Space Mapping Based Neuromodeling

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Abstract

A powerful concept in neuromodeling of microwave circuits based on Space Mapping technology is described. The ability of Artificial Neural Networks (ANN) to model high-dimensional and highly nonlinear problems is exploited in the implementation of the Space Mapping concept. By taking advantage of the vast set of empirical models already available for many microwave structures, Space Mapping based neuromodels decrease the number of EM simulations for training, improve the generalization and extrapolation performance and reduce the complexity of the ANN topology with respect to the conventional neuromodeling approach.

Five innovative techniques are proposed to create Space Mapping based neuromodels for microwave circuits: Space Mapped Neuromodeling (SMN), Frequency-Dependent Space Mapped Neuromodeling (FDSMN), Frequency Space Mapped Neuromodeling (FSMN), Frequency Mapped Neuromodeling (FMN) and Frequency Partial-Space Mapped Neuromodeling (FPSM). Excepting SMN, all these approaches establish a frequency-sensitive neuromapping to expand the frequency region of accuracy of the empirical models already available for microwave components that were developed using quasi-static analysis.

We contrast our approach with the conventional neuromodeling approach employed in the microwave arena, as well as with other state-of-the-art neuromodeling techniques. We use Huber optimization to efficiently train the simple ANN that implements the mapping in our SM-based neuromodels.

The five space mapping based neuromodeling techniques are illustrated by two case studies: a microstrip right angle bend and a high-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter.

Outline

conventional ANN approach for microwave modeling

neuromodeling using existing knowledge

SM-based neuromodeling

examples

other applications of SM-based neuromodeling

conclusions

Artificial Neural Networks (ANN) Modeling

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

ANN models are computationally efficient and more accurate than empirical models

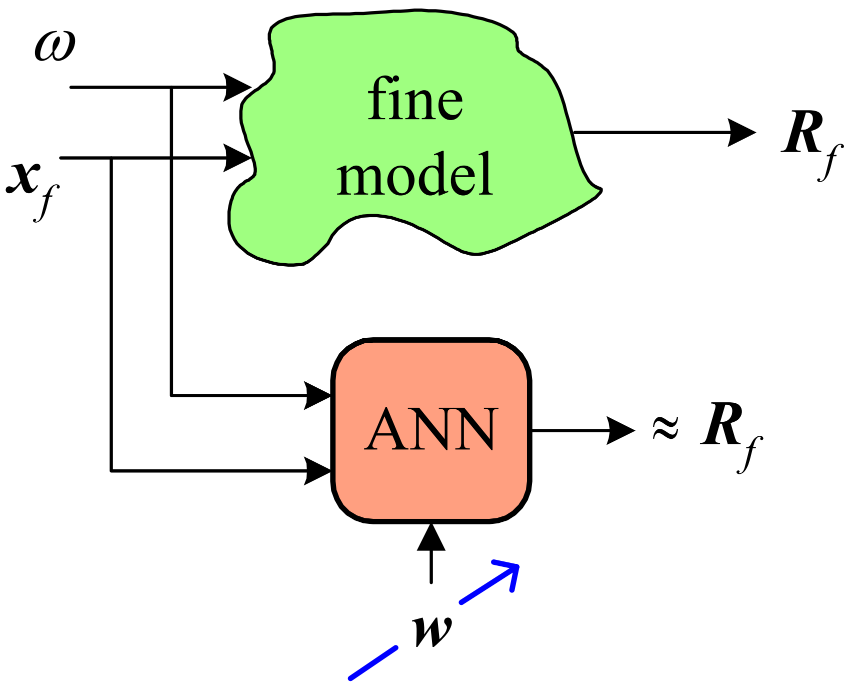
multilayer feedforward networks can approximate any measurable function to any desired level of accuracy, provided a deterministic relationship between input and target exists *(White et al., 1992)*

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)*

Conventional ANN Modeling Approach



many fine model simulations are usually needed

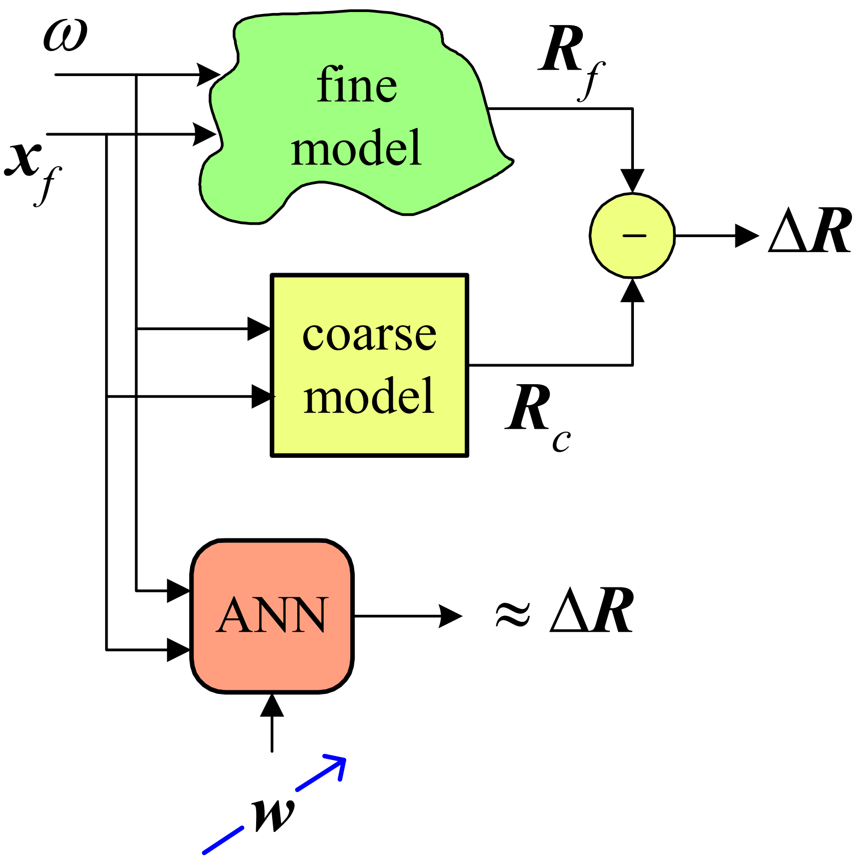
the number of learning samples needed to approximate a function grows exponentially with the ratio of the dimensionality to the function's degree of smoothness (*Stone, 1982*)

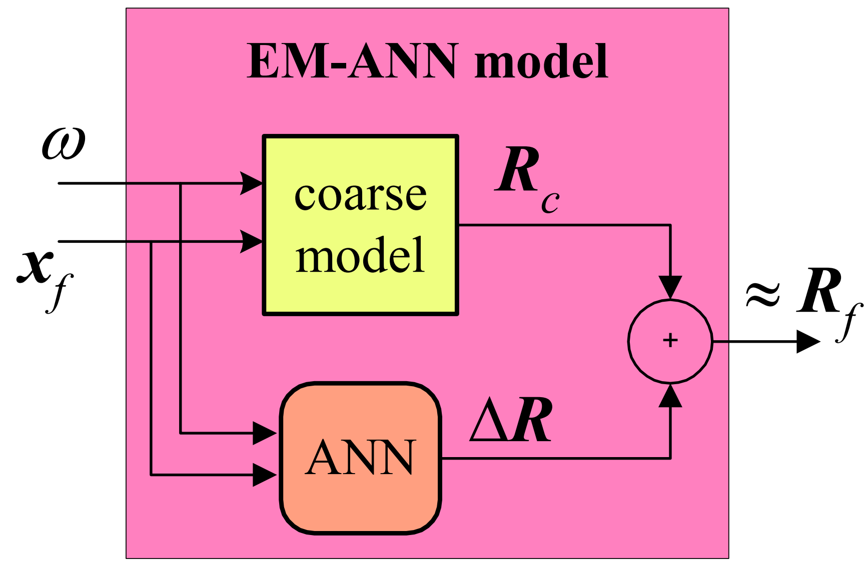
the reliability of multi-layer perceptrons for extrapolation is poor

introducing knowledge can alleviate these limitations

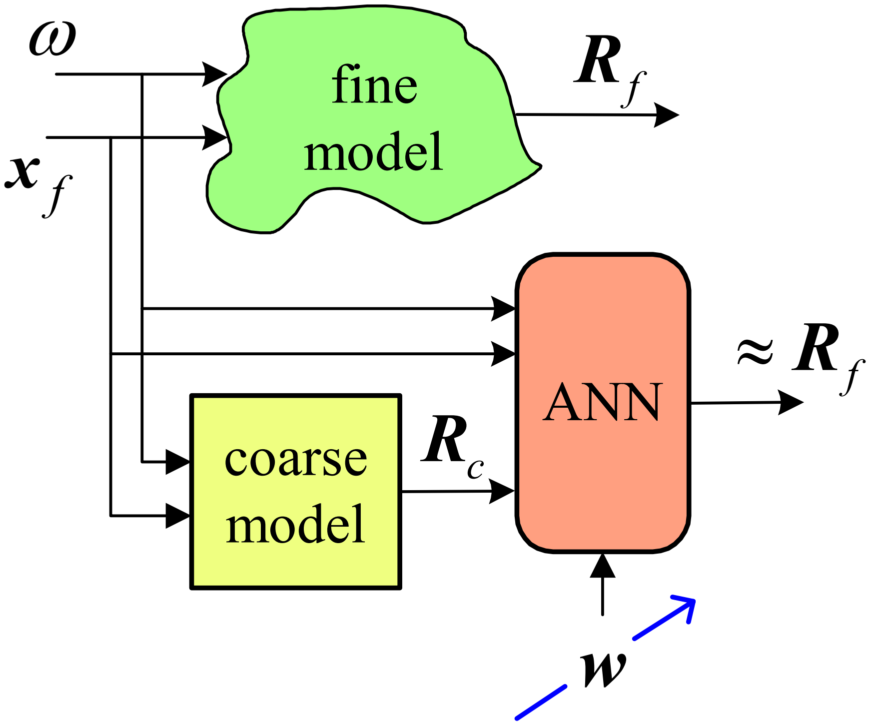
Hybrid "ΔS" EM-ANN Neuromodeling Concept

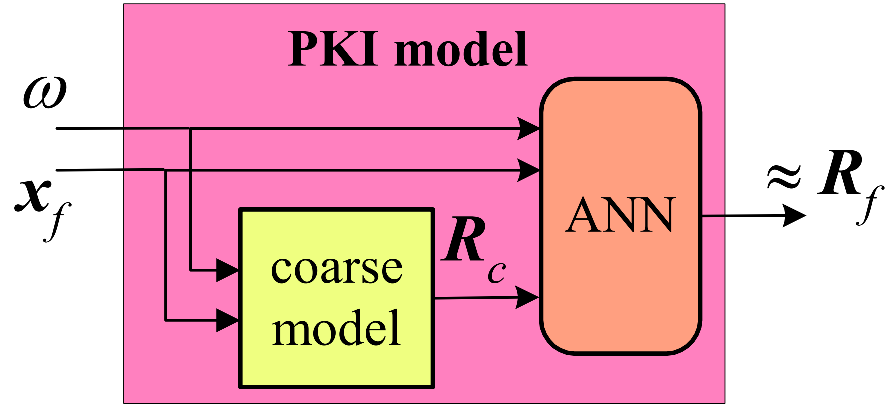
(Gupta et al., 1996)





