**ACCELERATED OPTIMIZATION OF
MIXED EM/CIRCUIT STRUCTURES**

J.W. Bandler, M.H. Bakr and J.E. Rayas-Sánchez

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Abstract

We review recent developments in Space Mapping (SM) optimization. The Aggressive Space Mapping (ASM) technique is illustrated through a step-by-step numerical example based on the Rosenbrock function. The Trust Region Aggressive Space Mapping (TRASM) algorithm is described. TRASM integrates a trust region methodology with the ASM technique. It improves the uniqueness of the extraction phase by utilizing a recursive multi-point parameter extraction process. The algorithm is illustrated by the design of an HTS filter using Sonnet's *em*. The new Hybrid Aggressive Space Mapping (HASM) algorithm is briefly reviewed. It is based on a novel lemma that enables smooth switching from SM optimization to direct optimization if SM is not converging. It is illustrated by the design of a six-section H-plane waveguide filter**.**

Basic Concepts of Space Mapping
(Bandler et al., 1993, 1994)

it is assumed that the circuit to be designed can be simulated using two models: a "fine" model and a "coarse" model

the fine model is accurate but computationally intensive

x_f is the vector of fine model design parameters
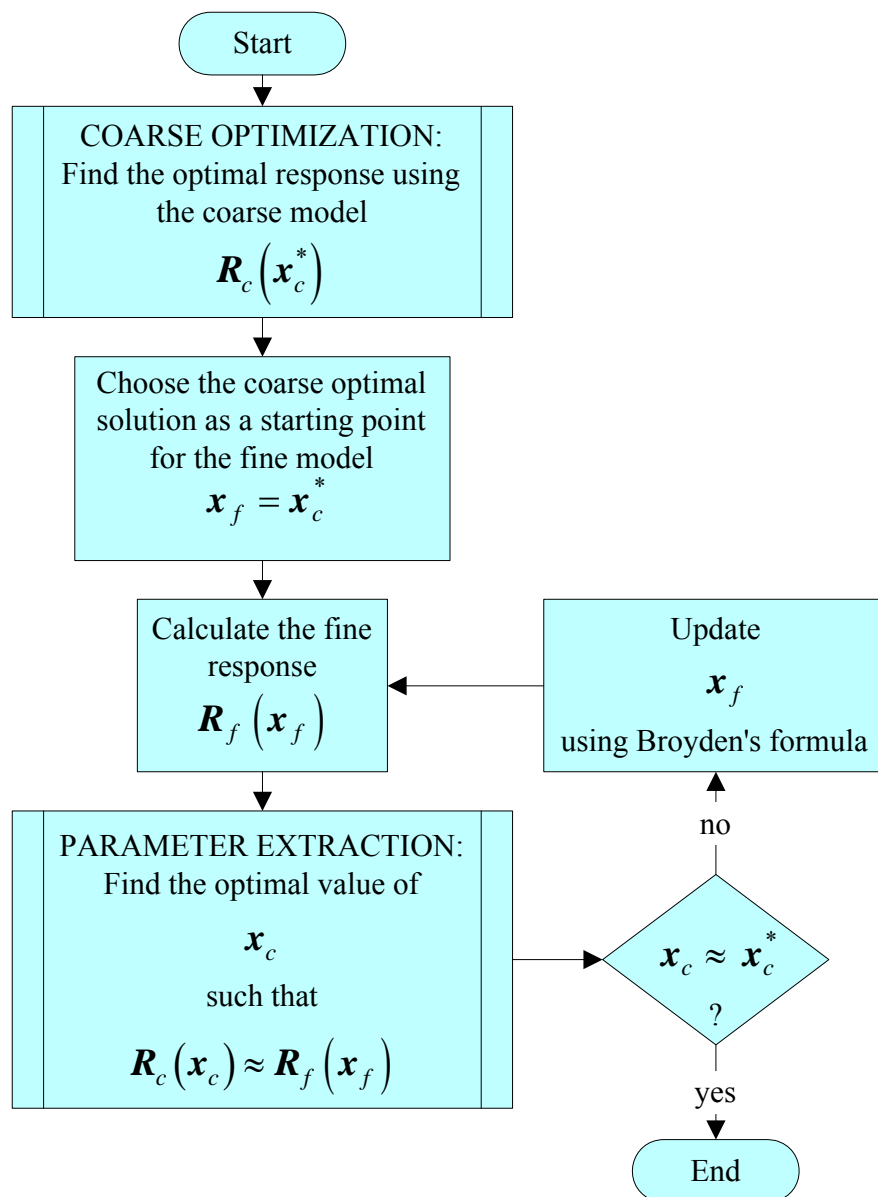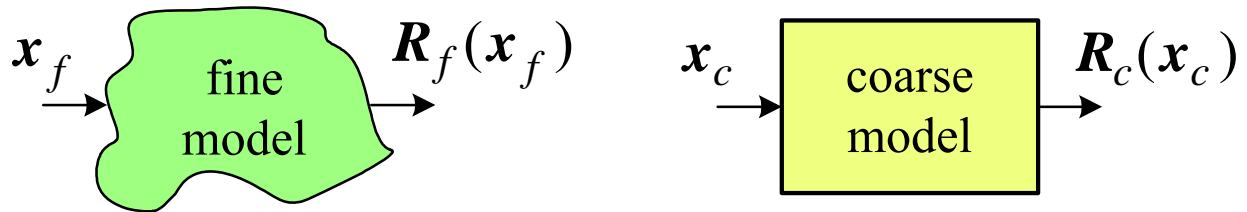
the coarse model is fast but less accurate

x_c is the vector of coarse model design parameters

Space Mapping aims at avoiding the computationally intensive direct optimization of the fine model by iteratively developing a mapping between x_f and x_c

we present illustrations and progress to date on this exciting concept applied to accelerated optimization of mixed EM/circuit structures

Aggressive Space Mapping (ASM) Concept

$$x_f \quad \text{fine model} \quad R_f(x_f) \qquad x_c \quad \text{coarse model} \quad R_c(x_c)$$

Start

COARSE OPTIMIZATION:
Find the optimal response using the coarse model

$$R_c\left(x_c^*\right)$$

Choose the coarse optimal solution as a starting point for the fine model

$$x_f = x_c^*$$

Calculate the fine response

$$R_f\left(x_f\right)$$

Update

$$x_f$$

using Broyden's formula

PARAMETER EXTRACTION:
Find the optimal value of

$$x_c$$

such that

$$R_c\left(x_c\right) \approx R_f\left(x_f\right)$$

$$x_c \approx x_c^*$$

?

no

yes

End

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

the initial fine model design is taken as x_c^*
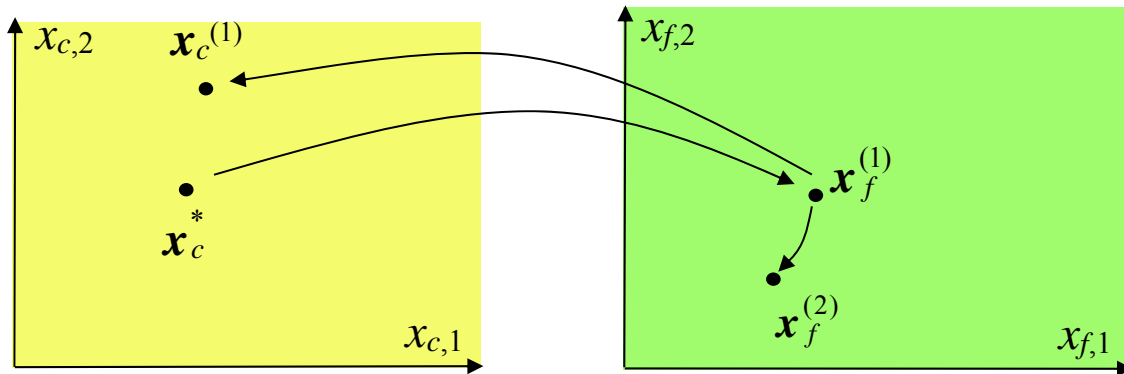
at the *j*th iteration

$$x_f^{(j+1)} = x_f^{(j)} + h^{(j)}$$

$h^{(j)}$ is obtained by solving

$$B^{(j)} h^{(j)} = -f(x_f^{(j)})$$

where

$$f = x_c^{(j)} - x_c^*$$

and $x_c^{(j)}$ is obtained through parameter extraction

ASM Algorithm

Step 0.　Initialize $x_f^{(1)} = x_c^*$, $B^{(1)} = I$, $j = 1$.

Step 1.　Evaluate $R_f(x_f^{(1)})$.

Step 2.　Extract $x_c^{(1)}$ such that $R_c(x_c^{(1)}) \approx R_f(x_f^{(1)})$.

Step 3.　Evaluate $f^{(1)} = x_c^{(1)} - x_c^*$. Stop if $\left\| f^{(1)} \right\| \le \eta$.

Step 4.　Solve $B^{(j)} h^{(j)} = -f^{(j)}$ for $h^{(j)}$.

Step 5.　Set $x_f^{(j+1)} = x_f^{(j)} + h^{(j)}$.

Step 6.　Evaluate $R_f(x_f^{(j+1)})$.

Step 7.　Extract $x_c^{(j+1)}$ such that $R_c(x_c^{(j+1)}) \approx R_f(x_f^{(j+1)})$.

Step 8.　Evaluate $f^{(j+1)} = x_c^{(j+1)} - x_c^*$. Stop if $\left\| f^{(j+1)} \right\| \le \eta$.

Step 9.　Update $B^{(j+1)} = B^{(j)} + \dfrac{f^{(j+1)} h^{(j)^T}}{h^{(j)^T} h^{(j)}}$.

Step 10.　Set $j = j + 1$; go to *Step* 4.
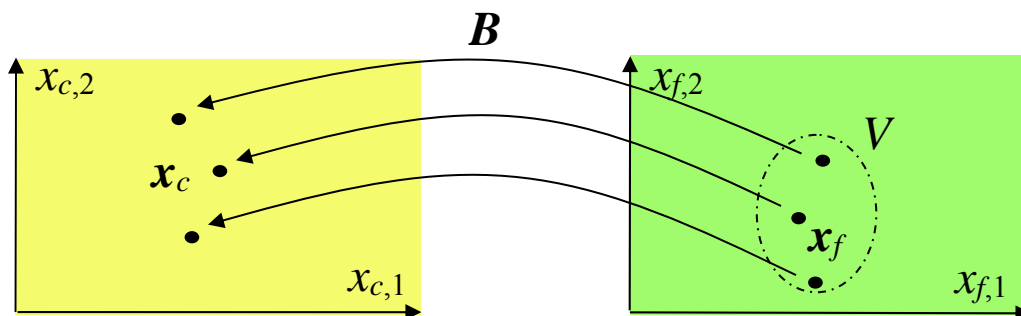
Parameter Extraction

single point parameter extraction aims at matching the responses
of both models at a single point
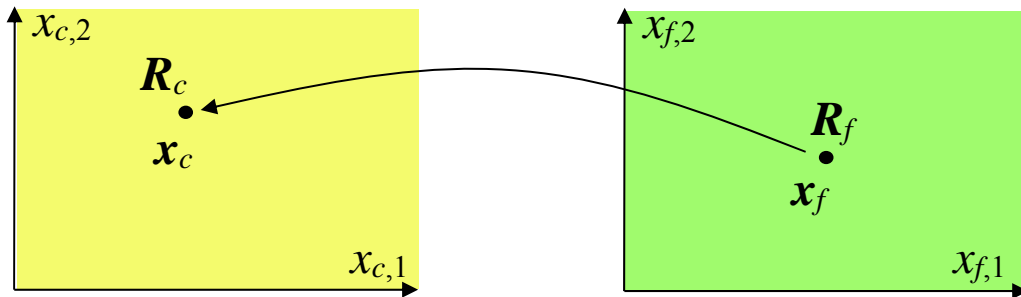
it can be formulated as

