Space Mapping Based Neuromodeling

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Outline

conventional ANN approach for microwave modeling

neuromodeling using existing knowledge

SM-based neuromodeling

examples

other applications of SM-based neuromodeling

conclusions

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Artificial Neural Networks (ANN) Modeling

ANNs are suitable in modeling high-dimensional and highly nonlinear problems

ANN models are computationally efficient and more accurate than empirical models

multilayer feedforward networks can approximate any function
to any desired level of accuracy *(White et al., 1992)*

ANNs that are too small cannot approximate the desired input-output relationship

ANNs with too many internal parameters perform correctly in the learning
set, but give poor generalization ability

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)

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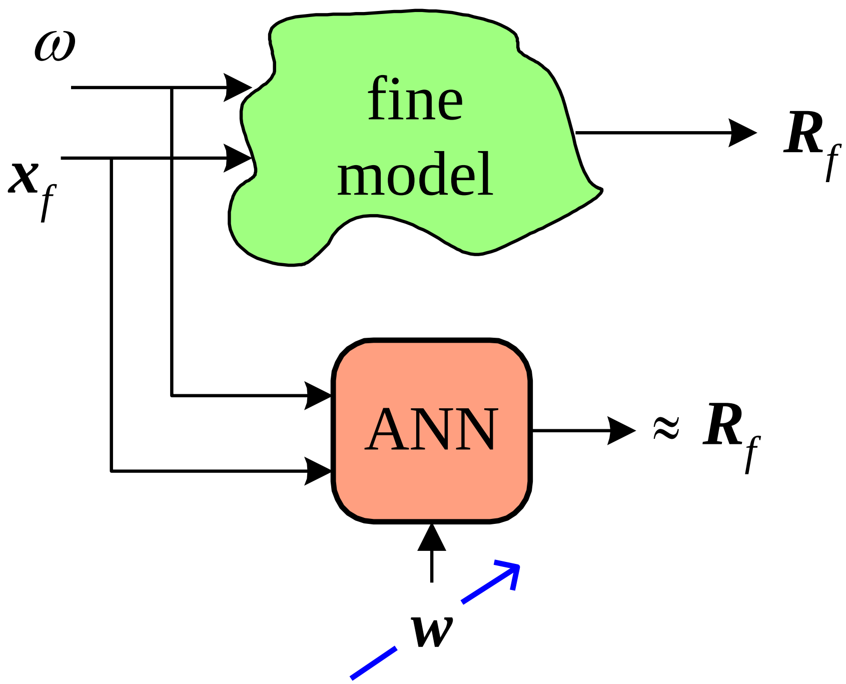
Conventional ANN Modeling Approach



many fine model simulations are usually needed

the number of learning samples grows exponentially with the dimensionality (*Stone, 1982*)

the reliability of multi-layer perceptrons for extrapolation is poor

introducing knowledge can alleviate these limitations

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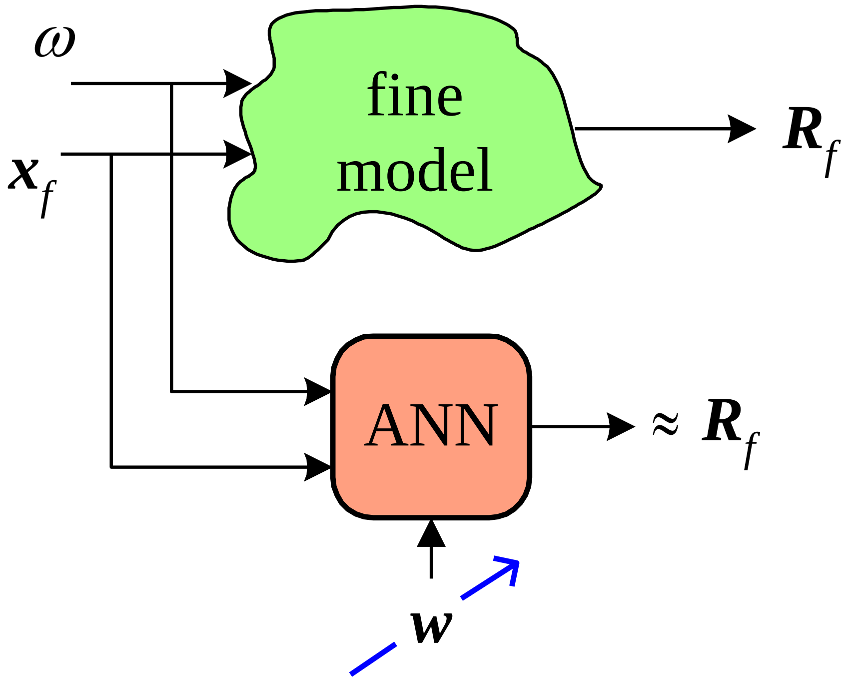

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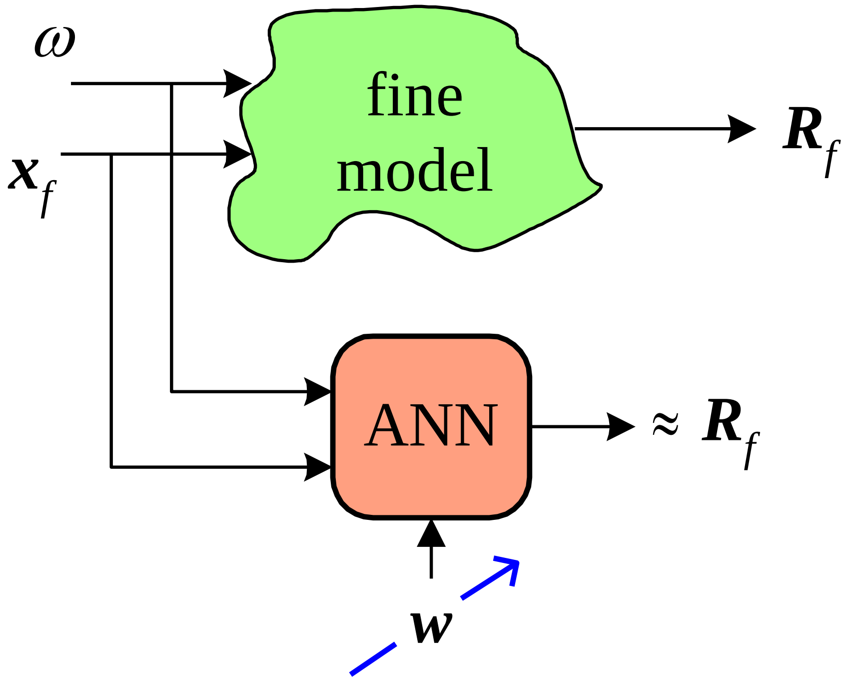

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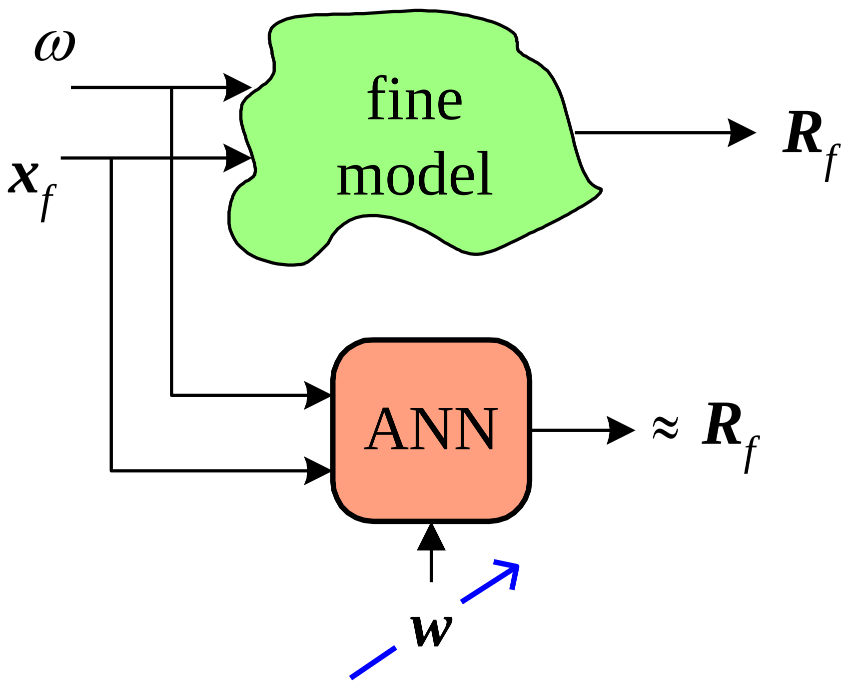

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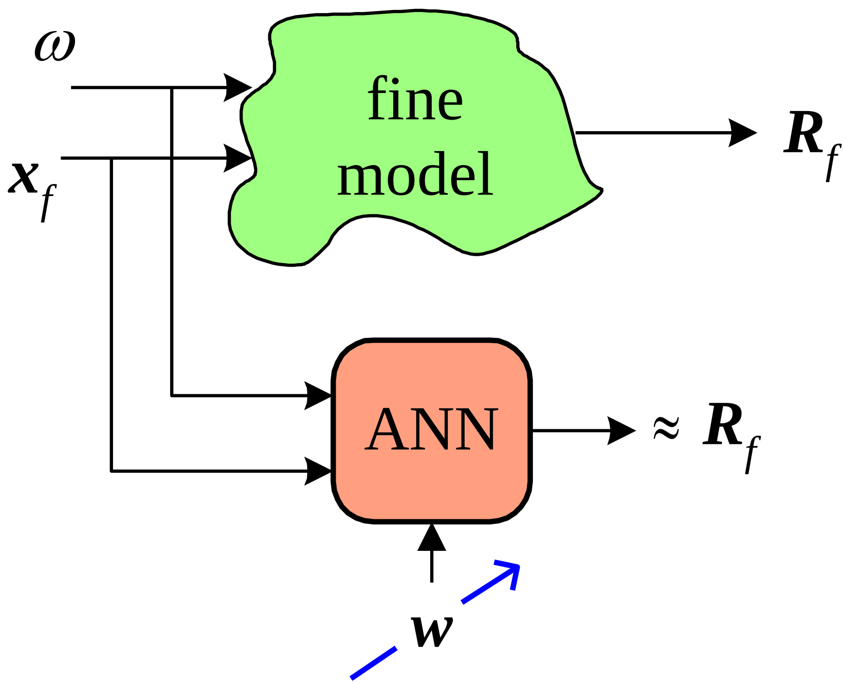