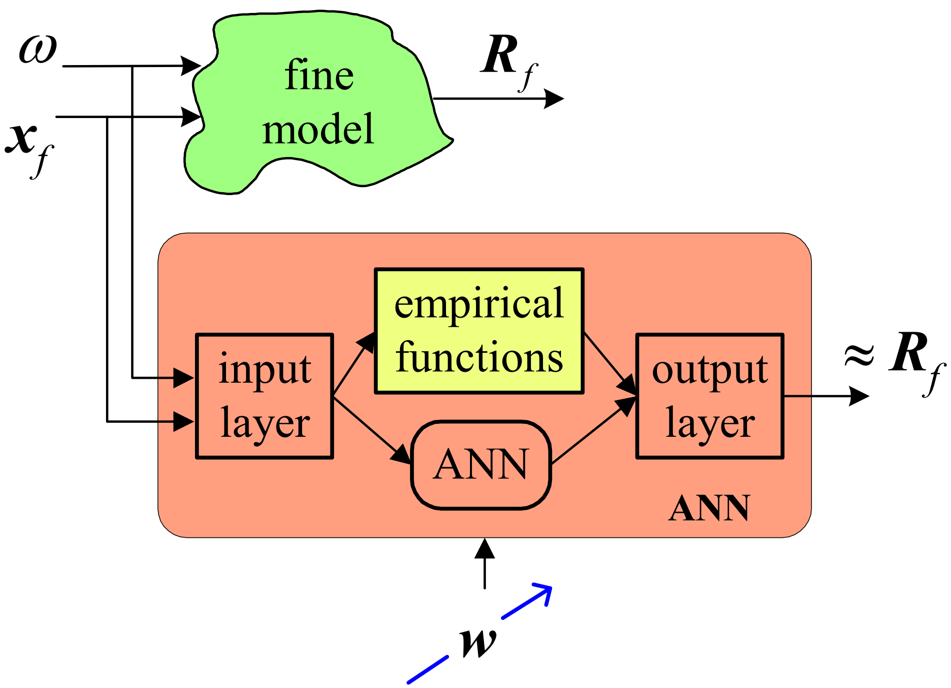
PKI Neuromodeling Concept
(Gupta et al., 1996)

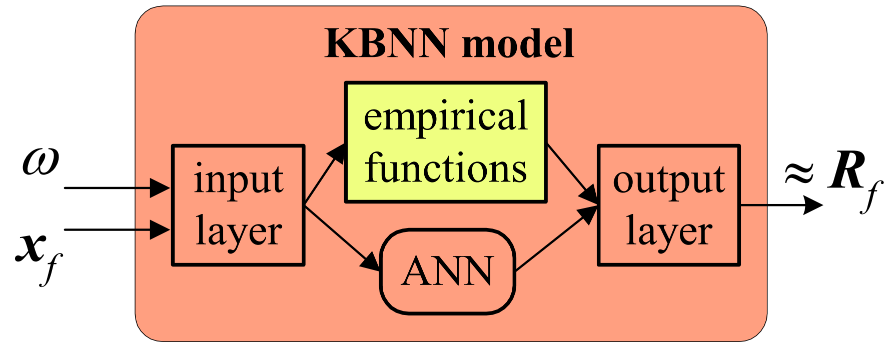




KBNN Neuromodeling Concept

(Zhang et al., 1997)

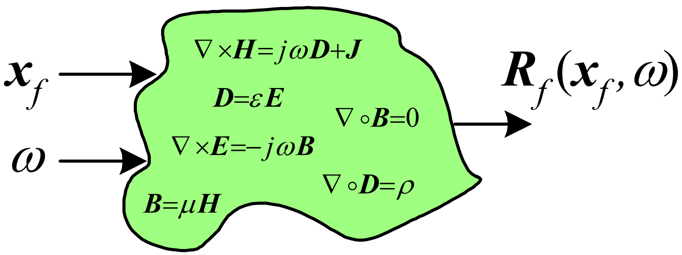




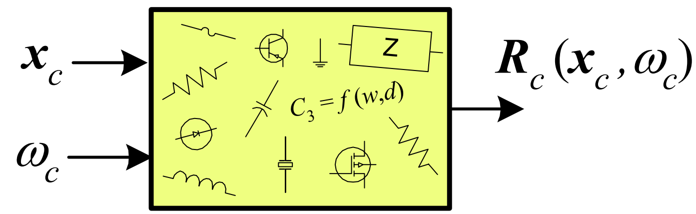
Exploiting Space Mapping for Neuromodeling

(Bandler et. al., 1999)

fine model



coarse model



find

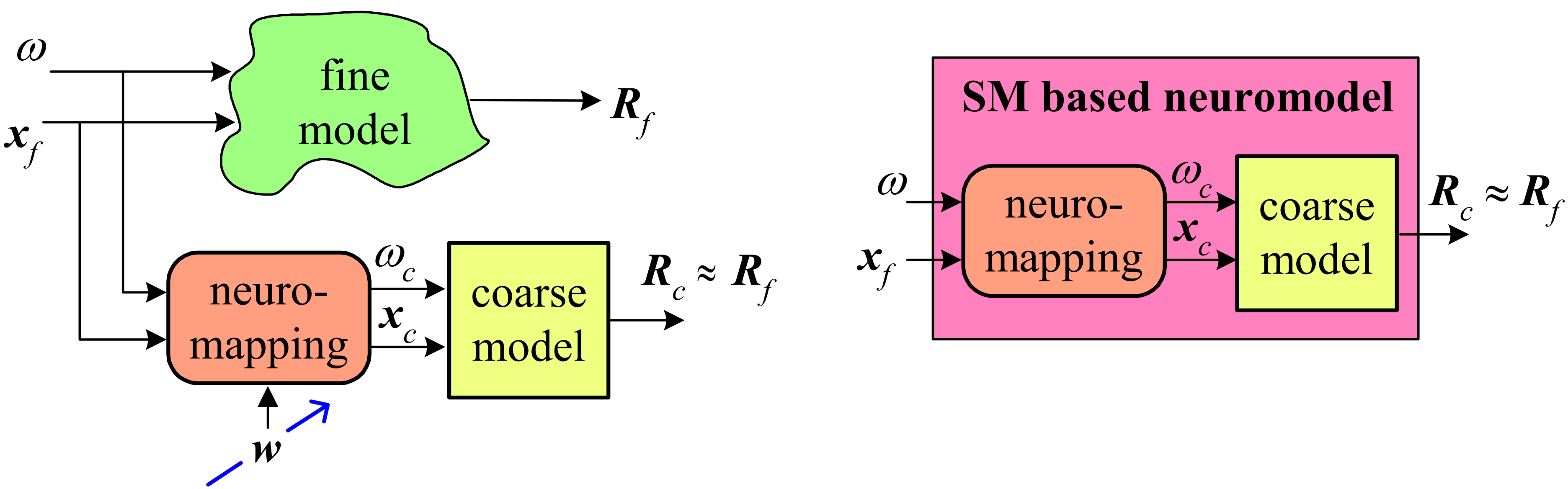
$$\begin{bmatrix}\boldsymbol{x}_c\\ \omega_c\end{bmatrix}=\boldsymbol{P}(\boldsymbol{x}_f,\omega)$$

such that

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

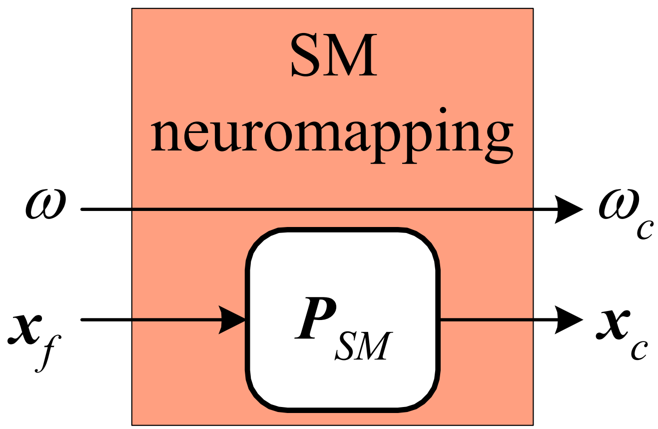
Space Mapping Based Neuromodeling

(Bandler et. al., 1999)

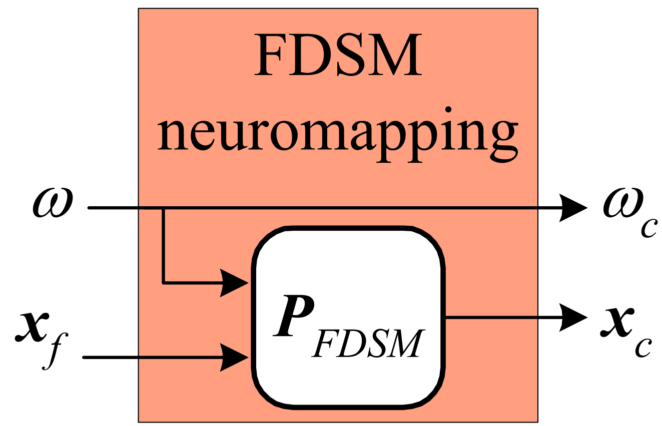


Neuromappings

Space Mapped neuromapping

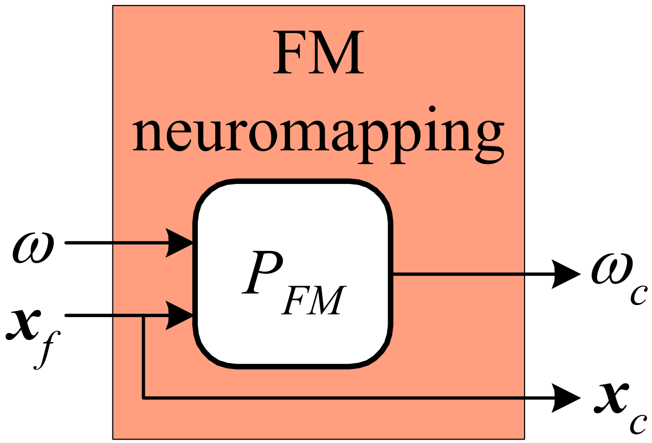


Frequency-Dependent Space Mapped neuromapping

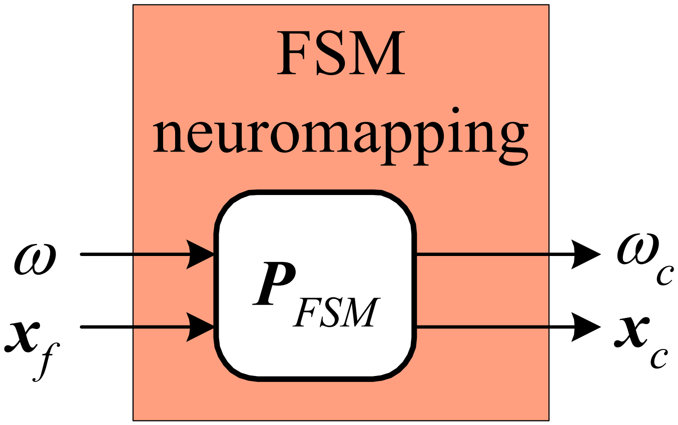


Neuromappings (continued)

Frequency Mapped neuromapping

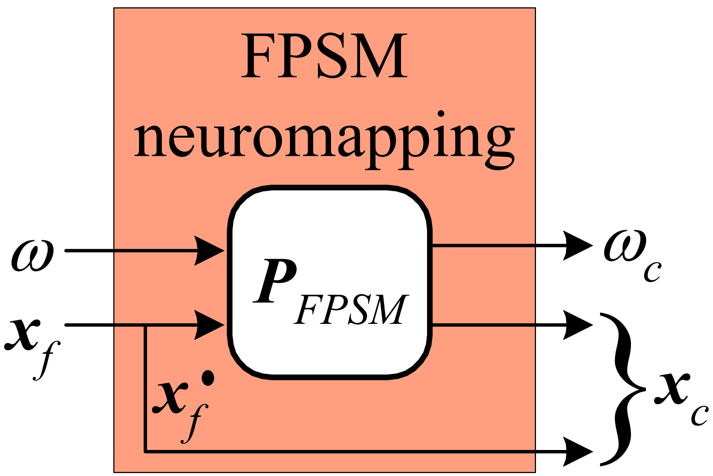


Frequency Space
Mapped neuromapping



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

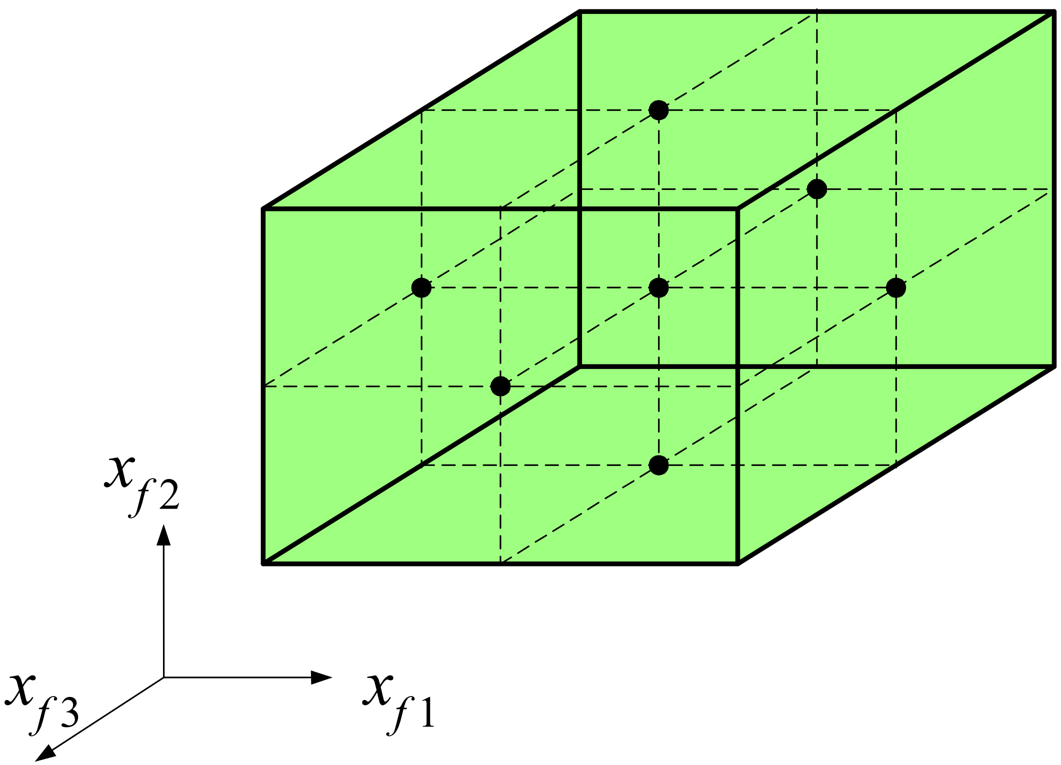
$2n+1$ is the number of training base points and F_p is the number of frequency points

