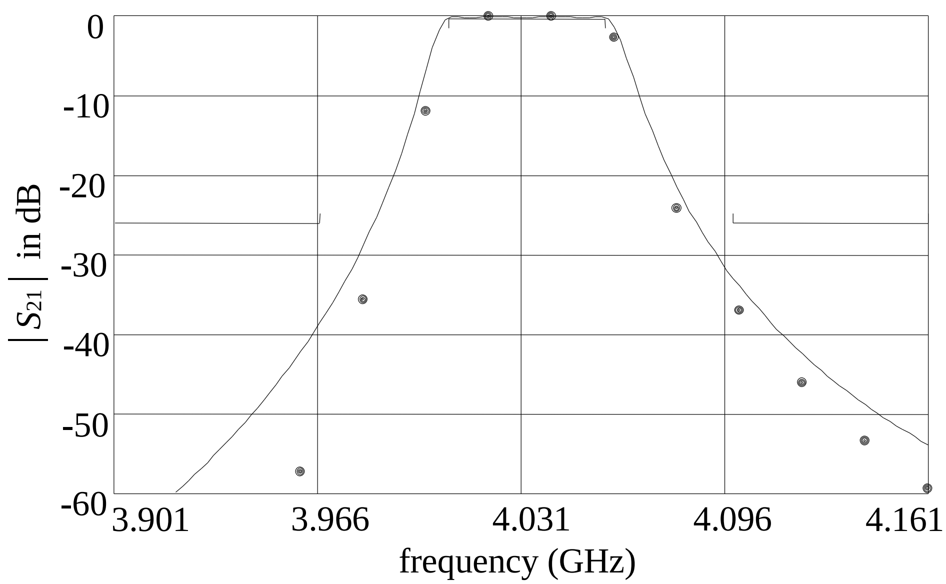
mapping ω, L_1 and S_1 with a 3LP:-7-5-3

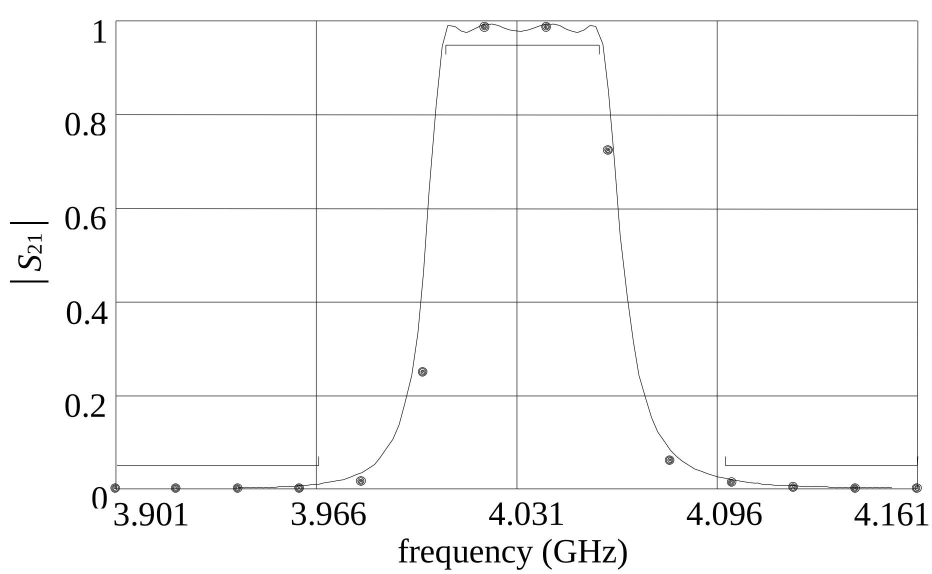


NSM Optimization of the HTS Filter (continued)

