Modeling and Design of Electronic Circuits using Artificial Neural Networks

Dr. José Ernesto Rayas-Sánchez

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Outline

- Conventional ANN-based optimization
- Neural EM-design exploiting knowledge
- Example of space mapping based neuromodeling
- Example of neural inverse space mapping optimization
- ANN-based statistical design
- Synthesis neural networks
- Transient EM-design using neural networks
- Future directions and conclusions

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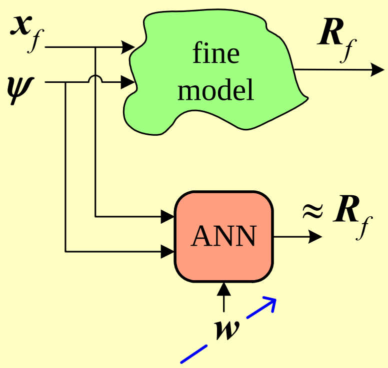
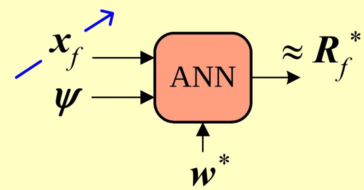
Conventional ANN-Based Optimization

Step 1



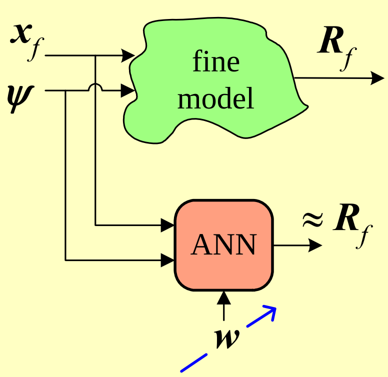
Step 2



Many fine model simulations are needed: the number of learning samples grows exponentially with the dimensionality *(Stone, 1982)*

Solutions predicted outside the training region are unreliable

Conventional Neural Optimization – Step 1



$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^T \quad \ldots \quad \boldsymbol{e}_L^T]^T \right\|$$

$$\boldsymbol{e}_k(\boldsymbol{w}) = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w})$$

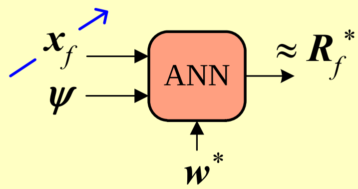
$$i = 1, \ldots, l$$

$$j = 1, \ldots, \tau$$

$$k = j + \tau(i-1)$$

L learning samples
$\boldsymbol{N}$ neural network output
l training base points for the design parameters
τ independent variable points

Conventional Neural Optimization – Step 2

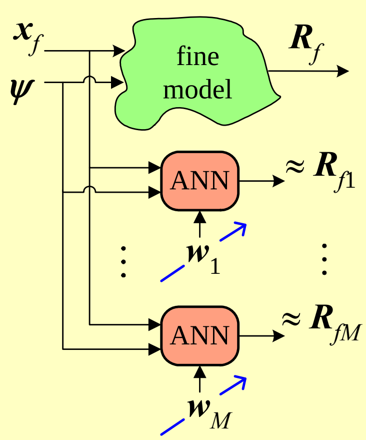


$$\boldsymbol{x}_f^* = \arg \min_{\boldsymbol{x}_f} U(\boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*))$$

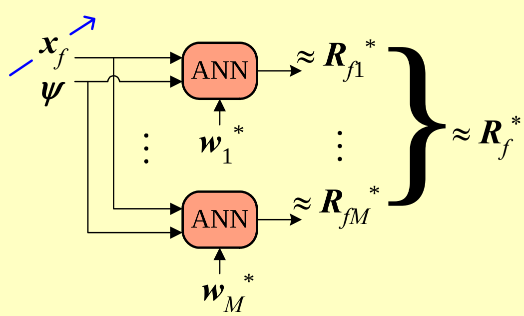
U is the objective function expressed in terms of the design specifications

Decomposed Conventional Neural Optimization

Step 1



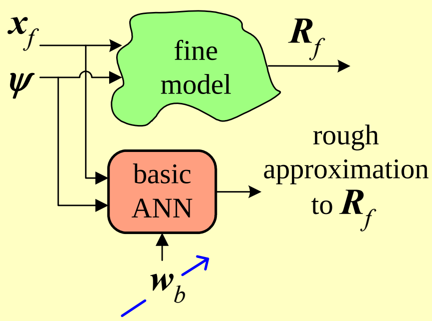
Step 2



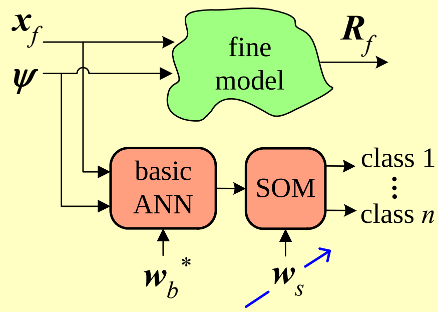
(Teyssier et al., 1999)

Clustered Self Organizing Feature Maps (SOM)

Step 1



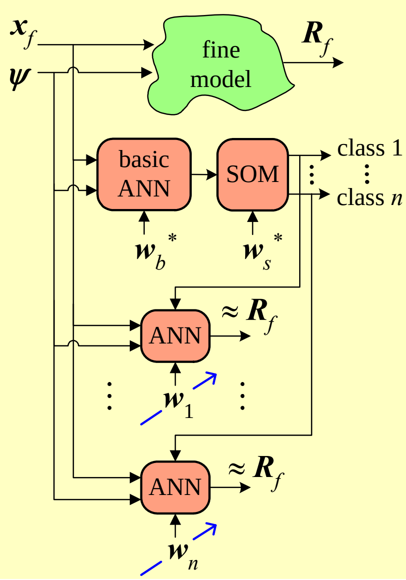
Step 2



(Mongiardo et al., 1999)

Clustered SOMs (continue)