Huber optimization is used to solve this problem

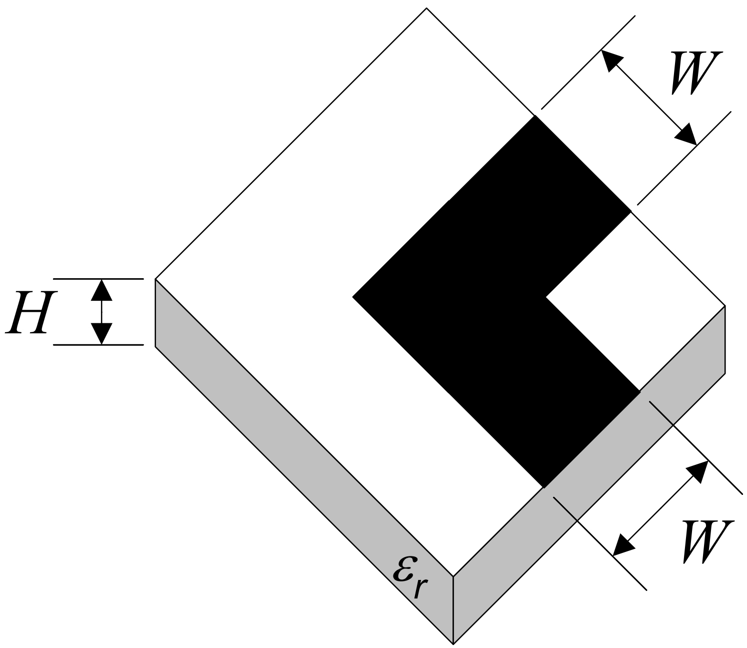
Starting Point and Learning Samples

we chose a unit mapping ($\boldsymbol{x}_c \approx \boldsymbol{x}_f$ and $\omega_c \approx \omega$) 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

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

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

"fine" model: Sonnet's ***em***™

learning set: 7 base points with "star" distribution

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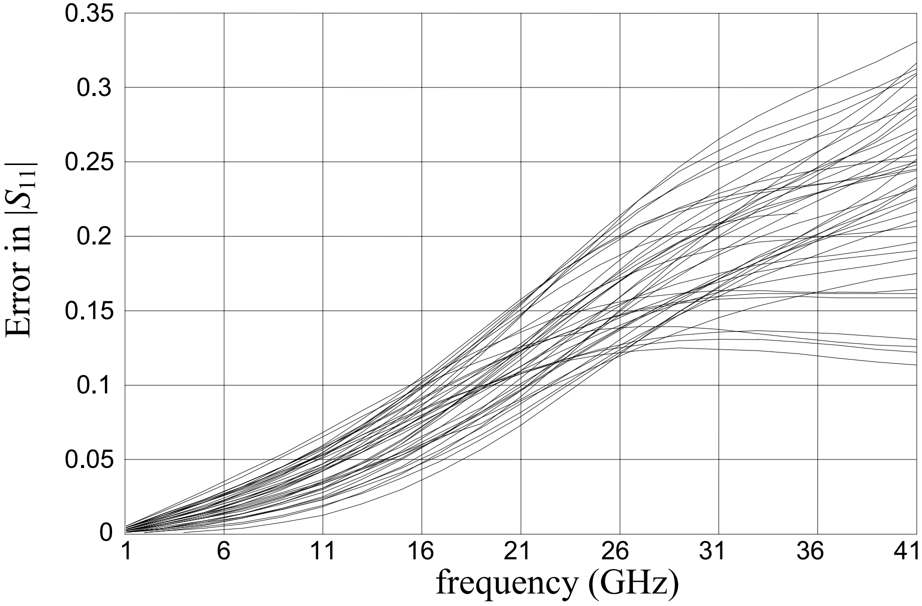
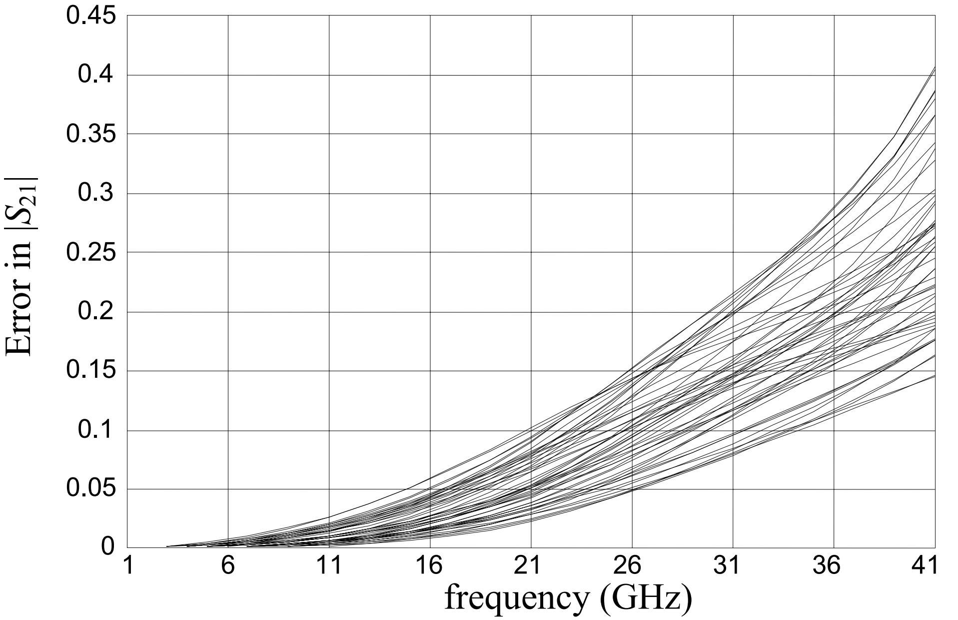
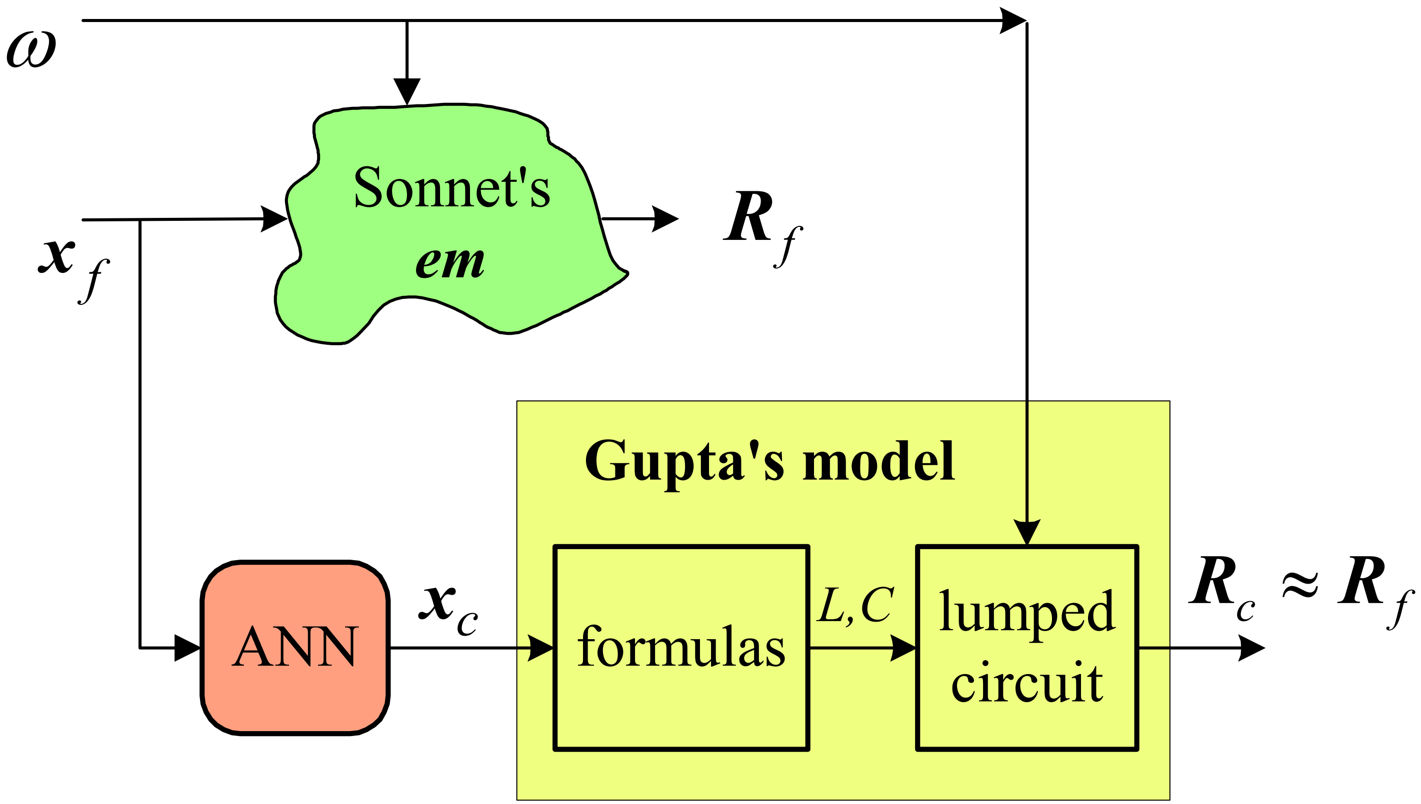
Microstrip Right Angle Bend Coarse Model Errors

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





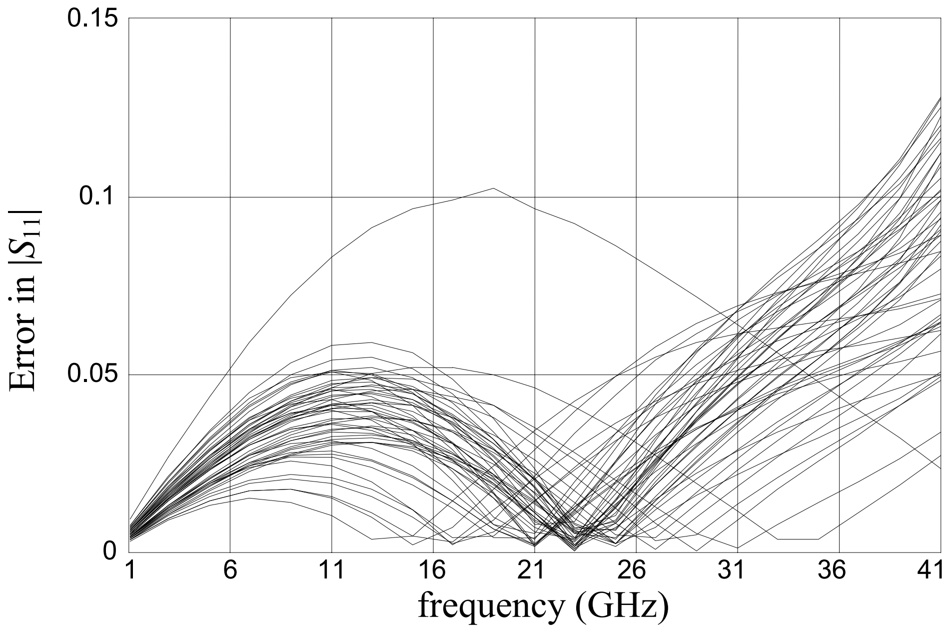
SM Neuromodel for the Right Angle Bend (3LP:3-6-3)

