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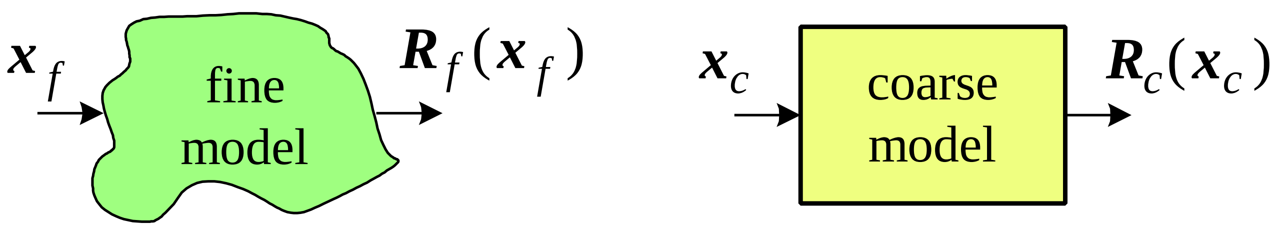
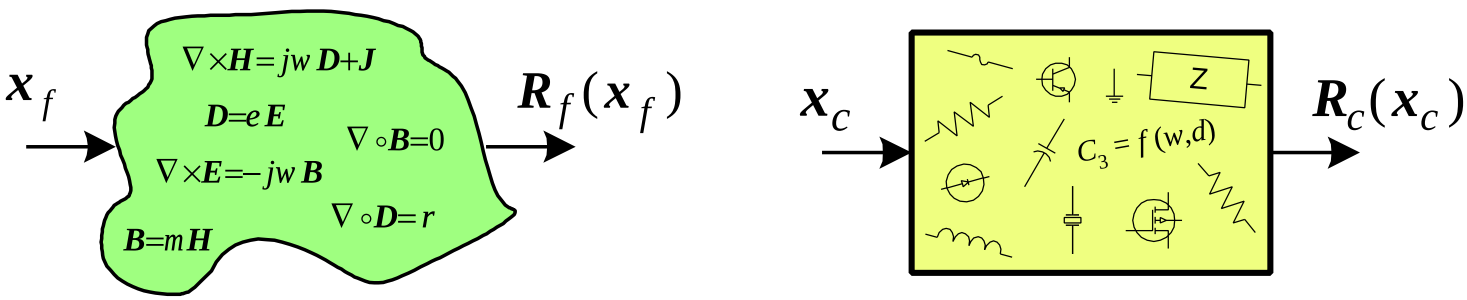
Abstract

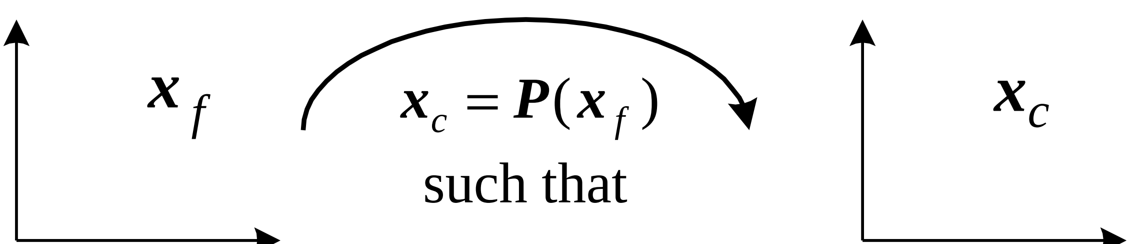
We present neuromodeling of microwave and high frequency circuits based on Space Mapping (SM) technology. Neuromodeling of microwave circuits is briefly reviewed. The aim of SM is described. An innovative scheme to combine SM technology and ANN for modeling is proposed. SM based neuromodels decrease the cost of training, improve generalization ability and reduce the complexity of the ANN topology w.r.t. classical neuromodeling. Huber optimization is proposed to train the neuro-space-mapping (NSM). Space-Mapped Neuromodeling (SMN) is illustrated by a microstrip line with high dielectric constant.

