# EM-Based Optimization of Microwave Circuits using Artificial Neural Networks

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### Abstract

Neural network applications in microwave engineering have been reported since the 1990s. Description of artificial neural networks and their key issues, namely architectures, paradigms, training methods, data sets formation, learning and generalization errors, learning speed, etc., in the context of microwave CAD, has been extensively reported. It is clear that neural networks have been widely used for modeling microwave devices and circuits, in many innovative ways.

In contrast, the use of neural networks for microwave design by optimization is at a less developed stage. This presentation aims at reviewing the most relevant work in electromagnetics-based design and optimization of microwave circuits exploiting artificial neural networks (ANNs). Measurement-based design of microwave circuits using ANNs is also considered.

The conventional and most popular microwave neural optimization approach is reviewed. Advantages and drawbacks of this strategy are emphasized. Improvements of this “black-box” approach such as segmentation, decomposition, hierarchy, design of experiments (DoE) and clusterization are mentioned.

The main limitations of the conventional neural optimization approach can be alleviated by incorporating available knowledge into the neural network training scheme. Several innovative strategies are reviewed, including the Difference Method (also called Hybrid EM-ANN), the Prior Knowledge Input (PKI) Method, the Knowledge-Based ANN approach (KBNN), the Neural Space Mapping (NSM) optimization method, the Extended Neural Space Mapping approach, and the Neural Inverse Space Mapping (NISM) optimization algorithm. Practical examples using these techniques are illustrated, including EM-based statistical design of relevant microwave problems.

Another strategy for ANN-based design of microwave circuits consists of using synthesis neural networks, also called “inverse neural models”. A synthesis neural network is trained to learn the mapping from the responses to the design parameters of the microwave circuit. Difficulties in developing synthesis neural networks are indicated.

Finally, the key issues on transient EM-based design using neural networks are described. Suitable paradigms for approximating nonlinear dynamic behaviors are mentioned, such us Recurrent Neural Networks (RNN) and their corresponding training techniques.

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## Outline

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

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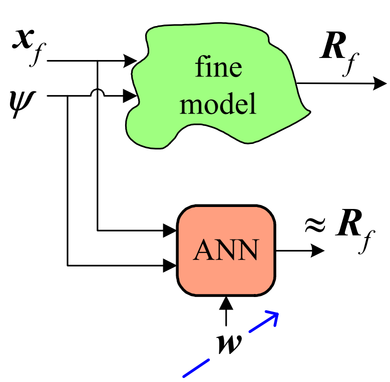
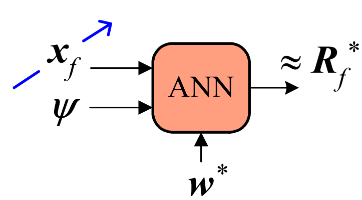
## Conventional ANN-Based Optimization

Step 1




Step 2




Many fine model simulations are needed

Solutions predicted outside the training region are unreliable

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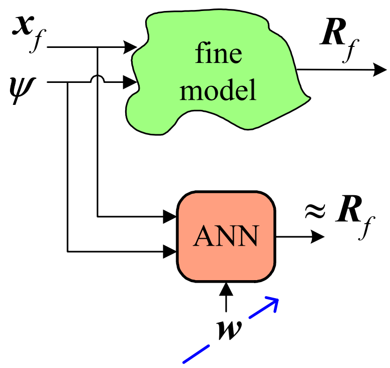
## Conventional Neural Optimization – Step 1




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

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

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

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

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

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

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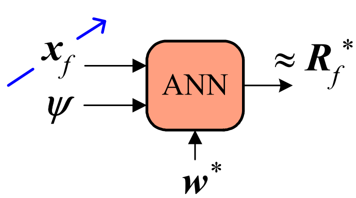
## Conventional Neural Optimization – Step 2




