ACCELERATED OPTIMIZATION OF MIXED EM/CIRCUIT STRUCTURES

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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

$\boldsymbol{x}_f$ is the vector of fine model design parameters

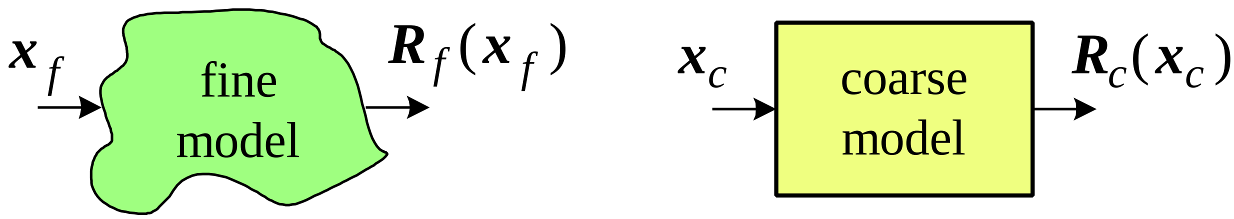
the coarse model is fast but less accurate

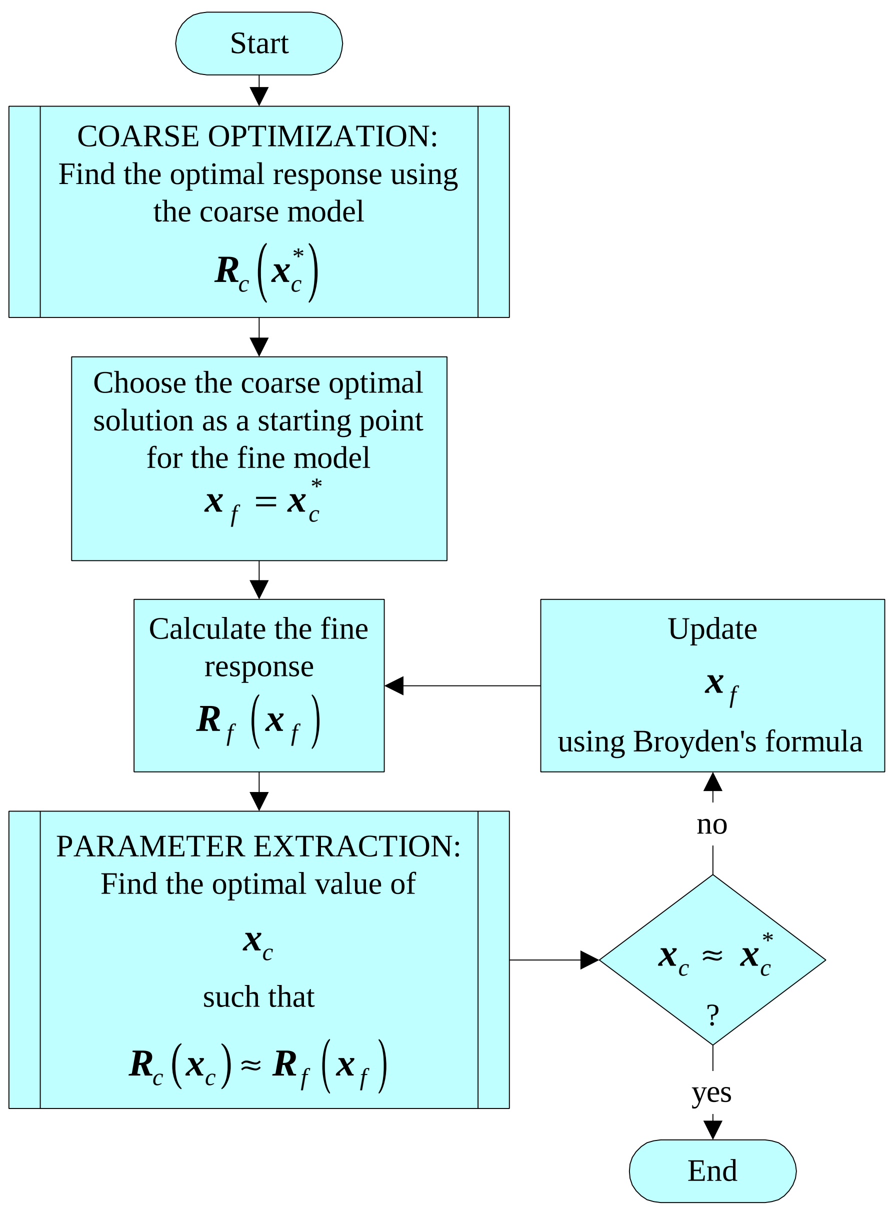
$\boldsymbol{x}_c$ is the vector of coarse model design parameters

Space Mapping aims at avoiding the computationally intensive direct optimization of the fine model by iteratively developing a mapping between $\boldsymbol{x}_f$ and $\boldsymbol{x}_c$

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

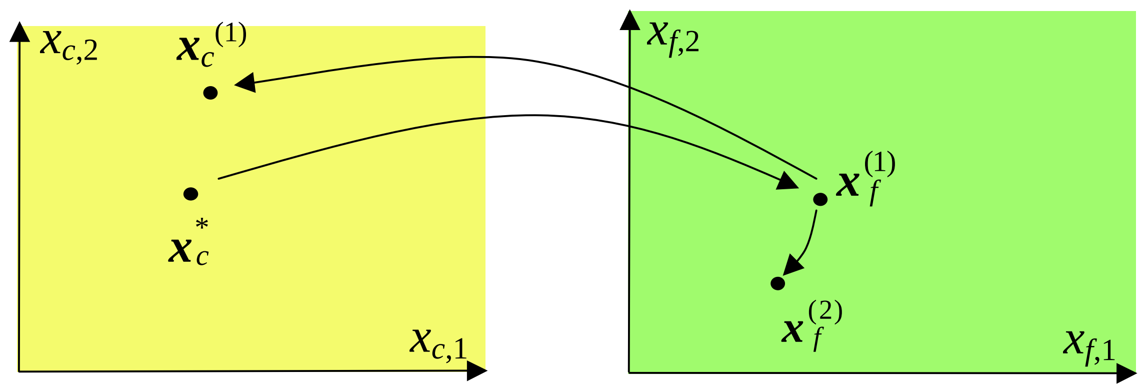
Aggressive Space Mapping (ASM) Concept





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

the initial fine model design is taken as $\boldsymbol{x}_c^*$



at the *j*th iteration

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

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

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

where

$$\boldsymbol{f} = \boldsymbol{x}_c^{(j)} - \boldsymbol{x}_c^*$$

and $\boldsymbol{x}_c^{(j)}$ is obtained through parameter extraction

ASM Algorithm

Step 0. Initialize $\boldsymbol{x}_f^{(1)} = \boldsymbol{x}_c^*$, $\boldsymbol{B}^{(1)} = \boldsymbol{1}$, $j = 1$.

Step 1. Evaluate $\boldsymbol{R}_f(\boldsymbol{x}_f^{(1)})$.

Step 2. Extract $\boldsymbol{x}_c^{(1)}$ such that $\boldsymbol{R}_c(\boldsymbol{x}_c^{(1)}) \approx \boldsymbol{R}_f(\boldsymbol{x}_f^{(1)})$.

