Neural Inverse Space Mapping EM-Optimization

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Neural Inverse Space Mapping EM-Optimization (NISM)

outline

- ANN approaches for microwave design
- NISM optimization
- statistical parameter extraction
- inverse neuromapping
- the NISM step vs. the quasi-Newton step
- examples
- conclusions

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statistical parameter extraction

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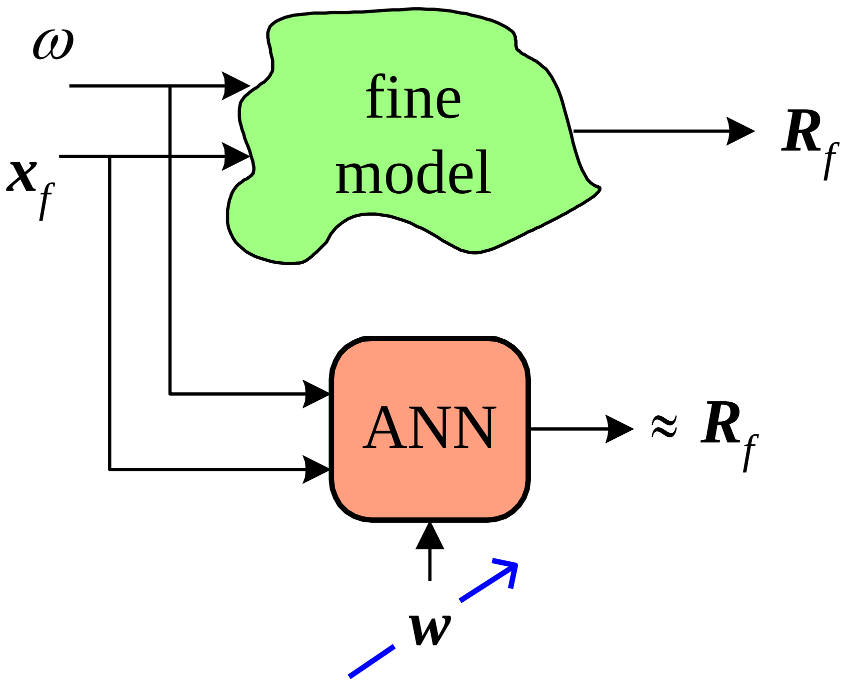
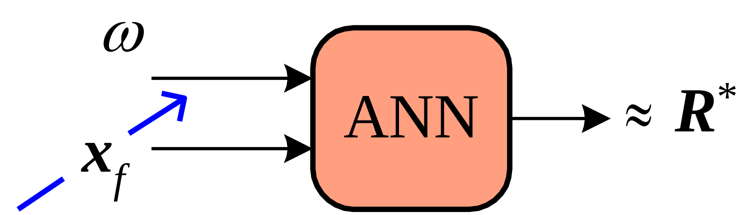
Conventional ANN-Based Optimization of Microwave Circuits

(Zaabab, Zhang and Nakhla, 1995, Gupta et al., 1997, Burrascano and Mongiardo, 1998)

