A HYBRID AGGRESSIVE SPACE MAPPING ALGORITHM FOR EM OPTIMIZATION

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M.H. Bakr, J.W. Bandler, N. Georgieva and K. Madsen

Simulation Optimization Systems Research Laboratory
and Department of Electrical and Computer Engineering
McMaster University, Hamilton, Canada L8S 4K1

bandler@mcmaster.ca
www.sos.mcmaster.ca

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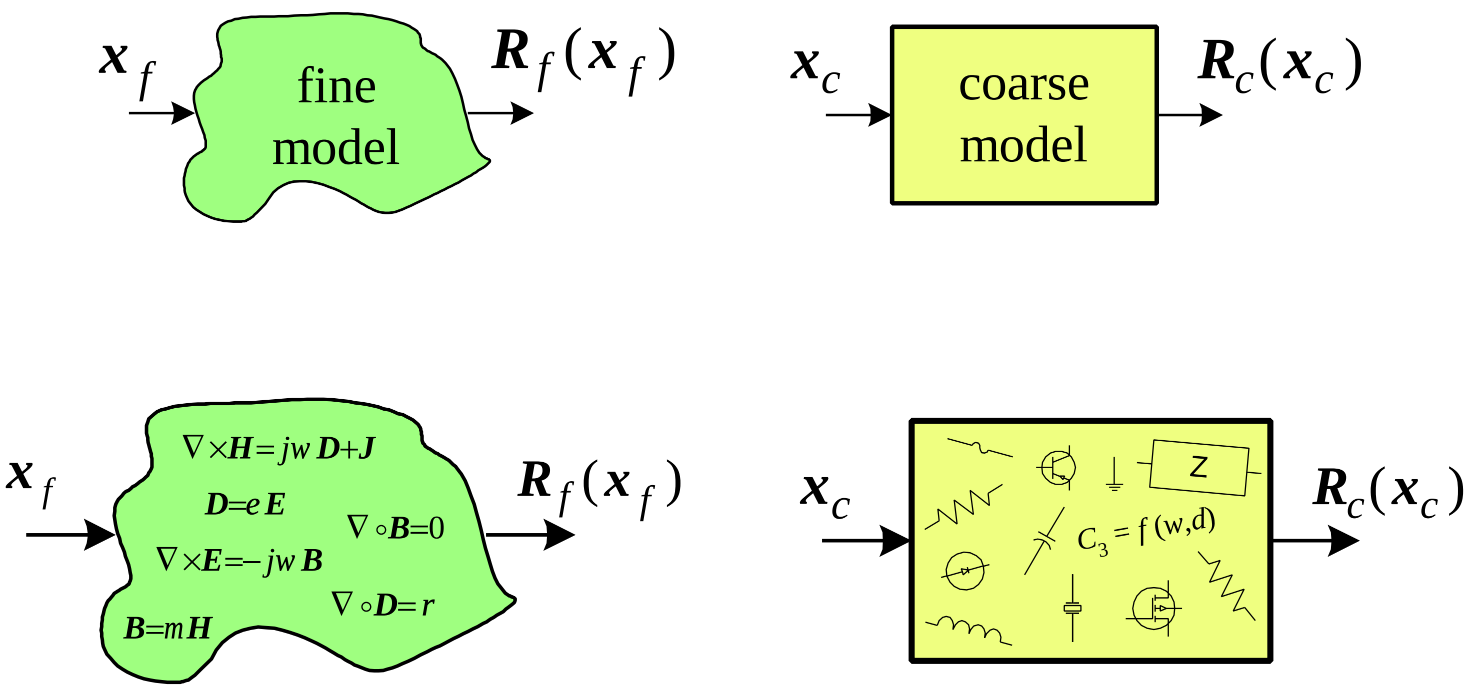
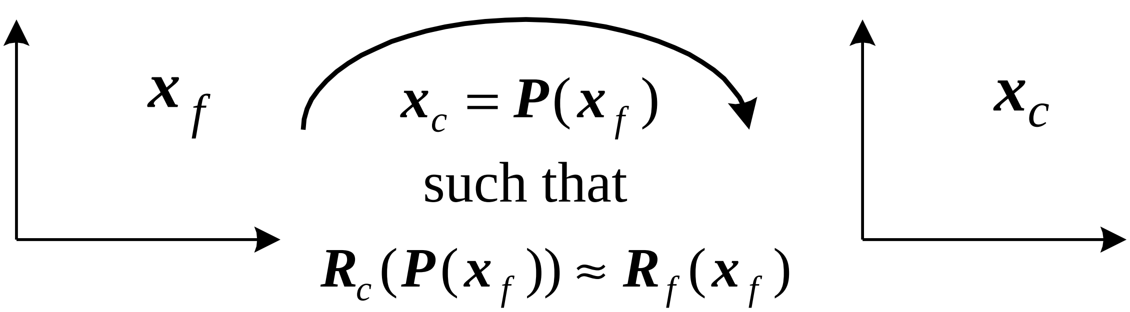
The Aim of Space Mapping

(*Bandler et al., 1994*-)

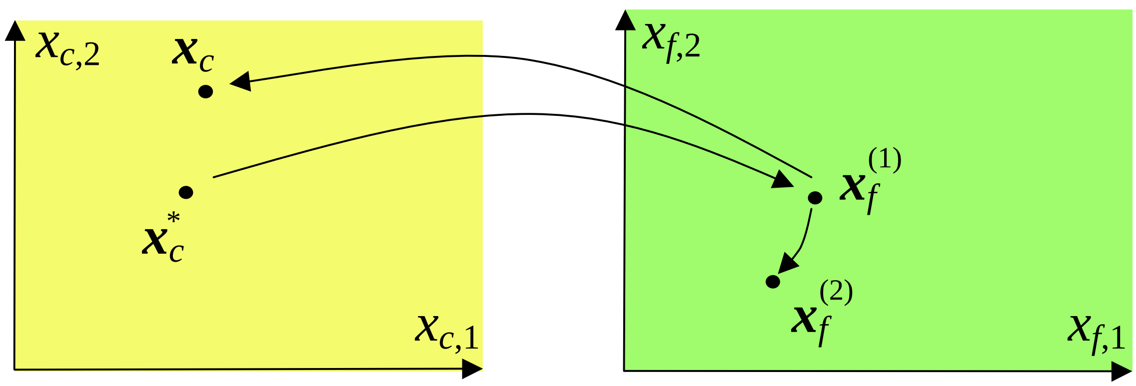




The Aggressive Space Mapping (ASM) Algorithm
(*Bandler et al., 1995***)**

the initial fine model design is the optimal coarse model design $\boldsymbol{x}_c^*$

parameter extraction is used to predict the step to be taken in the fine model space



in the *i*th iteration the new iterate is given by

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

$\boldsymbol{h}^{(i)}$ is obtained by solving

$$\boldsymbol{B}^{(i)}\boldsymbol{h}^{(i)} = -\boldsymbol{f}(\boldsymbol{x}_f^{(i)})$$

where

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

the nonuniqueness of the parameter extraction problem can lead to divergence or oscillation of the algorithm

The Trust Region Aggressive Space Mapping (TRASM) Algorithm
(*Bakr et al., 1998*)

this algorithm integrates a trust region methodology with the aggressive space mapping technique

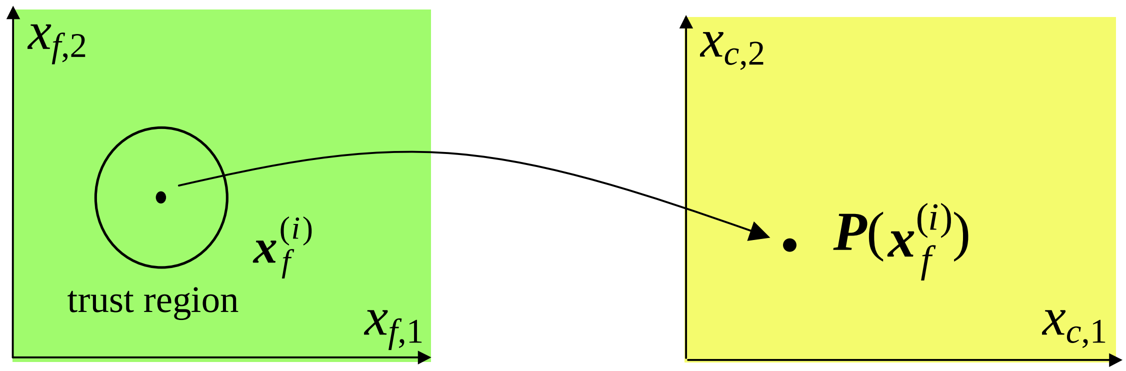
a certain success criterion must be satisfied at each iteration so as to accept the predicted step

a recursive multi-point parameter extraction procedure was introduced in the context of this algorithm