$$\underset{\boldsymbol{x}_c}{minimize} \left\| \boldsymbol{R}_f(\boldsymbol{x}_f) - \boldsymbol{R}_c(\boldsymbol{x}_c) \right\|$$

multi-point parameter extraction aims at simultaneously
matching the responses at a number of corresponding points
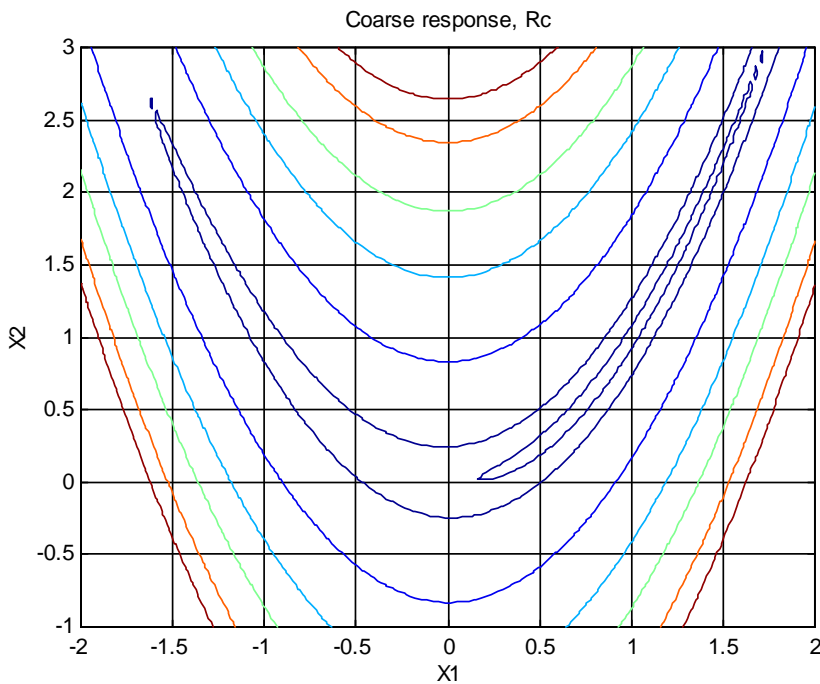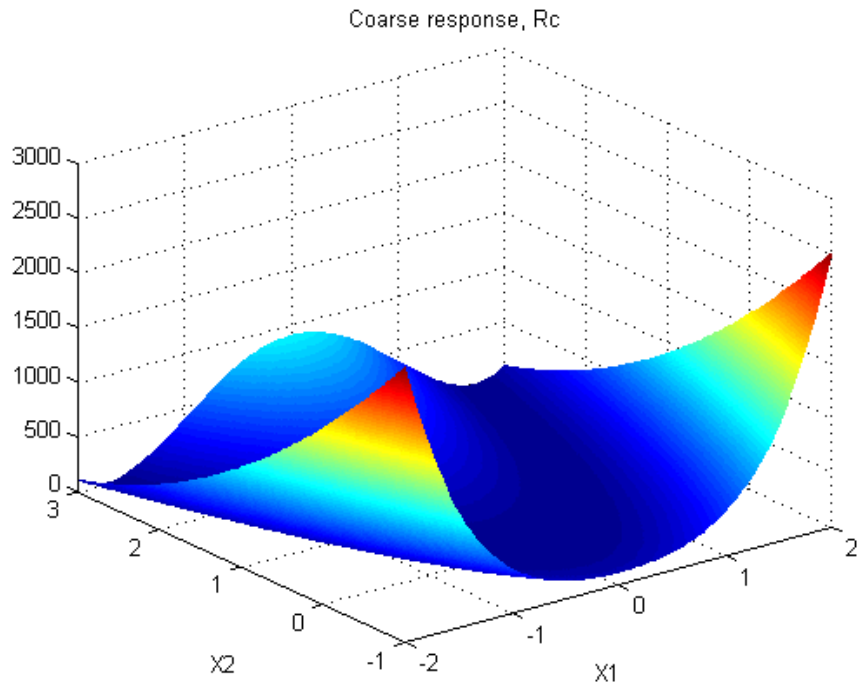

the extracted parameters should satisfy

$$\boldsymbol{R}_c(\boldsymbol{x}_c + \boldsymbol{B}\,(\boldsymbol{x} - \boldsymbol{x}_f)) = \boldsymbol{R}_f(\boldsymbol{x})$$

simultaneously for a set of points $\boldsymbol{x} \in V$

Coarse Model Example: Rosenbrock Function

$$R_c\,(\boldsymbol{x}) \;=\; 100\,(x_2 - x_1^2)^2 + (1 - x_1)^2 \;\;,\text{ where } \boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

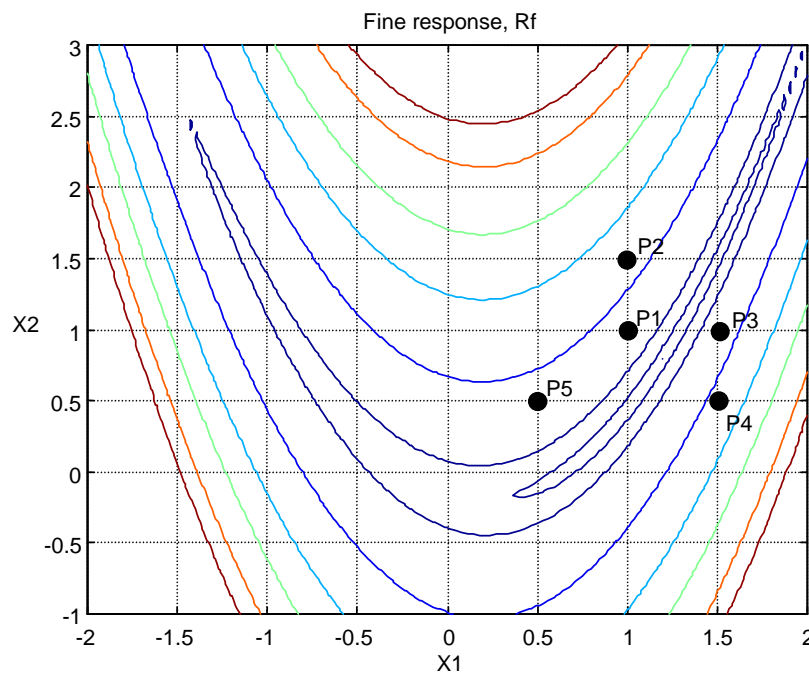Coarse response, Rc

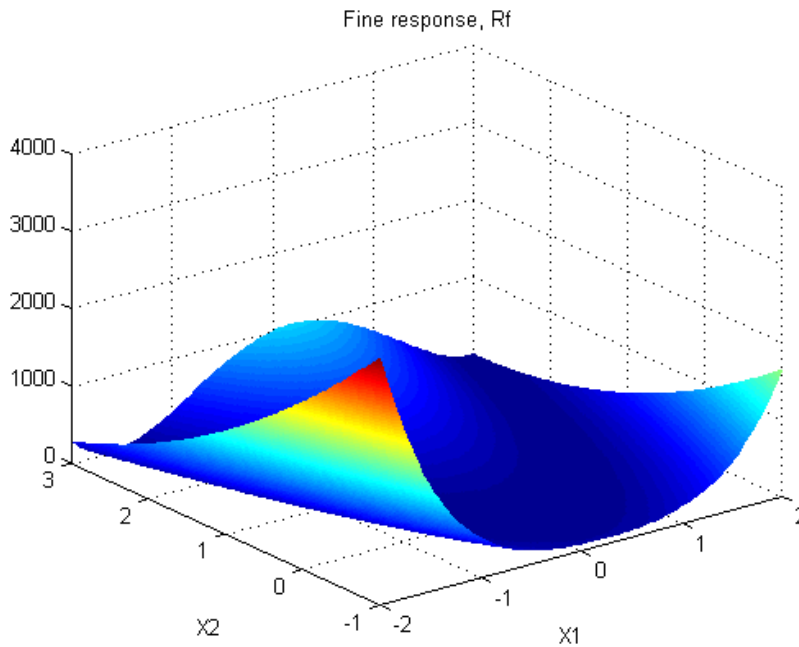Coarse response, Rc

$$\boldsymbol{x}_c^* = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$R_c^* = R_c\,(\boldsymbol{x}_c^*) \;=\; 0$$

Fine Model : Shifted Rosenbrock Function

$$R_f\ (\boldsymbol{x})\ =\ 100\,(u_2 - u_1^2)^2 + (1 - u_1)^2\ \text{ where }\ \boldsymbol{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \boldsymbol{x} + \begin{bmatrix} -0.2 \\ +0.2 \end{bmatrix}$$

Fine response, Rf

Fine response, Rf

Multi-Point Parameter Extraction

we minimize a parameter extraction objective function $\|\boldsymbol{E}\|_p$ considering five matching points, with error functions

$$E_i = R_c (\boldsymbol{x} + \boldsymbol{B}^{(j)} \Delta \boldsymbol{x}_i) - R_f (\boldsymbol{x}_c^* + \Delta \boldsymbol{x}_i)$$

where

$$\Delta \boldsymbol{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \; \Delta \boldsymbol{x}_2 = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix}, \; \Delta \boldsymbol{x}_3 = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}, \; \Delta \boldsymbol{x}_4 = \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix}, \; \Delta \boldsymbol{x}_5 = \begin{bmatrix} -0.5 \\ -0.5 \end{bmatrix}$$

since the matrix $\boldsymbol{B}^{(j)} = \boldsymbol{1}$ for the first parameter extraction optimization, the corresponding five error functions are taken as
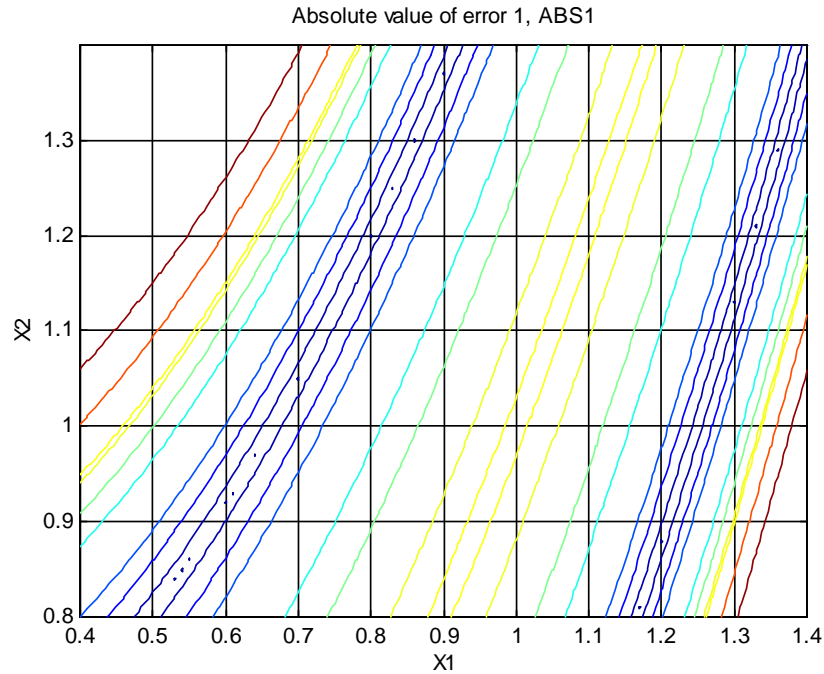
$$E_i = R_c (\boldsymbol{x} + \Delta \boldsymbol{x}_i) - R_f (\boldsymbol{x}_c^* + \Delta \boldsymbol{x}_i)$$