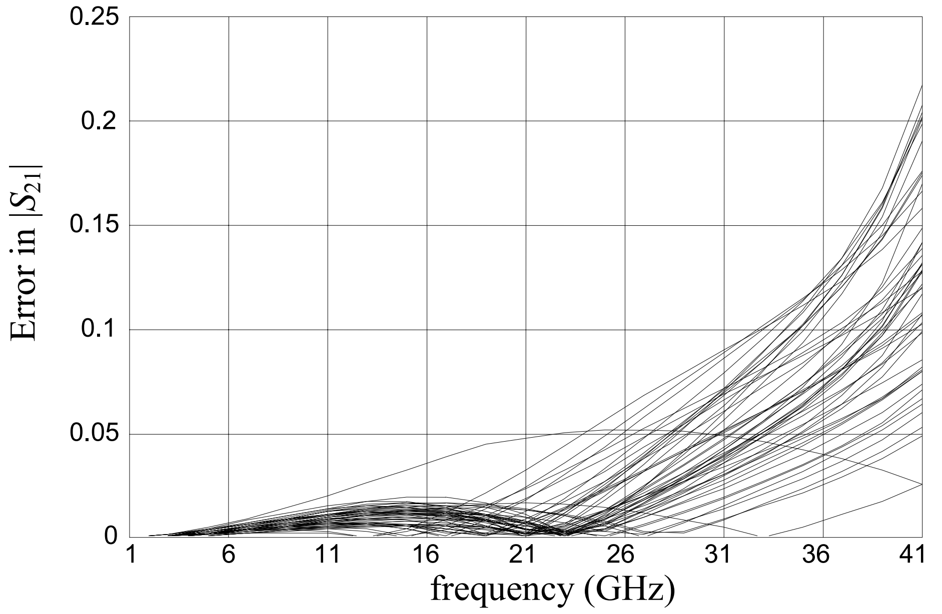


$$x_f = [W \;\; H \;\; \varepsilon_r]^T$$

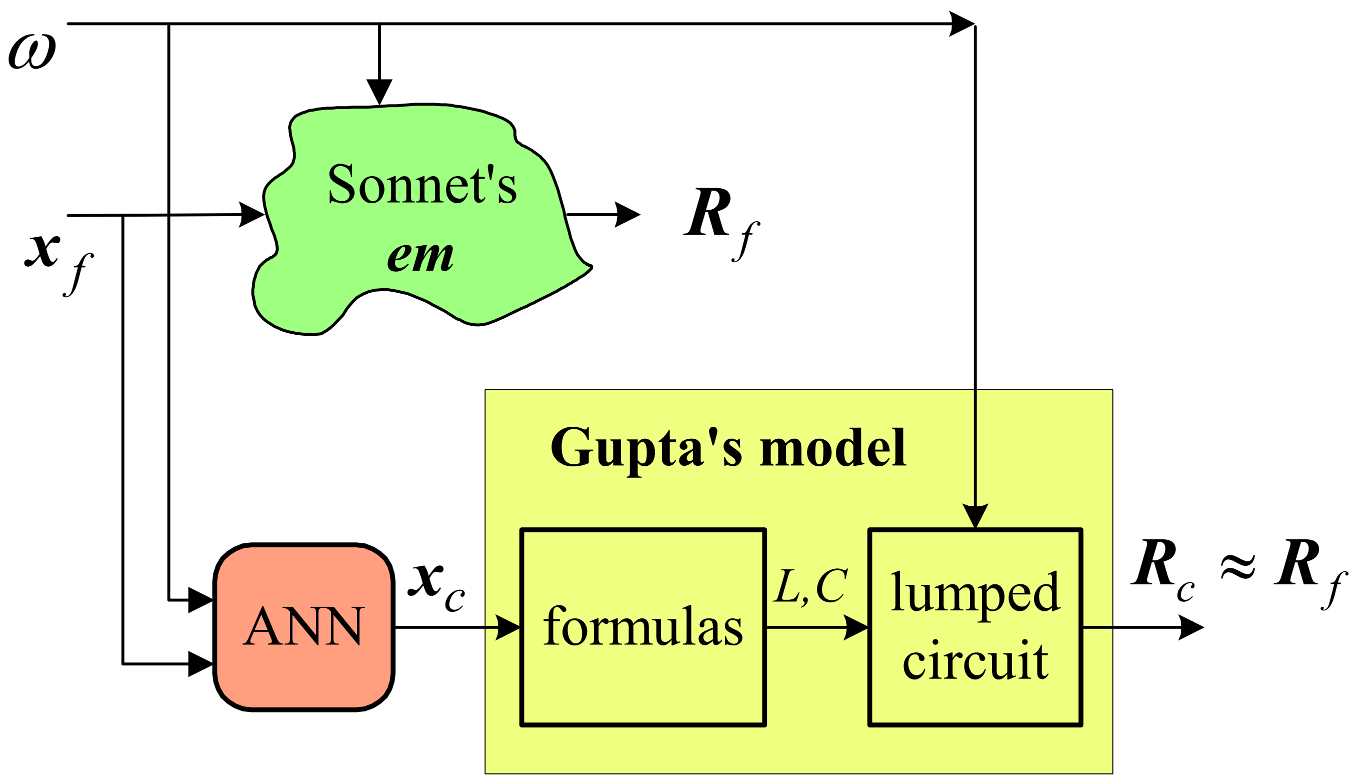
SM Neuromodel Results for the Right Angle Bend

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





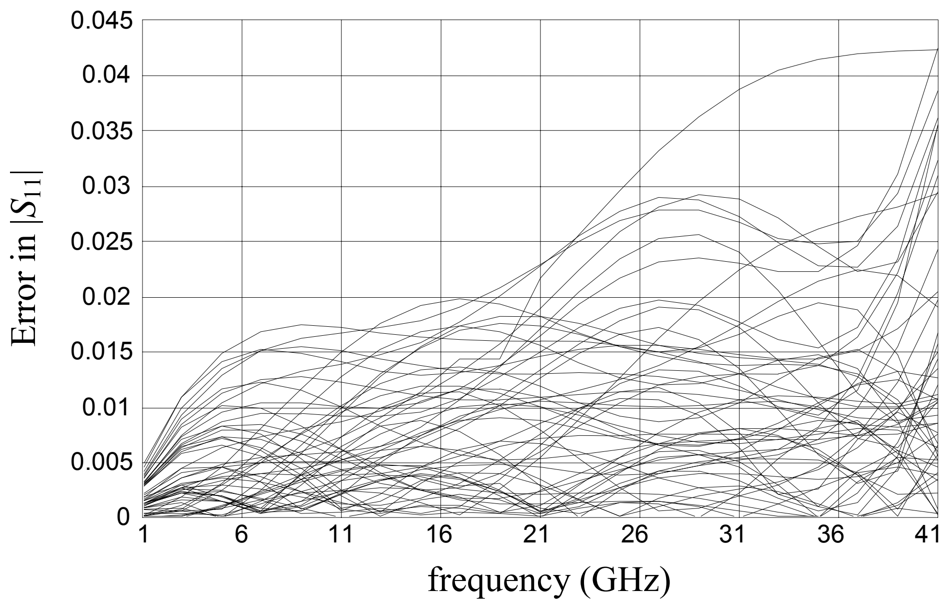
FDSM Neuromodel for the Right Angle Bend (3LP:4-7-3)

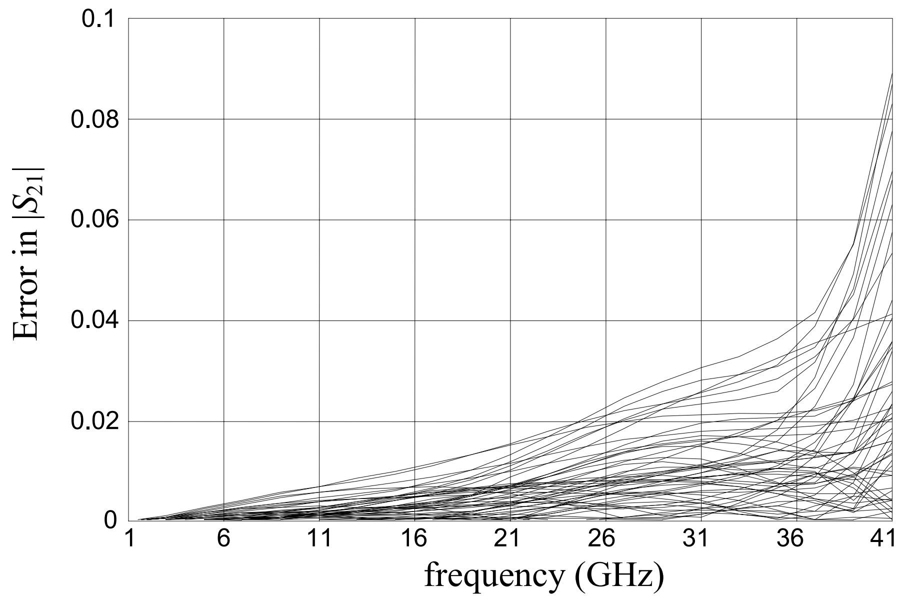


$$x_f = [W \;\; H \;\; \varepsilon_r]^T$$

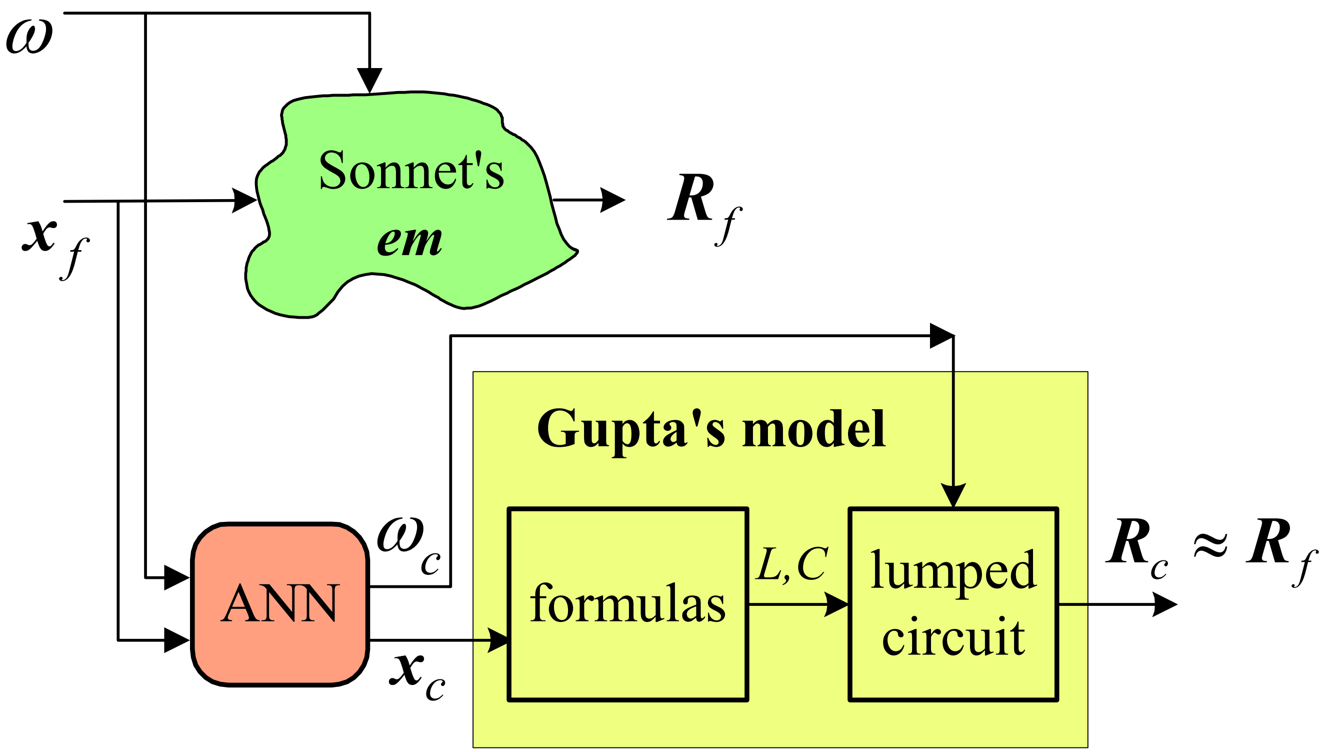
FDSM Neuromodel Results for the Right Angle Bend