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

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

Step 5. Set $\boldsymbol{x}_f^{(j+1)} = \boldsymbol{x}_f^{(j)} + \boldsymbol{h}^{(j)}$.

Step 6. Evaluate $\boldsymbol{R}_f(\boldsymbol{x}_f^{(j+1)})$.

Step 7. Extract $\boldsymbol{x}_c^{(j+1)}$ such that $\boldsymbol{R}_c(\boldsymbol{x}_c^{(j+1)}) \approx \boldsymbol{R}_f(\boldsymbol{x}_f^{(j+1)})$.

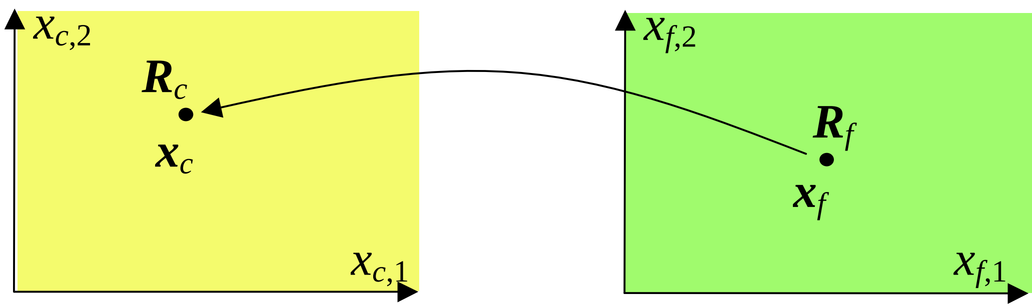
Step 8. Evaluate $\boldsymbol{f}^{(j+1)} = \boldsymbol{x}_c^{(j+1)} - \boldsymbol{x}_c^*$. Stop if $\left\| \boldsymbol{f}^{(j+1)} \right\| \le \eta$.

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

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

Parameter Extraction

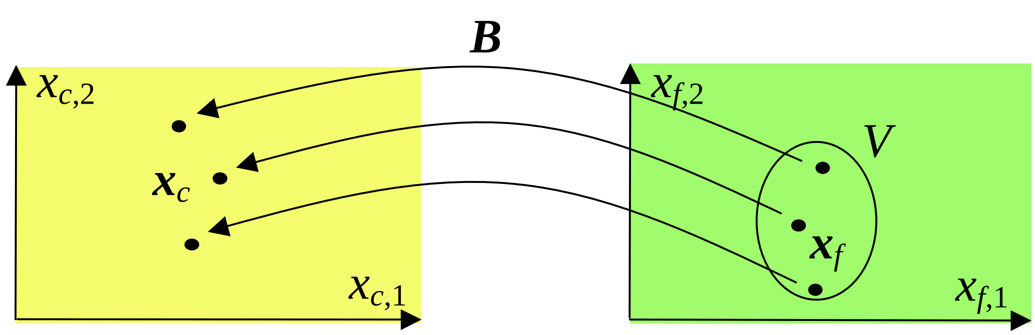
single point parameter extraction aims at matching the responses of both models at a single point



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



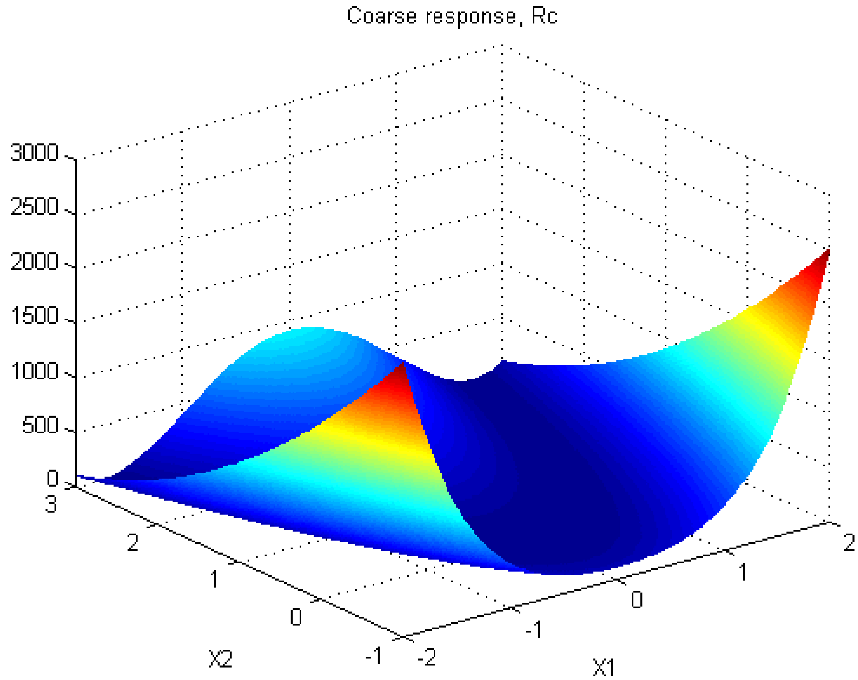
the extracted parameters should satisfy

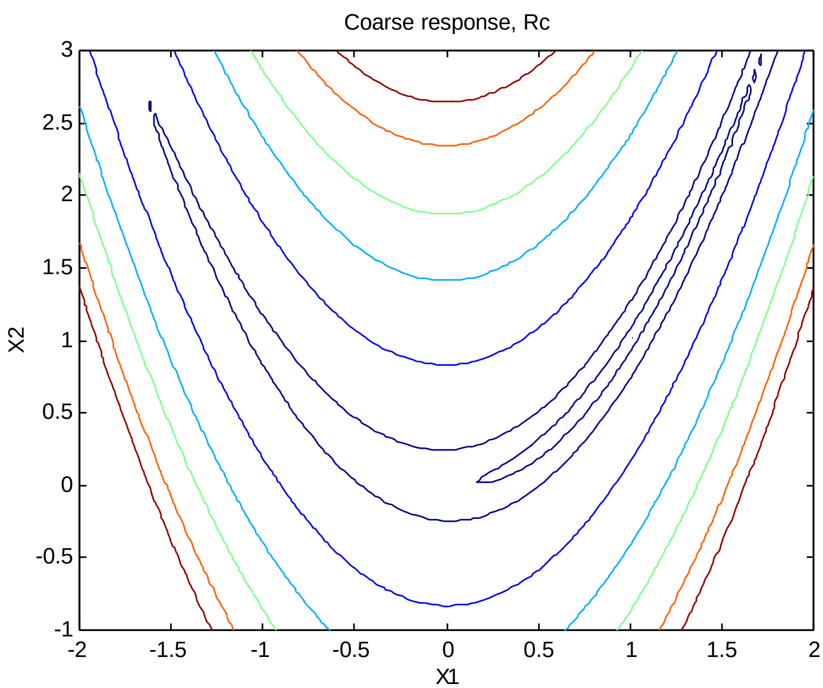
$$\boldsymbol{R}_c(\boldsymbol{x}_c + \boldsymbol{B}\,(\boldsymbol{x} - \boldsymbol{x}_f)) = \boldsymbol{R}_f(\boldsymbol{x})$$