The Aim of Space Mapping

(Bandler et al., 1994-)







$$\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_f)$$

such that

$$\boldsymbol{R}_c(\boldsymbol{P}(\boldsymbol{x}_f)) \approx \boldsymbol{R}_f(\boldsymbol{x}_f)$$

Artificial Neural Network (ANN) Modeling

Artificial Neural Networks can model high-dimensional and highly nonlinear problems

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

the size of an ANN does not grow exponentially with dimension *(White et al., 1992)*

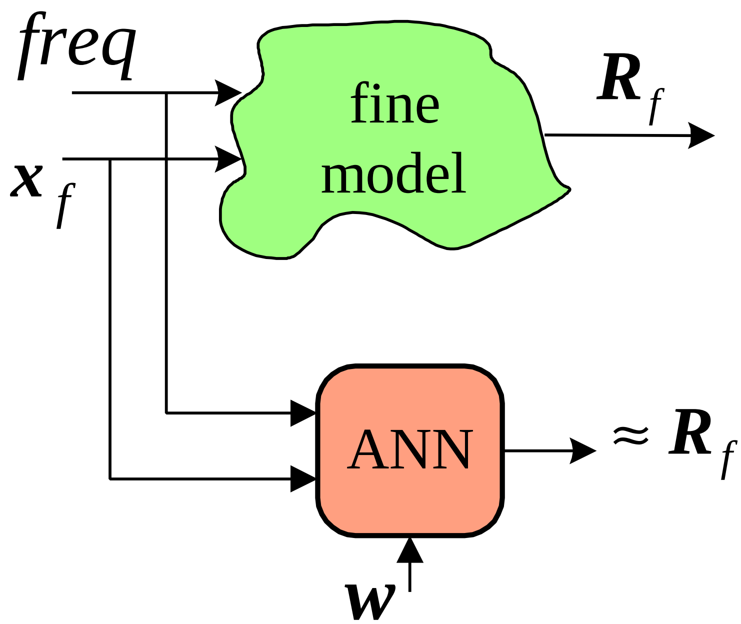
in theory, it can approximate any degree of nonlinearity to any desired level of accuracy, provided a deterministic relationship between input and target exists *(White et al., 1992)*