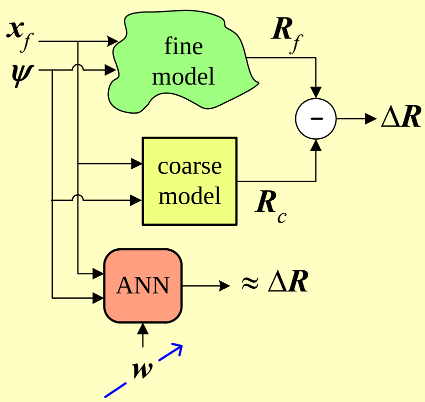
Step 3



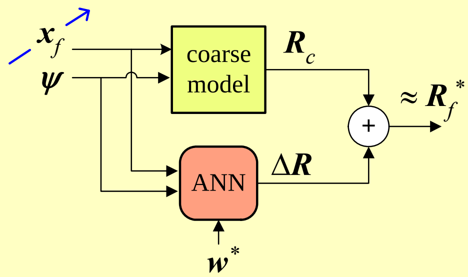
(Mongiardo et al., 1999)

The Difference Method for Neural Optimization

Step 1



Step 2

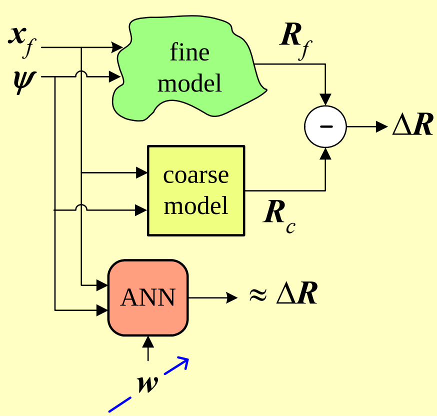


(Gupta et al., 1996, 1999)

The Difference Method – Step 1

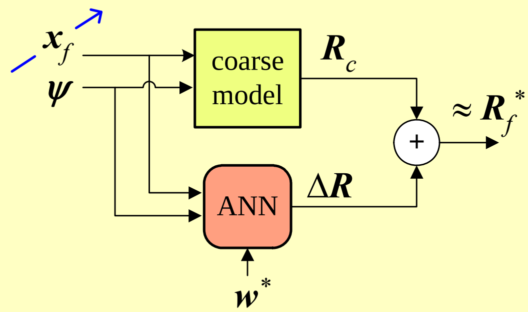
$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^T \quad \dots \quad \boldsymbol{e}_L^T]^T \right\|$$

$$\boldsymbol{e}_k(\boldsymbol{w}) = [\boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j)] - \boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w})$$



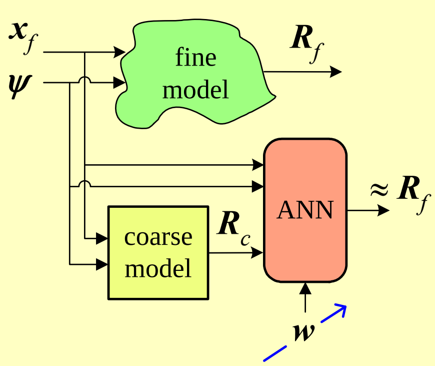
The Difference Method – Step 2

$$\boldsymbol{x}_f^* = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_c(\boldsymbol{x}_f, \boldsymbol{\psi}) + \boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*))$$

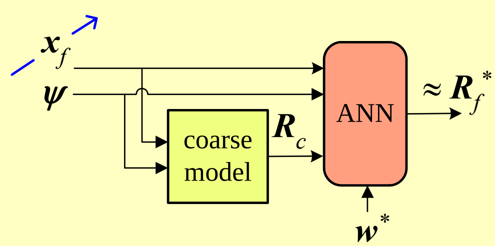


The PKI Method for Neural Optimization

Step 1



Step 2

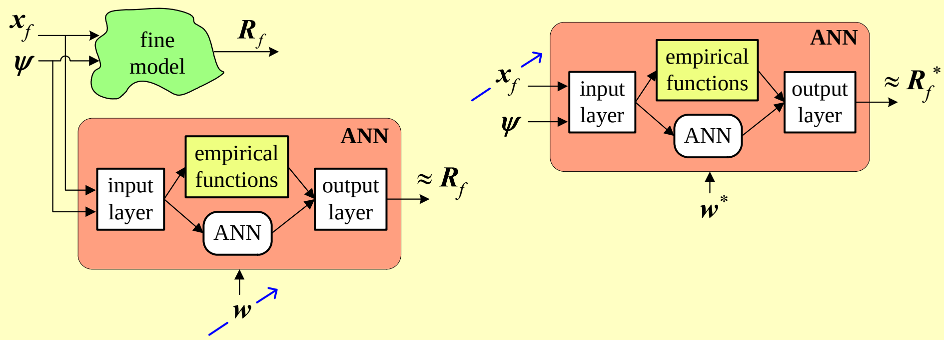


(Gupta et al., 1998, 1999)

Knowledge-Based Neural Networks (KBNN)

Step 1

Step 2



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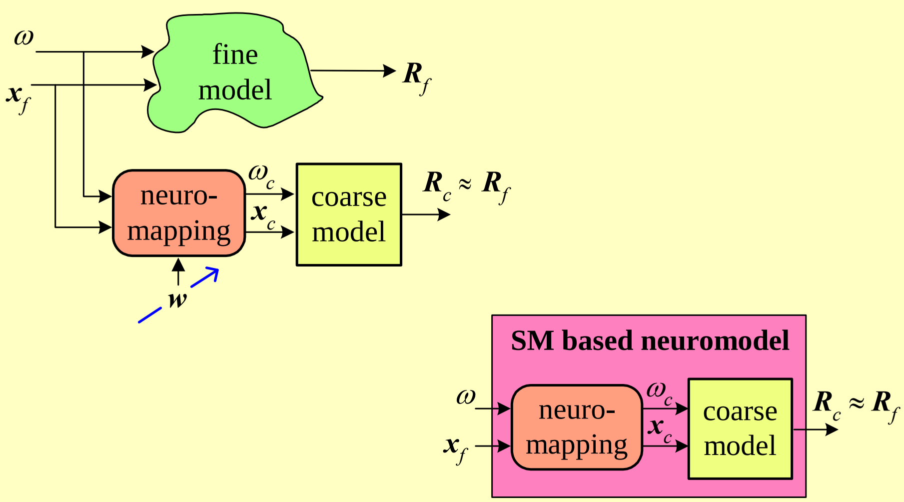
(Zhang et al., 1997, 2000)