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

Coarse Model Example: Rosenbrock Function

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



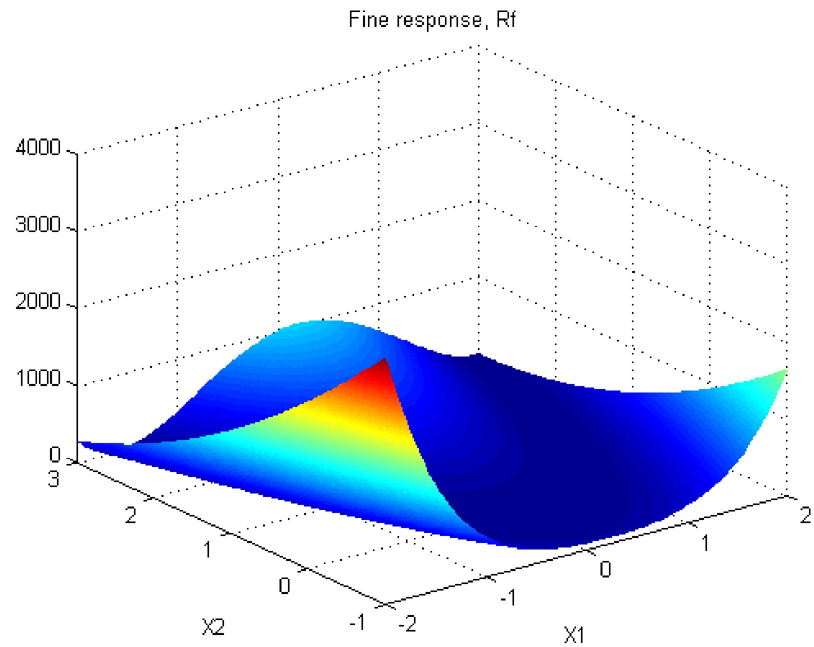


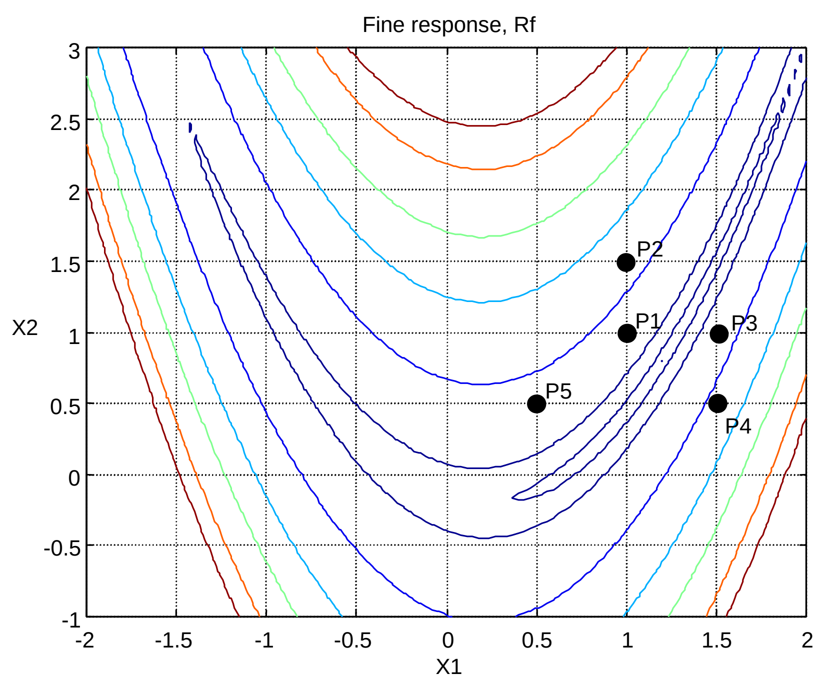
$$\boldsymbol{x}_c^* = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

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

Fine Model : Shifted Rosenbrock Function

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





Multi-Point Parameter Extraction

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

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

where

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

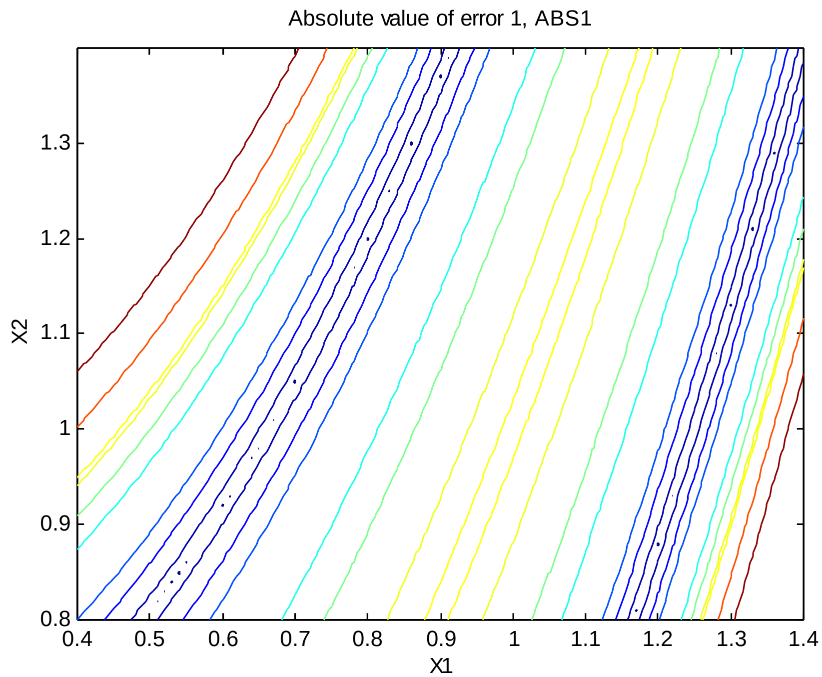
since the matrix $\boldsymbol{B}^{(j)} = \boldsymbol{1}$ for the first parameter extraction optimization, the corresponding five error functions are taken as

$$E_i = R_c\,(\boldsymbol{x} + ?\,\boldsymbol{x}_i) \; - R_f\;(\boldsymbol{x}_c^* + ?\,\boldsymbol{x}_i)$$

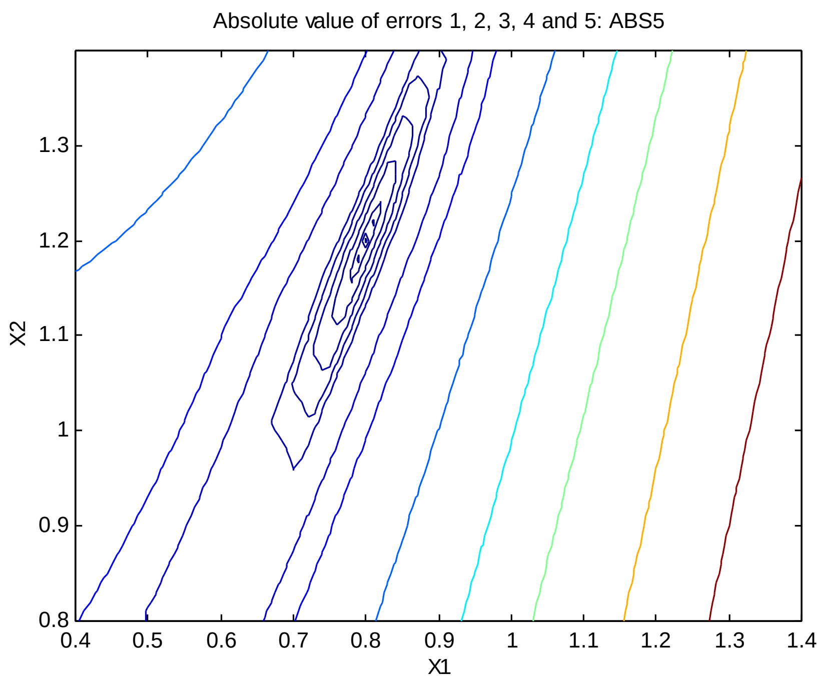
considering only $l_1$and l_2 norms, the corresponding objective functions can be taken as

