Expanded Space Mapping Optimization of Microwave Circuits Exploiting Preassigned Parameters

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presented at

First Annual McMaster Optimization Conference: Theory and Applications
Hamilton, ON, August 2, 2001

Expanded Space Mapping Optimization Exploiting Preassigned Parameters

outline

Space Mapping concept

Key Preassigned Parameters (KPP)

coarse model decomposition

Expanded Space Mapping Design Framework (ESMDF) algorithm

examples

conclusions

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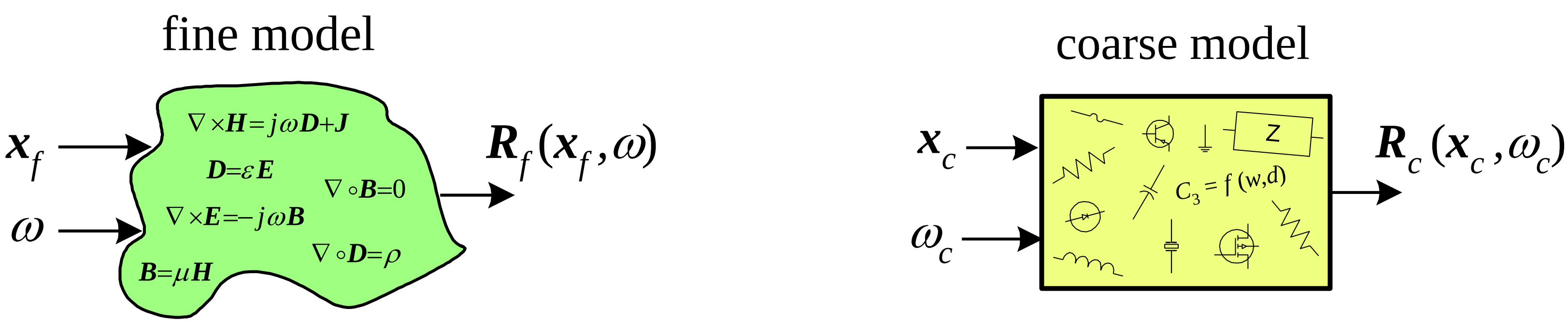
Space Mapping Concept

(Bandler et. al., 1994)



find

$$\begin{bmatrix} \boldsymbol{x}_c \\ \omega_c \end{bmatrix} = \boldsymbol{P}(\boldsymbol{x}_f, \omega)$$

such that

$$\boldsymbol{R}_c(\boldsymbol{x}_c, \omega_c) \approx \boldsymbol{R}_f(\boldsymbol{x}_f, \omega)$$

Key Preassigned Parameters (KPP)

the KPP are assumed to be non-optimizable

examples: dielectric constant, substrate height, etc.

the coarse model is very sensitive to KPP

the coarse model is calibrated to match the fine model by tuning the KPP

our algorithm establishes a mapping from some optimizable parameters to KPP

the mapping is updated iteratively

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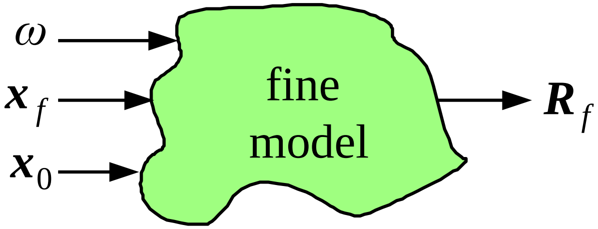

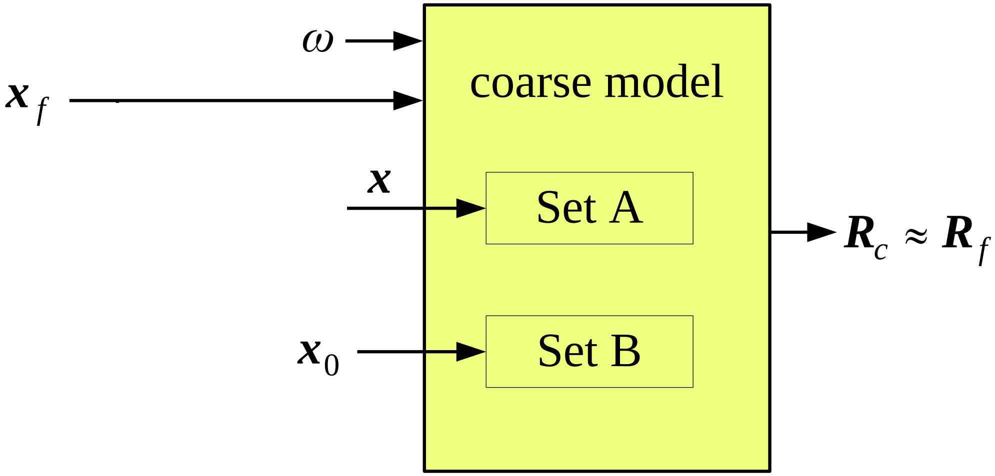

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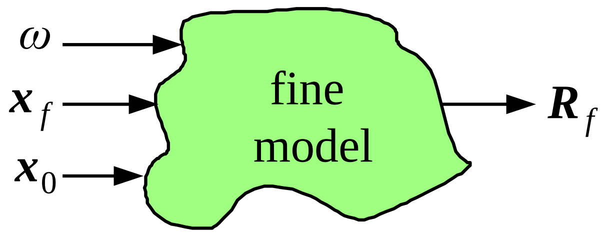
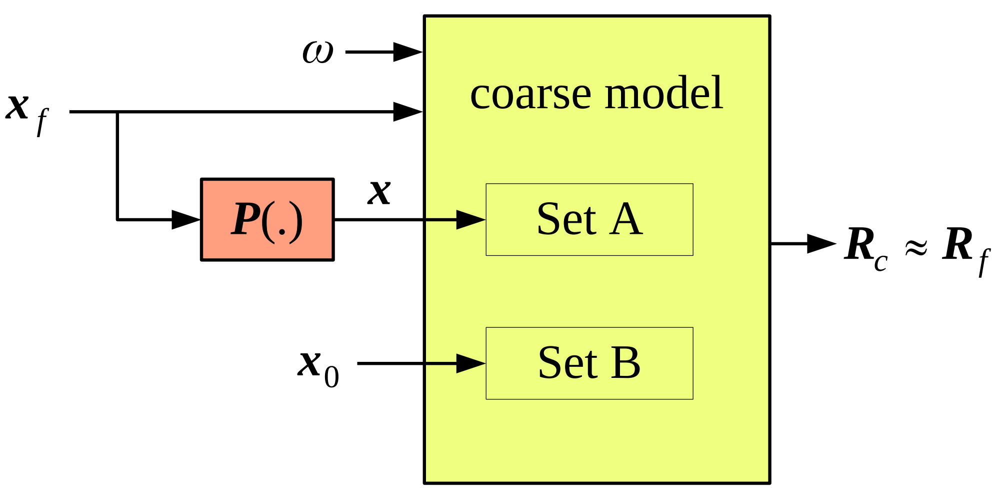