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

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

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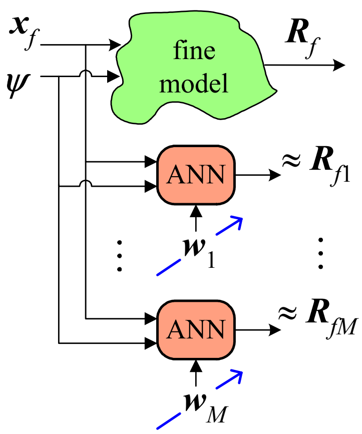
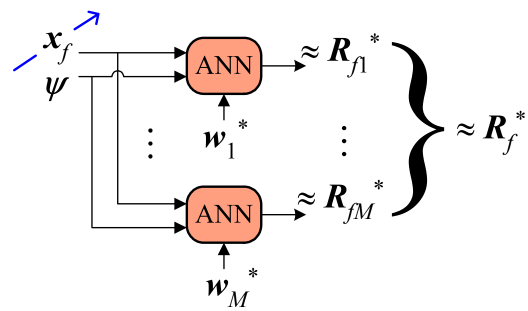
## Decomposed Conventional Neural Optimization

Step 1




Step 2

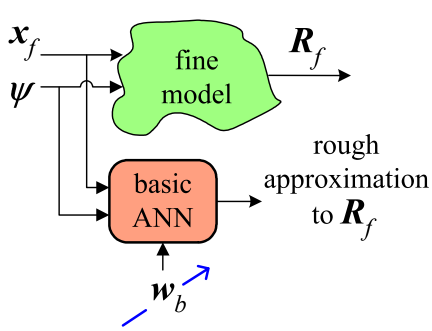



*(Teyssier et al., 1999)*

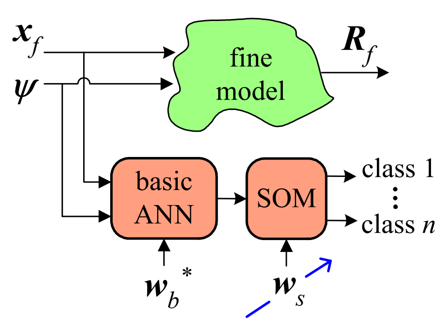


## Clustered Self Organizing Feature Maps (SOM)

Step 1



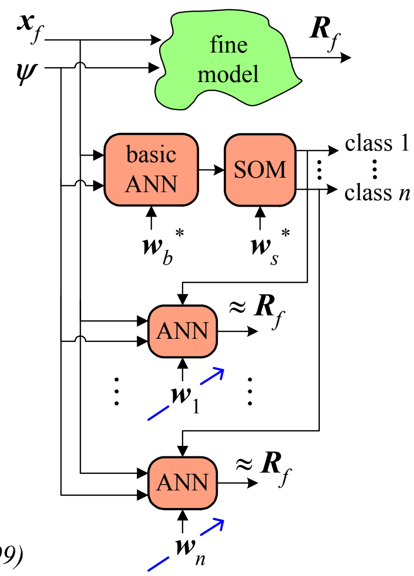

Step 2




*(Mongiardo et al., 1999)*

## Clustered SOMs (continue)

Step 3




*(Mongiardo et al., 1999)*

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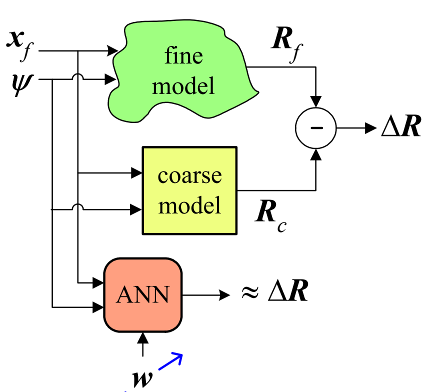
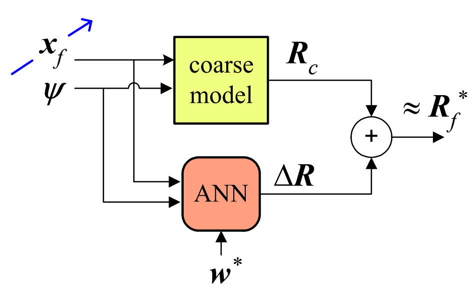
## The Difference Method for Neural Optimization

Step 1




Step 2




*(Gupta et al., 1996, 1999)*

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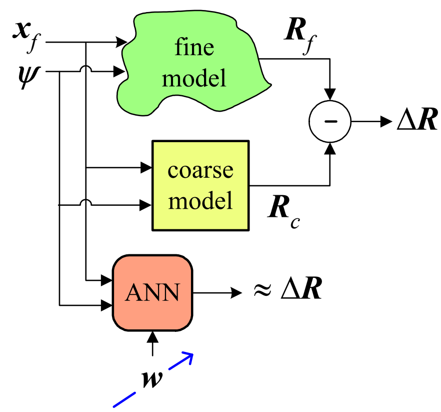
## The Difference Method – Step 1

