Yield-Driven EM Optimization using Space Mapping Based Neuromodels

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

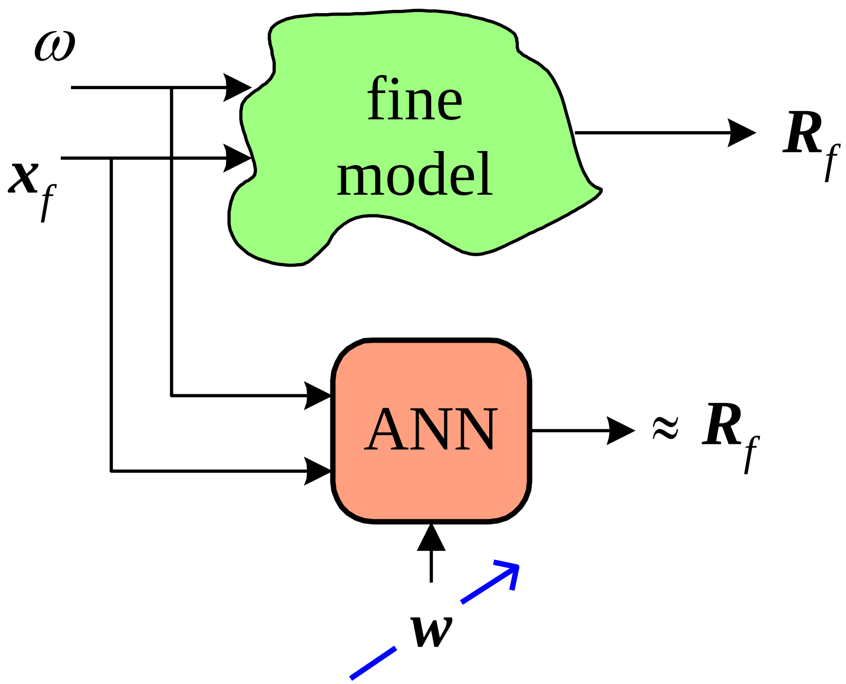
the principal drawback of this ANN optimization approach is the cost of generating sufficient learning samples

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

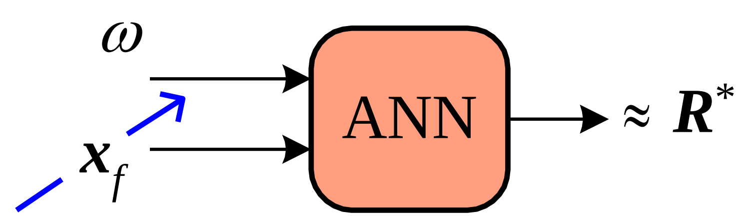
introducing knowledge can alleviate these limitations *(Gupta et al., 1999)*

Conventional ANN Optimization Approach

step 1



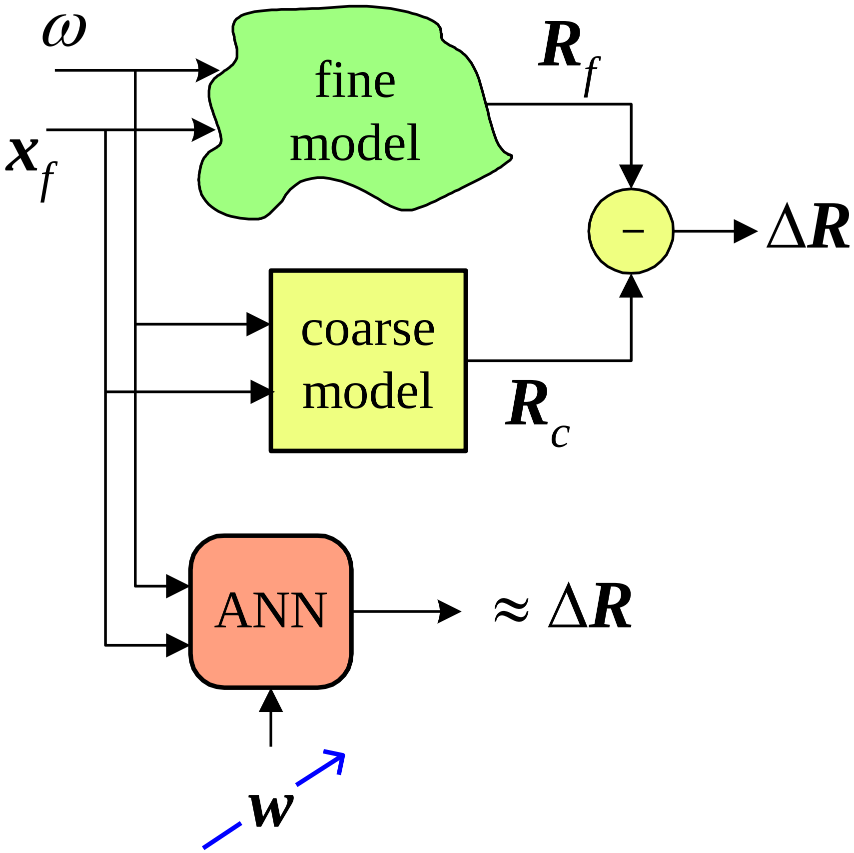
step 2

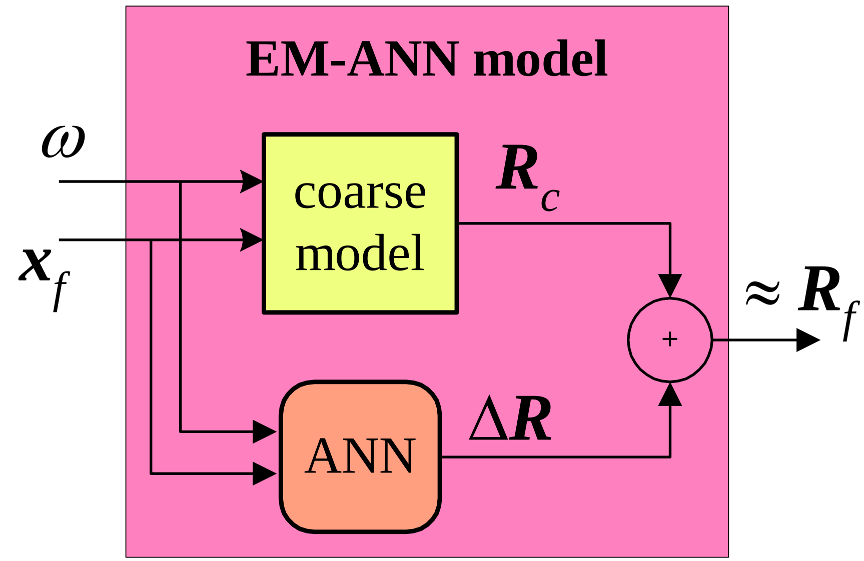


many fine model simulations are usually needed
solutions predicted outside the training region are unreliable

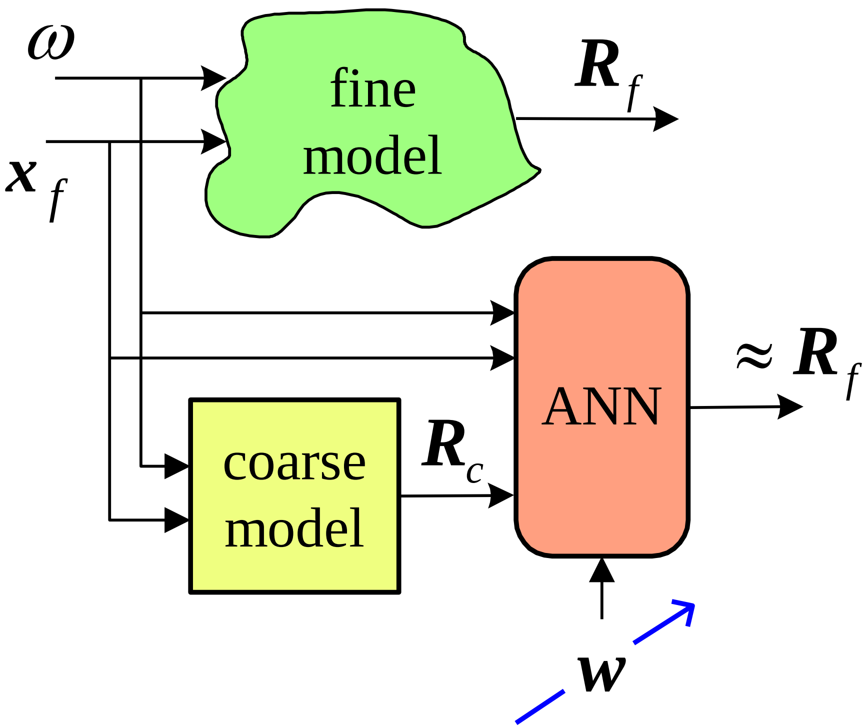
Hybrid "ΔS" EM-ANN Neuromodeling Concept