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





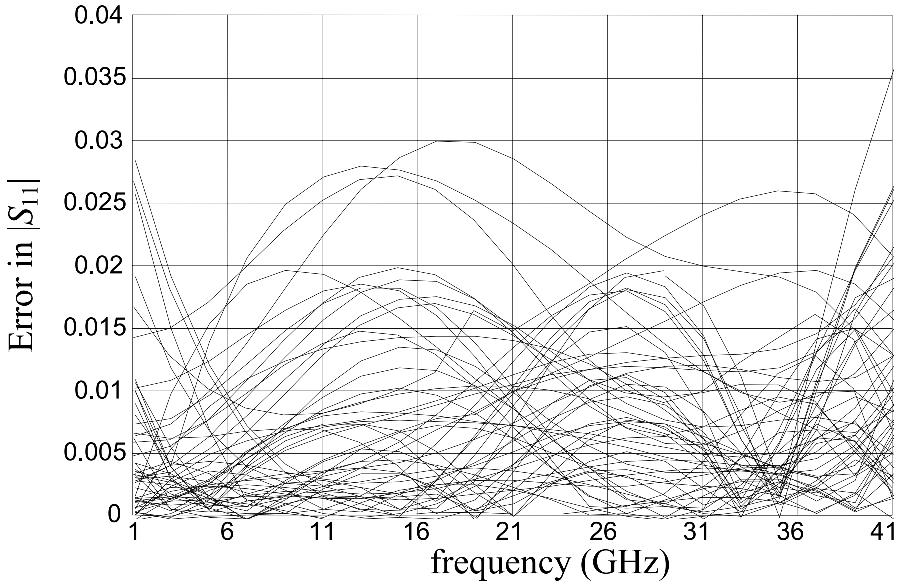
FSM Neuromodel for the Right Angle Bend (3LP:4-8-4)

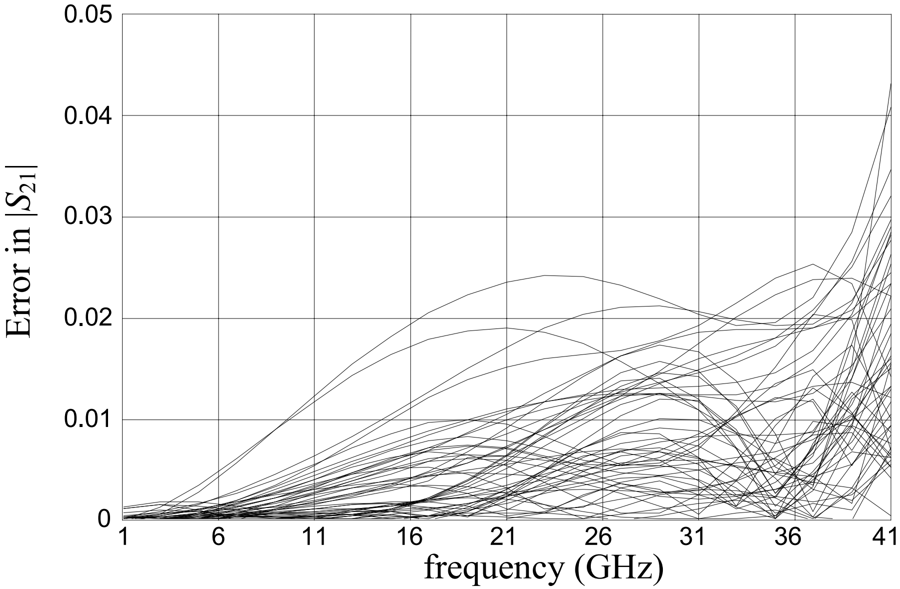


$$\boldsymbol{x}_f = [W \;\; H \;\; \varepsilon_r]^T$$

FSM Neuromodel Results for the Right Angle Bend

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

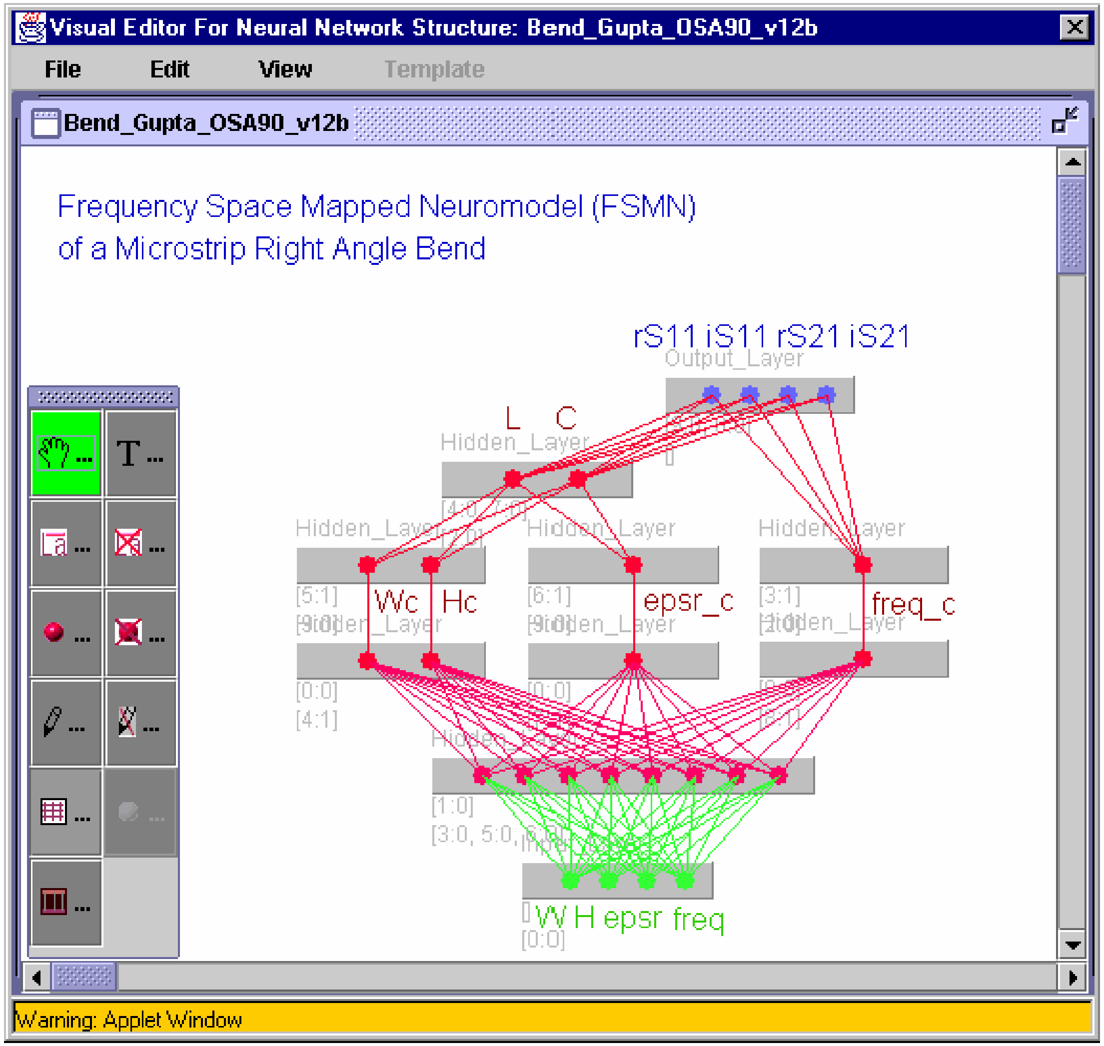




Implementations in *NeuroModeler*

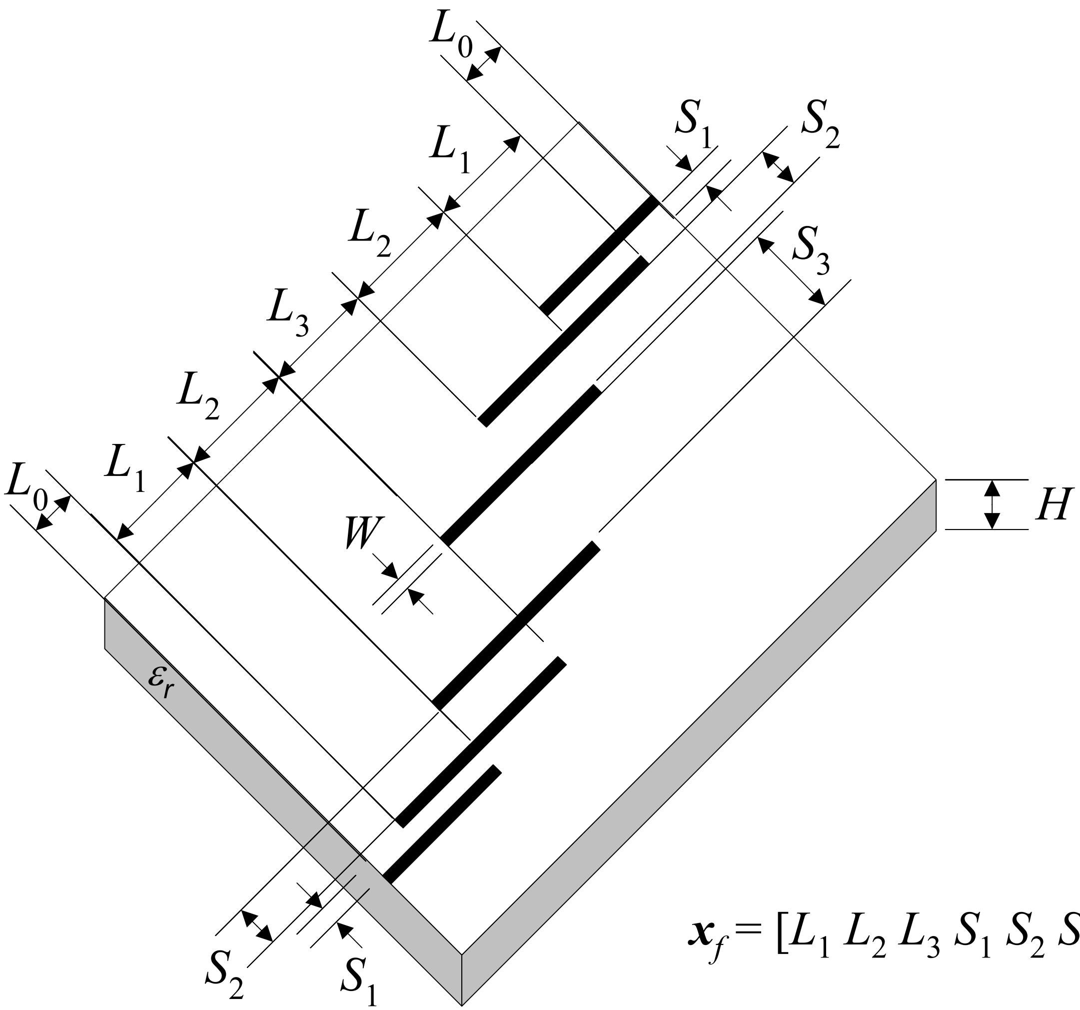
SM based neuromodels of several microstrip circuits have been developed using *NeuroModeler* version 1.2b (1999)