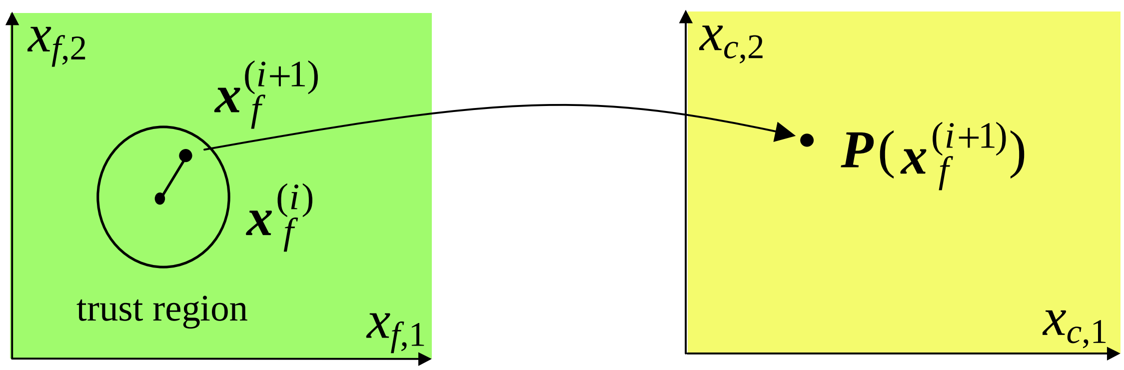
all available fine model simulations are utilized in order to improve the uniqueness of the parameter extraction step

the available information about the mapping between the two spaces is integrated in this extraction procedure

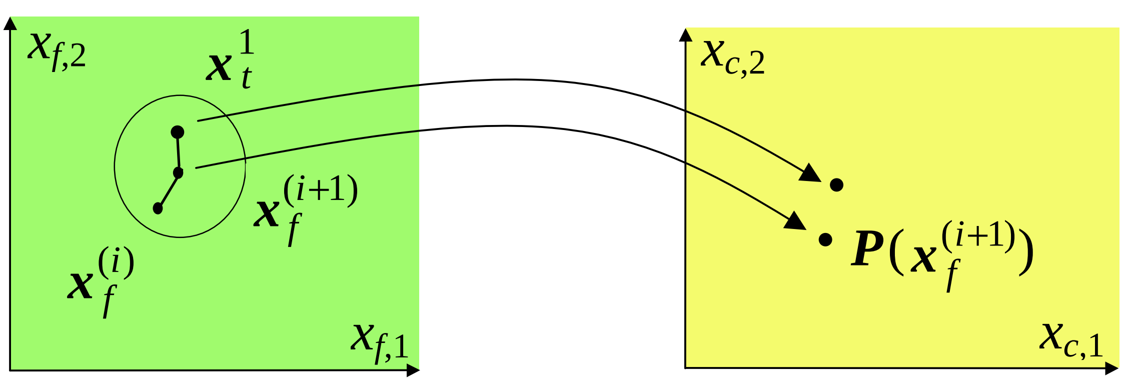
Illustration of the TRASM Algorithm



the current state at the *i*th iteration



initial parameter extraction at the suggested point



multi-point extraction is applied

Seven-Section Waveguide Transformer
(*Bandler et al., 1996*)

design specifications: *vswr* ≤ 1.01 for 1.06 GHz ≤ *f* ≤ 1.8 GHz

optimizable parameters: length and height of each waveguide section

coarse model: an analytical model that neglects junction discontinuities

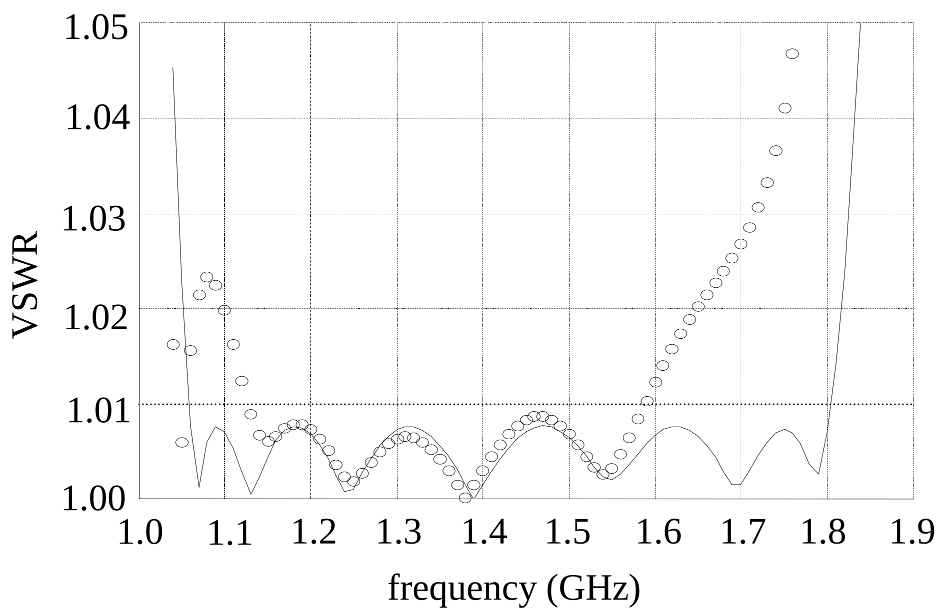
fine model: an analytical model that considers junction discontinuities

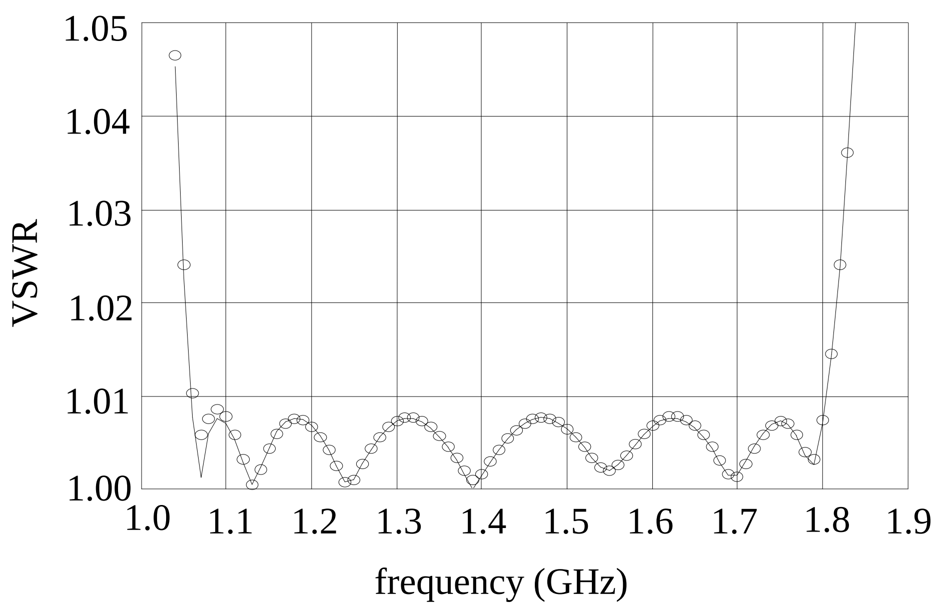
the optimal design is obtained in 3 TRASM iterations requiring 6 fine model simulations

21 frequency points were used per simulation

Seven-Section Waveguide Transformer Responses

the optimal coarse model (—) response and the fine model response (o) at the initial and final designs





The Motivation for a Hybrid Algorithm

the TRASM algorithm is efficient

the number of fine model simulations needed is of the order of the problem dimension

any SM algorithm assumes the existence of a coarse model which is fast and has sufficient accuracy

if the coarse model is severely misaligned from the fine model SM optimization may not converge

the solution obtained using the TRASM algorithm in most problems is a near optimal solution

however, optimality can not be guaranteed: the optimal coarse model response may be significantly different from the optimal fine model response

Illustrative Example: A Rosenbrock Function

consider a coarse model as

$$R_c = 100\,(x_2 - x_1^2)^2 + (1 - x_1)^2$$

and a fine model as

$$R_f = 100\,((x_2 + \alpha_2) - (x_1 + \alpha_1)^2)^2 + (1 - (x_1 + \alpha_1))^2$$

where α_1 and α_2 are constant shifts

suppose the target of the direct optimization problem is to minimize R_f

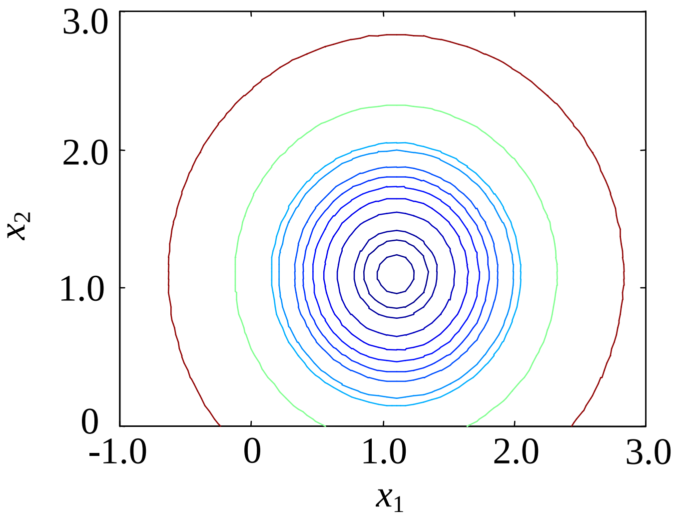
the optimal coarse model design is $\boldsymbol{x}_c^* = [1.0 \quad 1.0]^T$

the optimal fine model design is $\boldsymbol{x}_f^* = [(1 - \alpha_1) \quad (1 - \alpha_2)]^T$