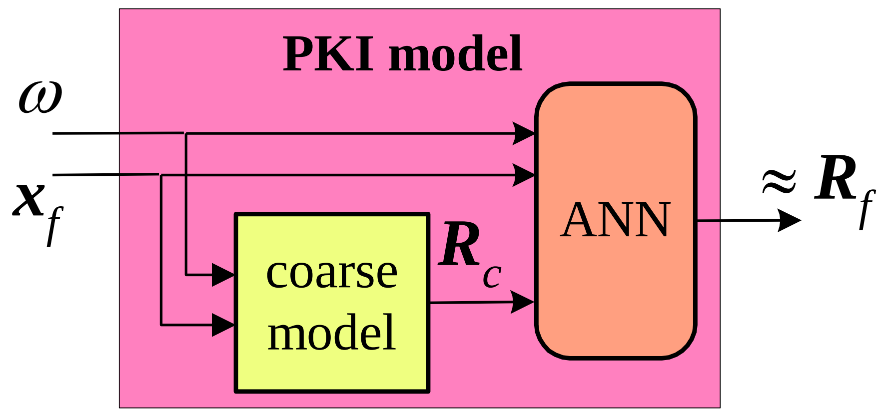
(Gupta et al., 1996)





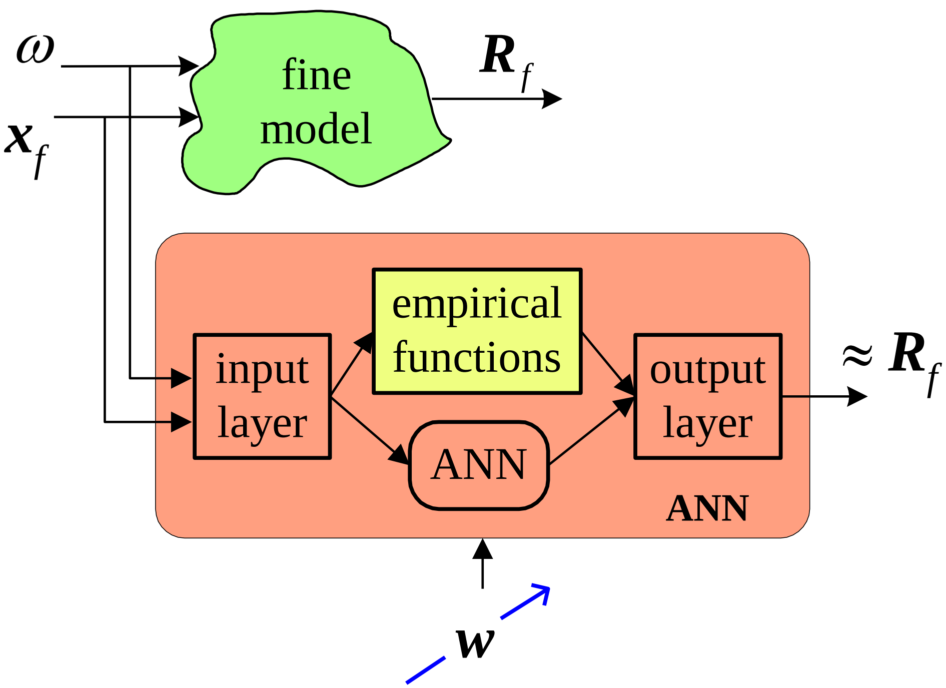
PKI Neuromodeling Concept
(Gupta et al., 1996)

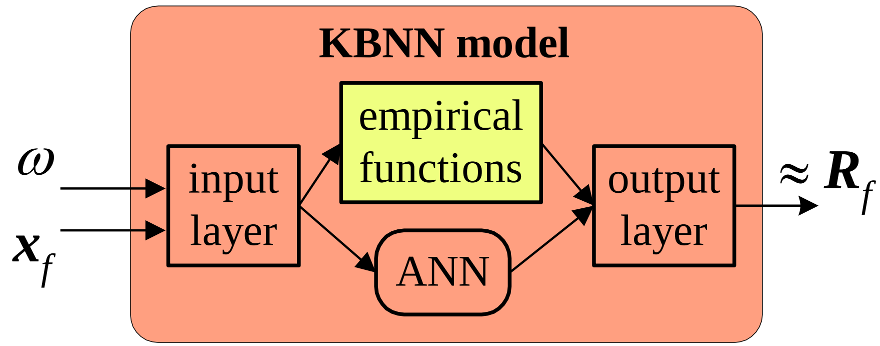




KBNN Neuromodeling Concept

(Zhang et al., 1997)

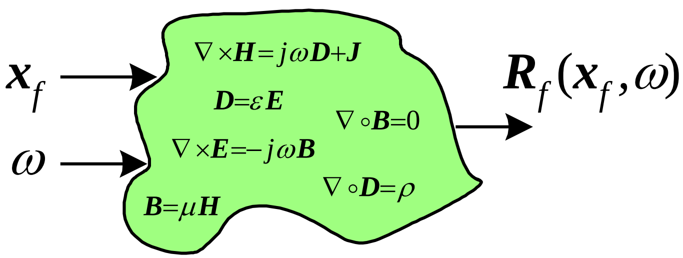




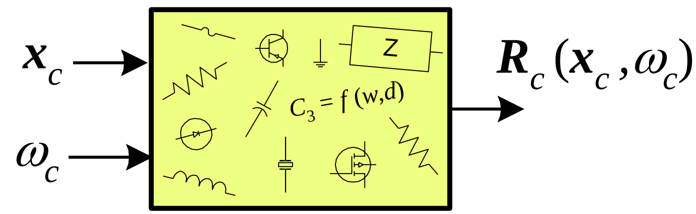
Exploiting Space Mapping for Neuromodeling

(Bandler et. al., 1999)

fine model



coarse model



find

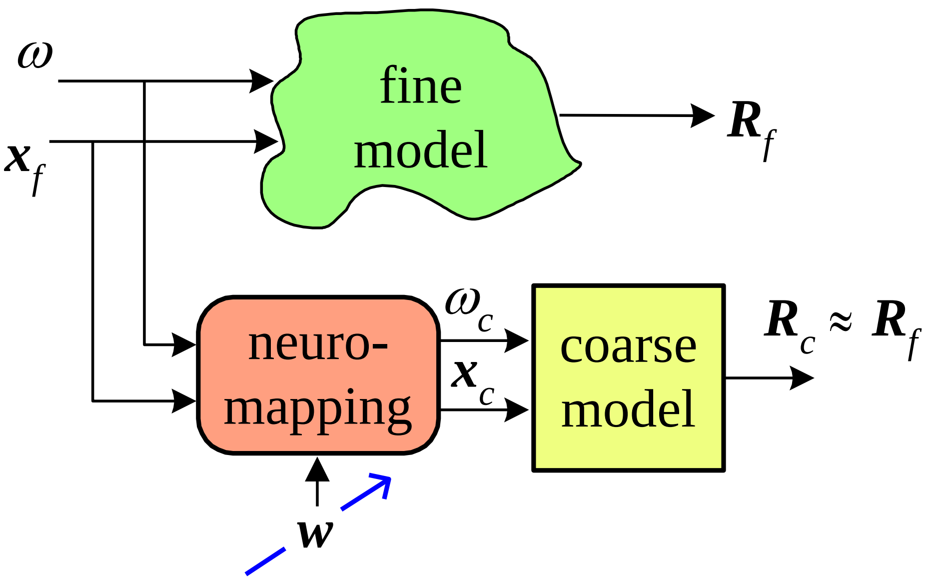
$$\begin{bmatrix} \boldsymbol{x}_c \\ \omega_c \end{bmatrix} = \boldsymbol{P}(\boldsymbol{x}_f, \omega)$$