considering only l_1 and l_2 norms, the corresponding objective functions can be taken as
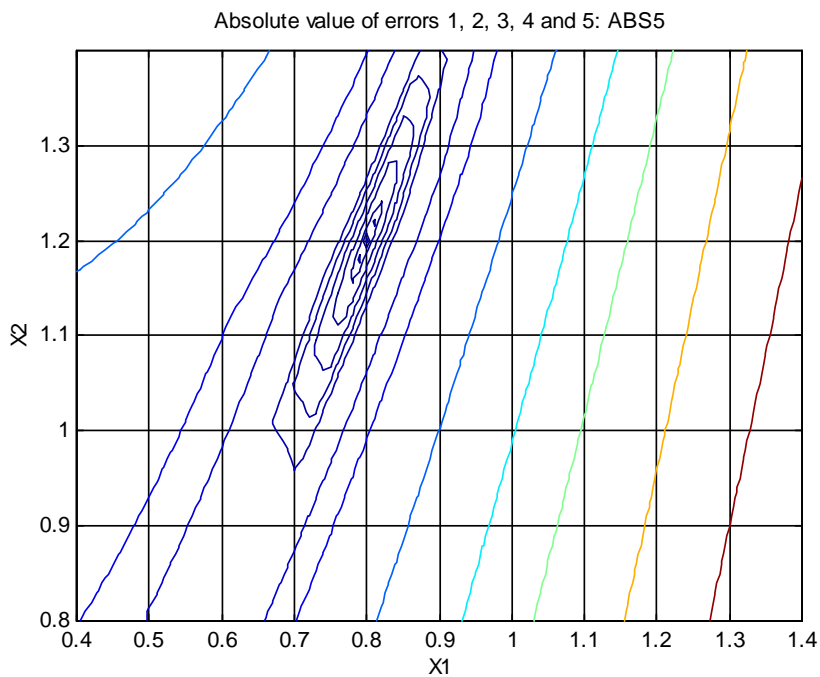
$$ABS_n = |E_1| + |E_2| + \ldots + |E_n|$$
$$SQR_n = (E_1)^2 + (E_2)^2 + \ldots + (E_n)^2$$

l_1 **Objective Function for the Parameter Extraction Problem**

Absolute value of error 1, ABS1

single point parameter extraction

Absolute value of errors 1, 2, 3, 4 and 5: ABS5
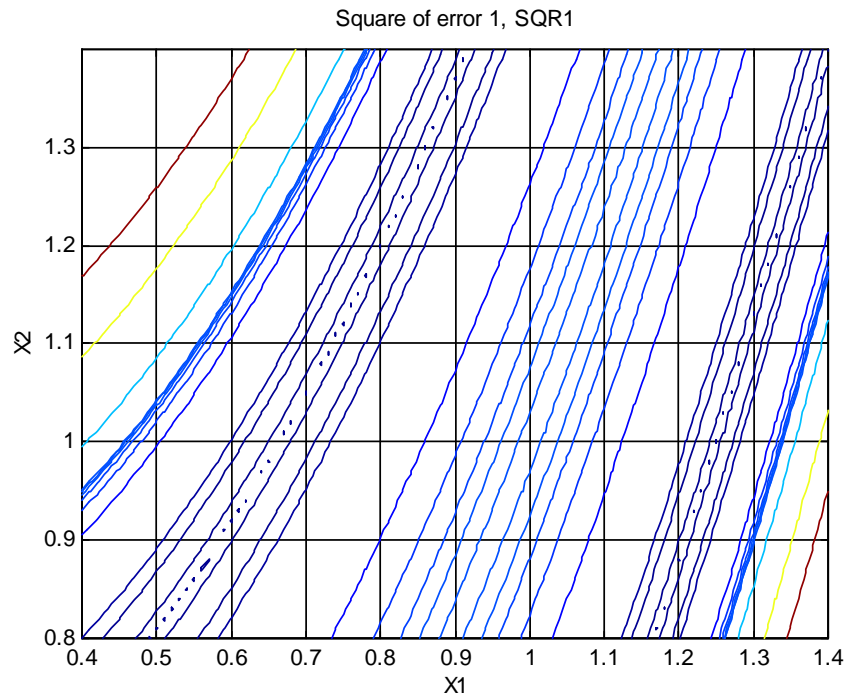
$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$$

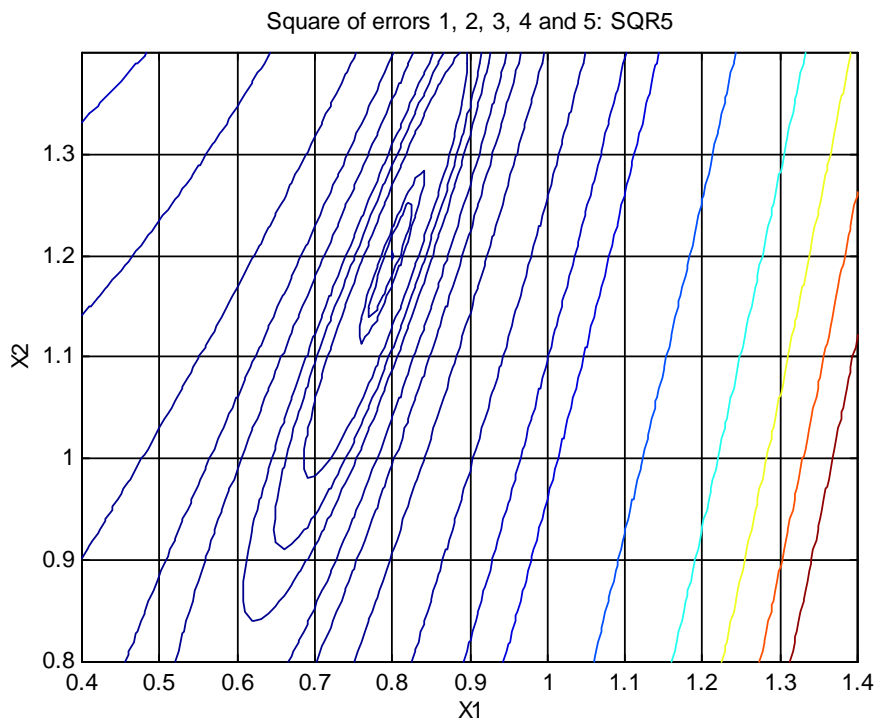multi-point parameter extraction (with 4 additional points)

99-8-11

l_2 **Objective Function for the Parameter Extraction Problem**

Square of error 1, SQR1

single point parameter extraction

Square of errors 1, 2, 3, 4 and 5: SQR5

$$x_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$$

multi-point parameter extraction (with 4 additional points)

Space Mapping Solution Process

Step 0. $\quad x_f^{(1)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $B^{(1)} = 1$, $j = 1$

Step 1. $\quad R_f(x_f^{(1)}) = 31.4$

Step 2. $\quad$ When $x_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$, $R_c(x_c^{(1)}) = R_f(x_f^{(1)})$

Step 3. $\quad f^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.2 \\ 0.2 \end{bmatrix}$

Step 4. $\quad$ Since $B^{(1)} = 1$, $h^{(1)} = \begin{bmatrix} 0.2 \\ -0.2 \end{bmatrix}$

Step 5. $\quad$ Set $x_f^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.2 \\ -0.2 \end{bmatrix} = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$

Step 6. $\quad R_f(x_f^{(2)}) = 0$

Step 7. $\quad x_c^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, because we know $R_c(x_c^{(2)}) = 0$

Step 8. $\quad$ Since $f^{(2)} = x_c^{(2)} - x_c^* = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, then $\bar{x}_f = x_f^{(2)} = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$
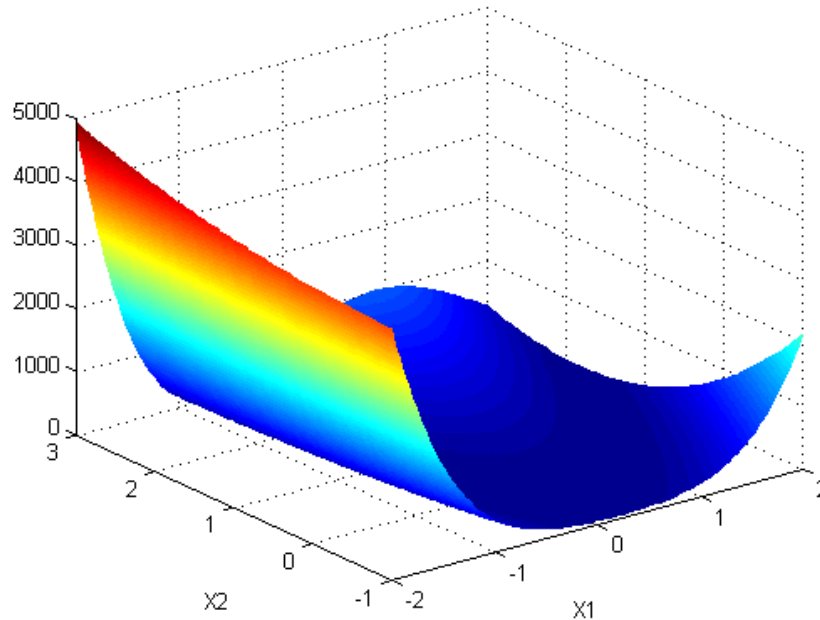
Fine Model Example: Transformed Rosenbrock Function
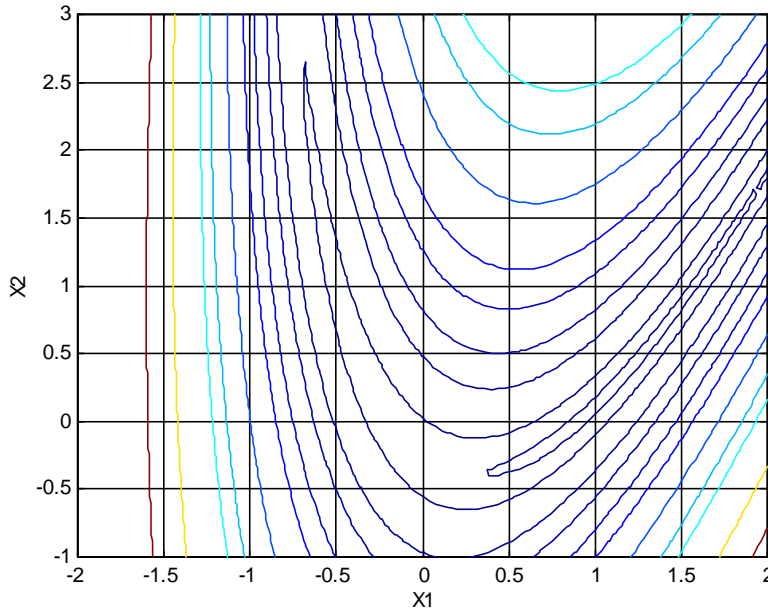
$$R_f(x) = 100(u_2 - u_1^2)^2 + (1 - u_1)^2 \quad \text{where}$$

$$u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix} x + \begin{bmatrix} -0.3 \\ 0.3 \end{bmatrix}$$