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

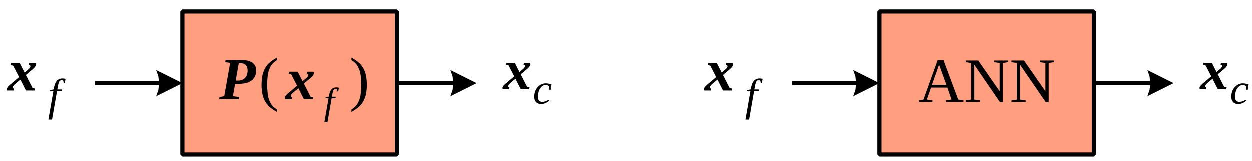


large amount of training data is usually needed to ensure model accuracy

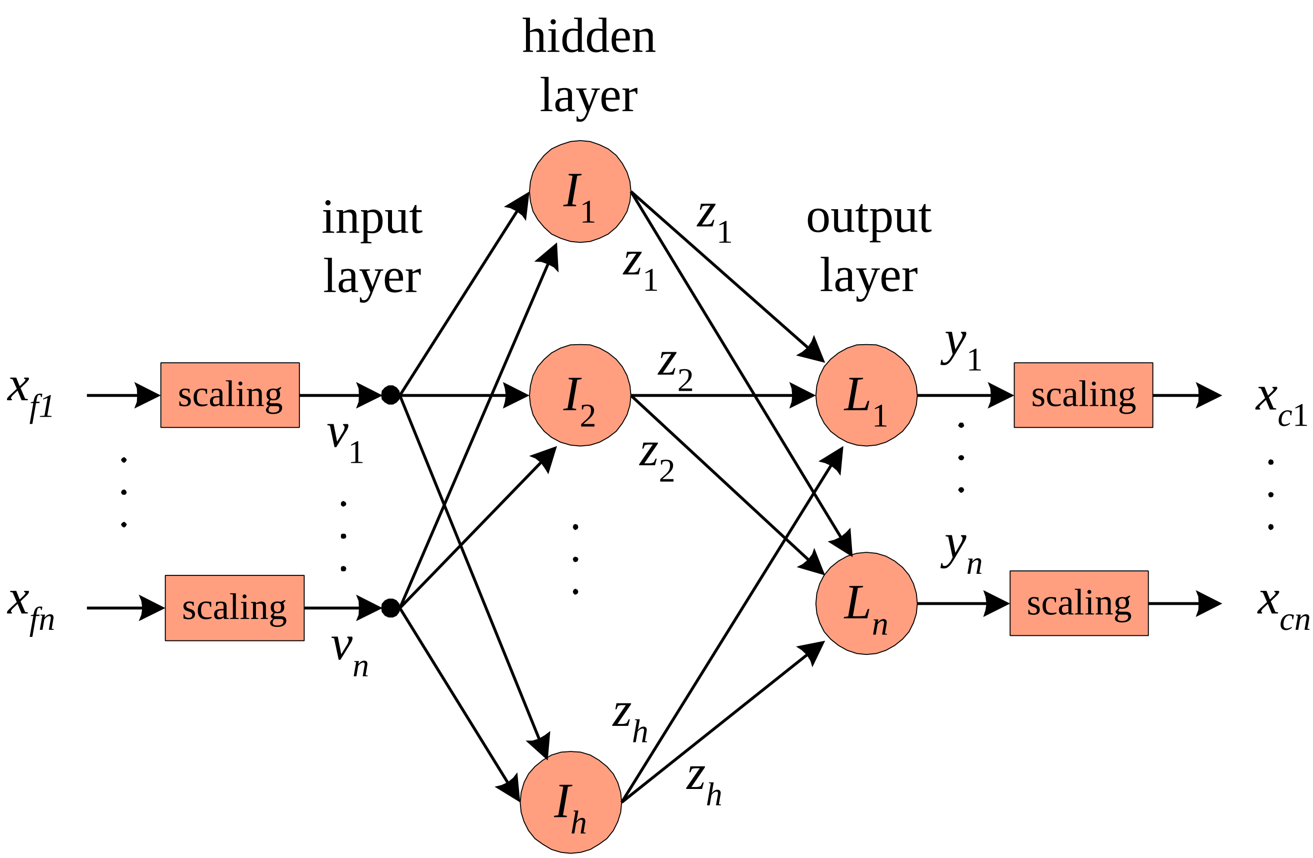
the number of learning samples needed to approximate a function grows exponentially with the ratio between the dimensionality and its degree of smoothness (*Stone*, *1982*)

