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, the neuromodels can be used for optimization within the region of training

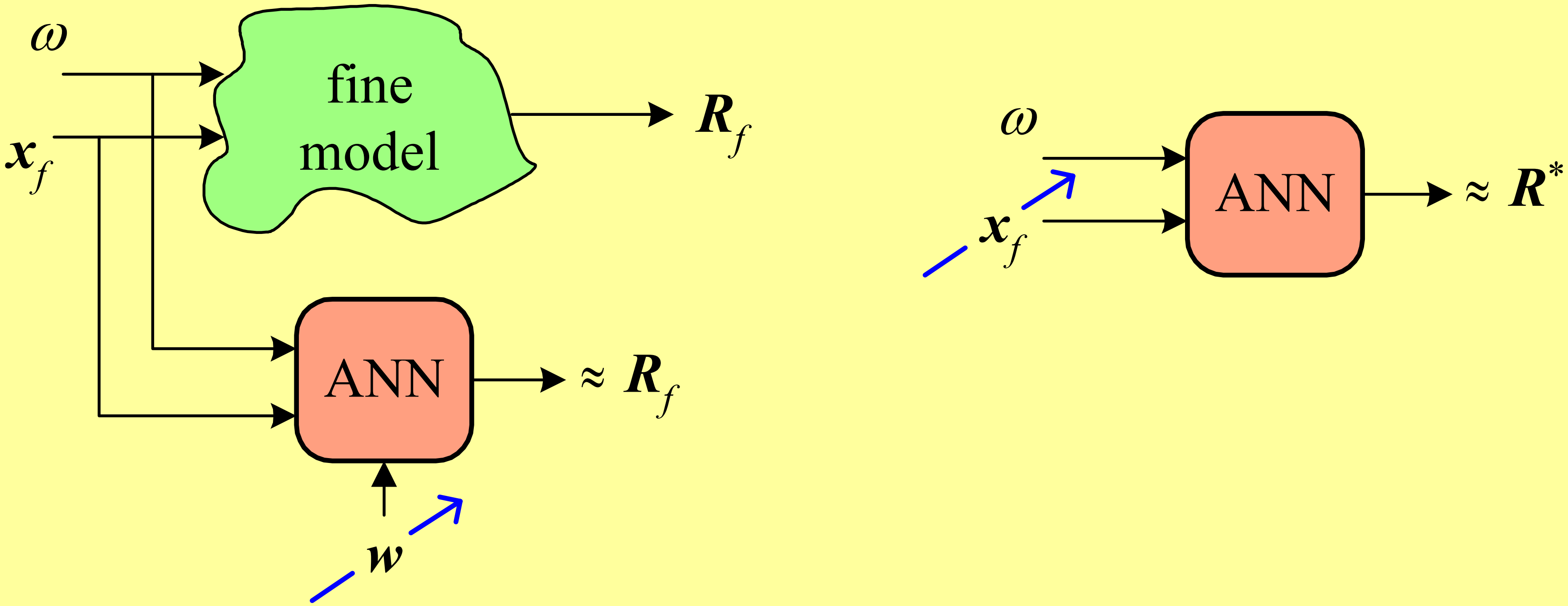
the principal drawback of this ANN optimization approach is the cost of generating sufficient learning samples

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 sources of knowledge that reduce the amount of learning data and improve the generalization and extrapolation performance

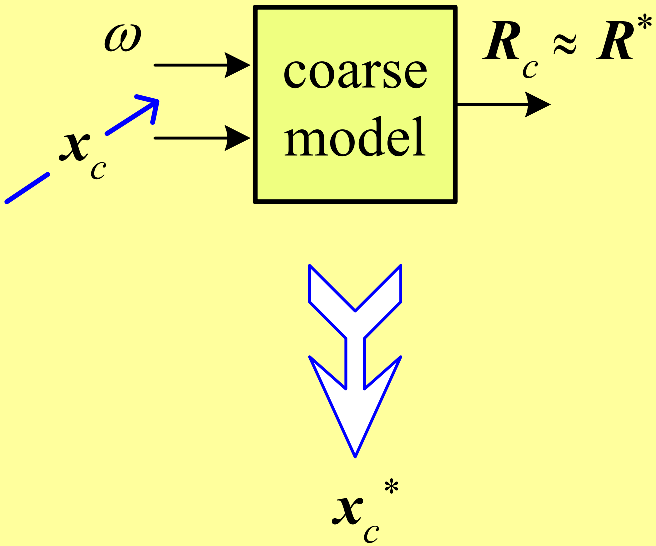
NSM requires a reduced set of upfront learning base points

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

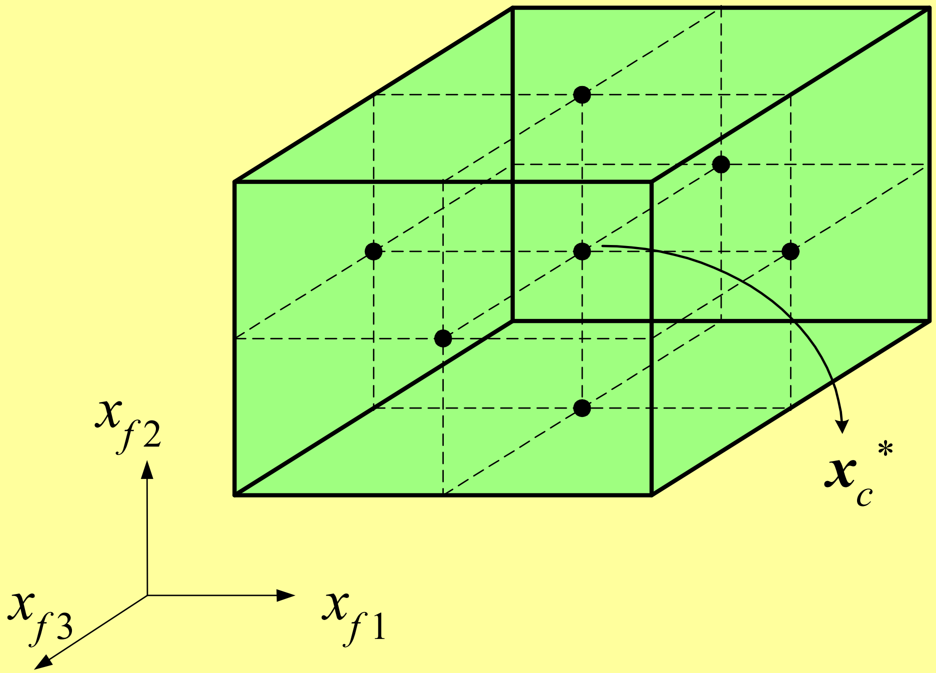
neuromappings are developed iteratively: their generalization performance is controlled by gradually increasing their complexity starting with a 3-layer perceptron with 0 hidden neurons