Fine response, Rf

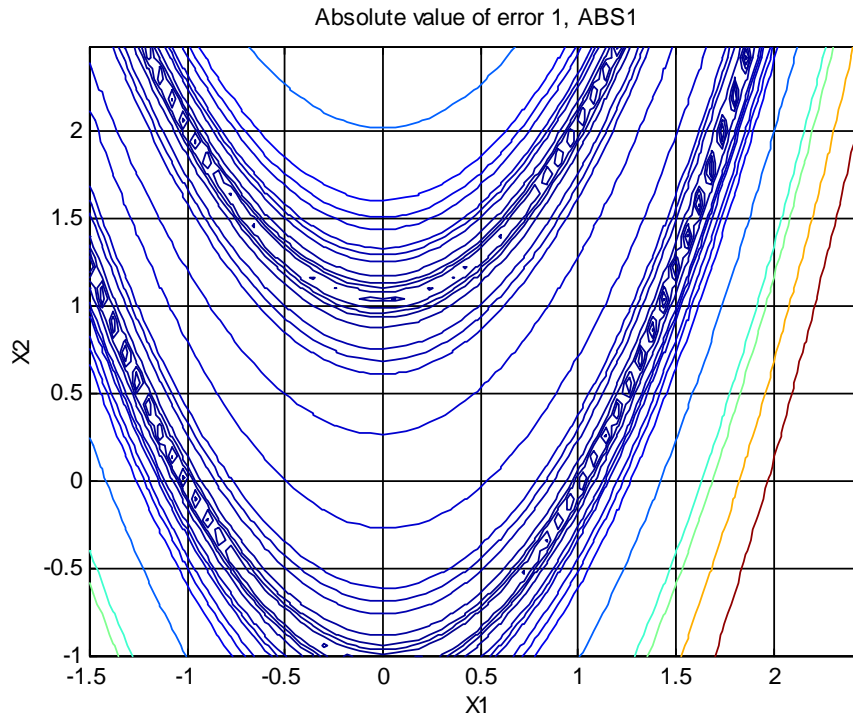Fine response, Rf

$$R_f(x_c^*) = 108.32$$

First l_1 Parameter Extraction

Absolute value of error 1, ABS1

single point parameter extraction
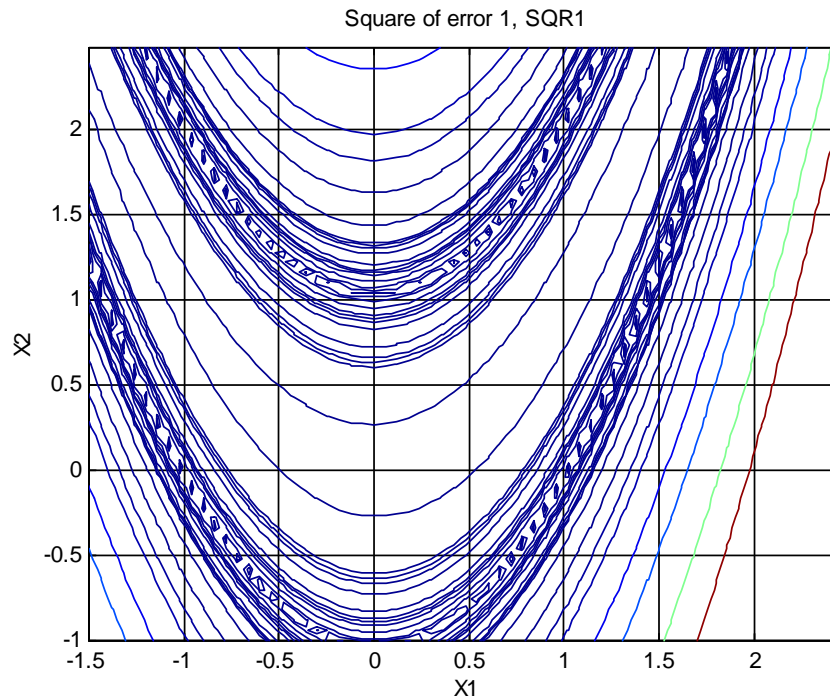
Absolute value of errors 1, 2 and 3: ABS3
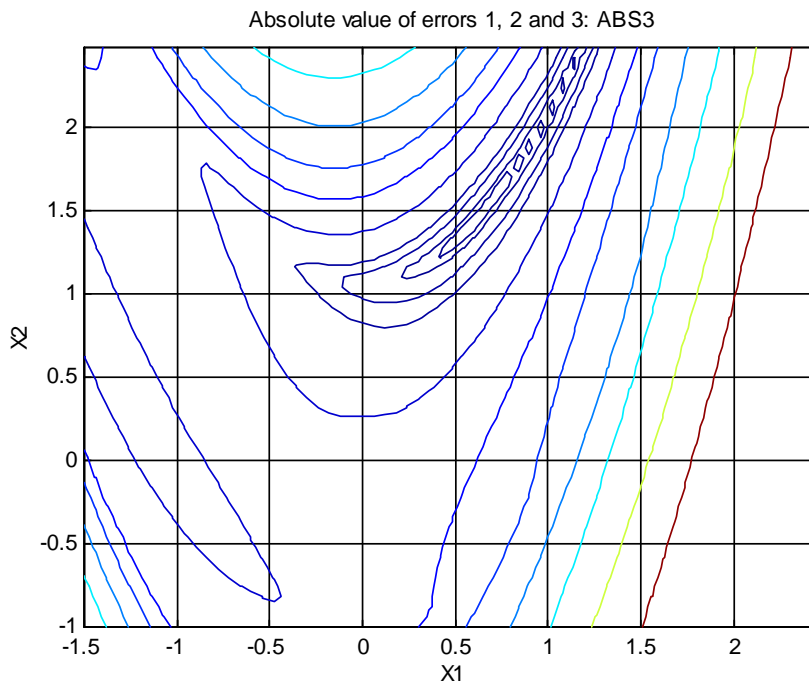
$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

multi-point parameter extraction (with 2 additional points)

First l_2 Parameter Extraction

Square of error 1, SQR1

single point parameter extraction

Square of errors 1, 2 and 3: SQR3
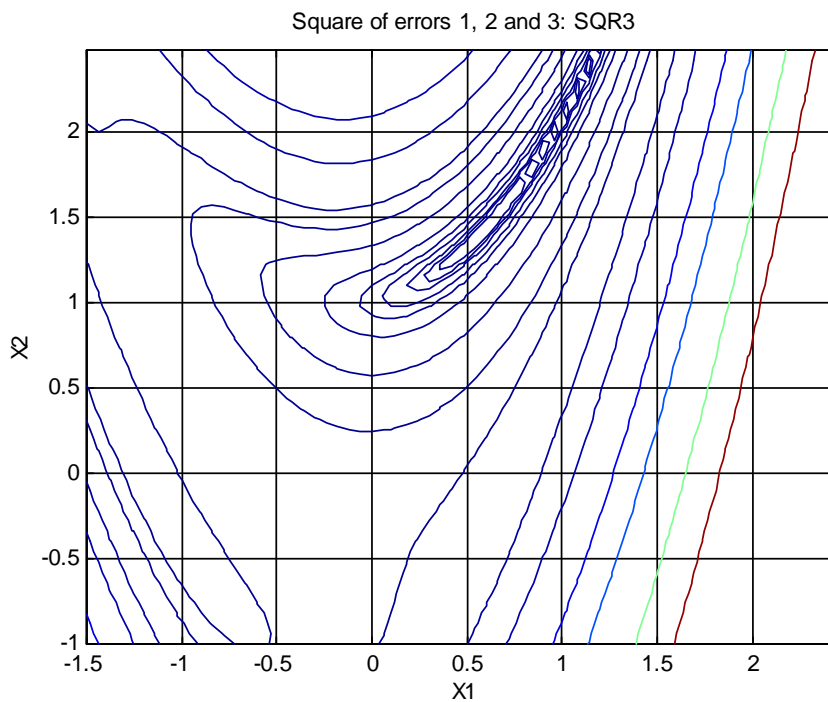
$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

multiple point parameter extraction (with 2 additional points)

Space Mapping Solution Process

Step 0. $x_f^{(1)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $B^{(1)} = 1$, $j = 1$

Step 1. $R_f(x_f^{(1)}) = 108.32$

Step 2. When $x_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$, $R_c(x_c^{(1)}) = R_f(x_f^{(1)})$

Step 3. $f^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -0.4 \\ 0.4 \end{bmatrix}$

Step 4. Since $B^{(1)} = 1$, $h^{(1)} = \begin{bmatrix} 0.4 \\ -0.4 \end{bmatrix}$

Step 5. Set $x_f^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.4 \\ -0.4 \end{bmatrix} = \begin{bmatrix} 1.4 \\ 0.6 \end{bmatrix}$

Step 6. $R_f(x_f^{(2)}) = 1.8207$

Step 7. When $x_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$, $R_c(x_c^{(2)}) = R_f(x_f^{(2)})$

Space Mapping Solution Process (continued)

Step 8. $f^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.12 \\ 0.12 \end{bmatrix}$

Step 9. $B^{(2)} = B^{(1)} + \dfrac{f^{(2)} h^{(1)^T}}{h^{(1)^T} h^{(1)}} = \begin{bmatrix} 1.15 & -0.15 \\ 0.15 & 0.85 \end{bmatrix}$

Step 4b. $h^{(2)} = -B^{(2)^{-1}} f^{(2)} = \begin{bmatrix} -0.12 \\ -0.12 \end{bmatrix}$

Step 5b.   Set $x_f^{(3)} = \begin{bmatrix} 1.4 \\ 0.6 \end{bmatrix} + \begin{bmatrix} -0.12 \\ -0.12 \end{bmatrix} = \begin{bmatrix} 1.28 \\ 0.48 \end{bmatrix}$

Step 6b. $R_f(x_f^{(3)}) = 0.1308$

Step 7b.   When $x_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$, $R_c(x_c^{(3)}) = R_f(x_f^{(3)})$

Step 8b. $f^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.012 \\ -0.012 \end{bmatrix}$

Space Mapping Solution Process (continued)

Step 9b. $\quad \boldsymbol{B}^{(3)} = \boldsymbol{B}^{(2)} + \dfrac{\boldsymbol{f}^{(3)}\boldsymbol{h}^{(2)^T}}{\boldsymbol{h}^{(2)^T}\boldsymbol{h}^{(2)}} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix}$

Step 4c. $\quad \boldsymbol{h}^{(3)} = -\boldsymbol{B}^{(3)^{-1}}\boldsymbol{f}^{(3)} = \begin{bmatrix} -0.0082 \\ 0.0151 \end{bmatrix}$