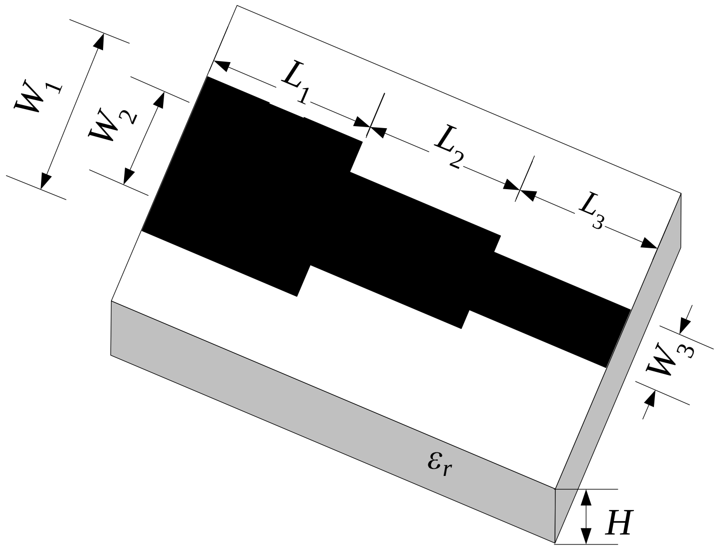


$$\boldsymbol{x} = \boldsymbol{P}(\boldsymbol{x}_r)$$

$$\boldsymbol{x}_f = [\boldsymbol{x}_r^T \quad \boldsymbol{x}_s^T]^T$$

$$\boldsymbol{x} = \boldsymbol{c} + \boldsymbol{B}_r \, \boldsymbol{x}_r$$

3:1 Microstrip Transformer



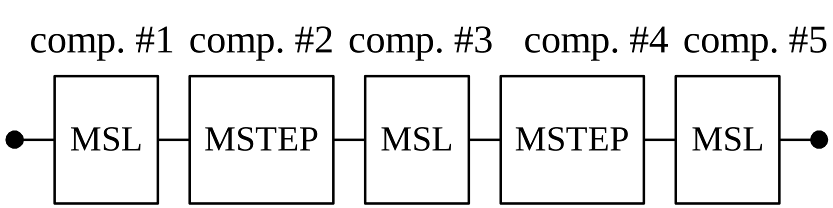
$$x_f = [W_1 \quad W_2 \quad W_3 \quad L_1 \quad L_2 \quad L_3]^T$$

$$x_r = [W_1 \quad W_2 \quad W_3]^T$$

$$x = [x_1^T \; x_3^T \; x_5^T]^T \qquad x_i = [\varepsilon_{ri} \quad H_i]^T$$

$$x = c + B_r \, x_r$$

$\varepsilon_r = 9.7$, $H = 25$ mil



Coarse Model Decomposition

$\boldsymbol{x}_i$ represents the KPP of the ith component, $i \in I = \{1,2,\ldots, N\}$

N is the number of coarse model components

Set A: contains "relevant" coarse model components

Set B: contains coarse model components for which the coarse model is insensitive to their KPP

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Coarse Model Decomposition

Step 1 for all $i \in I = \{1,2,\ldots,N\}$ evaluate

$$S_i = \left\| \left(\frac{\partial \boldsymbol{R}_c^{\mathrm{T}}}{\partial \boldsymbol{x}_i} \boldsymbol{D} \right)^{\mathrm{T}} \right\|_F , \quad \boldsymbol{D} = \mathrm{diag}(\boldsymbol{x}_0)$$

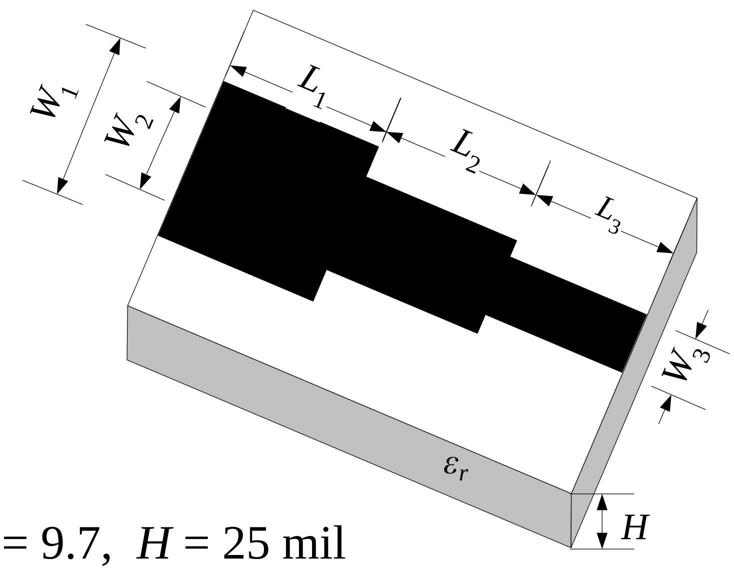
Step 2 evaluate

$$\hat{S}_i = \frac{S_i}{\max\limits_{j \in I}\{S_j\}}, \; i \in I$$

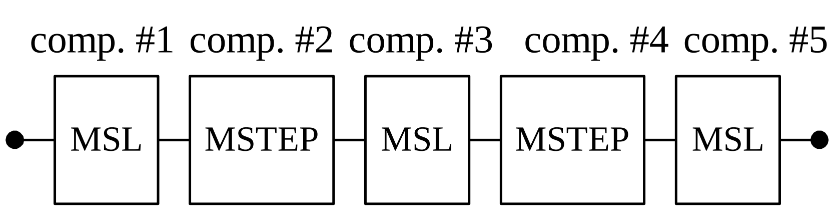
Step 3 put the ith component in Set A if $\hat{S}_i \geq \beta$
otherwise put it in Set B ($\beta = 0.2$)

Coarse Model Decomposition

example: 3:1 microstrip transformer



$\varepsilon_r = 9.7,\ \ H = 25$ mil



$$\boldsymbol{x}_i = [\varepsilon_{ri} \quad H_i]^T, \quad i = 1, \cdots, 5$$

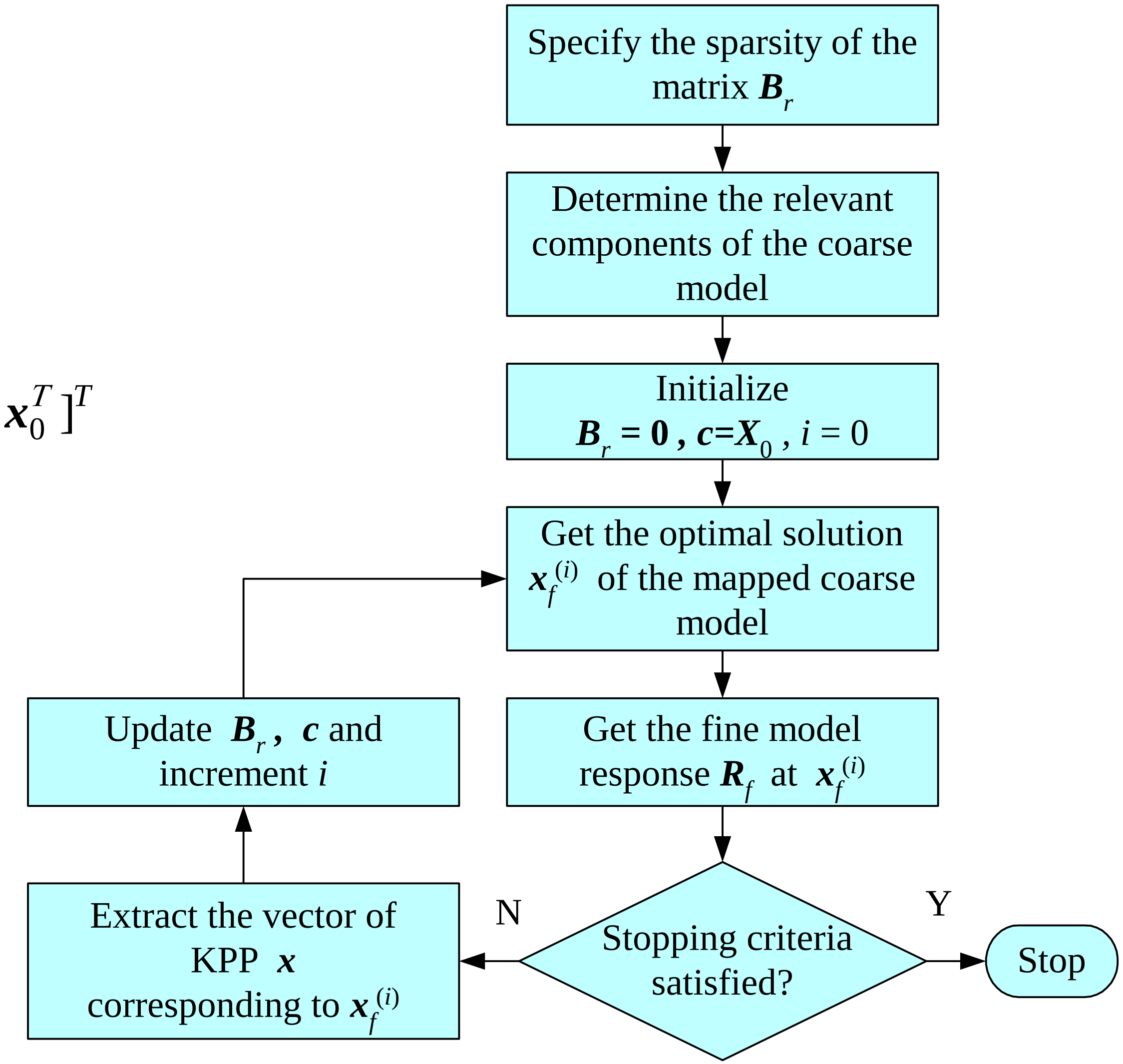
$$S_i = \left\| \left(\frac{\partial \boldsymbol{R}_c^{\mathrm{T}}}{\partial \boldsymbol{x}_i} \boldsymbol{D} \right)^{\mathrm{T}} \right\|_F$$