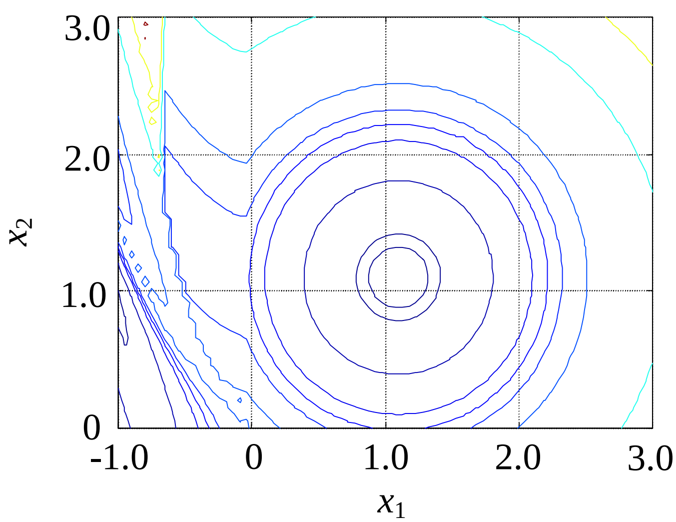
the misalignment between the two models is thus given by the two shifts α_1 and α_2

Illustrative Example: A Rosenbrock Function

consider the case $a_1 = a_2 = -0.1$



ideal contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$

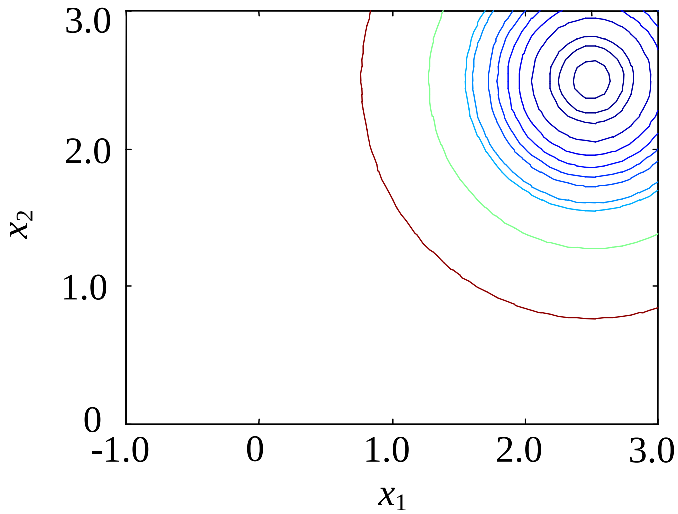


actual contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$

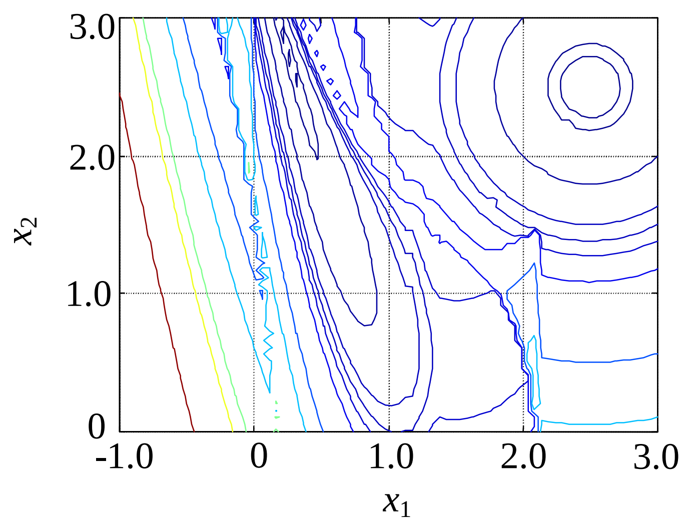
the TRASM algorithm is likely to converge

Illustrative Example: A Rosenbrock Function

consider the case $a_1 = a_2 = -1.5$



ideal contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$



actual contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$

the TRASM algorithm is unlikely to converge

The Relation Between SM Optimization and Direct Optimization

assume that $\boldsymbol{x}_c$ corresponds to $\boldsymbol{x}_f$ through a parameter extraction process

the Jacobian $\boldsymbol{J}_f$ of the fine model response at $\boldsymbol{x}_f$ and the Jacobian $\boldsymbol{J}_c$ of the coarse model response at $\boldsymbol{x}_c$ are related by

$$\boldsymbol{J}_f = \boldsymbol{J}_c \boldsymbol{B}$$

where $\boldsymbol{B}$ is a valid mapping at $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$

this relation enables switching from SM optimization to direct optimization if SM optimization is not converging

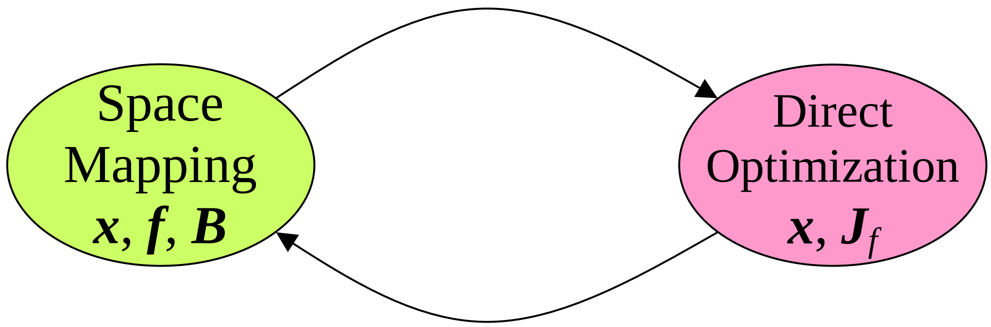
consequently

$$\boldsymbol{B} = \left(\boldsymbol{J}_c^T \boldsymbol{J}_c\right)^{-1} \boldsymbol{J}_c^T \boldsymbol{J}_f$$

which enables switching back from direct optimization to SM optimization

The Hybrid Aggressive Space Mapping (HASM) Algorithm

$$\boldsymbol{J}_f = \boldsymbol{J}_c \boldsymbol{B}$$



$$\boldsymbol{B} = \left(\boldsymbol{J}_c^T \boldsymbol{J}_c\right)^{-1} \boldsymbol{J}_c^T \boldsymbol{J}_f$$

to ensure optimality of the final design, minimax optimization is applied starting from the final solution reached by the second phase

The Hybrid Aggressive Space Mapping (HASM) Algorithm

the HASM algorithm is designed to handle severely misaligned cases

it utilizes two different phases

the first phase utilizes the TRASM algorithm

if the TRASM algorithm is not converging smoothly a switch takes place to the second phase

this switch utilizes the information accumulated about the mapping between the two spaces to supply an estimate of the Jacobian of the fine model response to the second phase

the second phase applies direct optimization to match the fine model response to the optimal coarse model response

a switch back to the first phase can take place if SM is potentially convergent

the Jacobian of the fine model response and parameter extraction are then utilized to recover the mapping matrix $\boldsymbol{B}$

several switches can take place between the two phases

The Hybrid Aggressive Space Mapping (HASM) Algorithm

the algorithm utilizes two objective functions: the space mapping objective function $\|\boldsymbol{f}\|_2^2 = \|\boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^*\|_2^2$ and the ℓ_2 objective function $\|\boldsymbol{g}\|_2^2 = \|\boldsymbol{R}_f(\boldsymbol{x}_f) - \boldsymbol{R}_c(\boldsymbol{x}_c^*)\|_2^2$

in the *i*th iteration, the step taken by the first phase is obtained by solving $(\boldsymbol{B}^{(i)T}\boldsymbol{B}^{(i)} + \lambda\boldsymbol{I})\boldsymbol{h}^{(i)} = -\boldsymbol{B}^{(i)T}\boldsymbol{f}^{(i)}$, where $\boldsymbol{f}^{(i)}$ is obtained through multi-point parameter extraction

if the new point $\boldsymbol{x}_f^{(i+1)} = \boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}$ satisfies certain success criteria with respect to the reduction in both $\|\boldsymbol{f}\|_2^2$ and $\|\boldsymbol{g}\|_2^2$, the first phase continues

if $\boldsymbol{x}_f^{(i+1)}$ does not satisfy the success criterion of $\|\boldsymbol{g}\|_2^2$ it is rejected and a switch to the second phase takes place using $\boldsymbol{J}_f^{(i)} = \boldsymbol{J}_c^{(i)}\boldsymbol{B}^{(i)}$

if $\boldsymbol{x}_f^{(i+1)}$ satisfies the success criterion of $\|\boldsymbol{g}\|_2^2$ but does not satisfy the success criterion of $\|\boldsymbol{f}\|_2^2$ for a trusted $\boldsymbol{f}^{(i+1)}$, this point is accepted and a switch to the second phase takes place using $\boldsymbol{J}_f^{(i+1)} = \boldsymbol{J}_c^{(i+1)}\boldsymbol{B}^{(i+1)}$