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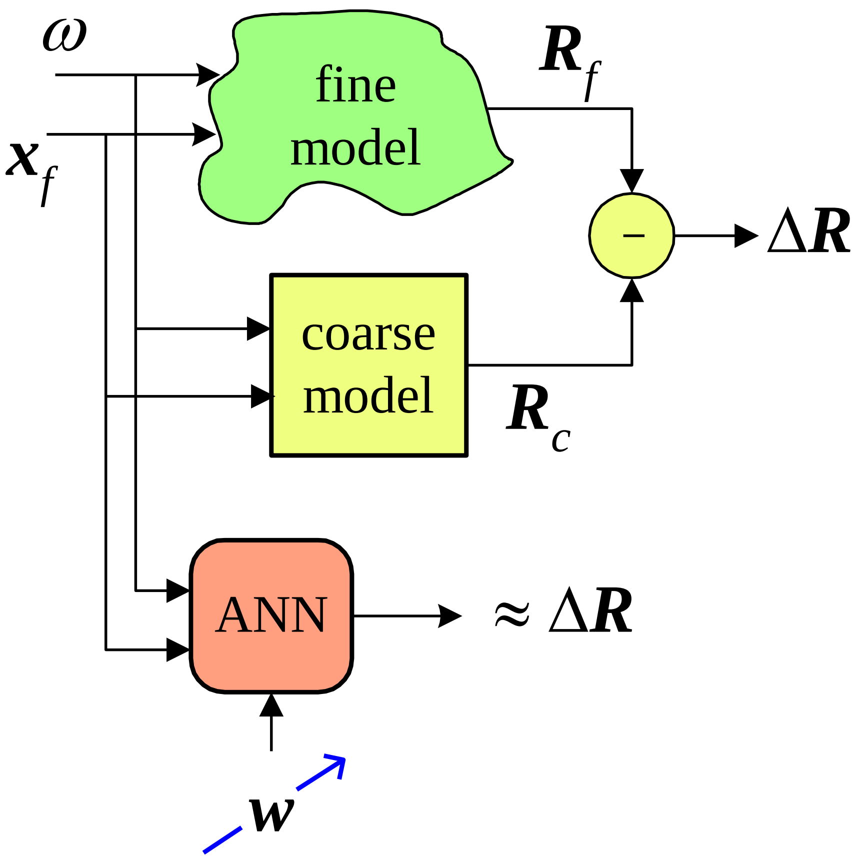
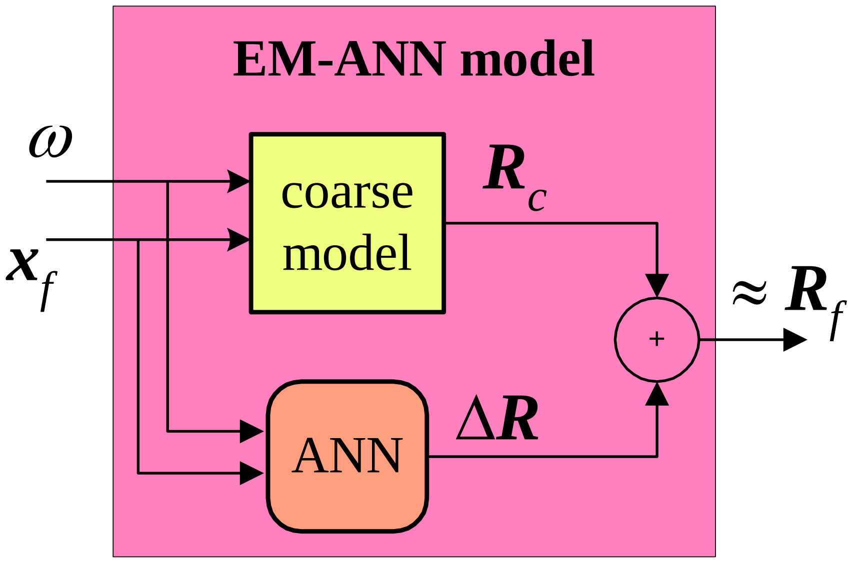
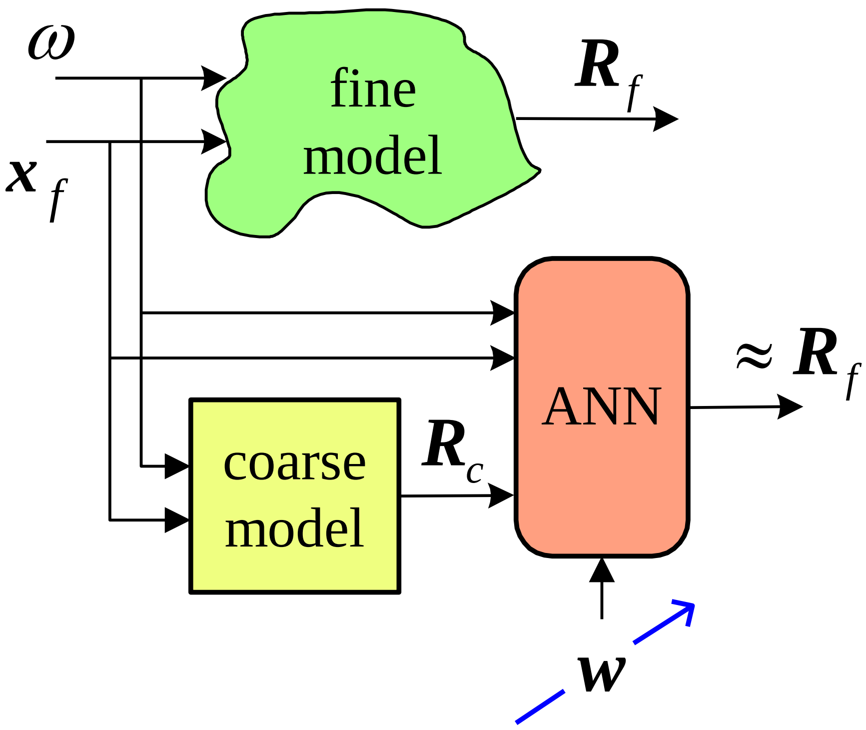
Hybrid "ΔS" EM-ANN Neuromodeling Concept

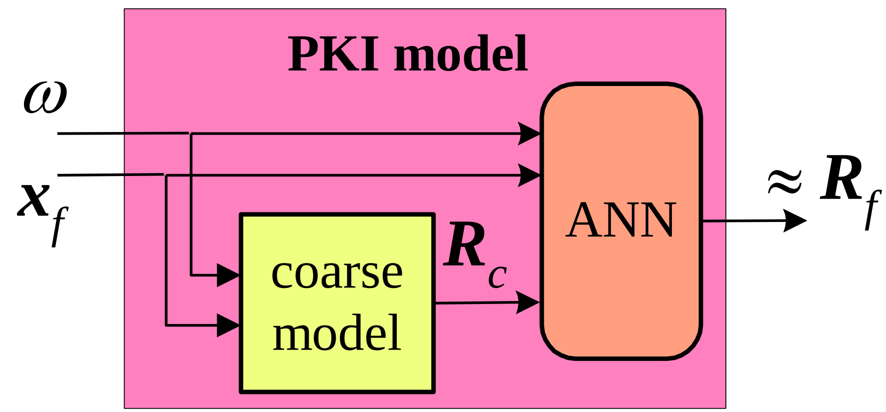
(Gupta et al., 1996)





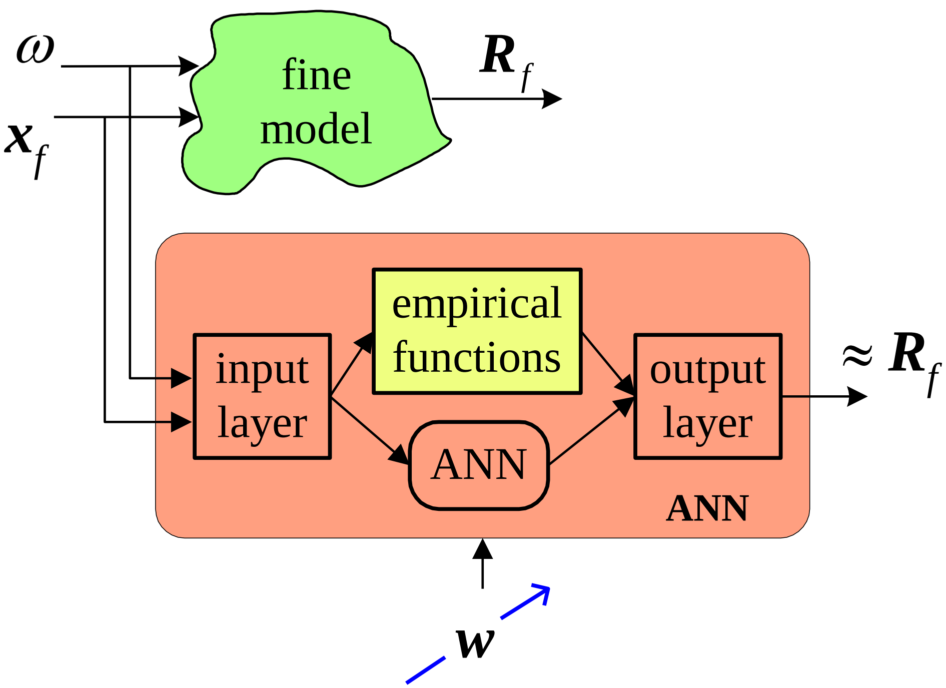
PKI Neuromodeling Concept
(Gupta et al., 1996)

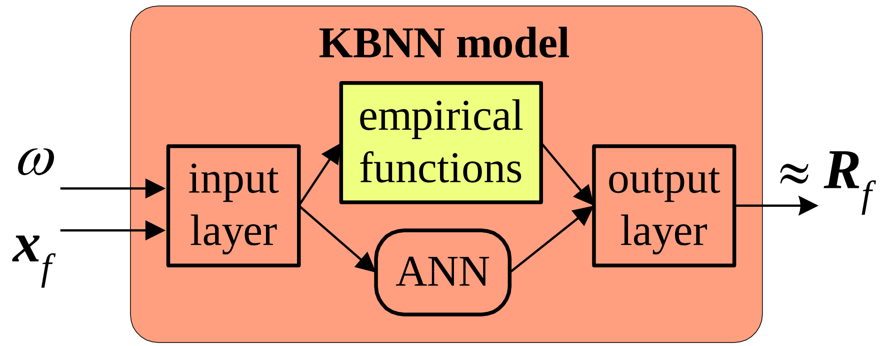




KBNN Neuromodeling Concept

(Zhang et al., 1997)

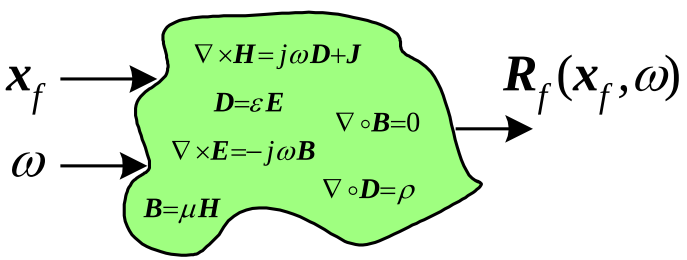




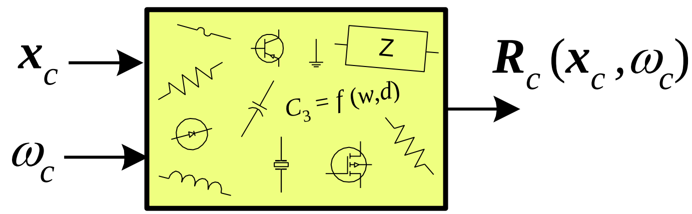
Exploiting Space Mapping for Neuromodeling

(Bandler et. al., 1999)

fine model



coarse model



find

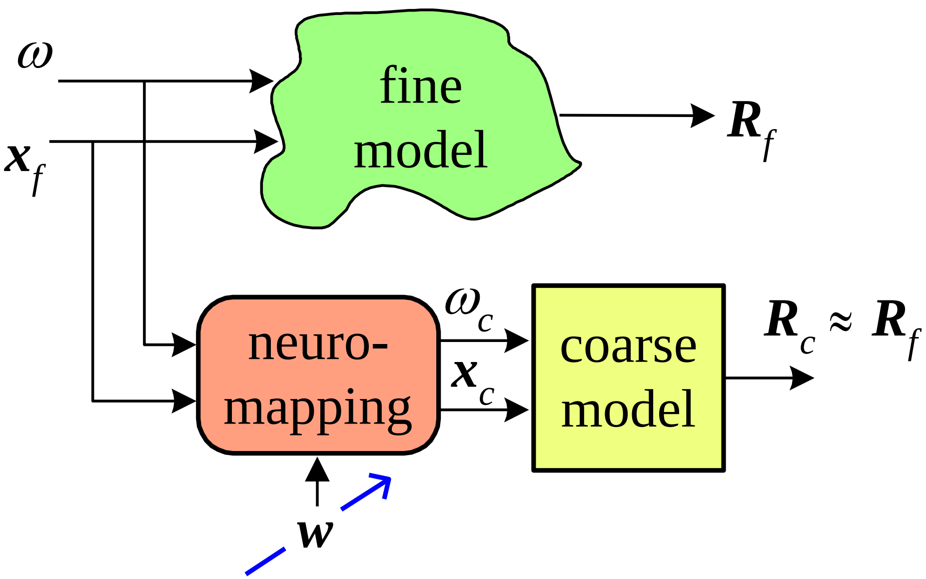
$$\begin{bmatrix} \boldsymbol{x}_c \\ \omega_c \end{bmatrix} = \boldsymbol{P}(\boldsymbol{x}_f, \omega)$$

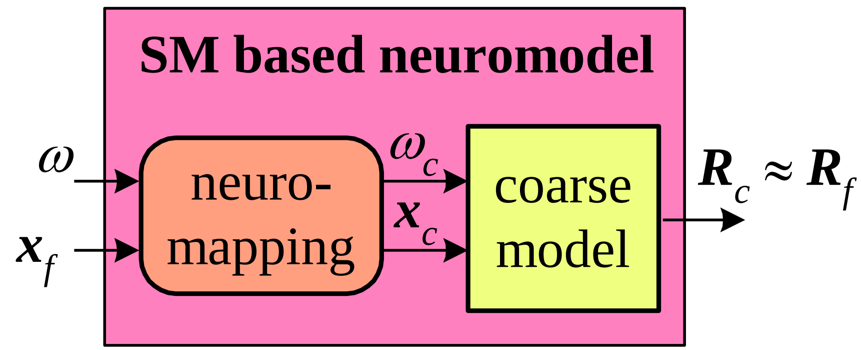
such that

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

Space Mapping Based Neuromodeling

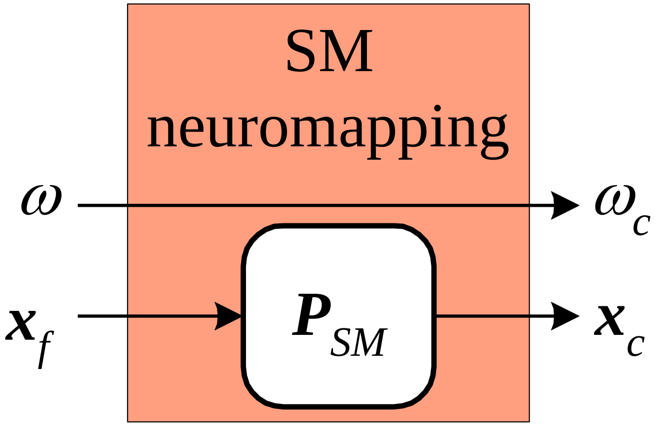
(Bandler et. al., 1999)



