EM-Based Statistical Analysis and Yield Estimation Using Linear-Input and Neural-Output Space Mapping

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Outline

- EM-based statistical analysis
- Input Space Mapping
- Linear-Input Neural-Output Space Mapping (LINO-SM)
- LINO-SM approach to yield estimation
- Constrained Broyden-Based Space Mapping
- Training the Output Neuromapping
- Examples
- Conclusions

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EM-based Statistical Analysis

- Statistical analysis and yield prediction are crucial for manufacturability
- Reliable yield prediction typically requires massive amount of high-fidelity simulations (full-wave EM simulations)
- Performing Monte Carlo yield analysis by directly using EM simulations is not feasible for most practical problems
- We propose using linear-input neural-output space mapping

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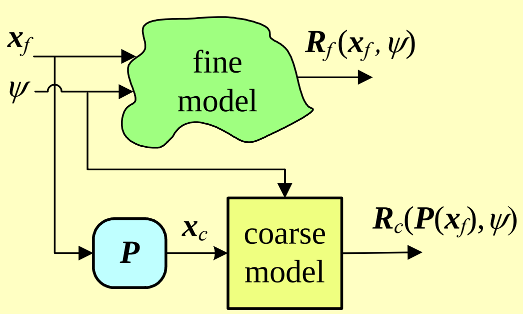
Input Space Mapping



☺ $R_f(x_f^{SM}, \psi) \approx R_c(x_c^{*}, \psi)$

☹ $R_c(P(x_f^{SM}))$ can not accurately estimate the fine model yield around x_f^{SM}

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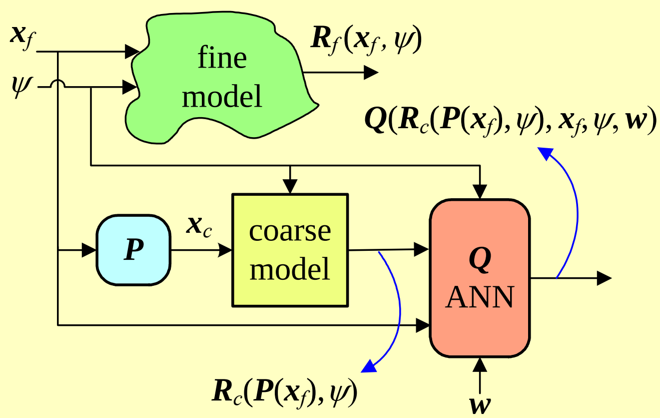
Linear-Input Neural Output Space Mapping



$$Q(R_c(Bx_f + c, \psi), x_f, \psi, w^*) = R_f(x_f, \psi)$$

for all x_f and ψ in the training region

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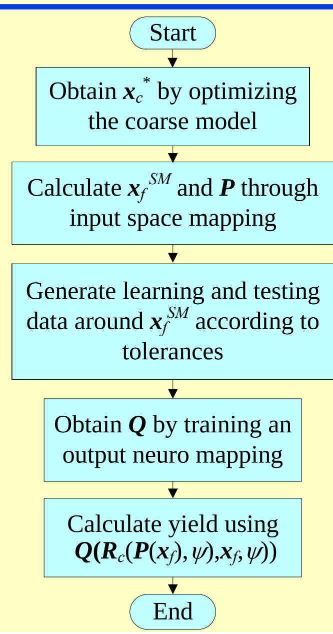
LINO-SM approach to Yield Estimation



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Obtaining $\boldsymbol{P}$ and $\boldsymbol{x}_f^{SM}$

We apply a constrained Broyden-based algorithm to solve the following system of nonlinear equations

$$\boldsymbol{f}(\boldsymbol{x}_f) = \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* = \boldsymbol{0}$$

where $\boldsymbol{x}_c = \boldsymbol{P}(\boldsymbol{x}_f)$ is evaluated through

$$\boldsymbol{P}(\boldsymbol{x}_f) = \arg\min_{\boldsymbol{x}_c} \left\| \begin{bmatrix} \boldsymbol{e}_1^T & \ldots & \boldsymbol{e}_p^T \end{bmatrix} \right\|_2^2$$

p is the number of points of the independent variable and the j-th parameter extraction error vector is given by

$$\boldsymbol{e}_j(\boldsymbol{x}_f) = \boldsymbol{R}_{fs}(\boldsymbol{x}_f, \psi_j) - \boldsymbol{R}_{cs}(\boldsymbol{x}_c, \psi_j)$$

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Algorithm for Constrained Broyden-Based SM

Begin

find $\boldsymbol{x}_c^*$ solving (1)

$i = 0$, $\boldsymbol{x}_f^{(i)} = \boldsymbol{x}_c^*$, $\boldsymbol{B}^{(i)} = \boldsymbol{I}$, $\delta = 0.3$

$\boldsymbol{f}^{(i)} = \boldsymbol{P}(\boldsymbol{x}_f^{(i)}) - \boldsymbol{x}_c^*$ using (2)

repeat until *stopping_criterion*

solve $\boldsymbol{B}^{(i)}\boldsymbol{h}^{(i)} = -\boldsymbol{f}^{(i)}$ for $\boldsymbol{h}^{(i)}$