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

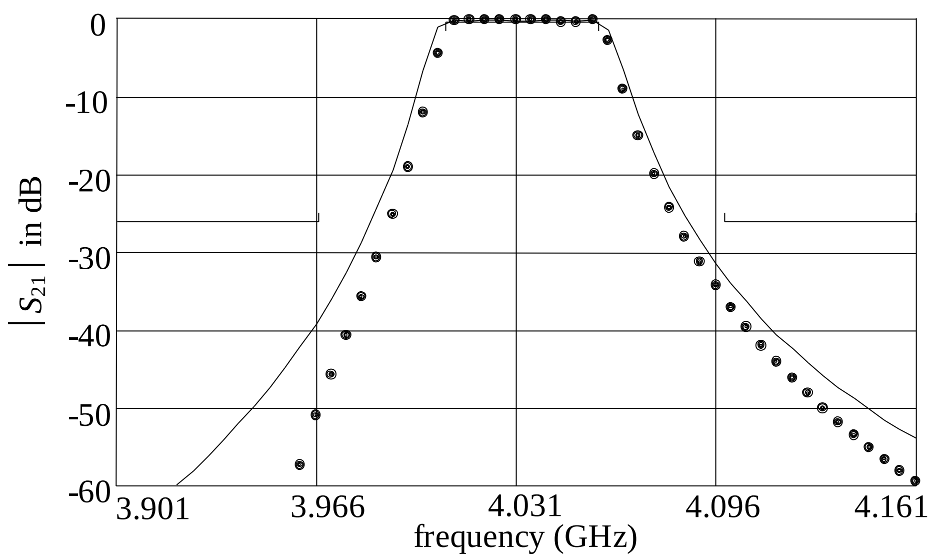
$\boldsymbol{x}_f^{(14)} = [185.37\ \ 195.01\ \ 184.24\ \ 21.04\ \ 86.36\ \ 91.39]^T$ (mils)

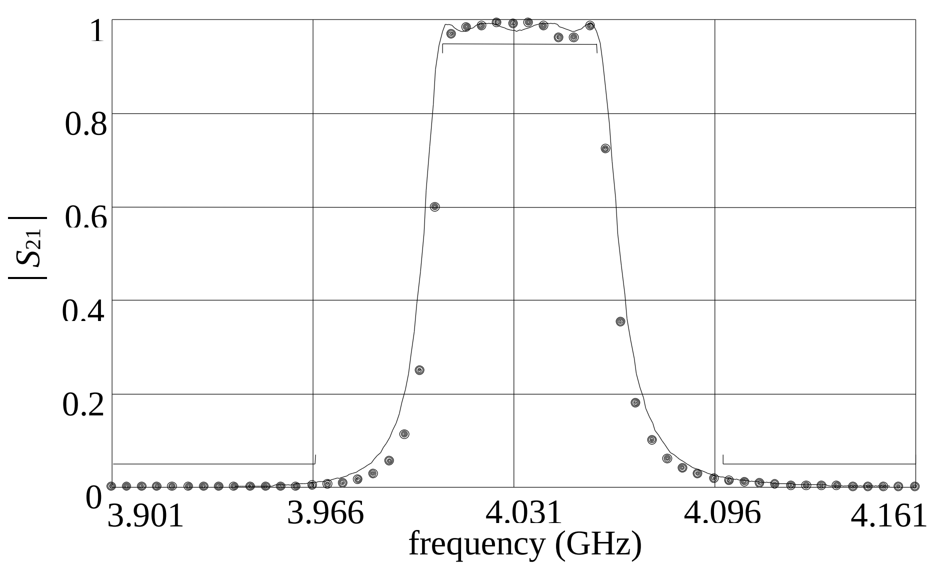




NSM Optimization of the HTS Filter (continued)