step 1



step 2

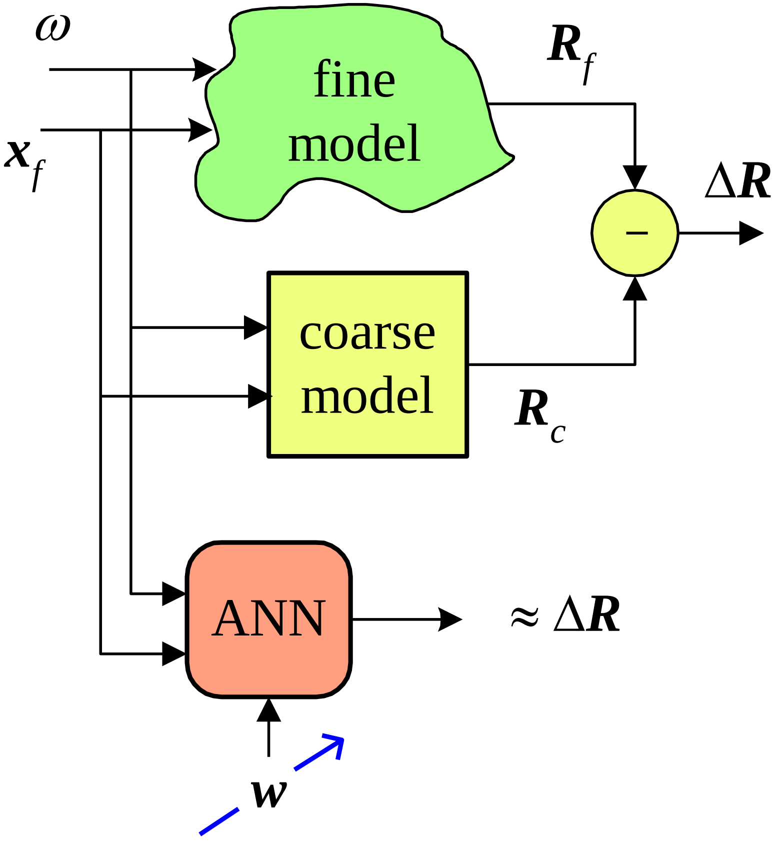


many fine model simulations are usually needed

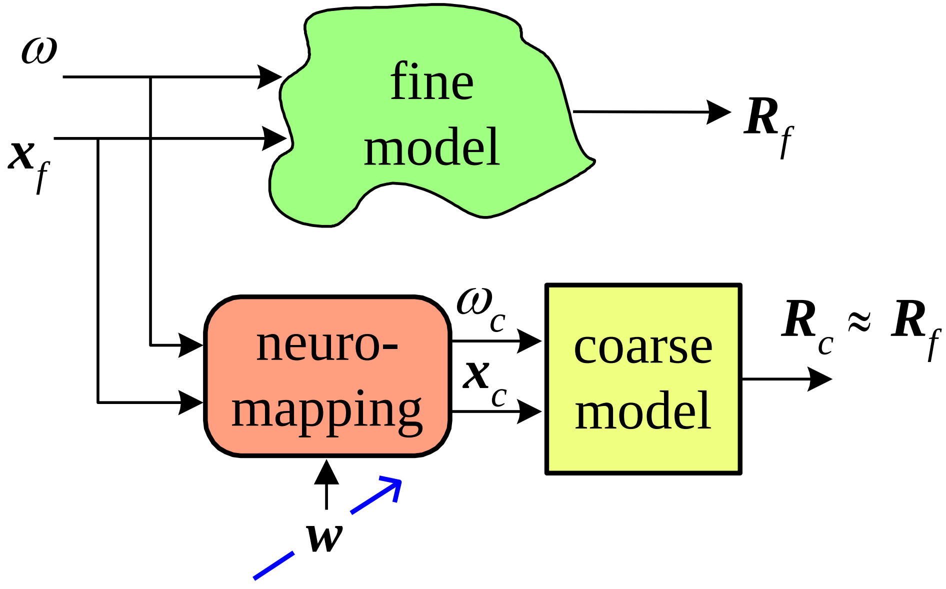
solutions predicted outside the training region are unreliable

ANN-Based Microwave Optimization Exploiting Available Knowledge

EM-ANN approach
(*Gupta et al., 1999*)



neural space mapping approach
(*Bandler et al., 2000*)



NSM optimization requires $2n+1$ upfront fine simulations

Objectives

develop an aggressive ANN-based space mapping optimization

avoid multipoint parameter extraction and frequency mappings

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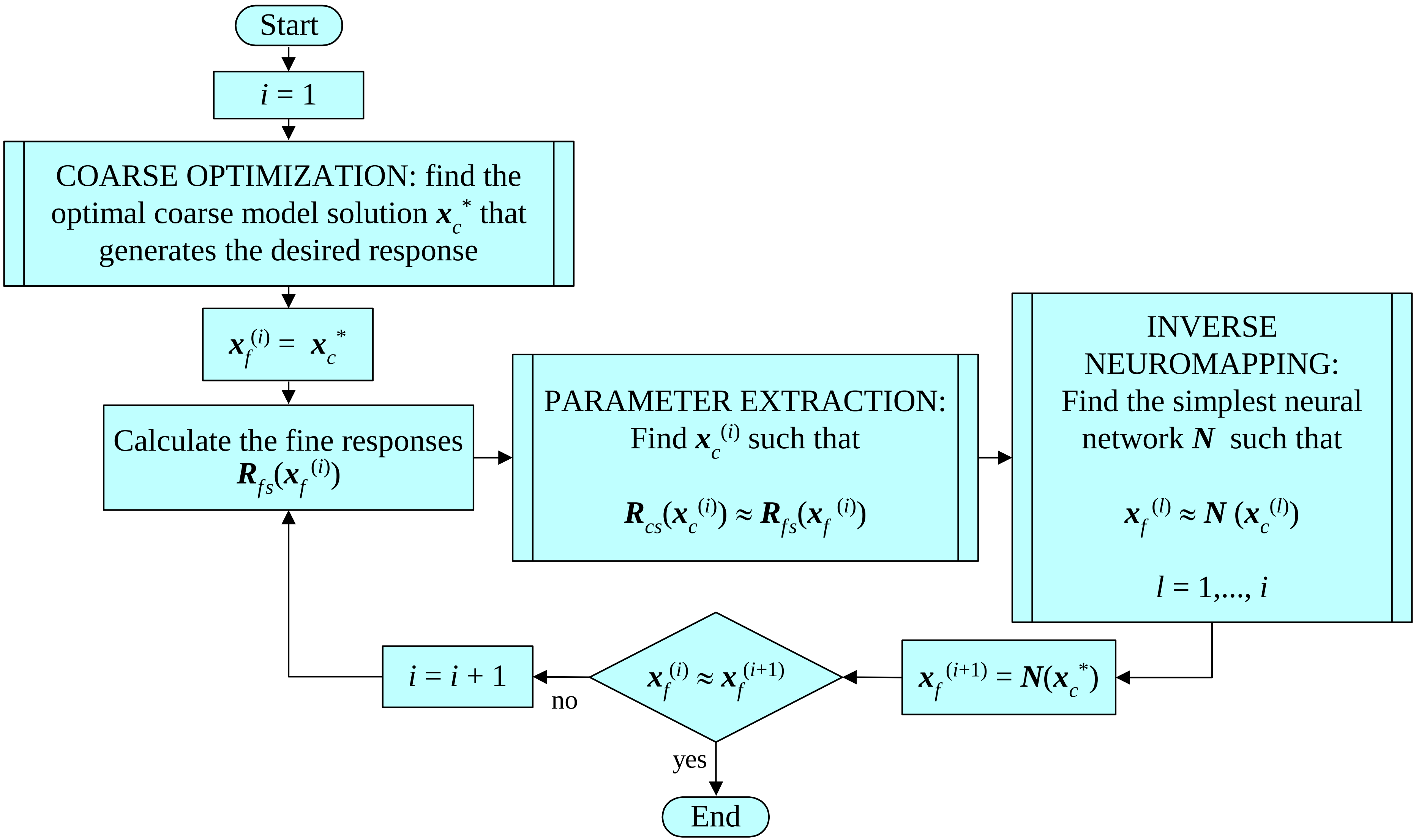
Neural Inverse Space Mapping Optimization