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)



$$x_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$$

region of interest

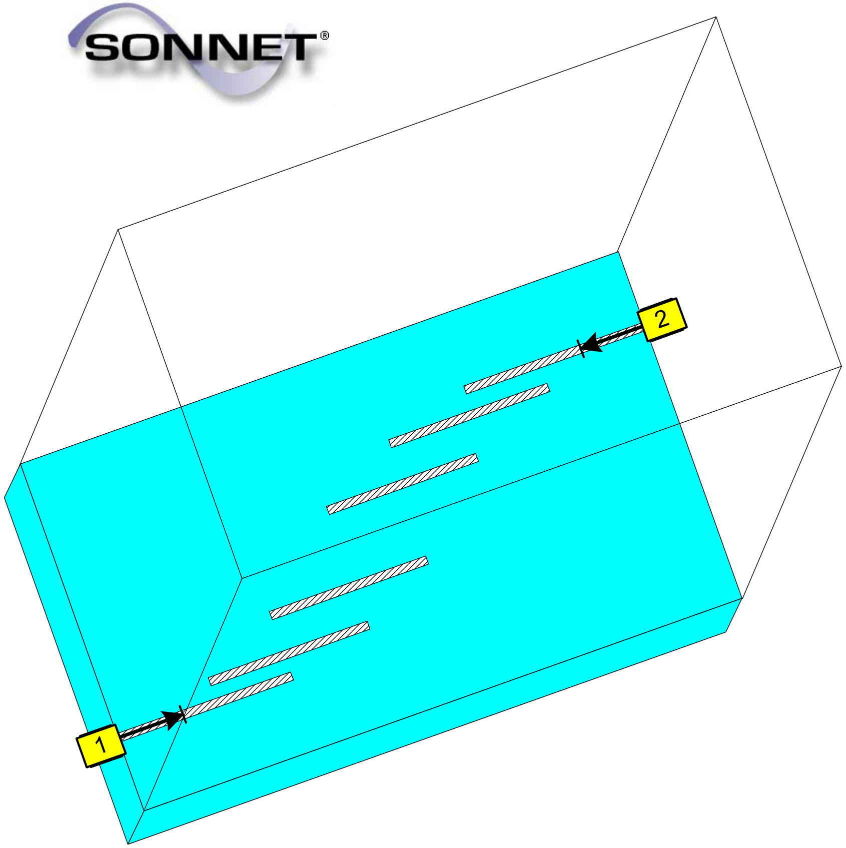
$$175\text{mil} \le L_1 \le 185\text{mil}$$
$$190\text{mil} \le L_2 \le 210\text{mil}$$
$$175\text{mil} \le L_3 \le 185\text{mil}$$
$$18\text{mil} \le S_1 \le 22\text{mil}$$
$$75\text{mil} \le S_2 \le 85\text{mil}$$
$$70\text{mil} \le S_3 \le 90\text{mil}$$
$$3.901\text{GHz} \le \omega \le 4.161\text{GHz}$$

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

HTS Microstrip Filter: Fine and Coarse Models

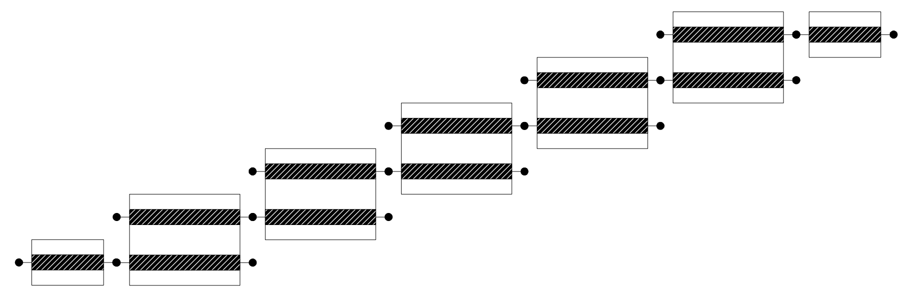
fine model:

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



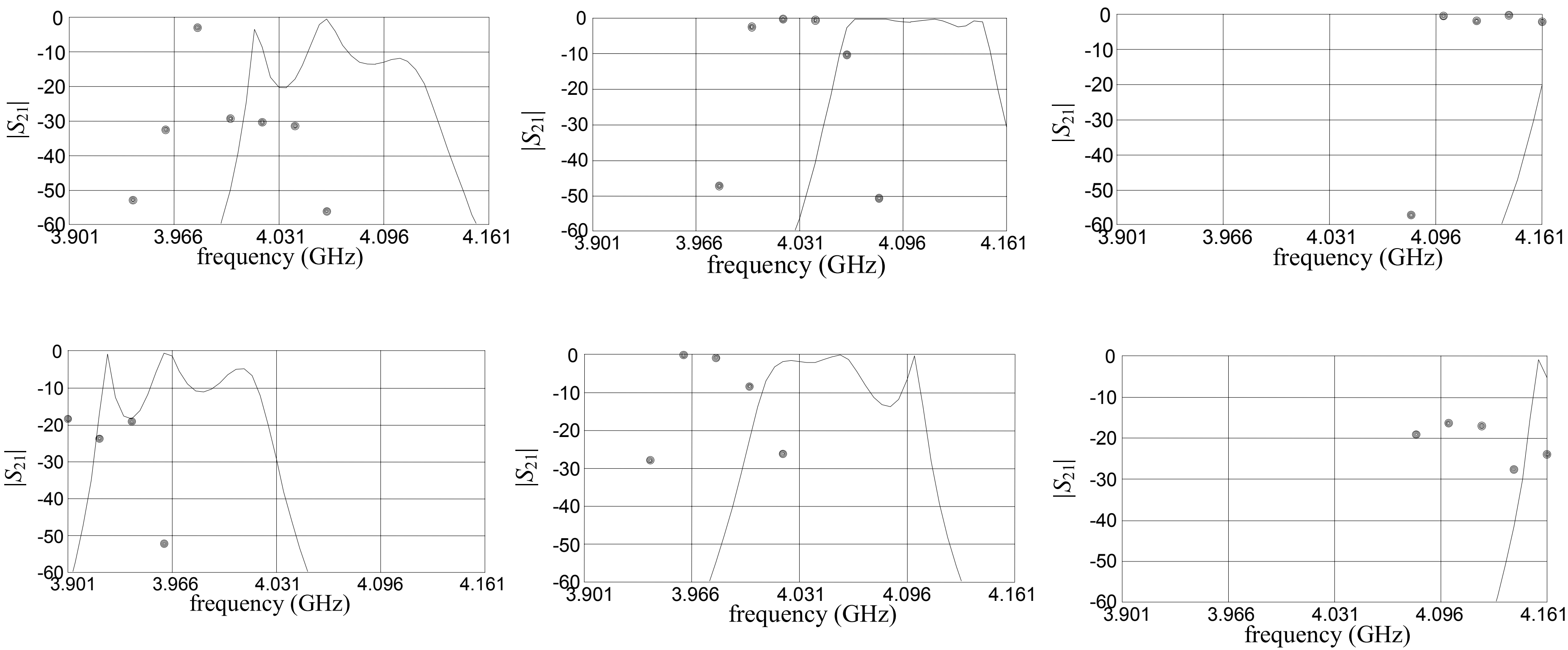
coarse model:

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

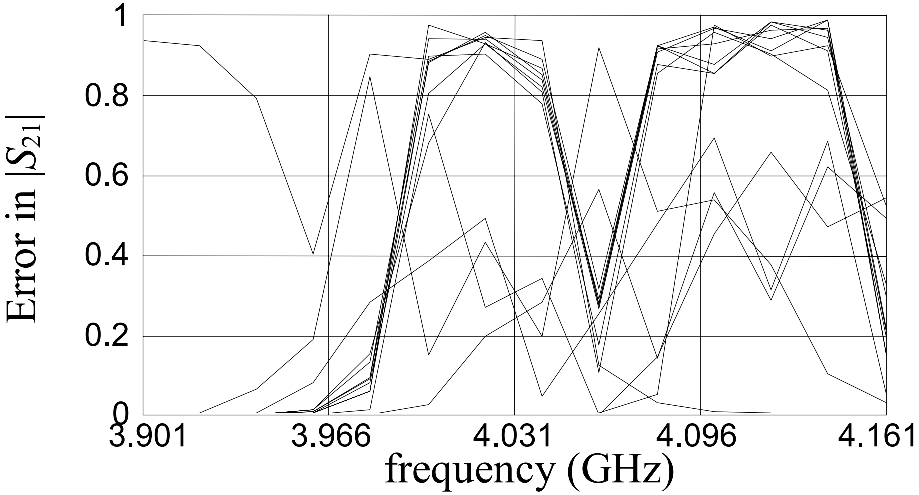


HTS Filter Responses Before Neuromodeling

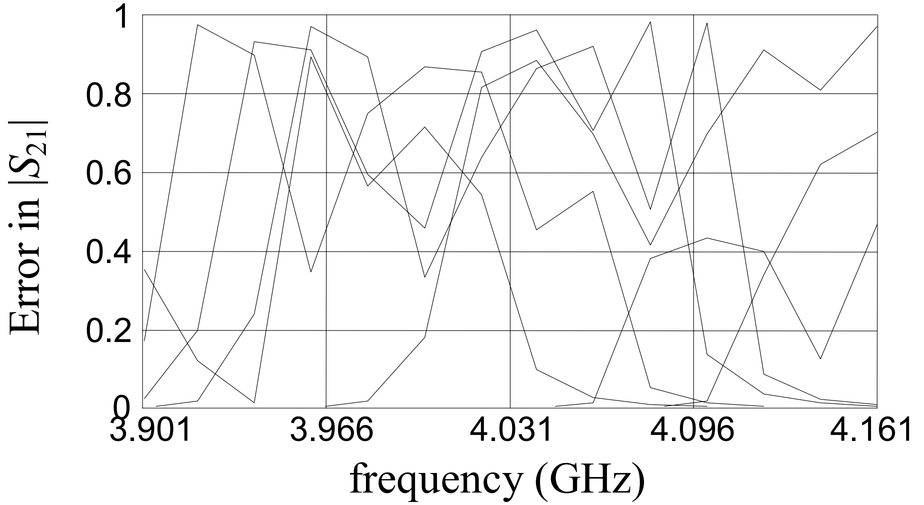
responses using ***em***™ (•) and OSA90/hope™ (–) at three learning and three test points



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



in the learning set

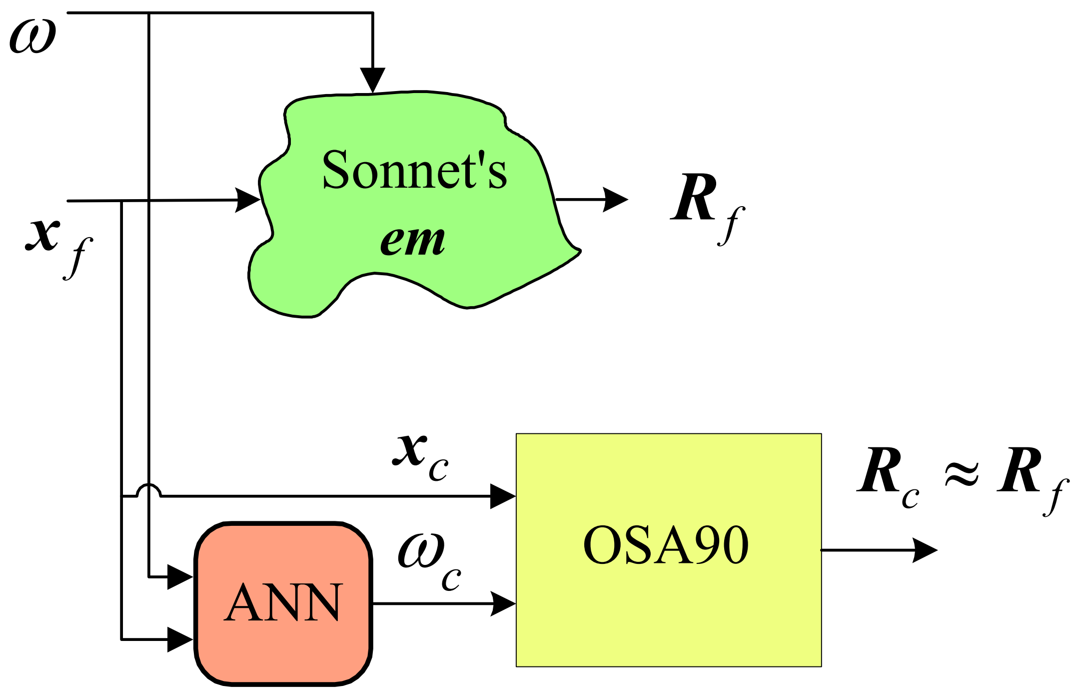


in the testing set

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)