Neural Space Mapping (NSM) Optimization Concept

step 1



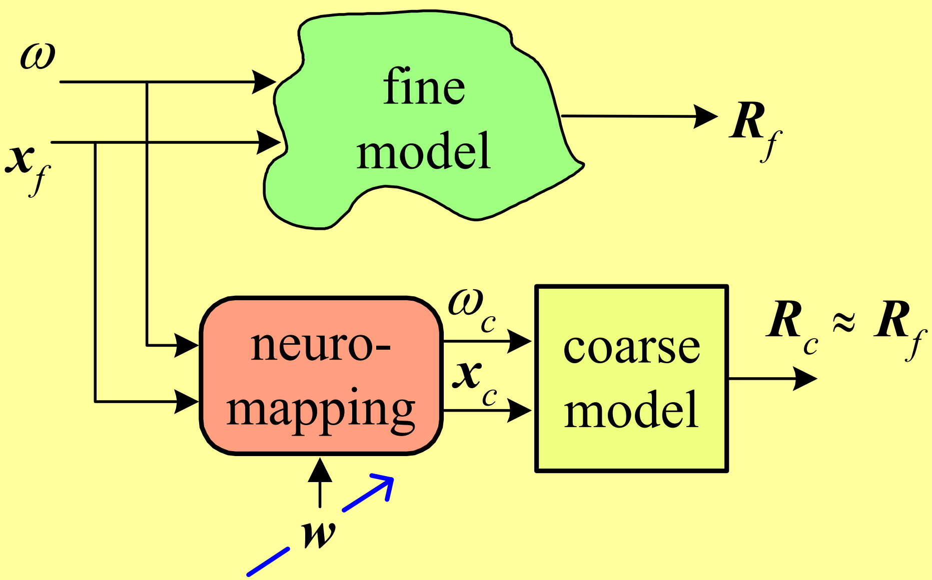
step 2



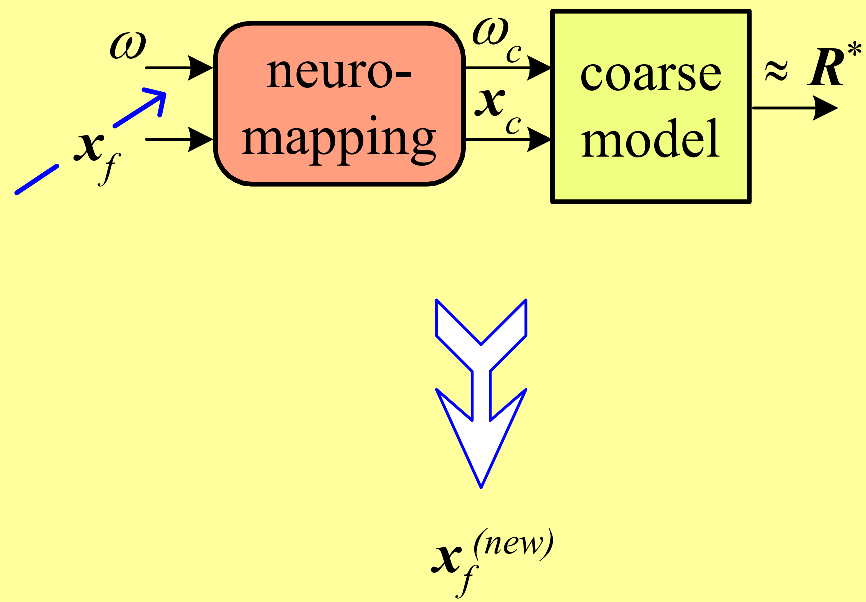
(2n + 1 learning base points for a microwave circuit with n design parameters)

Neural Space Mapping (NSM) Optimization Concept (continued)