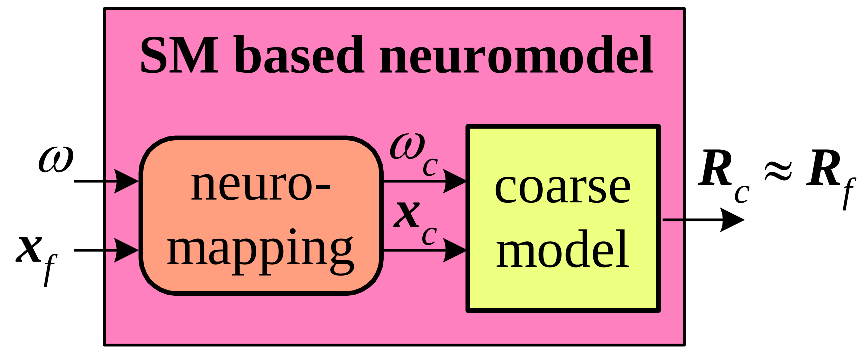
such that

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

Space Mapping Based Neuromodeling

(Bandler et. al., 1999)





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 ***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 Via SM-Based Neuromodels (continued)

if the mapping is implemented with a 3-layer perceptron with h hidden neurons

$$\boldsymbol{P}(\boldsymbol{x}_f, \omega) = \boldsymbol{W}^o \boldsymbol{\Phi}(\boldsymbol{x}_f, \omega) + \boldsymbol{b}^o, \qquad \boldsymbol{\Phi}(\boldsymbol{x}_f, \omega) = [\varphi(s_1) \quad \varphi(s_2) \quad \ldots \quad \varphi(s_h)]^T, \qquad \boldsymbol{s} = \boldsymbol{W}^h \begin{bmatrix} \boldsymbol{x}_f \\ \omega \end{bmatrix} + \boldsymbol{b}^h$$

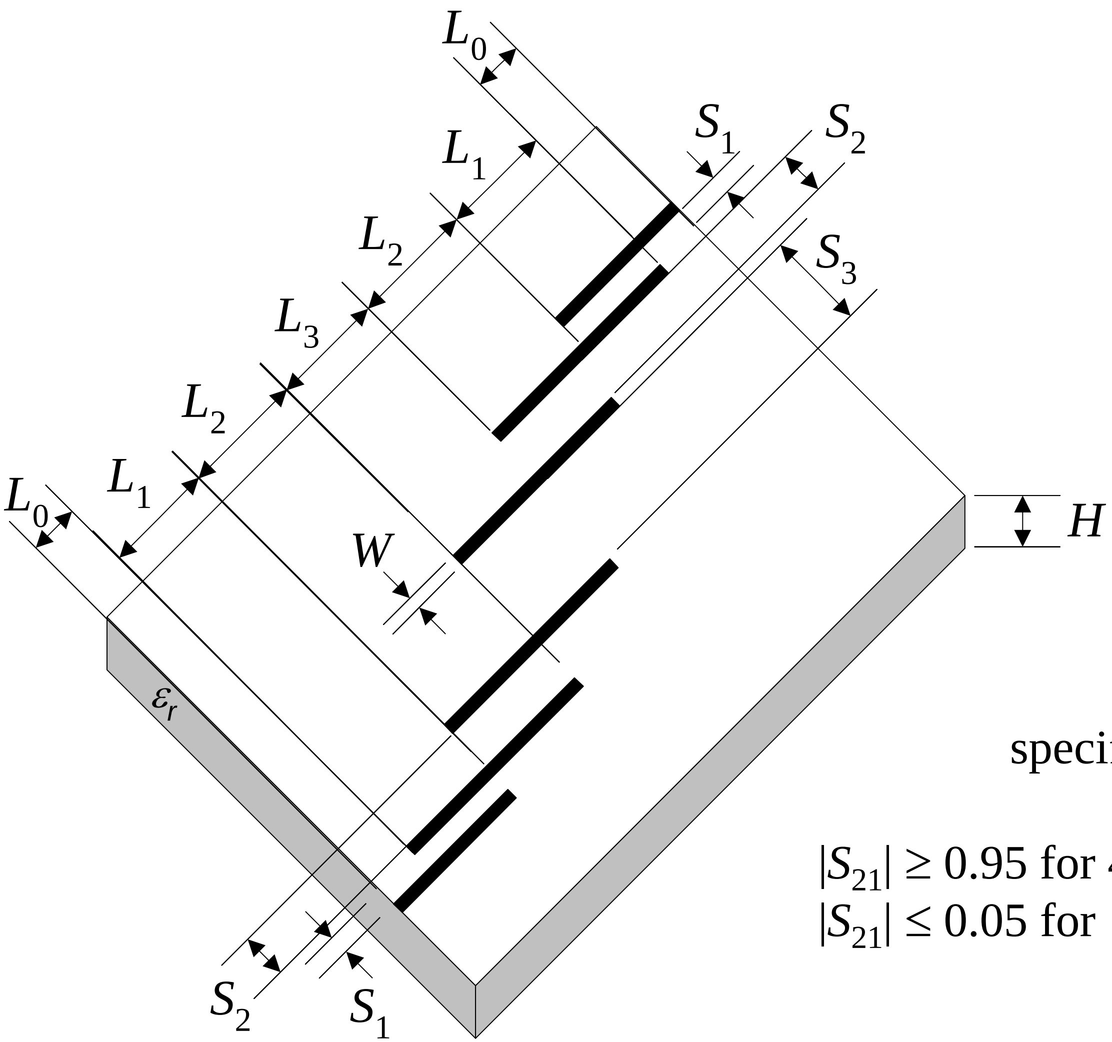
$\boldsymbol{W}^o \in \Re^{(n+1)\times h}$	matrix of output weighting factors
$\boldsymbol{b}^o \in \Re^{n+1}$	vector of output bias elements
$\boldsymbol{\Phi} \in \Re^h$	vector of hidden signals
$\boldsymbol{s} \in \Re^h$	vector of activation potentials
$\boldsymbol{W}^h \in \Re^{h\times(n+1)}$	matrix of hidden weighting factors
$\boldsymbol{b}^h \in \Re^h$	vector of hidden bias elements
$\varphi(\cdot)$	nonlinear activation functions

the Jacobian $\boldsymbol{J}_P$ is given by $\boldsymbol{J}_P = \boldsymbol{W}^o \boldsymbol{J}_\Phi \boldsymbol{W}^h$, where $\boldsymbol{J}_\Phi \in \Re^{h\times h}$ is a diagonal matrix given by $\boldsymbol{J}_\Phi = \mathrm{diag}(\varphi'(s_j))$, with $j = 1 \ldots h$

if the mapping employs a 2-layer perceptron, $\boldsymbol{J}_P = \boldsymbol{W}^o$