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

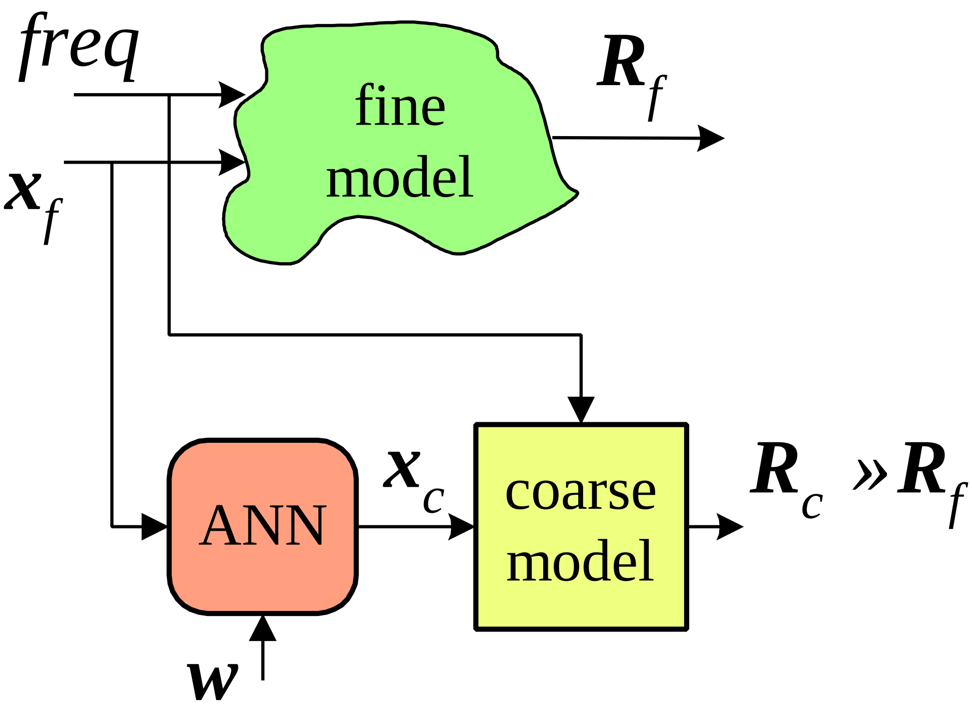
Neural Space Mapping



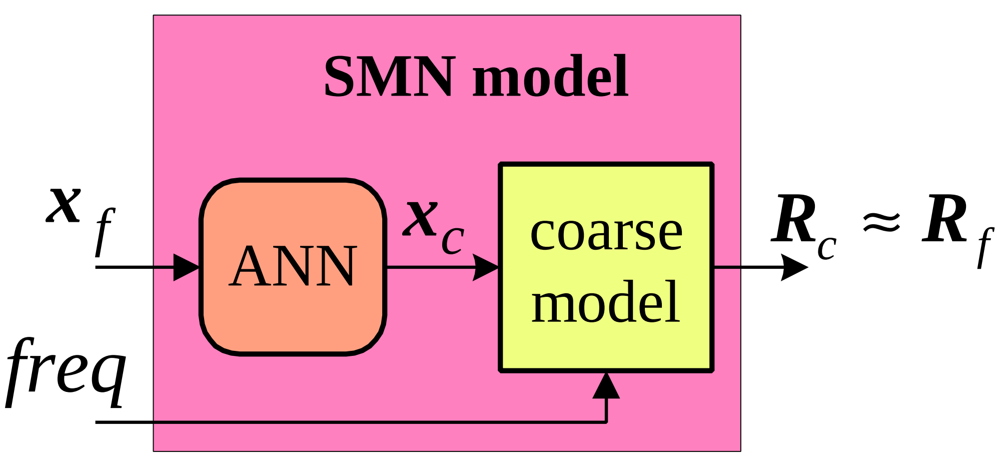
using a three layer perceptron (3LP)



