NEUROMODELING OF MICROWAVE CIRCUITS EXPLOITING SPACE MAPPING TECHNOLOGY

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Artificial Neural Network (ANN) Modeling

Artificial Neural Networks are suitable in modeling high-dimensional and highly nonlinear problems

ANN models are computationally efficient and can be more accurate than empirical models

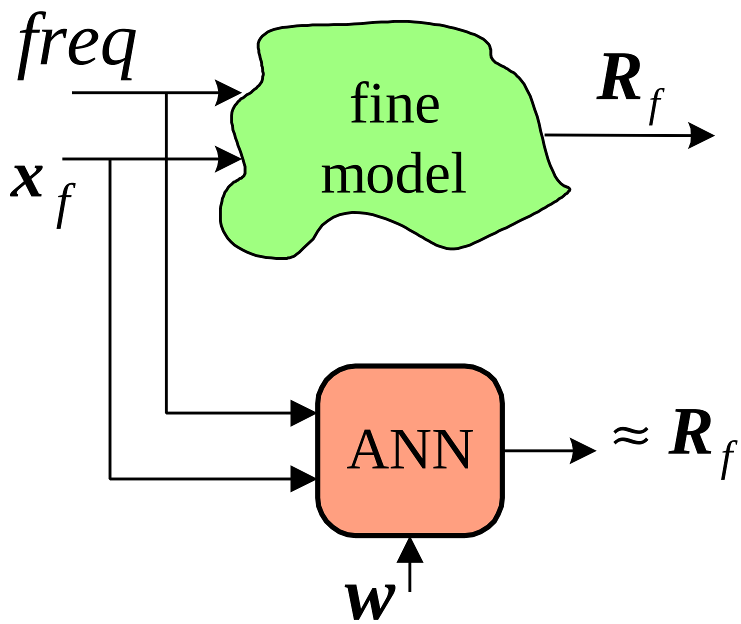
multilayer feedforward networks can approximate any measurable function to any desired level of accuracy, provided a deterministic relationship between input and target exists *(White et al., 1992)*

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)*

Classical Neuromodeling of Microwave Components



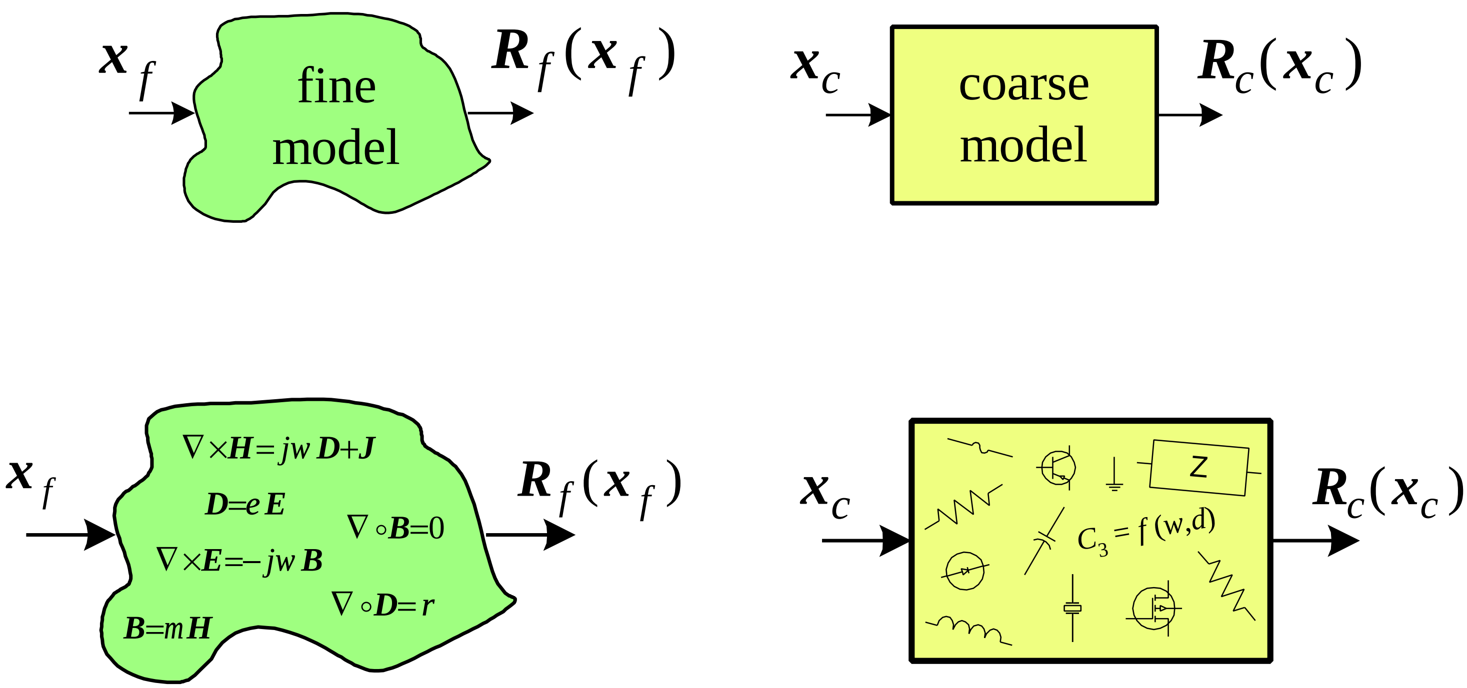
many learning samples are usually needed to ensure model accuracy

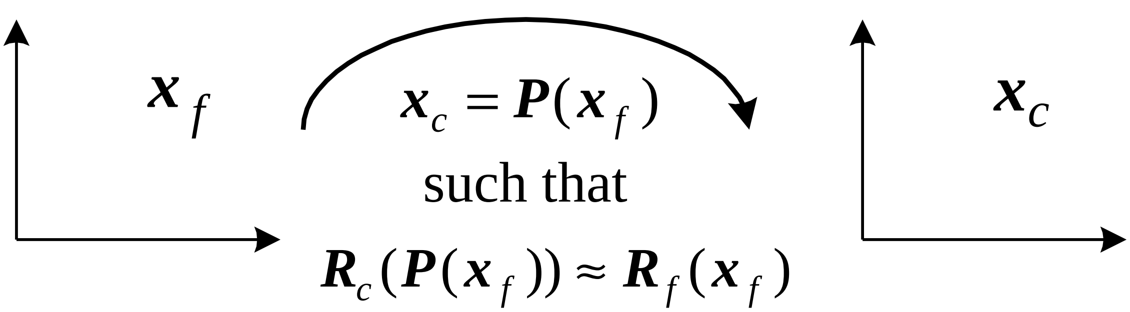
the number of learning samples needed to approximate a function grows exponentially with the ratio of the dimensionality to the function's degree of smoothness (*Stone, 1982*)

even with sufficient training data, the reliability of MLPs for extrapolation may be very poor

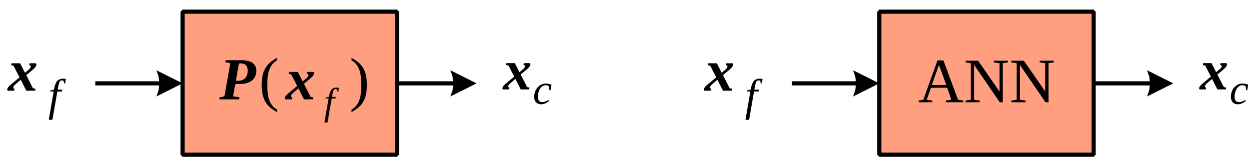
The Aim of Space Mapping

(Bandler et al., 1994-)