The Hybrid Aggressive Space Mapping (HASM) Algorithm

if the number of fine model points utilized reaches n+1, $\boldsymbol{J}_f^{(i+1)}$ is estimated using finite differences and a switch to the second phase takes place

the kth step taken by the second phase is given by

$$(\boldsymbol{J}_f^{(k)T}\boldsymbol{J}_f^{(k)}+\lambda\boldsymbol{I})\Delta\boldsymbol{x}=-\boldsymbol{J}_f^{(k)T}\boldsymbol{g}^{(k)}$$

this step is repeated for a decreased trust region until a certain success criterion for the reduction in $\|\boldsymbol{g}\|_2^2$ is satisfied or until the trust region shrinks to the termination value

parameter extraction is carried out after each successful step

a switch back to the first phase takes place if a certain success criterion for the reduction in $\|\boldsymbol{f}\|_2^2$ is satisfied; the mapping matrix is then recovered using

$$\boldsymbol{B}=\left(\boldsymbol{J}_c^{(k+1)T}\boldsymbol{J}_c^{(k+1)}\right)^{-1}\boldsymbol{J}_c^{(k+1)T}\boldsymbol{J}_f^{(k+1)}$$

Three-Section Waveguide Transformer
(*Bandler et al., 1996*)

design specifications

$$vswr \leq 1.04 \quad \text{for } 5.7 \text{ GHz} \leq f \leq 7.2 \text{ GHz}$$

the designable parameters are the heights of the waveguide sections b_1, b_2 and b_3 and the lengths of waveguide sections L_1, L_2 and L_3

the fine model exploits HP HFSS through HP Empipe3D

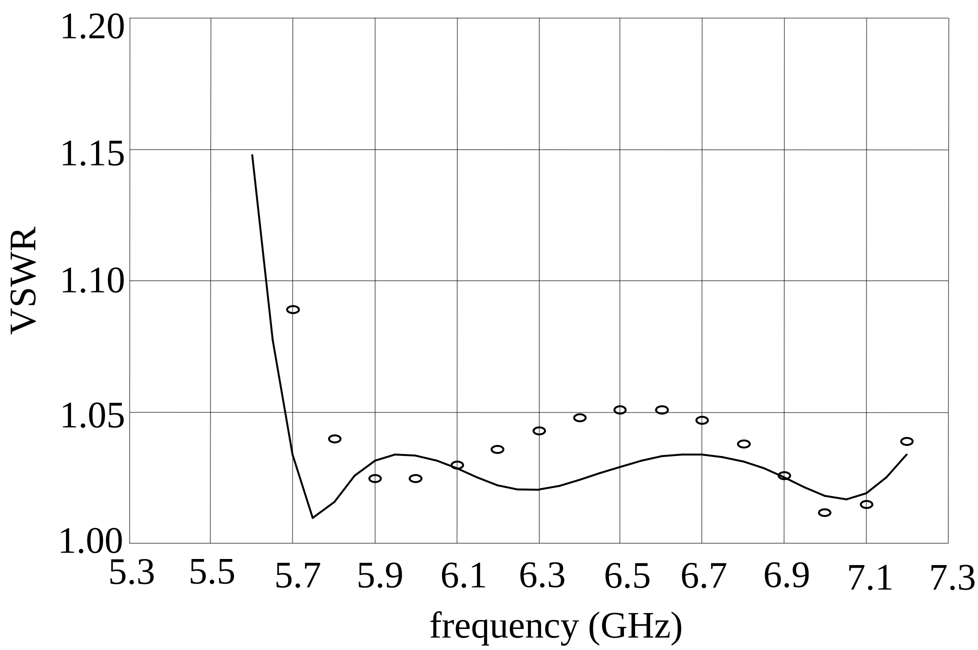
the coarse analytical model does not take into account the junction discontinuity effects

the first phase executed 2 iterations which required 4 fine model simulations

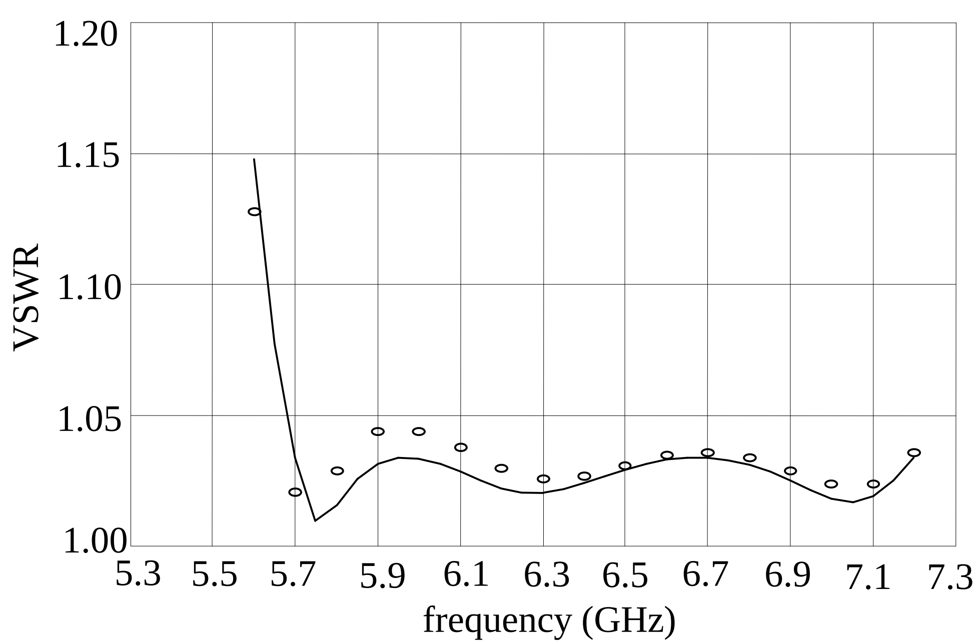
the second phase carried out only 1 iteration which required 2 fine model simulations

minimax optimization is then applied to the original problem starting from the second phase design