Component #	$\hat{S}_i$
1	1
2	0.05
3	0.39
4	0.04
5	0.77

hence $\quad \boldsymbol{x} = [\boldsymbol{x}_1^T \ \ \boldsymbol{x}_3^T \ \ \boldsymbol{x}_5^T]^T$

ESMDF Algorithm

$$X_0 = [x_0^T \;\; x_0^T \cdots x_0^T]^T$$



Expanded Space Mapping Optimization Algorithm

mapped coarse model optimization

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

$$\boldsymbol{x} = \boldsymbol{B}_r \ \boldsymbol{x}_r + \boldsymbol{c}$$

$$\boldsymbol{x}_f = [\boldsymbol{x}_r^T \quad \boldsymbol{x}_s^T]^T$$

Expanded Space Mapping Optimization Algorithm

mapped coarse model optimization
exploiting trust region methodology

$$\boldsymbol{h} = \arg\min_{\boldsymbol{h}} U(\boldsymbol{R}_c(\boldsymbol{x}_f^{(i\text{-}1)} + \boldsymbol{h}, \boldsymbol{B}_r\ \boldsymbol{x}_r^{(i\text{-}1)} + \boldsymbol{c}))$$

$$\text{subject to } \|\Lambda\, \boldsymbol{h}\| \le \delta$$

successful iteration

$$\boldsymbol{x}_f^{(i)} = \begin{cases} \boldsymbol{x}_f^{(i\text{-}1)} + \boldsymbol{h} & \text{if } U(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i\text{-}1)} + \boldsymbol{h})) < U(\boldsymbol{R}_f(\boldsymbol{x}_f^{(i\text{-}1)})) \\ \boldsymbol{x}_f^{(i\text{-}1)} & \text{otherwise} \end{cases}$$

Expanded Space Mapping Optimization Algorithm

KPP extraction

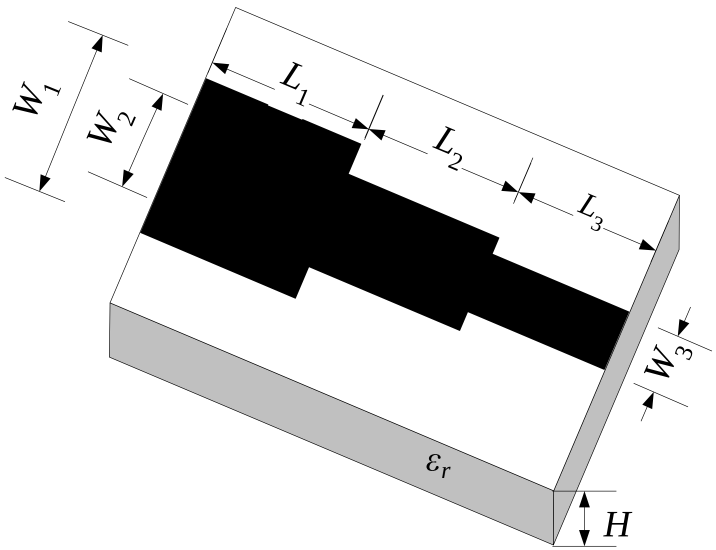
$$\boldsymbol{x}^{(i)} = \arg\min_{\boldsymbol{x}} \left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) - \boldsymbol{R}_c(\boldsymbol{x}_f^{(i)}, \boldsymbol{x}) \right\|$$

stopping criteria

$$\left\| \boldsymbol{x}_f^{(i)} - \boldsymbol{x}_f^{(i\text{-}1)} \right\| \leq \varepsilon_1$$

$$\left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) - \boldsymbol{R}_c(\boldsymbol{x}_f^{(i)}, \boldsymbol{x}^{(i\text{-}1)} + \boldsymbol{B}_r^{(i-1)} \boldsymbol{h}_r^{(i)}) \right\| \leq \varepsilon_2$$

3:1 Microstrip Transformer



load impedance is 50 Ω

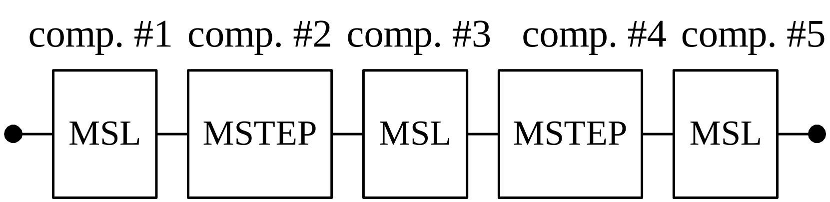
source impedance is 150 Ω

“fine” model: Sonnet’s ***em*** parameterized by OSA’s Empipe

“coarse” model: OSA90/hope

specifications

$|S_{11}| \leq -20$ dB for 5 GHz $\leq \omega \leq$ 15 GHz



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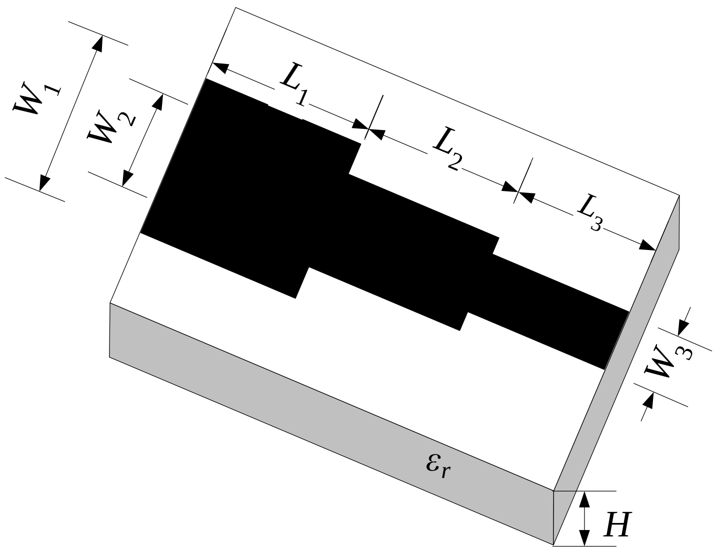

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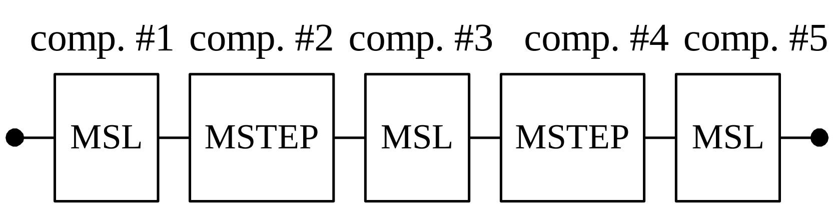