$$ABS_n = |E_1| + |E_2| + \ldots + |E_n|$$
$$SQR_n = (E_1)^2 + (E_2)^2 + \ldots + (E_n)^2$$

l_1 Objective Function for the Parameter Extraction Problem



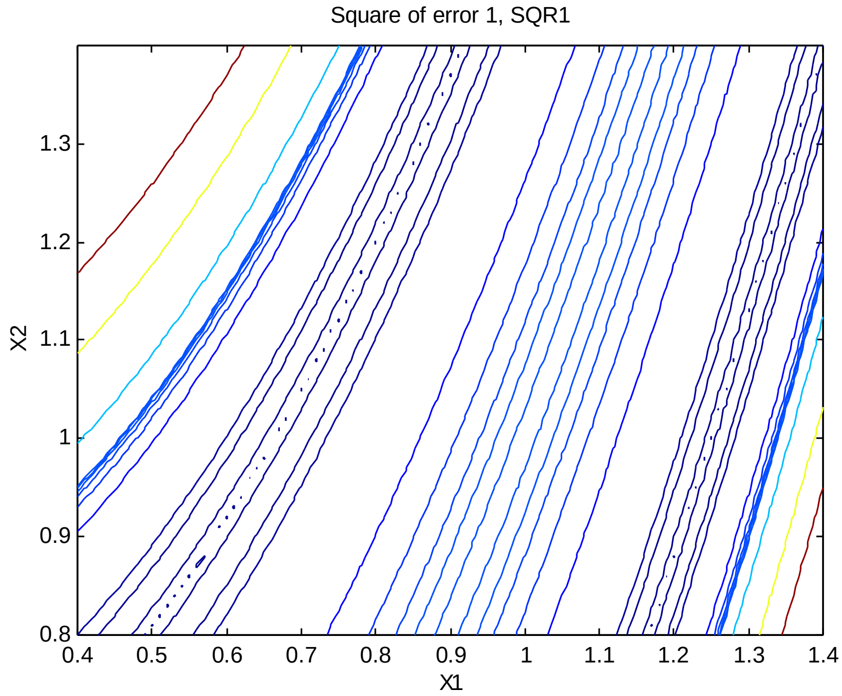
single point parameter extraction



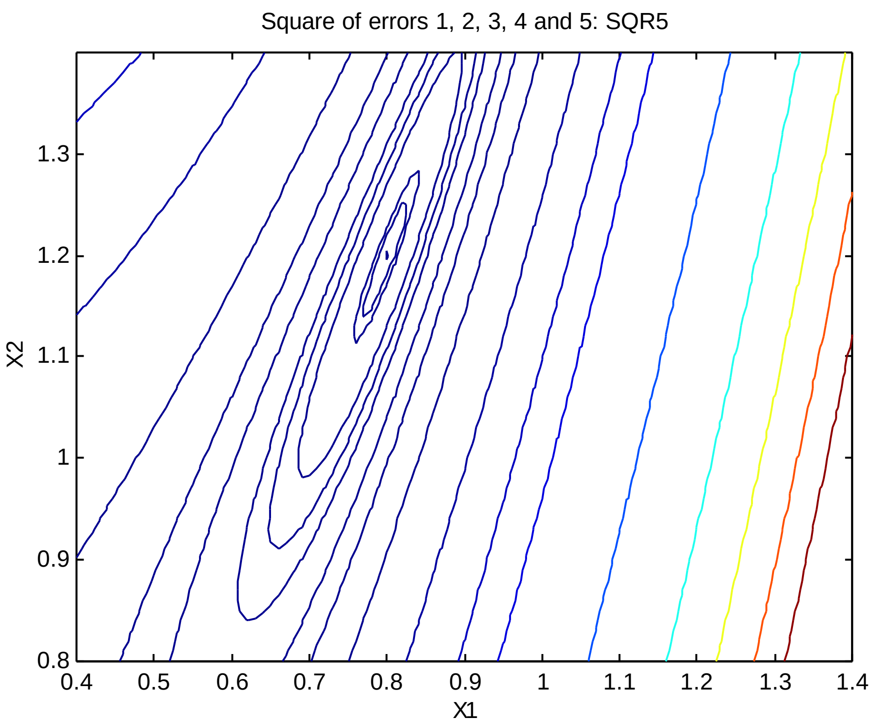
$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$$

multi-point parameter extraction (with 4 additional points)

l_2 Objective Function for the Parameter Extraction Problem



single point parameter extraction



$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$$

multi-point parameter extraction (with 4 additional points)

Space Mapping Solution Process

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

Step 1. $R_f(\boldsymbol{x}_f^{(1)}) = 31.4$

Step 2. When $\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}, \ R_c(\boldsymbol{x}_c^{(1)}) = R_f(\boldsymbol{x}_f^{(1)})$

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

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

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

Step 6. $R_f(\boldsymbol{x}_f^{(2)}) = 0$

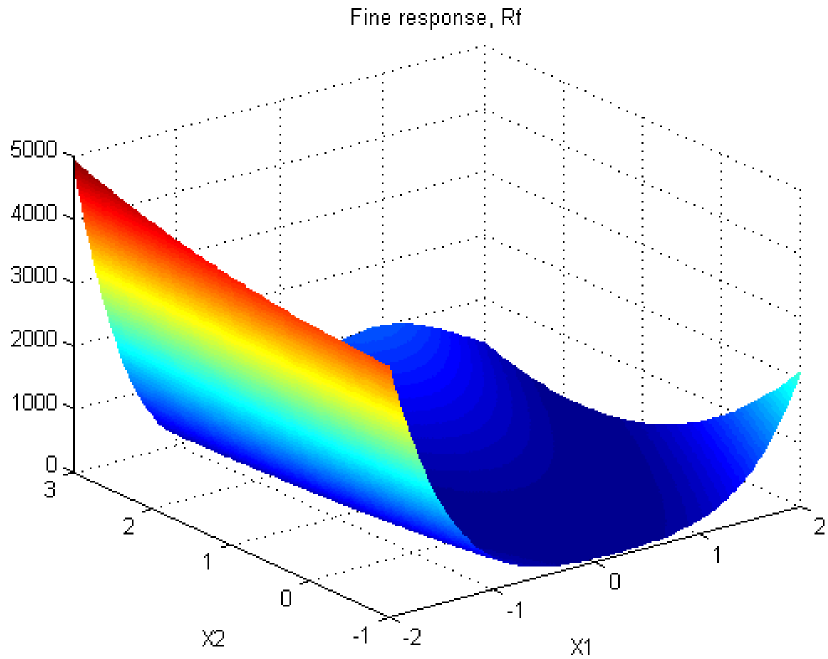
Step 7. $\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, because we know $R_c(\boldsymbol{x}_c^{(2)}) = 0$