Optimization Results for the Three-Section Waveguide Transformer

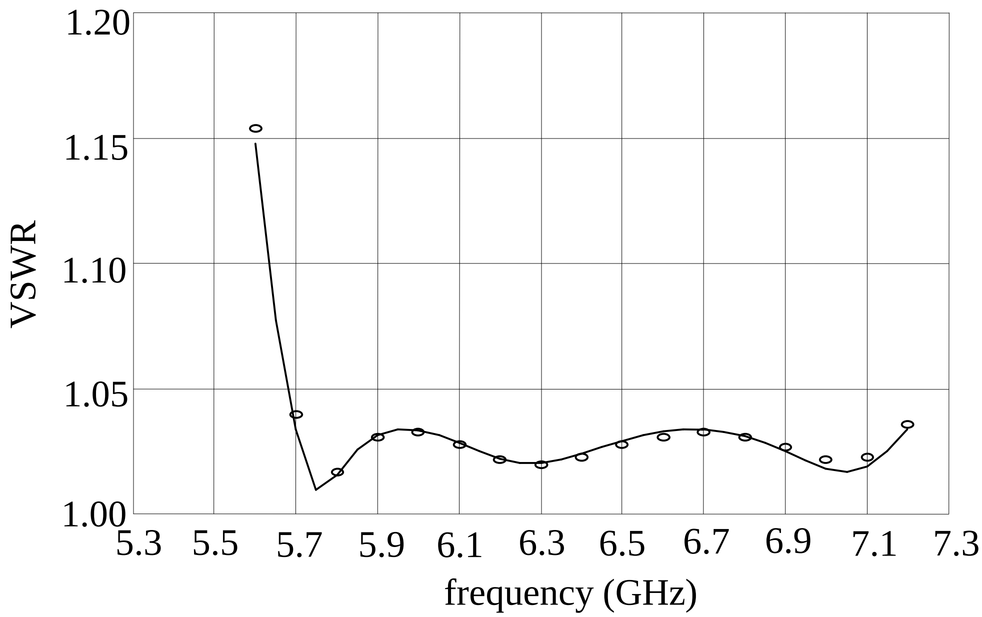


the initial fine model design

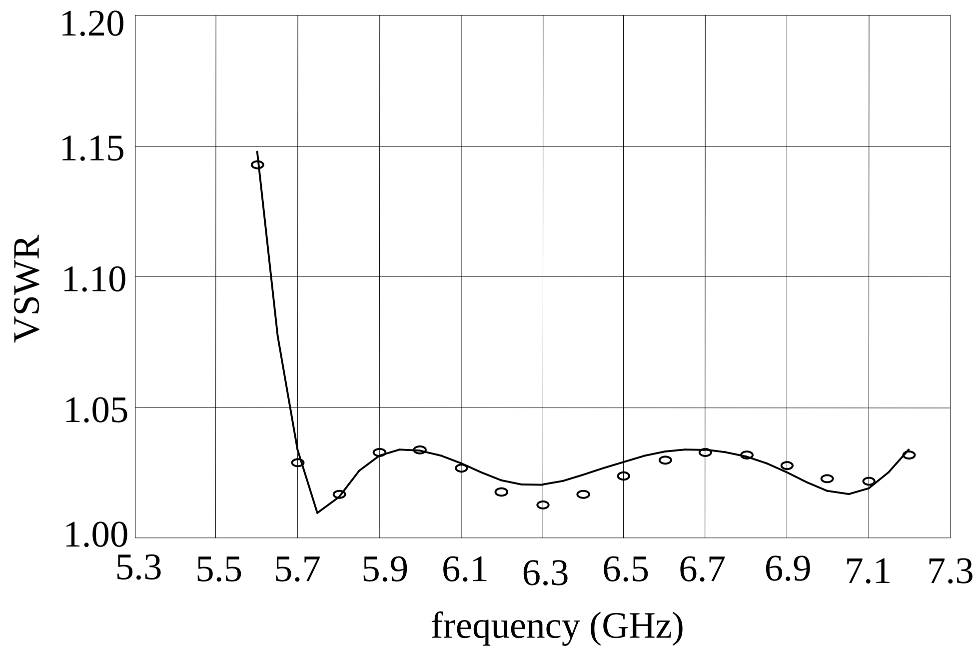


the first phase design

Optimization Results for the Three-Section Waveguide Transformer



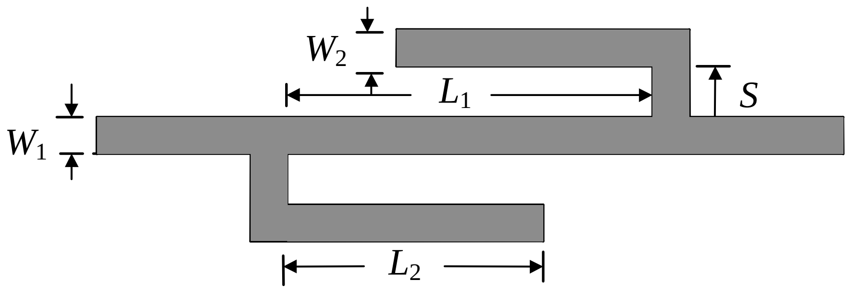
the second phase design

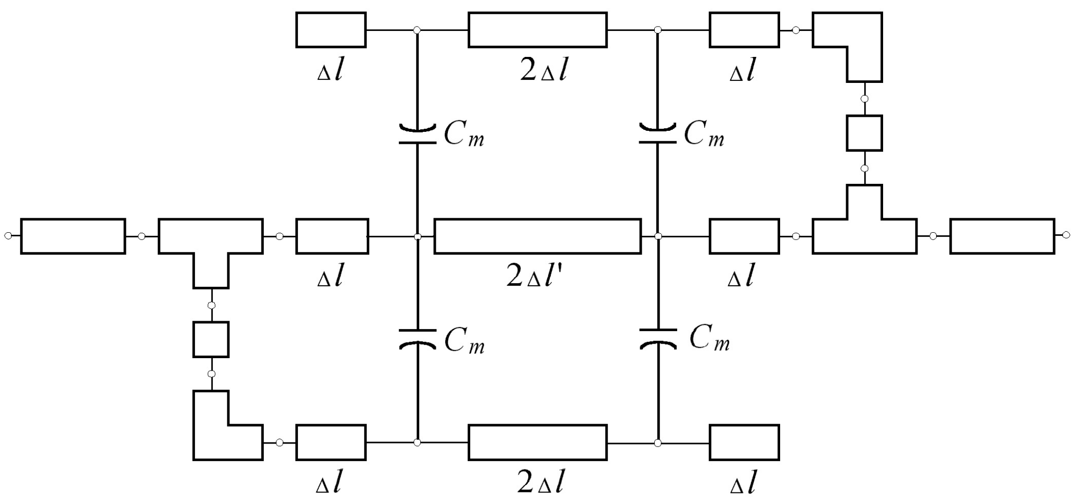


the optimal fine model design

Double-Folded Stub Microstrip Filter

(*Bandler et al., 1994*)





the fine model is the structure simulated by HP HFSS through HP Empipe3D

the coarse model exploits the microstrip line and microstrip T-junction models available in OSA90/hope

the coupling between the folded stubs and the microstrip line is simulated using equivalent capacitors (*Walker*, *1990*)

Double-Folded Stub Microstrip Filter

the folding effect of the stub is included utilizing the bend model (*Jansen et al., 1983*)

design specifications are

$$|S_{21}| \geq -3 \text{ dB} \;\; \text{for} \;\; f \leq 9.5 \text{ GHz} \;\; \text{and } 16.5 \text{ GHz} \leq f$$

and

$$|S_{21}| \leq -30 \text{ dB} \;\; \text{for} \;\; 12 \text{ GHz} \leq f \leq 14 \text{ GHz}$$

W_1 and W_2 are fixed at 4.8 mil

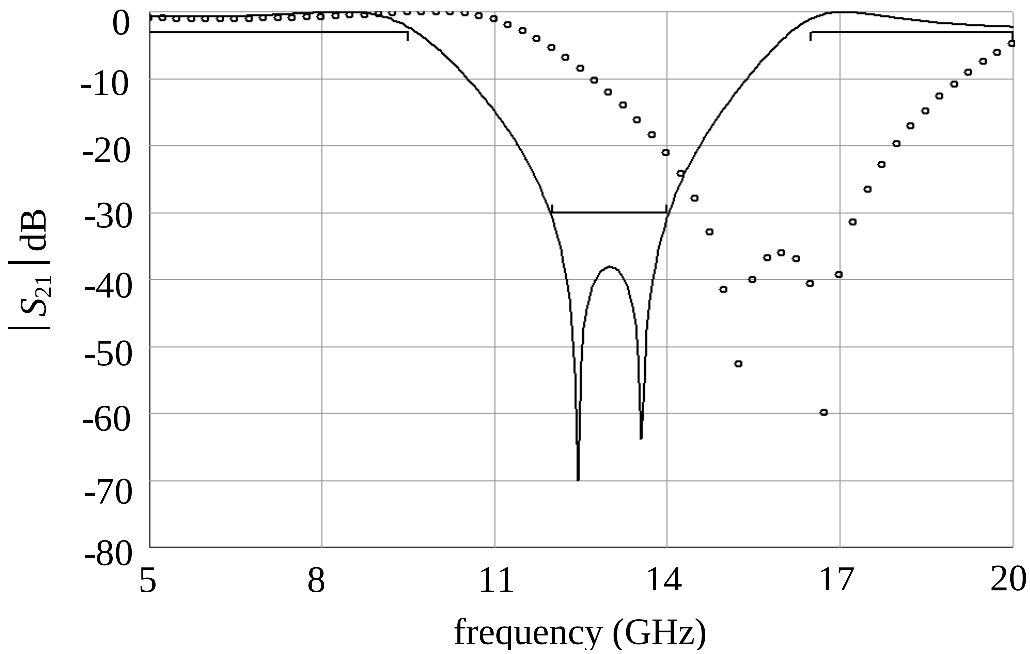
L_1, L_2 and S are chosen as optimization variables

the first phase successfully carried out 8 iterations that required 12 fine model simulations