Statistical Parameter Extraction

(1)

$$\boldsymbol{x}_c^{(i)} = \arg\min_{\boldsymbol{x}_c} \; U_{PE}(\boldsymbol{x}_c)$$

$$U_{PE}(\boldsymbol{x}_c) = \| \boldsymbol{e}(\boldsymbol{x}_c) \|_2^2$$

$$\boldsymbol{e}(\boldsymbol{x}_c) = \boldsymbol{R}_{fs}(\boldsymbol{x}_f^{(i)}) - \boldsymbol{R}_{cs}(\boldsymbol{x}_c)$$

(2)

$$\Delta_{\max} = \frac{\delta_{PE}}{\left\| \nabla U_{PE}(\boldsymbol{x}_c^*) \right\|_\infty}$$

(3)

$$\Delta x_k = \Delta_{\max}(2 rand_k - 1)$$

$$k = 1 \ldots n$$

begin

solve (1) using $\boldsymbol{x}_c^*$ as starting point

while $\left\| \boldsymbol{e}(\boldsymbol{x}_c^{(i)}) \right\|_\infty > \varepsilon_{PE}$

calculate $\Delta \boldsymbol{x}$ using (2) and (3)

solve (1) using $\boldsymbol{x}_c^* + \Delta \boldsymbol{x}$ as starting point

end

Inverse Neuromapping

(4)

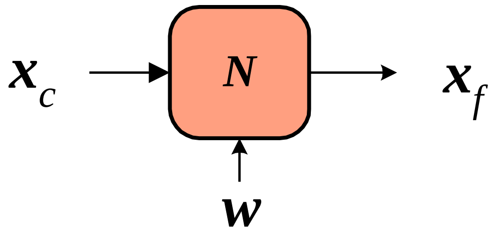
$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} U_N(\boldsymbol{w})$$

$$U_N(\boldsymbol{w}) = \left\| [\cdots \quad \boldsymbol{e}_l^T \quad \cdots]^T \right\|_2^2$$

$$\boldsymbol{e}_l = \boldsymbol{x}_f^{(l)} - \boldsymbol{N}(\boldsymbol{x}_c^{(l)}, \boldsymbol{w})$$

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

ANN (2LP or 3LP)



begin

  solve (4) using a 2LP

  $h = n$

  while $U_N(\boldsymbol{w}^*) > \varepsilon_L$

    solve (4) using a 3LP

    $h = h + 1$

end

Nature of the NISM Step

$\boldsymbol{x}_f^{(i+1)} = \boldsymbol{N}(\boldsymbol{x}_c^{\,*})$

evaluates the current ANN at the optimal coarse solution

is equivalent to a quasi-Newton step

departs from a quasi-Newton step as the nonlinearity needed in the inverse mapping increases