Space Mapped Neuromodeling (SMN) Concept



once the ANN is trained

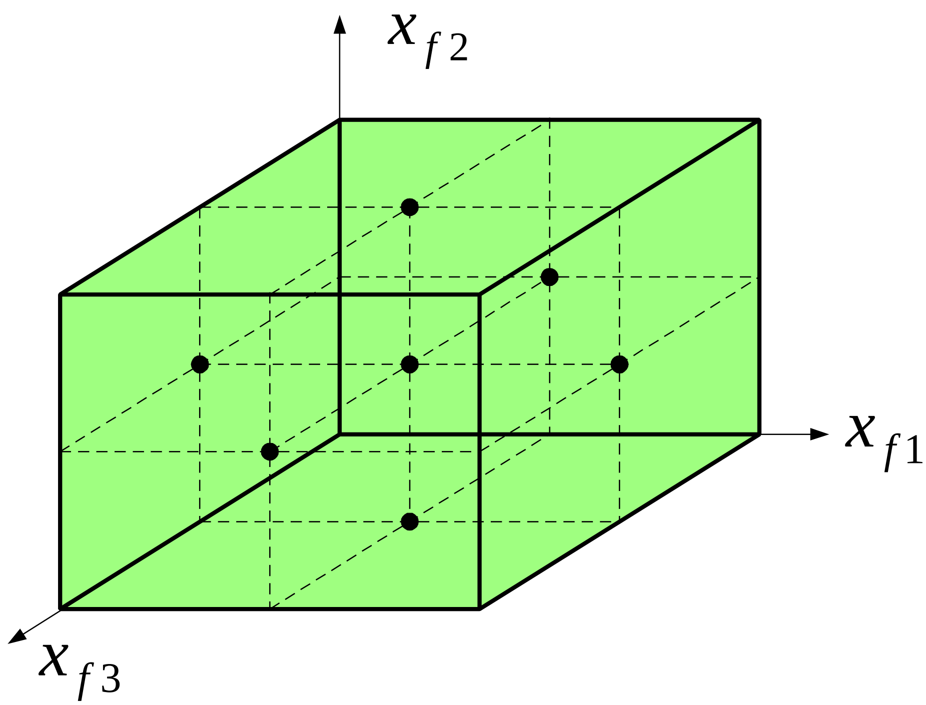


Starting Point and Learning Samples

the starting point for the optimization problem is chosen such that $\boldsymbol{x}_c \approx \boldsymbol{x}_f$

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 $B_p = 2n + 1$



Training the ANN for SMN

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

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

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

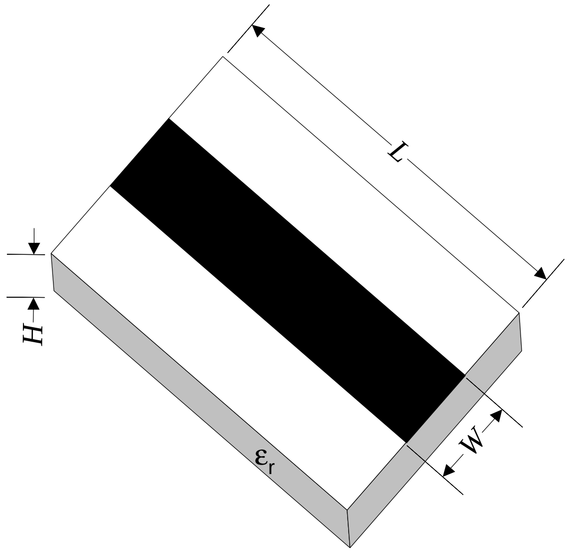
with

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

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

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

Microstrip Line with High Dielectric Constant



region of interest

$$5\text{mil} \le W \le 9\text{mil}$$
$$15\text{mil} \le H \le 25\text{mil}$$
$$40\text{mil} \le L \le 60\text{mil}$$
$$20 \le e_r \le 25$$
$$27\text{GHz} \le freq \le 30\text{GHz}.$$