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

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

specifications

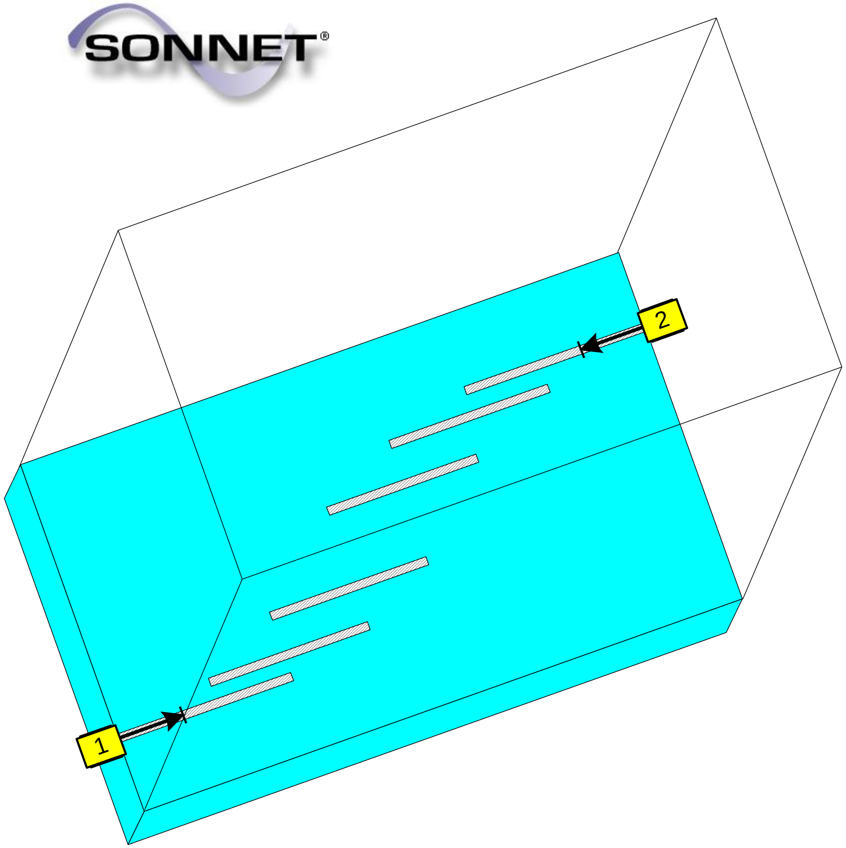
$|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq$ 4.058 GHz

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

HTS Microstrip Filter: Fine and Coarse Models

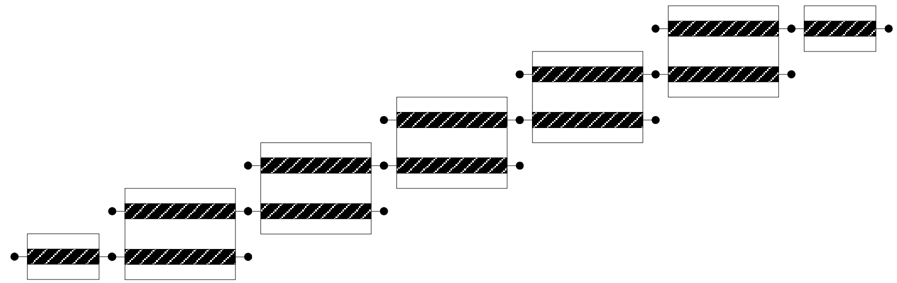
fine model:

Sonnet's ***em***™ with high resolution grid

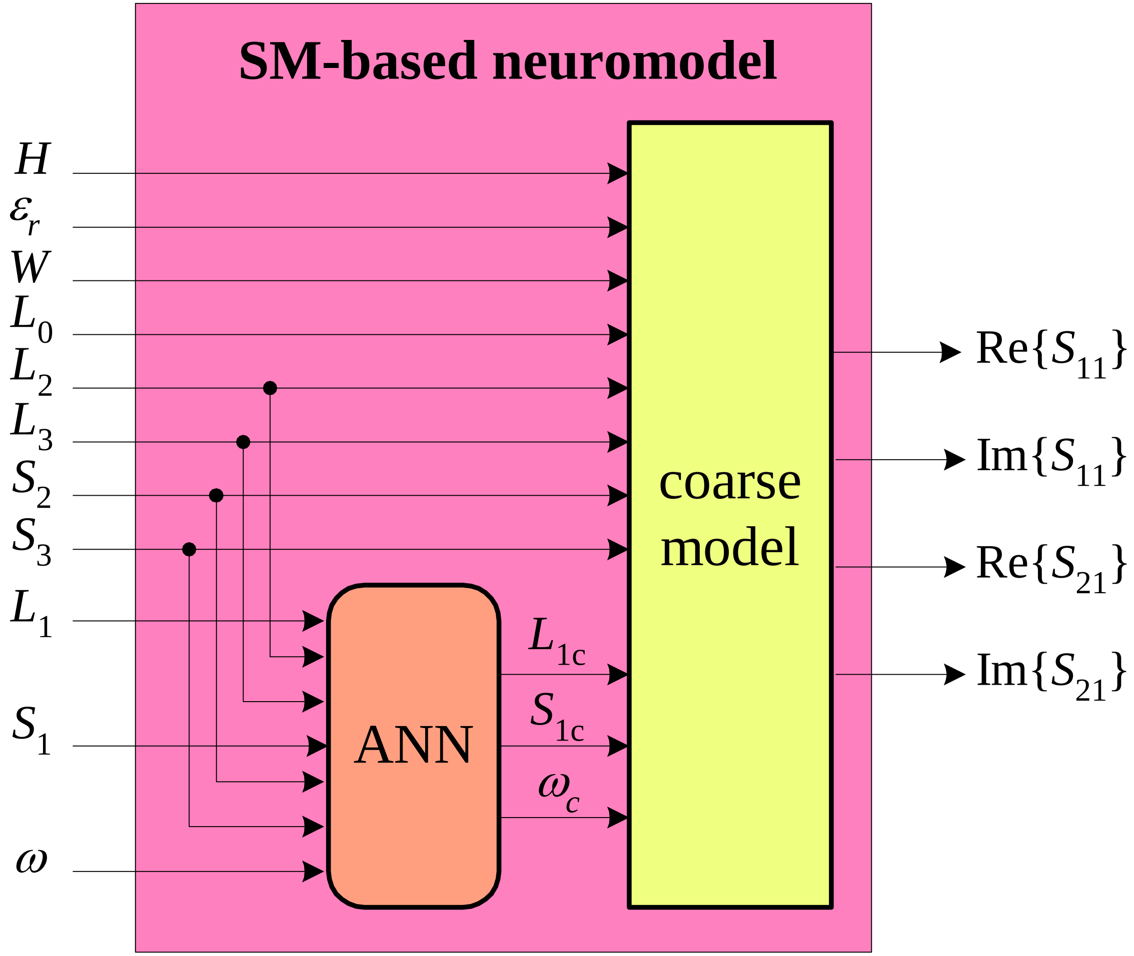


coarse model:

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



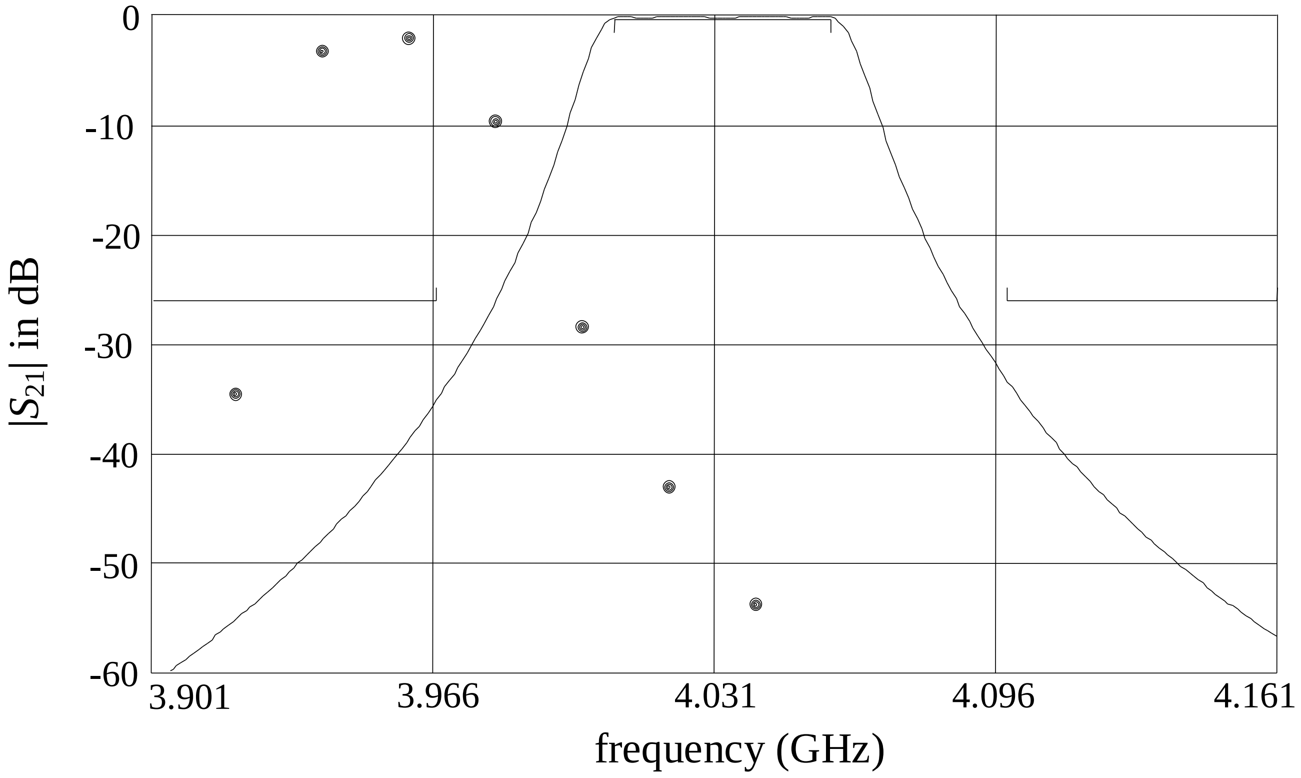
SM-based Neuromodel of the HTS Filter for Yield Optimization



Coarse Optimization of the HTS Filter

coarse and fine model responses at the optimal coarse solution

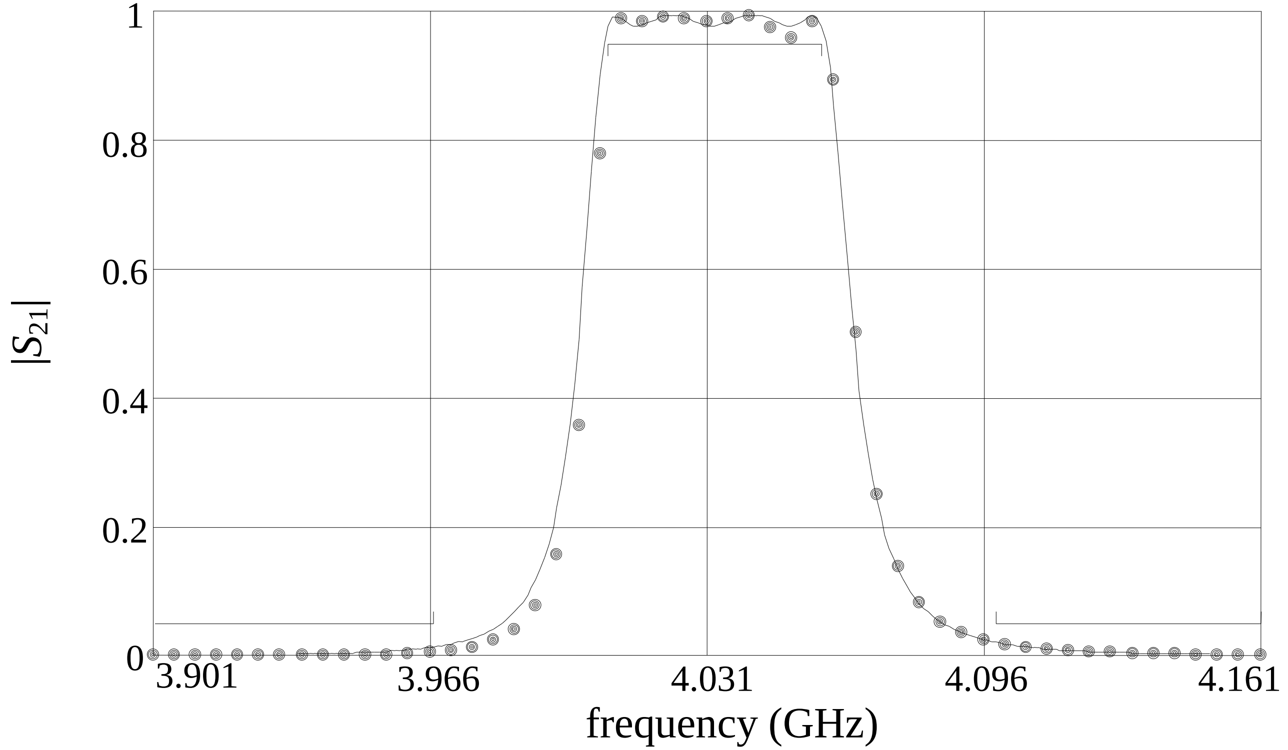
OSA90/hope™ (–) and ***em***™ (•)



Nominal Optimization of the HTS Filter

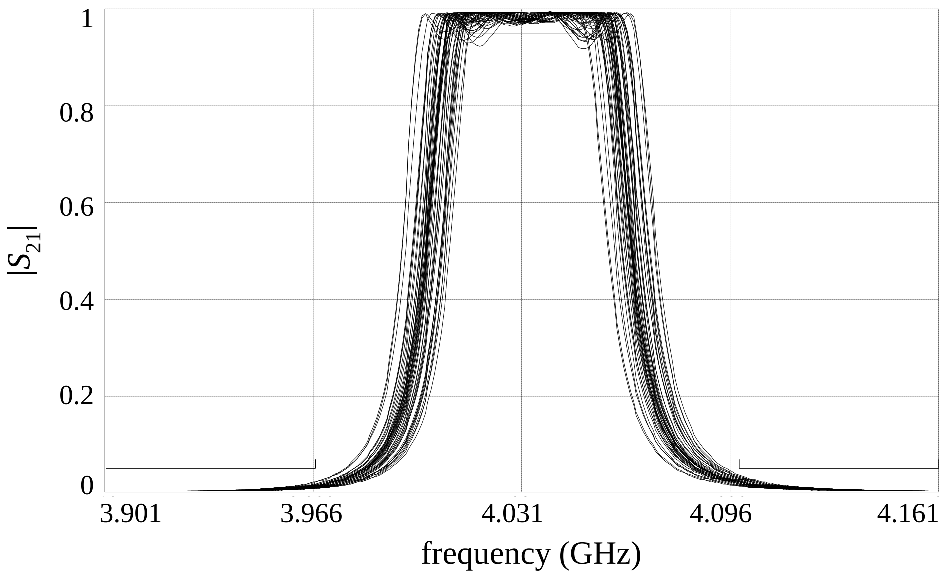
fine model response and SM-based neuromodel response
at the optimal nominal solution $\boldsymbol{x}_{SMBN}$