does not use classical updating formulas to approximate the Jacobian inverse

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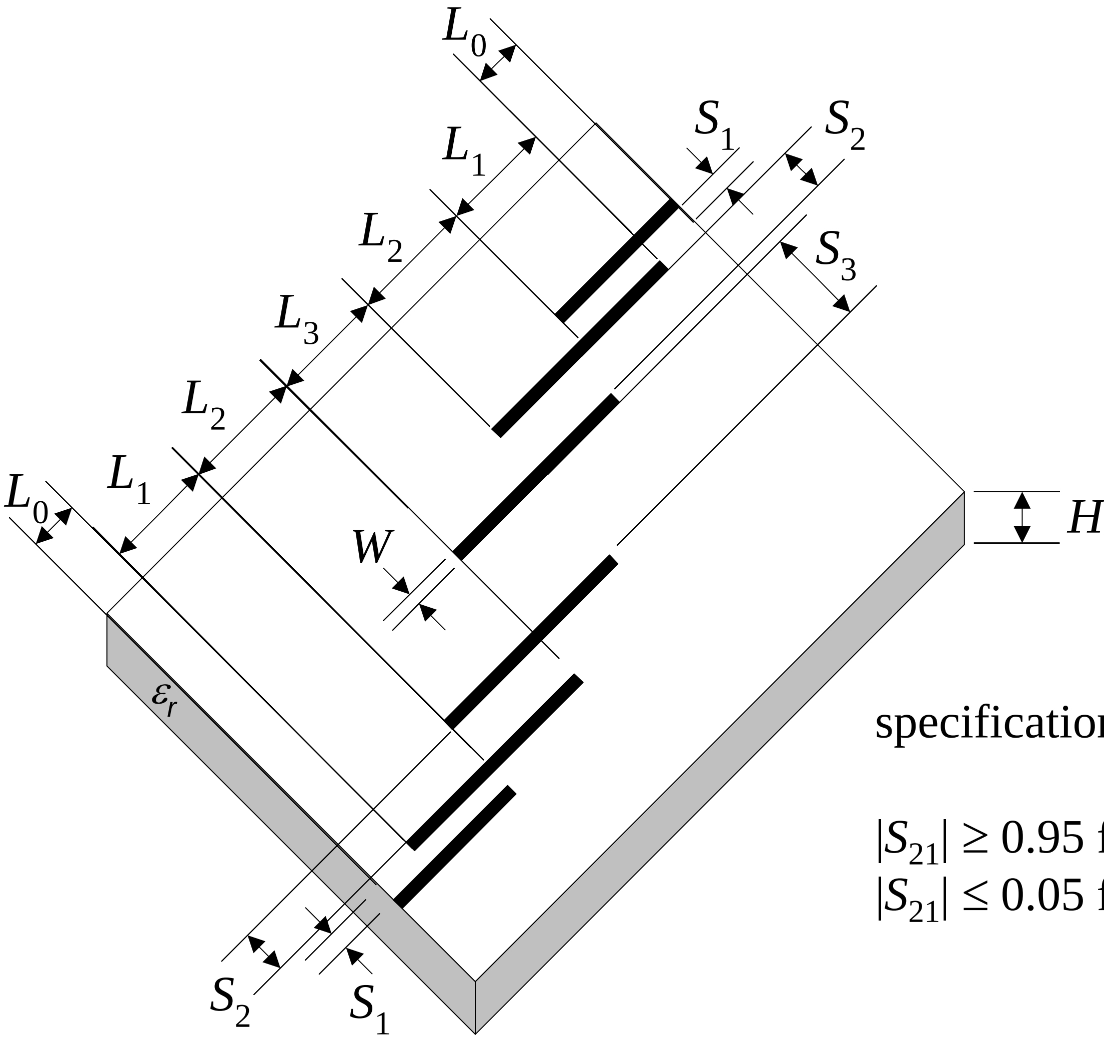
Termination Condition for NISM Optimization

$$\left\| \boldsymbol{x}_f^{(i+1)} - \boldsymbol{x}_f^{(i)} \right\|_2 \le \varepsilon_{end}(\varepsilon_{end} + \left\| \boldsymbol{x}_f^{(i)} \right\|_2) \qquad \vee \qquad i = 3n$$

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(Westinghouse, 1993)