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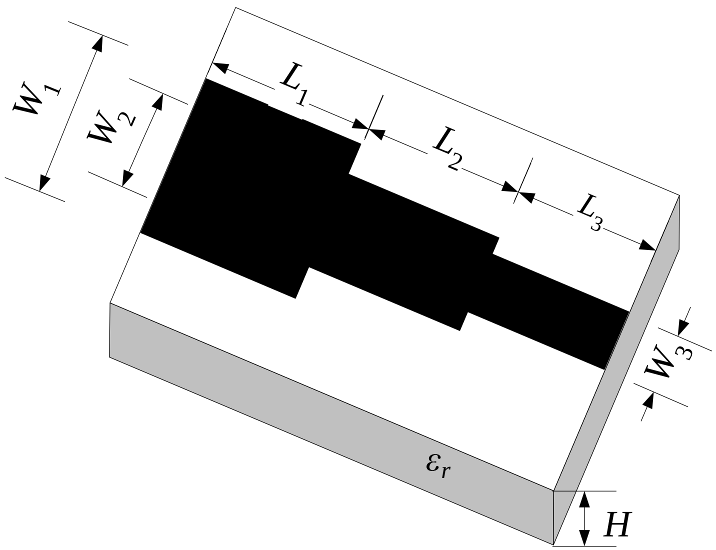

$$\boldsymbol{x}_f = [W_1 \quad W_2 \quad W_3 \quad L_1 \quad L_2 \quad L_3]^T$$

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$$\boldsymbol{x} = [\boldsymbol{x}_1^T \;\; \boldsymbol{x}_3^T \;\; \boldsymbol{x}_5^T]^T \qquad \boldsymbol{x}_i = [\varepsilon_{ri} \quad H_i]^T$$

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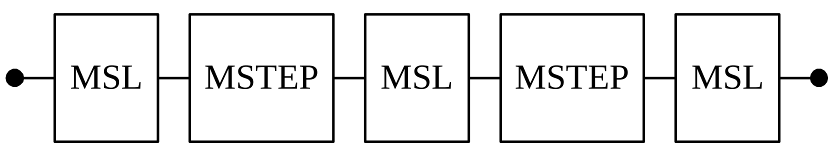
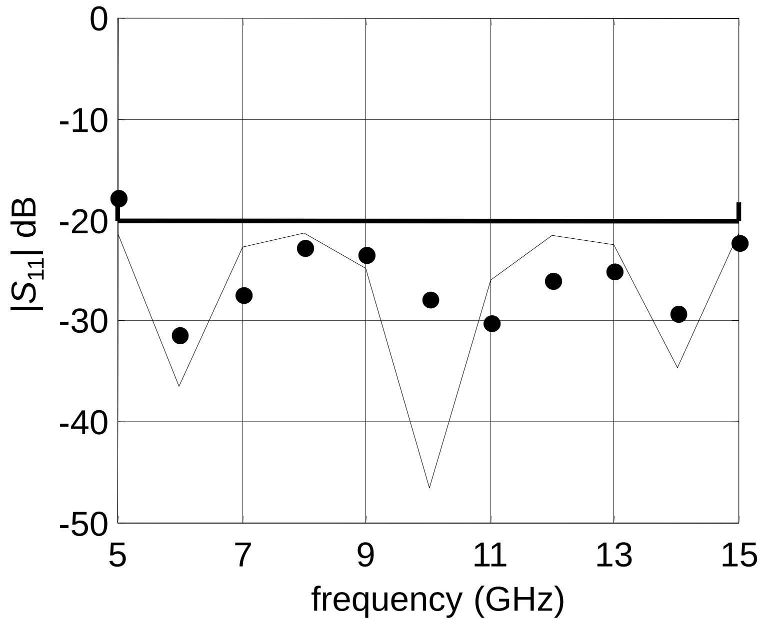


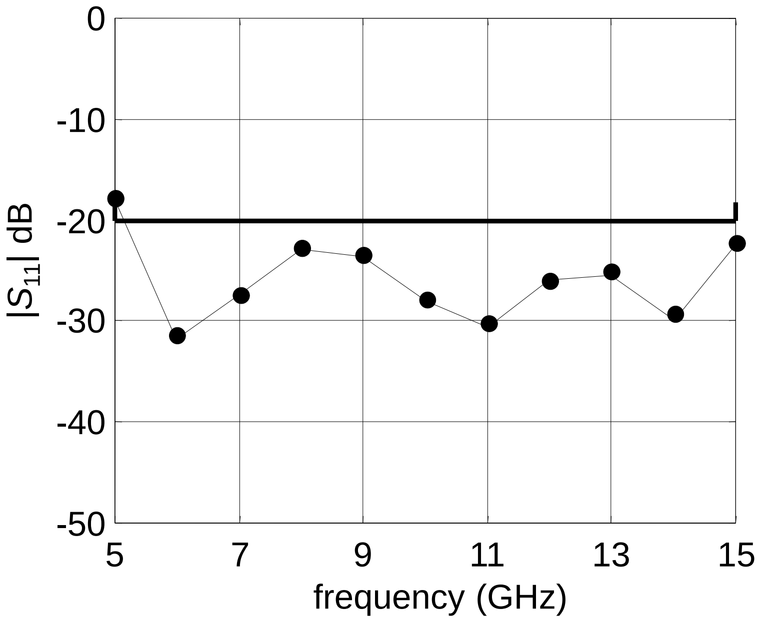
$$\begin{bmatrix} \varepsilon_{r1} \\ H_1 \\ \varepsilon_{r3} \\ H_3 \\ \varepsilon_{r5} \\ H_5 \end{bmatrix} = \boldsymbol{c} + \begin{bmatrix} \mathrm{x} & 0 & 0 \\ \mathrm{x} & 0 & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & 0 & \mathrm{x} \\ 0 & 0 & \mathrm{x} \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ W_3 \end{bmatrix}$$