$\boldsymbol{x}_f^{(test)} = \boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}$

while $\boldsymbol{x}_f^{(test)} \prec \boldsymbol{x}_f^{\min} \vee \boldsymbol{x}_f^{(test)} \succ \boldsymbol{x}_f^{\max}$

$\boldsymbol{h}^{(i)} = \delta\, \boldsymbol{h}^{(i)}$

$\boldsymbol{x}_f^{(test)} = \boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}$

end

$\boldsymbol{x}_f^{(i+1)} = \boldsymbol{x}_f^{(test)}$

$\boldsymbol{f}^{(i+1)} = \boldsymbol{P}(\boldsymbol{x}_f^{(i+1)}) - \boldsymbol{x}_c^*$ using (2)

$\boldsymbol{B}^{(i+1)} = \boldsymbol{B}^{(i)} + \dfrac{\boldsymbol{f}^{(i+1)}\boldsymbol{h}^{(i)T}}{\boldsymbol{h}^{(i)T}\boldsymbol{h}^{(i)}}$, $i = i + 1$

end

(1)

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

(2)

$$\boldsymbol{P}(\boldsymbol{x}_f) = \arg\min_{\boldsymbol{x}_c} \left\| \begin{bmatrix} \boldsymbol{e}_1^T & \ldots & \boldsymbol{e}_p^T \end{bmatrix} \right\|_2^2$$

$$\boldsymbol{e}_j(\boldsymbol{x}_f) = \boldsymbol{R}_{fs}(\boldsymbol{x}_f, \psi_j) - \boldsymbol{R}_{cs}(\boldsymbol{x}_c, \psi_j)$$

$$\boldsymbol{x}_f^{SM} = \boldsymbol{x}_f^{(i)}$$

$$\boldsymbol{P}(\boldsymbol{x}_f) = \boldsymbol{B}\boldsymbol{x}_f + \boldsymbol{c}$$

where $\boldsymbol{B} = \boldsymbol{B}^{(i)}$ and $\boldsymbol{c} = \boldsymbol{x}_c^* - \boldsymbol{B}\boldsymbol{x}_f^{SM}$

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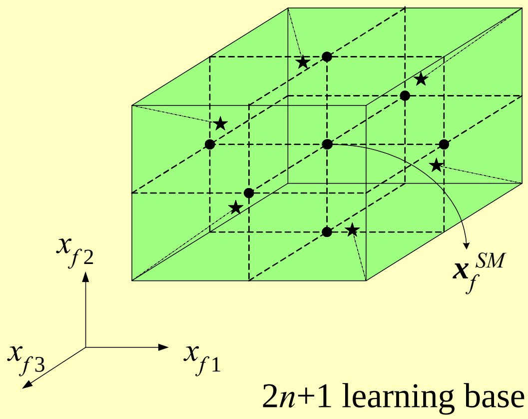
Generating Learning and Testing Points

- ● learning base point
- ★ testing base point



$2n$+1 learning base points in a star distribution
$2n$ testing base points in a rotated star distribution

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Training the Output Neuro Mapping

Begin

Generate $\boldsymbol{R}_{CL}$, $\boldsymbol{R}_{CT}$, $\boldsymbol{R}_{FL}$ and $\boldsymbol{R}_{FT}$

$\varepsilon_L^{old} = \| \boldsymbol{R}_{CL} - \boldsymbol{R}_{FL} \|_F$, $\varepsilon_T^{old} = \| \boldsymbol{R}_{CT} - \boldsymbol{R}_{FT} \|_F$

$h = m$, $i = 1$

$\boldsymbol{w}^{(i)} = \arg \min_{\boldsymbol{w}} \| \boldsymbol{E}_L(\boldsymbol{w}) \|_F$

$\varepsilon_L = \| \boldsymbol{Q}_L(\boldsymbol{w}^{(i)}) - \boldsymbol{R}_{FL} \|_F$

$\varepsilon_T = \| \boldsymbol{Q}_T(\boldsymbol{w}^{(i)}) - \boldsymbol{R}_{FT} \|_F$

while $\varepsilon_T^{old} \geq \varepsilon_T \;\vee\; \varepsilon_L \geq \varepsilon_T$

$\varepsilon_T^{old} = \varepsilon_T$, $\varepsilon_L^{old} = \varepsilon_L$, $i = i + 1$, $h = h + 1$

$\boldsymbol{w}^{(i)} = \arg \min_{\boldsymbol{w}} \| \boldsymbol{E}_L(\boldsymbol{w}) \|_F$

$\varepsilon_L = \| \boldsymbol{Q}_L(\boldsymbol{w}^{(i)}) - \boldsymbol{R}_{FL} \|_F$