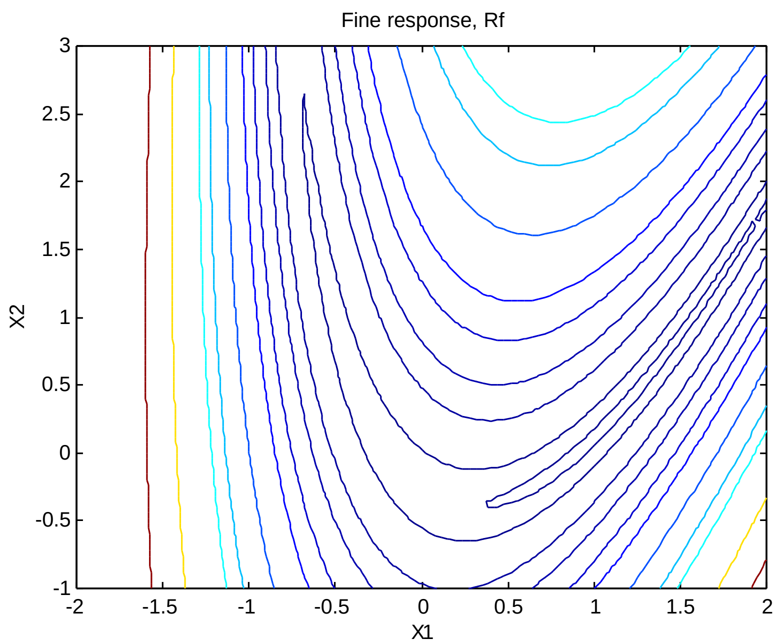
Step 8. Since $\boldsymbol{f}^{(2)} = \boldsymbol{x}_c^{(2)} - \boldsymbol{x}_c^{*} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, then $\bar{\boldsymbol{x}}_f = \boldsymbol{x}_f^{(2)} = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$

Fine Model Example: Transformed Rosenbrock Function

$$R_f(\boldsymbol{x}) = 100(u_2 - u_1^2)^2 + (1-u_1)^2 \quad \text{where}$$

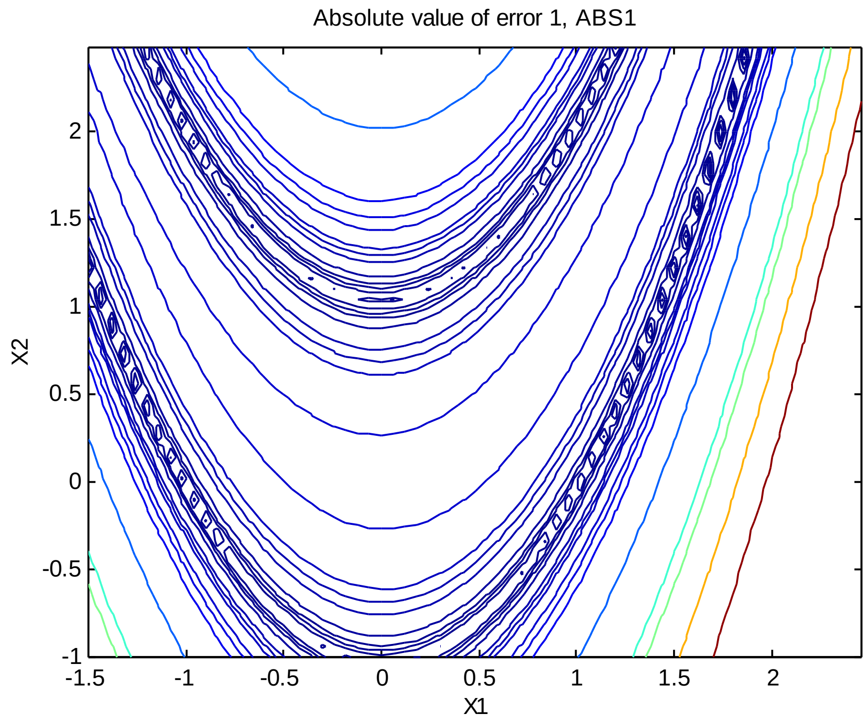
$$\boldsymbol{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix} \boldsymbol{x} + \begin{bmatrix} -0.3 \\ 0.3 \end{bmatrix}$$