Step 5c. $\quad$ Set $\boldsymbol{x}_f^{(4)} = \begin{bmatrix} 1.28 \\ 0.48 \end{bmatrix} + \begin{bmatrix} -0.0082 \\ 0.0151 \end{bmatrix} = \begin{bmatrix} 1.2718 \\ 0.4951 \end{bmatrix}$
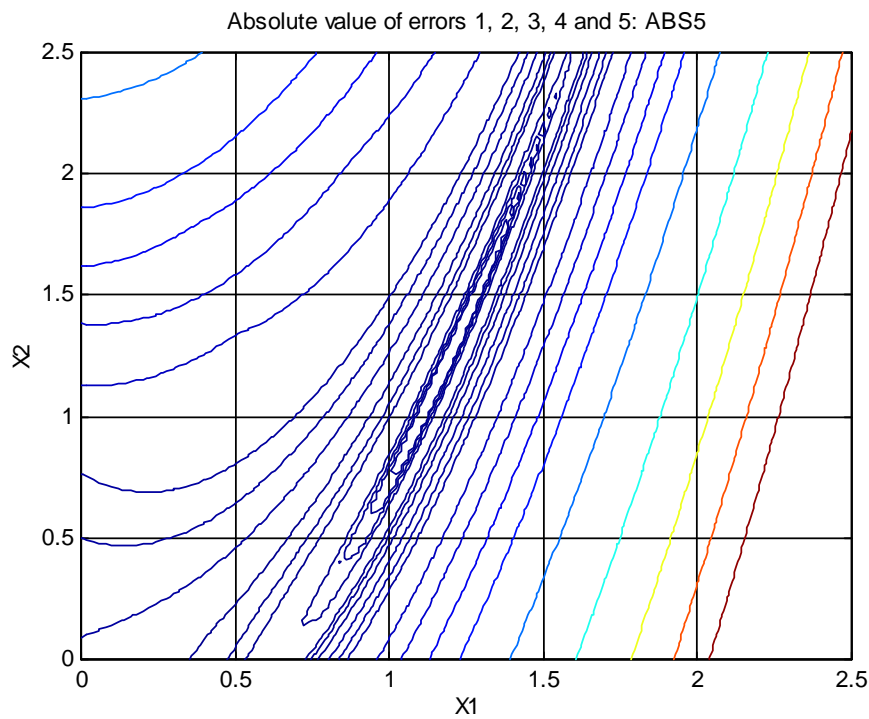
Step 6c. $\quad \boldsymbol{R}_f(\boldsymbol{x}_f^{(4)}) = 9.2 \times 10^{-8}$, then $\bar{\boldsymbol{x}}_f = \boldsymbol{x}_f^{(4)}$ and we can end the algorithm

Second l_1 Parameter Extraction
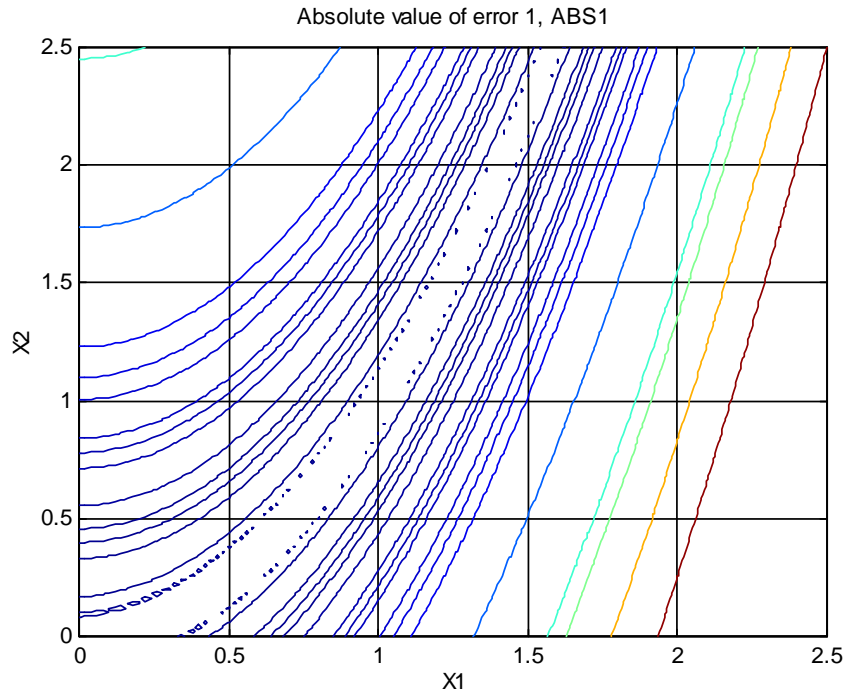
Absolute value of error 1, ABS1

single point parameter extraction

Absolute value of errors 1, 2, 3, 4 and 5: ABS5
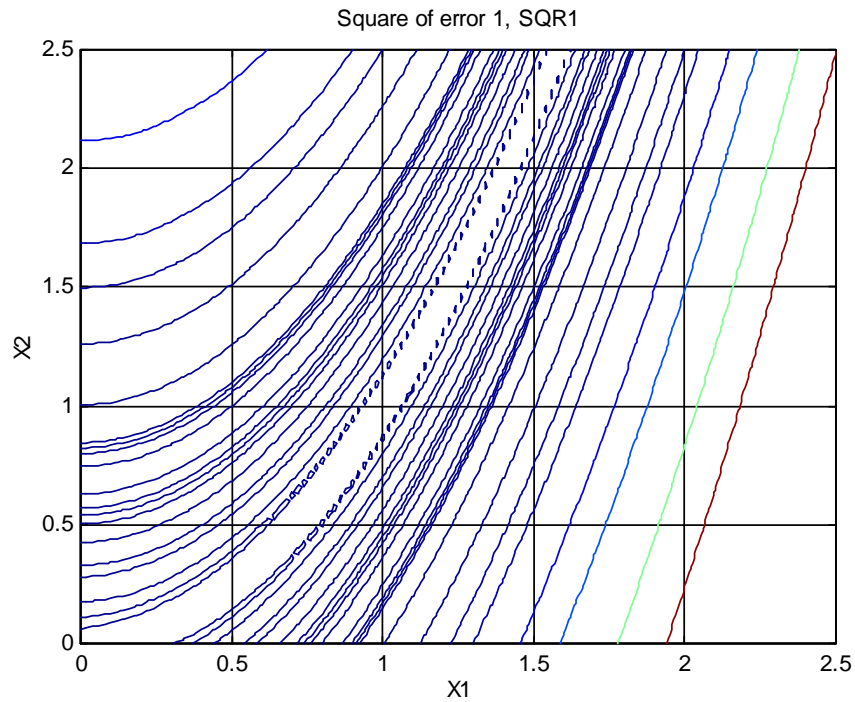

$$x_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$$

multi-point parameter extraction (4 additional points)

Second l_2 Parameter Extraction

Square of error 1, SQR1

single point parameter extraction

Square of errors 1, 2, 3, 4 and 5: SQR5
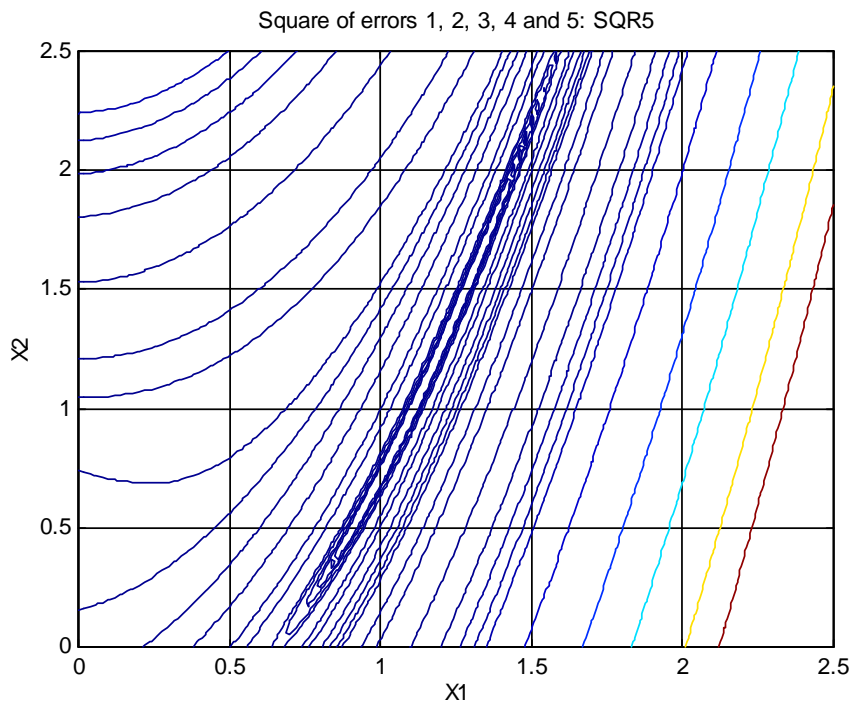
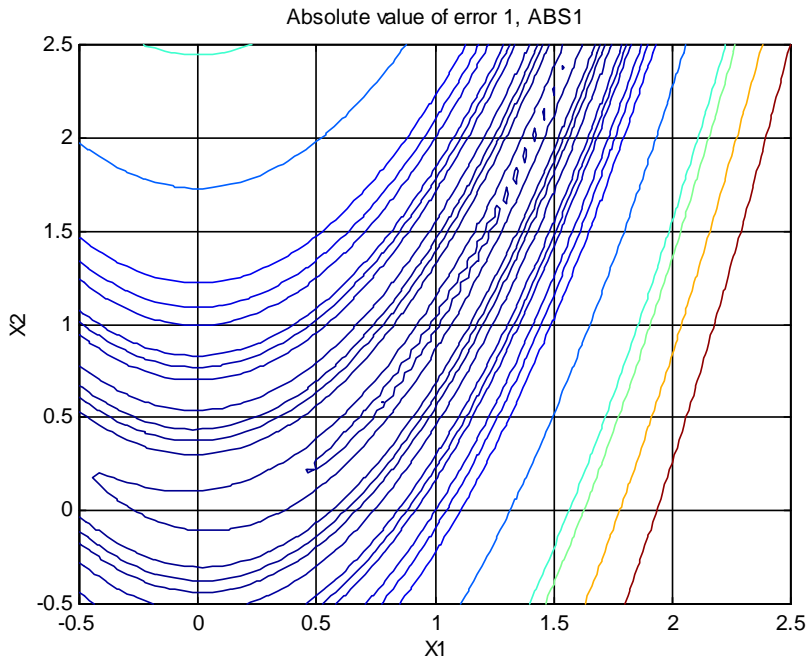$$\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$$

multi-point parameter extraction (with 4 additional points)

Third Parameter Extraction

Absolute value of error 1, ABS1

single point l_1 parameter extraction
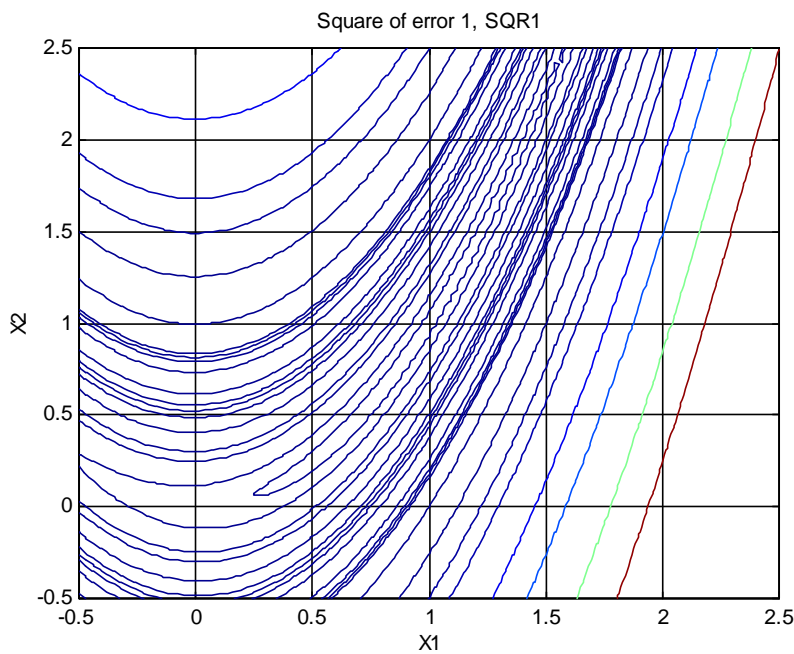
$$x_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$$