$\varepsilon_T = \| \boldsymbol{Q}_T(\boldsymbol{w}^{(i)}) - \boldsymbol{R}_{FT} \|_F$

end

$\boldsymbol{w}^* = \boldsymbol{w}^{(i-1)}$

end

$$\boldsymbol{E}_L(\boldsymbol{w}) = \boldsymbol{R}_{FL} - \boldsymbol{Q}_L(\boldsymbol{w})$$

$$\boldsymbol{Q}(\boldsymbol{R}_c(\boldsymbol{B}\boldsymbol{x}_f + \boldsymbol{c}, \psi), \boldsymbol{x}_f, \psi, \boldsymbol{w}^*) = \boldsymbol{R}_f(\boldsymbol{x}_f, \psi)$$

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

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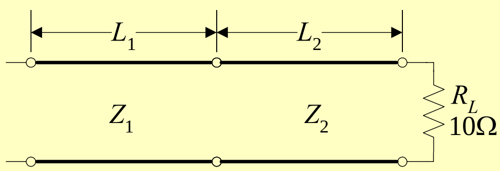
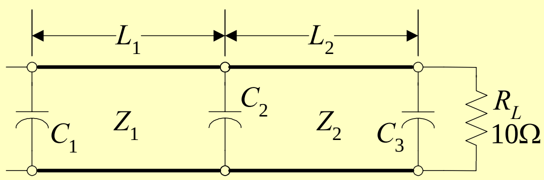
Two-Section Impedance Transformer

Coarse Model



"Fine" Model



$C_1 = C_2 = C_3 = 10\text{pF}$
$Z_1 = 2.23615\Omega$, $Z_2 = 4.47230\Omega$

Specs
$|S_{11}| \leq 0.5$ for
$0.5 \text{ GHz} \leq f \leq 1.5 \text{ GHz}$

$\boldsymbol{x}_f = [L_1 \;\; L_2]^T$

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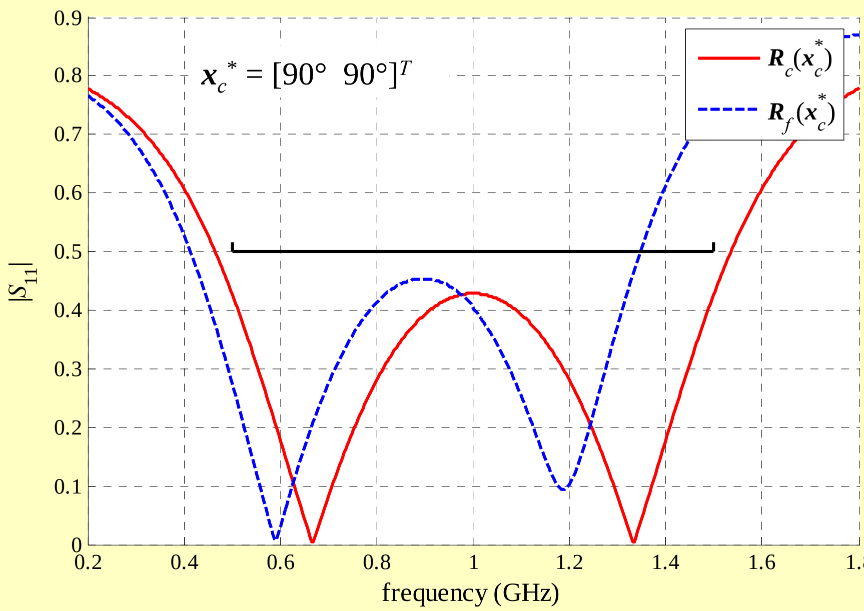
Impedance Transformer – Starting Point



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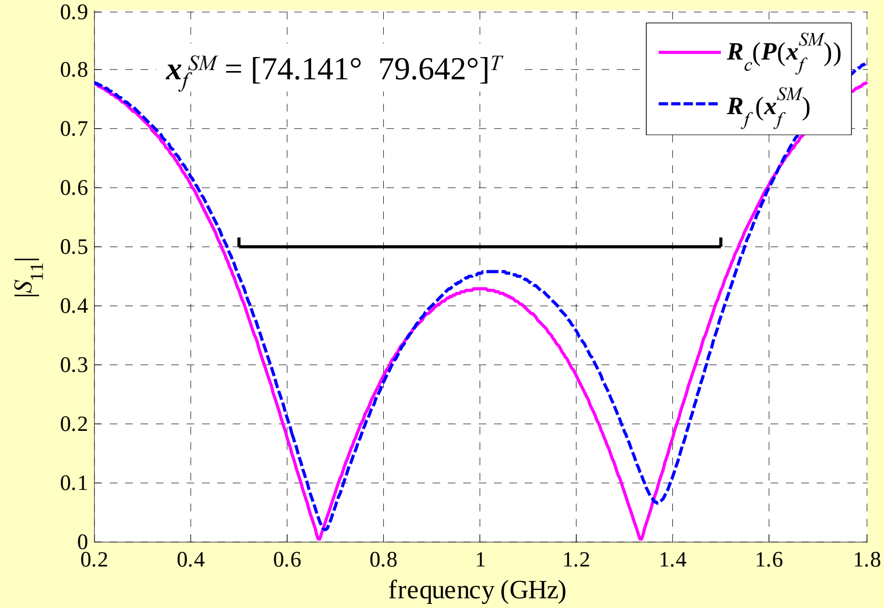
Impedance Transformer – SM Solution