3:1 Microstrip Transformer

initial iteration



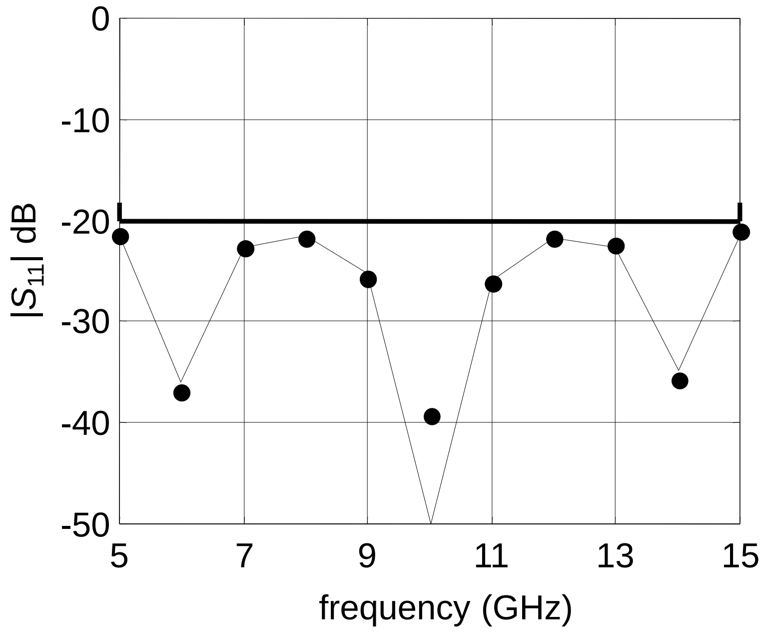
before KPP extraction



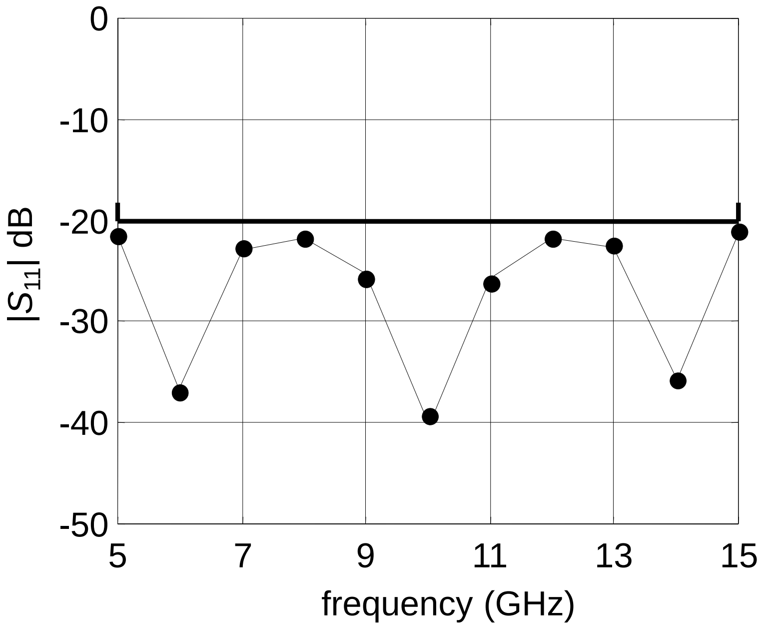
after KPP extraction

3:1 Microstrip Transformer

next iteration



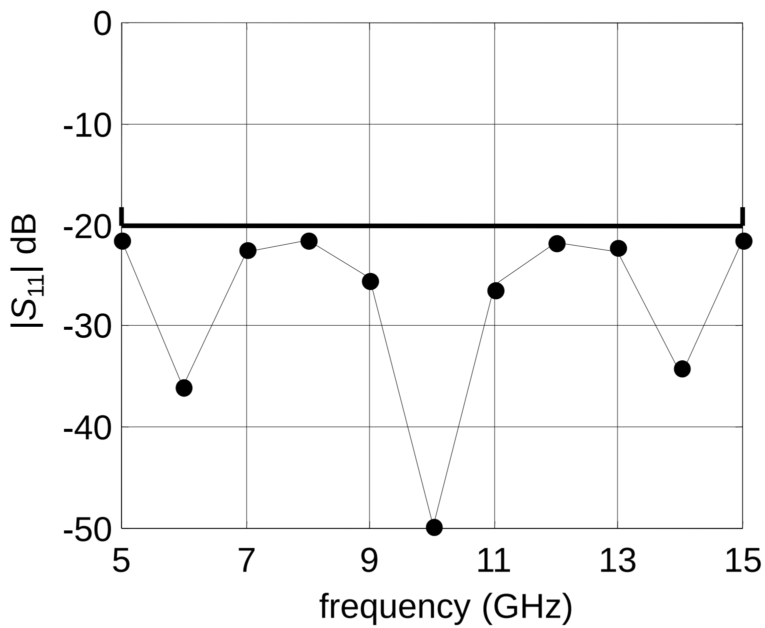
before KPP extraction



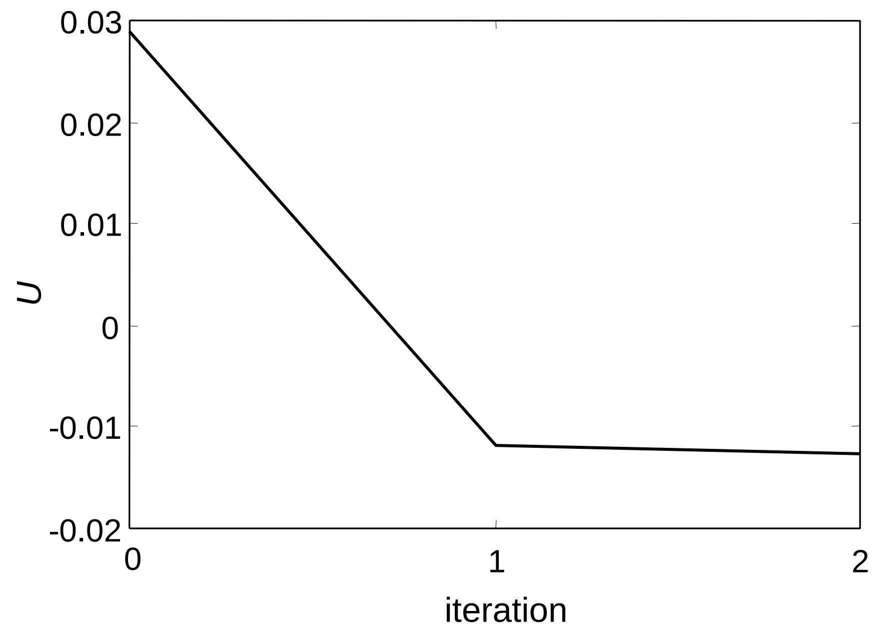
after KPP extraction

3:1 Microstrip Transformer

final iteration



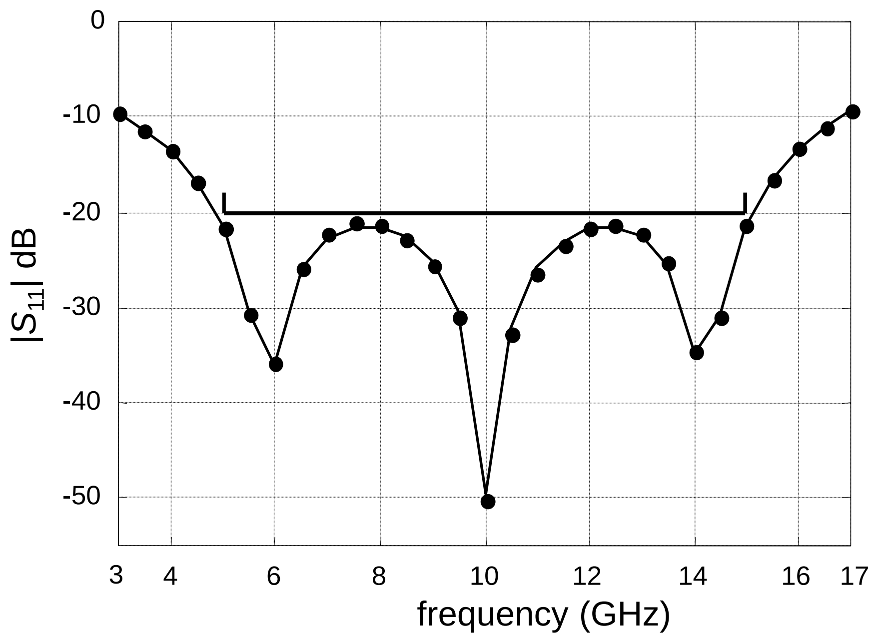
fine model objective function



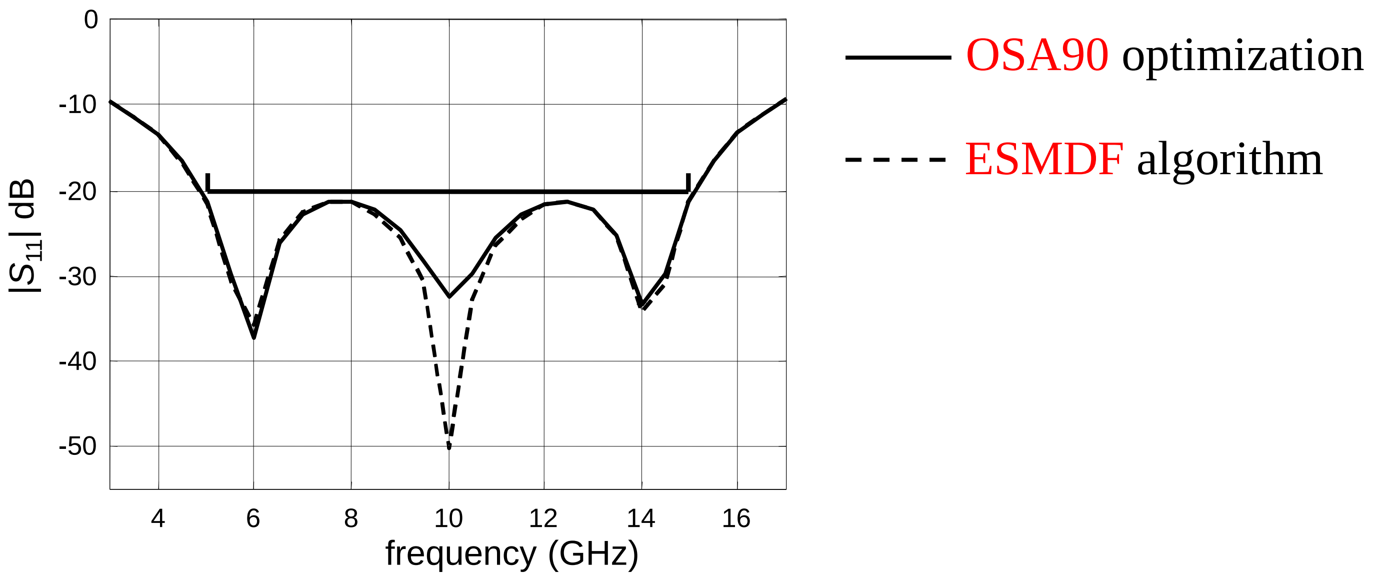
elapsed time by the ESMDF algorithm: 17 min