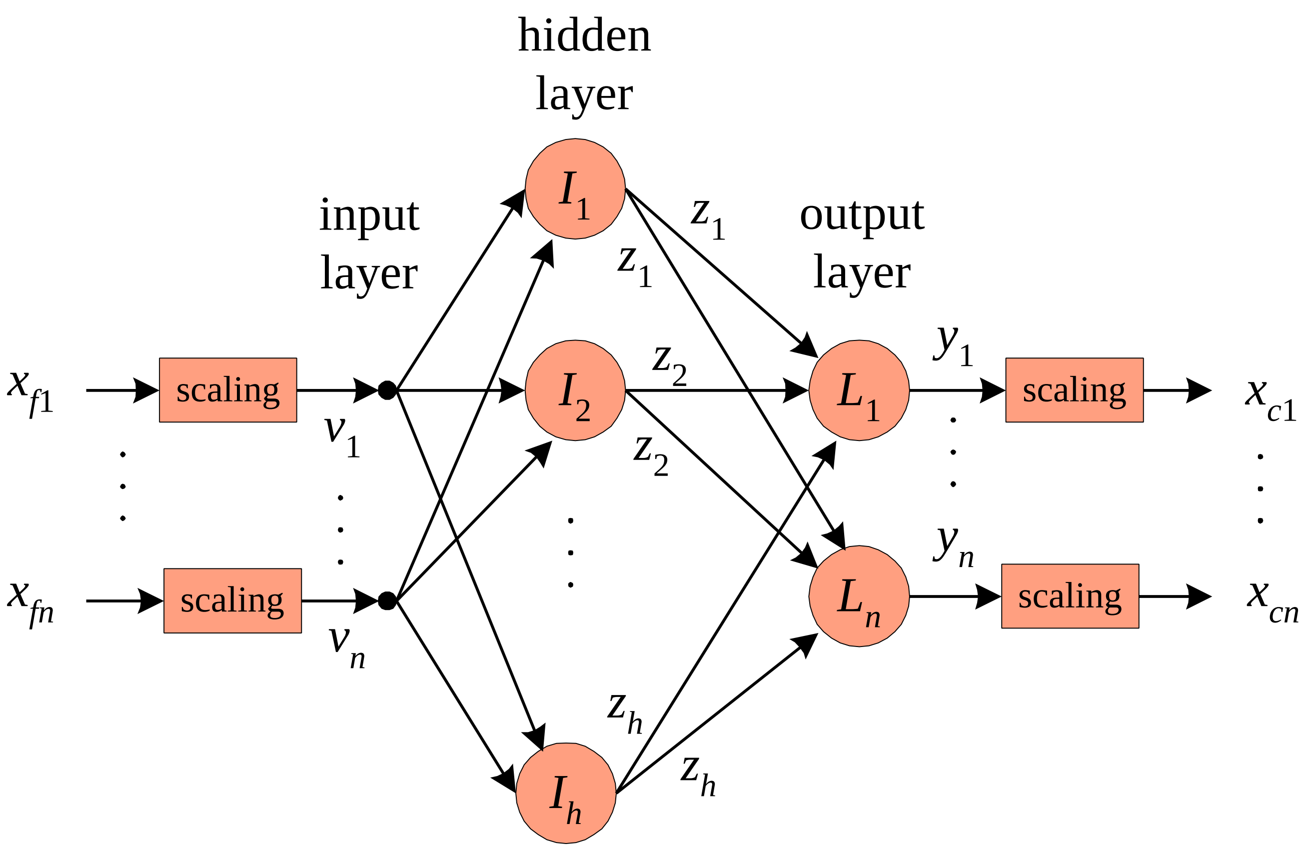




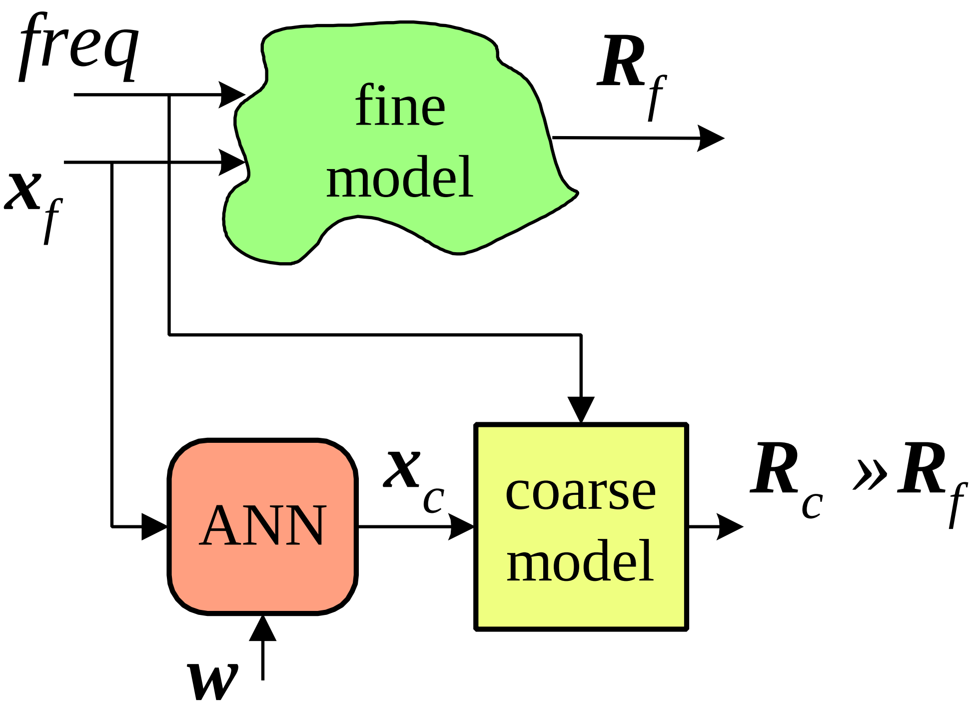
Neural Space Mapping



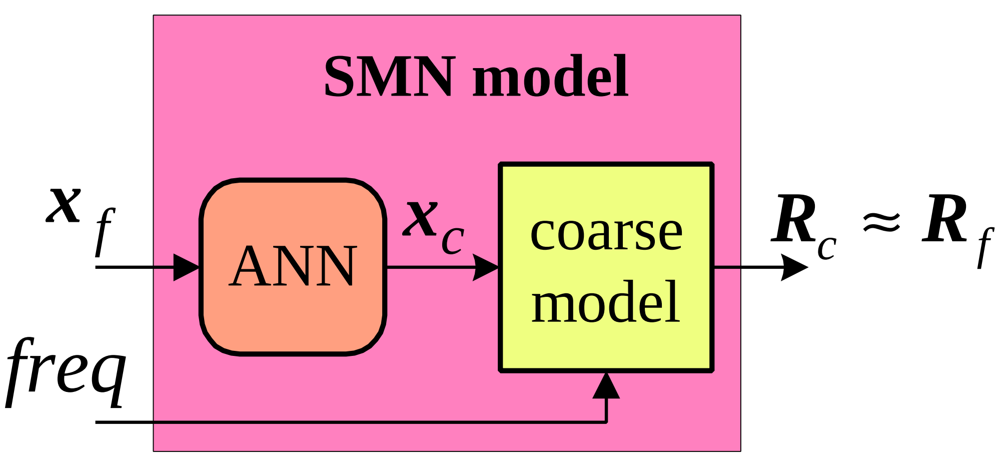
using a three layer perceptron (3LP)



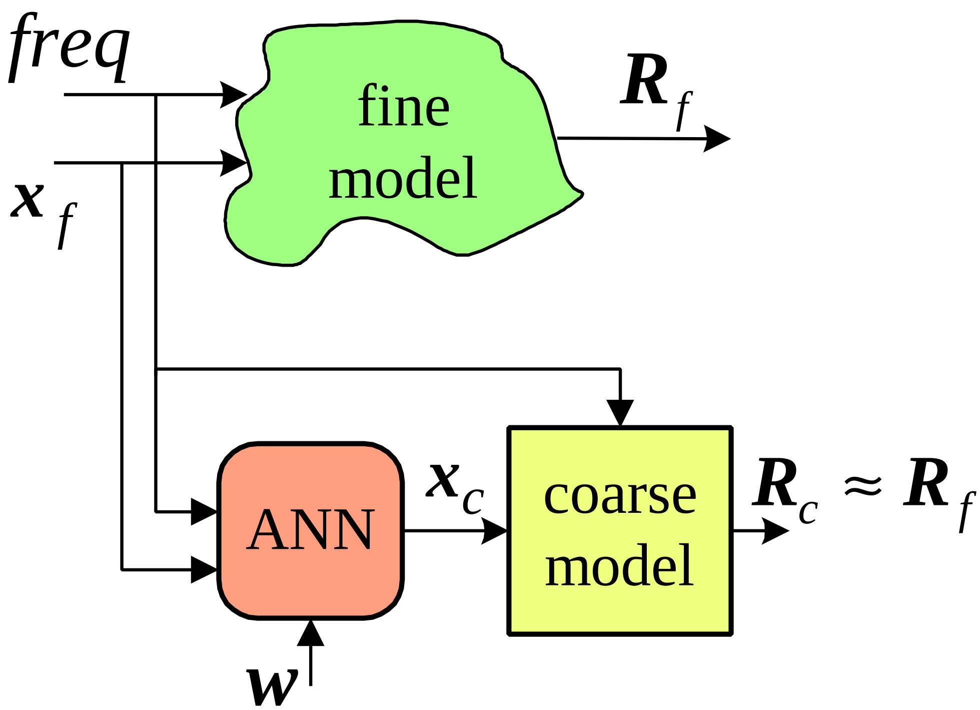
Space Mapped Neuromodeling (SMN) Concept



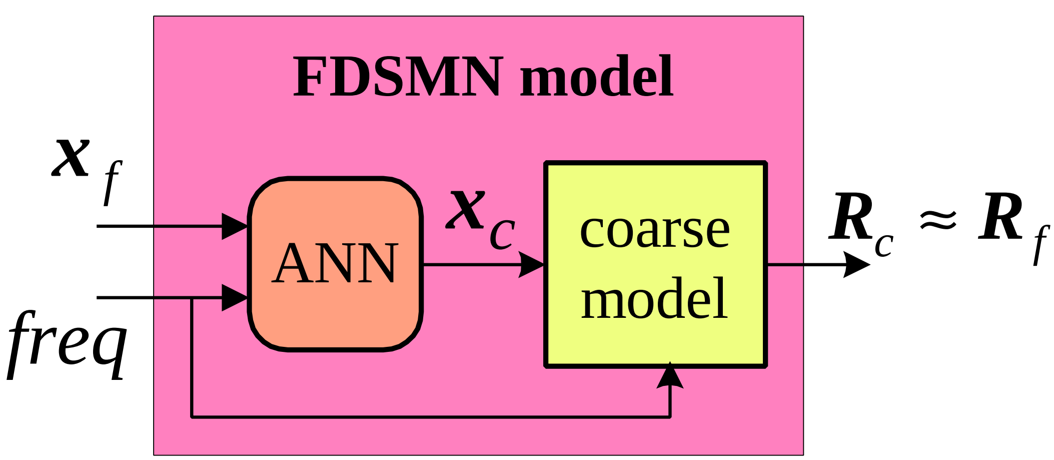
once the ANN is trained



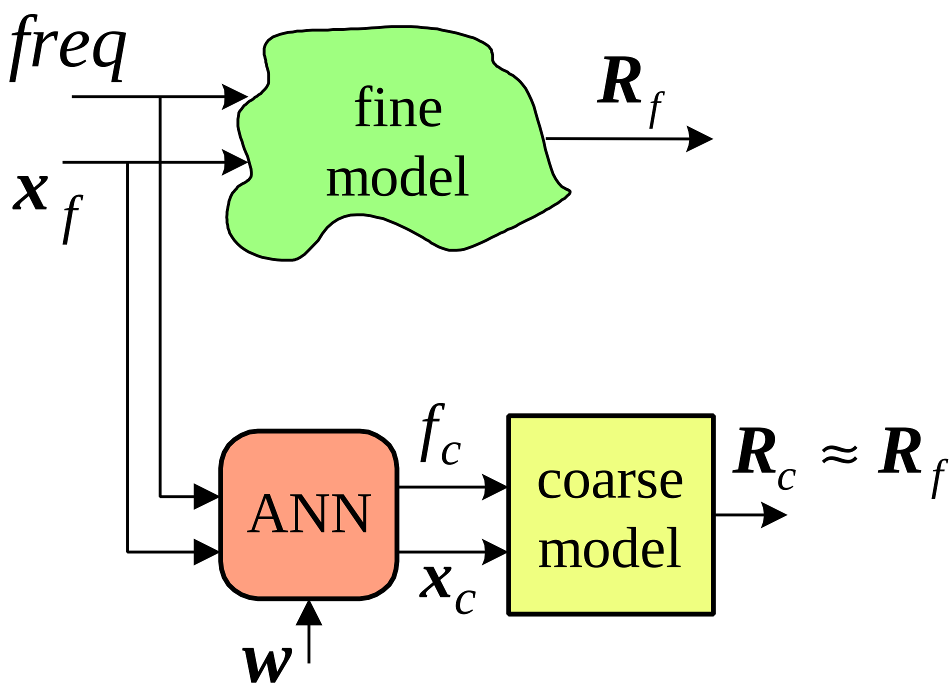
Frequency-Dependent Space Mapped Neuromodeling (FDSMN) Concept



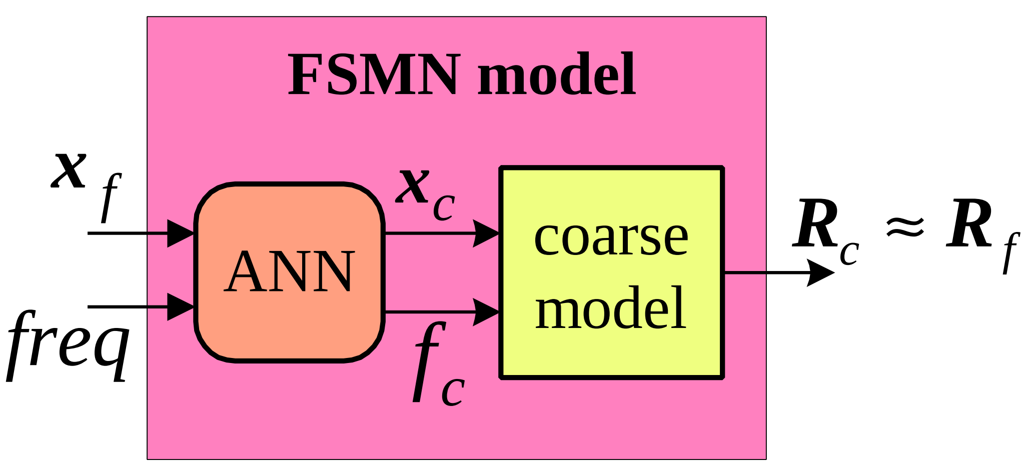
once the ANN is trained



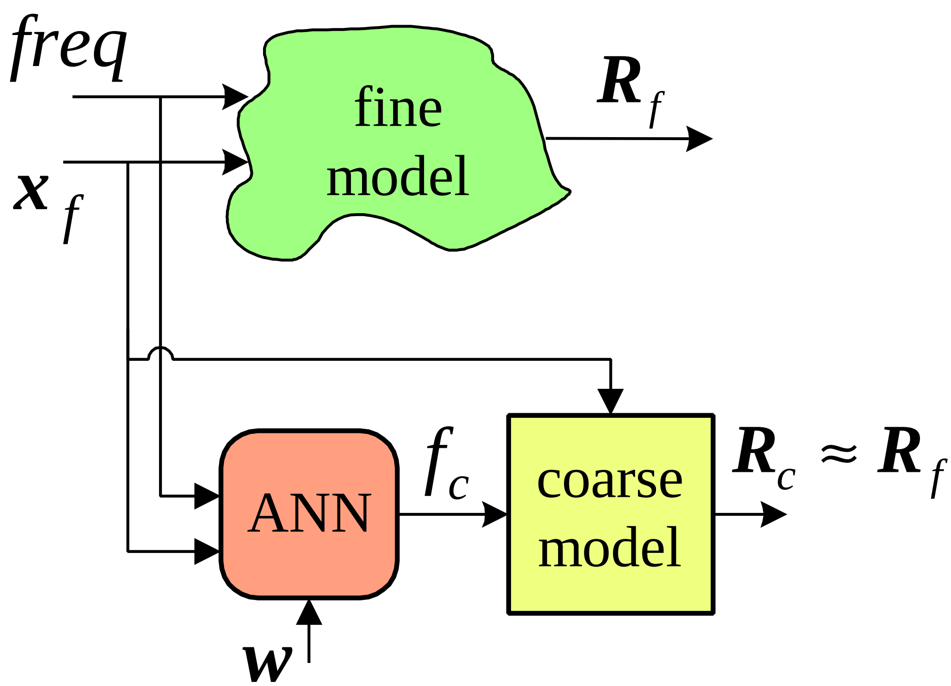
Frequency Space Mapped Neuromodeling (FSMN) Concept