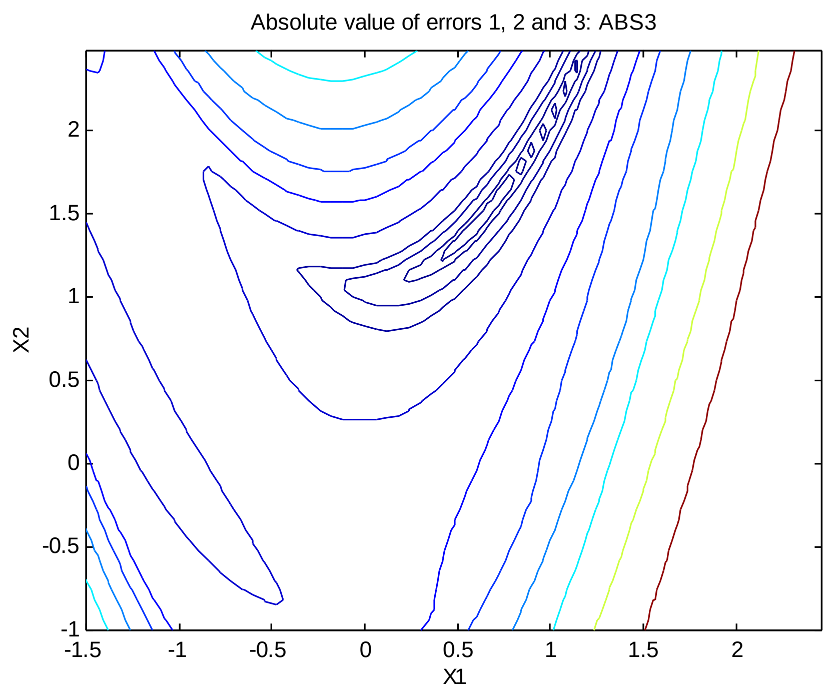


$$\boldsymbol{R}_f(\boldsymbol{x}_c^*) = 108.32$$

First l_1 Parameter Extraction



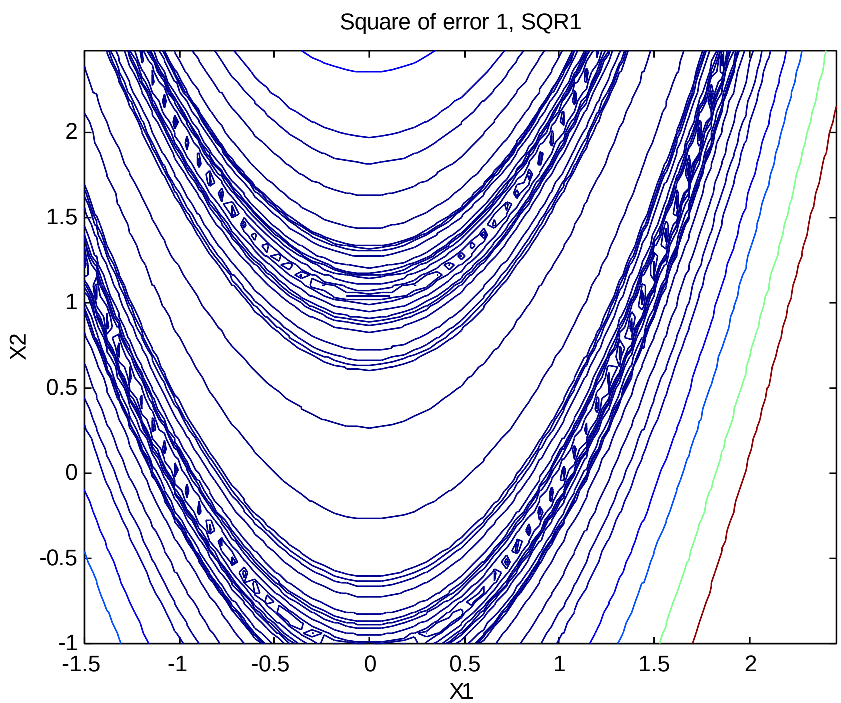
single point parameter extraction



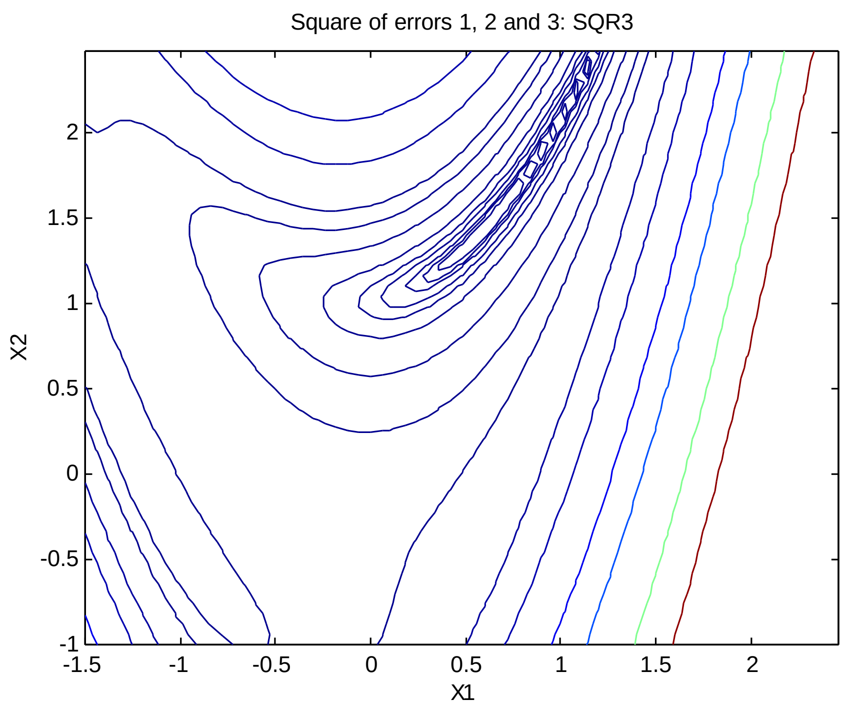
$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

multi-point parameter extraction (with 2 additional points)

First l_2 Parameter Extraction



single point parameter extraction



$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$$

multiple point parameter extraction (with 2 additional points)

Space Mapping Solution Process

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

Step 1. $R_f(\boldsymbol{x}_f^{(1)}) = 108.32$

Step 2. When $\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.6 \\ 1.4 \end{bmatrix}$, $R_c(\boldsymbol{x}_c^{(1)}) = R_f(\boldsymbol{x}_f^{(1)})$

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

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

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

Step 6. $R_f(\boldsymbol{x}_f^{(2)}) = 1.8207$

Step 7. When $\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$, $R_c(\boldsymbol{x}_c^{(2)}) = R_f(\boldsymbol{x}_f^{(2)})$

Space Mapping Solution Process (continued)

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

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

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

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

Step 6b. $$R_f(\boldsymbol{x}_f^{(3)}) = 0.1308$$

Step 7b. When $\boldsymbol{x}_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$, $R_c(\boldsymbol{x}_c^{(3)}) = R_f(\boldsymbol{x}_f^{(3)})$

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

Space Mapping Solution Process (continued)

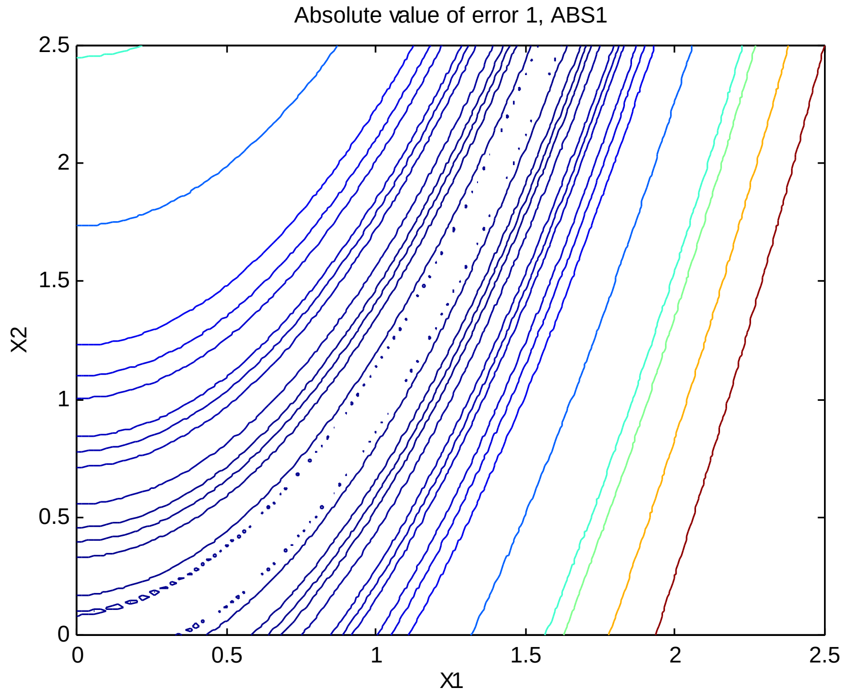
Step 9b. $\boldsymbol{B}^{(3)} = \boldsymbol{B}^{(2)} + \dfrac{\boldsymbol{f}^{(3)}\boldsymbol{h}^{(2)^T}}{\boldsymbol{h}^{(2)^T}\boldsymbol{h}^{(2)}} = \begin{bmatrix} 1.1 & -0.2 \\ 0.2 & 0.9 \end{bmatrix}$