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

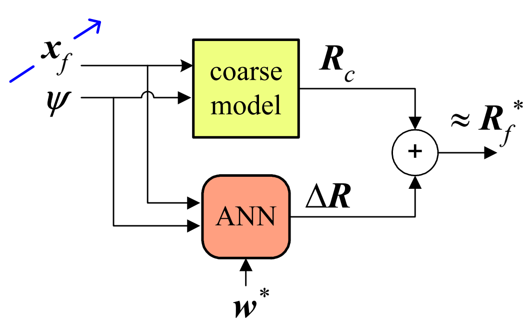
$$\boldsymbol{e}_k(\boldsymbol{w}) = [\boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j)] - \boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w})$$





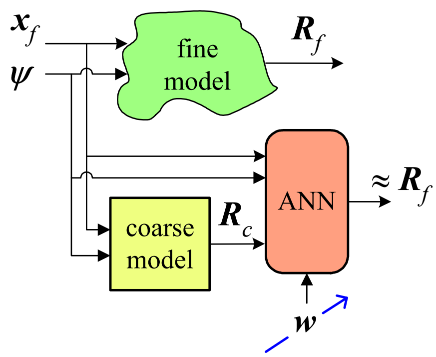

## The Difference Method – Step 2

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

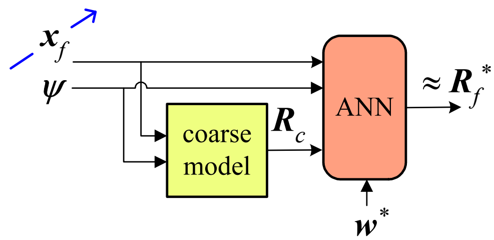


## The PKI Method for Neural Optimization

Step 1




Step 2

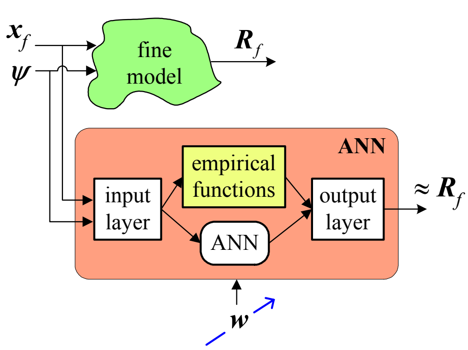



*(Gupta et al., 1998, 1999)*

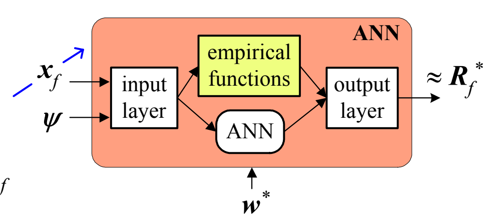


## Knowledge-Based Neural Networks (KBNN)

Step 1

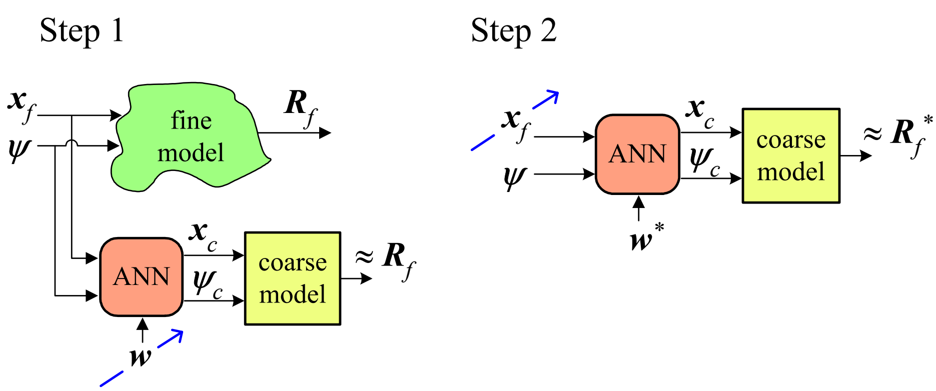



Step 2




*(Zhang et al., 1997, 2000)*

## Neural Space Mapping (NSM) Optimization



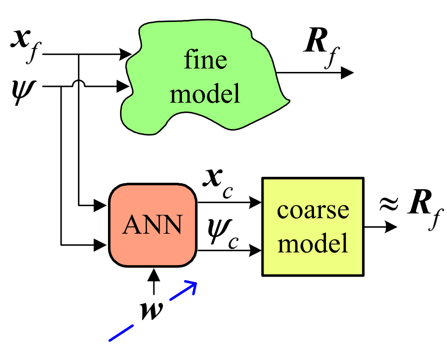