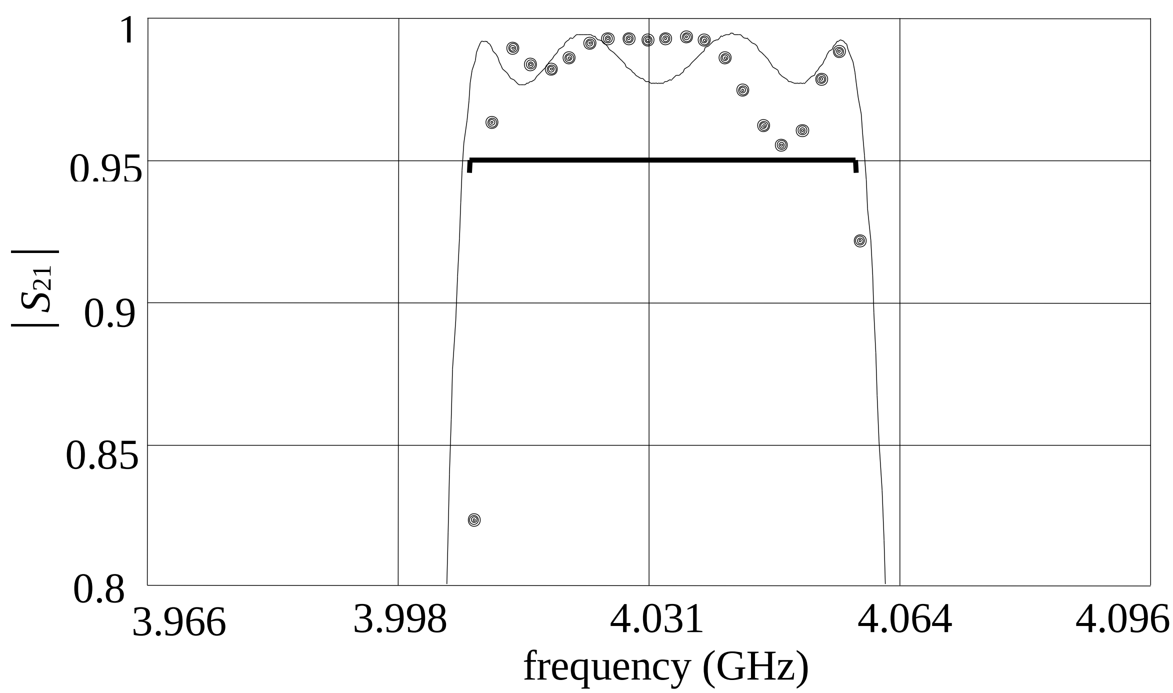
em™ (•) and FPSM 7-5-3 (–) model responses at the NSM solution using a fine frequency sweep