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

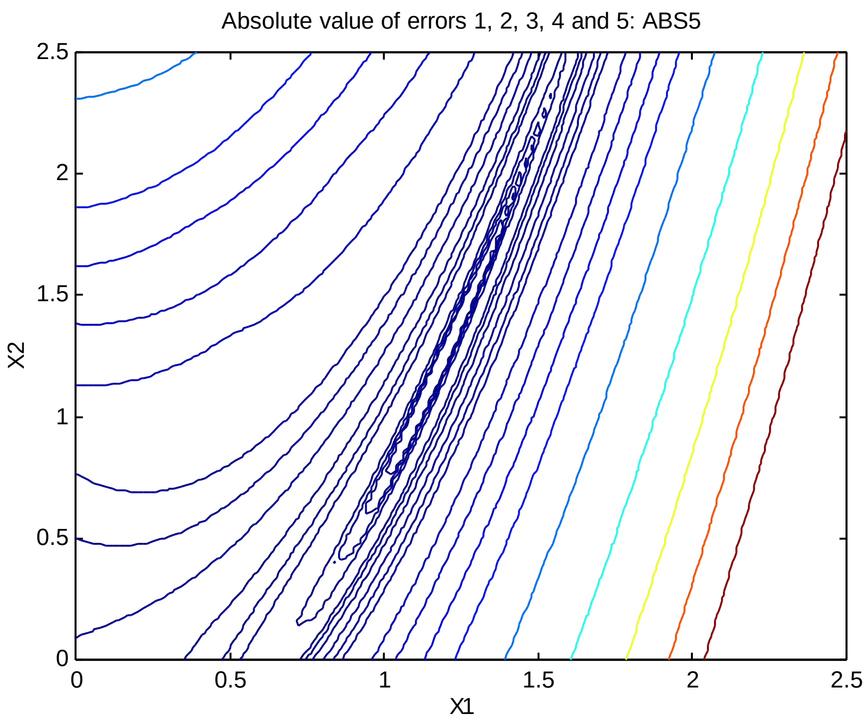
Step 5c. Set $\boldsymbol{x}_f^{(4)} = \begin{bmatrix} 1.28 \\ 0.48 \end{bmatrix} + \begin{bmatrix} -0.0082 \\ 0.0151 \end{bmatrix} = \begin{bmatrix} 1.2718 \\ 0.4951 \end{bmatrix}$

Step 6c. $\boldsymbol{R}_f(\boldsymbol{x}_f^{(4)}) = 9.2\times10^{-8}$, then $\bar{\boldsymbol{x}}_f = \boldsymbol{x}_f^{(4)}$ and we can end the algorithm

Second l_1 Parameter Extraction



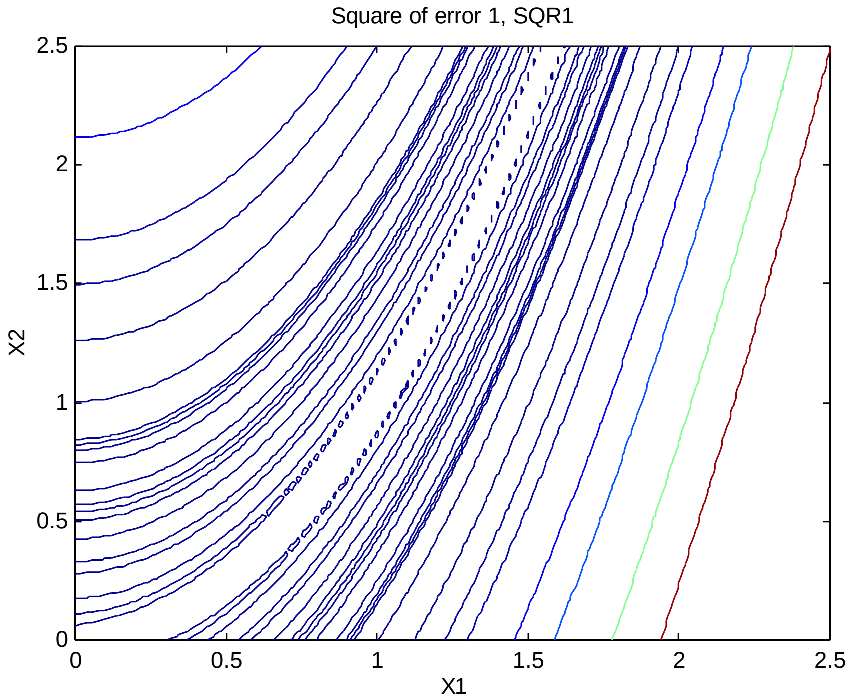
single point parameter extraction



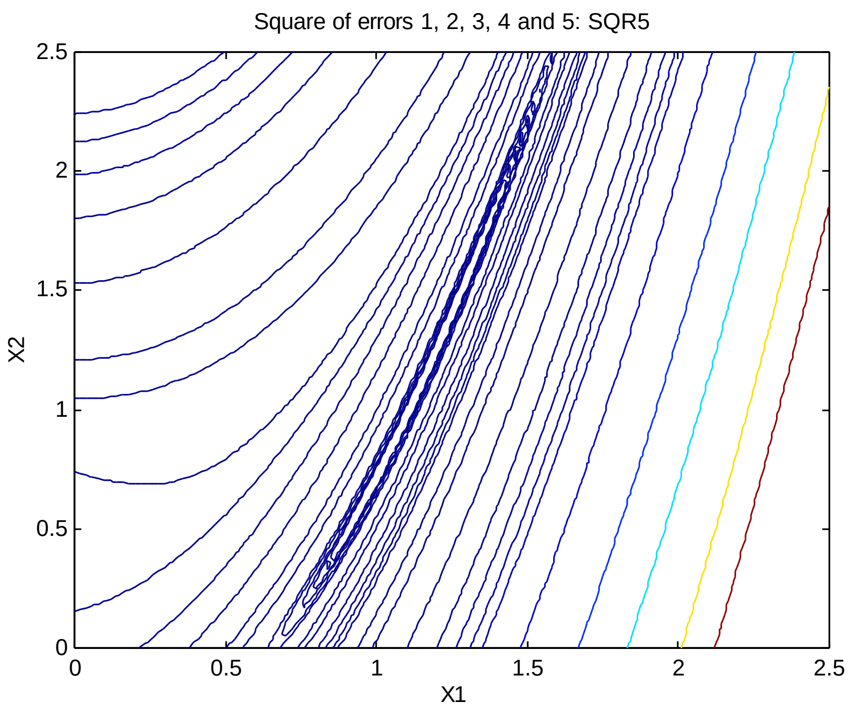
$$\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$$

multi-point parameter extraction (4 additional points)

Second l_2 Parameter Extraction



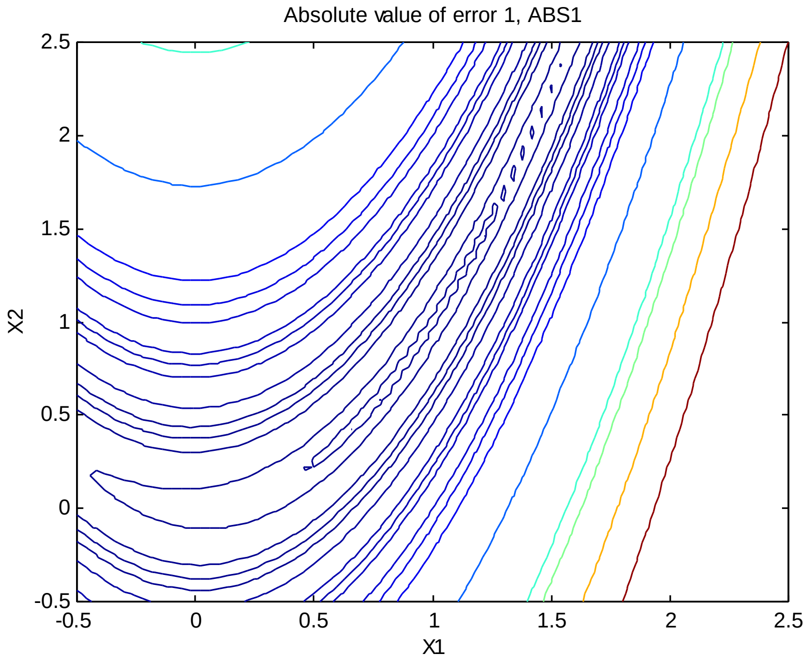
single point parameter extraction



$$\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.12 \\ 1.12 \end{bmatrix}$$