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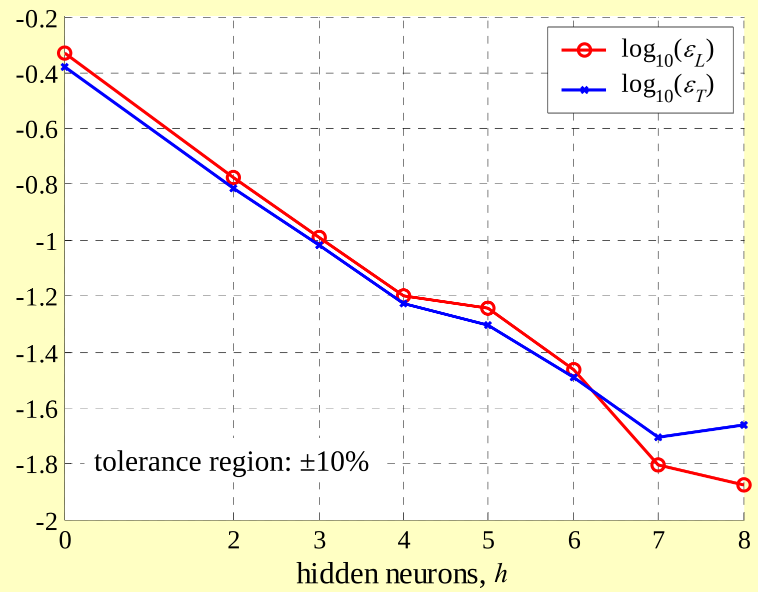
Impedance Transformer – Training *Q*



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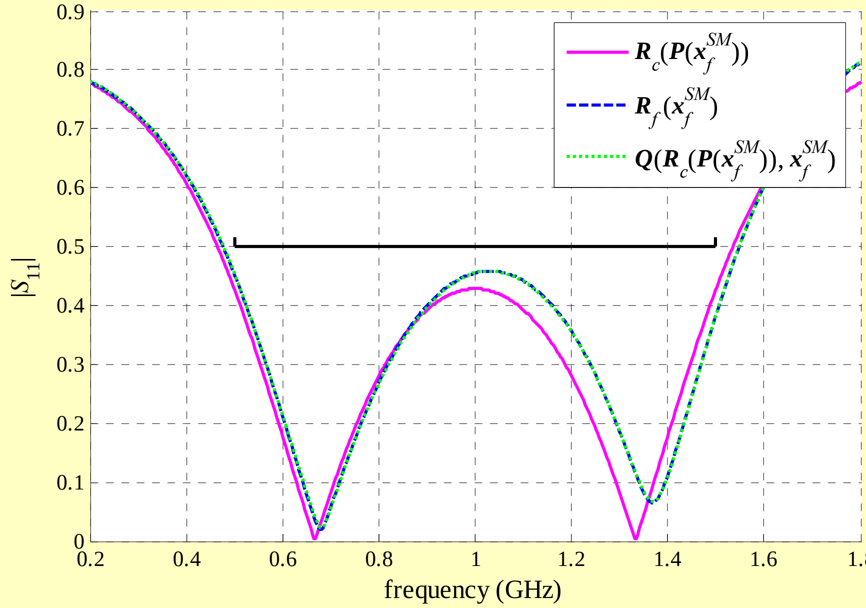
Impedance Transformer – LINOSM Solution



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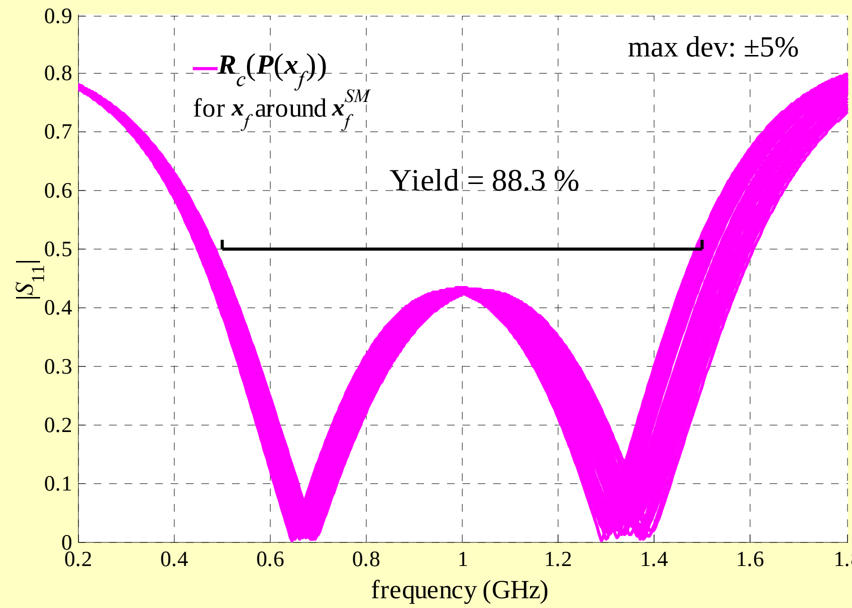
Impedance Transformer – LISM Yield