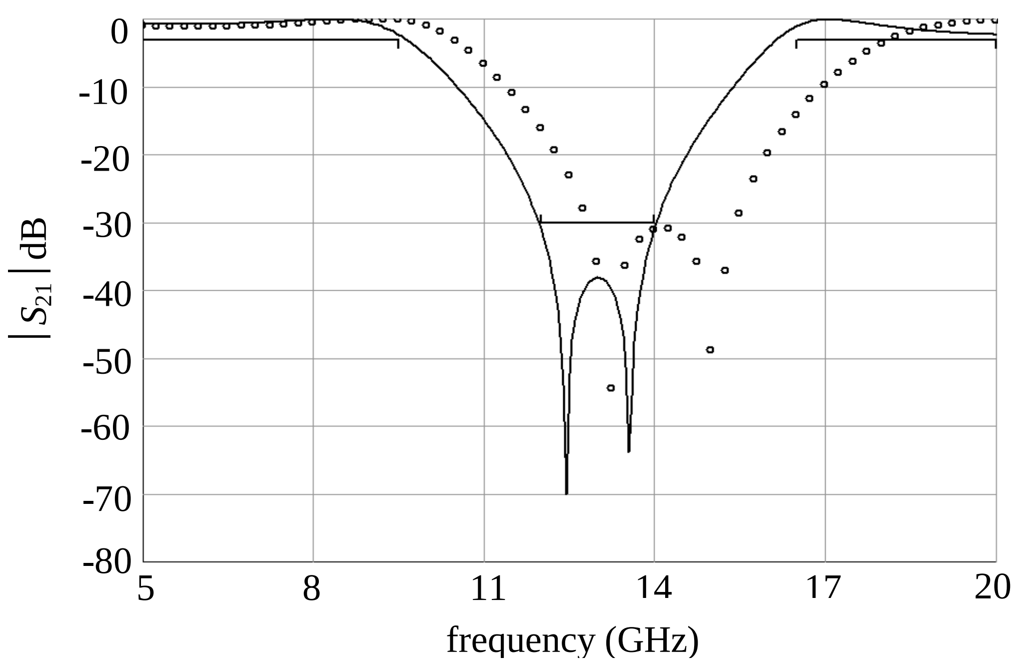
the first phase reached a local minimum for the SM optimization and a switch to the second phase took place

the second phase design is taken as the starting point for the minimax optimizer

Optimization Results for the DFS Filter

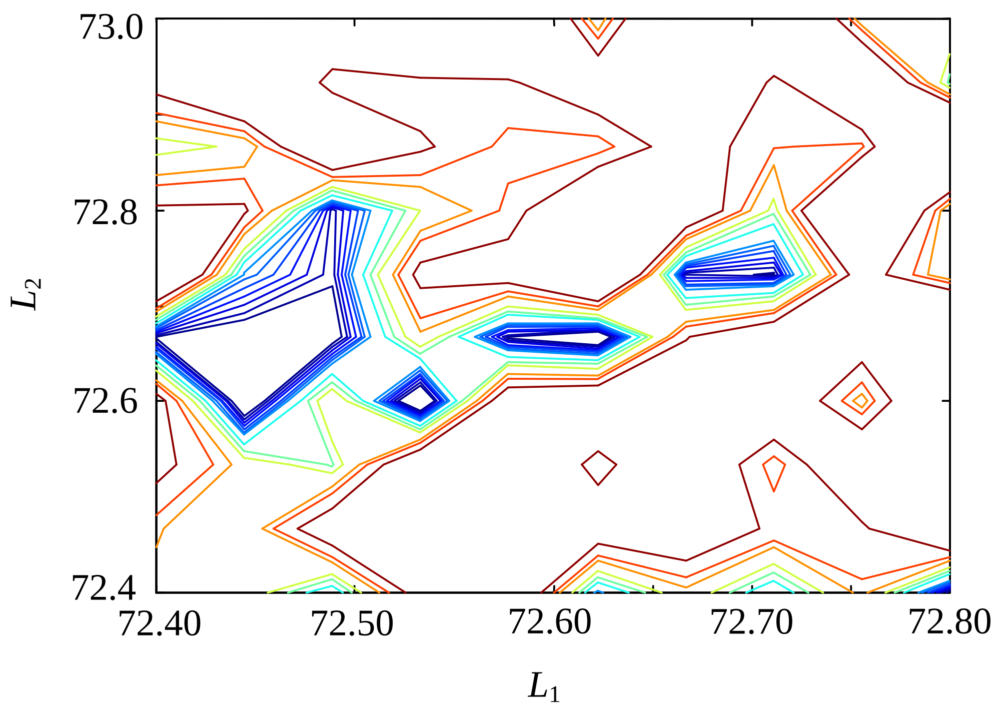


the initial fine model design

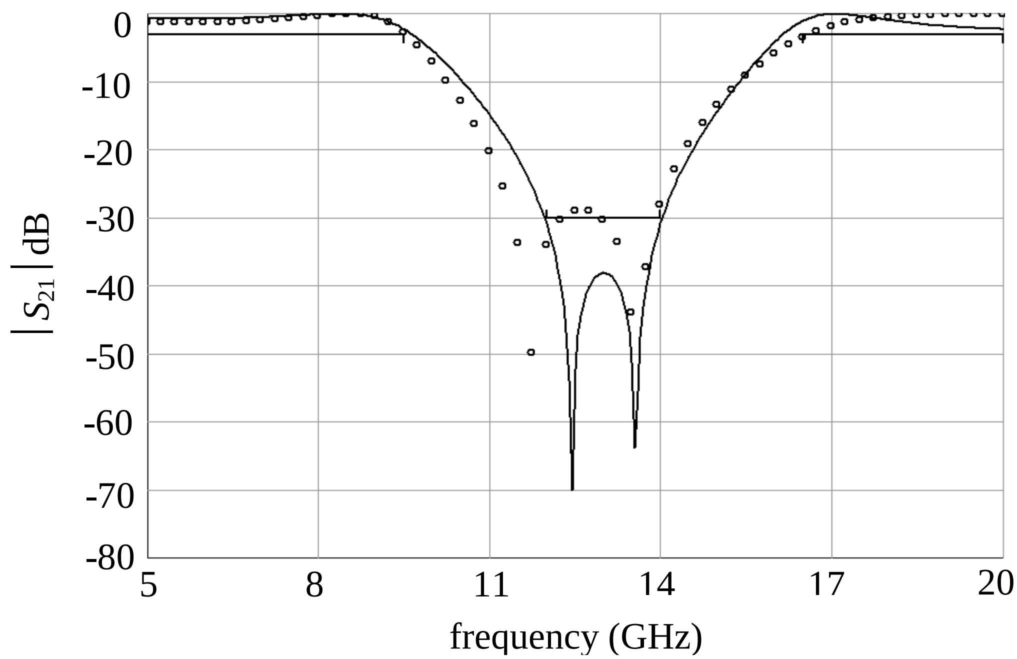


the first phase design

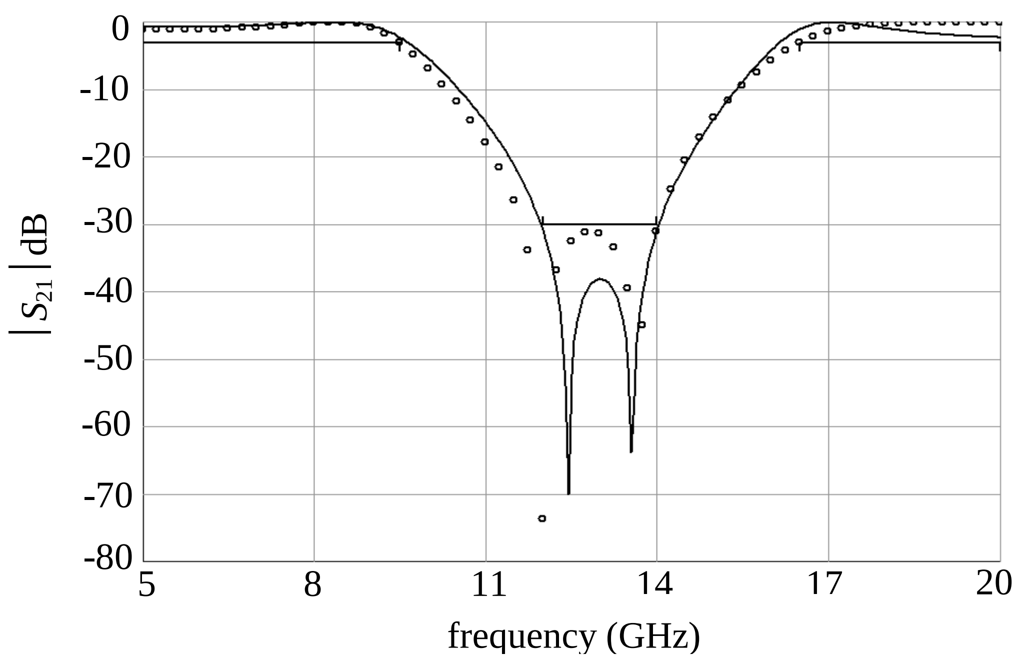
Contours of the Space Mapping Objective Function at the End of the First Phase