Space Mapping Based Neuromodeling



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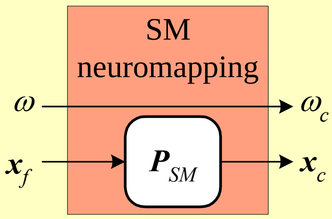
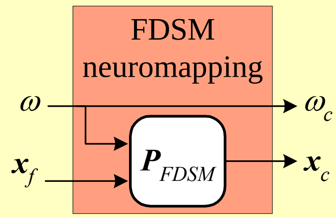
(Bandler et al., 1999)

Neuromappings

Space mapped (SM) neuromapping



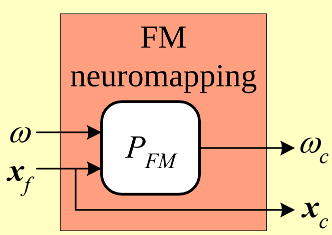
Frequency-dependent space mapped (FDSM) neuromapping



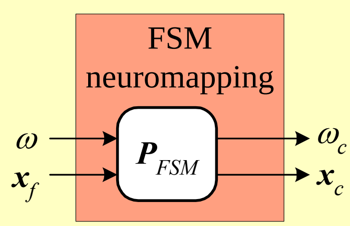
(Bandler et al., 1999)

Neuromappings (cont.)

Frequency mapped (FM) neuromapping



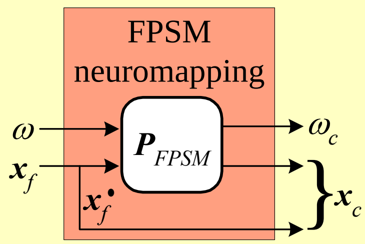
Frequency space mapped (FSM) neuromapping



(Bandler et al., 1999)

Neuromappings (cont.)

Frequency partial space mapped (FPSM) neuromapping



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

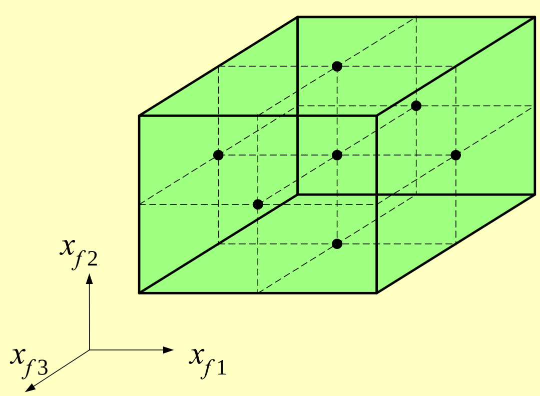
Coarse model sensitivities can be used to select the mapped parameters

(Bandler et al., 1999)

SM-based Neuromodeling – Training Region

Star distribution of learning base points

Random distribution of testing base points

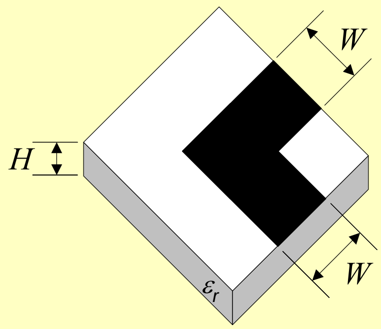


$2n+1$ learning based points are used for a circuit with n design parameters

(Bandler et al., 1999)

SM-based Neuromodeling – Example

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

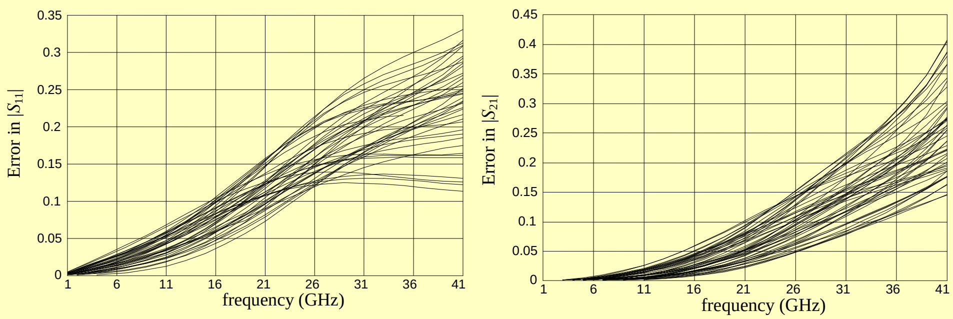
Testing set: 50 random base points

(Bandler et al., 1999)

SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

Errors of the coarse model with respect to the fine model at 50 random base points

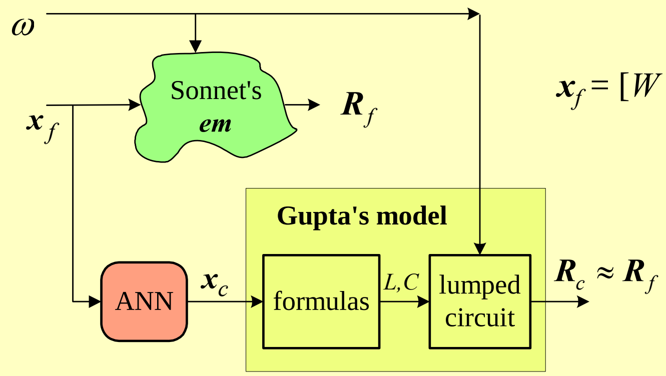


(Bandler et al., 1999)

SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

SM neuromodel for the right angle bend (3LP:3-6-3)