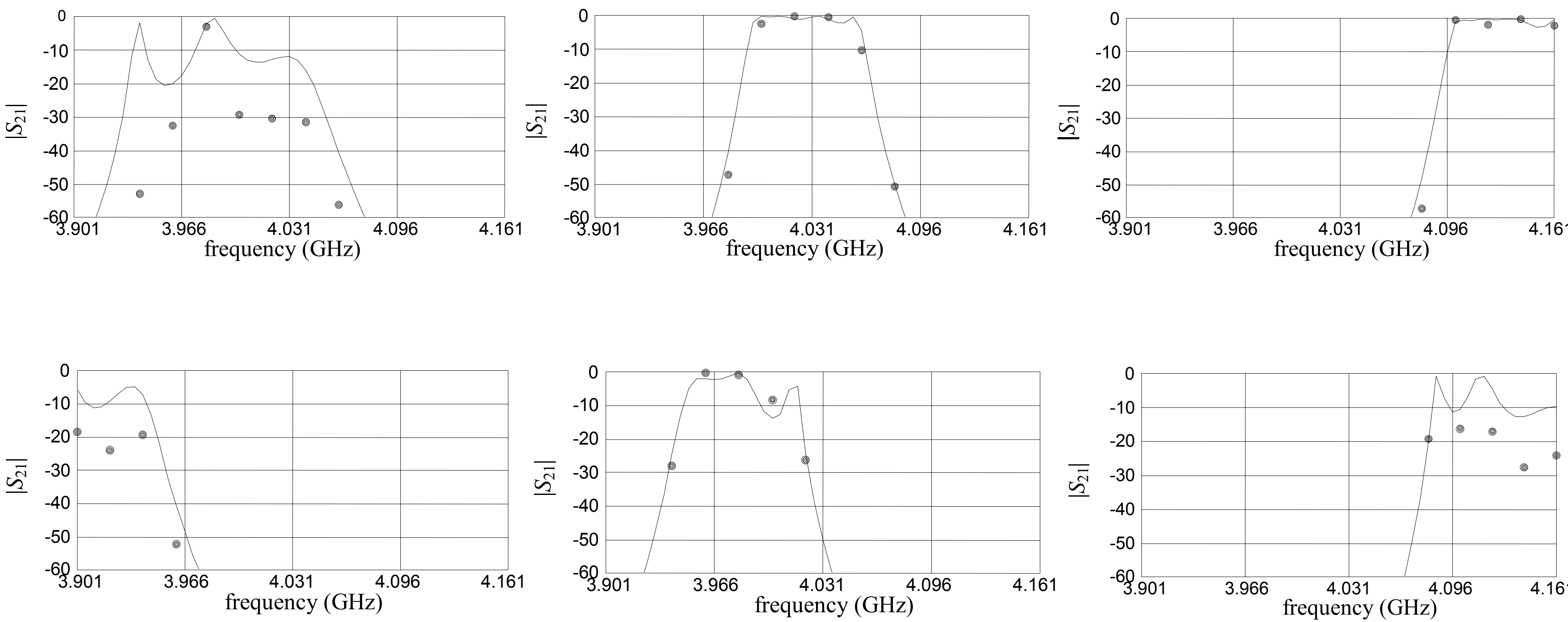
FM Neuromodel for the HTS Filter (3LP:7-5-1)



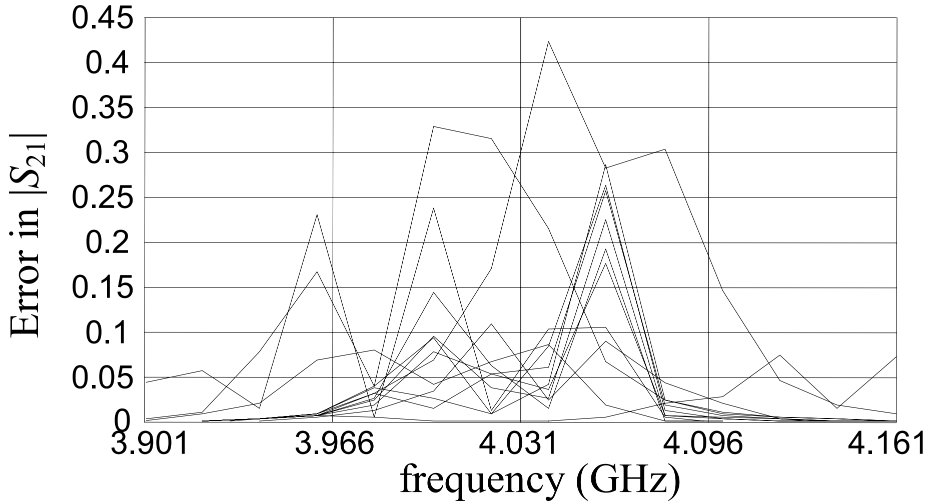
$$\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$$

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

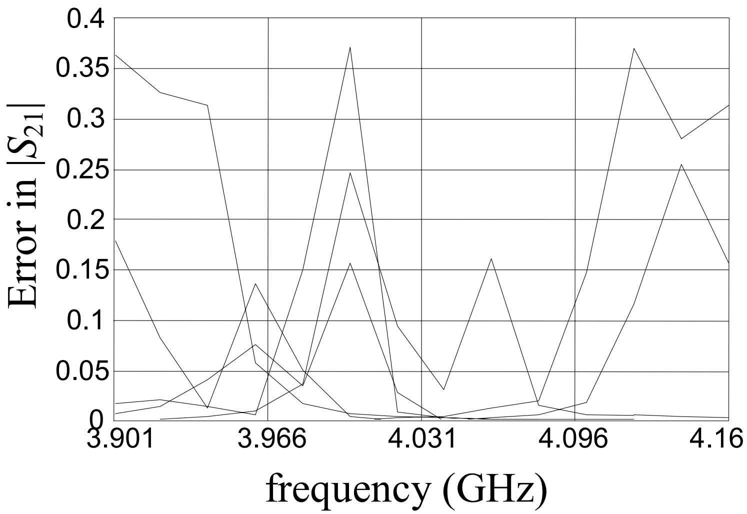
responses using ***em***™ (•) and FMN model (–) at the three learning and three testing points



HTS FM Neuromodel Error w.r.t. *em*™

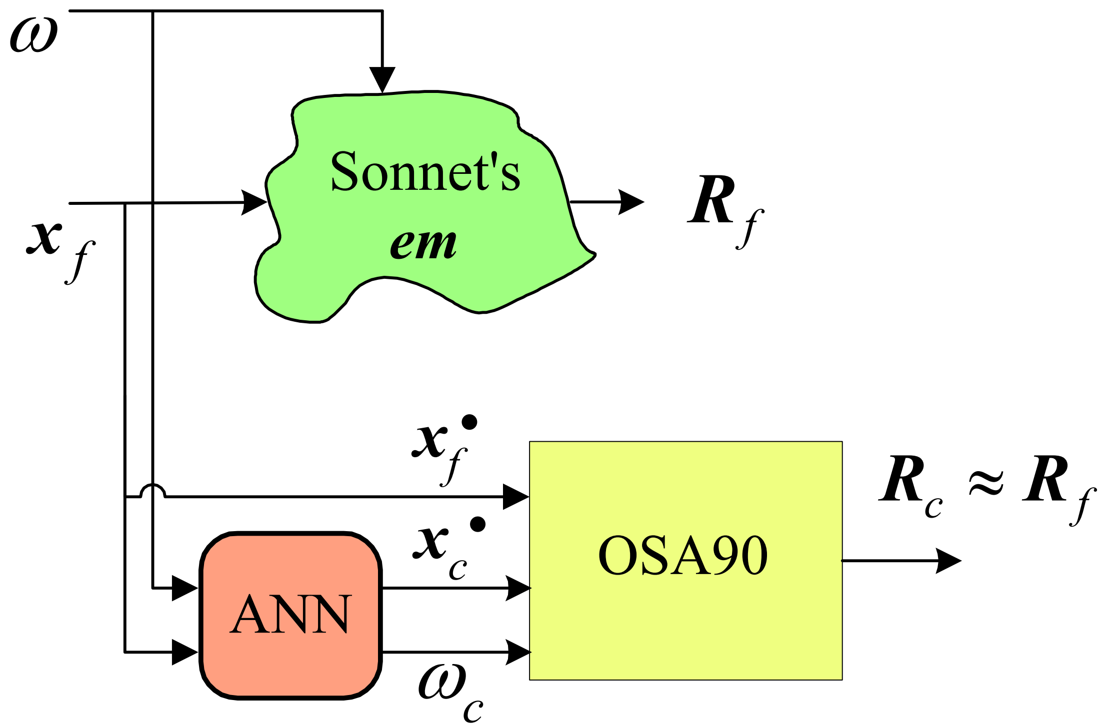


in the learning set



in the testing set

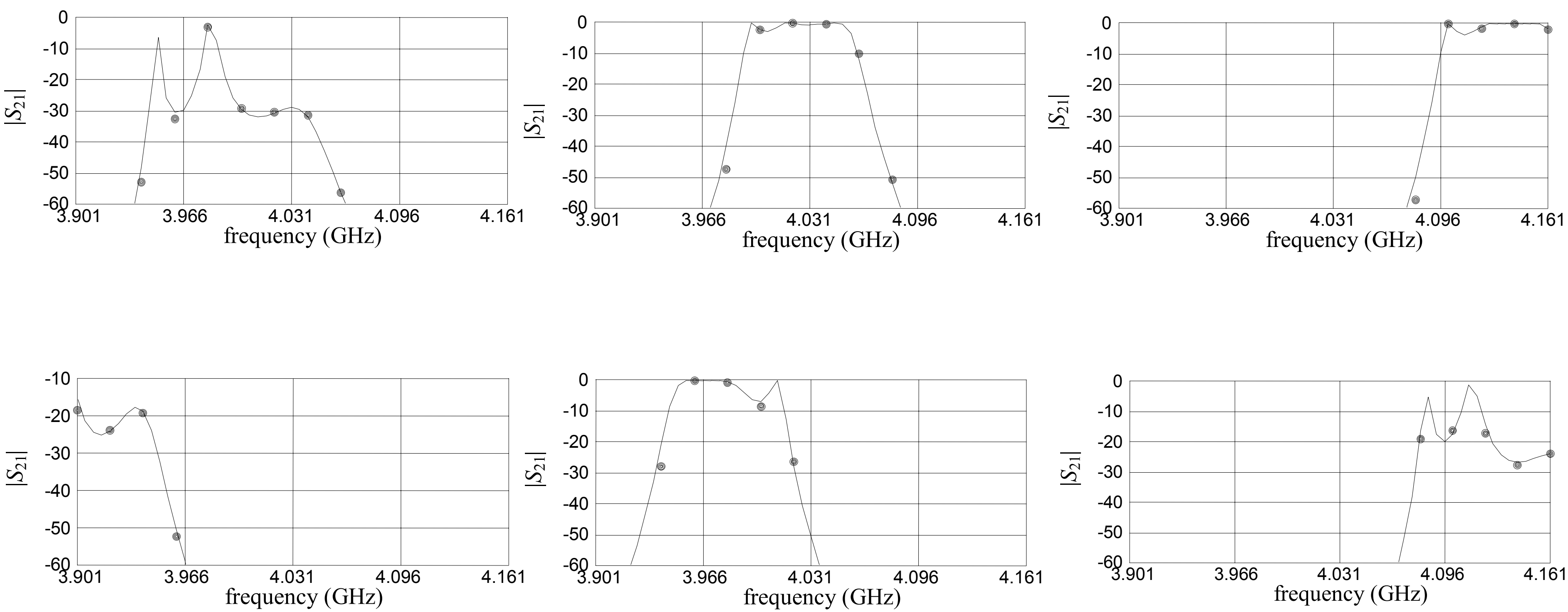
FPSM Neuromodel for the HTS Filter (3LP:7-7-3)



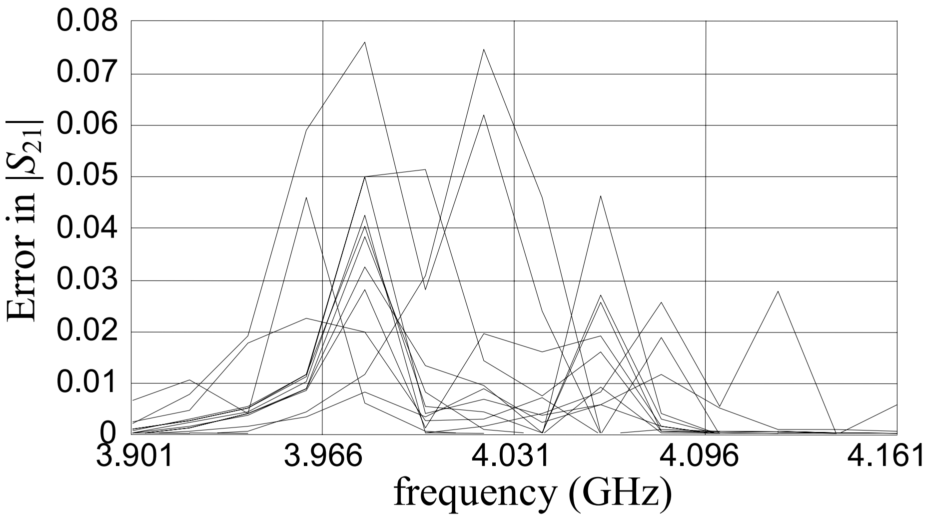
$x_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$ $x_f^\bullet = [L_2\ L_3\ S_2\ S_3]^T$ $x_c^\bullet = [L_{1c}\ S_{1c}]^T$