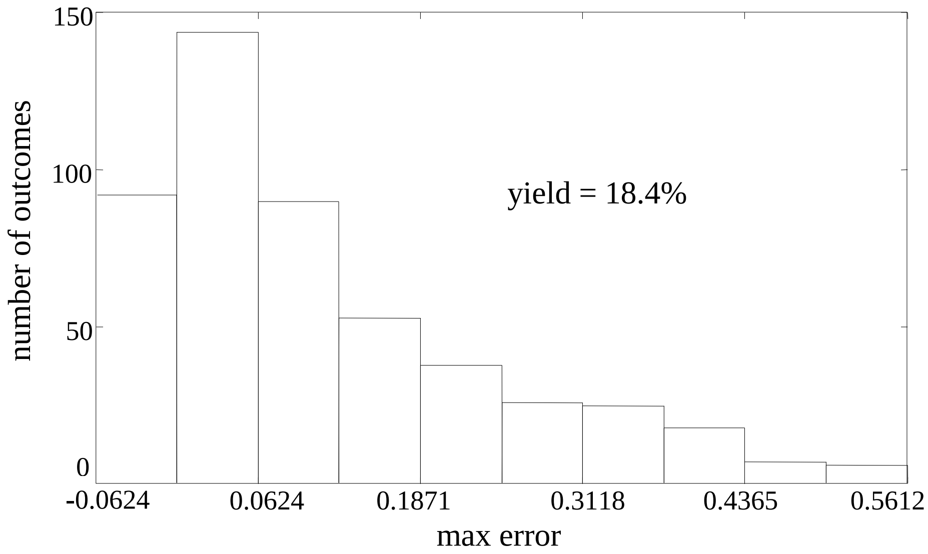
OSA90/hope™ (–) and ***em***™ (•)



Yield Analysis of the HTS Filter

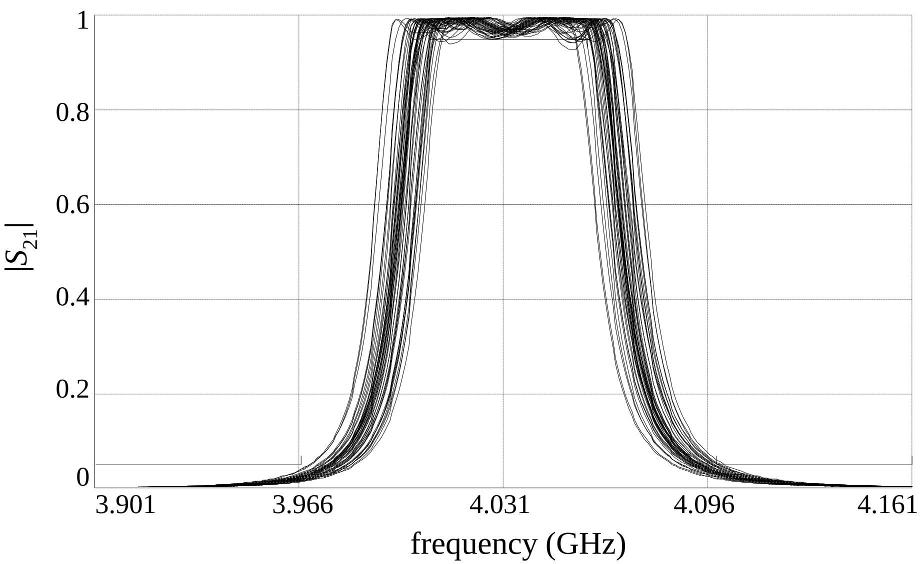
at the nominal solution $\boldsymbol{x}_{SMBN}$ (starting point): yield = 18.4%