*(Bandler et al., 2000)*



## NSM Optimization – Step 1

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

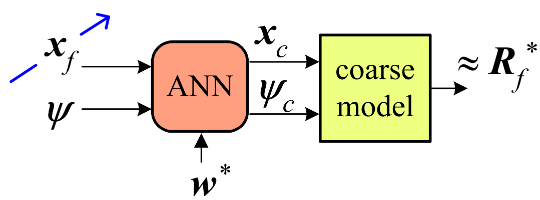
$$\boldsymbol{e}_k(\boldsymbol{w}) = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w}))$$




*(Bandler et al., 2000)*

# NSM Optimization – Step 2

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




*(Bandler et al., 2000)*

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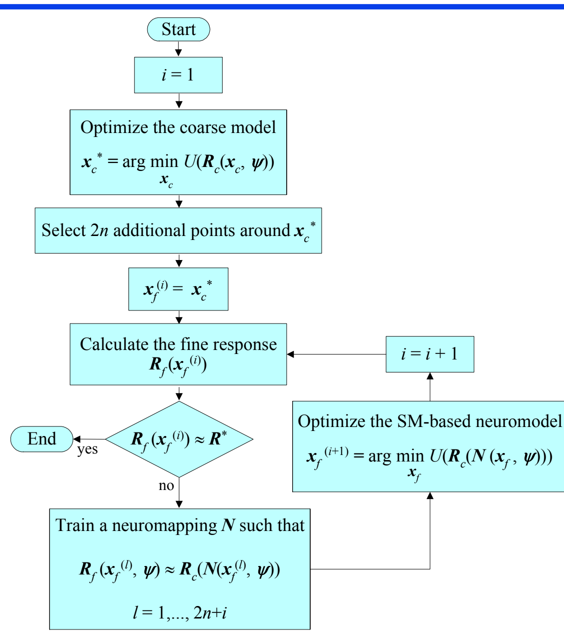
# NSM Algorithm

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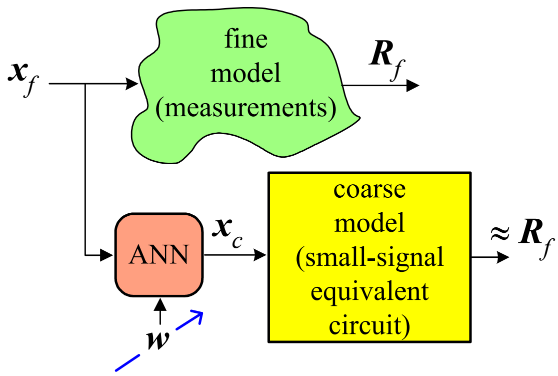
## Extended NSM Modeling Approach




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

$x_f = [V_{GS}\ \ V_{DS}]^T$

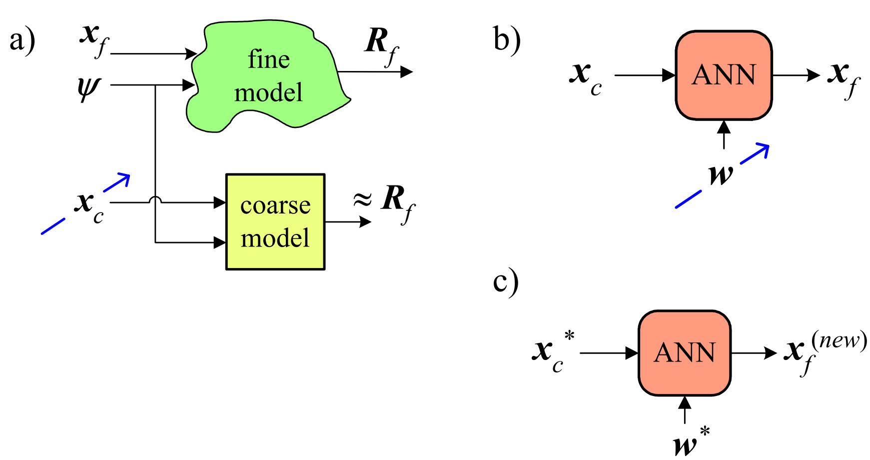
$R_f$ contains the S-parameters measured at various bias settings