Square of error 1, SQR1

single point l_2 parameter extraction

$$x_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$$

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

TRASM integrates a trust region methodology with ASM

a certain success criterion must be satisfied in each iteration to
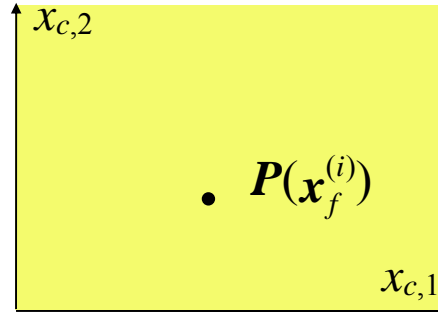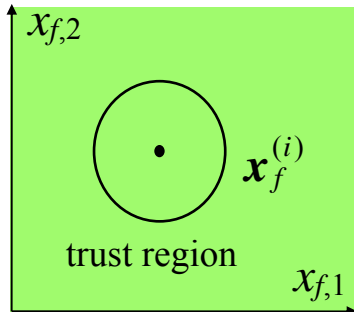accept the predicted step

a recursive multi-point parameter extraction procedure is
introduced

all available fine model simulations are utilized to improve
parameter extraction uniqueness

available mapping information is integrated into this extraction
procedure

Illustration of the TRASM Algorithm

$x_{f,2}$ $\boldsymbol{x}_f^{(i)}$

trust region $x_{f,1}$

$x_{c,2}$ $\boldsymbol{P}(\boldsymbol{x}_f^{(i)})$ $x_{c,1}$

the current state at the *i*th iteration

$x_{f,2}$ $\boldsymbol{x}_f^{(i+1)}$ $\boldsymbol{x}_f^{(i)}$

trust region $x_{f,1}$

$x_{c,2}$ $\boldsymbol{P}(\boldsymbol{x}_f^{(i+1)})$ $x_{c,1}$
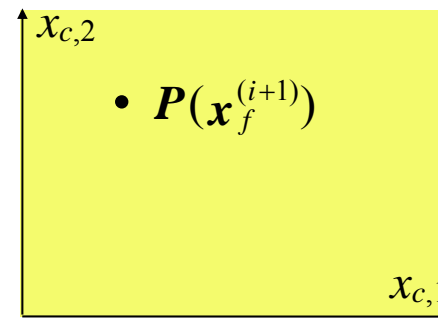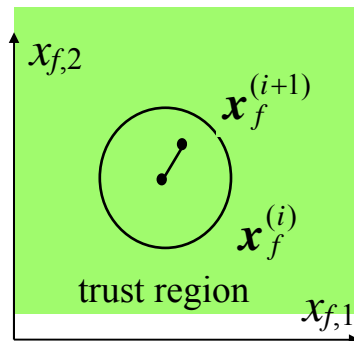
initial parameter extraction at the
suggested point

$x_{f,2}$ $\boldsymbol{x}_t^1$ $\boldsymbol{x}_f^{(i+1)}$ $\boldsymbol{x}_f^{(i)}$ $x_{f,1}$

$x_{c,2}$ $\boldsymbol{P}(\boldsymbol{x}_f^{(i+1)})$ $x_{c,1}$
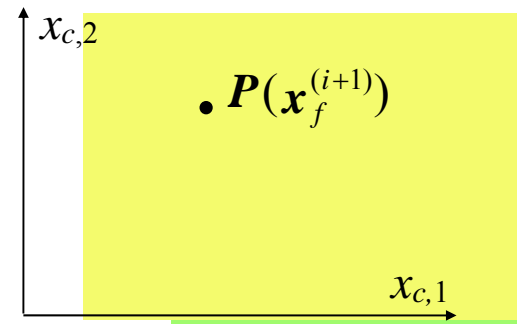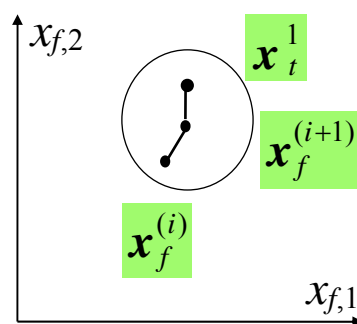
multi-point extraction is applied

TRASM Algorithm
(Bakr et al., 1998)

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

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

this corresponds to minimizing $\left\|\boldsymbol{f}^{(i)} + \boldsymbol{B}^{(i)}\boldsymbol{h}^{(i)}\right\|_2^2$ subject to

$\left\|\boldsymbol{h}^{(i)}\right\|_2 \le \delta$ where δ is the size of the trust region

λ, which correlates to δ, can be determined (*Moré et al., 1983*)

single point parameter extraction is performed at the new point $\boldsymbol{x}_f^{(i+1)} = \boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}$ to get $\boldsymbol{f}^{(i+1)}$

if $\boldsymbol{f}^{(i+1)}$ satisfies a certain success criterion for the reduction in the l_2 norm of the vector $\boldsymbol{f}$, the point $\boldsymbol{x}_f^{(i+1)}$ is accepted and the matrix $\boldsymbol{B}^{(i)}$ is updated using Broyden's update

otherwise a temporary point is generated using $\boldsymbol{x}_f^{(i+1)}$ and $\boldsymbol{f}^{(i+1)}$ and is added to the set of points to be used for multi-point parameter extraction

a new $\boldsymbol{f}^{(i+1)}$ is obtained through multi-point parameter extraction

TRASM Algorithm (continued)

the last three steps are repeated until a success criterion is satisfied or the step is declared a failure

step failure has two forms

(1) f may approach a limiting value without satisfying the success criterion or

(2) the number of fine model points simulated since the last successful step reaches $n+1$

Case (1): the parameter extraction is trusted but the linearization used is suspect; the size of the trust region is decreased and a new point $\boldsymbol{x}_f^{(i+1)}$ is obtained

Case (2): sufficient information is available for an approximation to the Jacobian of the fine model responses w.r.t. the fine model parameters used to predict the new point $\boldsymbol{x}_f^{(i+1)}$

the mapping between the two spaces is exploited in the parameter extraction step by solving

$$\underset{\boldsymbol{x}_c}{minimize} \left\| \boldsymbol{R}_c(\boldsymbol{x}_c + \boldsymbol{B}^{(i)}(\boldsymbol{x} - \boldsymbol{x}_f^{(i+1)})) - \boldsymbol{R}_f(\boldsymbol{x})) \right\|$$
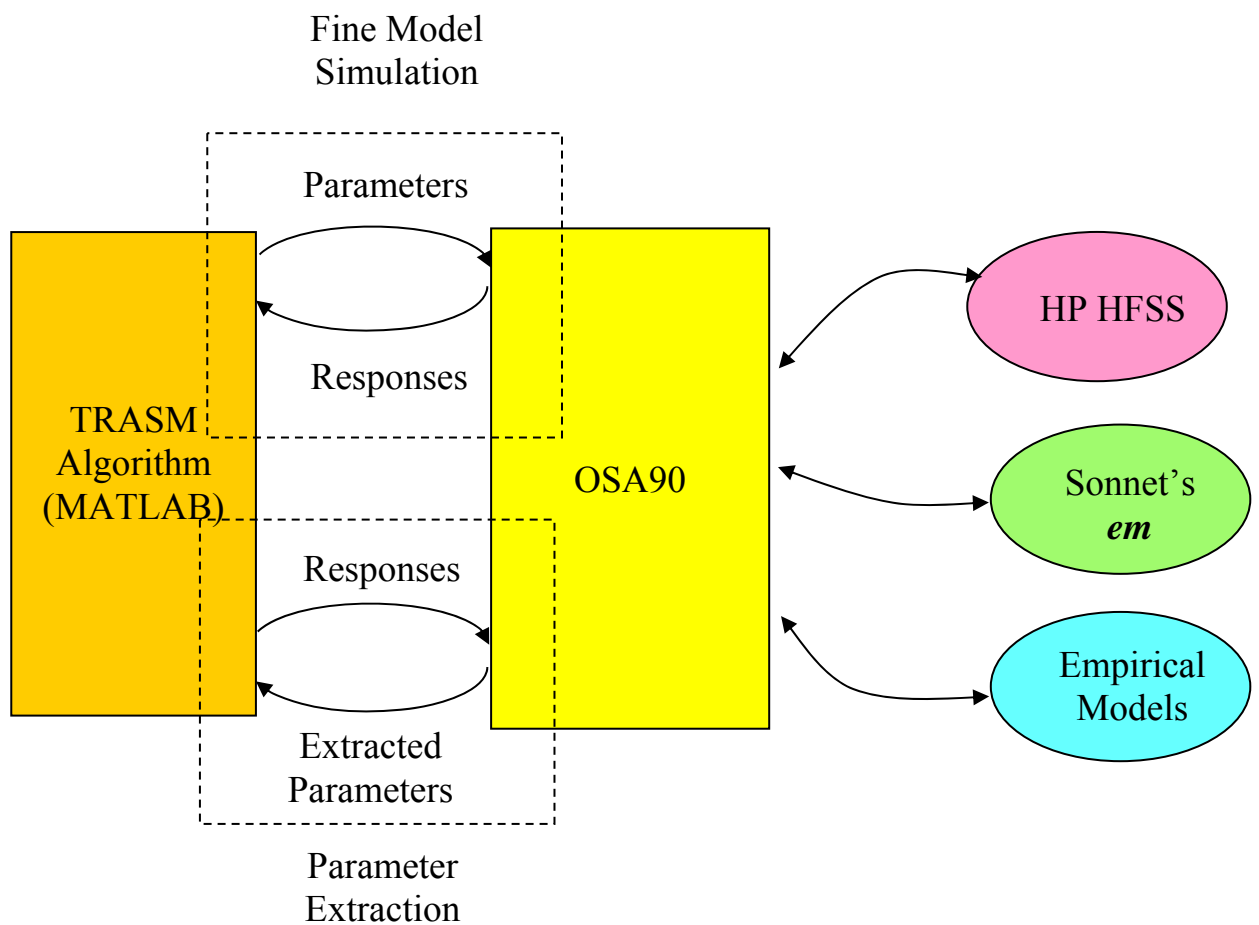
simultaneously for a set of points $\boldsymbol{x}$

The Current Implementation

the algorithm is currently implemented in MATLAB

OSA90 is used as a platform for the multi-point parameter extraction and for the fine model simulations

Fine Model
Simulation

Parameters

TRASM
Algorithm
(MATLAB)