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

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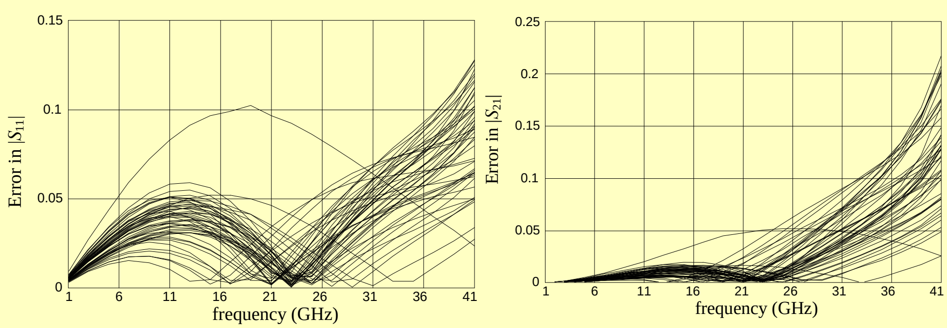
(Bandler et al., 1999) 21

SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

Errors of the SM neuromodel for the right angle bend (3LP:3-6-3)



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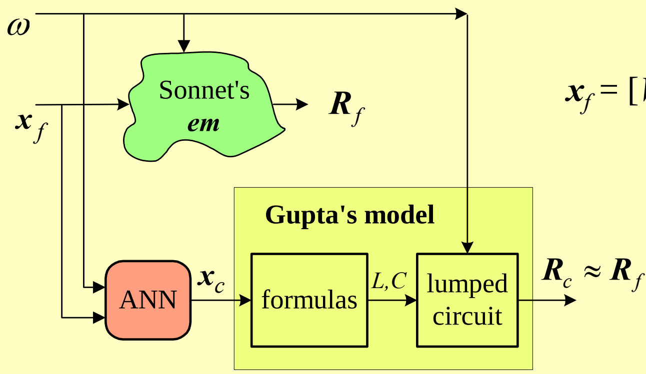
(Bandler et al., 1999) 22

SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

FDSM neuromodel for the right angle bend (3LP:4-7-3)

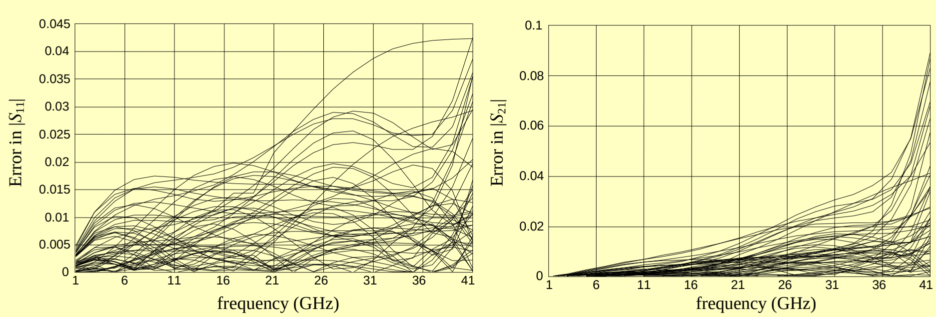


$\boldsymbol{x}_f = [W \;\; H \;\; \varepsilon_r]^T$

SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

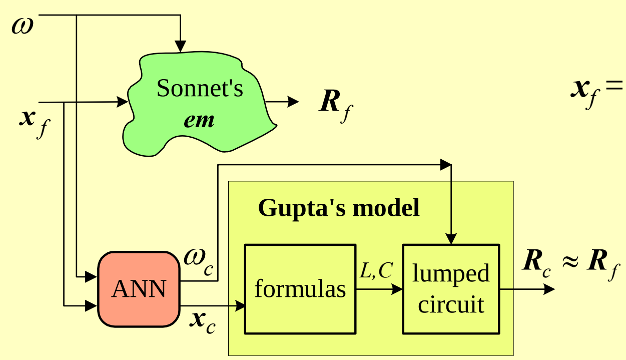
Errors of the FDSM neuromodel for the right angle bend (3LP:4-7-3)



SM-based Neuromodeling – Example (cont.)

Microstrip right angle bend

FSM neuromodel for the right angle bend (3LP:4-8-4)

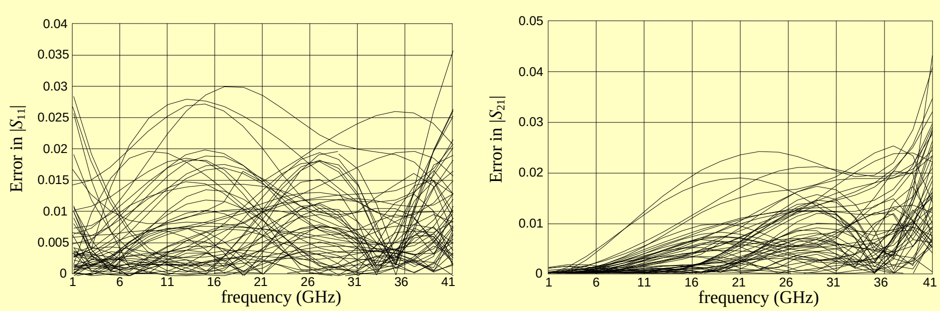


$$x_f = [W \;\; H \;\; \varepsilon_r]^T$$

SM-based Neuromodeling – Example (cont.)