step 3

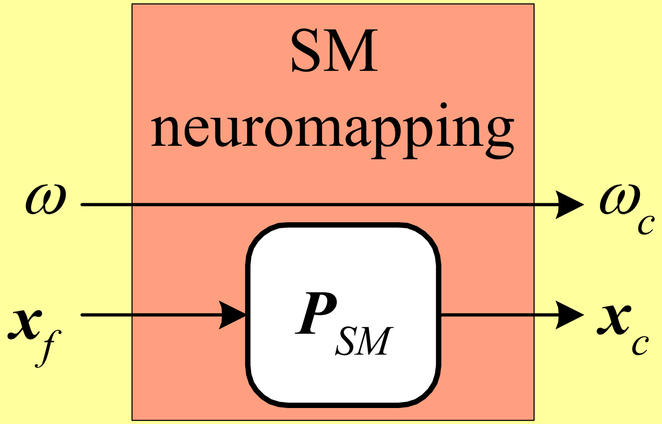


step 4

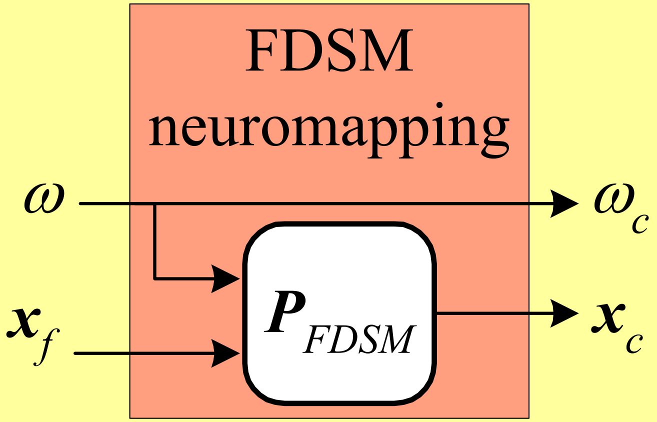


Neuromappings

Space Mapped neuromapping

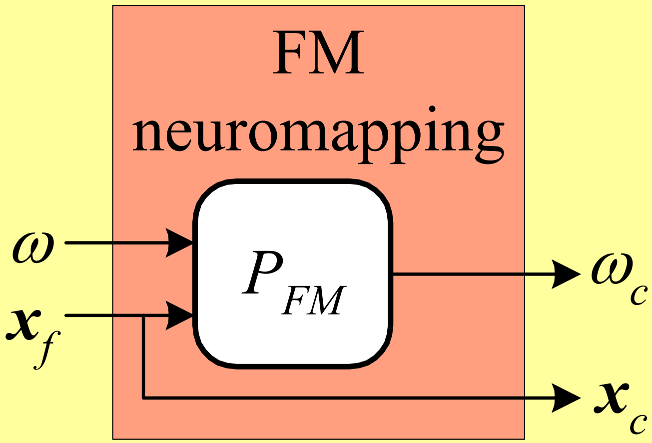


Frequency-Dependent Space Mapped neuromapping

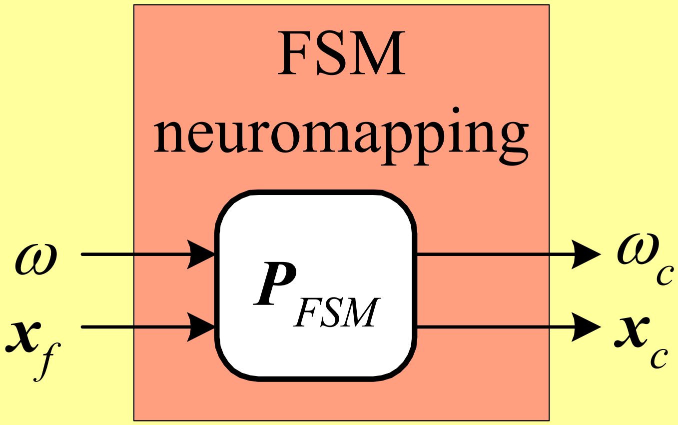


Neuromappings (continued)

Frequency Mapped neuromapping

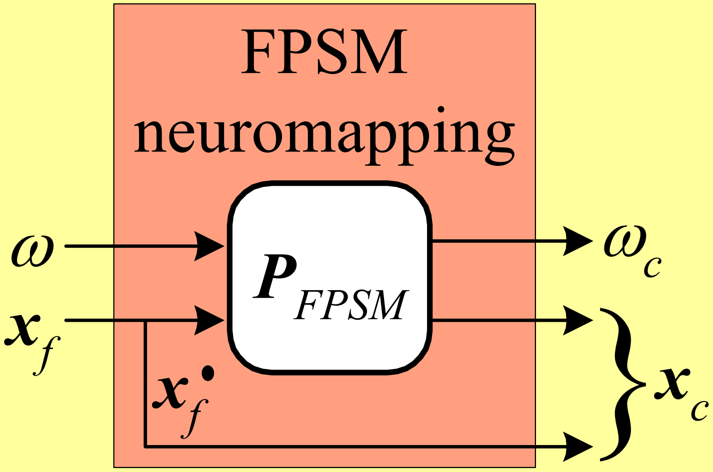


Frequency Space
Mapped neuromapping

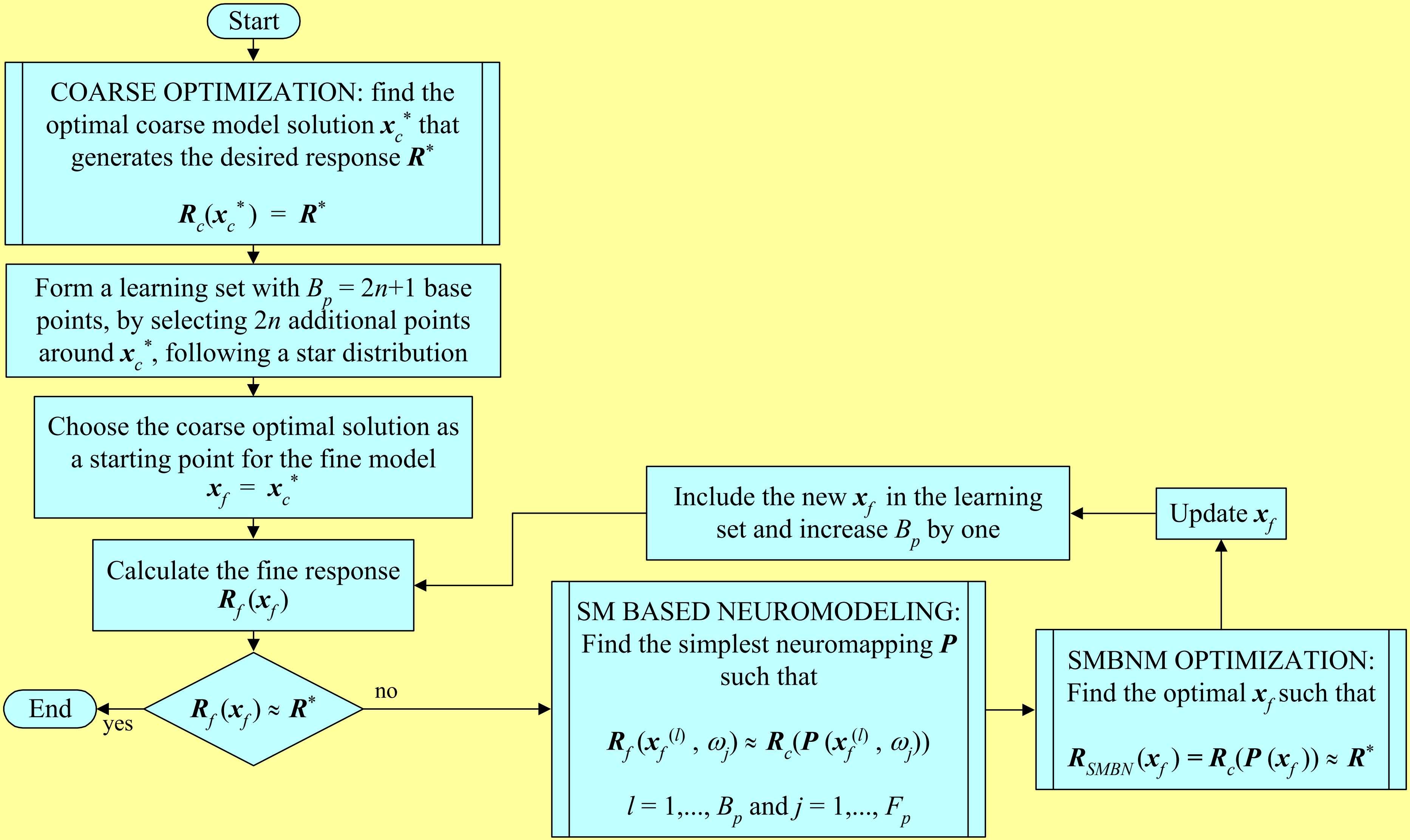


Neuromappings (continued)