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

the design parameters are

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

specifications

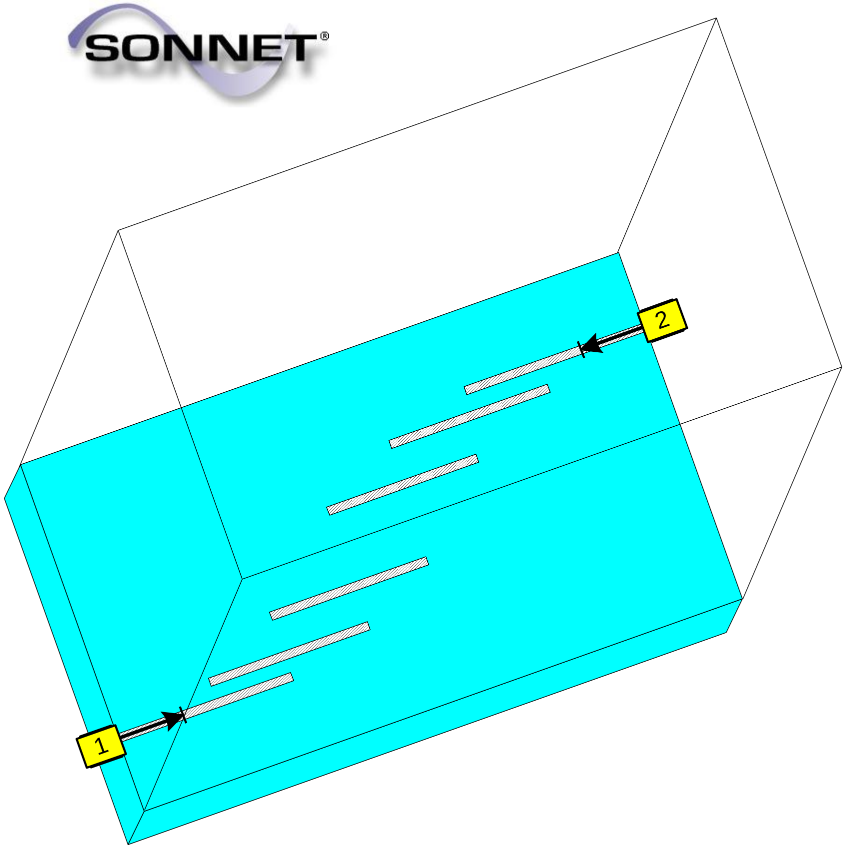
$|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq$ 4.058 GHz

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

HTS Microstrip Filter: Fine and Coarse Models

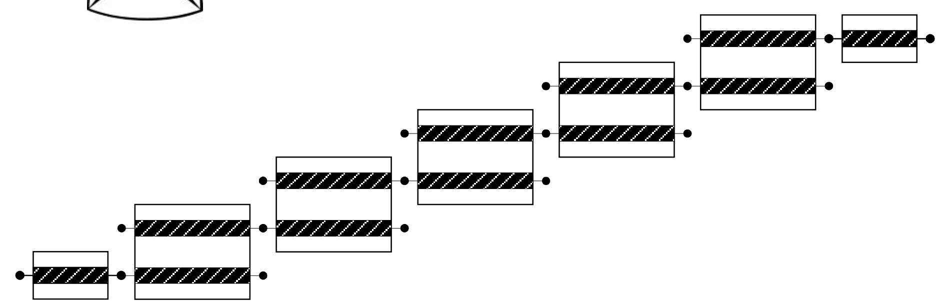
fine model:

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



coarse model:

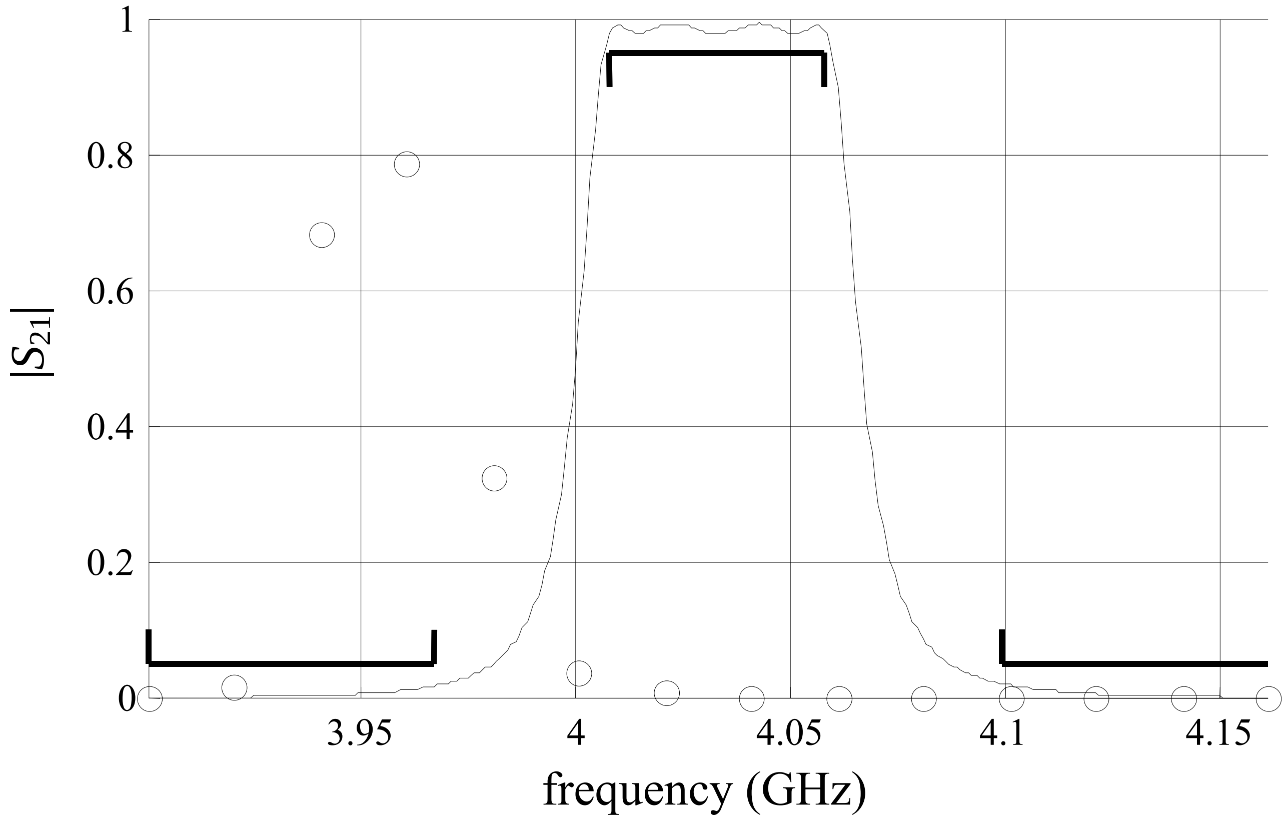
OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines



NISM Optimization of the HTS Filter

responses using ***em***™ (○) and OSA90/hope™ (–)

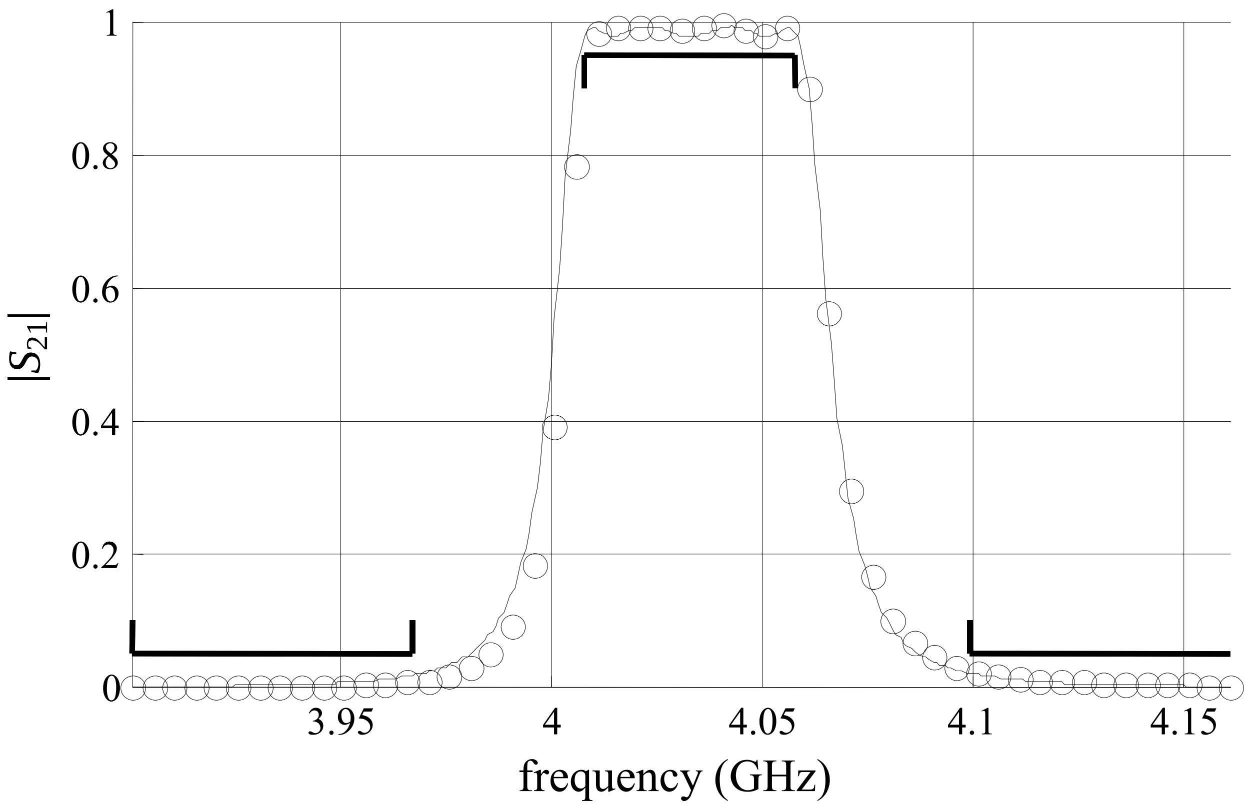
at the starting point



NISM Optimization of the HTS Filter (continued)