3:1 Microstrip Transformer

detailed frequency sweep of the optimal response



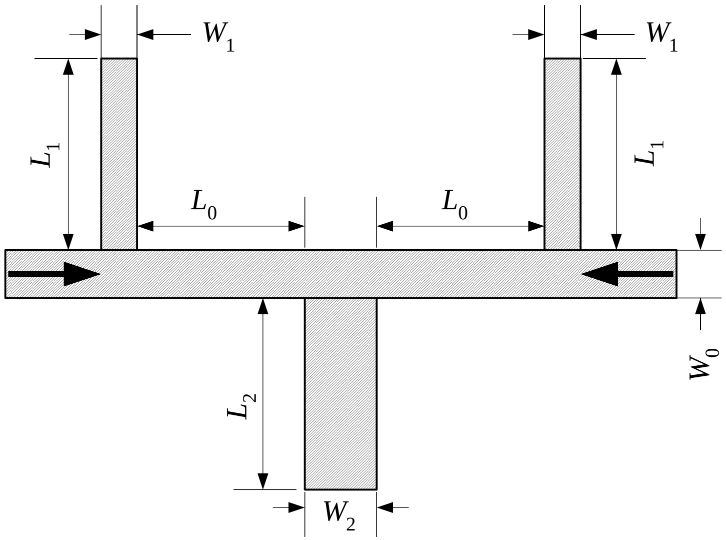
3:1 Microstrip Transformer Direct EM Optimization

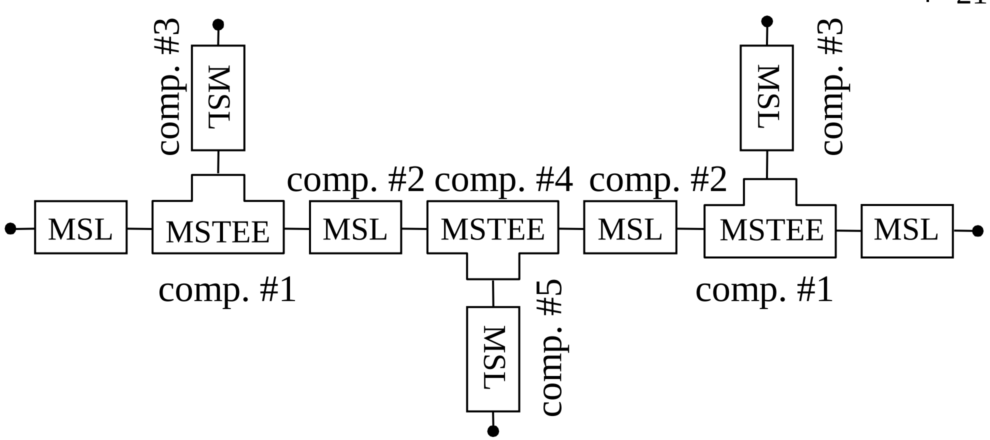


elapsed time by OSA90 minimax optimization (using quadratic interpolation): 153 min

elapsed time by the ESMDF algorithm: 17 min

Microstrip Bandstop Filter with Open Stubs





“fine” model: Momentum
(Agilent EEsof EDA)

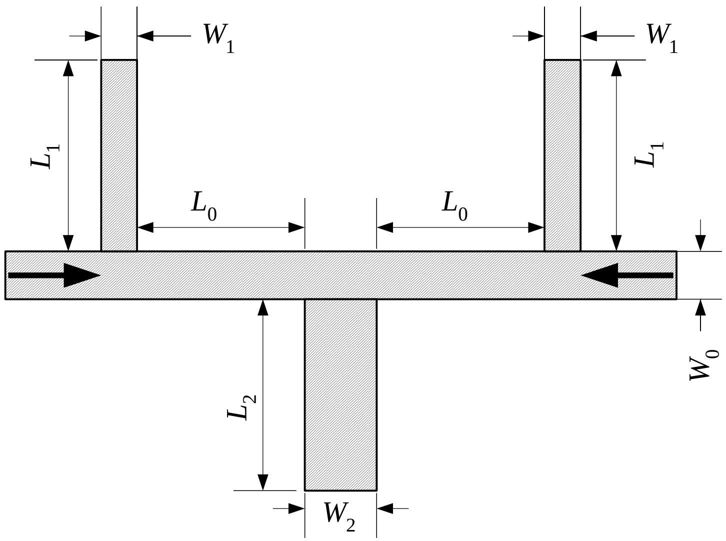
“coarse” model: OSA90/hope

specifications

$|S_{21}| \geq -1$ dB for $\omega \geq 12$ GHz and $\omega \leq 8$ GHz

$|S_{21}| \leq -25$ dB for 9 GHz $\leq \omega \leq$ 11 GHz

Microstrip Bandstop Filter with Open Stubs



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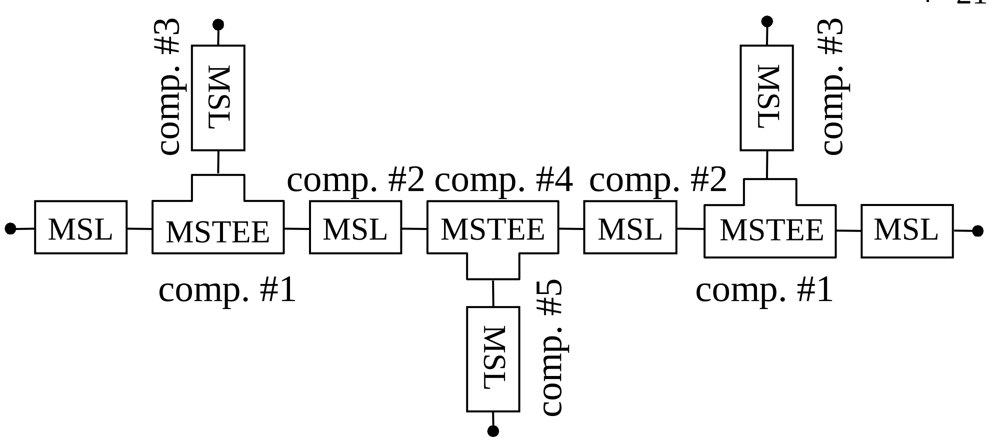
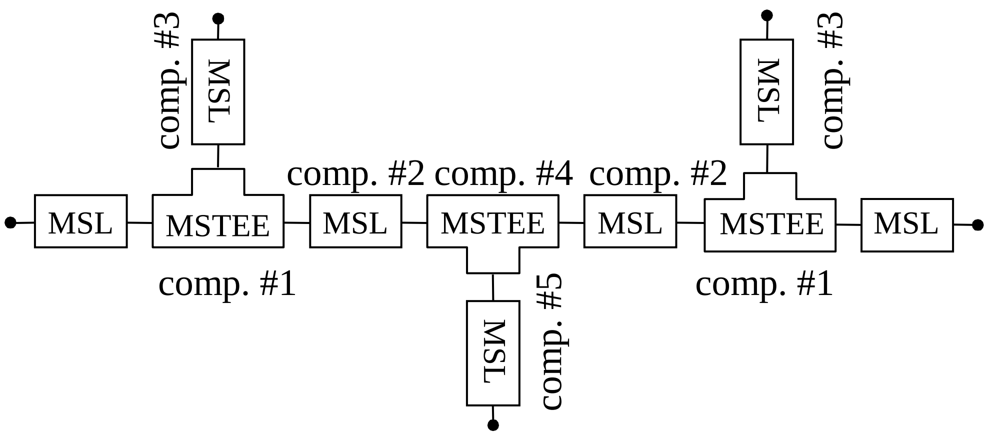