Frequency Partial-Space
Mapped neuromapping

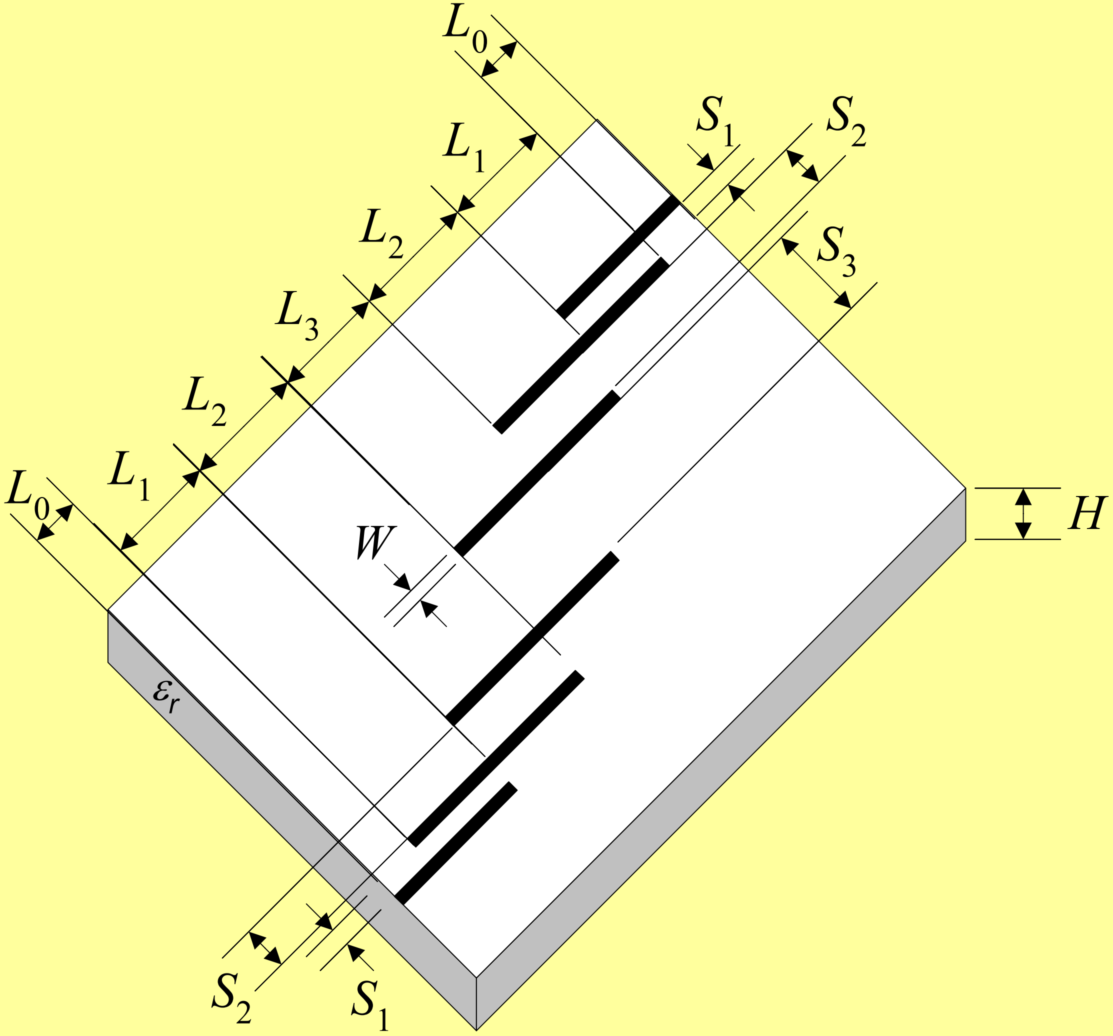


Neural Space Mapping (NSM) Optimization Algorithm



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

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

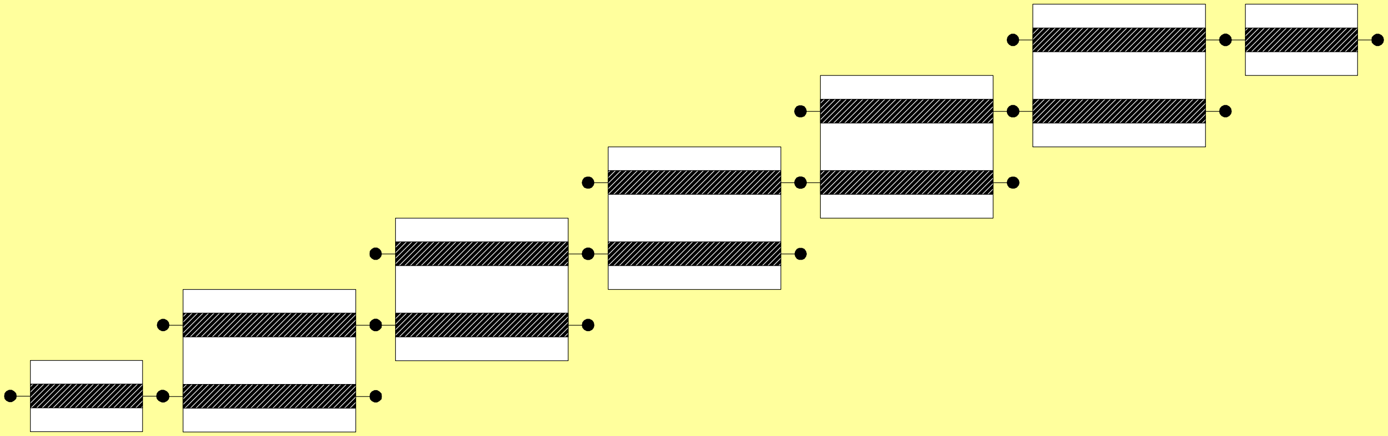
NSM Optimization of the HTS Microstrip Filter