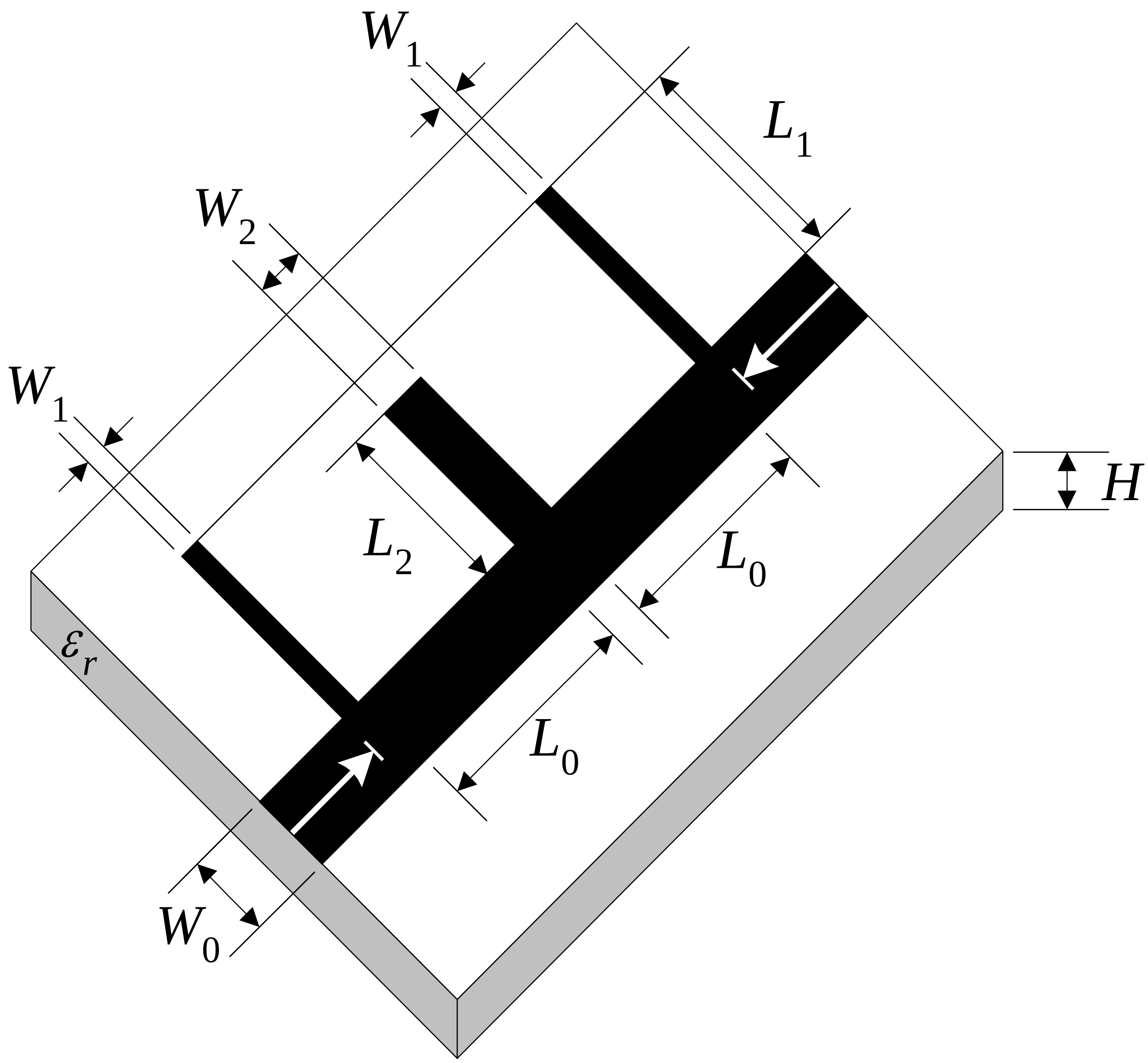


NSM Optimization of the HTS Filter (continued)

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



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

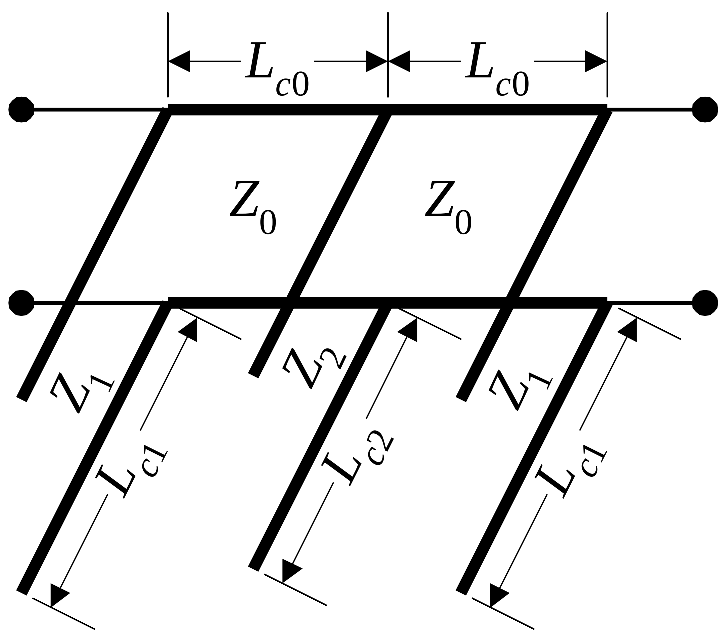
NSM Optimization of the Bandstop Filter

specifications

$|S_{21}| \le 0.01$ in the stopband and $|S_{21}| \ge 0.9$ in the passband,

where the stopband lies between 9.3 GHz and 10.7 GHz, and the passband includes frequencies below 8 GHz and above 12 GHz

“coarse” model: transmission line sections and empirical formulas



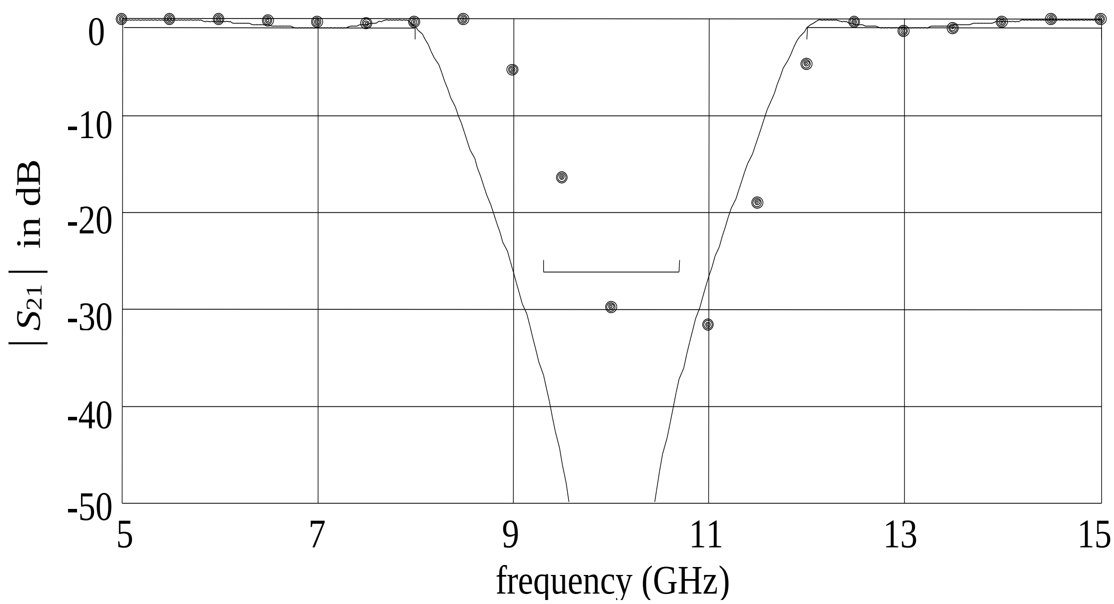
“fine” model: Sonnet’s ***em***™ with high resolution grid