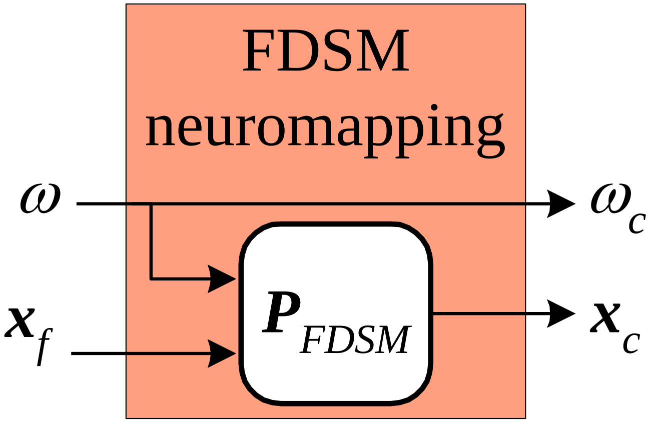


Neuromappings

Space Mapped neuromapping

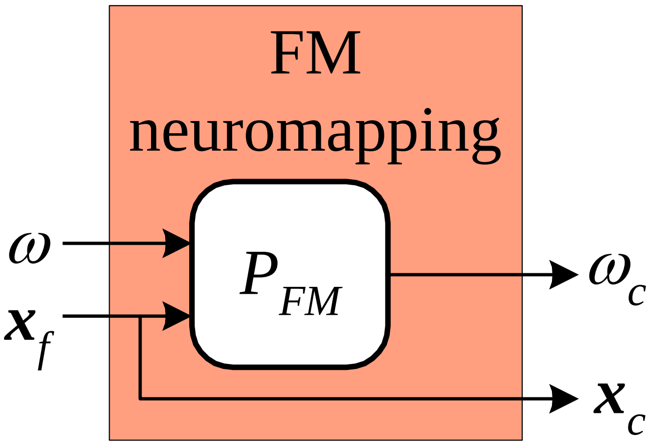


Frequency-Dependent Space Mapped neuromapping

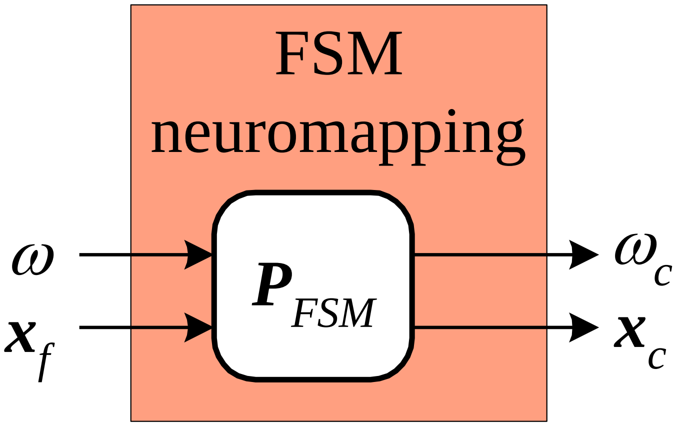


Neuromappings (continued)

Frequency Mapped neuromapping

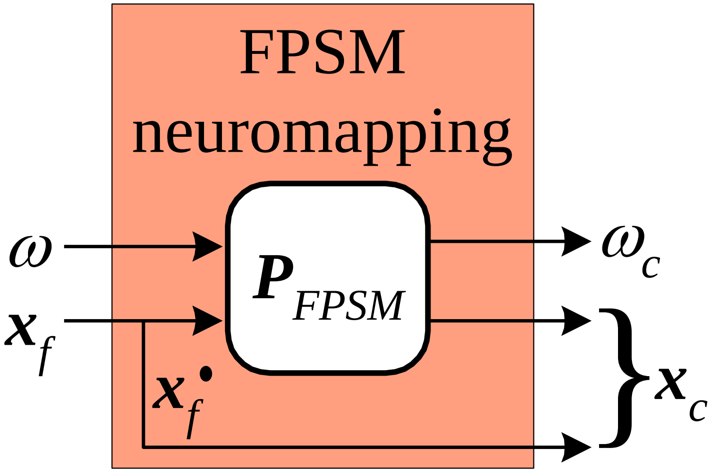


Frequency Space
Mapped neuromapping



Neuromappings (continued)

Frequency Partial-Space
Mapped neuromapping



it is not always necessary to map the whole set of design parameters

coarse model sensitivities can be used to select the mapped parameters

Training the SM-Based Neuromodel

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

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

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

$$j = 1, \ldots, F_p \qquad l = 1, \ldots, 2n+1 \qquad s = j + F_p(l-1)$$

r is the number of responses in the model

$\boldsymbol{P}$ is the neuromapping function and $\boldsymbol{w}$ contains the free parameters of the ANN

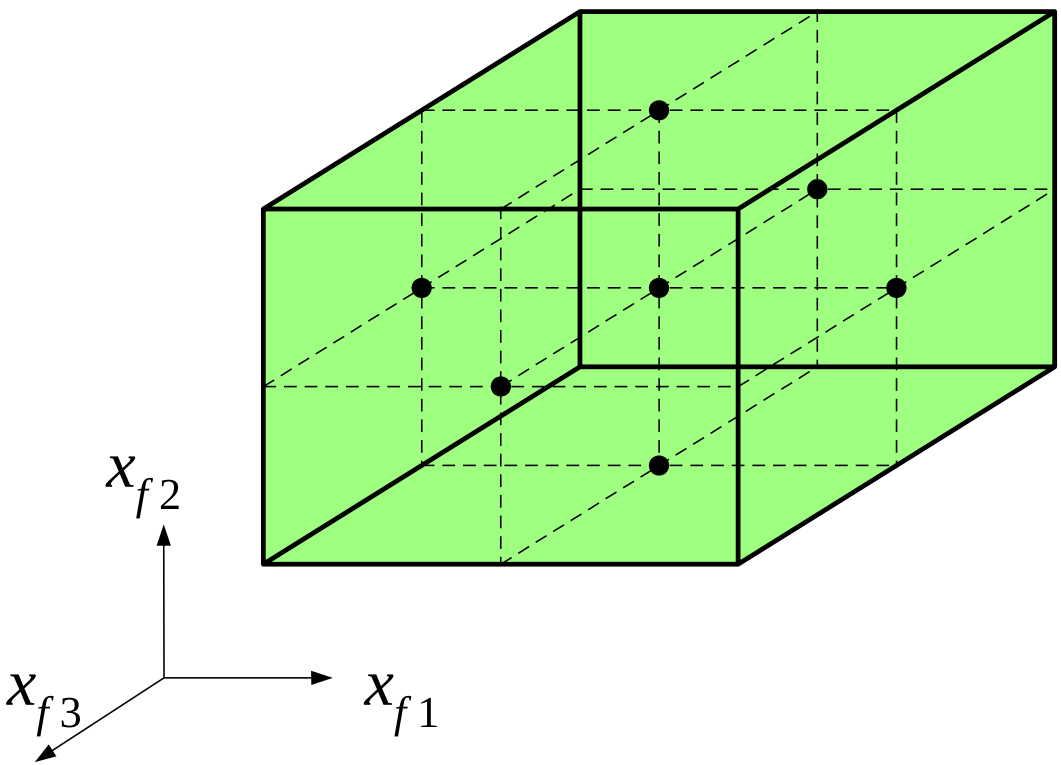
$2n$+1 is the number of training base points and F_p is the number of frequency points

Huber optimization is used to solve this problem

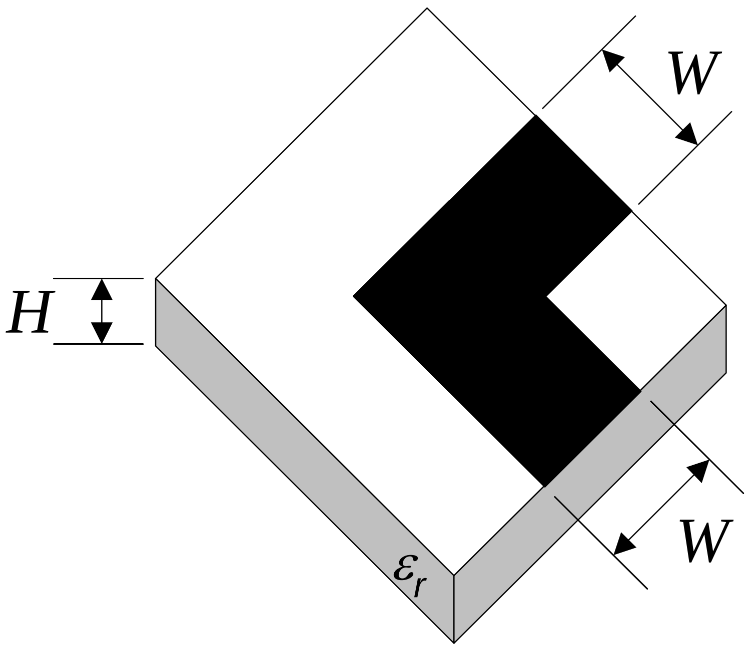
Starting Point and Learning Samples

we chose a unit mapping ($\boldsymbol{x}_c = \boldsymbol{x}_f$ and $\omega_c = \omega$) as the starting point for the optimization problem

$2n+1$ points are used for a microwave circuit with n design parameters



Microstrip Right Angle Bend



region of interest

$$20\text{mil} \le W \le 30\text{mil}$$
$$8\text{mil} \le H \le 16\text{mil}$$
$$8 \le \varepsilon_r \le 10$$
$$1\text{GHz} \le \omega \le 41\text{GHz}$$

"coarse" model: equivalent circuit model *(Gupta, Garg and Bahl, 1979)*

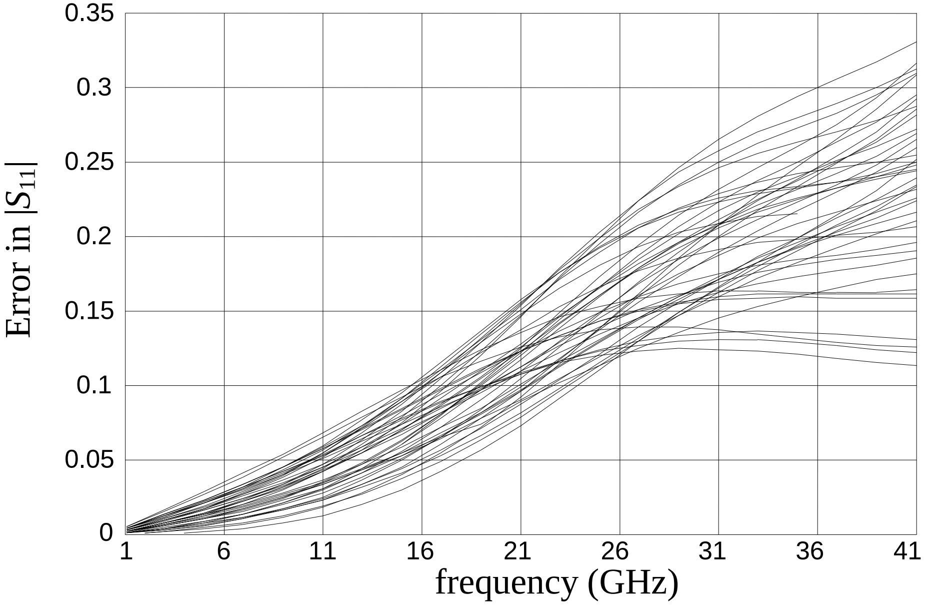
"fine" model: Sonnet's ***em***™

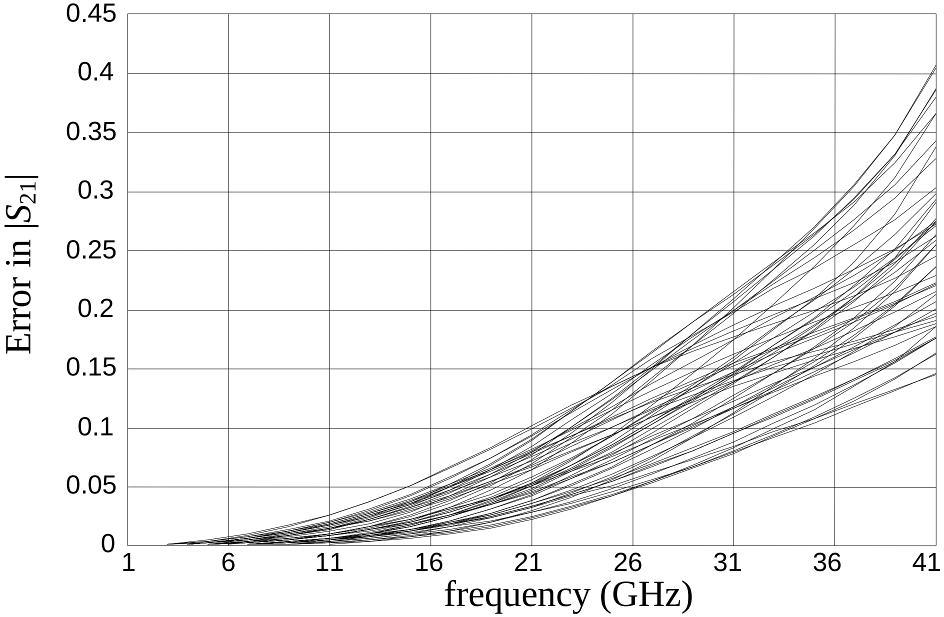
learning set: 7 base points with "star" distribution