OSA90

Responses

HP HFSS

Sonnet's
em

Responses

Extracted
Parameters

Empirical
Models

Parameter
Extraction

TRASM: Trust Region Aggressive Space Mapping

99−8−27

High-Temperature Superconducting Filter
(*Westinghouse, 1993*)
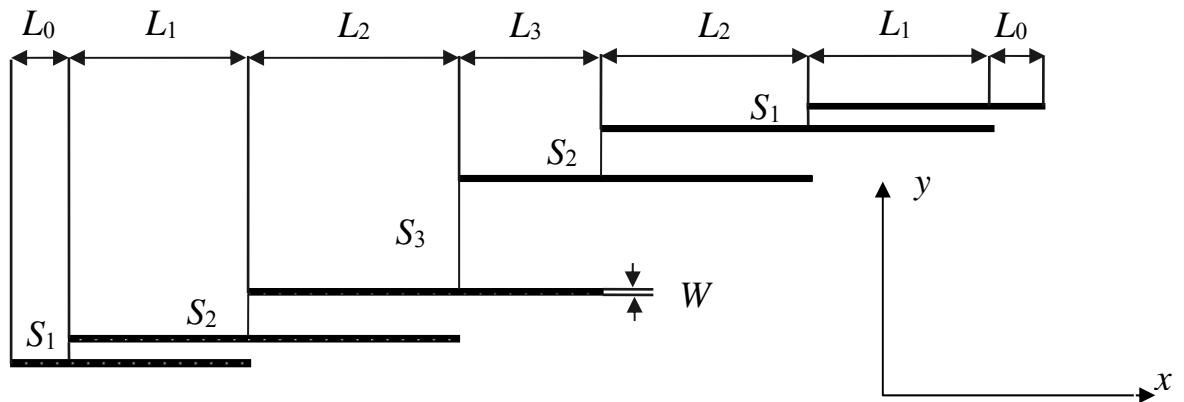
20 mil thick substrate

the dielectric constant is 23.4

passband specifications: $|S_{21}| \geq 0.95$ for $f \leq 3.967$ GHz and
4.099 GHz $\leq f$

stopband specifications: $|S_{21}| \leq 0.05$ for 4.008 GHz $\leq f \leq 4.058$
GHz

designable parameters L_1, L_2, L_3, S_1, S_2 and S_3; L_0 and W are kept
fixed

coarse model exploits the empirical models of microstrip lines,
coupled lines and open stubs available in OSA90/hope

High-Temperature Superconducting Filter Fine Model

the fine model employs a fine-grid Sonnet *em* simulation

the x and y grid sizes for *em* are 1.0 and 1.75 mil

100 elapsed minutes are needed for *em* analysis at single frequency on a Sun SPARCstation 10
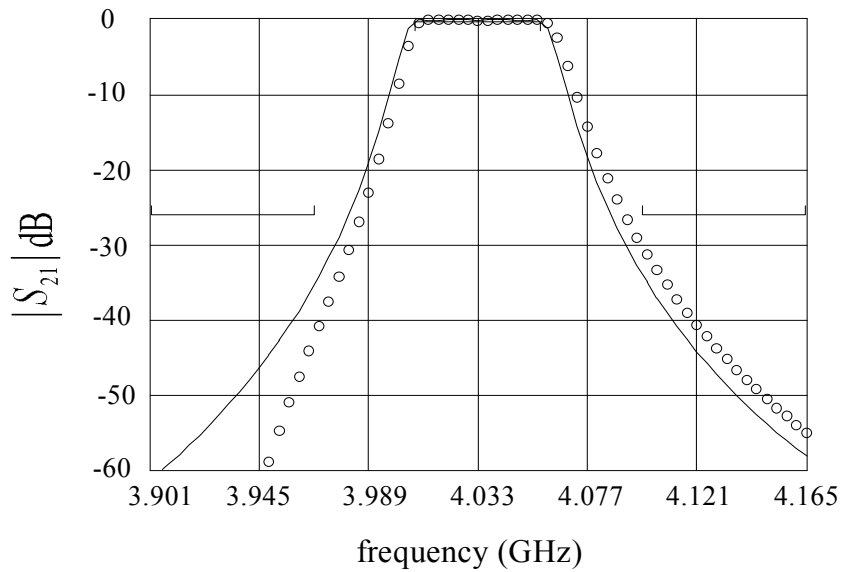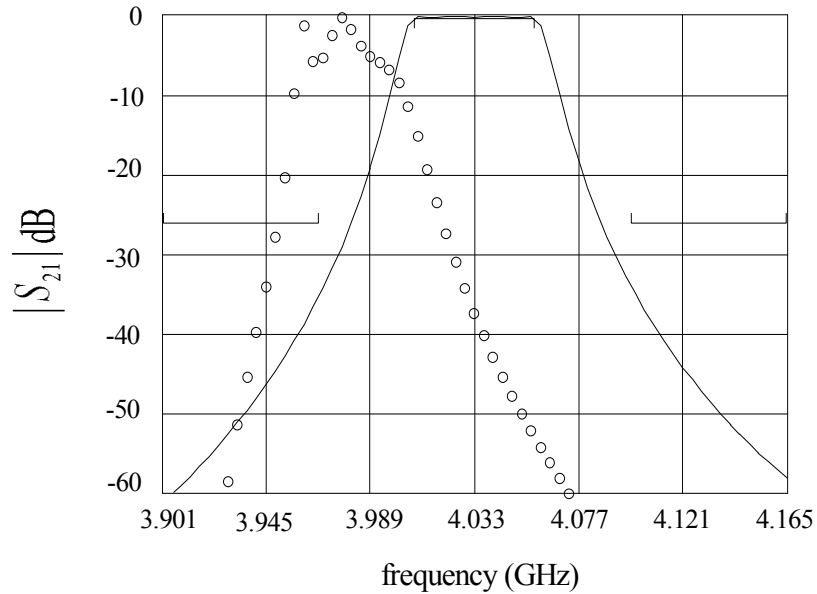
final design is obtained in 5 TRASM iterations, requiring 8 *em* simulations
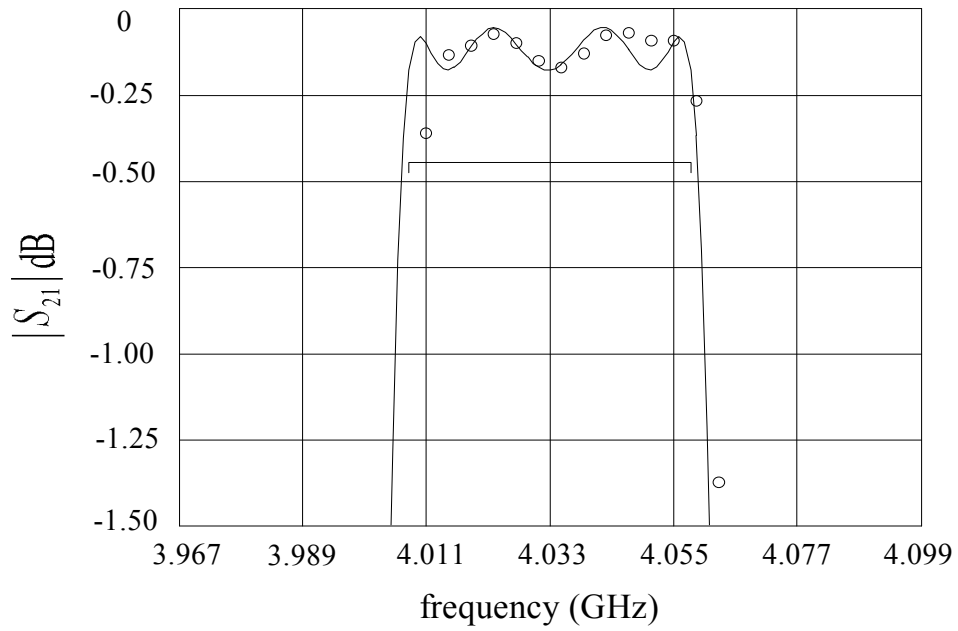
15 frequency points are used per *em* simulation

High-Temperature Superconducting Filter Responses

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

Passband Details for the High-Temperature Superconducting Filter

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 TRASM for most problems is a near an optimal solution

however, optimality can not be guaranteed as the optimal coarse model may significantly deviate from the optimal fine model

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

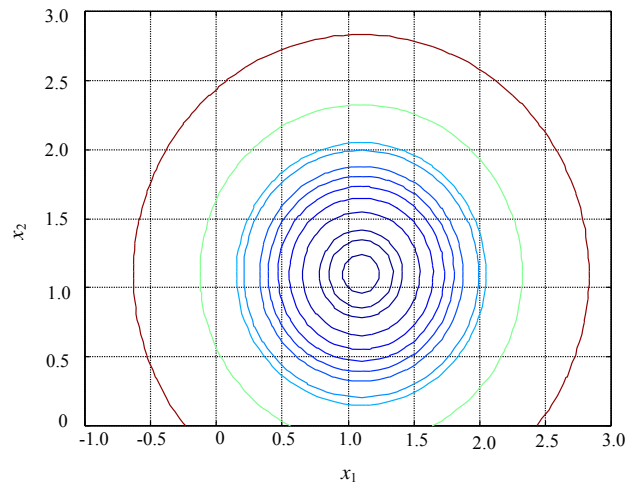the optimal coarse model design is $\boldsymbol{x}_c^* = [1.0 \quad 1.0]^T$

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

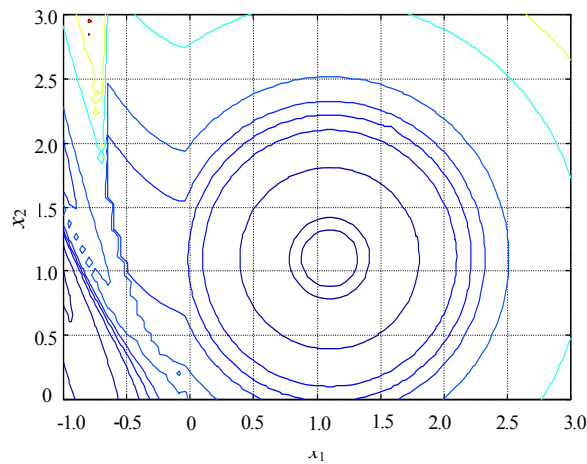the misalignment between the two models is thus given by the two shifts α_1 and α_2

Illustrative Example: A Rosenbrock Function

consider the case $\alpha_1 = \alpha_2 = -0.1$

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 $\alpha_1 = \alpha_2 = -1.5$
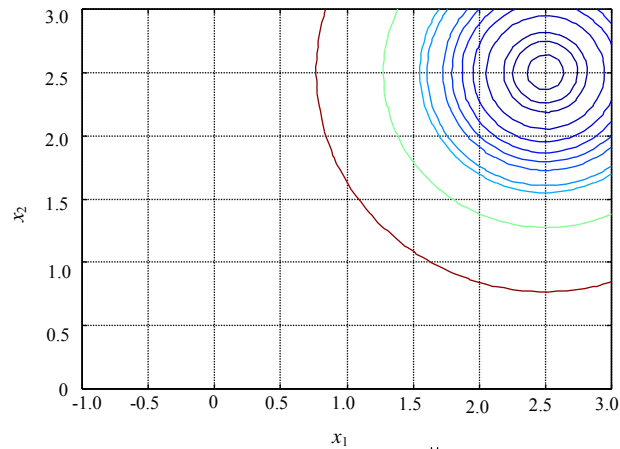
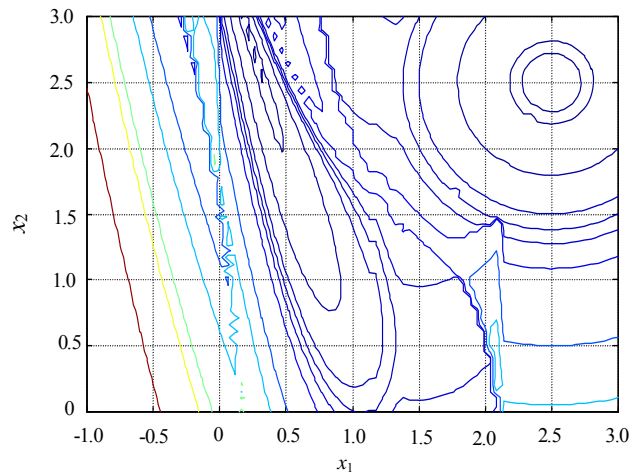ideal contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$