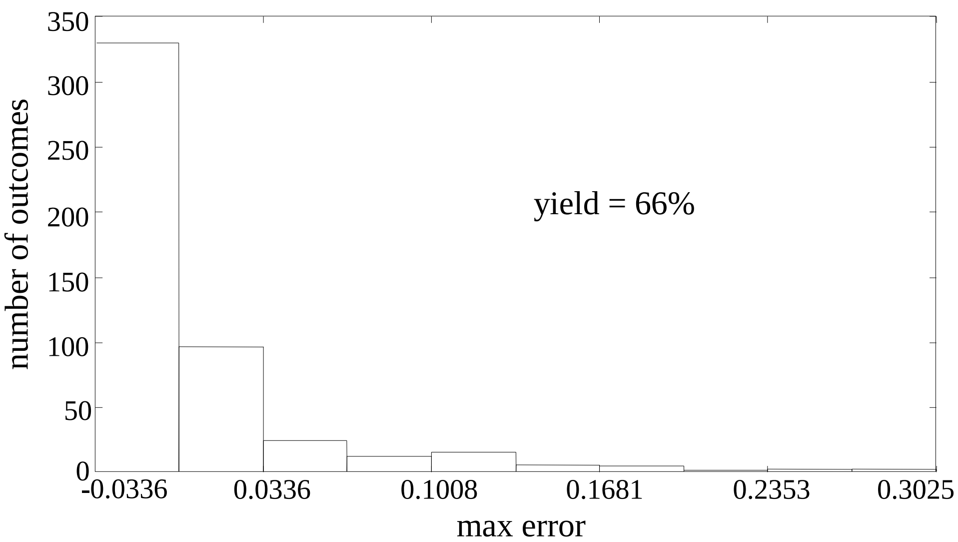




Yield Optimization of the HTS Filter

at the optimal yield solution $\boldsymbol{x}_{SMBN}^{Y*}$: yield = 66%

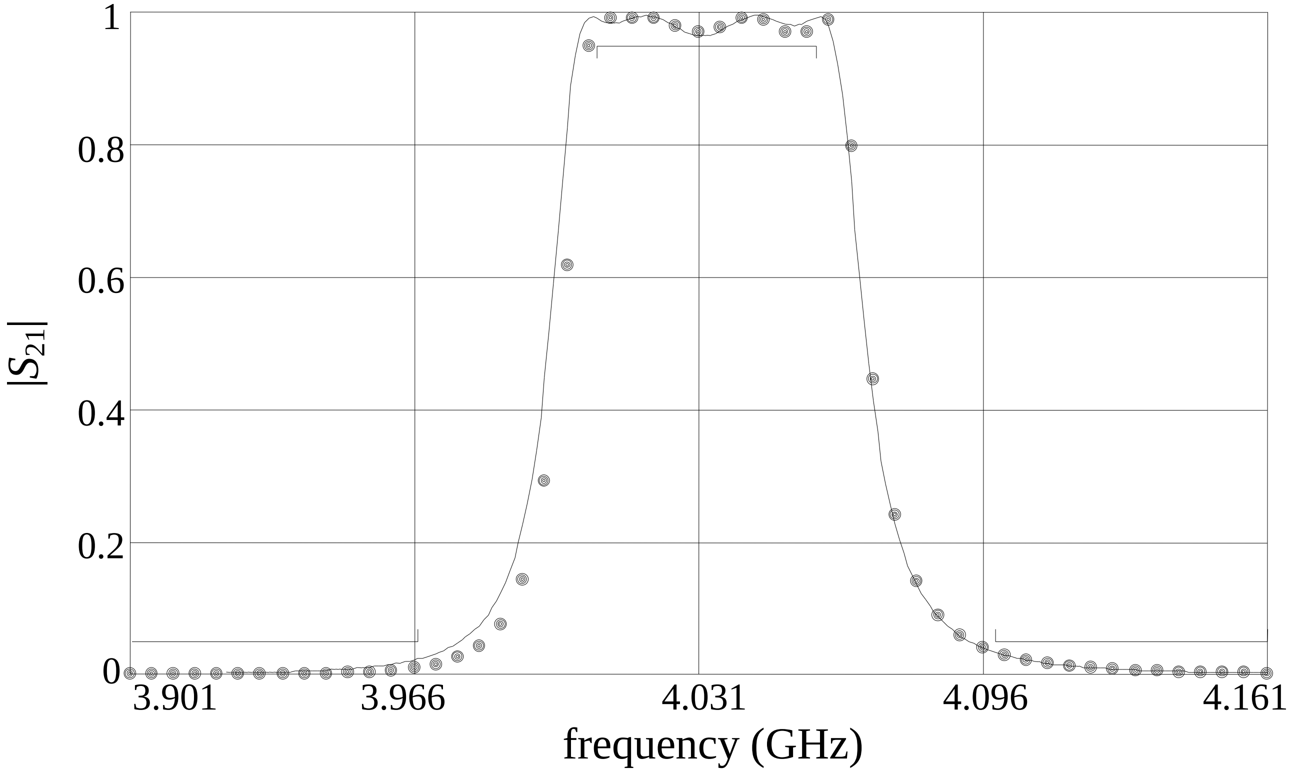




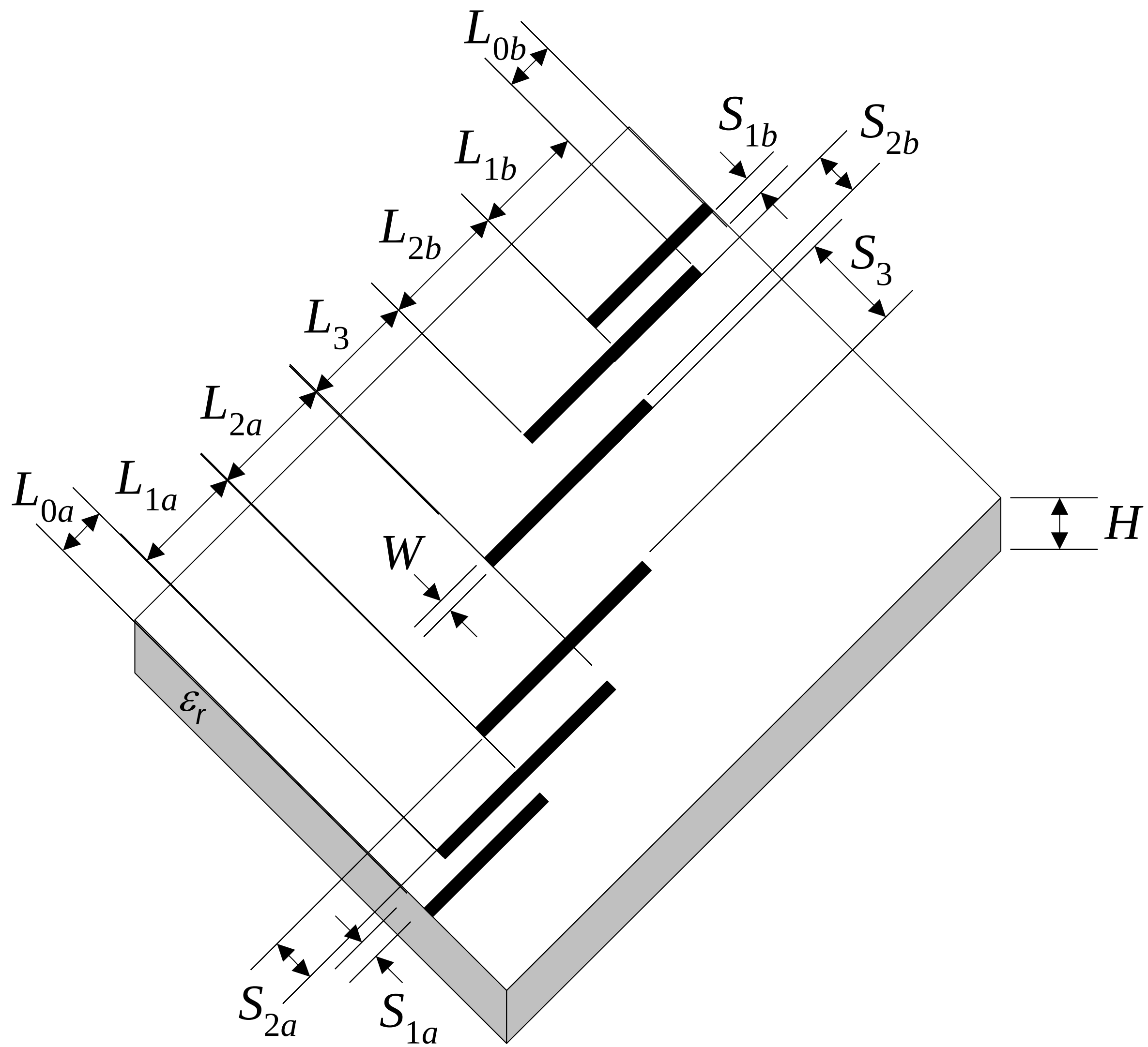
Yield Optimization of the HTS Filter (continued)

fine model response and SM-based neuromodel response
at the optimal yield solution $\boldsymbol{x}_{SMBN}^{Y*}$

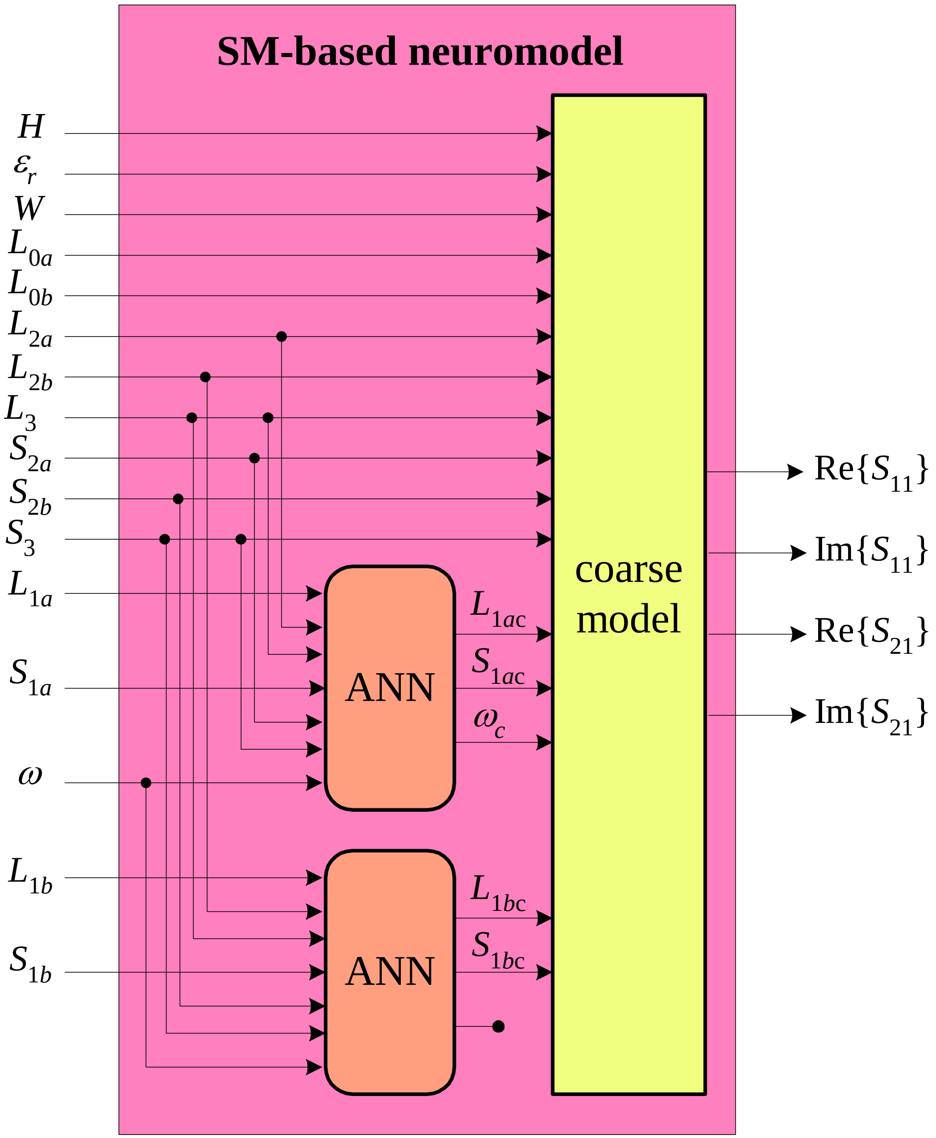
OSA90/hope™ (–) and ***em***™ (•)