specifications

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

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

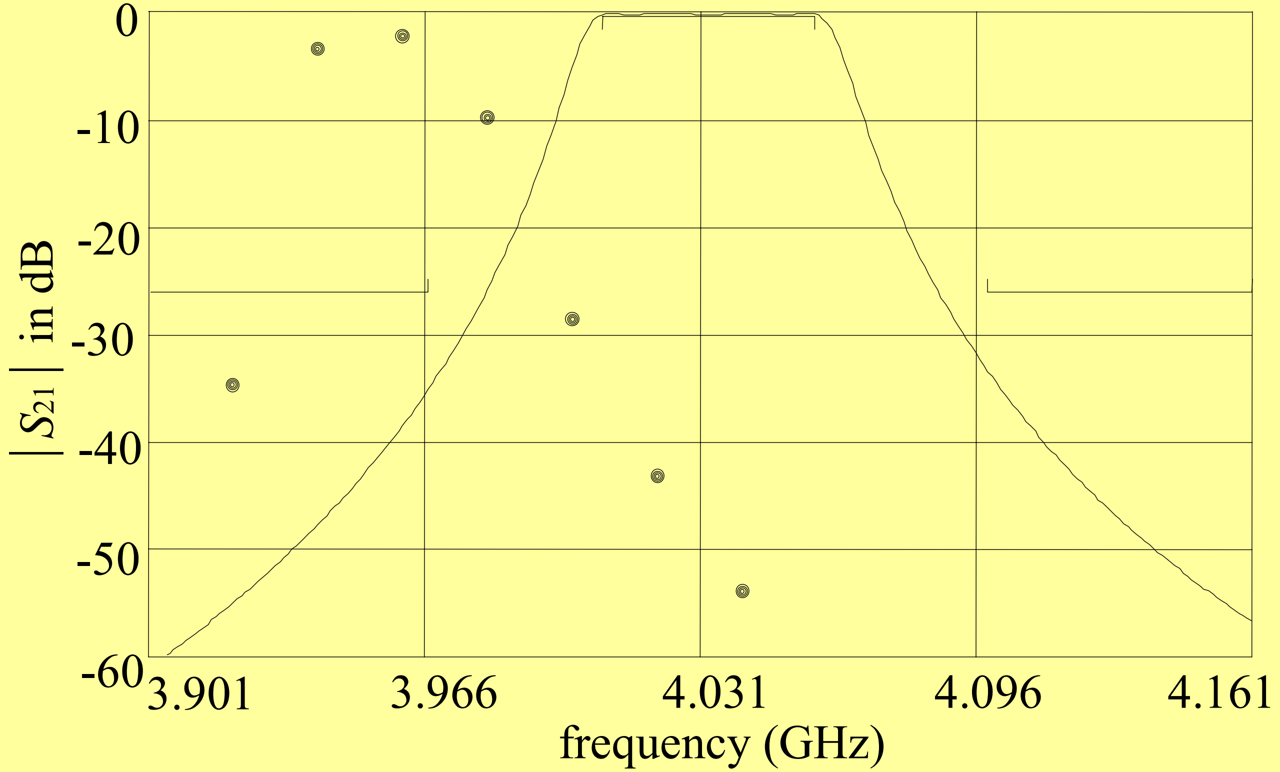
"coarse" model: OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines



NSM Optimization of the HTS Filter (continued)

coarse and fine model responses at the optimal coarse solution

OSA90/hope™ (–) and ***em***™ (•)

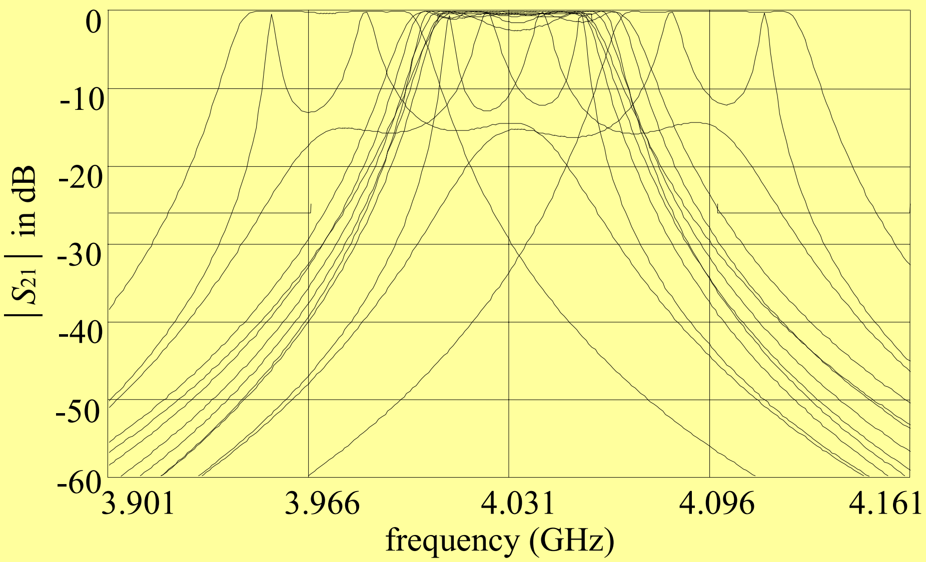


NSM Optimization of the HTS Filter (continued)

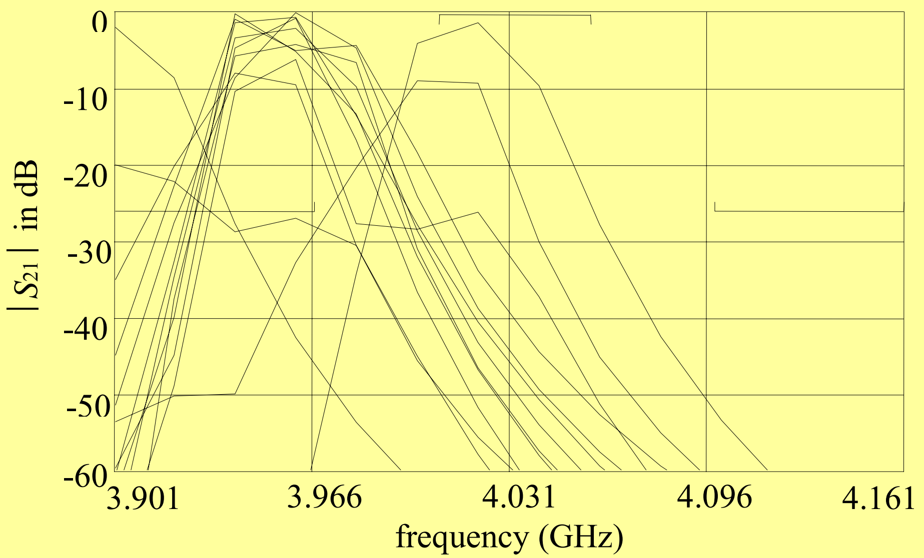
the initial 2n+1 points are chosen by performing sensitivity analysis on the coarse model: a 3% deviation from $\boldsymbol{x}_c^*$ for L_1, L_2, and L_3 is used, while a 20% is used for S_1, S_2, and S_3