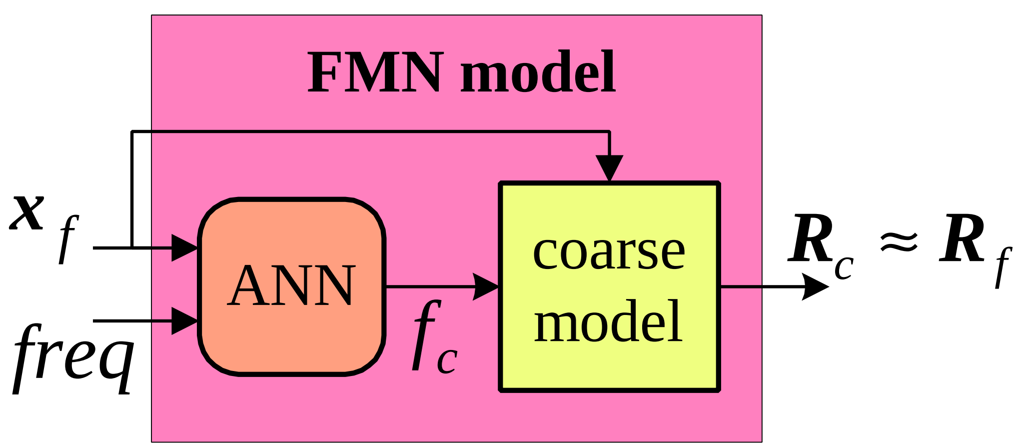
once the ANN is trained



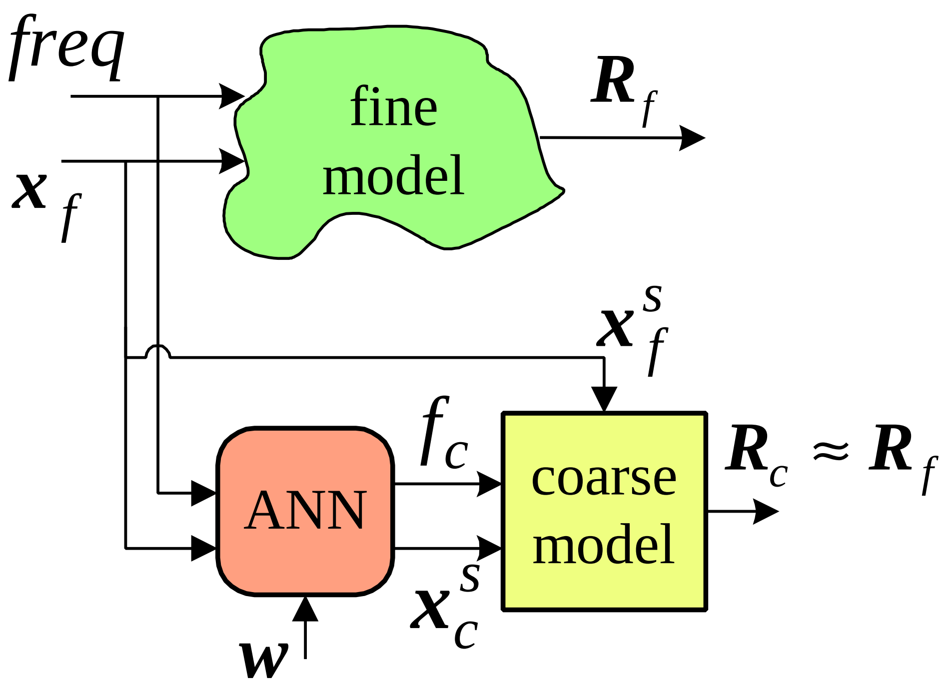
Frequency Mapped Neuromodeling (FMN) Concept



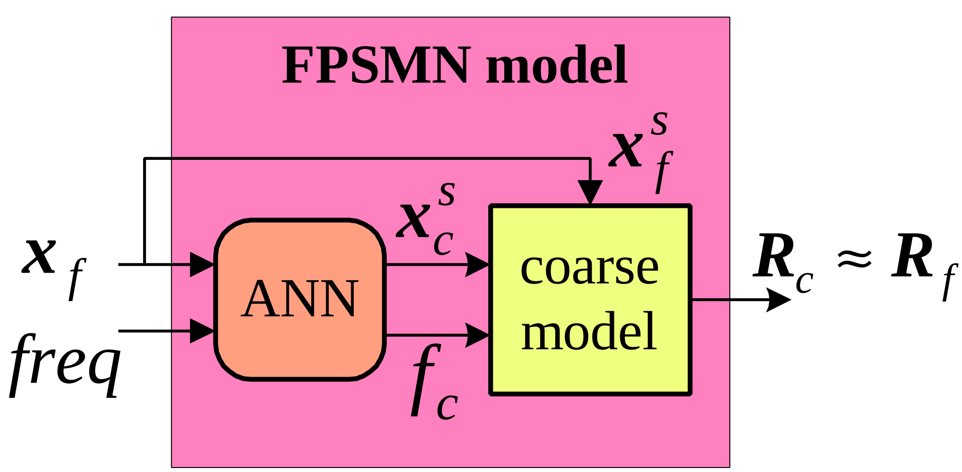
once the ANN is trained



Frequency Partial-Space Mapped Neuromodeling (FPSMN) Concept



once the ANN is trained



Training the ANN

the neuromapping can be found by solving the optimization problem

$$\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^{\,T} \quad \boldsymbol{e}_2^{\,T} \quad \cdots \quad \boldsymbol{e}_l^{\,T}]^T \right\|$$

$\boldsymbol{w}$ contains the internal parameters of the ANN (weights, bias, etc.) selected as optimization variables

l is the total number of learning samples

$\boldsymbol{e}_k$ is the error vector given by

for SMN

$$\boldsymbol{e}_k = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \, freq_j) - \boldsymbol{R}_c(\boldsymbol{x}_c, \, freq_j)$$

$$\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_{f_i})$$

for FDSMN

$$\boldsymbol{e}_k = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \, freq_j) - \boldsymbol{R}_c(\boldsymbol{x}_c, \, freq_j)$$

$$\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_{f_i}, \, freq_j)$$

for FSMN

$$\boldsymbol{e}_k = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \, freq_j) - \boldsymbol{R}_c(\boldsymbol{x}_c, \, f_c)$$

Training the ANN (continued)

$$\begin{bmatrix} \boldsymbol{x}_c \\ f_c \end{bmatrix} = \boldsymbol{P}\,(\boldsymbol{x}_{f\,i},\ freq_{\,j})$$

for FMN

$$\boldsymbol{e}_k = \boldsymbol{R}_f(\boldsymbol{x}_{f\,i},\ freq_{\,j}) - \boldsymbol{R}_c(\boldsymbol{x}_{f\,i},\ f_c)$$

$$f_c = P\,(\boldsymbol{x}_{f\,i},\ freq_{\,j})$$

for FPSMN

$$\boldsymbol{e}_k = \boldsymbol{R}_f(\boldsymbol{x}_{f\,i},\ freq_{\,j}) - \boldsymbol{R}_c(\boldsymbol{x}^{s}_{f\,i},\ \boldsymbol{x}^{s}_{c},\ f_c)$$

$$\begin{bmatrix} \boldsymbol{x}^{s}_c \\ f_c \end{bmatrix} = \boldsymbol{P}\,(\boldsymbol{x}_{f\,i},\ freq_{\,j})$$

with

$$i = 1, \ldots, B_p$$

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

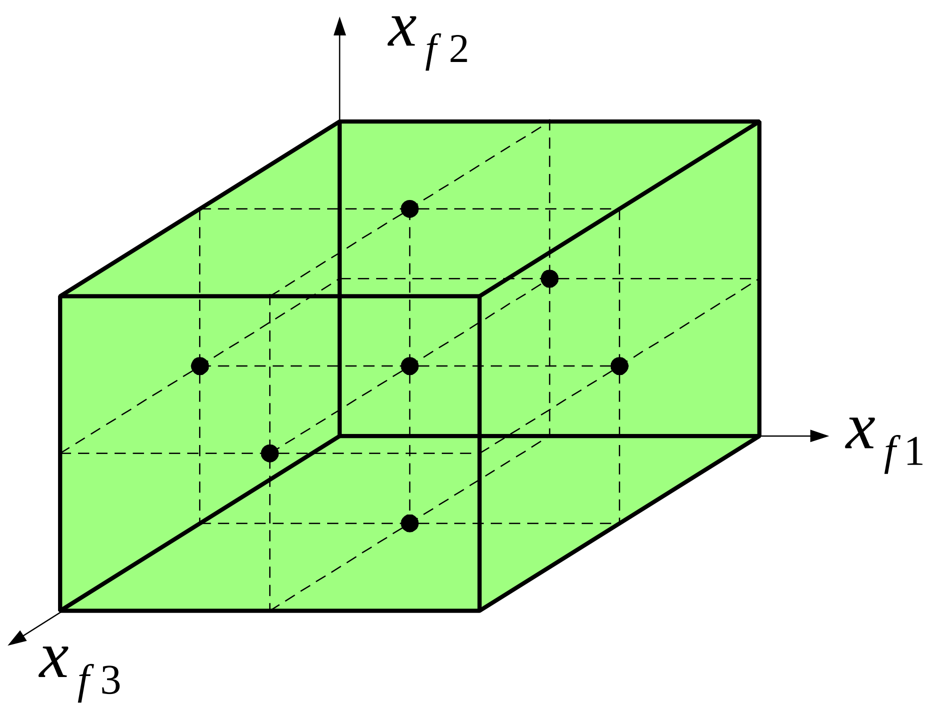
$$k = j + F_p(i-1)$$

Starting Point and Learning Samples

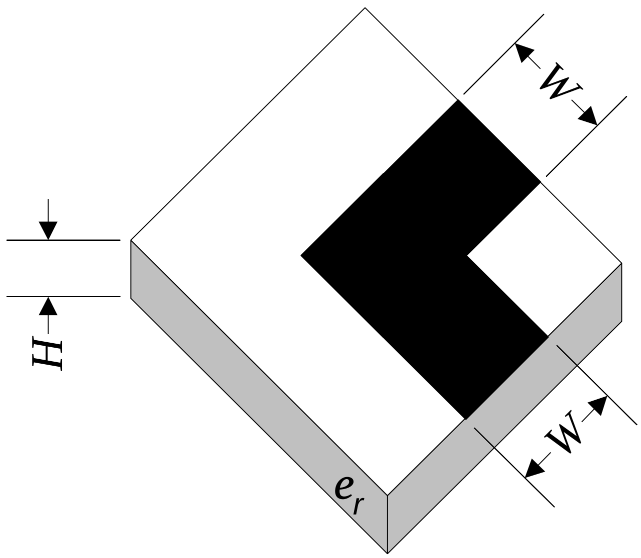
we chose a unit mapping ($\boldsymbol{x}_c \approx \boldsymbol{x}_f$ and $f_c \approx freq$) as the starting point for the optimization problem

to keep a reduced set of learning data samples, we consider an *n*-dimensional star distribution for the learning base points *(Bandler et al., 1989)*

the number of learning base points for a microwave circuit with n design parameters is $B_p = 2n + 1$



Microstrip Right Angle Bend



region of interest

$$20\text{mil} \leq W \leq 30\text{mil}$$
$$8\text{mil} \leq H \leq 16\text{mil}$$
$$8 \leq e_r \leq 10$$
$$1\text{GHz} \leq freq \leq 41\text{GHz}$$