*(Shirakawa et al., 1998,1999)*



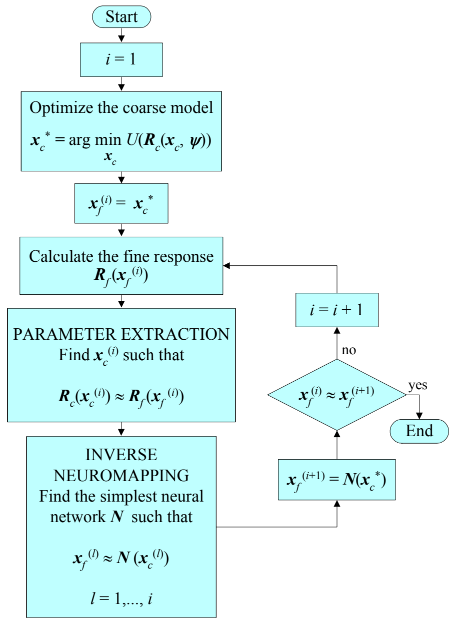
## Neural Inverse Space Mapping (NISM)

Main subprocesses



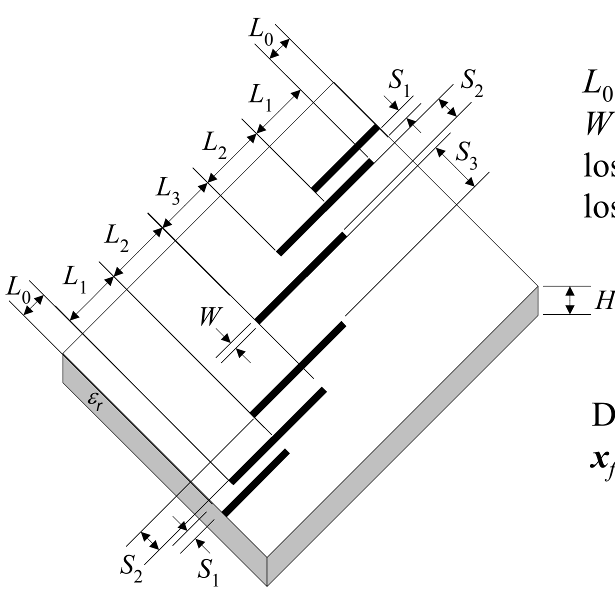

*(Bandler et al., 2001)*

# NISM Optimization Algorithm






# HTS Filter *(Westinghouse, 1993)*




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

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

# 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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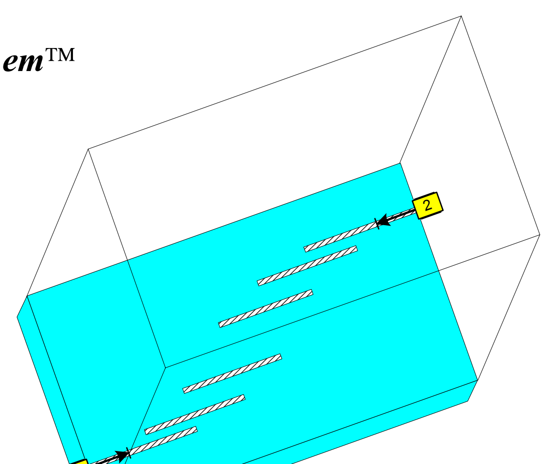
# NISM Optimization of the HTS Microstrip Filter

Fine model

Sonnet's ***em***™

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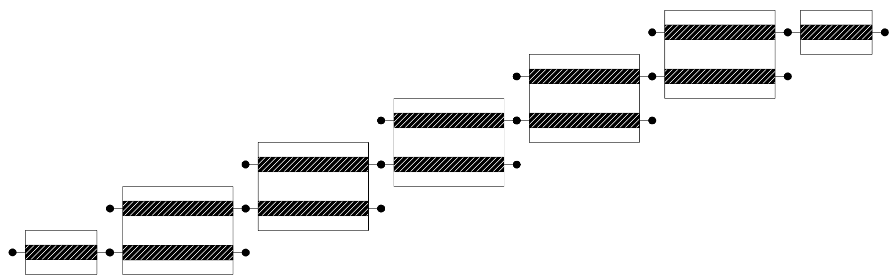
# NISM Optimization of the HTS Microstrip Filter