“coarse” model: Pozar’s formulas *(Pozar, 1998)*

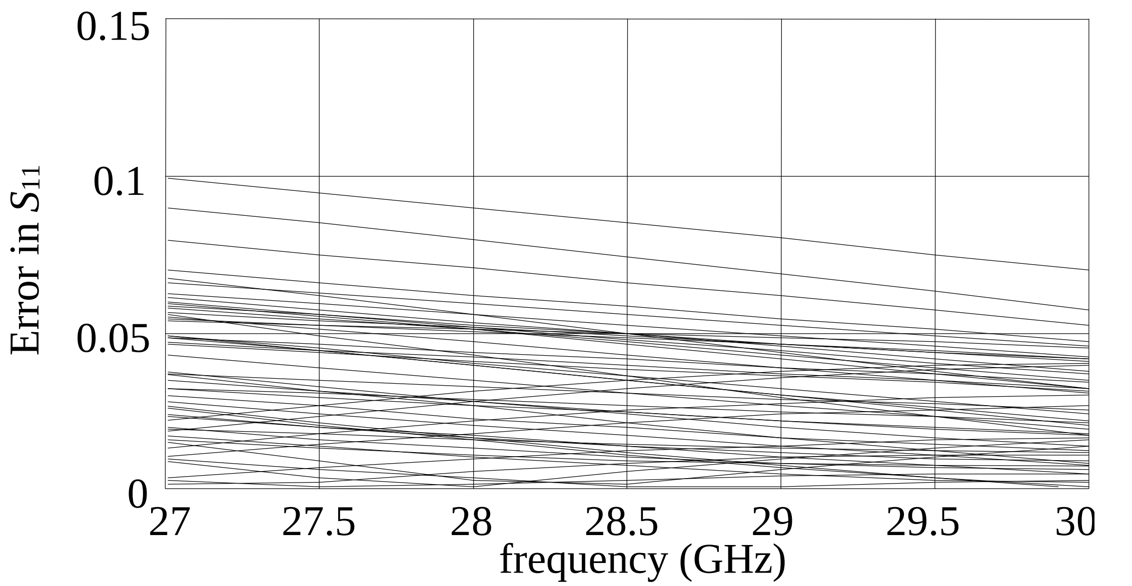
“fine” model: Sonnet’s ***em***™

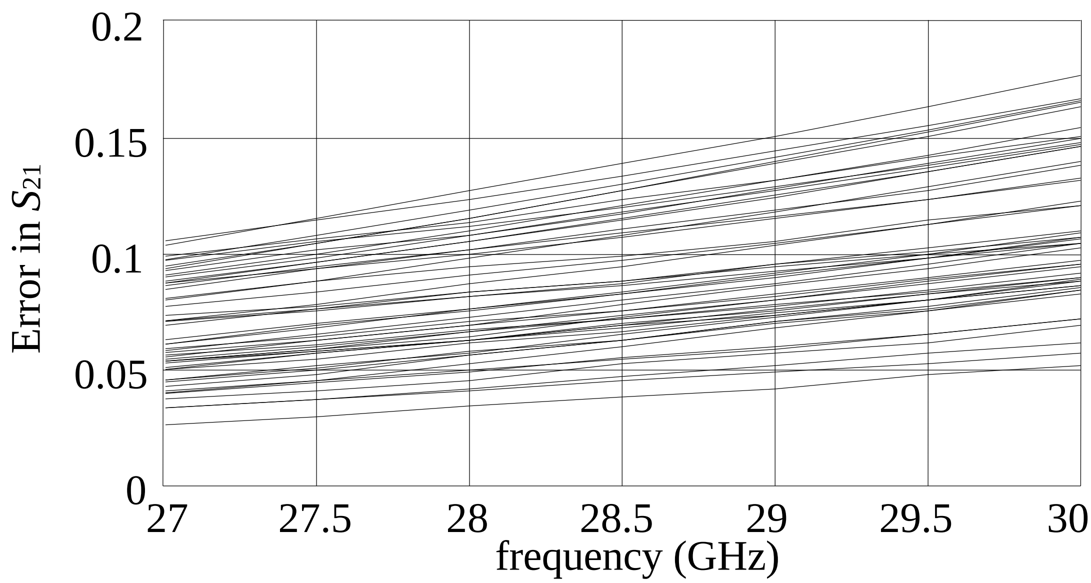
learning set: 9 base points with “star” distribution