NSM Optimization of the Bandstop Filter (continued)

coarse and fine model responses at the optimal coarse solution,

$\boldsymbol{x}_c^* = [6.00 \;\; 9.01 \;\; 106.45 \;\; 110.15 \;\; 108.81]^T$ (mils)

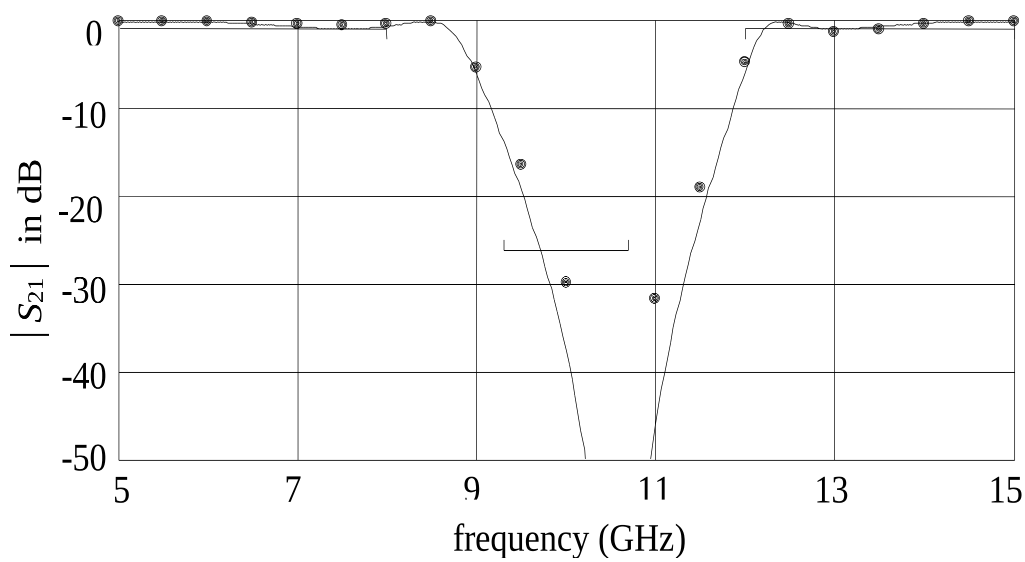
coarse model (–) and ***em***™ (●)