HTS Filter Considering Asymmetry

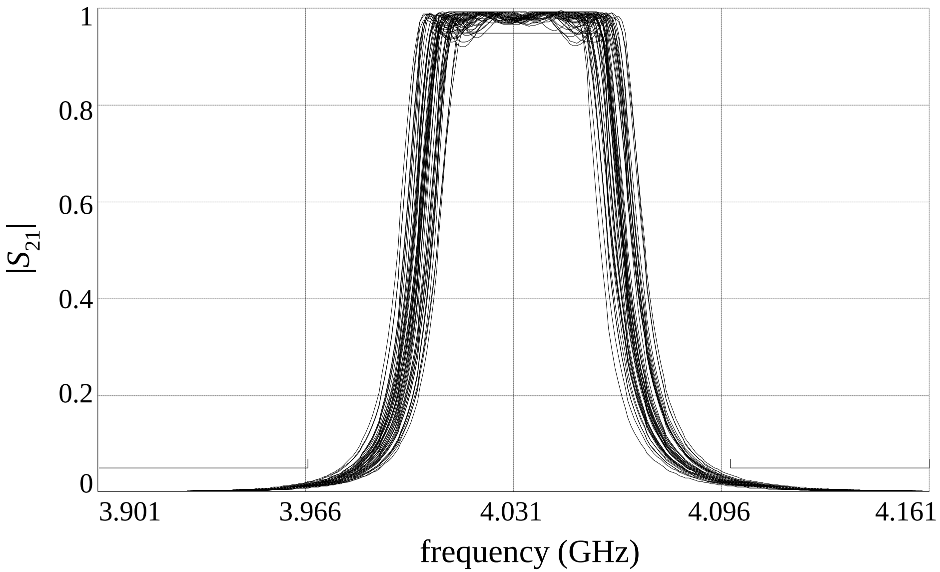


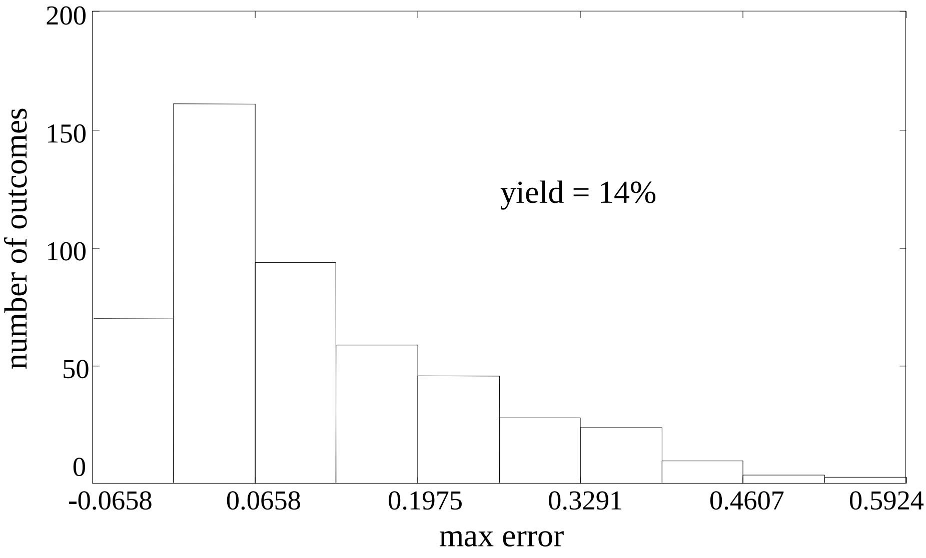
SM-based Neuromodel for the Asymmetric HTS Filter



Yield Analysis of the Asymmetric HTS Filter

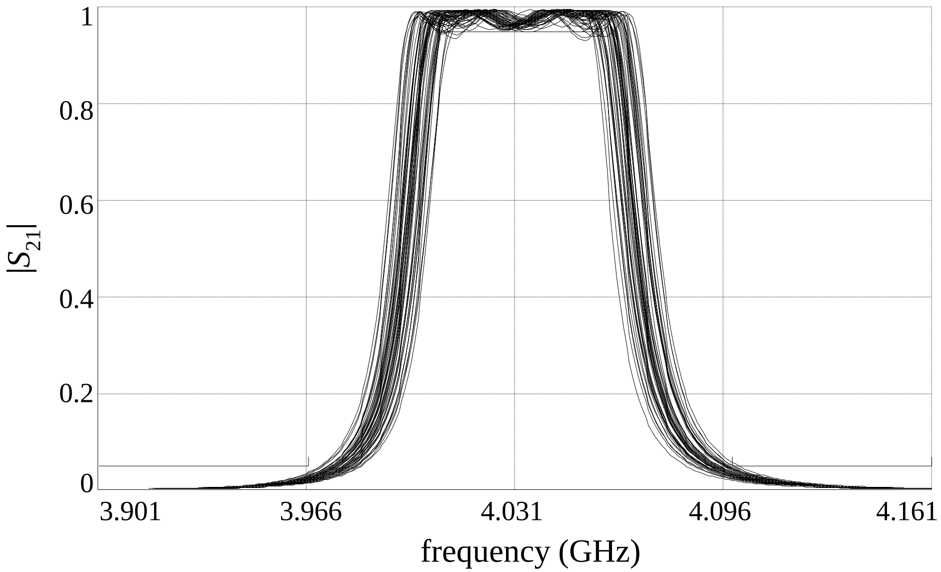
at the nominal solution $\boldsymbol{x}_{SMBN}$ (starting point): yield = 14%

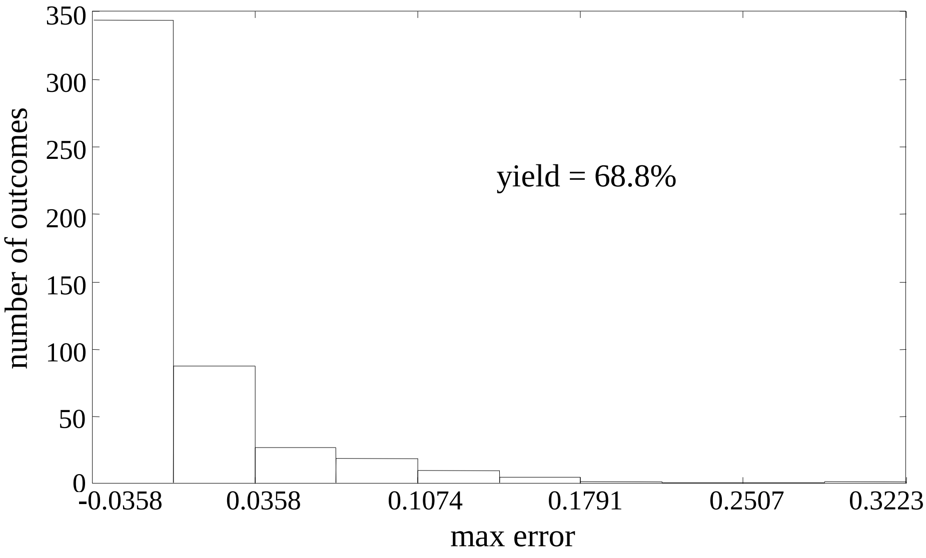




Yield Analysis of the Asymmetric HTS Filter (continued)

at the optimal yield solution $\boldsymbol{x}_{SMBN}^{Y*}$: yield = 68.8%





Conclusions

we propose EM-based statistical analysis and yield optimization using SM-based neuromodels

we relate the fine model sensitivities to the coarse model sensitivities through the Jacobian of the neuromapping

we consider a high-temperature superconducting (HTS) microstrip filter

we reuse the symmetrically derived neuromapping for asymmetric tolerance variations in the physical parameters

the HTS filter yield is increased from 14% to 69%

we find excellent agreement between EM and SM-based neuromodel responses at both the optimal nominal solution and the optimal yield solution