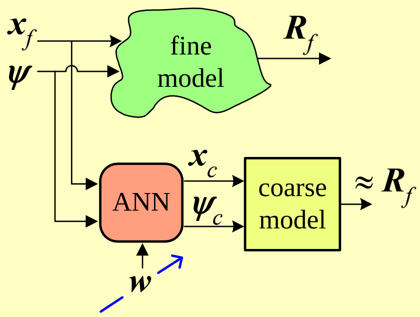
Microstrip right angle bend

Errors of the FSM neuromodel for the right angle bend (3LP:4-8-4)

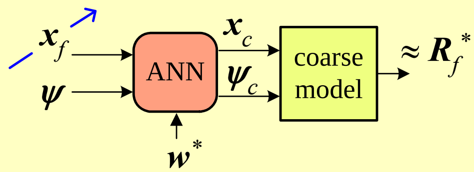


Neural Space Mapping (NSM) Optimization

Step 1



Step 2

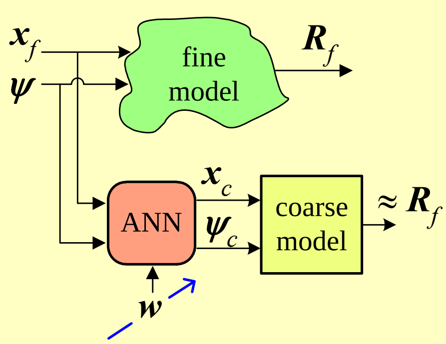


(Bandler et al., 2000)

NSM Optimization – Step 1

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^T \quad \ldots \quad \boldsymbol{e}_L^T]^T \right\|$$

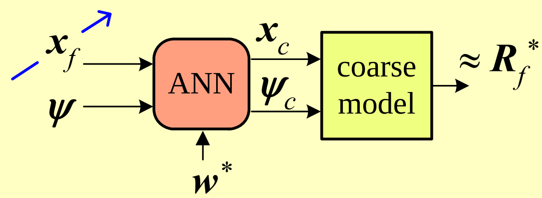
$$\boldsymbol{e}_k(\boldsymbol{w}) = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w}))$$



(Bandler et al., 2000)

NSM Optimization – Step 2

$$\boldsymbol{x}_f^{(i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_c(\boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*)))$$



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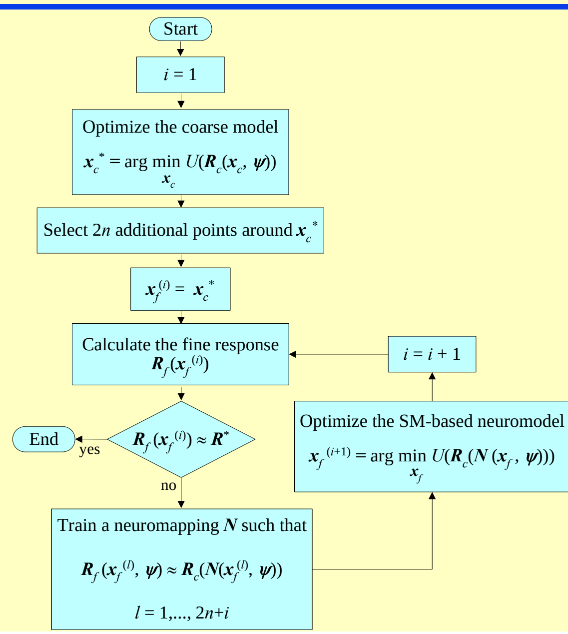
(Bandler et al., 2000) 29

NSM Algorithm



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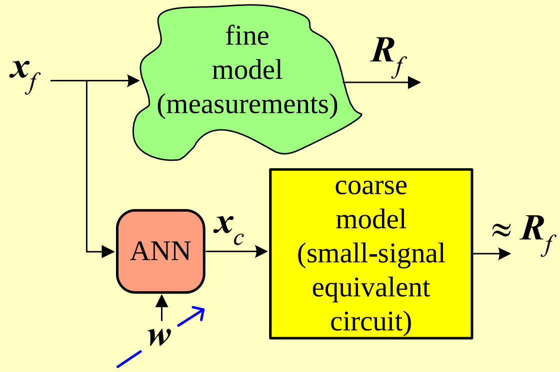
Extended NSM Modeling Approach



$\boldsymbol{x}_c = [C_{gs}\ \ R_i\ \ C_{gd}\ \ g_m\ \ \tau\ \ g_{ds}\ \ C_{ds}]^T$

$\boldsymbol{x}_f = [V_{GS}\ \ V_{DS}]^T$

$\boldsymbol{R}_f$ contains the S-parameters measured at various bias settings

(Shirakawa et al., 1998,1999)

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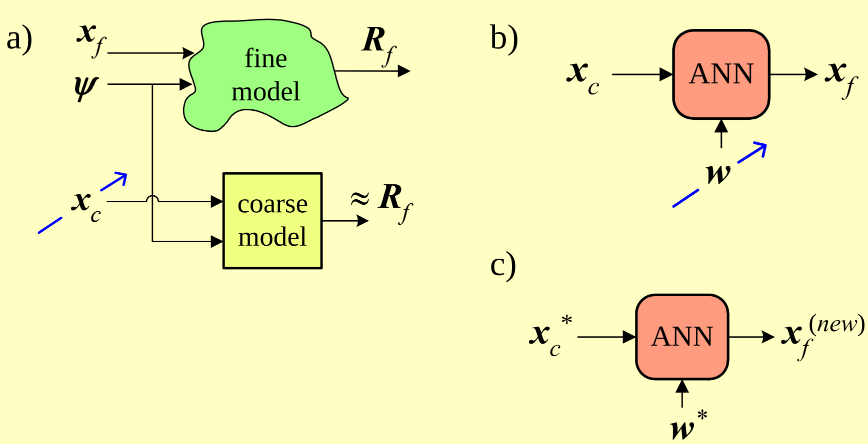
Neural Inverse Space Mapping (NISM)

Main subprocesses



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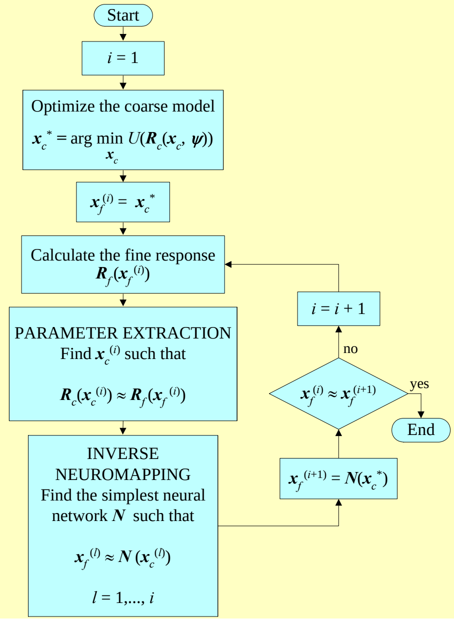
NISM Optimization Algorithm