Microstrip Bandstop Filter with Open Stubs

coarse model decomposition



$$S_i = \left\| \left(\frac{\partial \boldsymbol{R}_c^{\mathrm{T}}}{\partial \boldsymbol{x}_i} \boldsymbol{D} \right)^{\mathrm{T}} \right\|_F$$

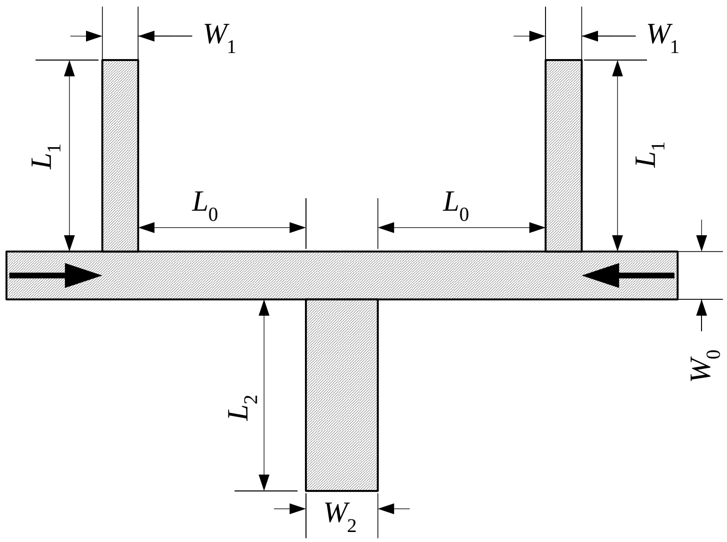
Component #	$\hat{S}_i$
1	0.1420
2	0.6359
3	0.8395
4	0.1858
5	1.0000

$\varepsilon_r = 9.4$, $H = 25$ mil

$$\boldsymbol{x}_i = [\varepsilon_{ri} \quad H_i]^T, \quad i = 1, \cdots, 5$$

hence $\quad \boldsymbol{x} = [\boldsymbol{x}_2^T \;\; \boldsymbol{x}_3^T \;\; \boldsymbol{x}_5^T]^T$

Microstrip Bandstop Filter with Open Stubs



$$\boldsymbol{x}_f = [W_1 \quad W_2 \quad L_0 \quad L_1 \quad L_2]^T$$

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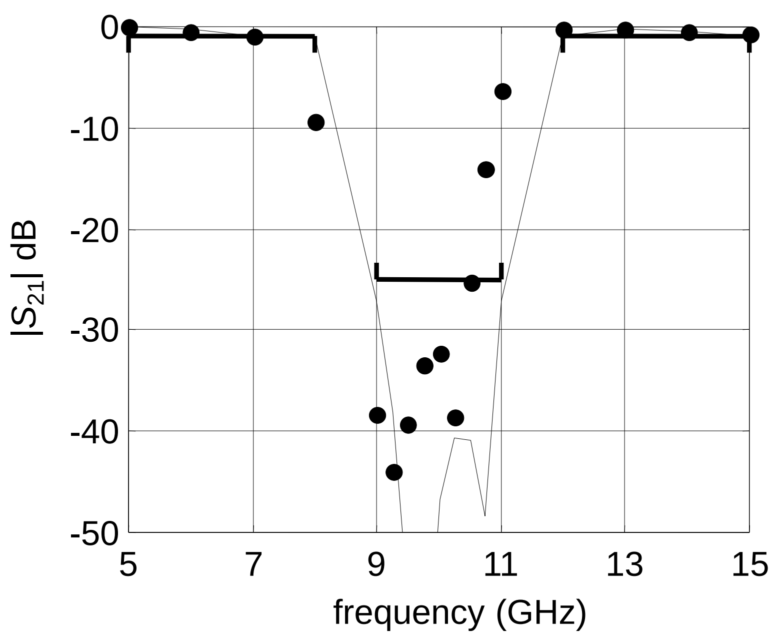
$$\boldsymbol{x} = \boldsymbol{c} + \boldsymbol{B}_r \ \boldsymbol{x}_r$$

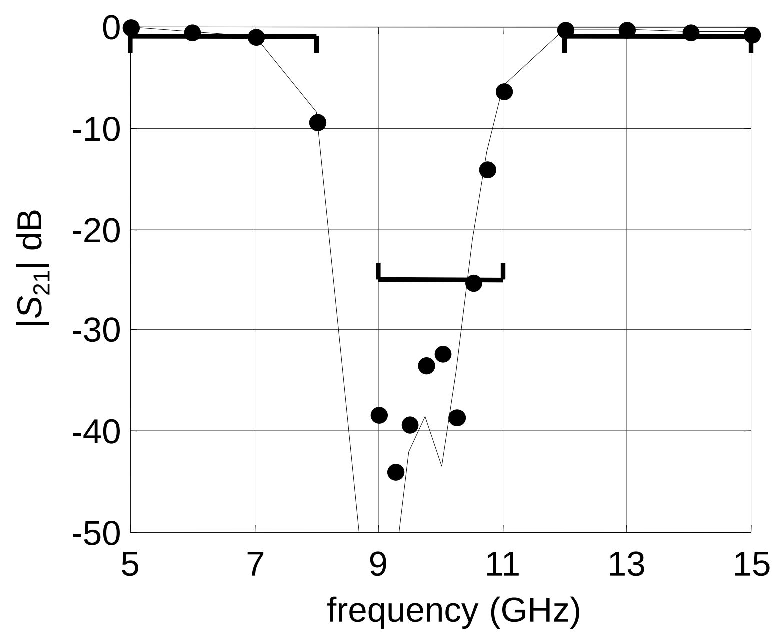
$$\begin{bmatrix} \varepsilon_{r2} \\ H_2 \\ \varepsilon_{r3} \\ H_3 \\ \varepsilon_{r5} \\ H_5 \end{bmatrix} = \boldsymbol{c} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \mathrm{x} & 0 \\ \mathrm{x} & 0 \\ 0 & \mathrm{x} \\ 0 & \mathrm{x} \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}$$