testing set: 50 random base points

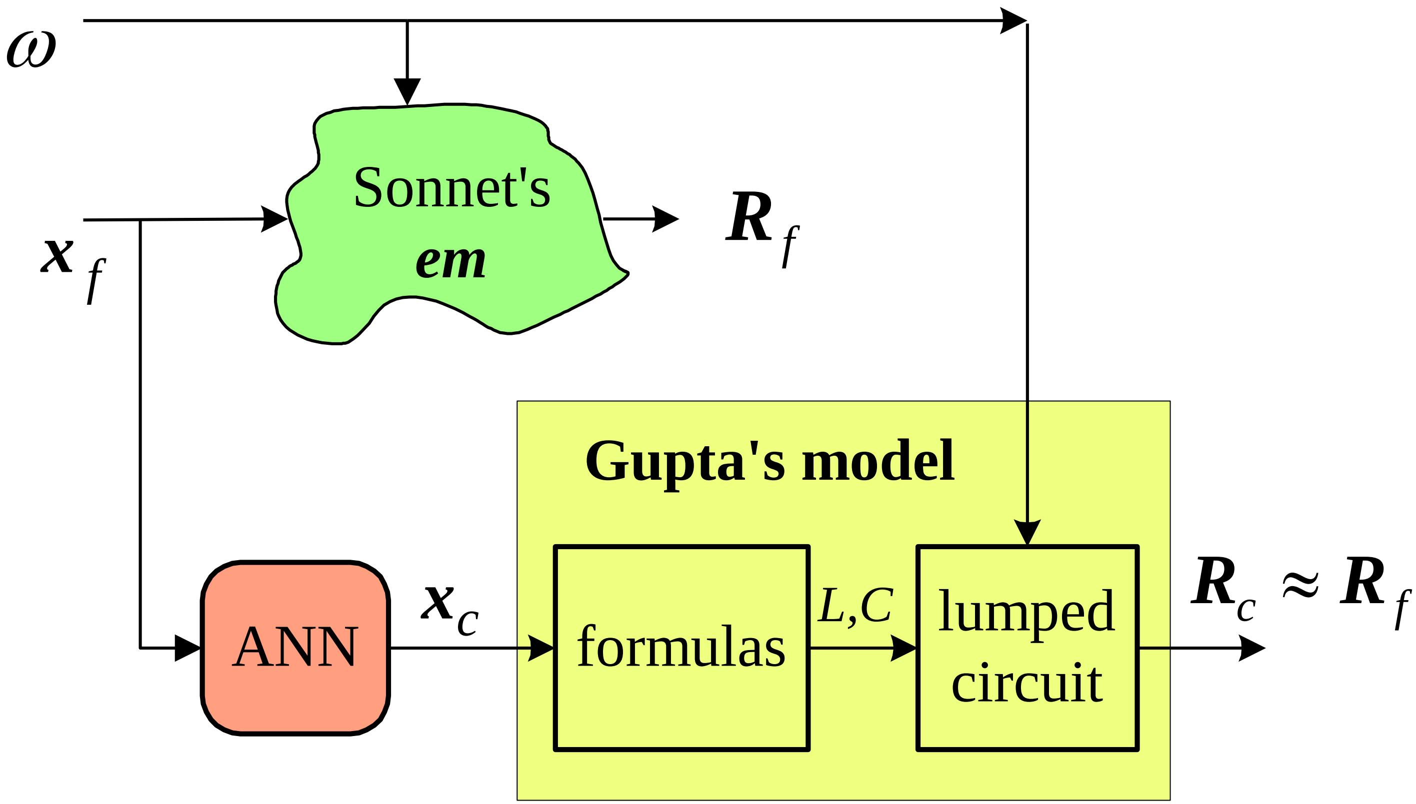
Microstrip Right Angle Bend Coarse Model Errors

comparison between ***em***™ and coarse model at 50 random test points





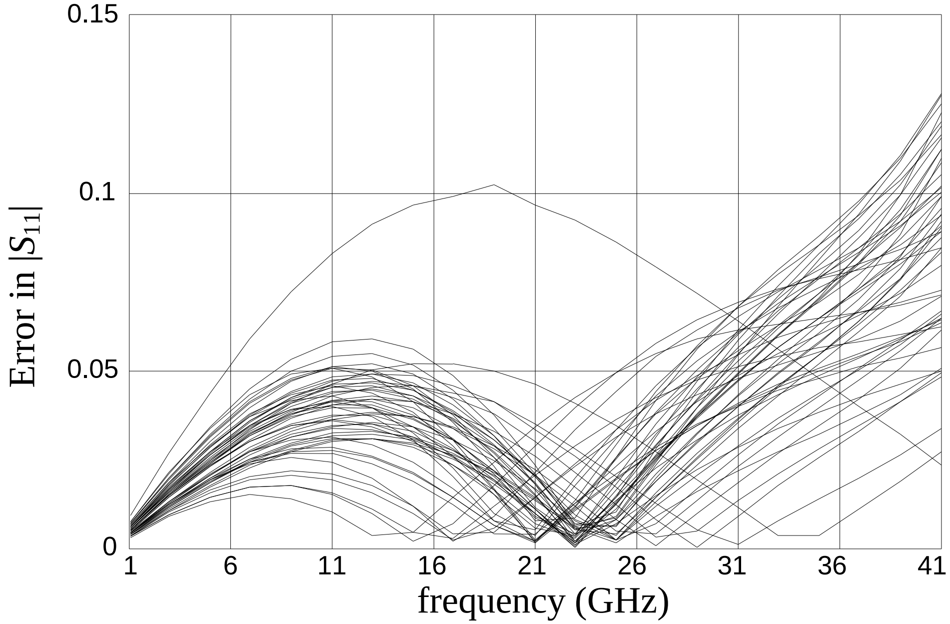
SM Neuromodel for the Right Angle Bend (3LP:3-6-3)

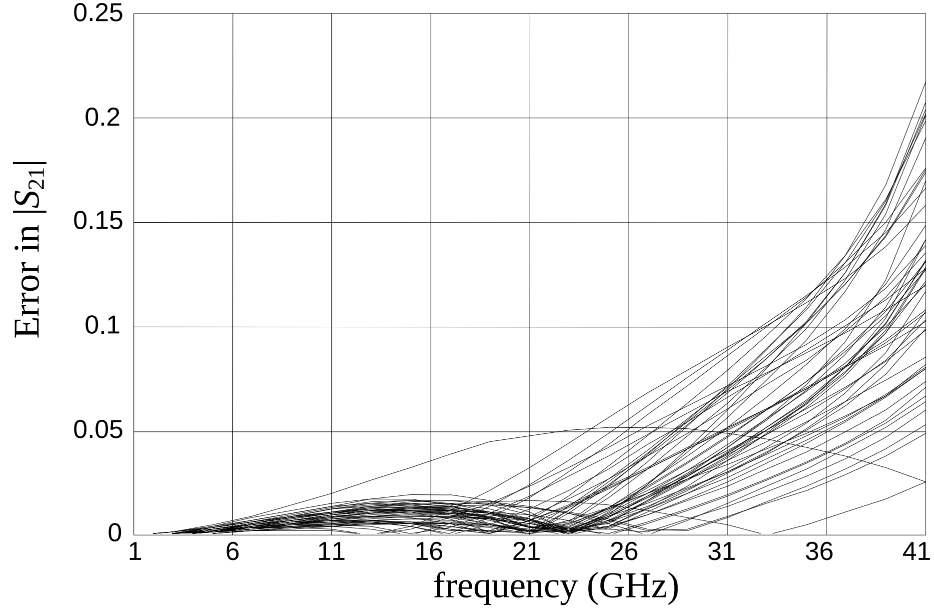


$x_f = [W \;\; H \;\; \varepsilon_r]^T$

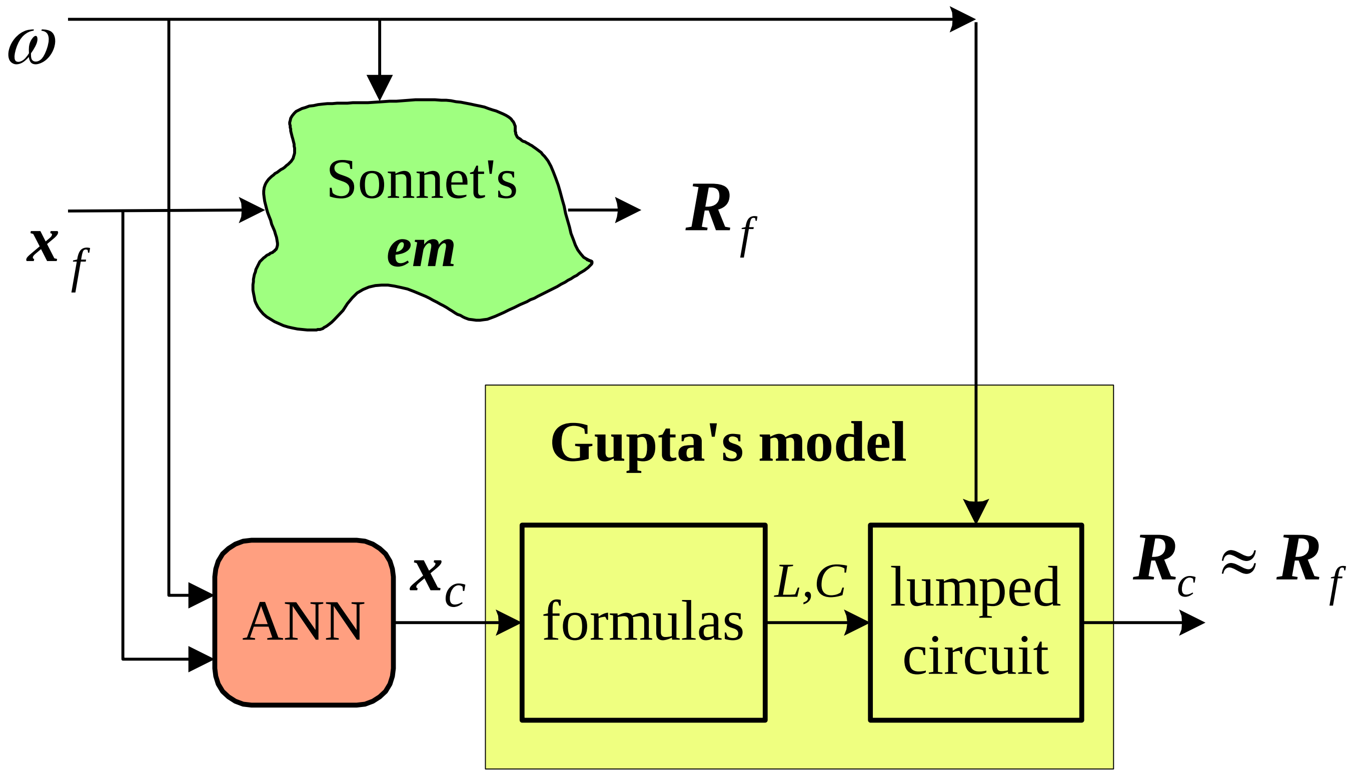
SM Neuromodel Results for the Right Angle Bend

comparison between ***em***™ and the SM neuromodel





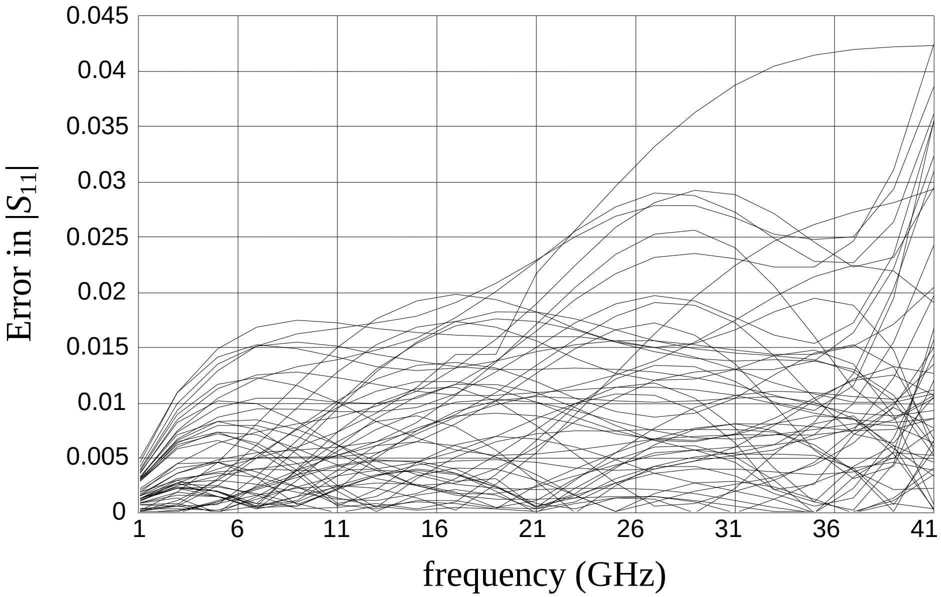
FDSM Neuromodel for the Right Angle Bend (3LP:4-7-3)