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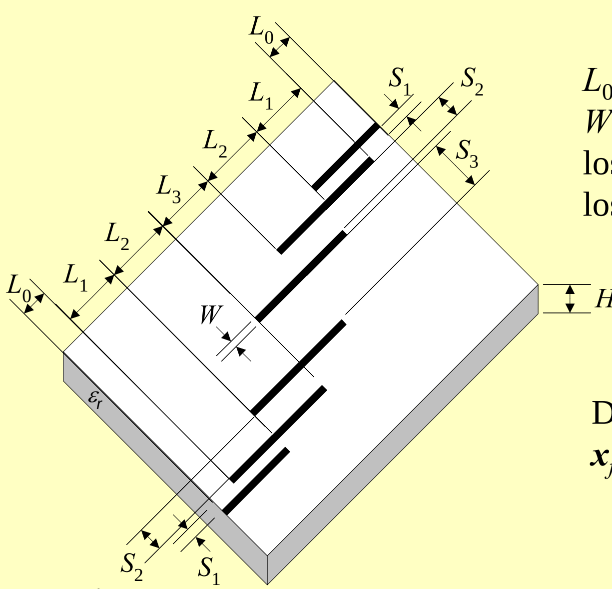
HTS Filter *(Westinghouse, 1993)*



L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; lossless metalization

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

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NISM Optimization of the HTS Microstrip Filter

Specifications

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

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

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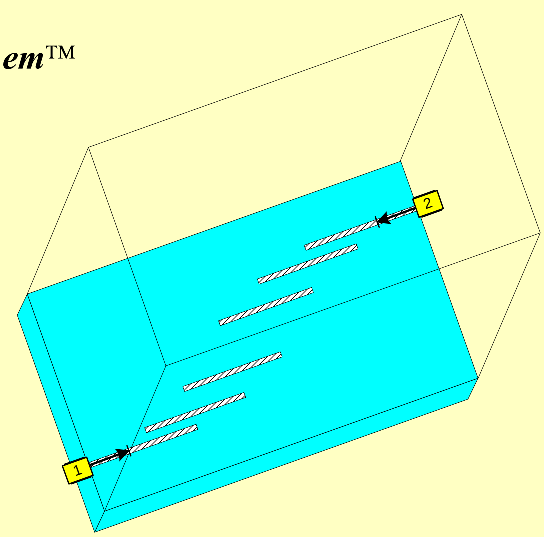
NISM Optimization of the HTS Microstrip Filter

Fine model

Sonnet's ***em***™



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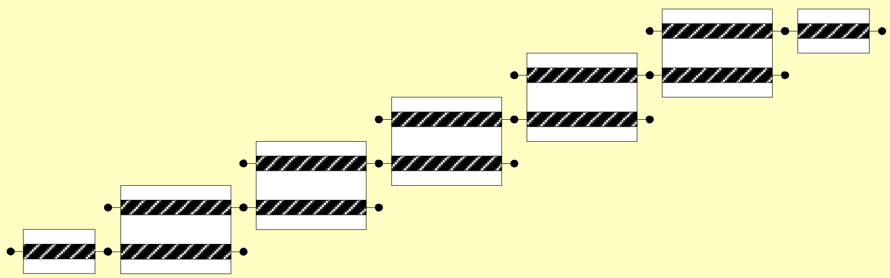
NISM Optimization of the HTS Microstrip Filter

Coarse model

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



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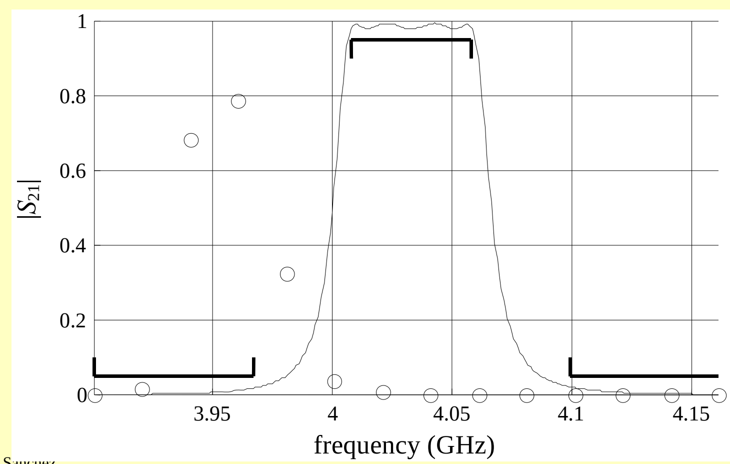
NISM Optimization of the HTS Microstrip Filter

Starting point

OSA90/hope™ (–) and ***em***™ (o) at $\boldsymbol{x}_c^*$



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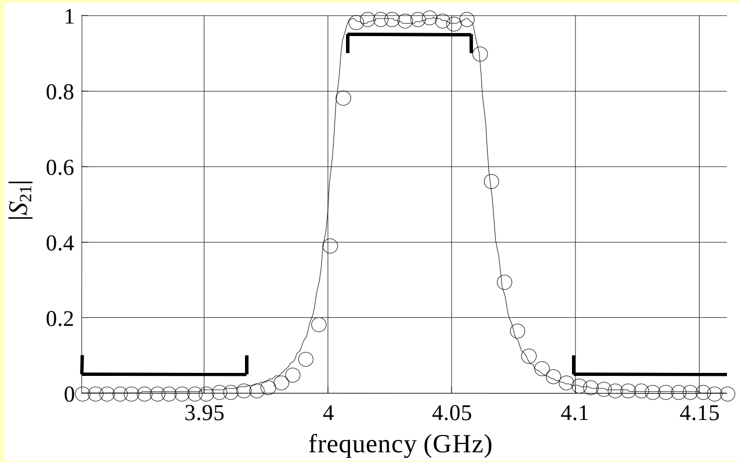
NISM Optimization of the HTS Filter (cont)