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

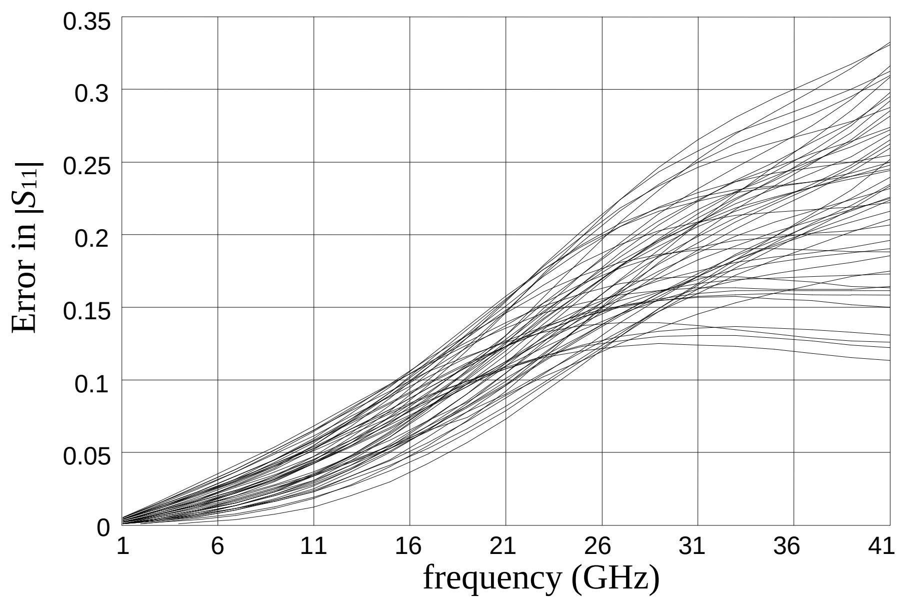
"fine" model: Sonnet's ***em***™

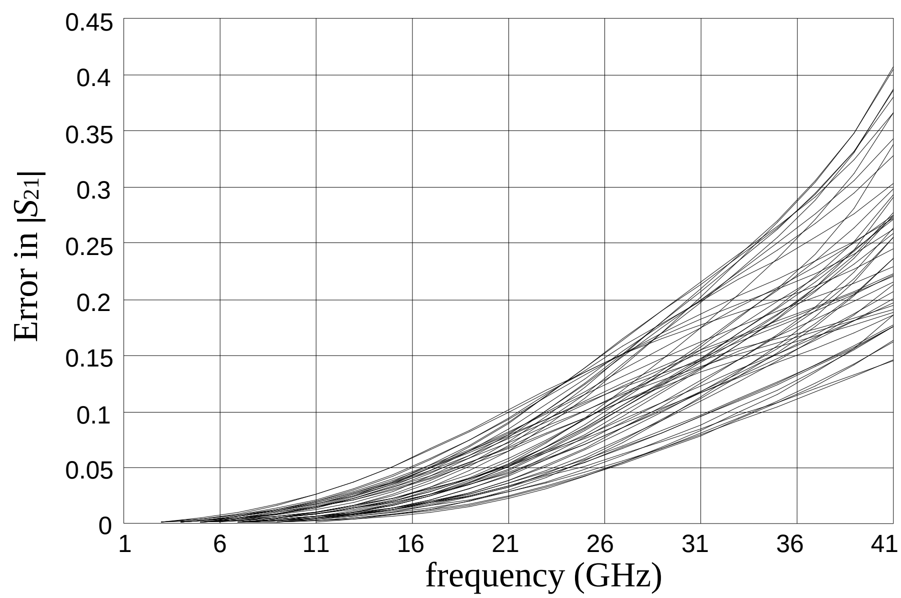
learning set: 7 base points with "star" distribution

testing set: 50 random base points in the region of interest

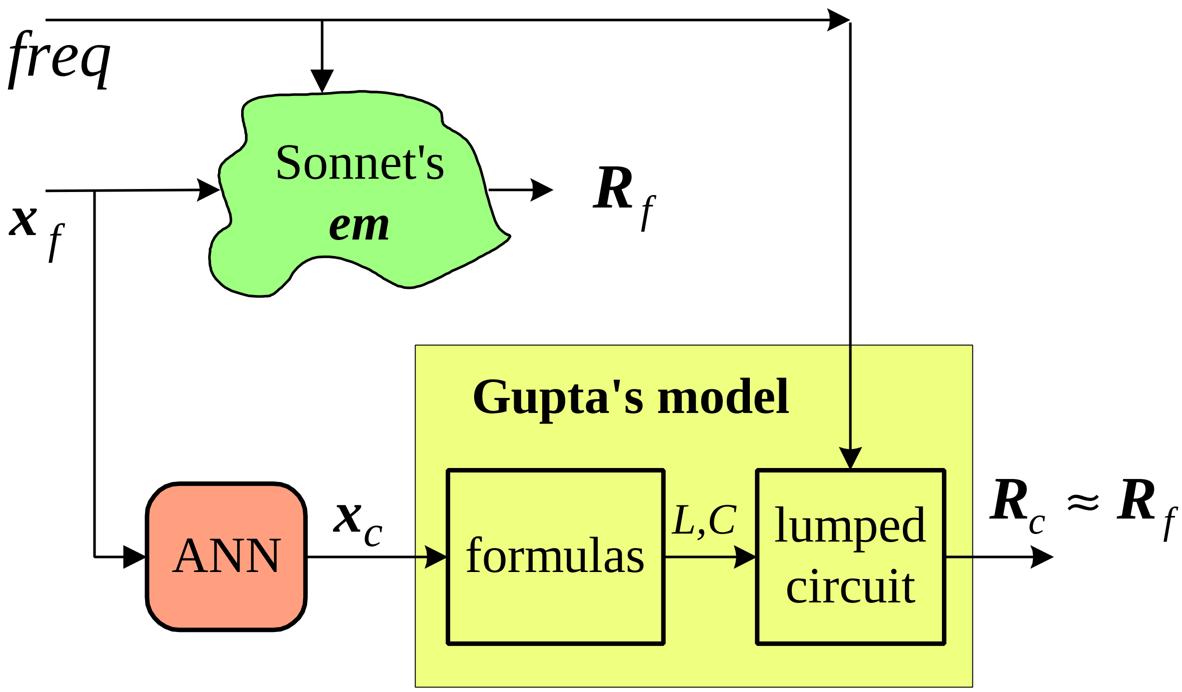
Microstrip Right Angle Bend Response Errors

comparison before neuromodeling between ***em***™ and Gupta model at 50 random test points



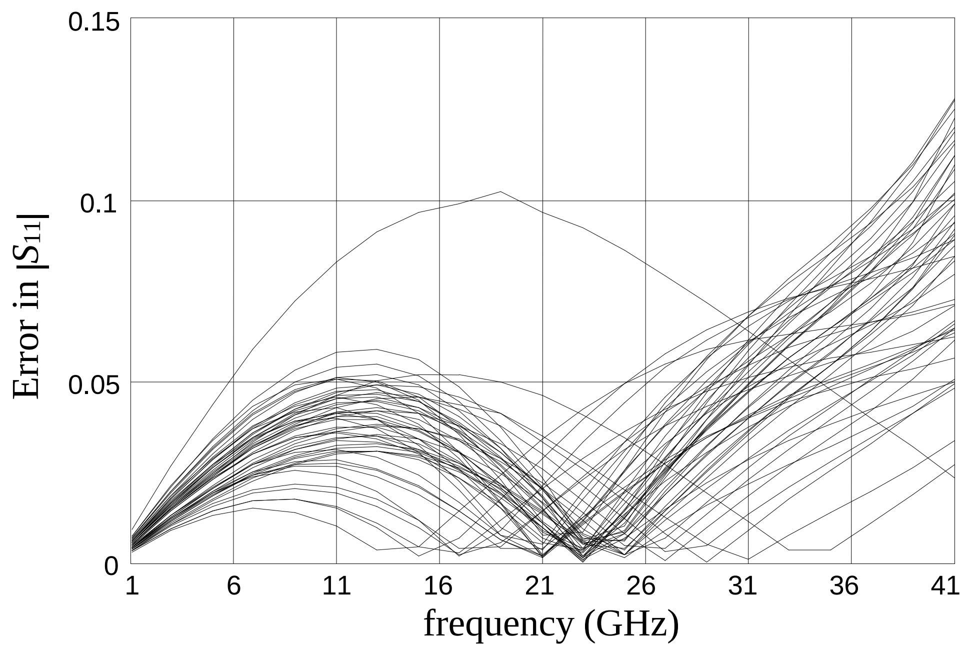


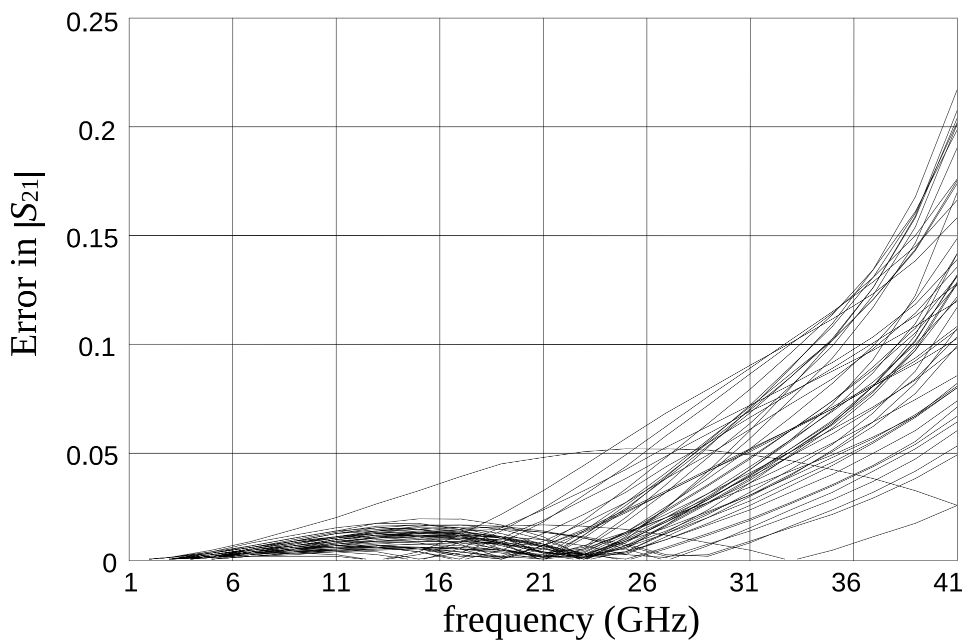
SMN Model for the Right Angle Bend (3LP:3-6-3)



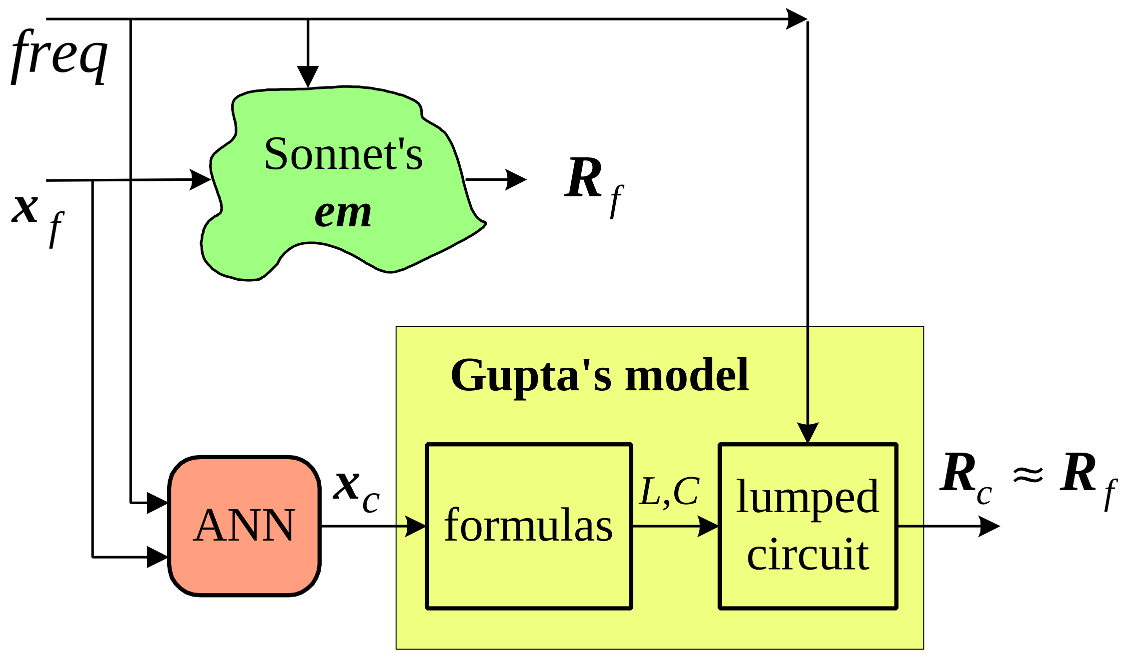
SMN Model Results for the Right Angle Bend