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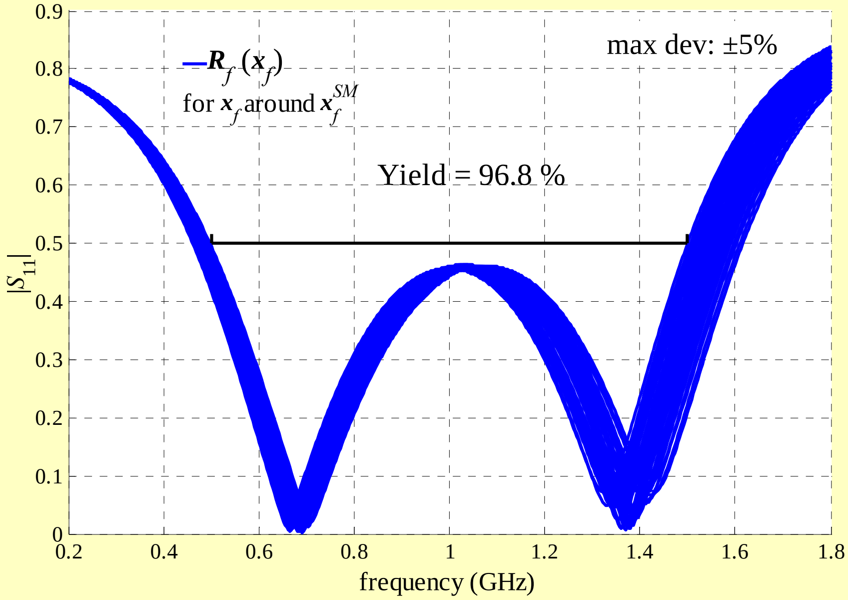
Impedance Transformer – Fine Model Yield



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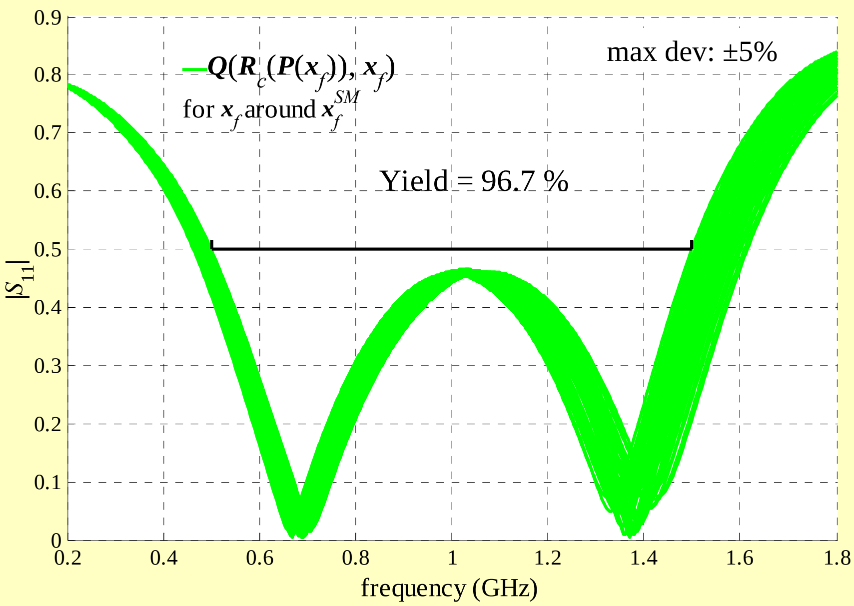
Impedance Transformer – LINOSM Yield



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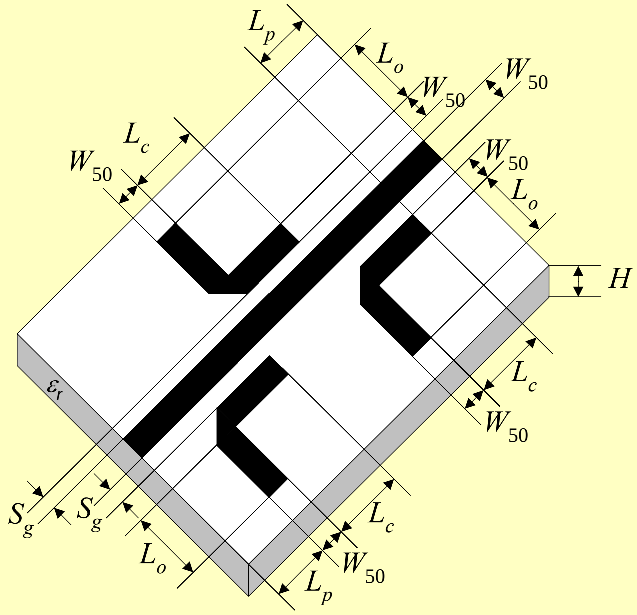
Microstrip Notch Filter