responses using OSA90/hope™ (–) at x_c^* and ***em***™ (○) at the NISM solution

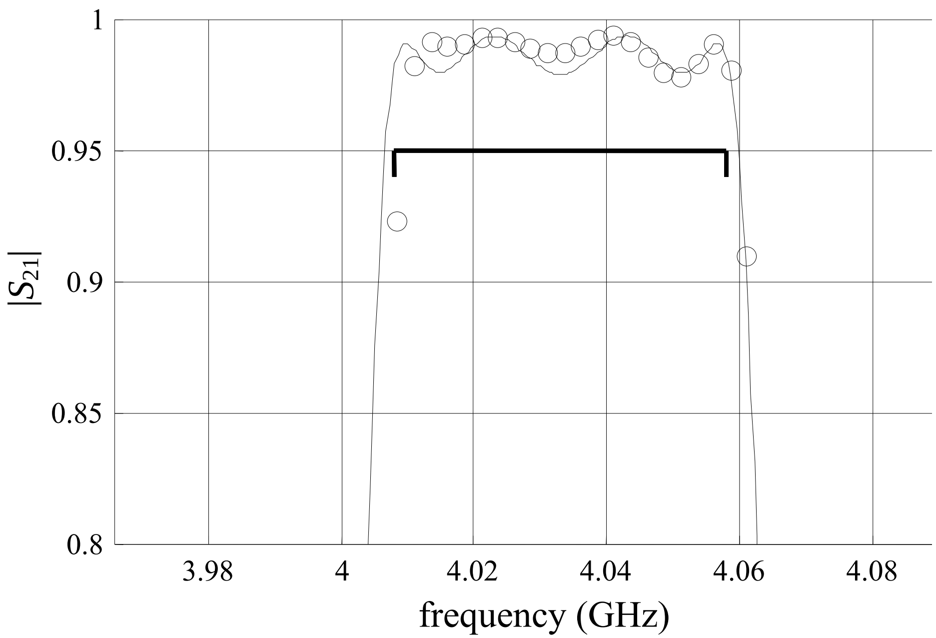
(after 3 NISM iterations)



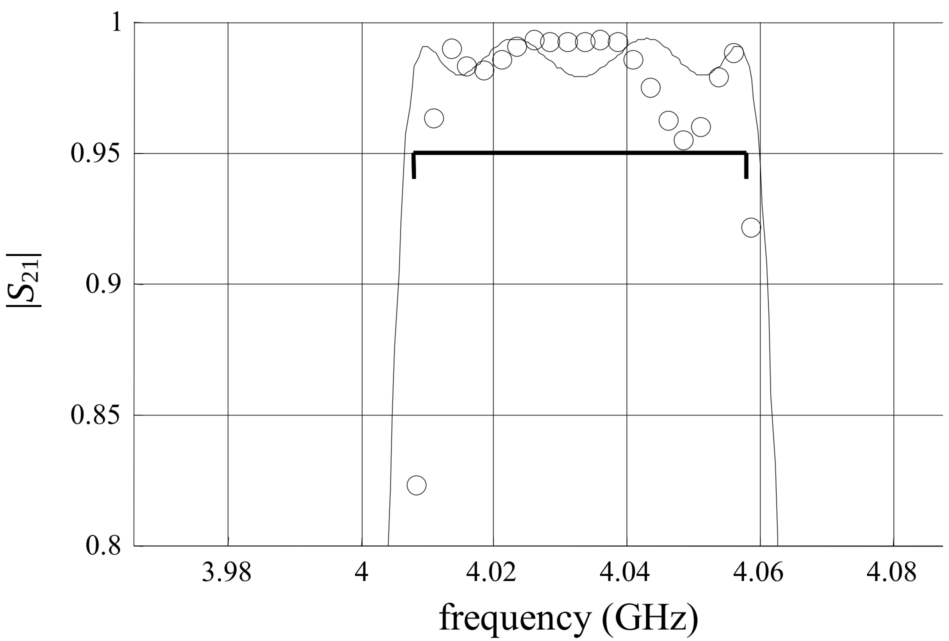
NISM vs. NSM Optimization

HTS filter optimal responses in the passband

after NISM (3 fine simulations)