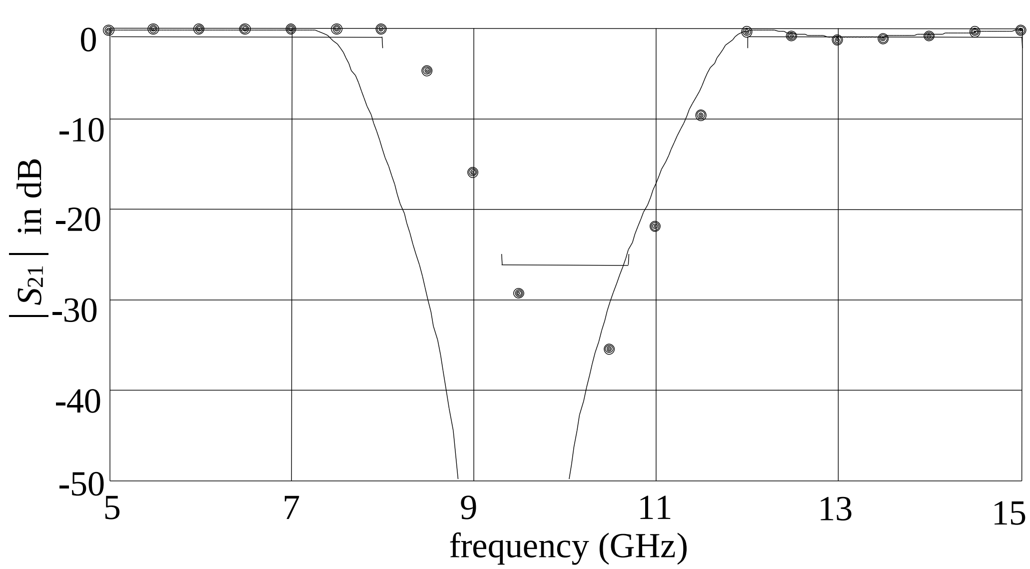
the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 50% deviation from $\boldsymbol{x}_c^*$ for W_1, W_2, and L_0 is used, while a 15% is used for L_1, and L_2.

NSM Optimization of the Bandstop Filter (continued)

FM (3LP:6-2-1,ω) neuromodel (–) and the fine model (•) responses at the optimal coarse solution

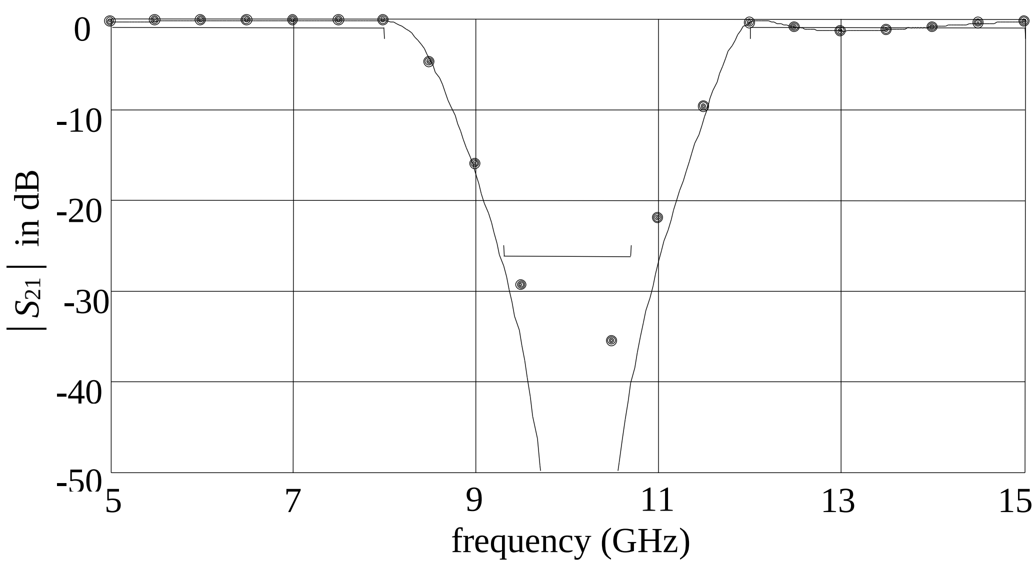


coarse (–) and fine model (•) responses at the next point predicted by the first NSM iteration