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

the TRASM algorithm is unlikely to converge

The Hybrid Aggressive Space Mapping (HASM) Algorithm
(Bakr et al., 1999)

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 mapping information to supply a Jacobian estimate for 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 convergence is potentially smooth

the Jacobian of the fine model response and parameter extraction are then utilized to recover the mapping matrix B

several switches can take place between the two phases

The Hybrid Aggressive Space Mapping (HASM) Algorithm

$$J_f = J_c B$$

$$\text{Space Mapping } x, f, B \qquad \text{Direct Optimization } x, J_f$$

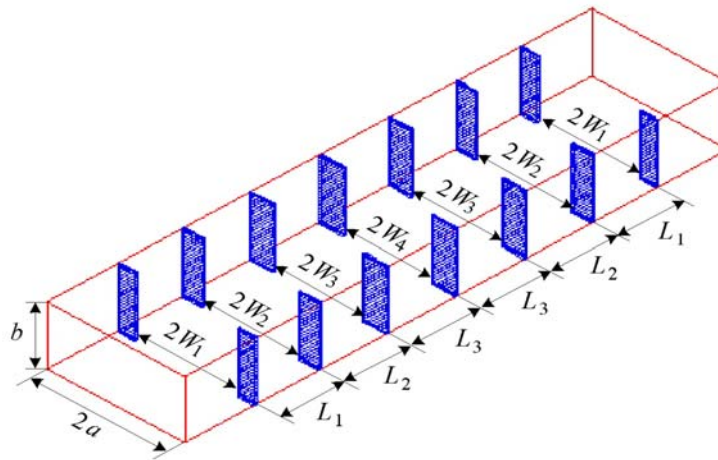$$B = \left(J_c^T J_c \right)^{-1} J_c^T J_f$$
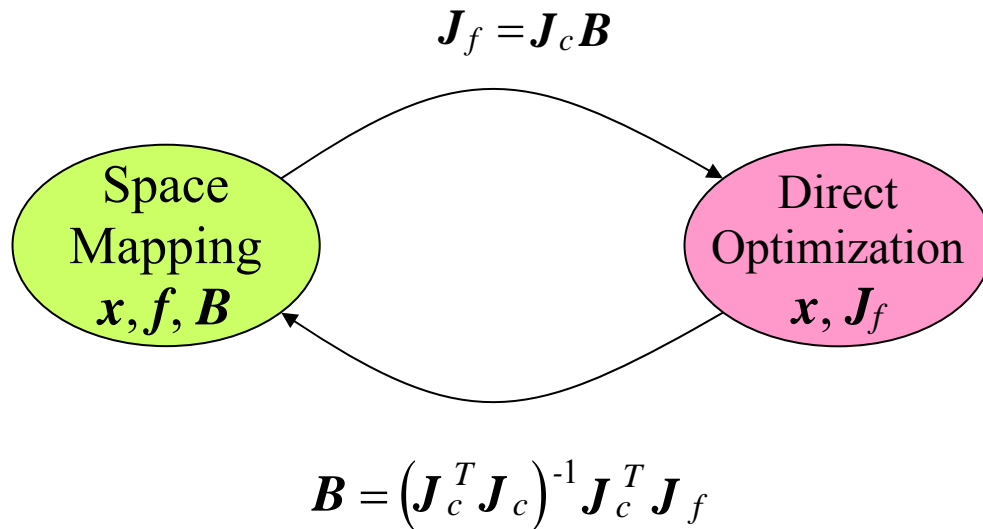
to ensure optimality of the final design, minimax optimization is applied from the final solution reached by the second phase
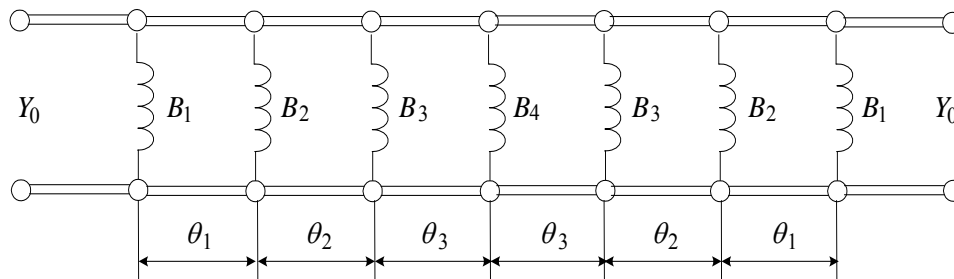
Six-Section H-plane Waveguide Filter
(Matthaei et al., 1964, Bakr et al., 1999)

the fine model

the coarse model

design specifications are taken as

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

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

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

Six-Section H-plane Waveguide Filter

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

the fine model exploits HP HFSS through HP Empipe3D

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
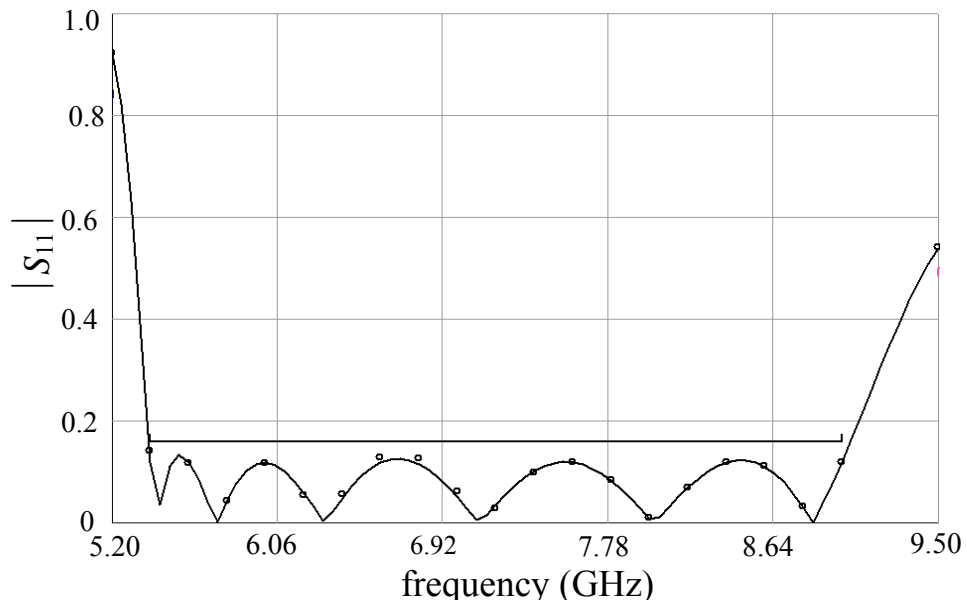
the convergence of TRASM is smooth: the fine model response at the end of the first phase is almost identical to the optimal fine model response
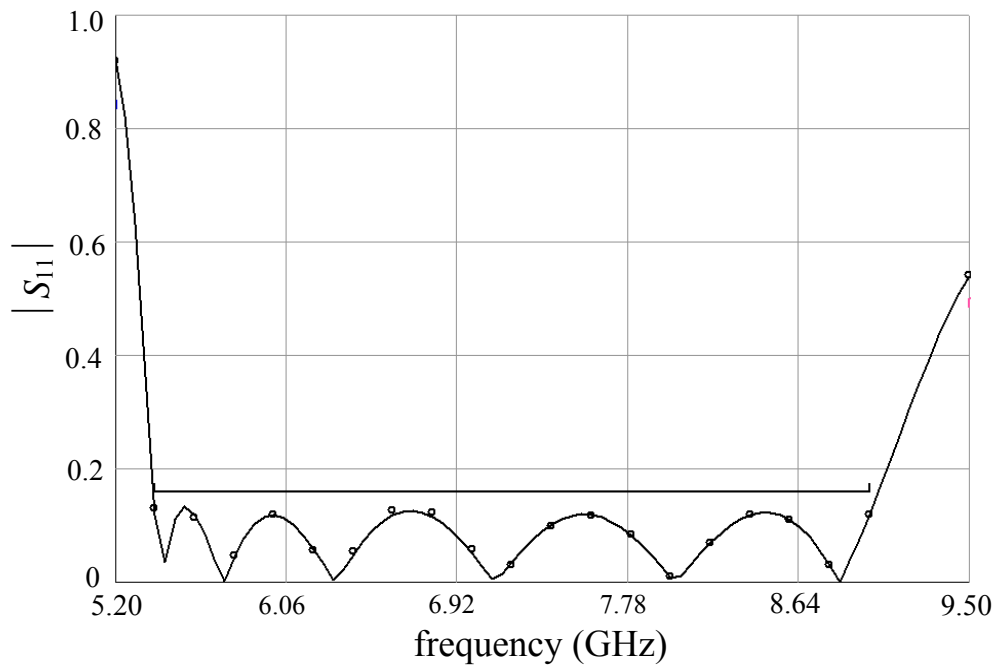
Six-Section H-plane Waveguide Filter
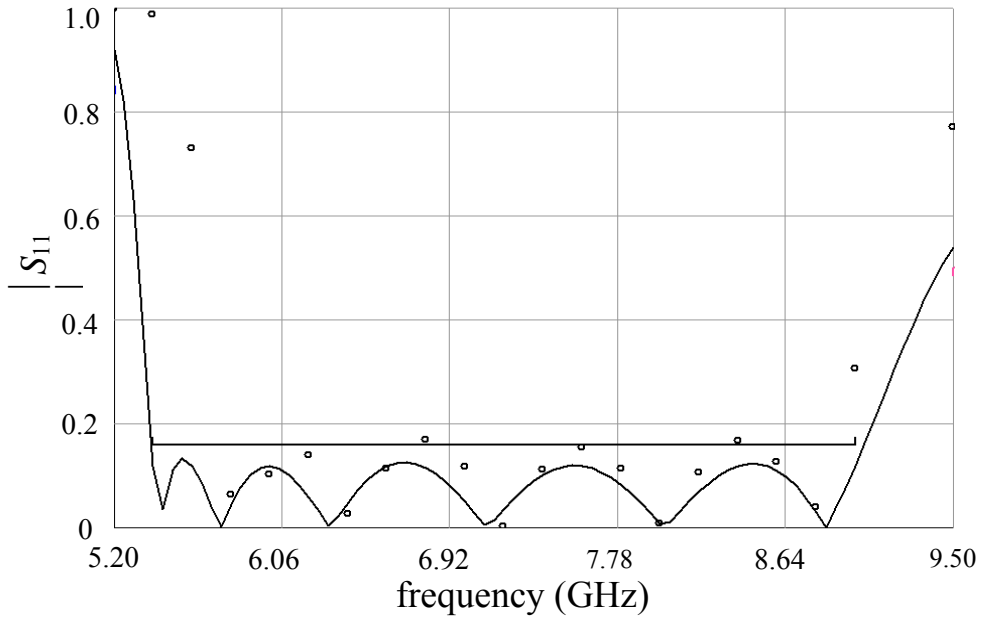
the initial fine model design

the second phase design

Six-Section H-plane Waveguide Filter

the optimal fine model design

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