comparison between ***em***™ and the SMN model



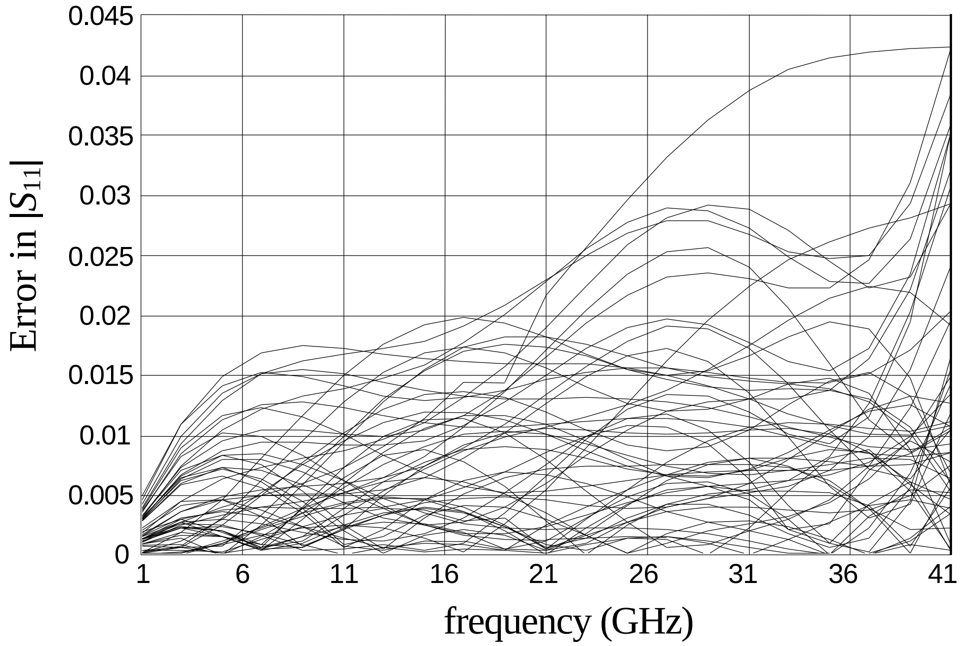


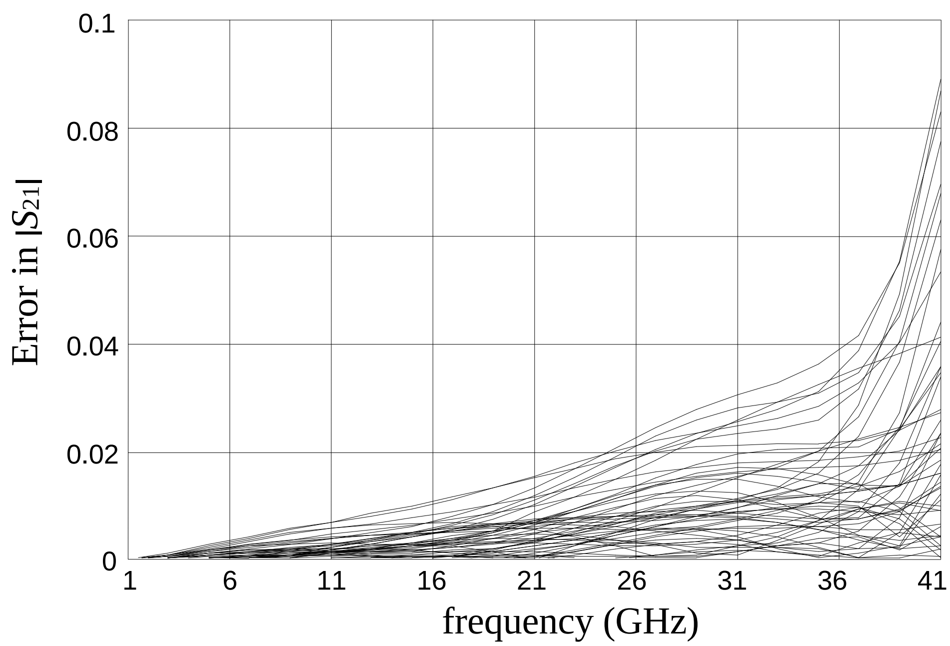
FDSMN Model for the Right Angle Bend (3LP:4-7-3)



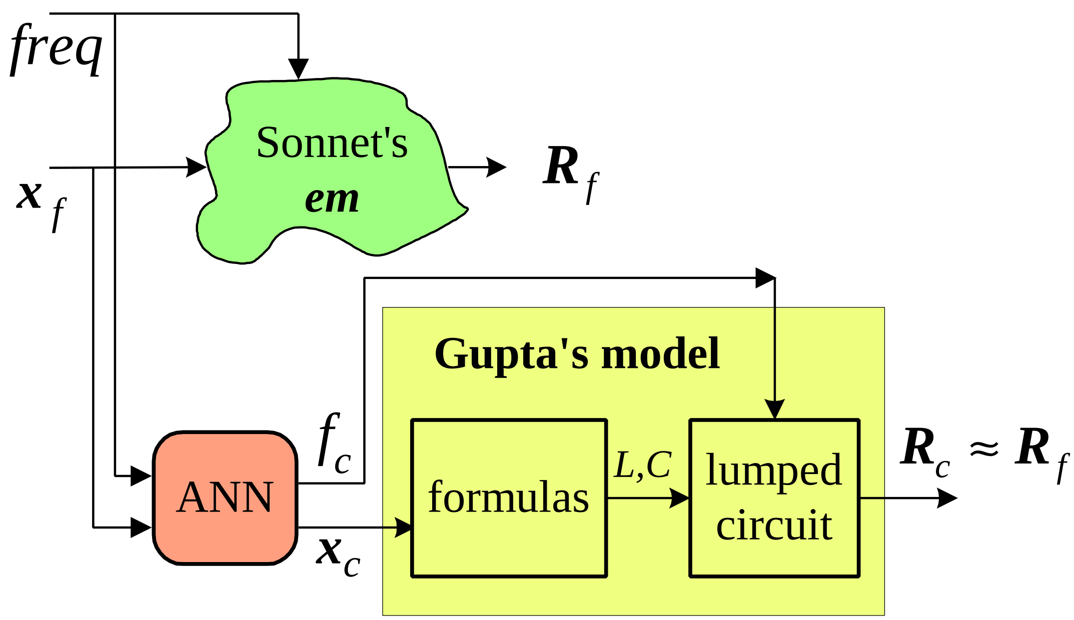
FDSMN Model Results for the Right Angle Bend

comparison between ***em***™ and the FDSMN model





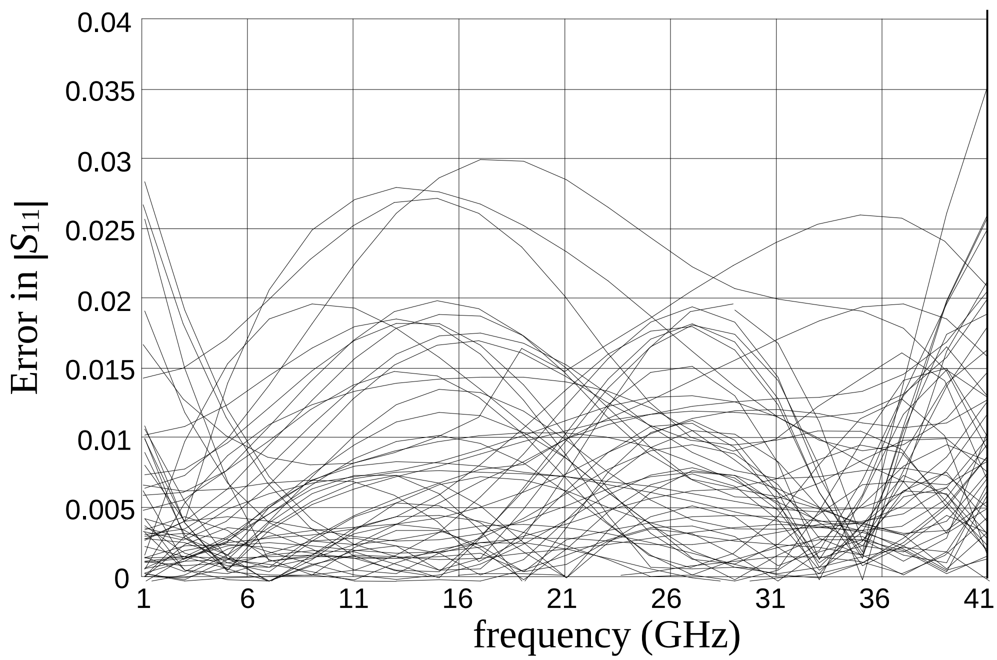
FSMN Model for the Right Angle Bend (3LP:4-8-4)

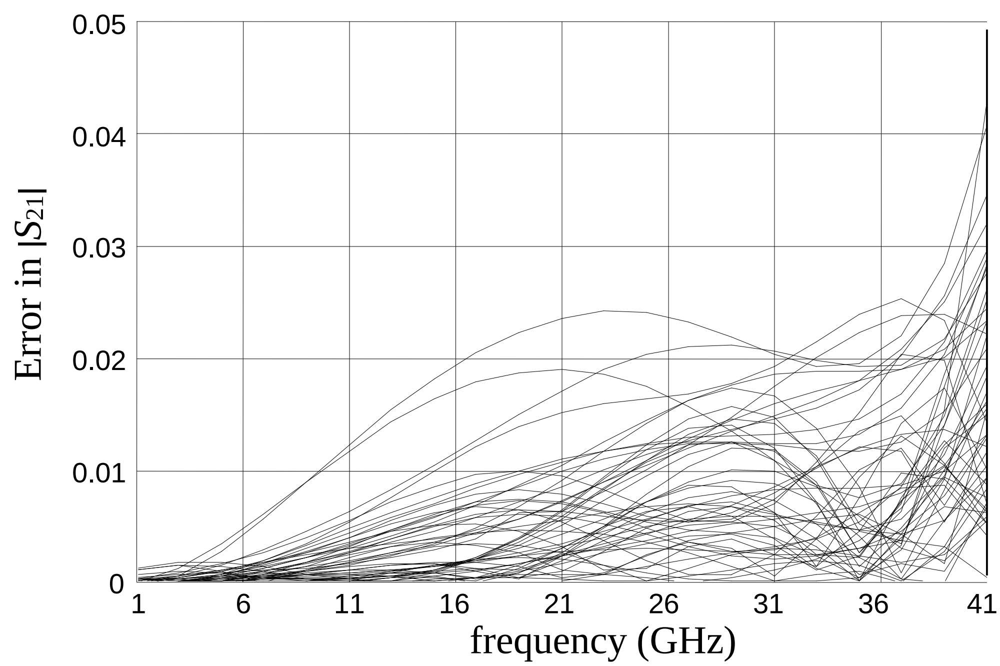


implementation: an OSA90/hope™ child program simulates the coarse model at a different frequency variable through Datapipe