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

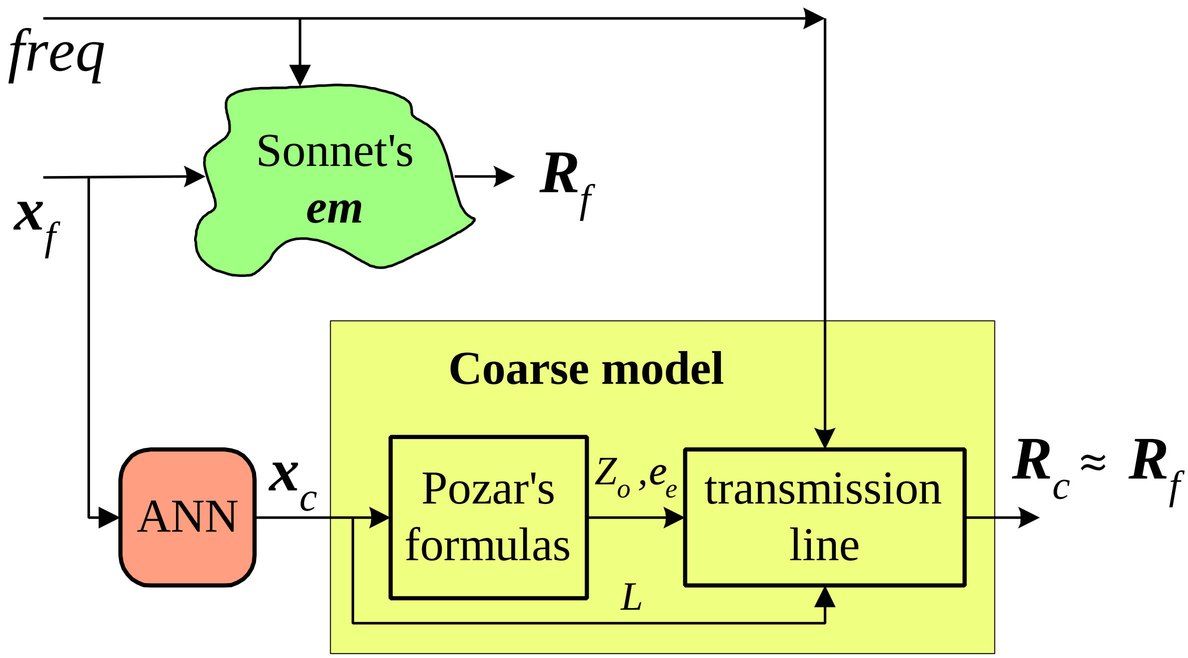
Microstrip Line Response Errors

comparison before neuromodeling between ***em***™ and Pozar's model at 50 random test points