Optimization Results for the DFS Filter



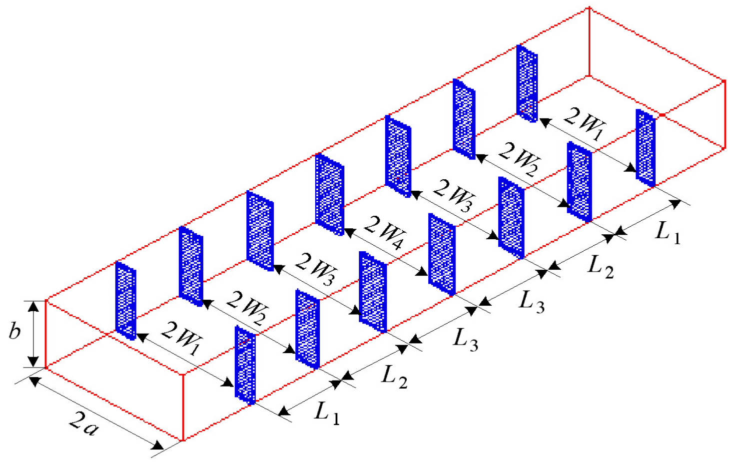
the second phase design

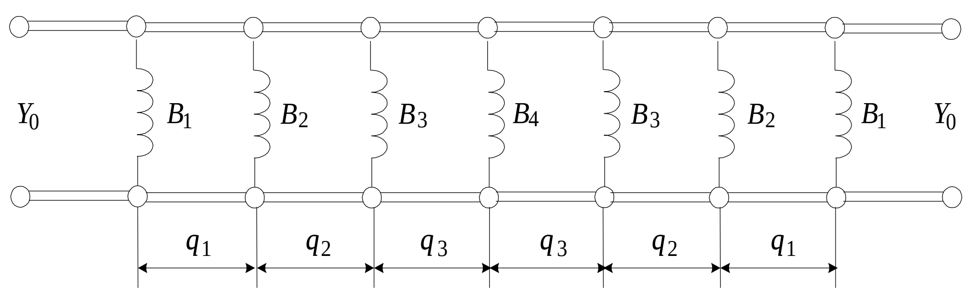


the optimal fine model design

Six-Section H-Plane Waveguide Filter

(Matthaei et al., 1964)





design specifications are taken as

$$|S_{11}| \leq 0.16 \text{ for } 5.4 \text{ GHz} \leq f \leq 9.0 \text{ GHz}$$

and

$$|S_{11}| \geq 0.85 \text{ for } f \leq 5.2 \text{ GHz and } |S_{11}| \geq 0.5 \text{ for } 9.5 \text{ GHz} \leq f$$

the fine model exploits HP HFSS through HP Empipe3D

a waveguide with a cross-section of 1.372 inches by 0.622 inches (3.485 cm by 1.58 cm) is used

Six-Section H-Plane Waveguide Filter

each septum has a finite thickness of 0.02 inches (0.508 mm)

the coarse model consists of lumped inductances and dispersive transmission line sections

a simplified version of a formula (*Marcuvitz, 1951*) is utilized in evaluating the inductances

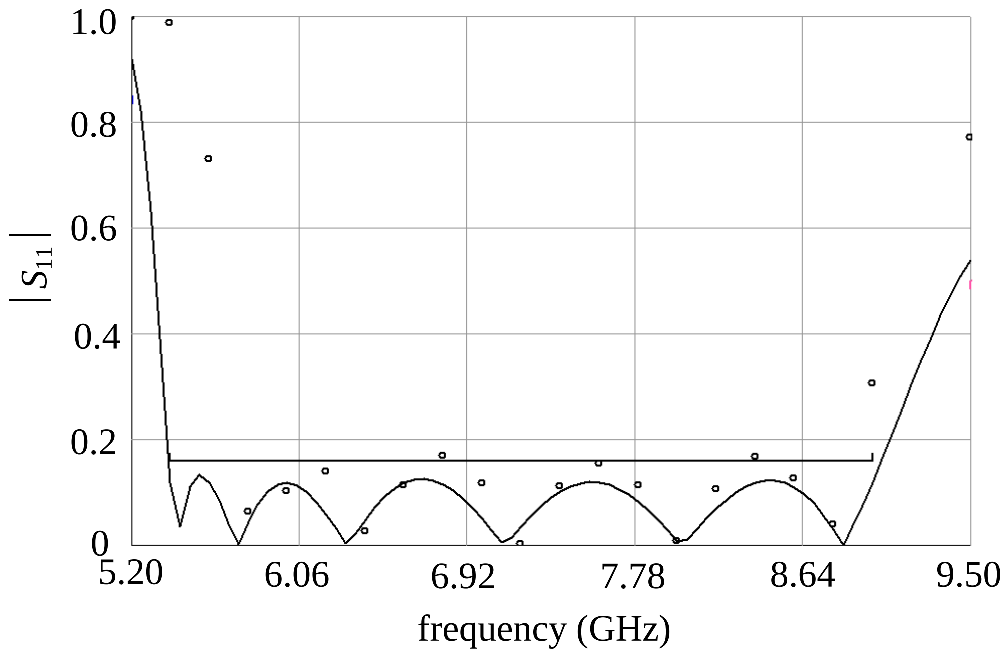
optimizable parameters are the four septa widths W_1, W_2, W_3 and W_4 and the three waveguide-section lengths L_1, L_2 and L_3

the first phase executed 4 iterations requiring a total of 5 fine model simulations

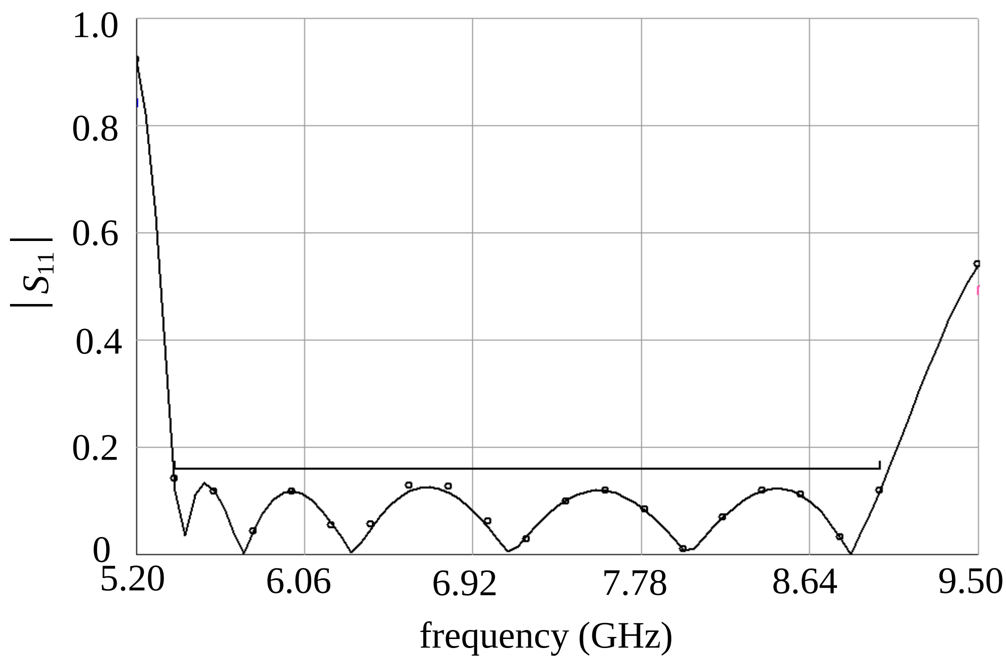
the second phase did not produce successful iterations