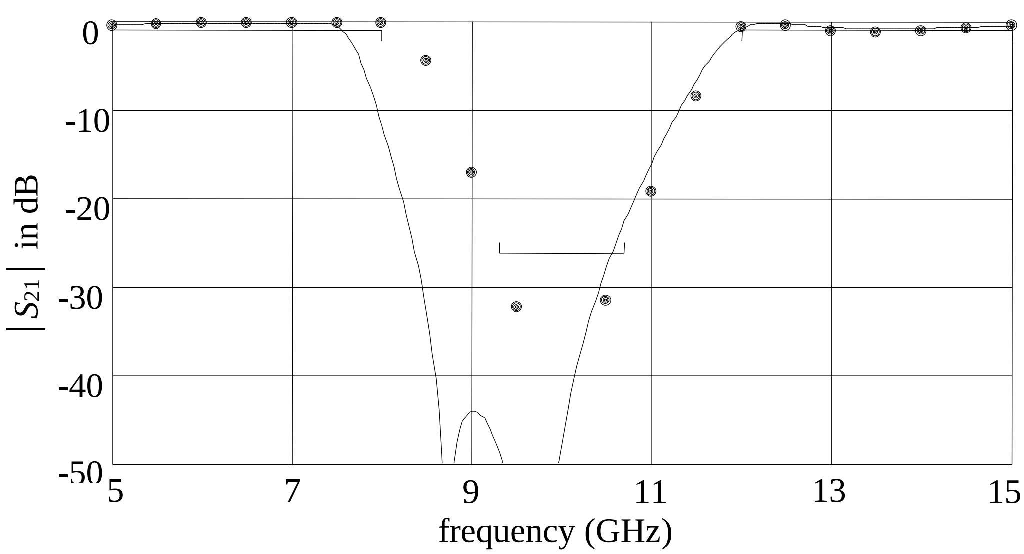


NSM Optimization of the Bandstop Filter (continued)

FPSM (3LP:6-3-2,ω,W_2) neuromodel (–) and the fine model (•) responses at the point predicted by the first NSM iteration



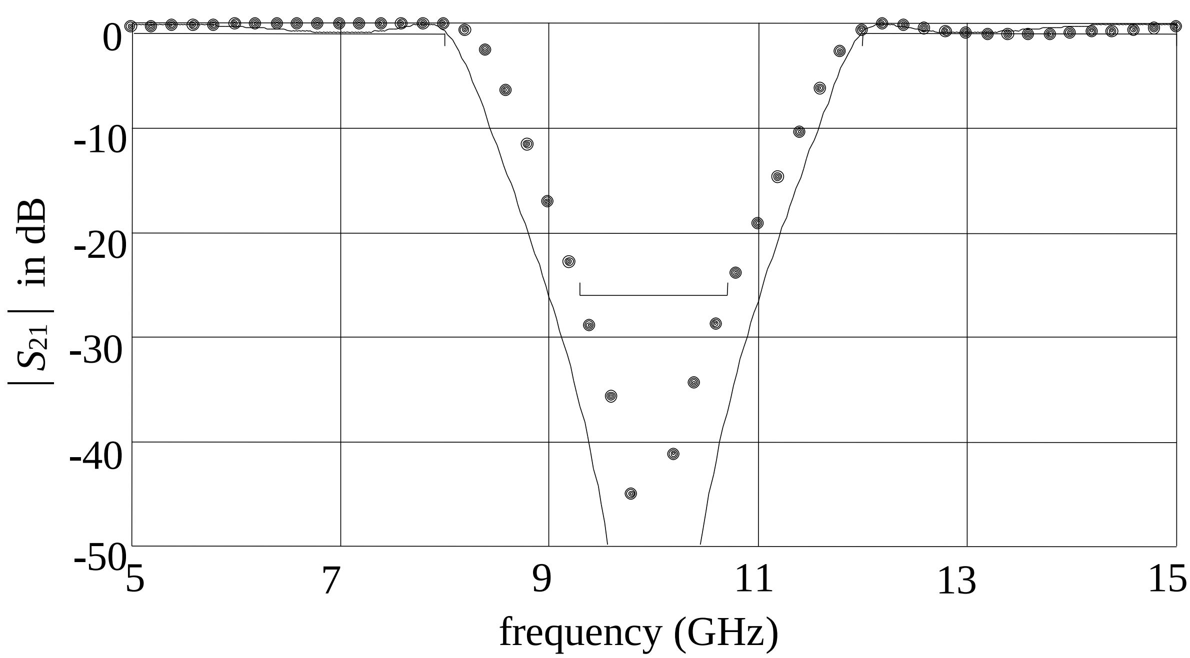
coarse (–) and fine model (•) responses at the next point predicted by the second NSM iteration



NSM Optimization of the Bandstop Filter (continued)

fine model response (•) at the next point predicted by the second NSM iteration and optimal coarse response (–), using a fine frequency sweep

$\boldsymbol{x}_f^{(13)} = [5.92 \;\; 13.54 \;\; 83.34 \;\; 114.14 \;\; 124.81]^T$ (mils)



Conclusions

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

NFSM 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

the 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 and a bandstop microstrip filter illustrate our optimization technique