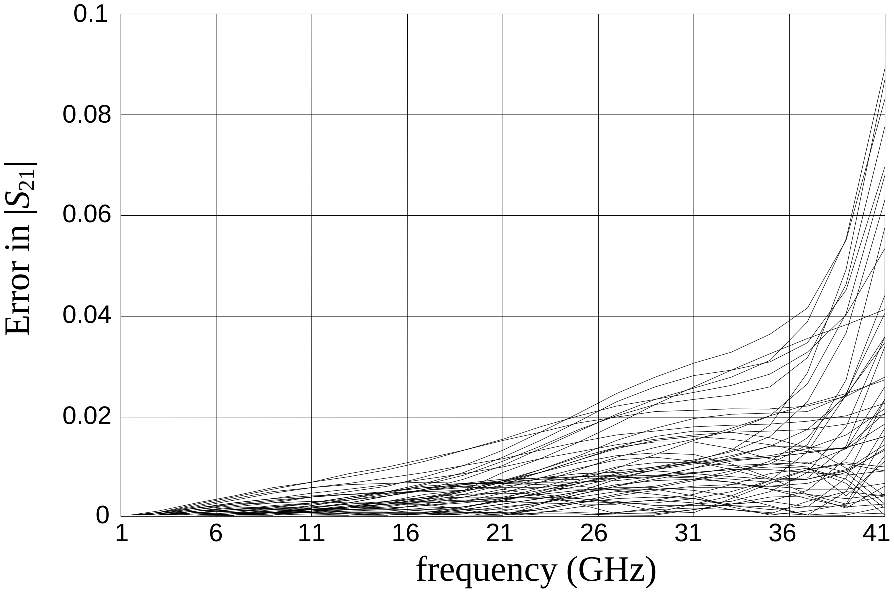


$$\boldsymbol{x}_f = [W \;\; H \;\; \varepsilon_r]^T$$

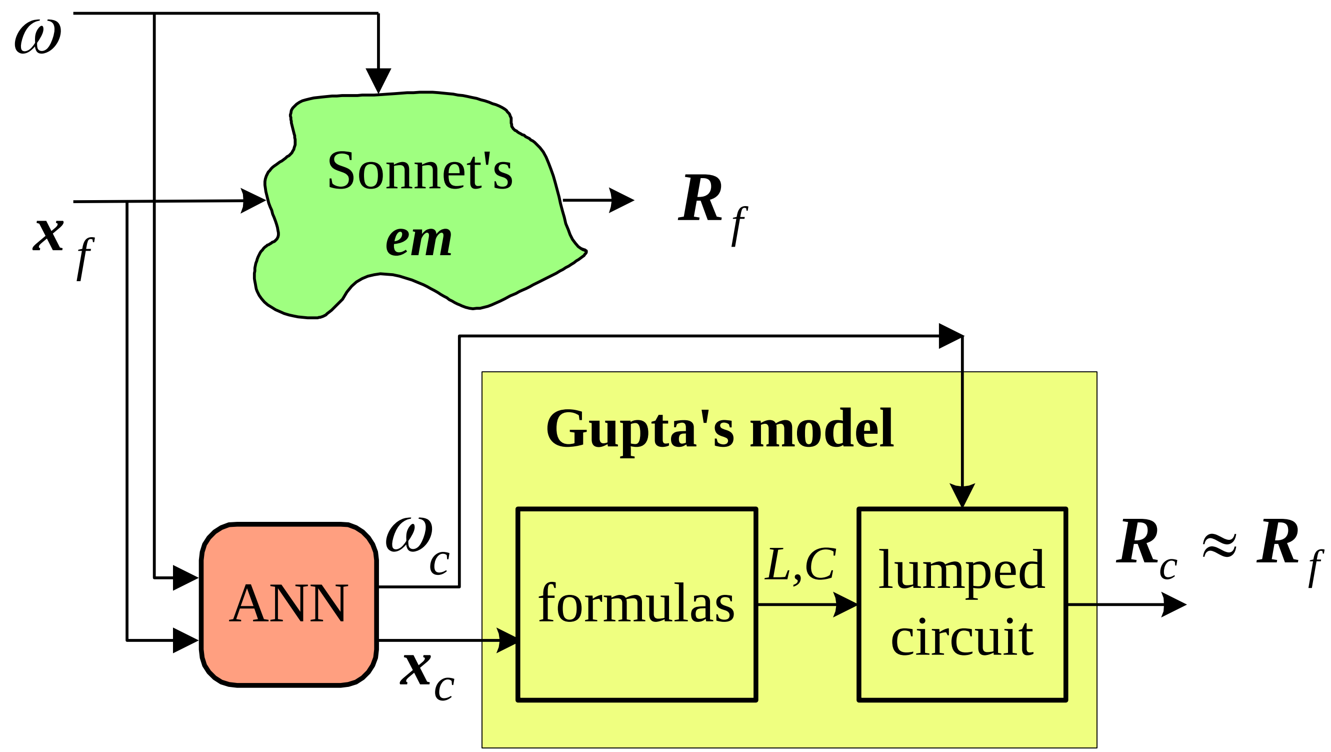
FDSM Neuromodel Results for the Right Angle Bend

comparison between ***em***™ and the FDSM neuromodel





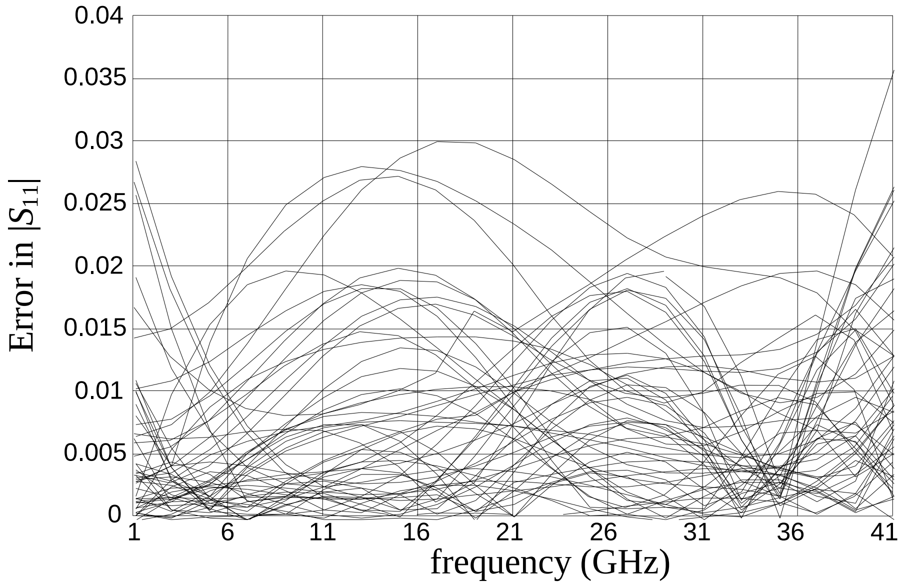
FSM Neuromodel for the Right Angle Bend (3LP:4-8-4)