Responses using OSA90/hope™ (–) at $\boldsymbol{x}_c^*$ and ***em***™ (o) at the NISM solution (after 3 NISM iterations)



Yield Optimization with SM-based Neuromodels

$$\boldsymbol{R}_f(\boldsymbol{x}_f,\omega) \approx \boldsymbol{R}_{SMBN}(\boldsymbol{x}_f,\omega)$$

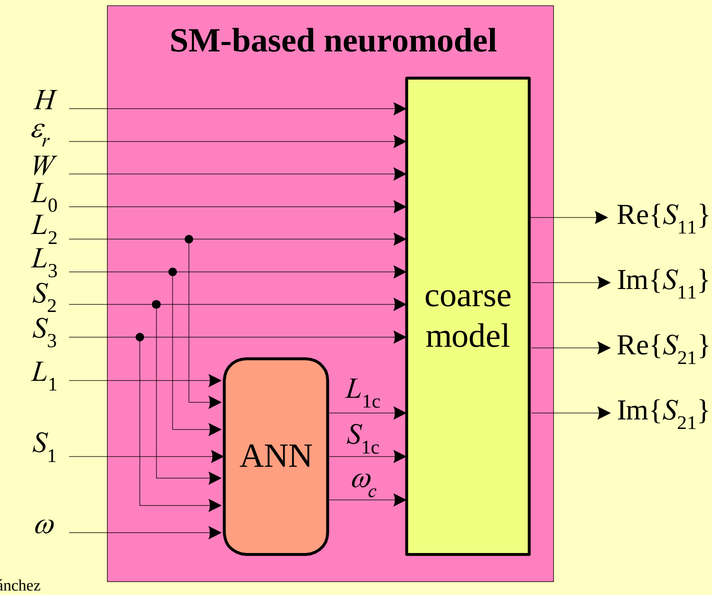
for all $\boldsymbol{x}_f$ and ω in the training region

We can show that

$$\boldsymbol{J}_f \approx \boldsymbol{J}_c\,\boldsymbol{J}_P$$

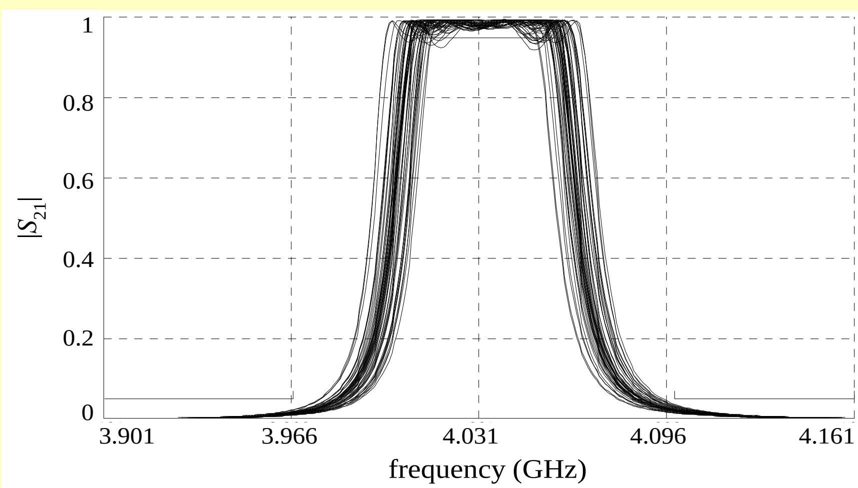
$\boldsymbol{J}_f \in \Re^{r\times n}$	Jacobian of the fine model responses w.r.t. the fine model parameters
$\boldsymbol{J}_c \in \Re^{r\times(n+1)}$	Jacobian of the coarse model responses w.r.t. the coarse model parameters and mapped frequency
$\boldsymbol{J}_P \in \Re^{(n+1)\times n}$	Jacobian of the mapping function w.r.t. the fine model parameters

SM-based Neuromodel of the HTS Filter



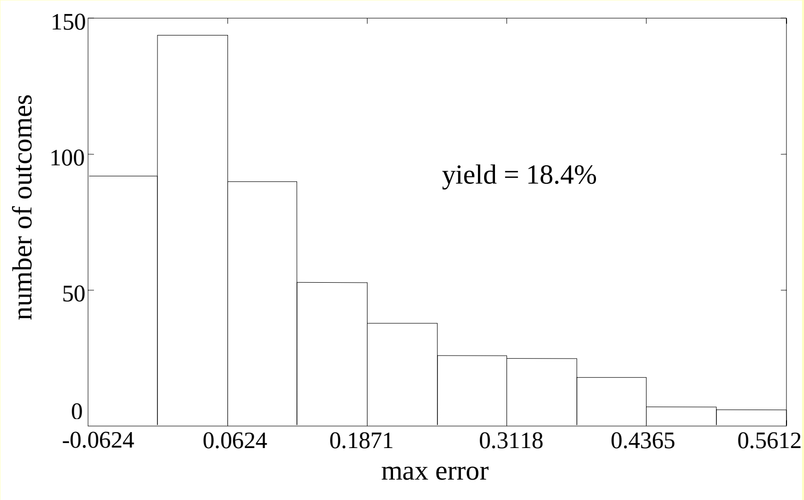
Yield Analysis of the HTS Filter (cont)