Microstrip Bandstop Filter with Open Stubs

initial response



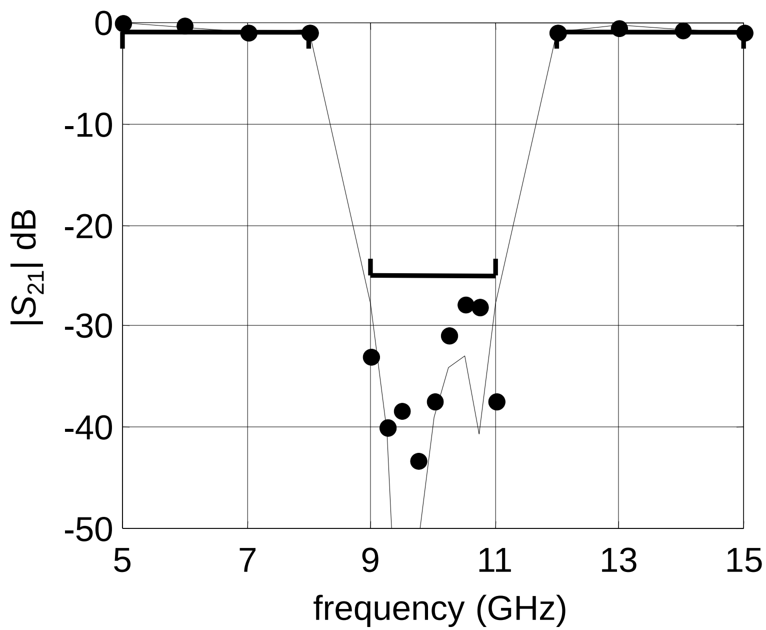
before KPP extraction



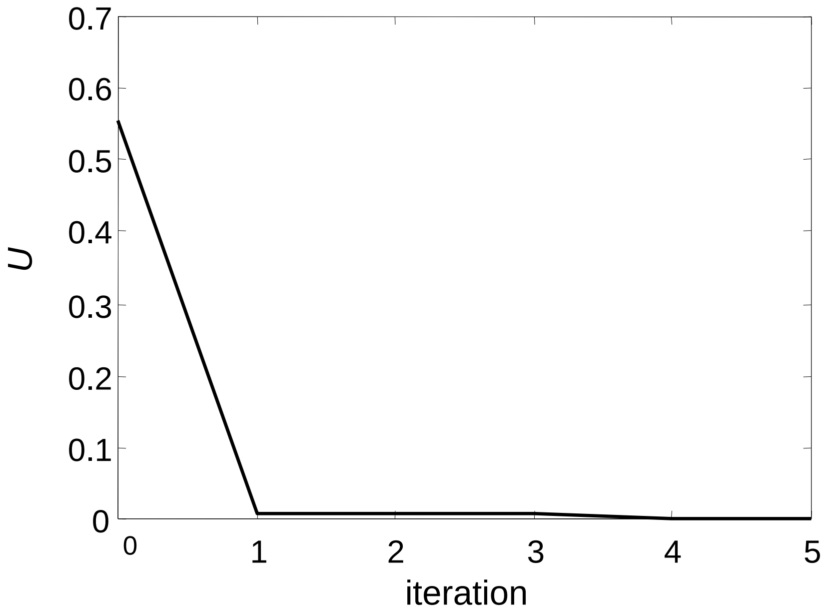
after KPP extraction

Microstrip Bandstop Filter with Open Stubs

final response



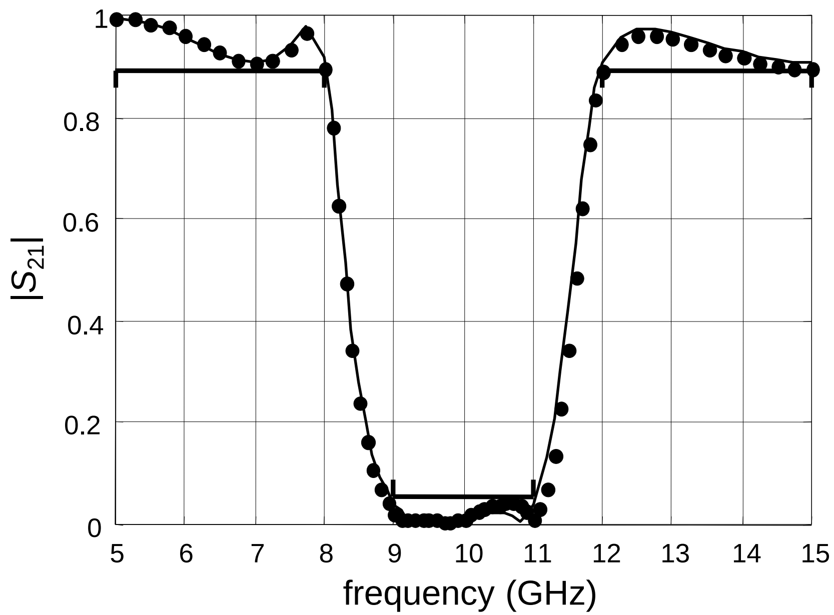
fine model objective function

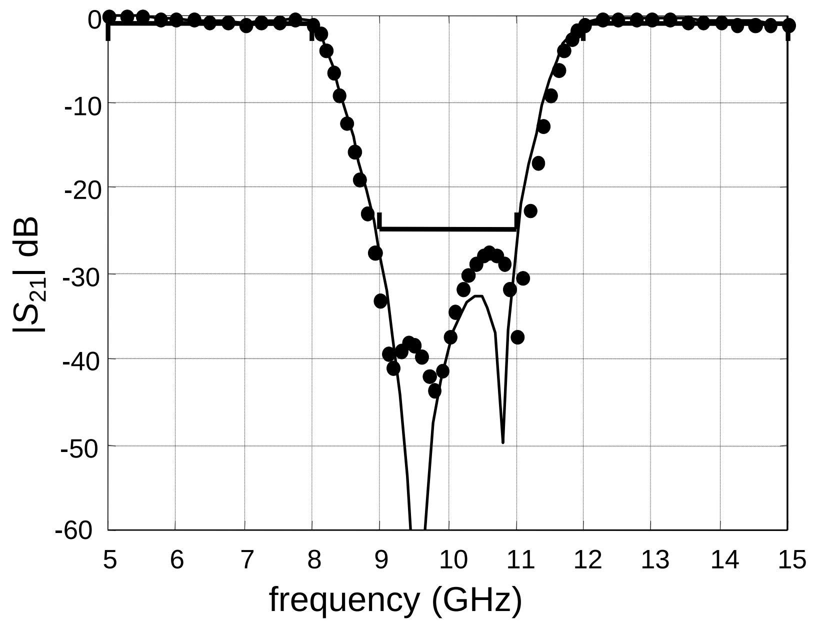


elapsed time by the ESMDF algorithm: 1.5 hr

Microstrip Bandstop Filter with Open Stubs

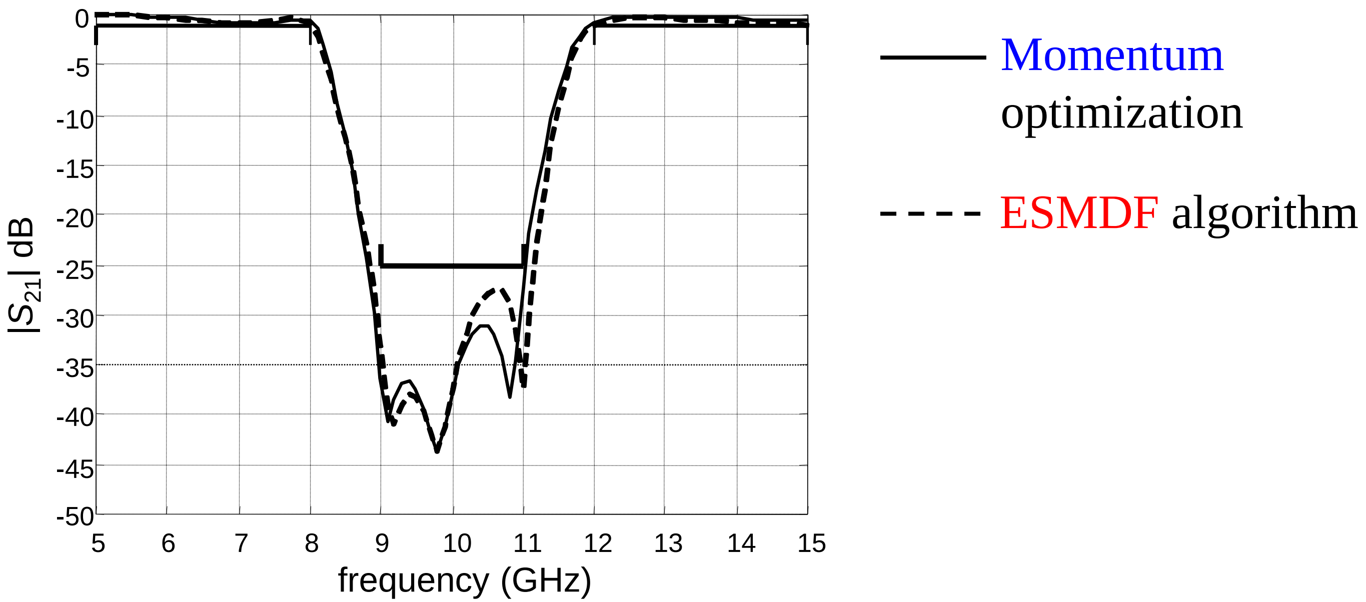
detailed frequency sweep at the optimal solution





Microstrip Bandstop Filter with Open Stubs

direct optimization



elapsed time by Momentum optimization (using quadratic interpolation): 10 hr

elapsed time by the ESMDF algorithm: 1.5 hr

Conclusions

we expand the original space mapping approach

we exploit key preassigned parameters (KPP)

we tune the KPP in "relevant components" of the coarse model
to align it with the fine model

a mapping is established from the optimization variables to the KPP

the mapping is updated iteratively

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