Coarse model

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

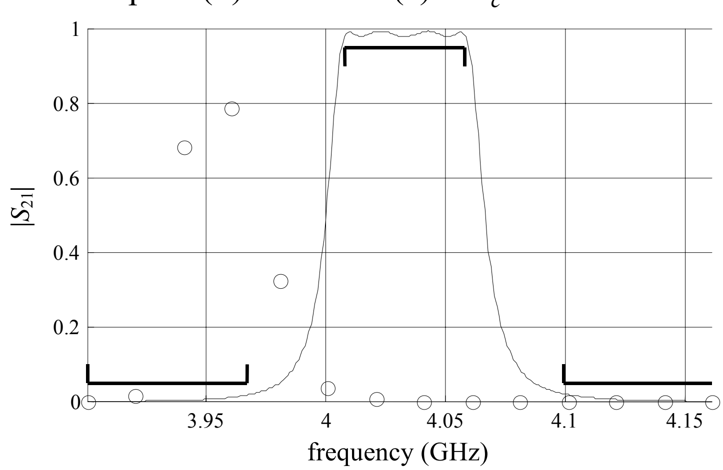




# NISM Optimization of the HTS Microstrip Filter

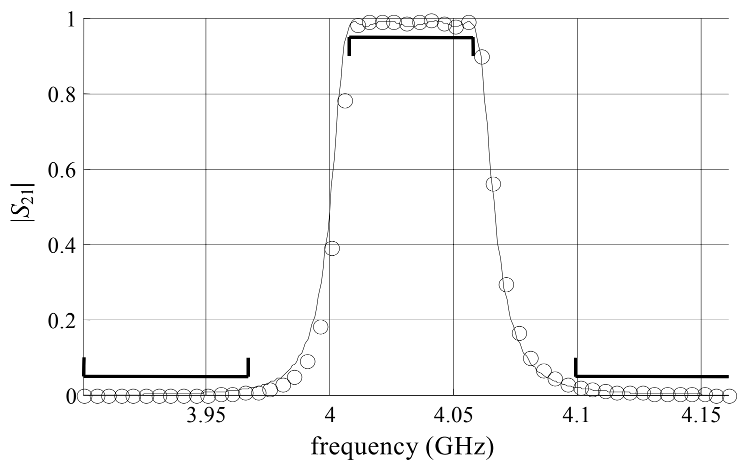
Starting point

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



# NISM Optimization of the HTS Filter (cont)

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






# Yield Optimization with SM-based Neuromodels

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

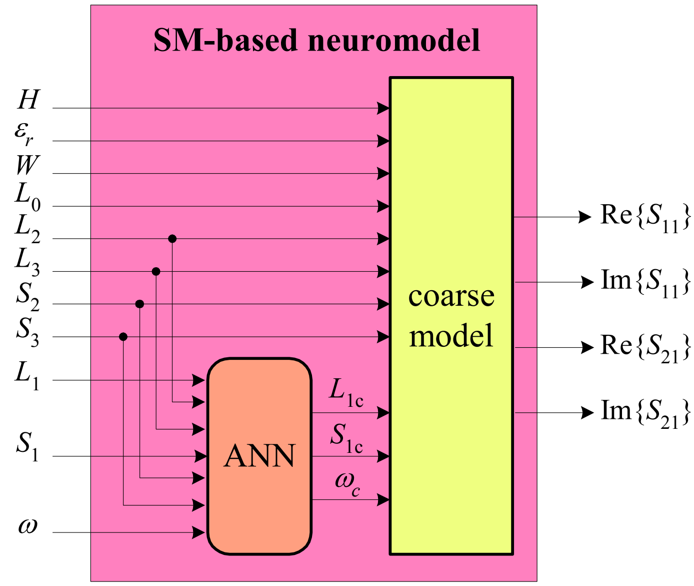
for all $\boldsymbol{x}_f$ and $\omega$ in the training region