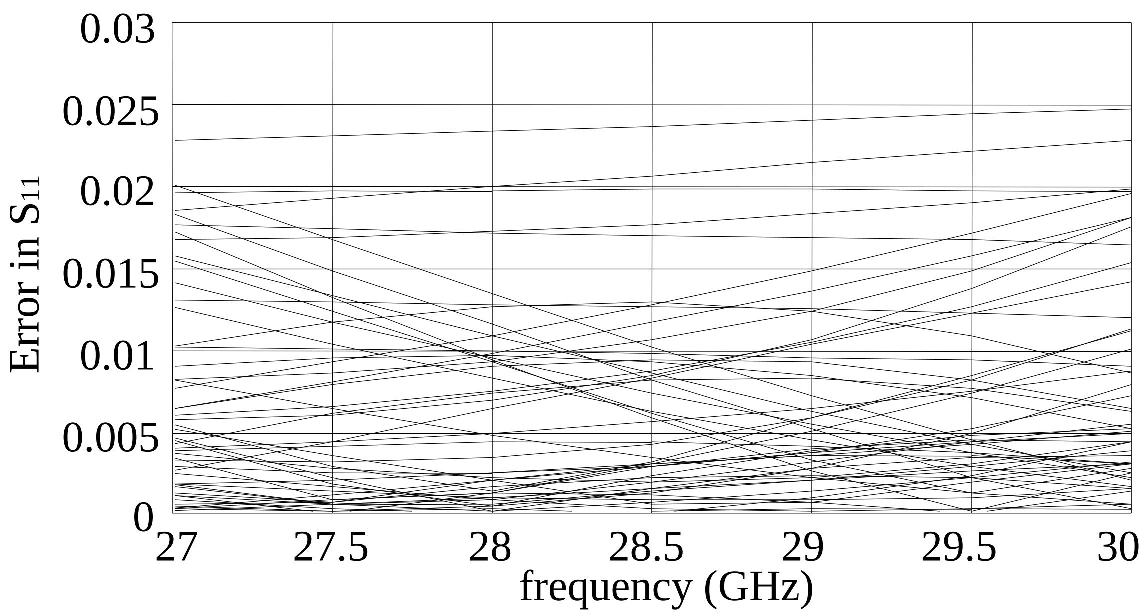


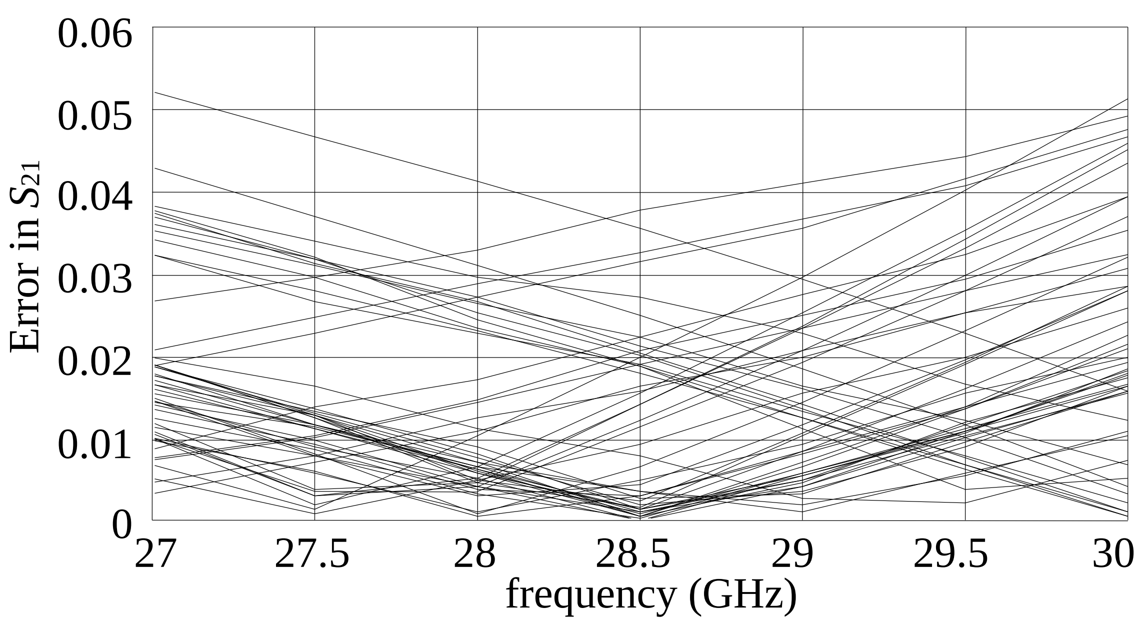
SMN Model for the Microstrip Line (3LP:4-3-4)



SMN Model Results for the Microstrip Line

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





Other SM Based Neuromodeling techniques

four new SM based neuromodeling techniques have been developed

Frequency-Dependent Space Mapped Neuromodeling (FDSMN)

Frequency Space Mapped Neuromodeling (FSMN)

Frequency Mapped Neuromodeling (FMN)

Frequency Partial-Space Mapped Neuromodeling (FPSMN)

they make even better use of the implicit knowledge of the coarse model

these techniques have been applied to a microstrip right angle bend and to an HTS filter, with excellent results

New Results

J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "Neuromodeling of microwave circuits exploiting space mapping technology," *IEEE MTT-S Int. Microwave Symp.* (Anaheim, CA), June 1999.

J.W. Bandler and J.E. Rayas-Sánchez, "Circuit CAD and modeling through space mapping," *IEEE MTT-S Int. Microwave Symp.*, Workshop WSFD (Anaheim, CA), June 1999.

J.W. Bandler, M.A. Ismail, J.E. Rayas-Sánchez and Q.J. Zhang, "New directions in model development for RF/microwave components utilizing artificial neural networks and space mapping," *IEEE AP-S Int. Symp.* (Orlando, FL), July 1999.

J.W. Bandler, J.E. Rayas-Sánchez and Q.J. Zhang, "Neural modeling and space mapping: two approaches to circuit design," *XXVI URSI General Assembly* (Toronto, ON), August 1999.

Conclusions

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

Space Mapped Neuromodels (SMN) are described and illustrated

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

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