H = 10mil
W_{50} = 31mil
ε_r = 2.2
loss tan = 0.0009
(RT Duroid 5880)

$\boldsymbol{x}_f = [L_c \;\; L_o \;\; S_g]^T$

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Microstrip Notch Filter (cont)

Specifications

$|S_{21}| \leq 0.05$ for $13.19\text{GHz} \leq f \leq 13.21\text{GHz}$

$|S_{21}| \geq 0.95$ for $f \leq 13\text{GHz}$ and $f \geq 13.4\text{GHz}$

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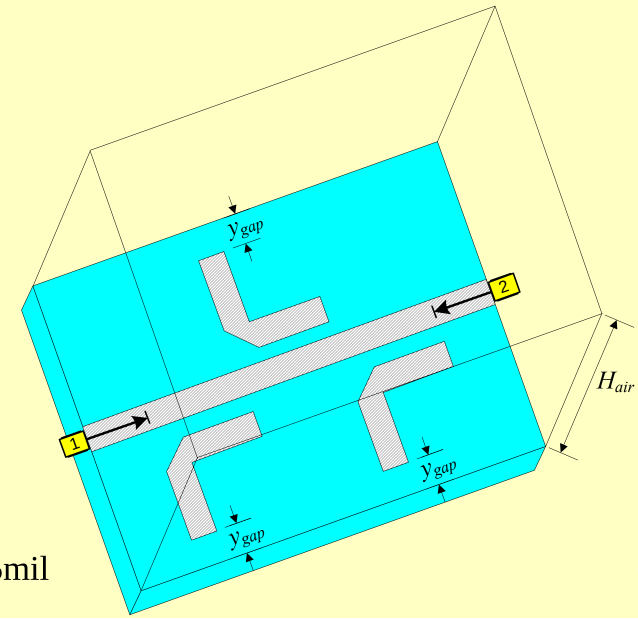
Microstrip Notch Filter – Fine Model

SONNET



H_{air} = 60 mil
$L_p = ½(L_o+L_c)$
$Y_{gap} = L_o$
grid = 0.5mil×0.5mil

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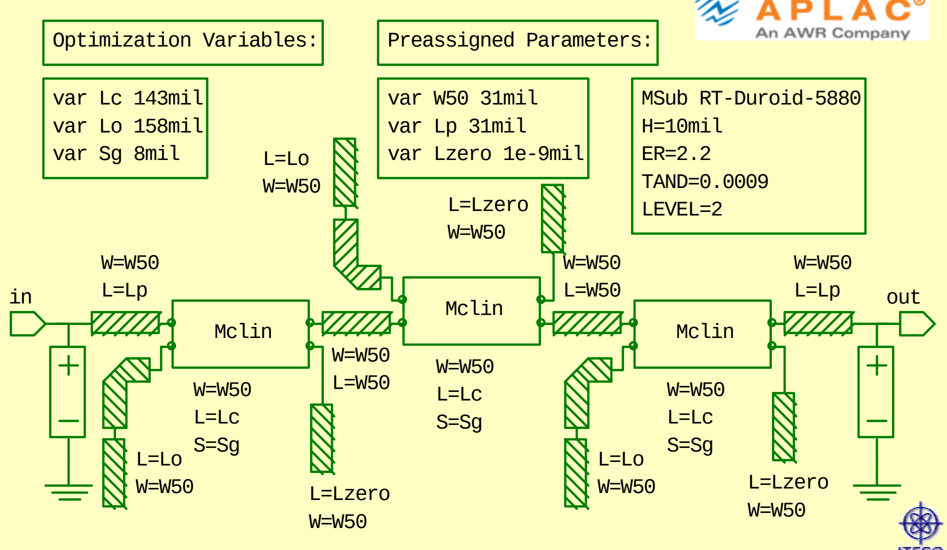
Microstrip Notch Filter – Coarse Model

APLAC An AWR Company



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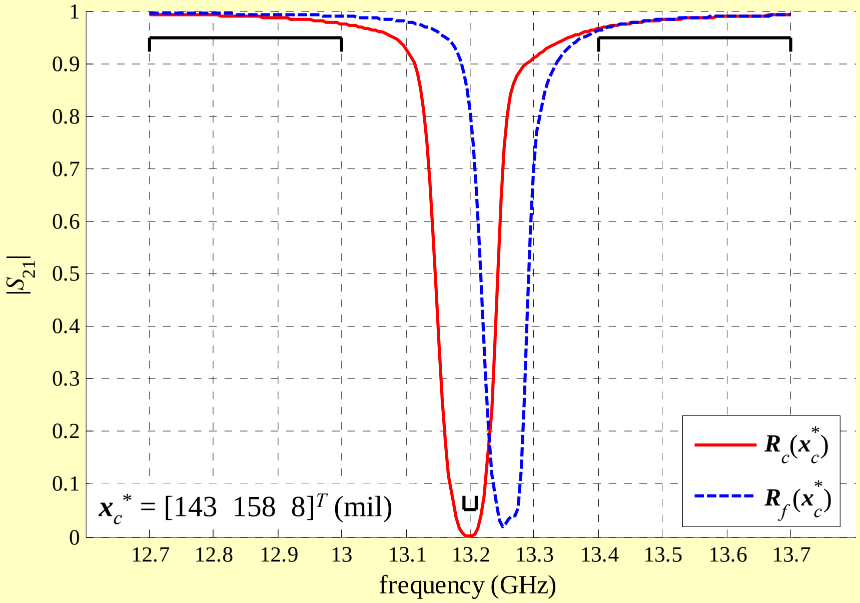
Microstrip Notch Filter – Starting Point