the optimal fine model design is obtained using minimax optimization

Optimization Results for the Six-Section H-Plane Filter

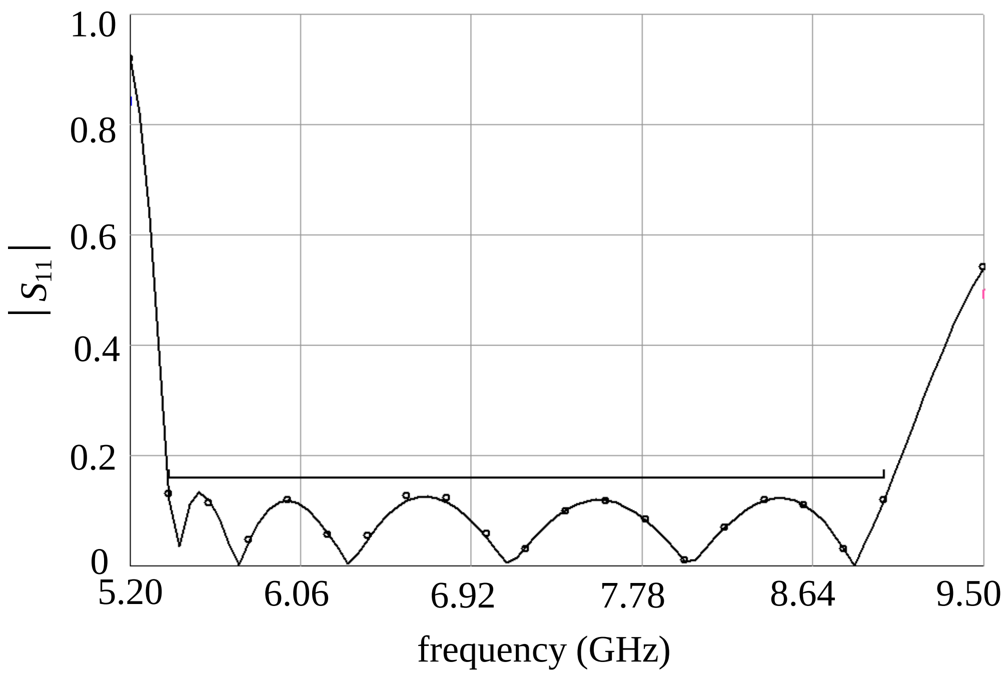


the initial fine model design



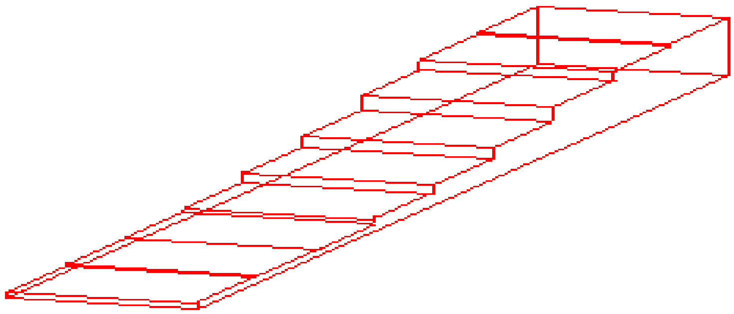
the first phase design

Optimization Results for the Six-Section H-Plane Filter



the optimal fine model design

Seven-Section Waveguide Transformer
(*Bandler, 1969*)



the design specifications are taken as

$$vswr \leq 1.01 \text{ for } 1.06 \text{ GHz} \leq f \leq 1.8 \text{ GHz}$$

the fine model is simulated using HP HFSS through HP Empipe3D

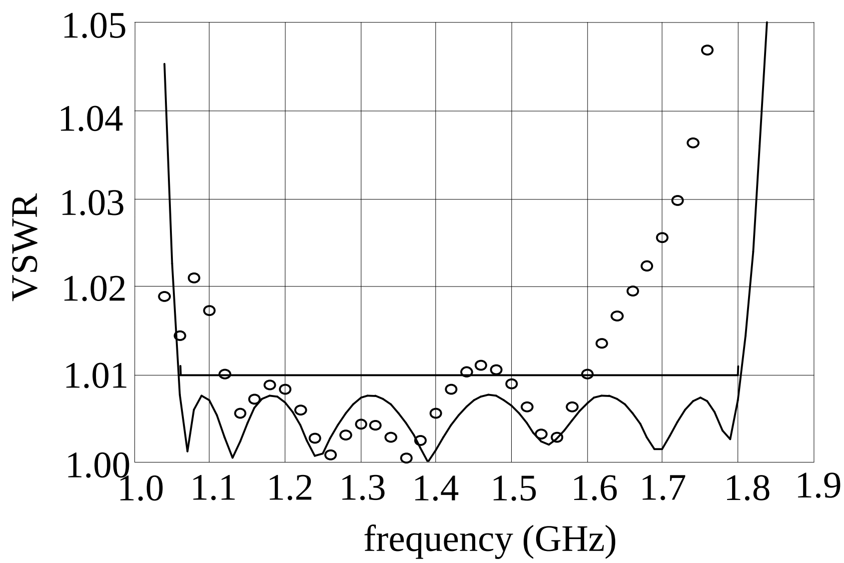
the coarse model is an analytical model which neglects the junction discontinuities

optimizable parameters are the height and length of each waveguide section

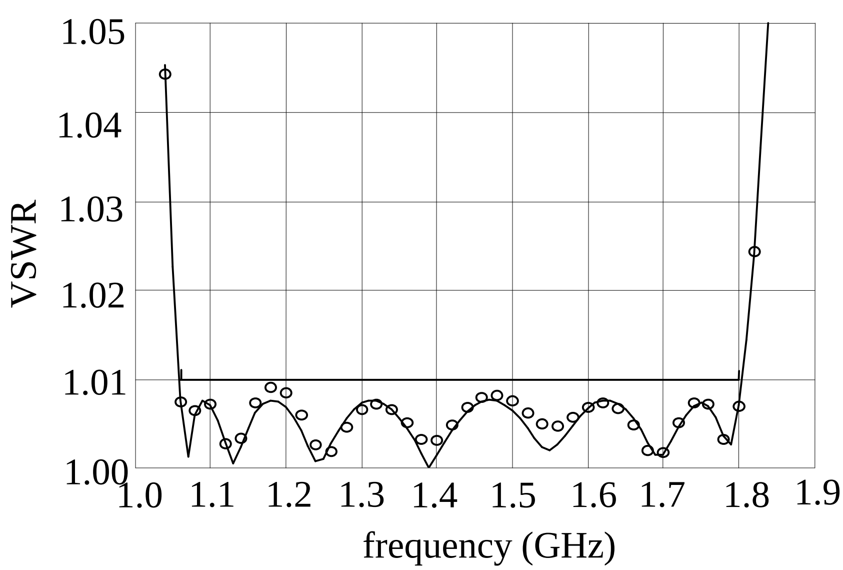
the first phase executed 3 successful iterations that required 6 fine model simulations

the second phase executed 4 iterations

Optimization Results for the Seven-Section Waveguide Transformer

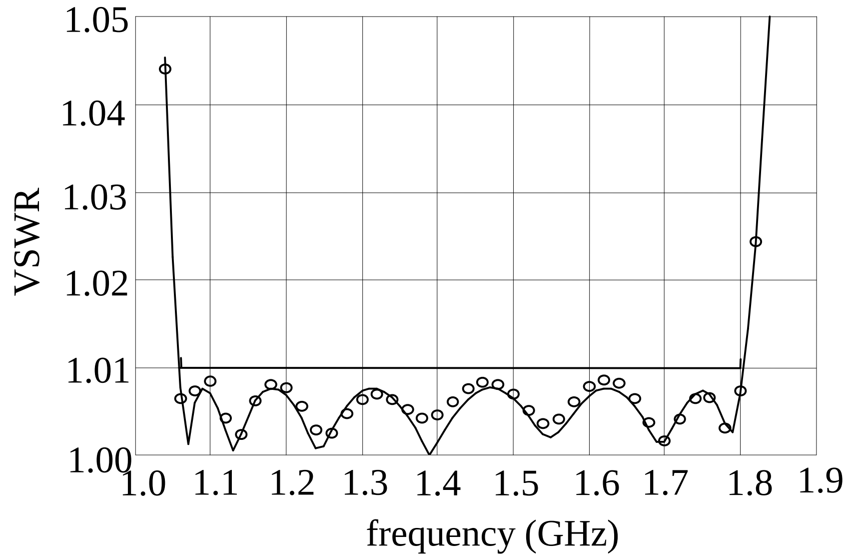


the initial fine model design

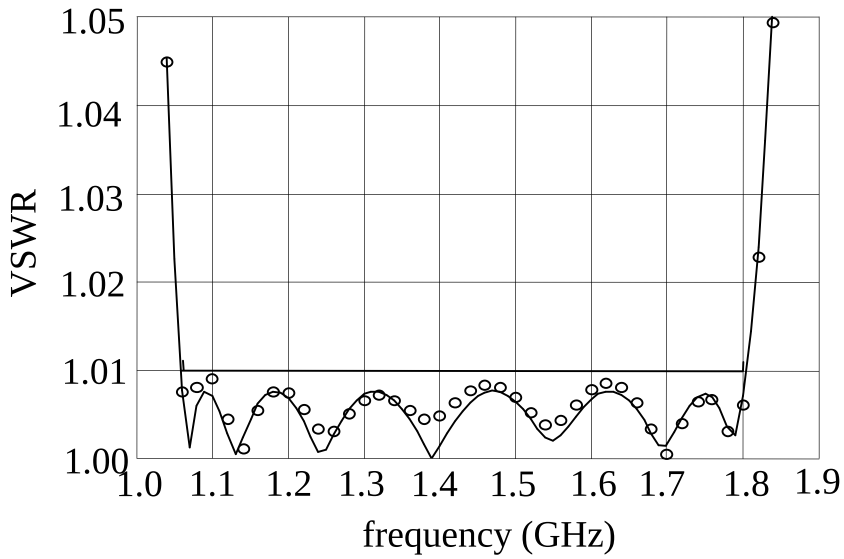


the first phase design

Optimization Results for the Seven-Section Waveguide Transformer



the second phase design



the optimal fine model design

Conclusions

we present a novel, Hybrid Aggressive Space Mapping (HASM) optimization algorithm

the algorithm enables switching from SM optimization to direct optimization if SM fails

the direct optimization phase utilizes all available information accumulated by SM in direct optimization

switching back to Space Mapping takes place if SM is potentially convergent

the connection between SM and direct optimization is based on a novel lemma

the technique is successfully demonstrated through the design of waveguide transformers and filters