FSMN Model Results for the Right Angle Bend

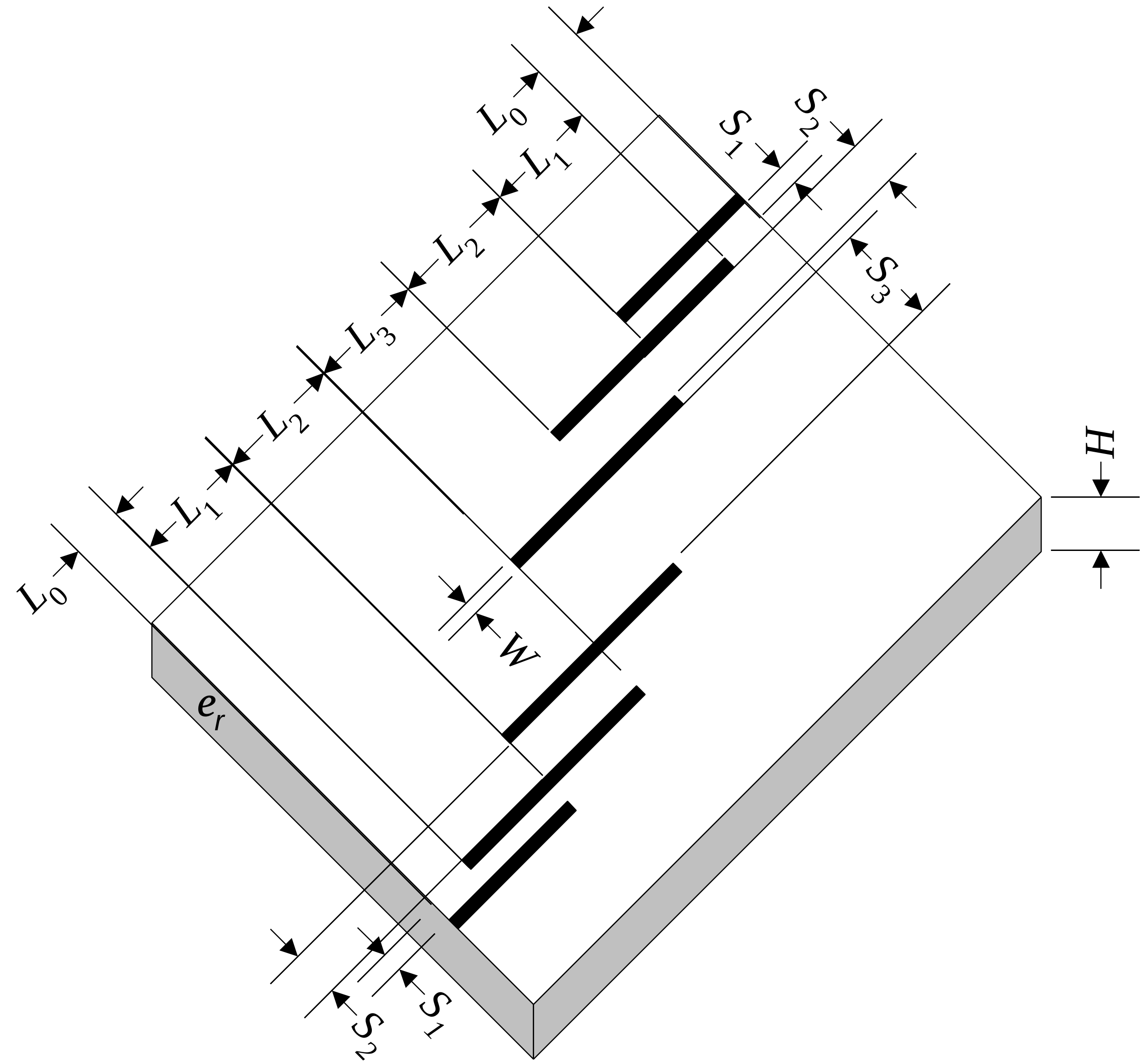
comparison between ***em***™ and the FSMN model





HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(Westinghouse, 1993)



SM Based Neuromodeling of the HTS Filter

region of interest

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

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

“coarse” model: OSA90/hope™ empirical models

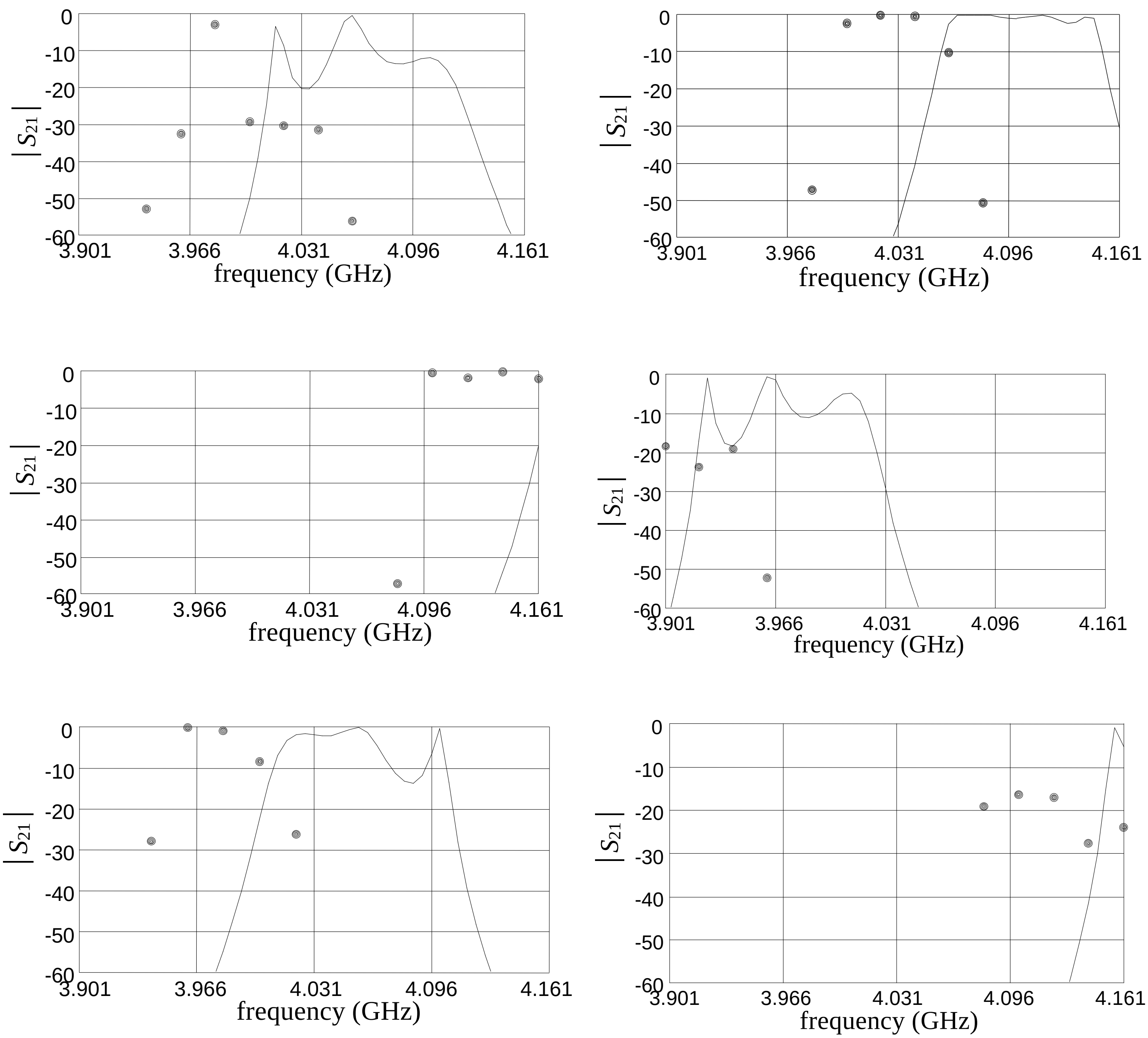
“fine” model: Sonnet’s ***em***™ with high resolution grid

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)

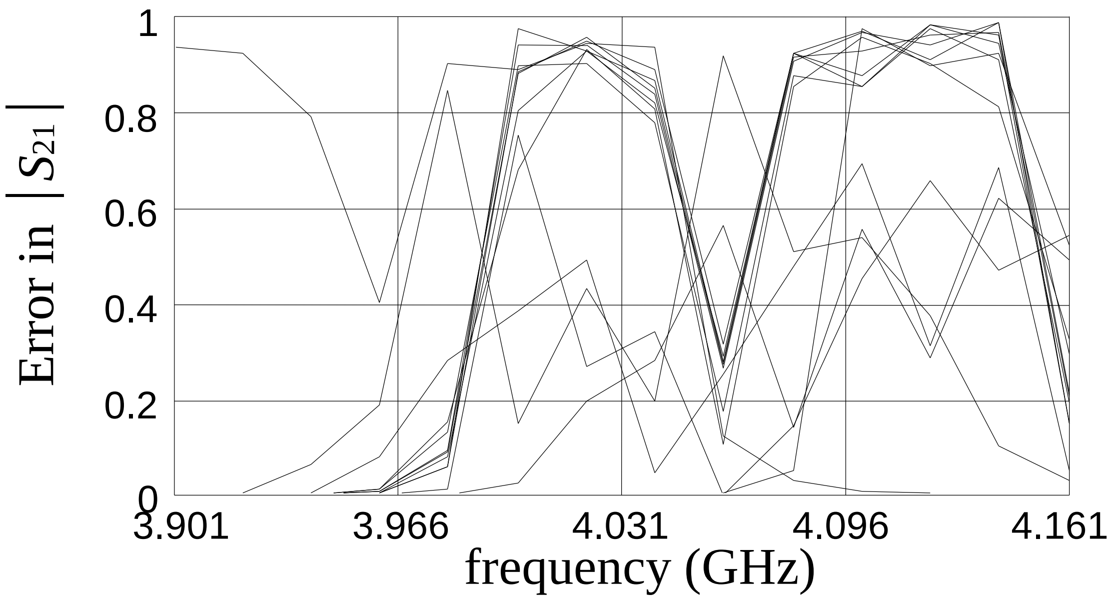
HTS Filter Responses Before Neuromodeling

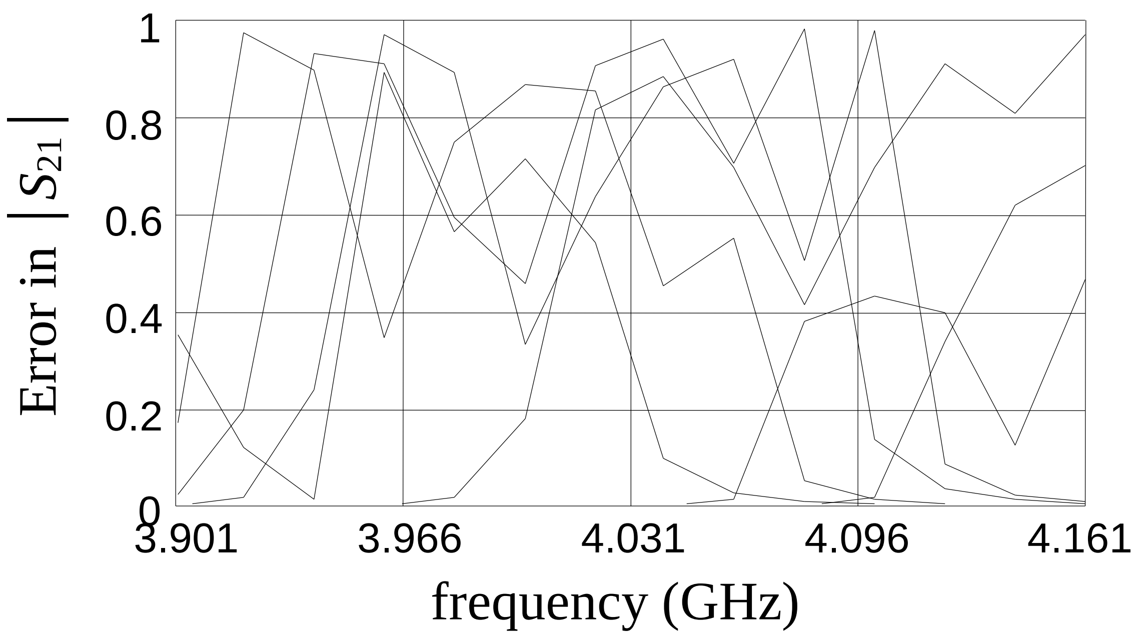
responses using ***em***™ (•) and OSA90/hope™ (–) at three learning and three test points