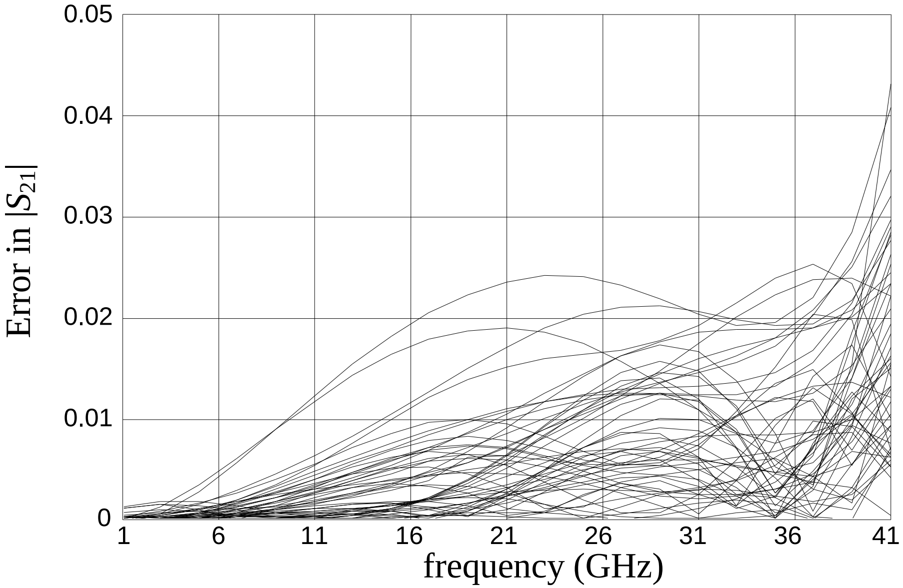


$$\boldsymbol{x}_f = [W \;\; H \;\; \varepsilon_r]^T$$

FSM Neuromodel Results for the Right Angle Bend

comparison between ***em***™ and the FSM neuromodel

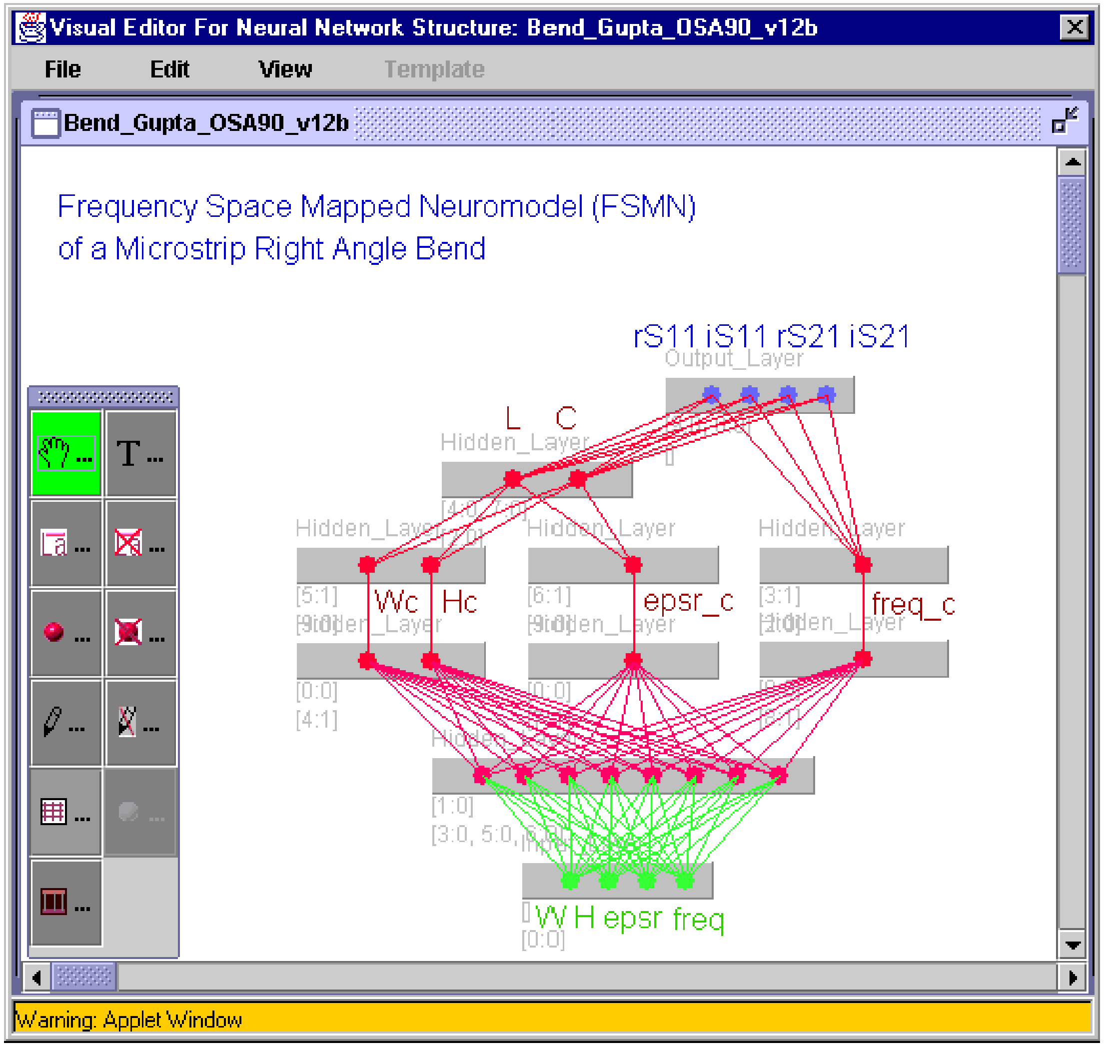




Implementations in *NeuroModeler*

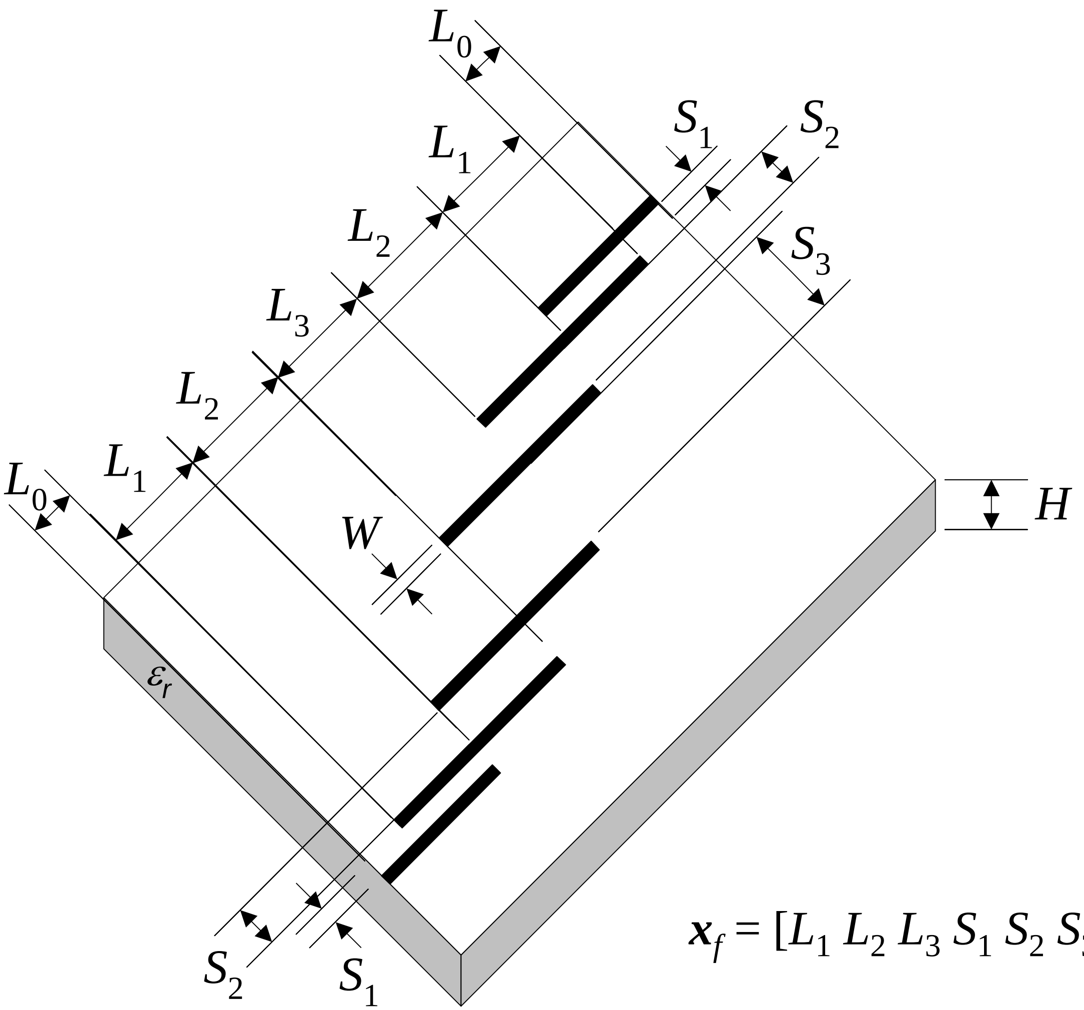
SM based neuromodels of several microstrip circuits have been developed using *NeuroModeler* version 1.2b (1999)

they are entered into HP ADS version 1.1 (1999) as library components through an ADS plugin module



HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(Westinghouse, 1993)



region of interest

$$175\text{mil} \le L_1 \le 185\text{mil}$$
$$190\text{mil} \le L_2 \le 210\text{mil}$$
$$175\text{mil} \le L_3 \le 185\text{mil}$$
$$18\text{mil} \le S_1 \le 22\text{mil}$$
$$75\text{mil} \le S_2 \le 85\text{mil}$$
$$70\text{mil} \le S_3 \le 90\text{mil}$$
$$3.901\text{GHz} \le \omega \le 4.161\text{GHz}$$

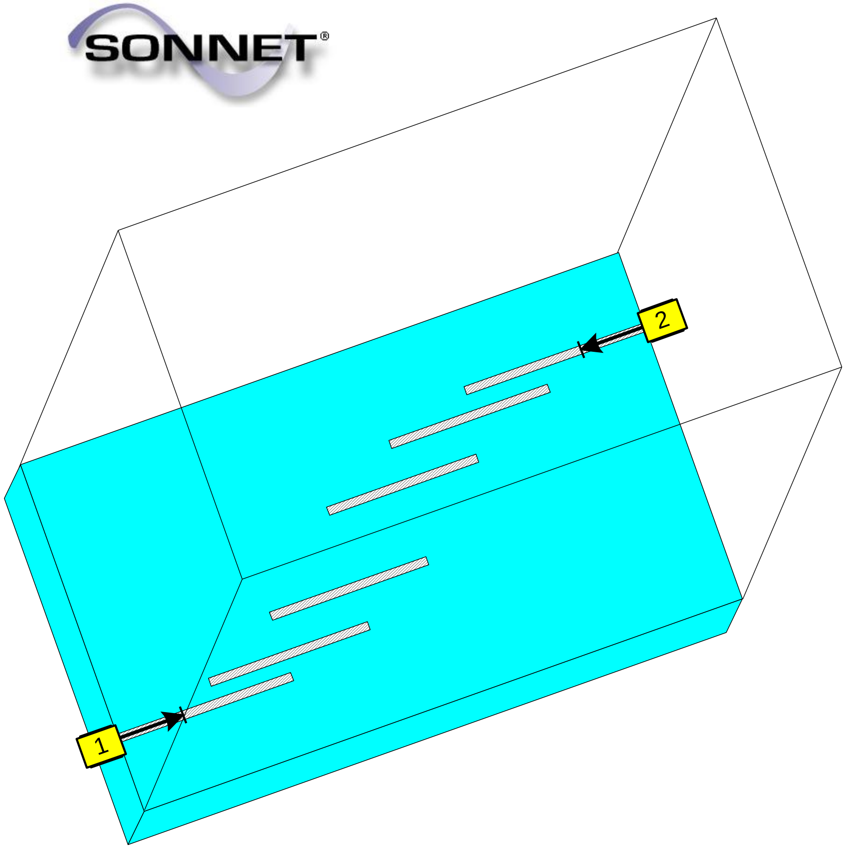
$$L_0 = 50\text{mil}$$
$$H = 20\text{mil}$$
$$W = 7\text{mil}$$
$$\varepsilon_r = 23.425$$
$$\text{loss tangent} = 3\times10^{-5}$$

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

HTS Microstrip Filter: Fine and Coarse Models

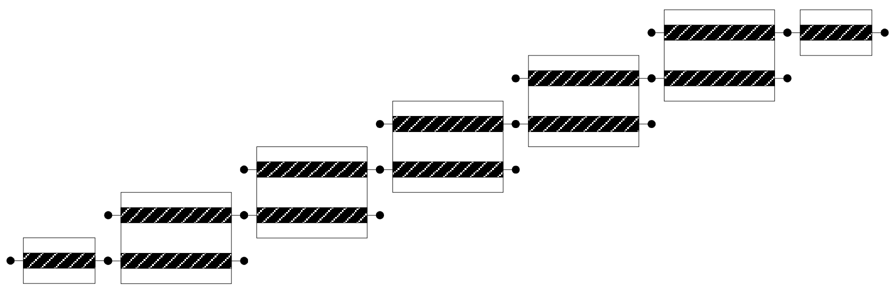
fine model:

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



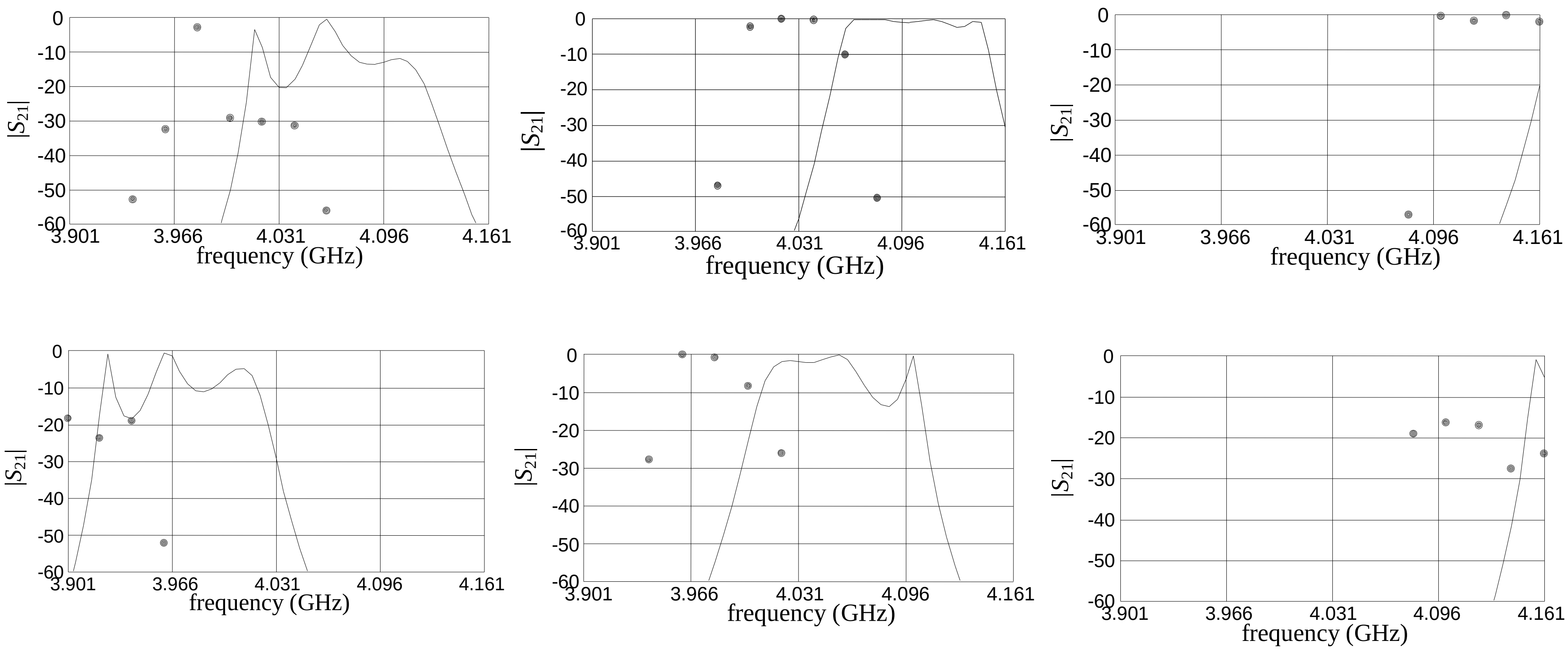
coarse model:

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

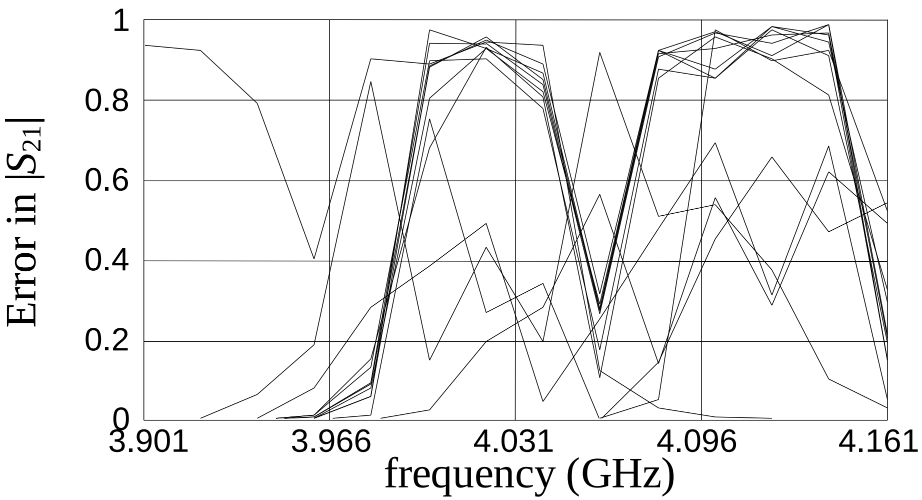


HTS Filter Responses Before Neuromodeling

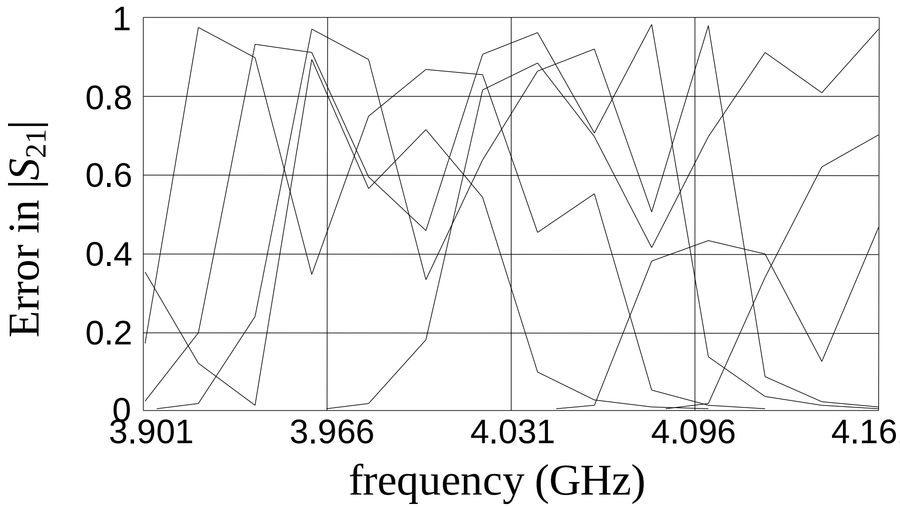
responses using ***em***™ (•) and OSA90/hope™ (–) at three learning and three test points



HTS Coarse Model Error w.r.t. *em*™ before any Neuromodeling



in the learning set

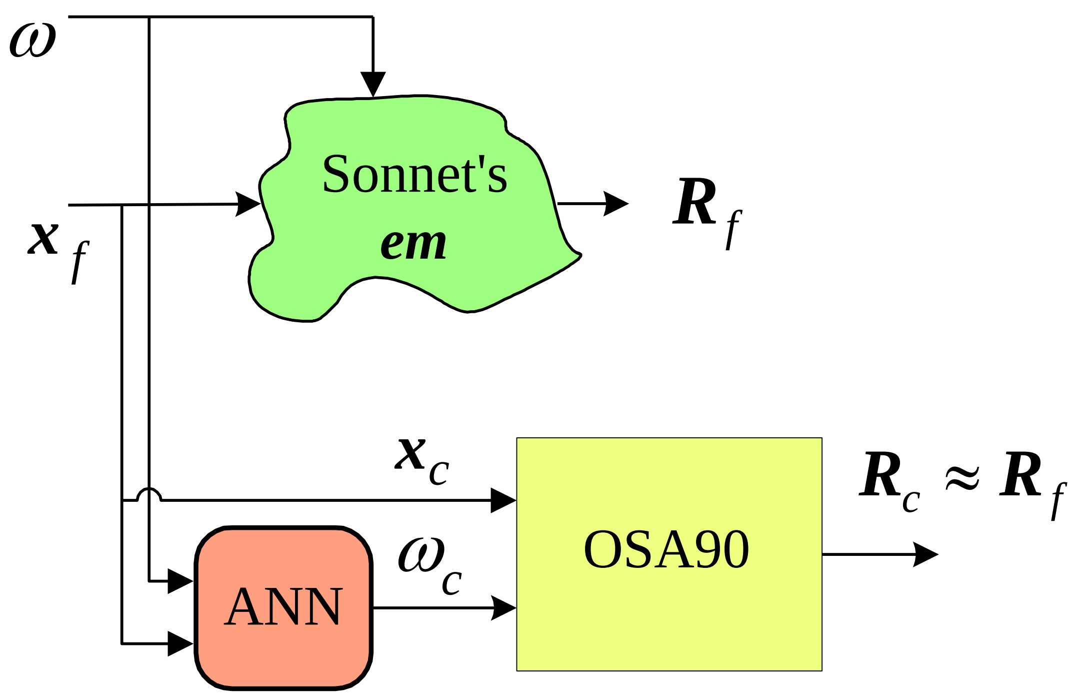


in the testing set

learning set: 13 base points with "star" distribution

testing set: 7 random base points in the region of interest
(not seen in the learning set)

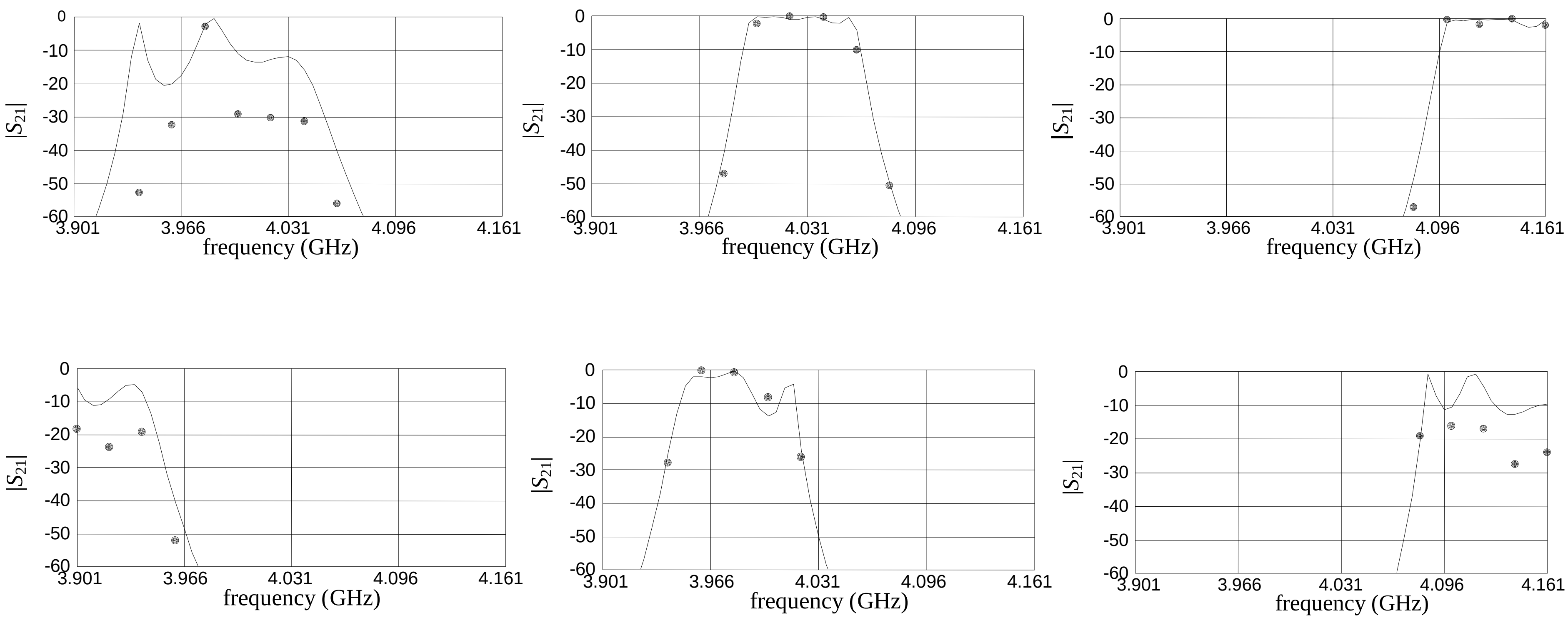
FM Neuromodel for the HTS Filter (3LP:7-5-1)



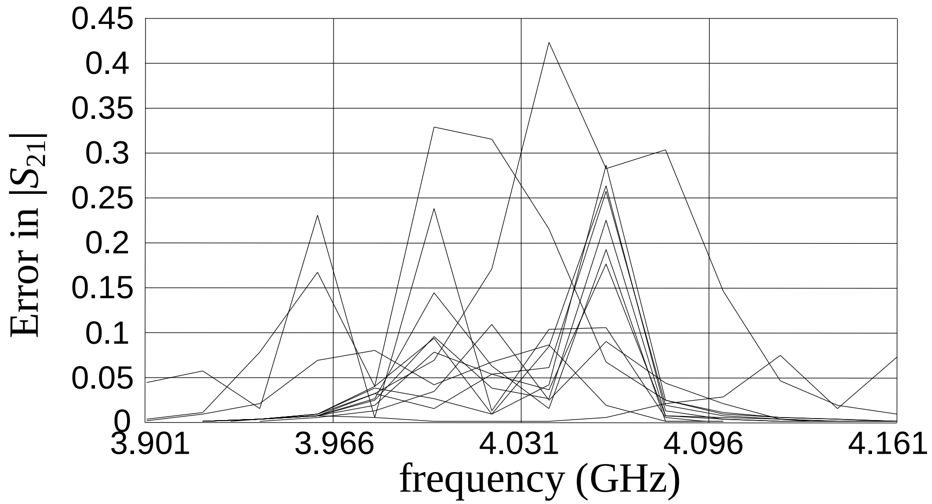
$$\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$$

FM Neuromodel for the HTS Filter (3LP:7-5-1)

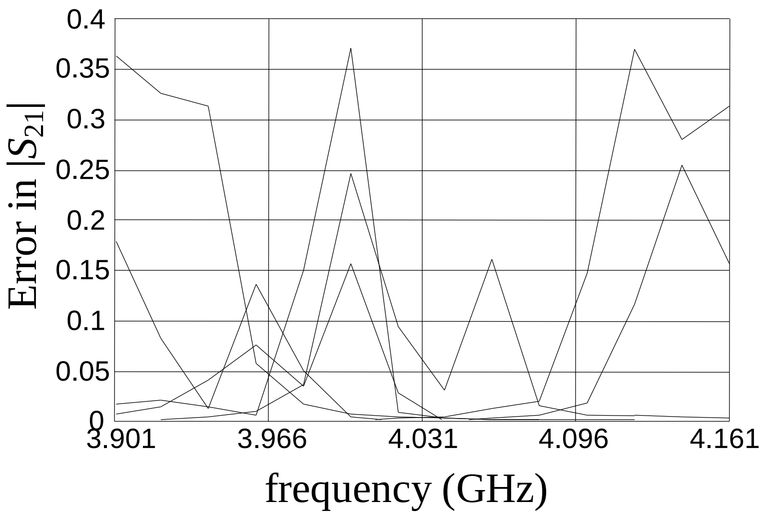
responses using ***em***™ (•) and FMN model (–) at the three learning and three testing points



HTS FM Neuromodel Error w.r.t. *em*™

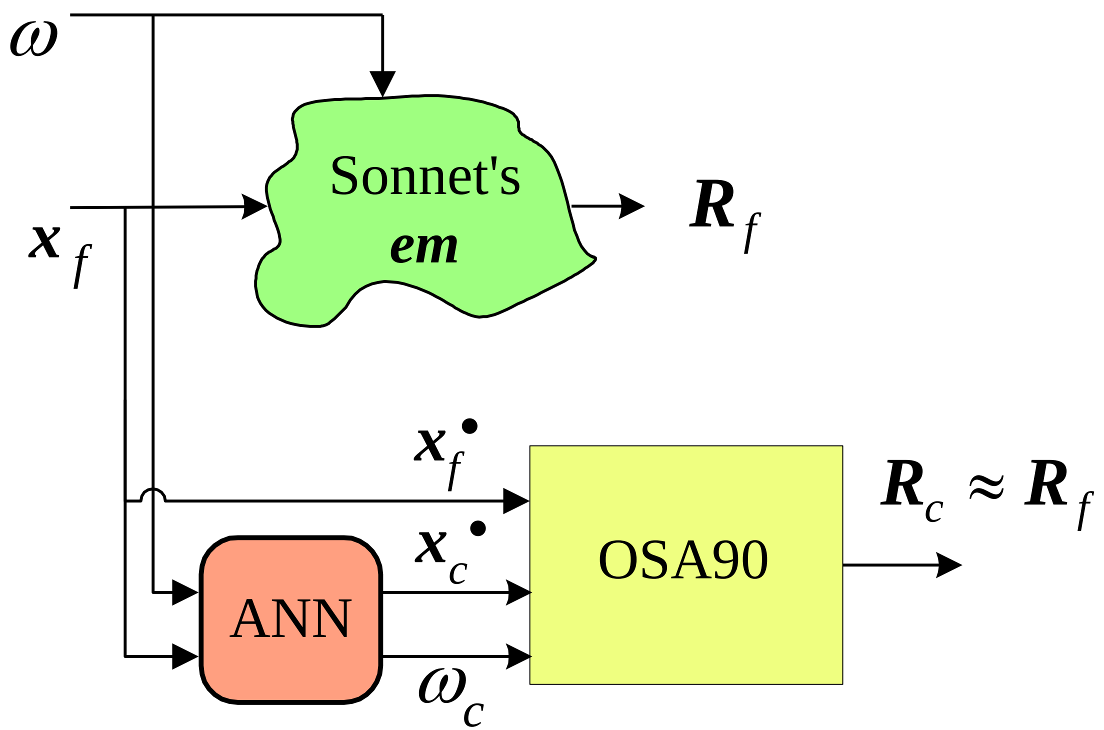


in the learning set



in the testing set

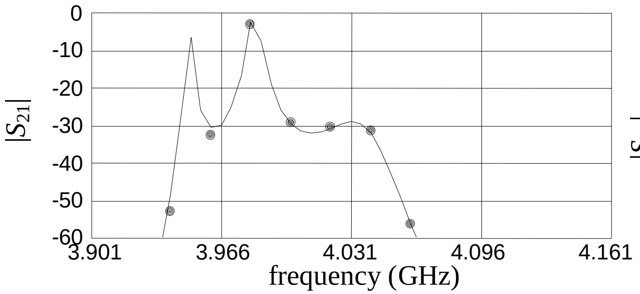
FPSM Neuromodel for the HTS Filter (3LP:7-7-3)