coarse and fine model responses at base points

OSA90/hope™



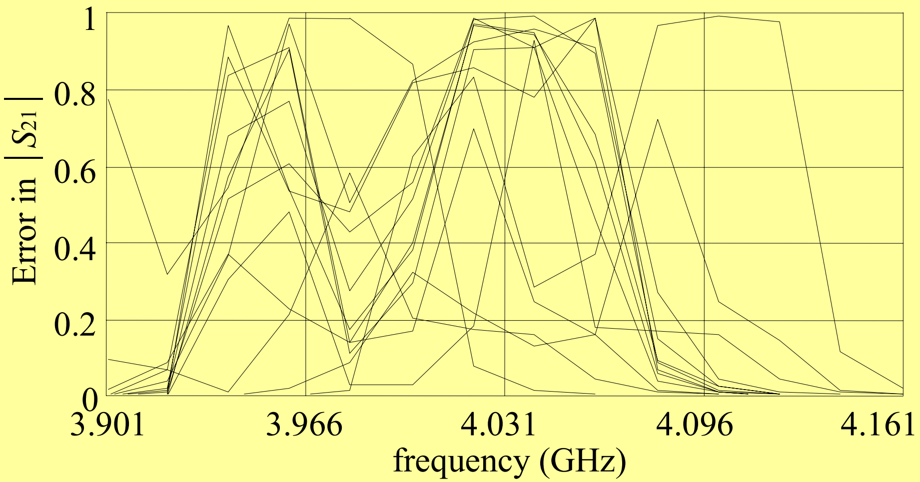
em™



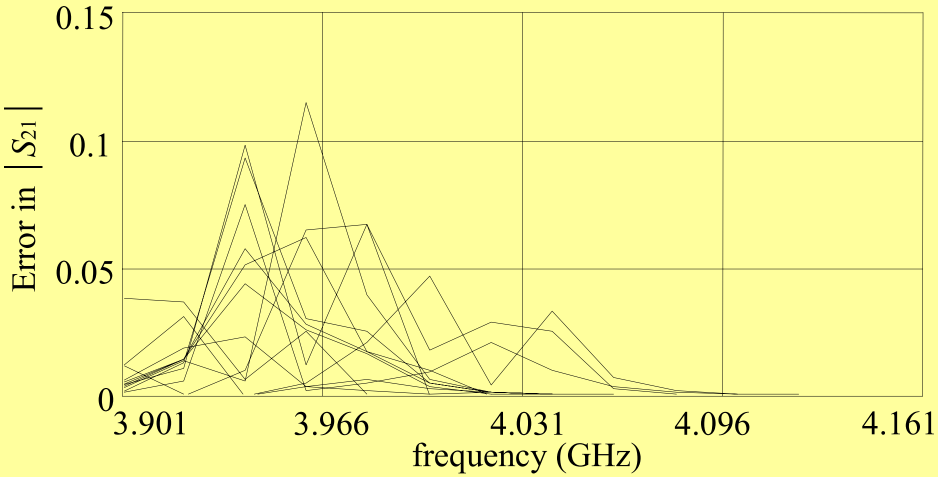
NSM Optimization of the HTS Filter (continued)

learning errors at base points

before any neuromapping



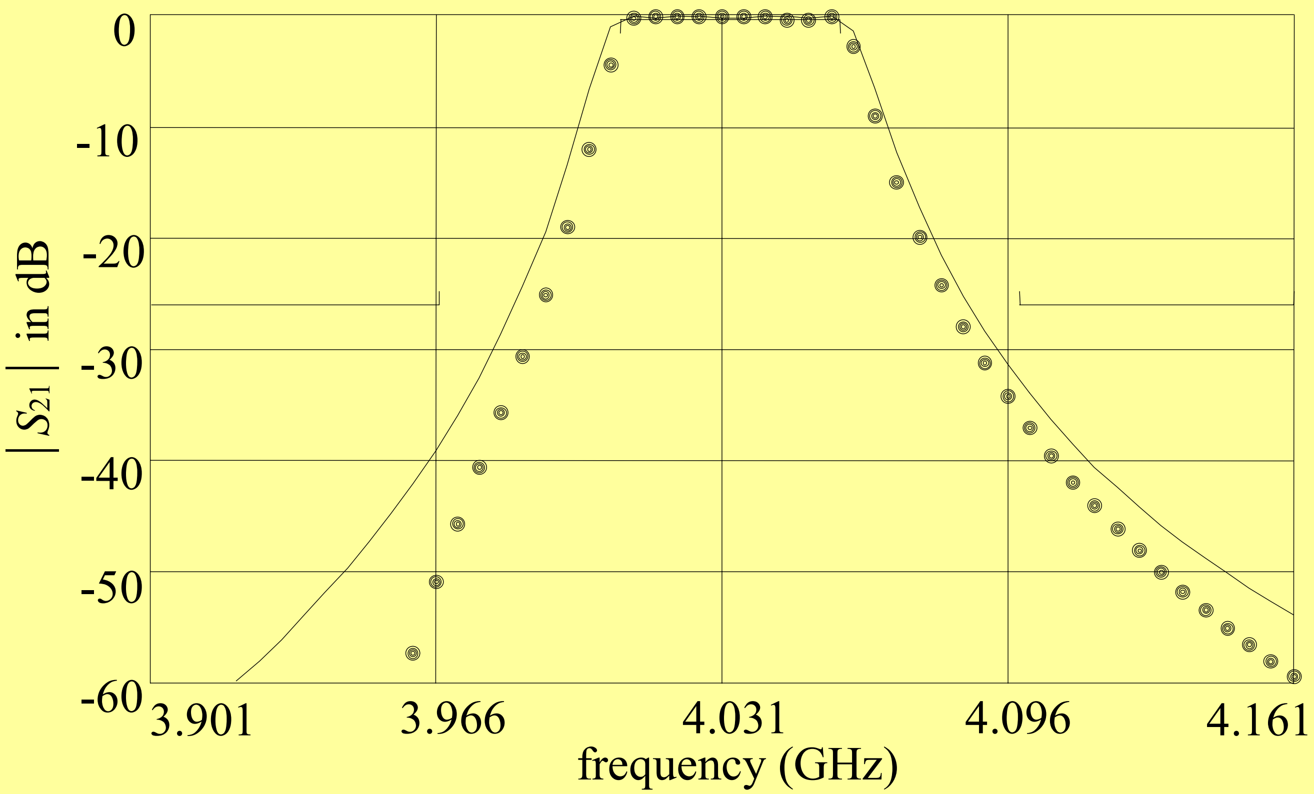
mapping ω, L_1 and S_1 with a 3LP:-7-5-3