At the nominal SM-solution: yield = 18.4%



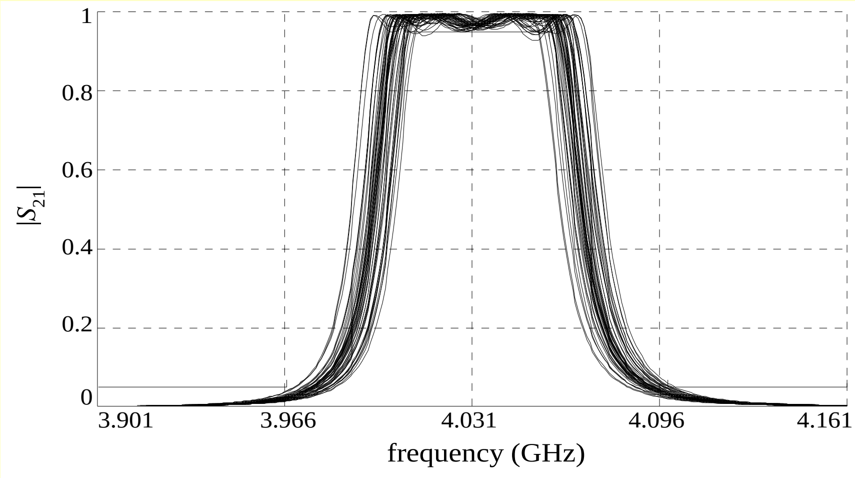
Yield Analysis of the HTS Filter (cont)

At the nominal SM-solution: yield = 18.4%



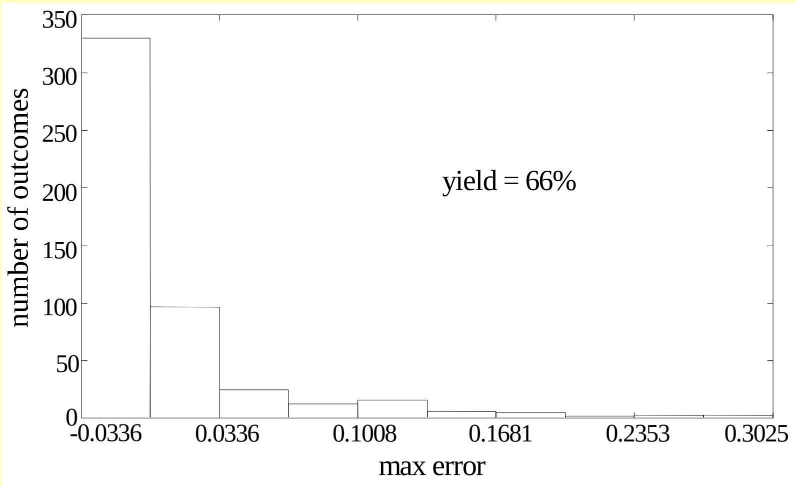
Yield Optimization of the HTS Filter

At the optimal yield SM-solution: yield = 66%



Yield Optimization of the HTS Filter (cont)

At the optimal yield SM-solution: yield = 66%



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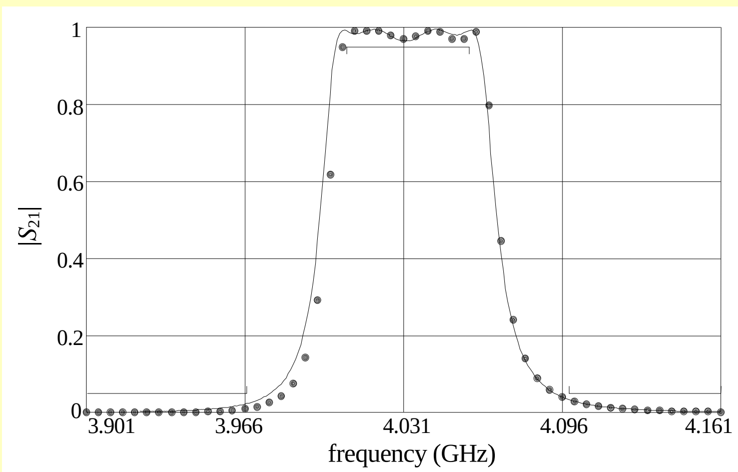
Yield Optimization of the HTS Filter (cont)

em™ (•) response and SM-based neuromodel (–) response at the optimal yield SM-solution



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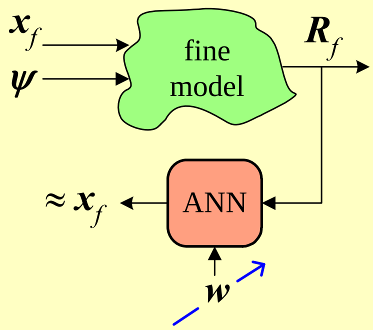
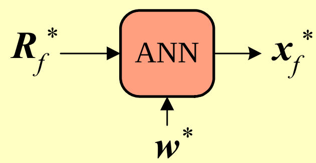
Synthesis ANNs for Microwave Design

Step 1



Step 2



The mapping usually is multi-valued

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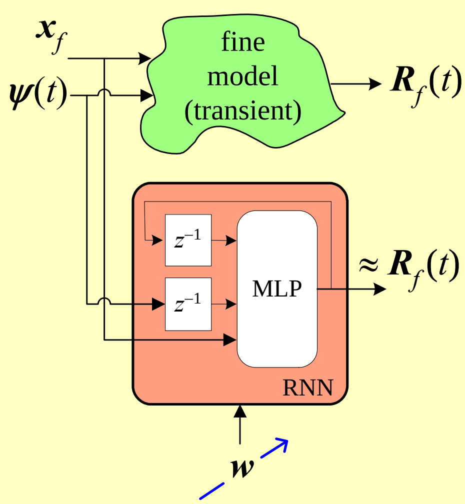
(Gupta et al., 1999 , Selleri et al., 2002) 47

Neuromodels for Transient Domain



$\psi(t)$ input waveforms

$R_f(t)$ fine model output waveforms amplitudes

Critical issues for training RNNs:

- sampling cycle
- number of unit-delay elements in each bank of delays

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(Zhang et al., 2000, 2002) 48

Some Future Directions

- More algorithmic on-line approaches to neural EM-based design (e.g., exploiting parallel computing)
- An integrated transient and frequency domain ANN-based design approach
- More ANN EM-based design methods exploiting circuital models

Conclusions

- Relevant work in EM-based design and optimization of microwave circuits exploiting ANNs is reviewed
- The conventional ANN optimization approach is described
- Strategies for ANN EM-based design that exploit knowledge are reviewed
- ANN-based design using synthesis neural networks is mentioned
- Key issues on transient EM-based design using ANNs are described
- Future directions of ANN techniques for microwave design are mentioned