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 |

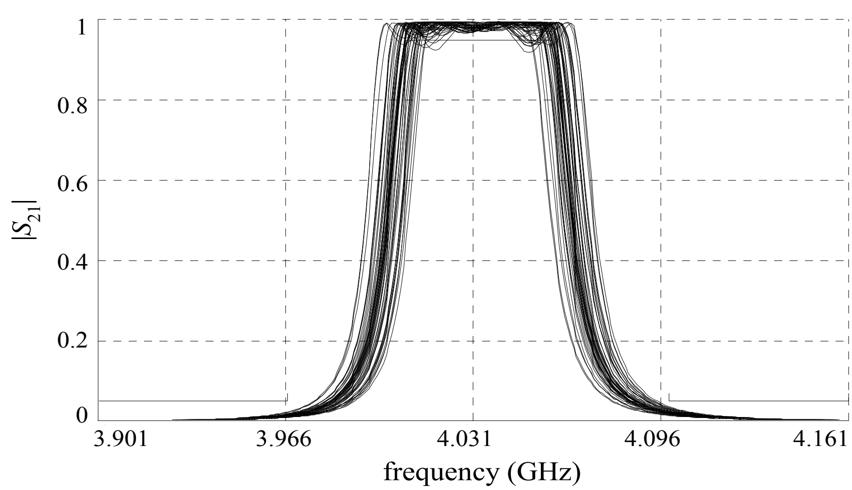
# SM-based Neuromodel of the HTS Filter





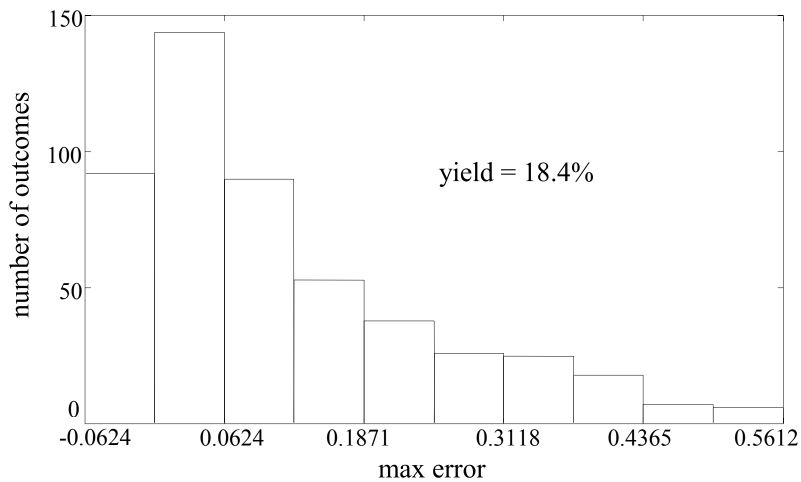

# Yield Analysis of the HTS Filter (cont)

At the nominal SM-solution: yield = 18.4%



# Yield Analysis of the HTS Filter (cont)

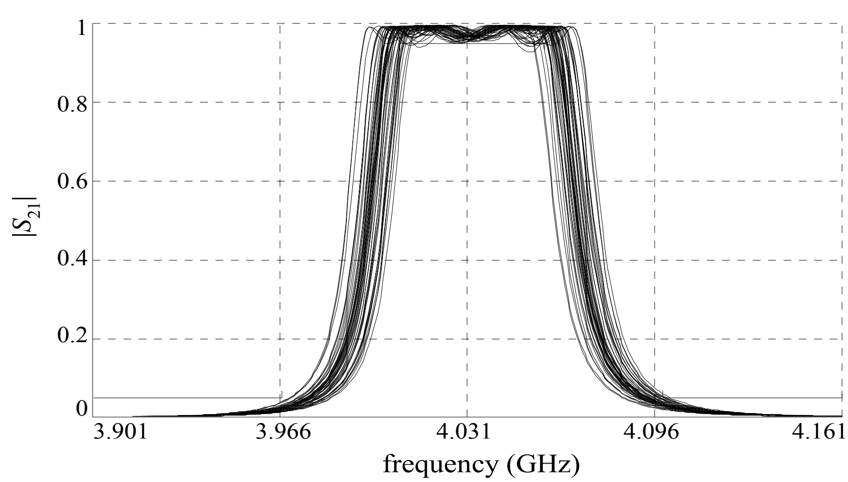
At the nominal SM-solution: yield = 18.4%