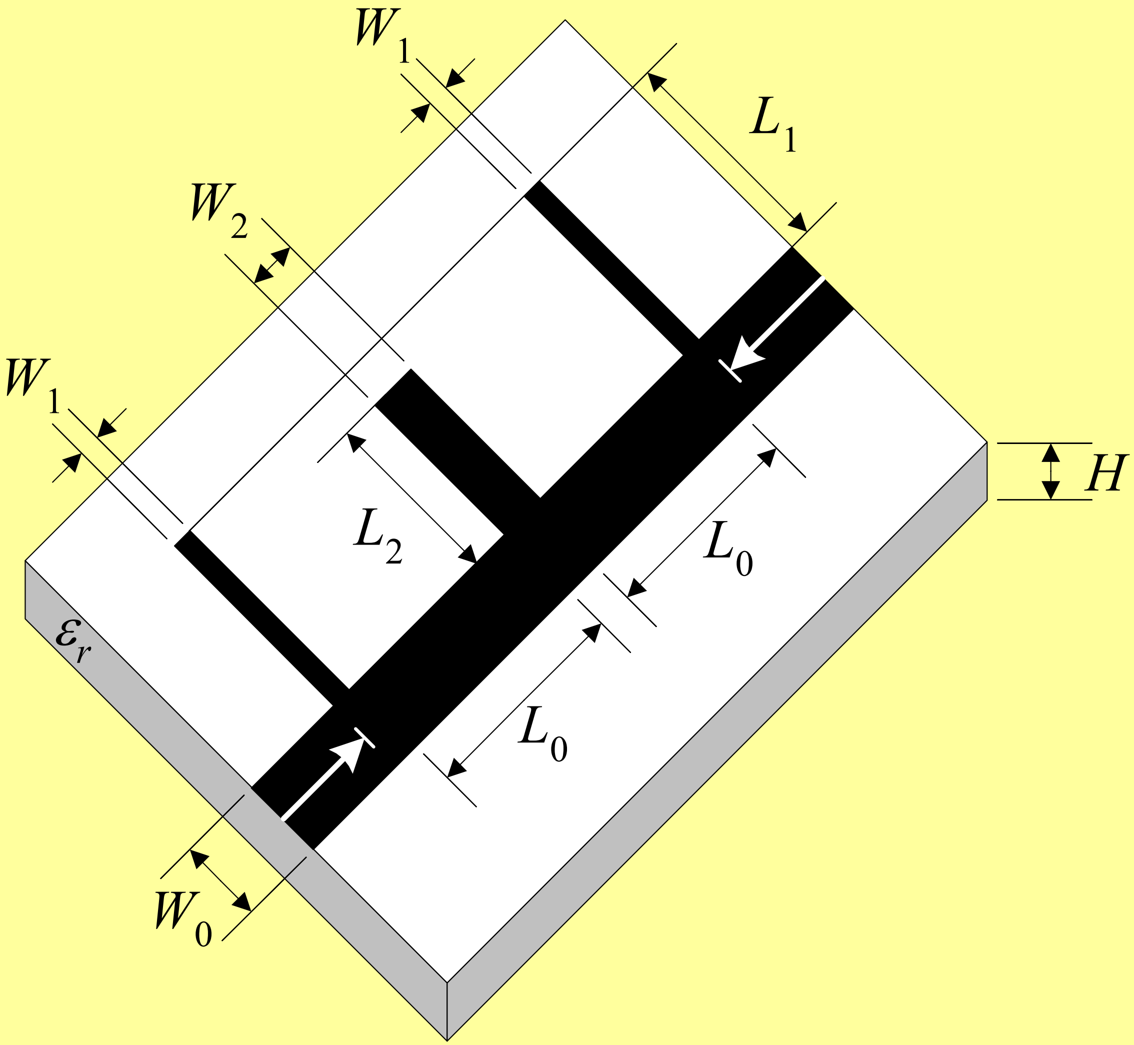
NSM Optimization of the HTS Filter (continued)