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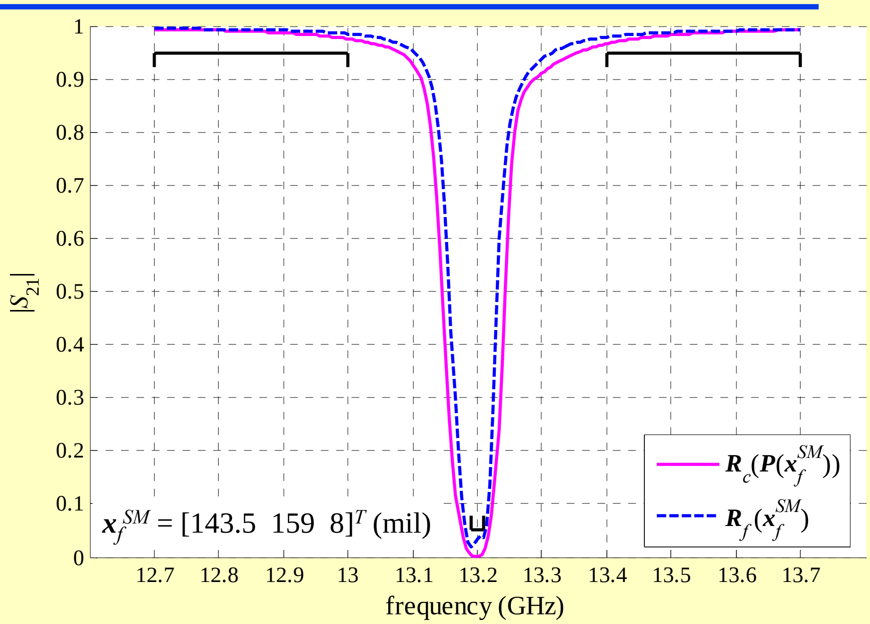
Microstrip Notch Filter – SM Solution



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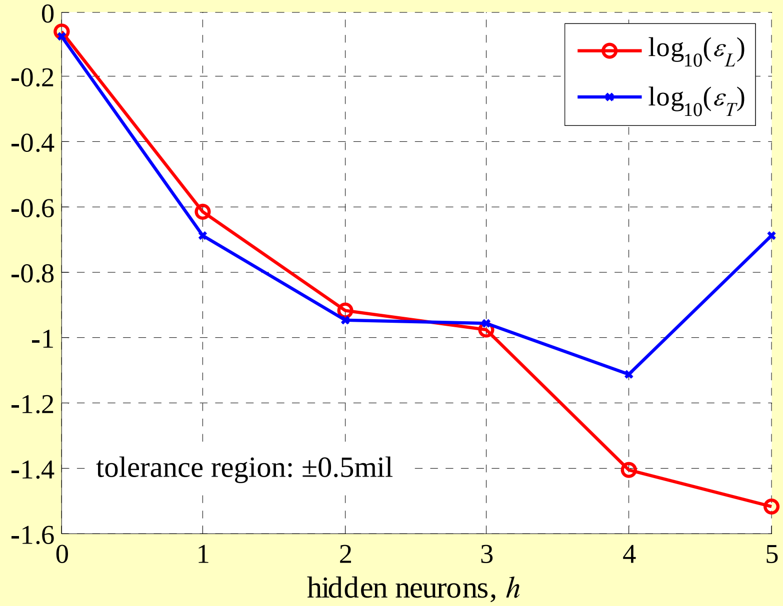
Microstrip Notch Filter – Training *Q*



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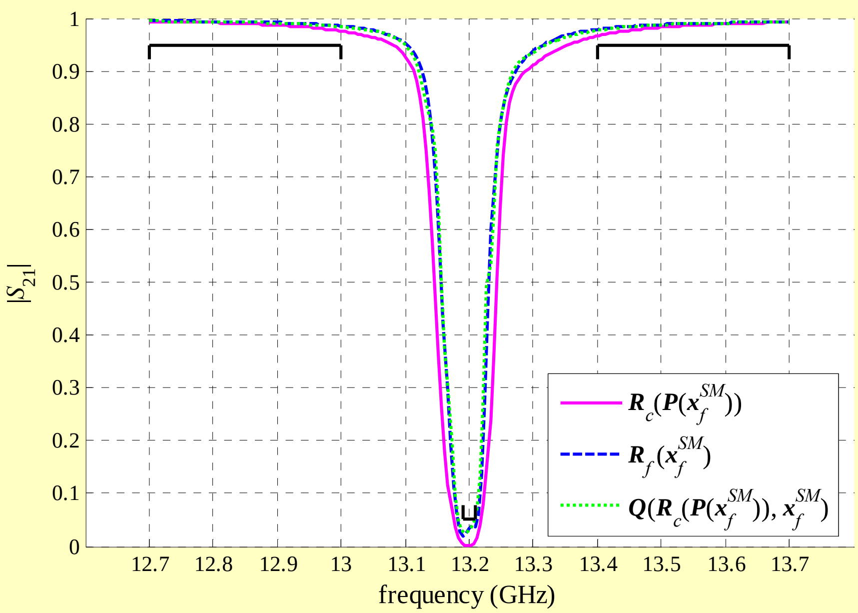
Microstrip Notch Filter – LINOSM Solution