HTS Filter Response Errors Before Neuromodeling

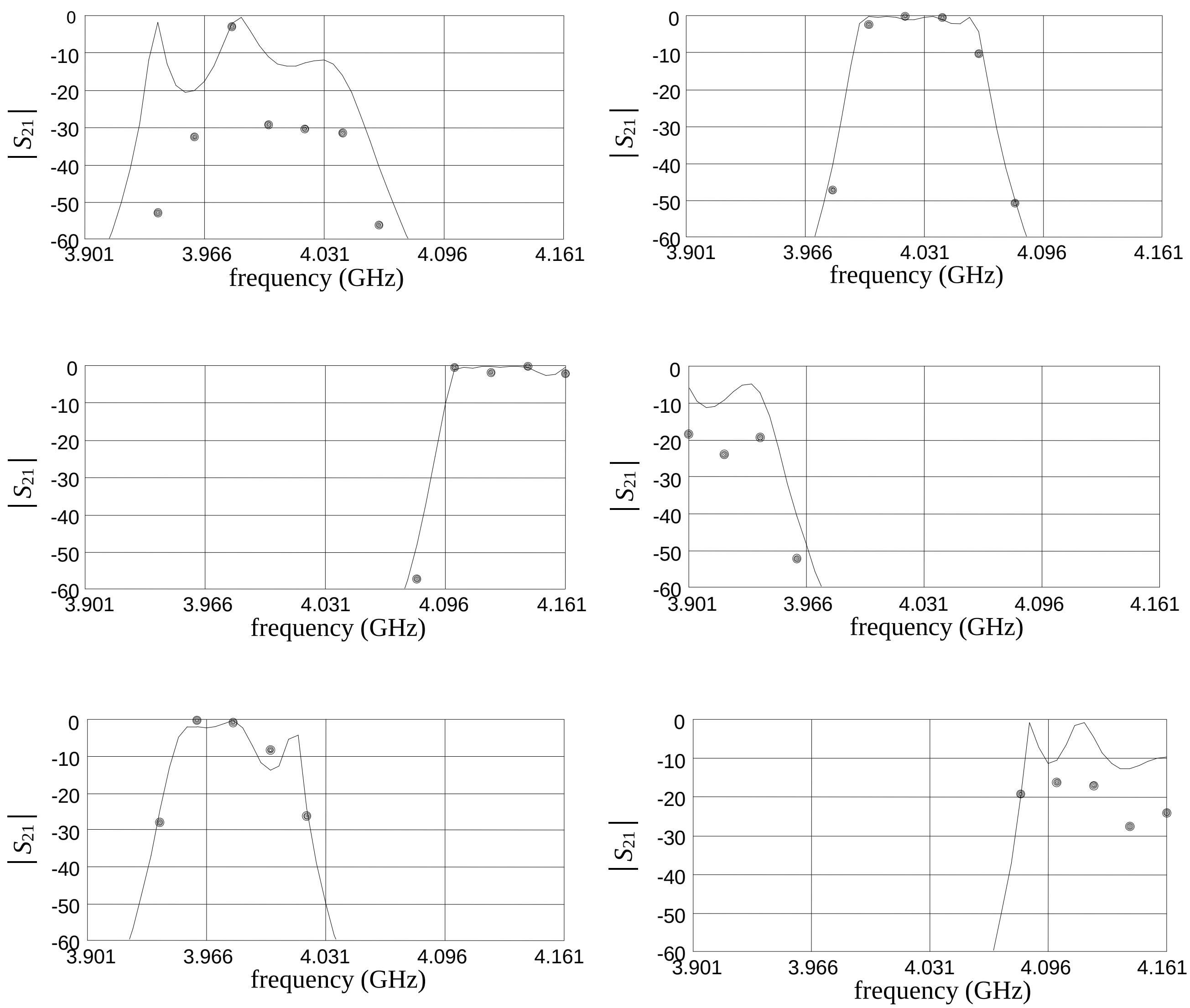
coarse model error w.r.t. ***em***™ at the learning and testing sets





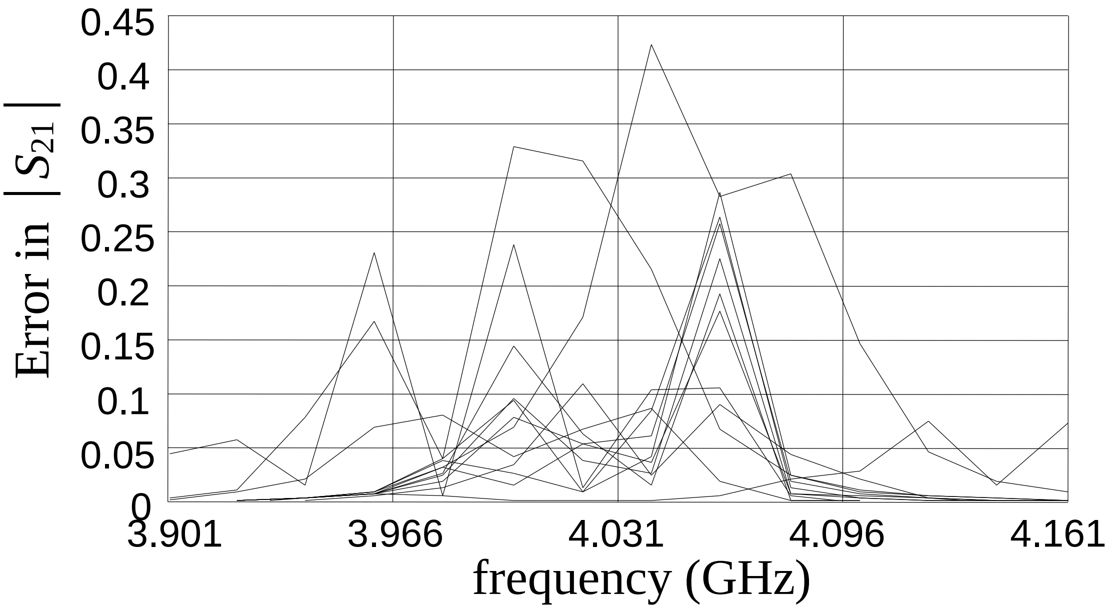
FMN Model for the HTS Filter (3LP:7-5-1)

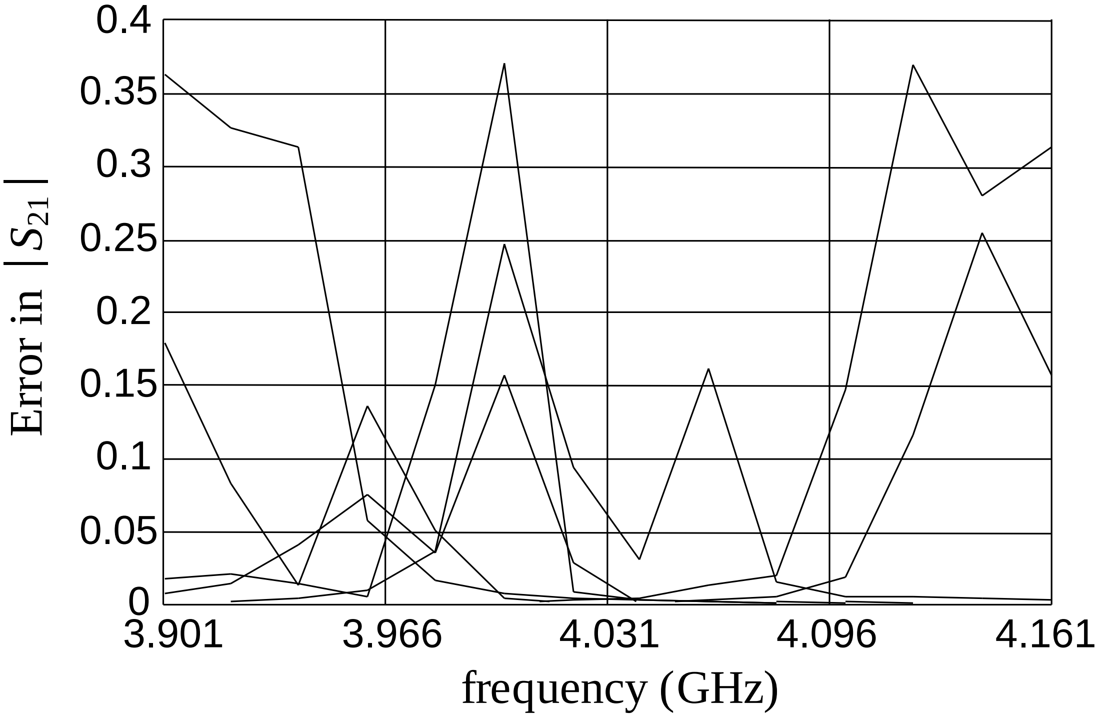
responses using ***em***™ (•) and FMN model (–) at the three learning and three testing points



FMN Model Response Errors for the HTS Filter

FMN model error w.r.t. ***em***™ at the learning and testing sets

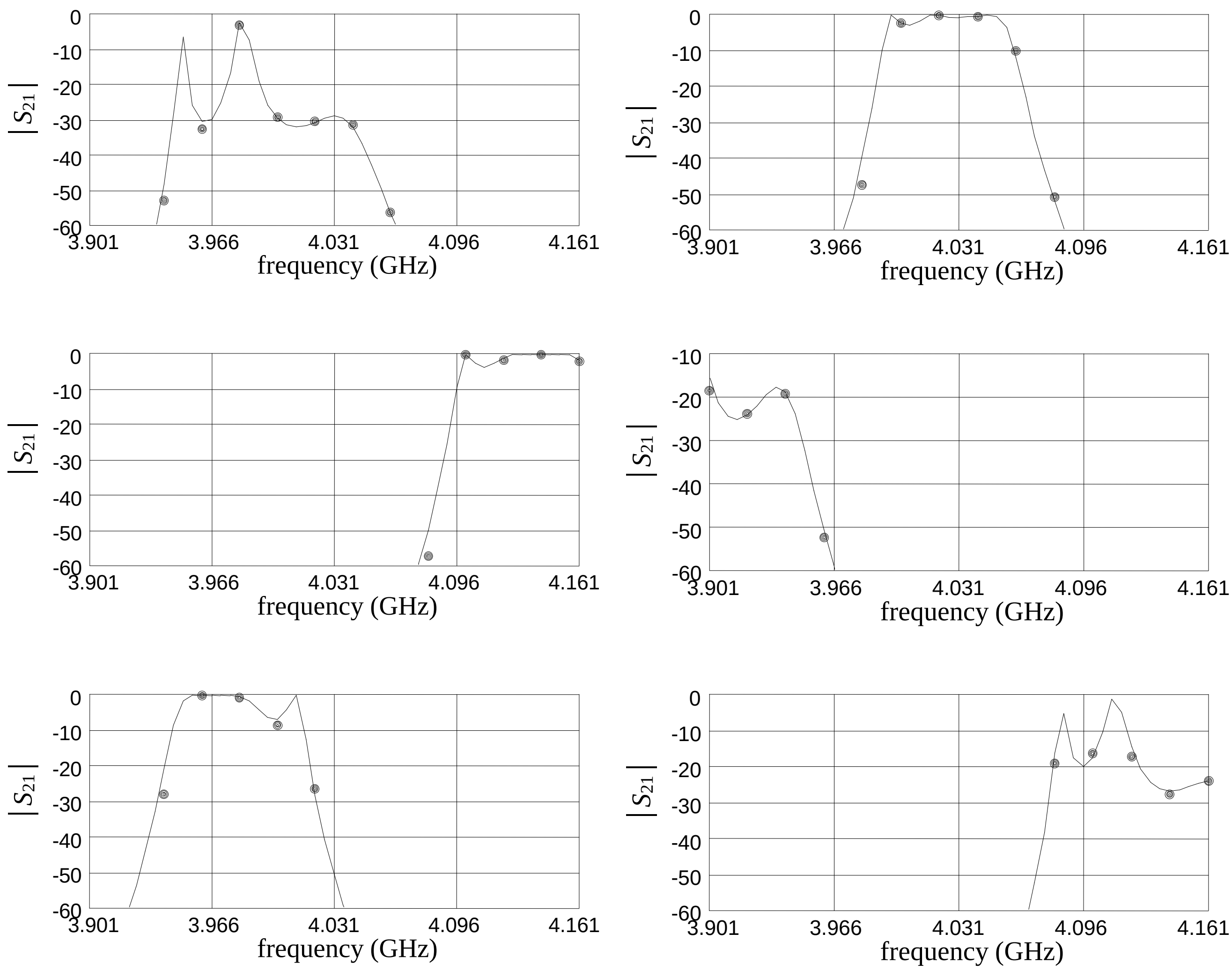




FPSMN Model Responses for the HTS Filter (3LP:7-7-3)