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

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

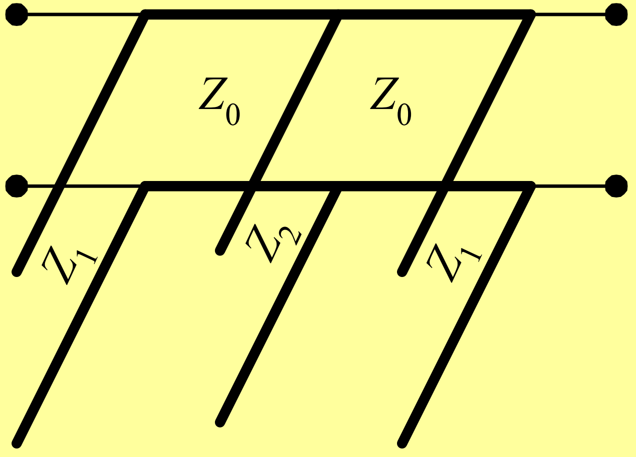
NSM Optimization of the Bandstop Filter

specifications

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

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

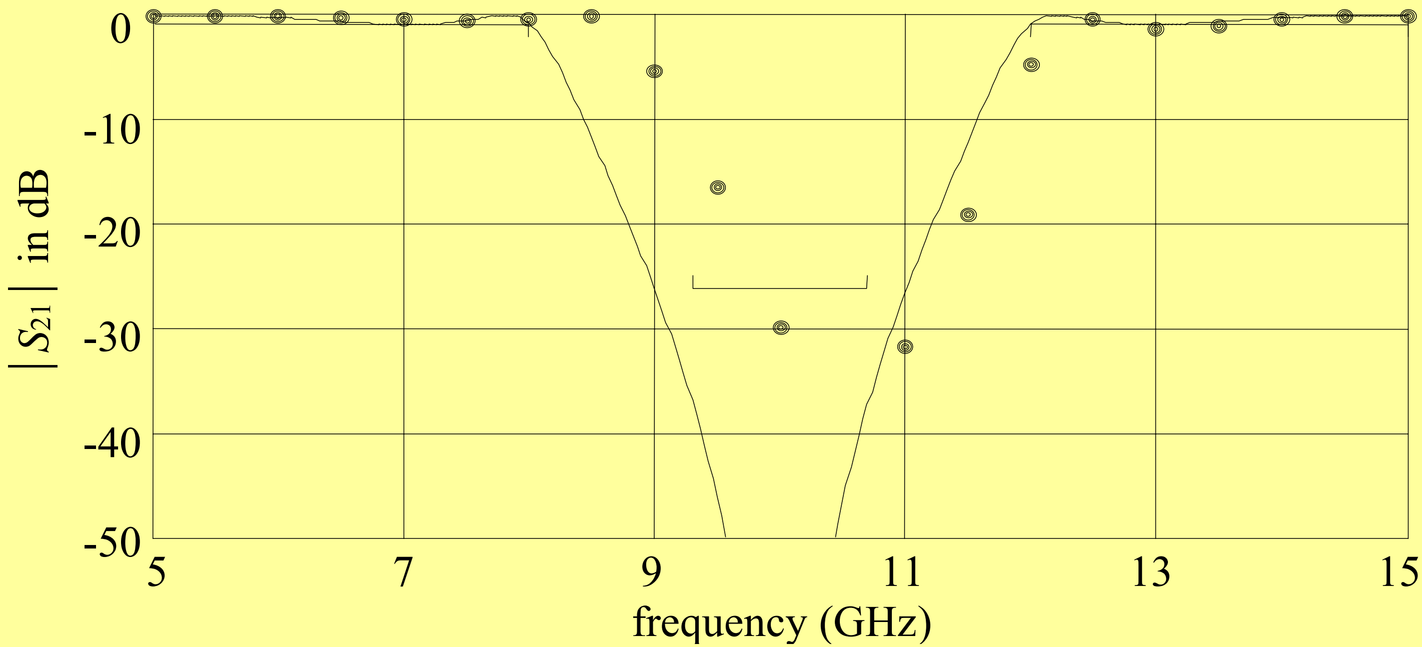
"coarse" model: transmission line sections and empirical formulas



NSM Optimization of the Bandstop Filter (continued)

coarse and fine model responses at the optimal coarse solution

coarse model (–) and ***em***™ (•)

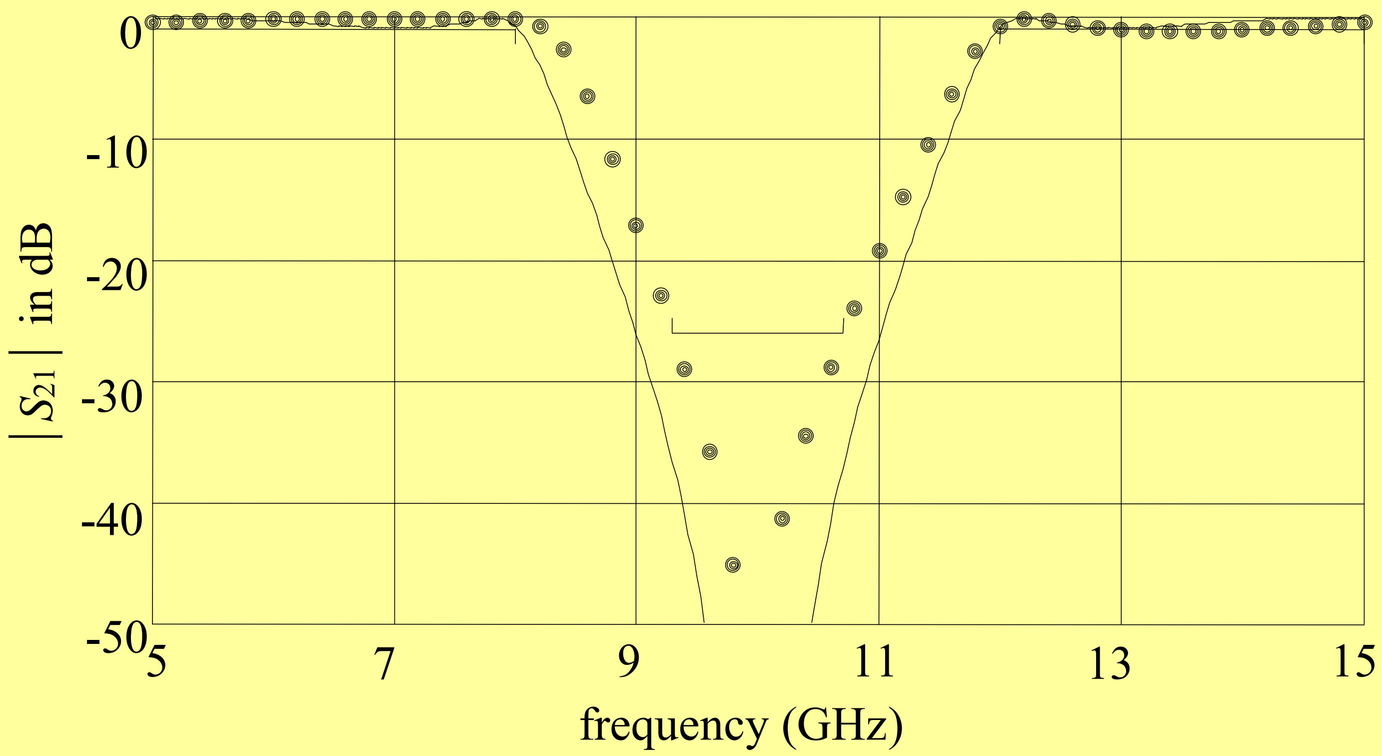


the initial $2n+1$ points are chosen by performing sensitivity analysis on the coarse model: a 50% deviation from $\boldsymbol{x}_c^*$ for W_1, W_2, and L_0 is used, while a 15% is used for L_1, and L_2

NSM Optimization of the Bandstop Filter (continued)

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

(3LP:6-3-2,ω,W_2)



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

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