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

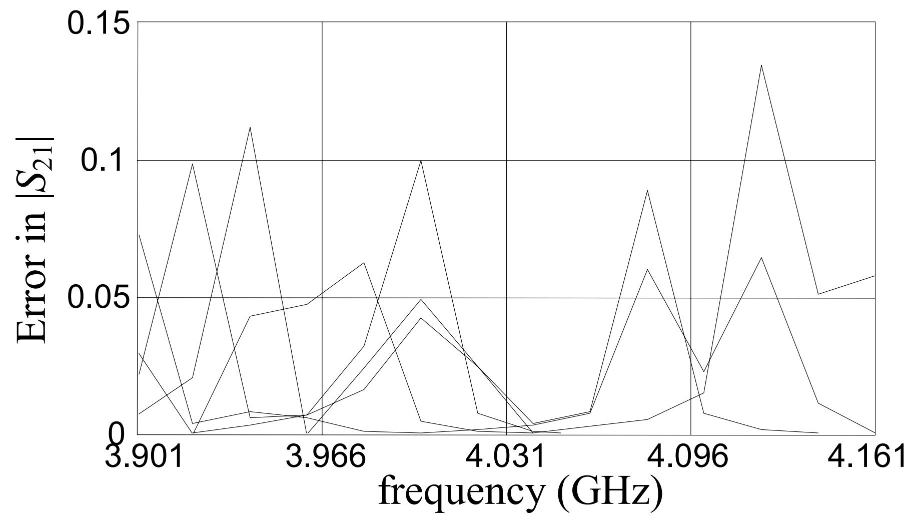
responses using ***em***™ (•) and FPSMN model (–) at the three learning and three testing points



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



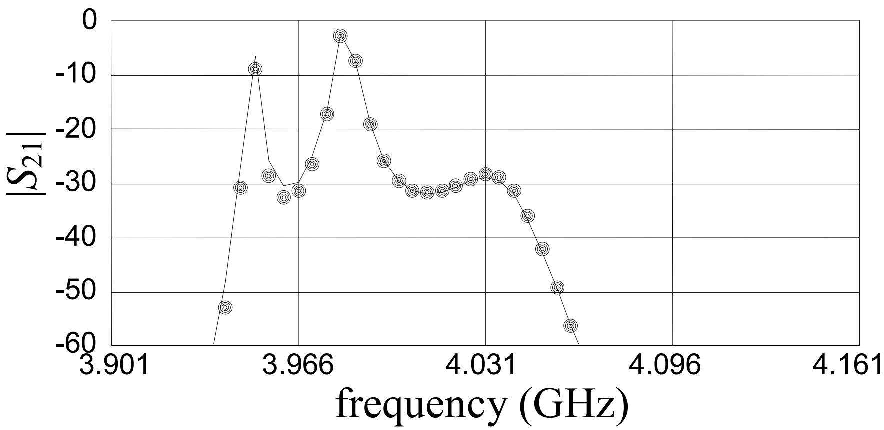
in the learning set

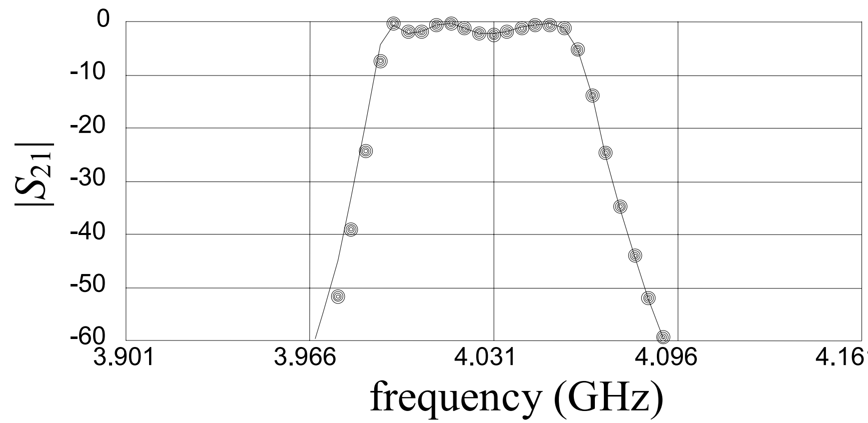


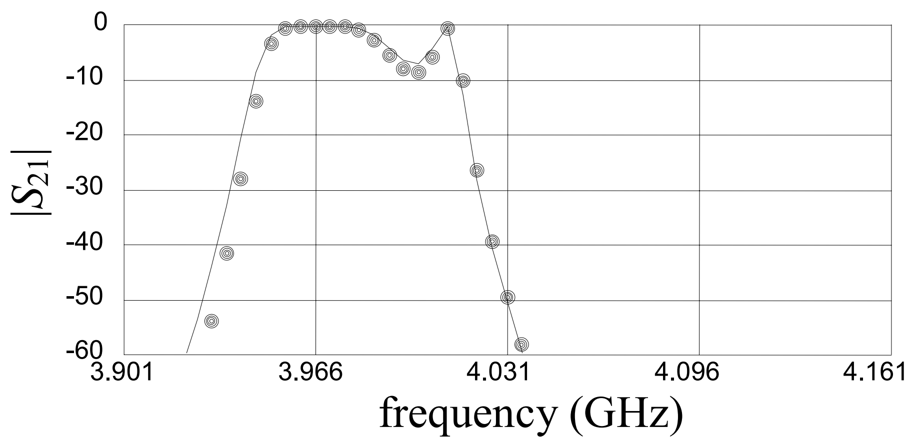
in the testing set

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

Conclusions

we describe novel applications of Space Mapping technology to neuromodeling

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

Space Mapping based neuromodels can be exploited for efficient EM optimization, statistical analysis and yield optimization

References

C.J. Stone, “Optimal global rates of convergence for nonparametric regression,” *Ann. Stat.*, vol. 10, 1982, pp. 1040-1053.

J.W. Bandler, S.H. Chen, R.M. Biernacki, L. Gao, K. Madsen and H. Yu, “Huber optimization of circuits: a robust approach,” *IEEE Trans. Microwave Theory Tech.*, vol. 41, 1993, pp. 2279-2287.

J.W. Bandler, R.M. Biernacki, S.H. Chen, P.A. Grobelny and R.H. Hemmers, “Space mapping technique for electromagnetic optimization,” *IEEE Trans. Microwave Theory Tech.*, vol. 42, 1994, pp. 2536-2544.

J.W. Bandler, R.M. Biernacki, S.H. Chen, R.H. Hemmers and K. Madsen, “Electromagnetic optimization exploiting aggressive space mapping,” *IEEE Trans. Microwave Theory Tech.*, vol. 43, 1995, pp. 2874-2882.

J.W. Bandler, R.M. Biernacki, S.H. Chen, W.J. Getsinger, P.A. Grobelny, C. Moskowitz and S.H. Talisa, “Electromagnetic design of high-temperature superconducting microwave filters,” *Int. J. Microwave and Millimeter-Wave CAE*, vol. 5, 1995, pp. 331-343.

A.H. Zaabab, Q.J. Zhang and M.S. Nakhla, “A neural network modeling approach to circuit optimization and statistical design,” *IEEE Trans. Microwave Theory Tech.*, vol. 43, 1995, pp. 1349-1358.

P.M. Watson and K.C. Gupta, “Design and optimization of CPW circuits using EM-ANN models for CPW components,” *IEEE Trans. Microwave Theory Tech.*, vol. 45, 1997, pp. 2515-2523.

G.L. Creech, B.J. Paul, C.D. Lesniak, T.J. Jenkins and M.C. Calcatera, “Artificial neural networks for fast and accurate EM-CAD of microwave circuits,” *IEEE Trans. Microwave Theory Tech.*, vol. 45, 1997, pp. 794-802.

OSA90/hope™ and Empipe™ Version 4.0, formerly Optimization Systems Associates Inc., P.O. Box 8083, Dundas, Ontario, Canada L9H 5E7, 1997, now Agilent EEsof EDA, 1400 Fountaingrove Parkway, Santa Rosa, CA 95403-1799.

References (continued)

F. Wang and Q.J. Zhang, "Knowledge based neuromodels for microwave design," *IEEE Trans. Microwave Theory Tech.*, vol. 45, 1997, pp. 2333-2343.

em™ Version 5.1a, Sonnet Software, Inc., 1020 Seventh North Street, Suite 210, Liverpool, NY 13088, 1998.

P. Burrascano, M. Dionigi, C. Fancelli and M. Mongiardo, "A neural network model for CAD and optimization of microwave filters," *IEEE MTT-S Int. Microwave Symp. Digest* (Baltimore, MD), 1998, pp. 13-16.

P.M. Watson, K.C. Gupta and R.L. Mahajan, "Development of knowledge based artificial neural networks models for microwave components," *IEEE MTT-S Int. Microwave Symp. Digest* (Baltimore, MD), 1998, pp. 9-12.

P. Burrascano and M. Mongiardo, "A review of artificial neural networks applications in microwave CAD," *Int. J. RF and Microwave CAE*, Special Issue on Applications of ANN to RF and Microwave Design, vol. 9, 1999, pp. 158-174.

J.W. Bandler, N. Georgieva, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "A generalized space mapping tableau approach to device modeling," 29*th European Microwave Conf.* (Munich, Germany), vol. 3, 1999, pp. 231-234.

V.K. Devabhaktuni, C. Xi, F. Wang and Q.J. Zhang, "Robust training of microwave neural models," *IEEE MTT-S Int. Microwave Symp. Digest* (Anaheim, CA), 1999, pp. 145-148.

S. Haykin, *Neural Networks: A Comprehensive Foundation*. New Jersey, MA: Prentice Hall, 1999.

NeuroModeler Version 1.2b, Prof. Q.J. Zhang, Dept. of Electronics, Carleton University, 1125 Colonel By Drive, Ottawa, Ontario, Canada, K1S 5B6, 1999.

P.M. Watson, C. Cho and K.C. Gupta, "Electromagnetic-artificial neural network model for synthesis of physical dimensions for multilayer asymmetric coupled transmission structures," *Int. J. RF and Microwave CAE*, vol. 9, 1999, pp. 175-186.

References (continued)

J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE Trans. Microwave Theory Tech.*, vol. 47, 1999, pp. 2417-2427.

J.W. Bandler, J.E. Rayas-Sánchez, F. Wang and Q.J. Zhang, "Realizations of Space Mapping based neuromodels of microwave components," *AP2000 Millennium Conf. on Antennas & Propagation* (Davos, Switzerland), vol. 1, 2000, pp. 460.

M.H. Bakr, J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neural space mapping optimization for EM-based design," *IEEE Trans. Microwave Theory Tech*., 2000, pp. 2307-2315.

Q.J. Zhang and K.C. Gupta, *Neural Networks for RF and Microwave Design*. Norwood, MA: Artech House, 2000.

J.W. Bandler, N. Georgieva, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "A generalized space mapping tableau approach to device modeling," *IEEE Trans. Microwave Theory Tech*., vol. 49, 2001, pp. 67-79.

J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neural inverse space mapping EM-optimization," *IEEE MTT-S Int. Microwave Symp. Digest* (Phoenix, AZ), 2001.

J.W. Bandler, M.A. Ismail and J.E. Rayas-Sánchez, "Expanded space mapping design framework exploiting preassigned parameters," *IEEE MTT-S Int. Microwave Symp. Digest* (Phoenix, AZ), 2001.

M.H. Bakr, J.W. Bandler, Q.S. Cheng, M.A. Ismail and J.E. Rayas-Sánchez, "SMX—A novel object-oriented optimization system," *IEEE MTT-S Int. Microwave Symp. Digest* (Phoenix, AZ), 2001.