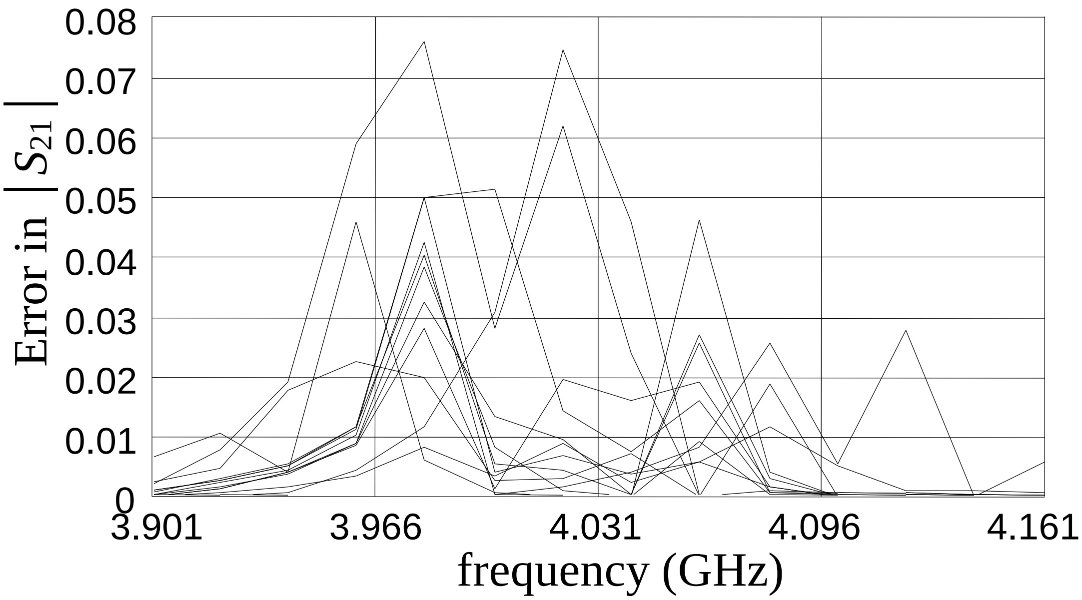
taking $x^s_c = [L_{1c}\ S_{1c}]^T$ and $x^s_f = [L_2\ L_3\ S_2\ S_3]^T$

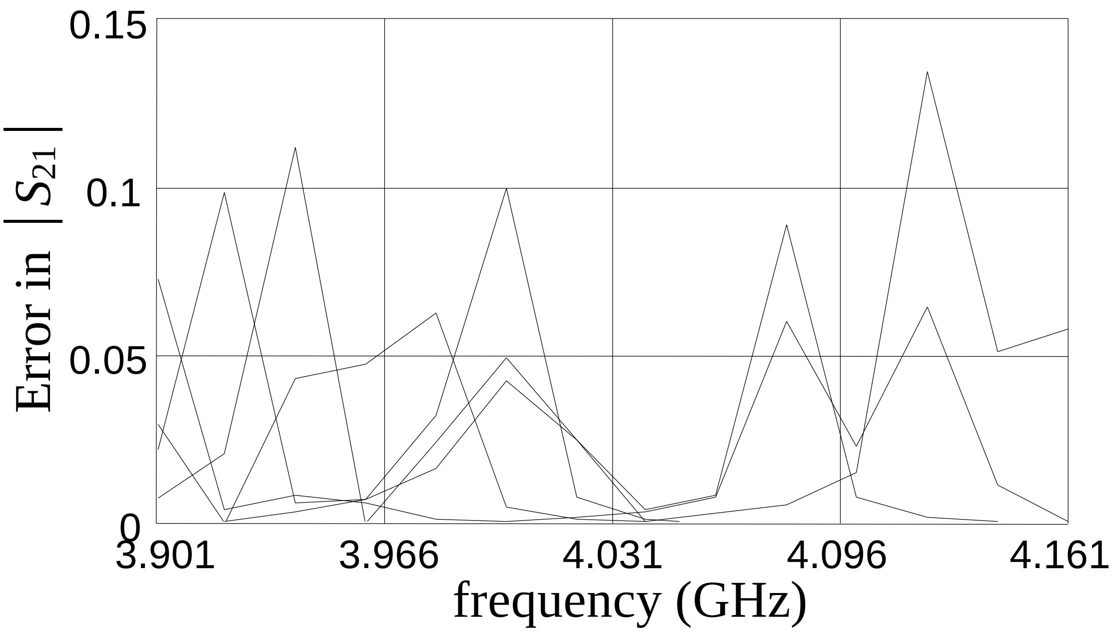
responses using *em*™ (•) and FPSMN model (–) at the three learning and three testing points



FPSMN Model Response Errors for the HTS Filter

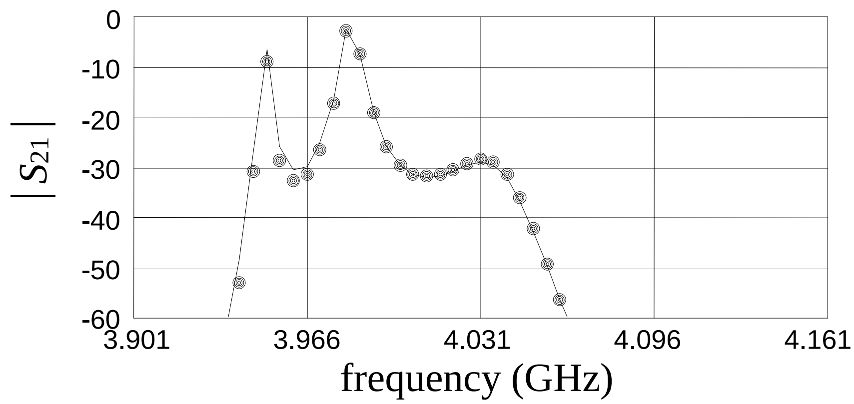
FPSMN model error w.r.t. ***em***™ at the learning and testing sets

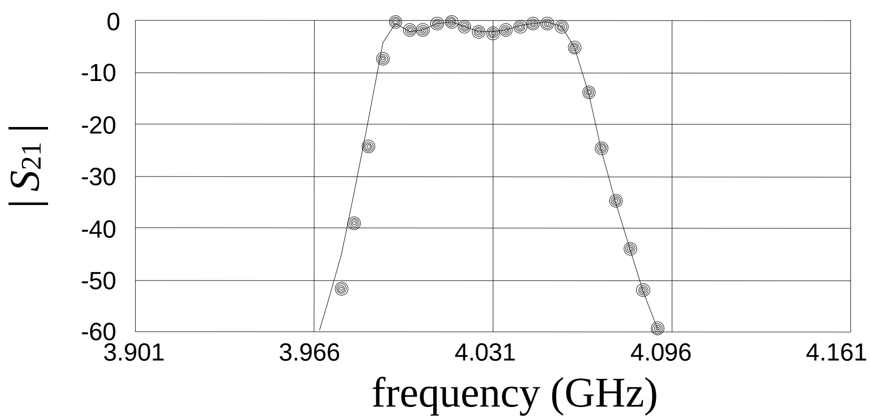


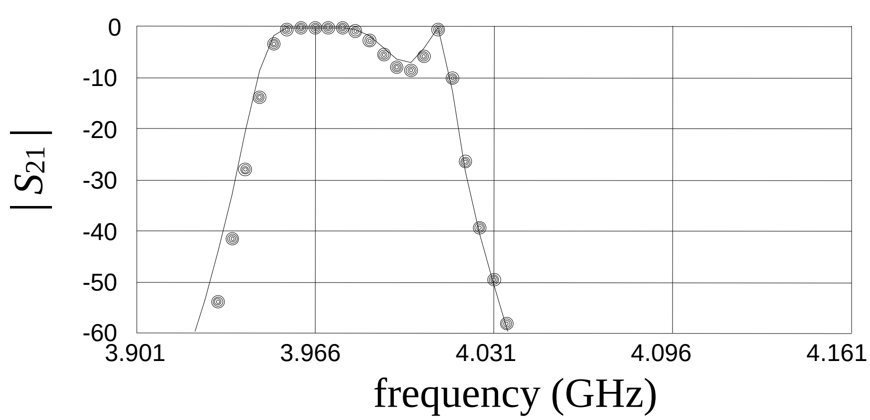


FPSMN Model for the HTS Filter: Fine Frequency Sweep

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



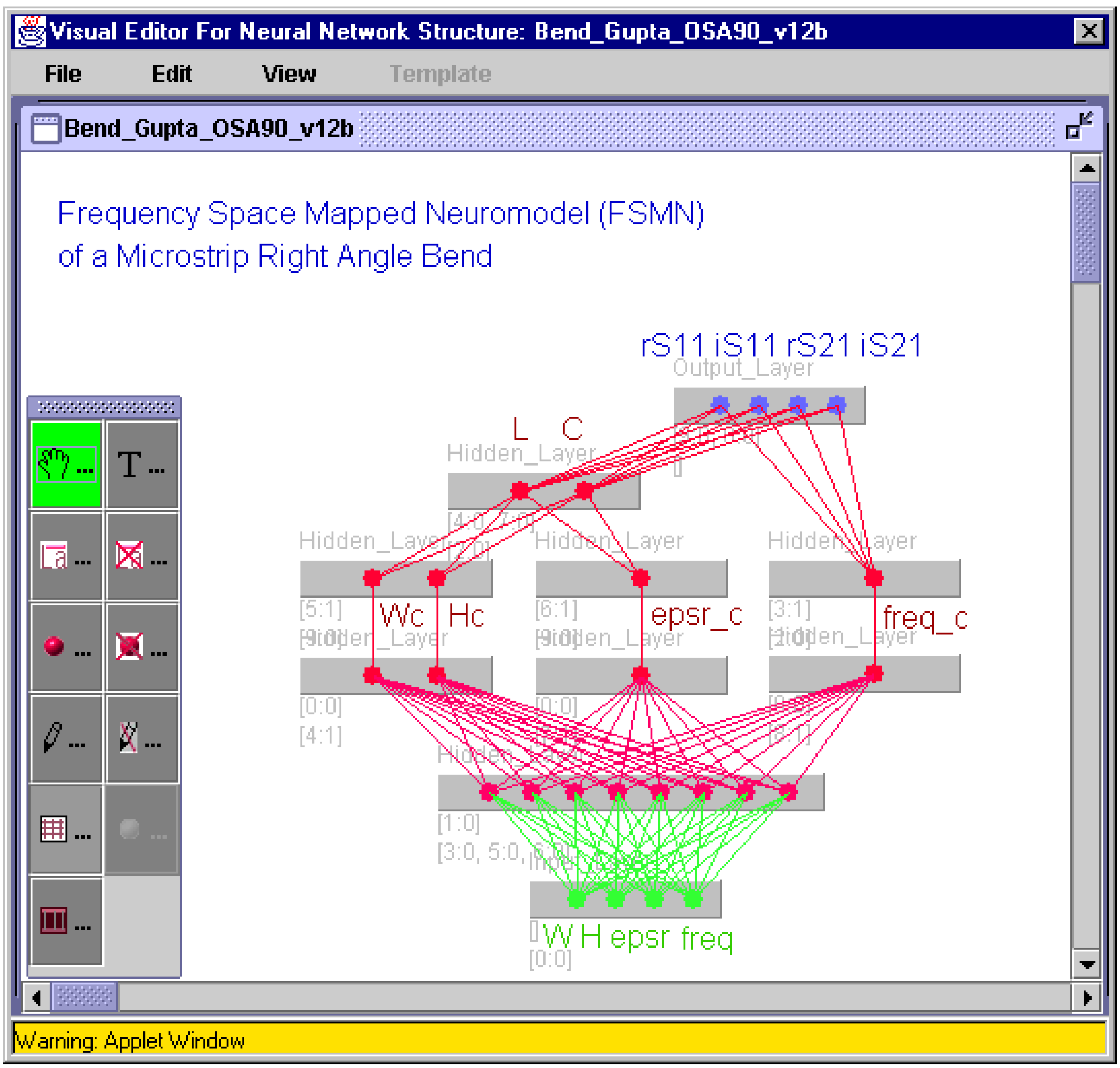




New Realizations in NeuroModeler

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



Conclusions

we present novel applications of Space Mapping technology to the neuromodeling of microwave circuits

five powerful SM based neuromodeling techniques are described and illustrated

- Space Mapped Neuromodeling (SMN)
- Frequency-Dependent Space Mapped Neuromodeling (FDSMN)
- Frequency Space Mapped Neuromodeling (FSMN)
- Frequency Mapped Neuromodeling (FMN)
- Frequency Partial-Space Mapped Neuromodeling (FPSMN)

these techniques

- exploit the vast set of empirical models already available
- decrease the fine model evaluations needed for training
- improve generalization ability
- reduce complexity of the ANN topology
  - w.r.t. the classical neuromodeling approach

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

FMN effectively aligns frequency-shifted responses

Huber optimization efficiently trains the neuromappings, exploiting its robust characteristics for data fitting