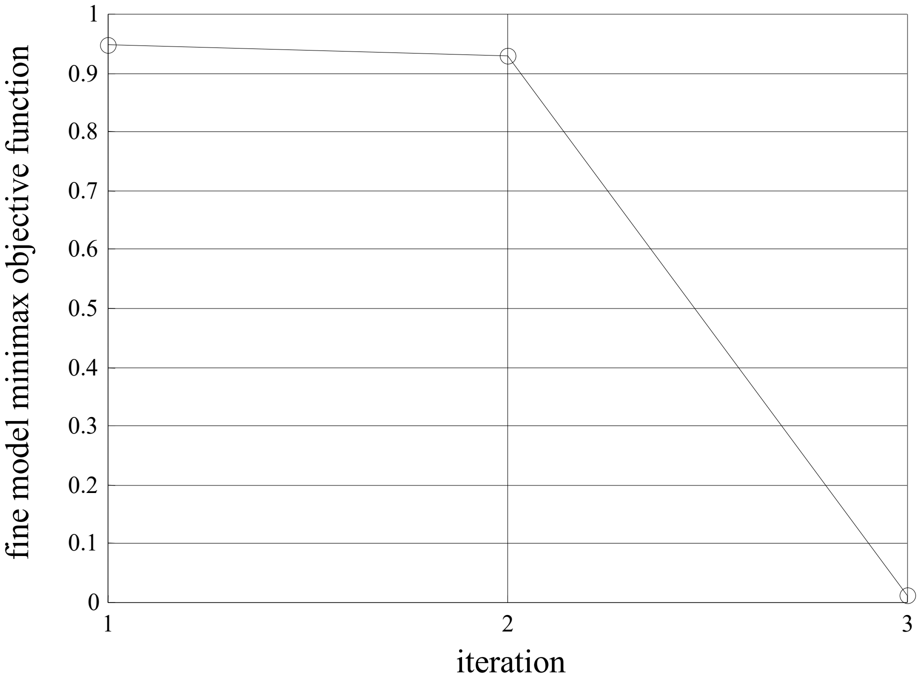
after NSM (14 fine simulations)
(*Bandler et al., 2000*)



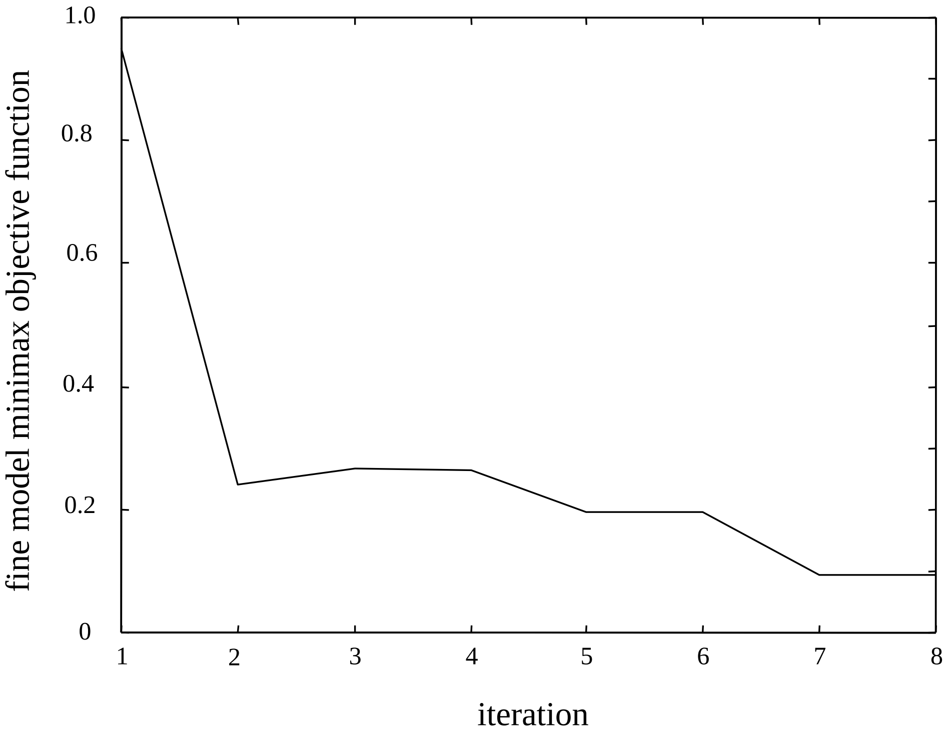
NISM vs. Trust Region Aggressive Space Mapping (TRASM) Exploiting Surrogates

fine model minimax objective function

after NISM (3 fine simulations)



after TRASM Exploiting Surrogates
(8 fine simulations) (*Bakr et al., 2000*)



Conclusions

we propose Neural Inverse Space Mapping (NISM) optimization

up-front EM simulations, multipoint parameter extraction or frequency mapping are not required

a statistical procedure overcomes poor local minima during parameter extraction

an ANN approximates the inverse of the mapping

the next iterate is obtained from evaluating the ANN at the optimal coarse solution

this is a quasi-Newton step

NISM optimization exhibits superior performance to NSM optimization and Trust Region Aggressive Space Mapping Exploiting Surrogates

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