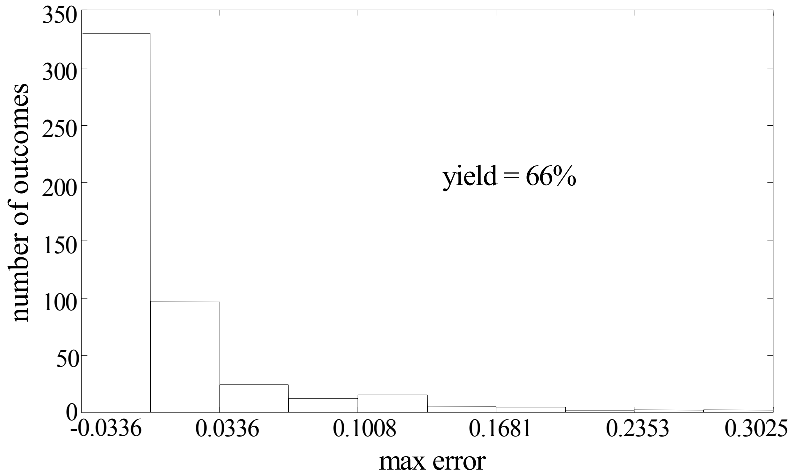

# Yield Optimization of the HTS Filter

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



# Yield Optimization of the HTS Filter (cont)

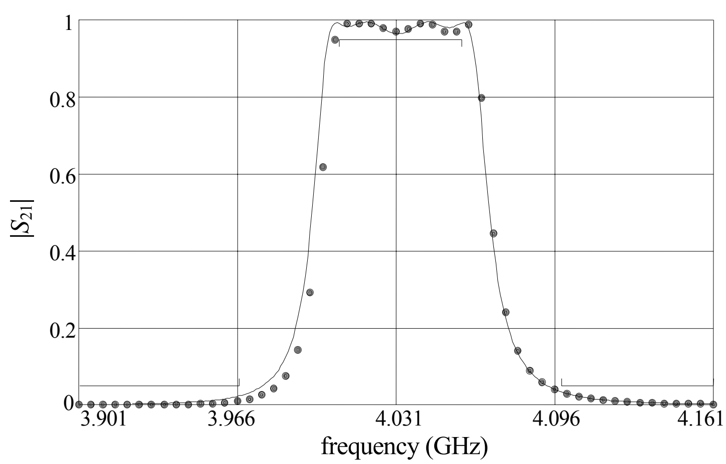
At the optimal yield SM-solution: yield = 66%



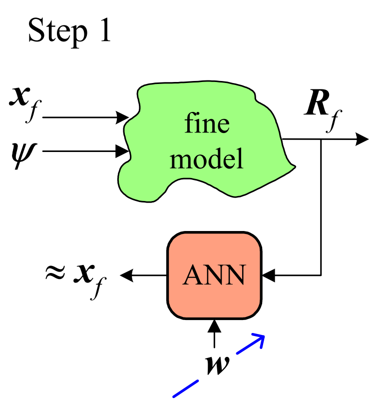


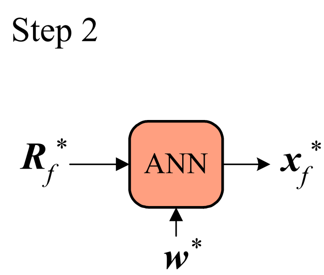

# Yield Optimization of the HTS Filter (cont)

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



## Synthesis ANNs for Microwave Design



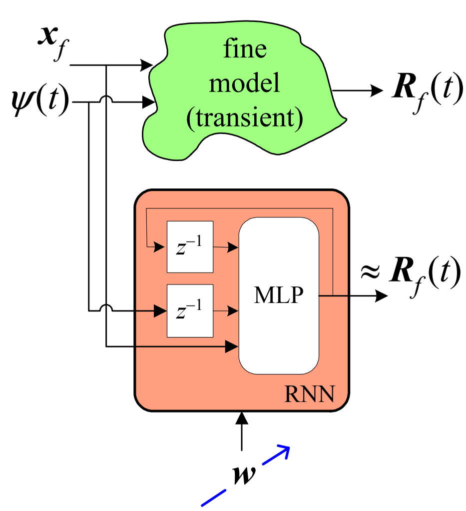




The mapping usually is multi-valued

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



## 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

*(Zhang et al., 2000, 2002)*

## Some Future Directions

- More algorithmic on-line approaches to neural EM-based design
- An integrated transient and frequency domain ANN-based design approach
- More ANN EM-based design methods exploiting circuital models

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## 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
- An attempt to predict some future directions of ANN techniques for microwave design is realized

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