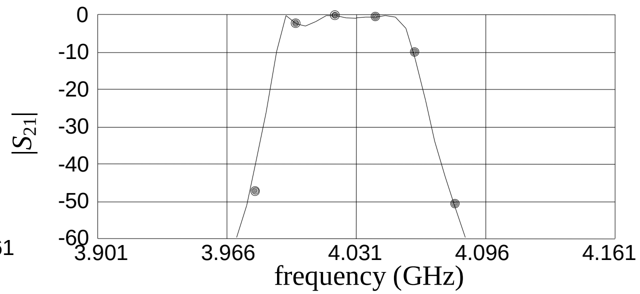


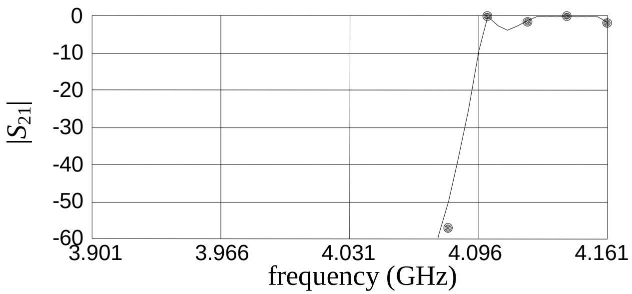
$\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$ $\boldsymbol{x}_f^{\bullet} = [L_2\ L_3\ S_2\ S_3]^T$ $\boldsymbol{x}_c^{\bullet} = [L_{1c}\ S_{1c}]^T$

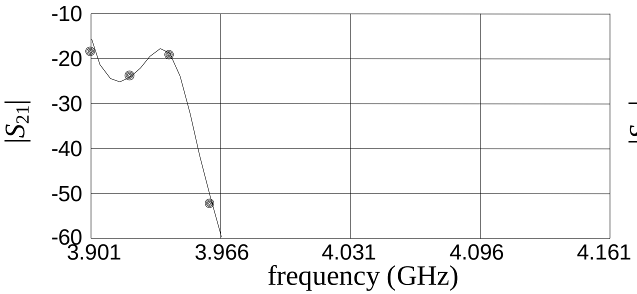
FPSM Neuromodel for the HTS Filter (3LP:7-7-3)

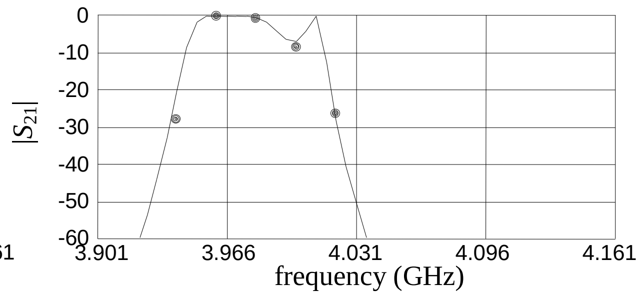
responses using ***em***™ (•) and FPSMN model (–) at the three learning and three testing points

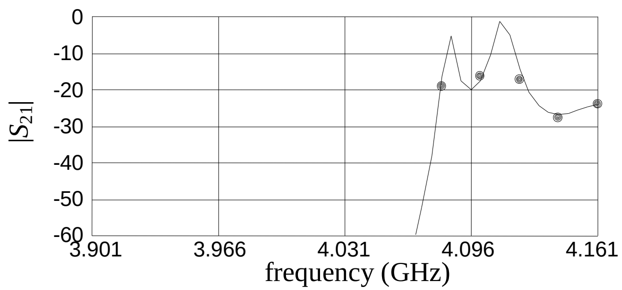




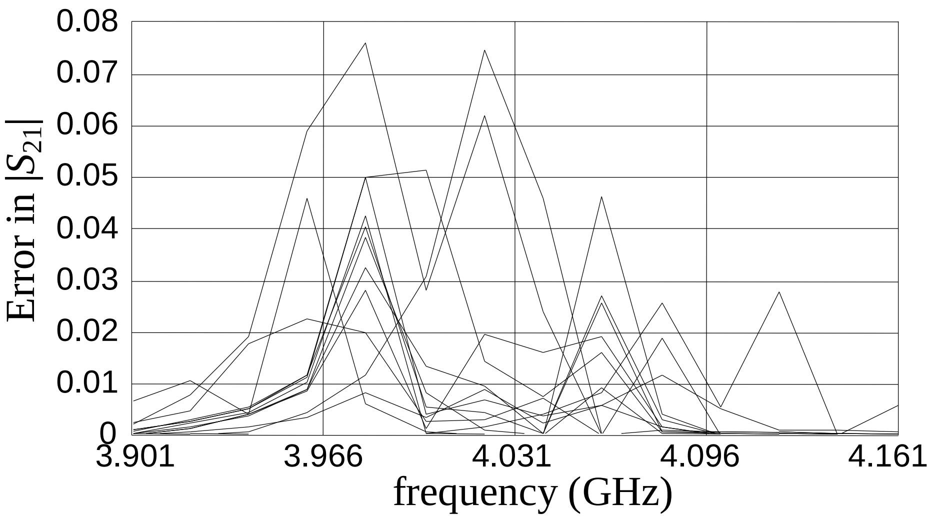




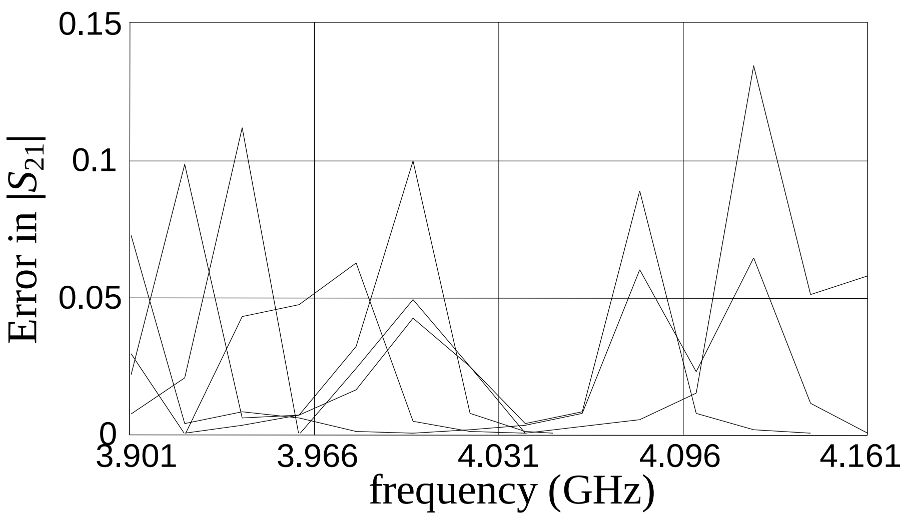




HTS FPSM Neuromodel Error w.r.t. *em*™



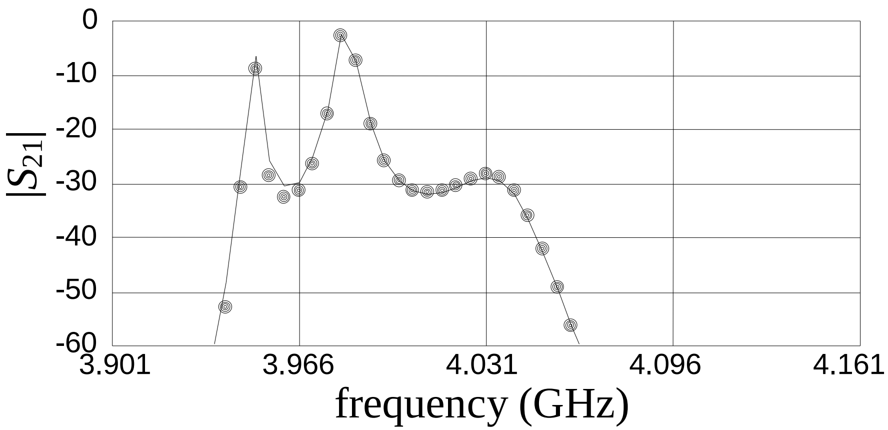
in the learning set

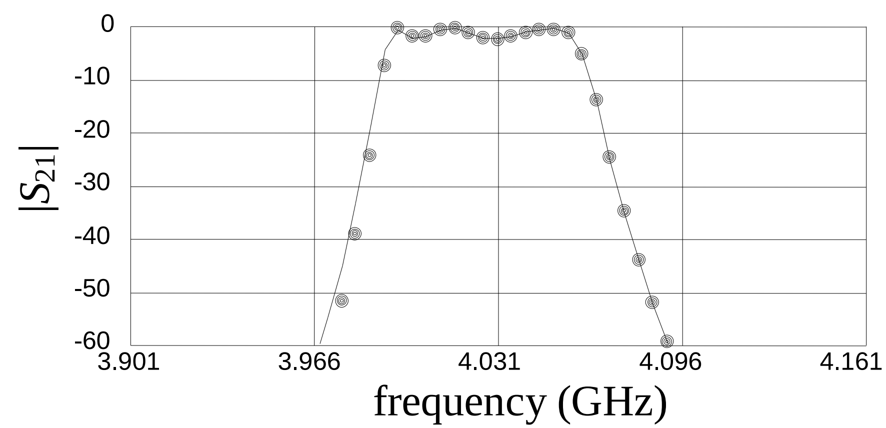


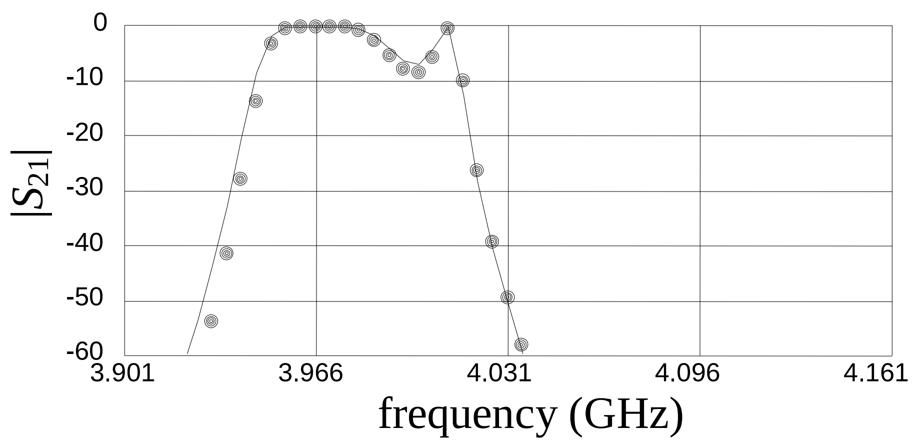
in the testing set

FPSM Neuromodel for the HTS Filter: Fine Frequency Sweep Results

comparison between ***em***™ (●) and FPSMN model (–) at two learning and one testing points







Other Applications of SM based Neuromodels
(Bandler et al., 2000, 2001)

Neural Space Mapping (NSM) Optimization

EM-based Statistical Analysis

EM-based Yield Optimization

Neural Inverse Space Mapping (NISM) Optimization

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five powerful SM based neuromodeling techniques are described

these techniques
- exploit the vast set of available empirical models
- decrease the fine model evaluations needed for training
- improve generalization ability
- reduce complexity of the ANN topology

w.r.t. classical neuromodeling

frequency-sensitive neuromappings expand the usefulness of empirical quasi-static models

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