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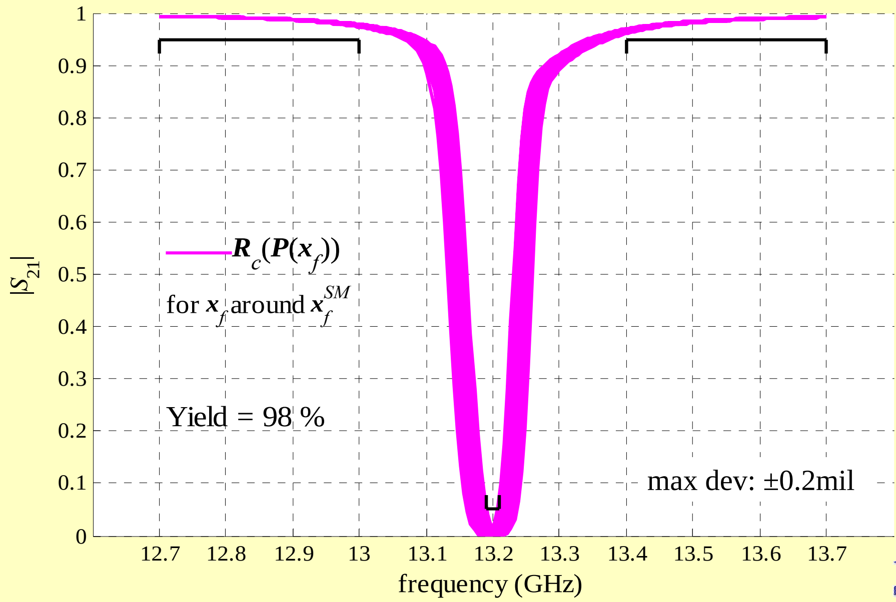
Microstrip Notch Filter – LISM Yield



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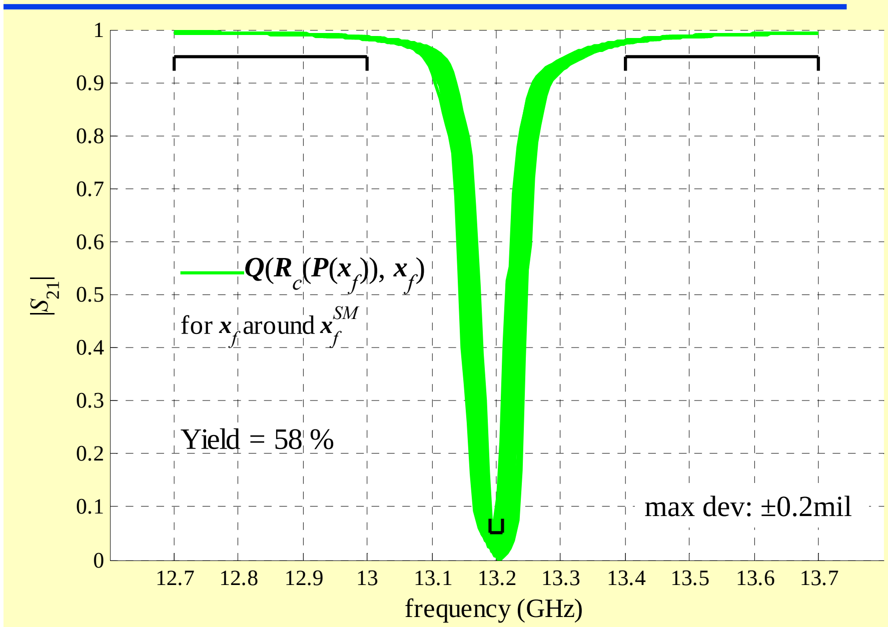
Microstrip Notch Filter – LINOSM Yield



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Conclusions

- We describe a method for highly accurate EM-based statistical analysis and yield estimation of RF and microwave circuits
- It consists of applying a constrained Broyden-based linear-input space mapping, followed by a neural-output space mapping, in which the responses, the design parameters and independent variable are mapped
- The output neuromodel is trained using reduced sets of learning and testing samples
- The resultant linear-input neural-output space mapped model is used as a very efficient vehicle for accurate statistical analysis and yield prediction

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