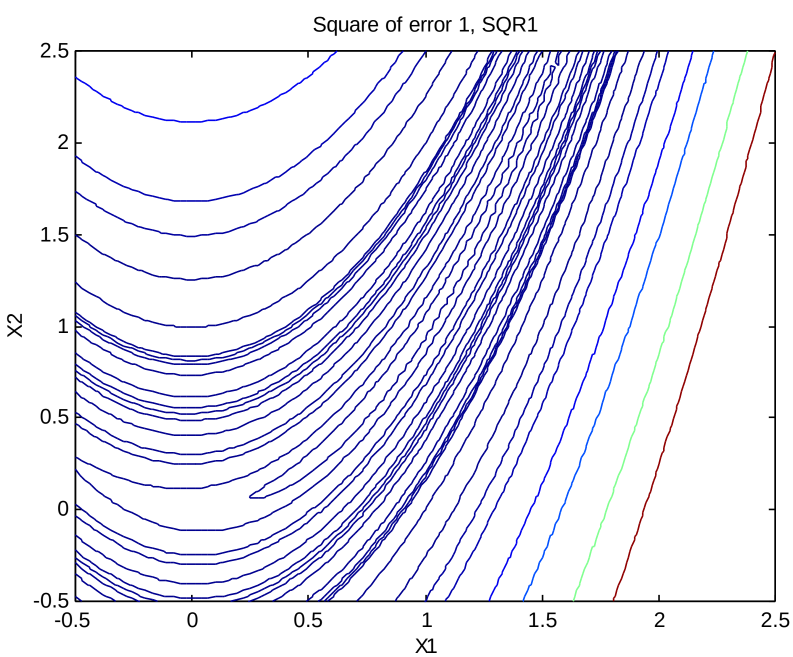
multi-point parameter extraction (with 4 additional points)

Third Parameter Extraction



$$\boldsymbol{x}_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$$

single point l_1 parameter extraction



$$\boldsymbol{x}_c^{(3)} = \begin{bmatrix} 1.012 \\ 0.988 \end{bmatrix}$$

single point l_2 parameter extraction

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

TRASM integrates a trust region methodology with ASM

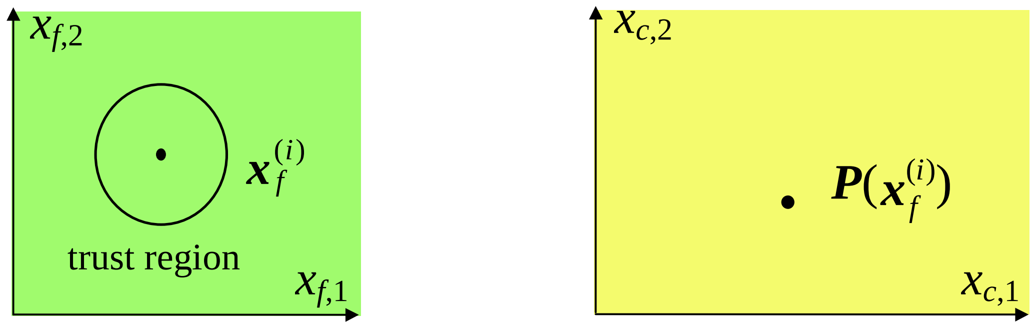
a certain success criterion must be satisfied in each iteration to accept the predicted step

a recursive multi-point parameter extraction procedure is introduced

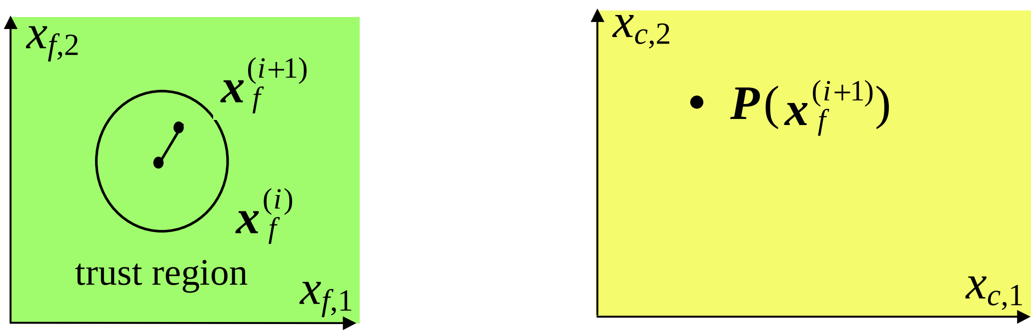
all available fine model simulations are utilized to improve parameter extraction uniqueness

available mapping information is integrated into this extraction procedure

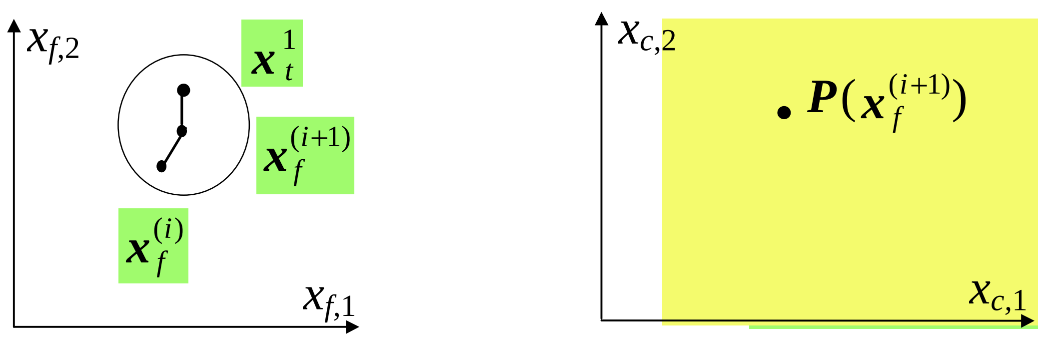
Illustration of the TRASM Algorithm



the current state at the *i*th iteration



initial parameter extraction at the suggested point



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

this corresponds to minimizing $\left\|\boldsymbol{f}^{(i)} + \boldsymbol{B}^{(i)}\boldsymbol{h}^{(i)}\right\|_2^2$ subject to $\left\|\boldsymbol{h}^{(i)}\right\|_2 \le \boldsymbol{d}$ where $\boldsymbol{d}$ is the size of the trust region

l, which correlates to d, 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) $\boldsymbol{f}$ 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

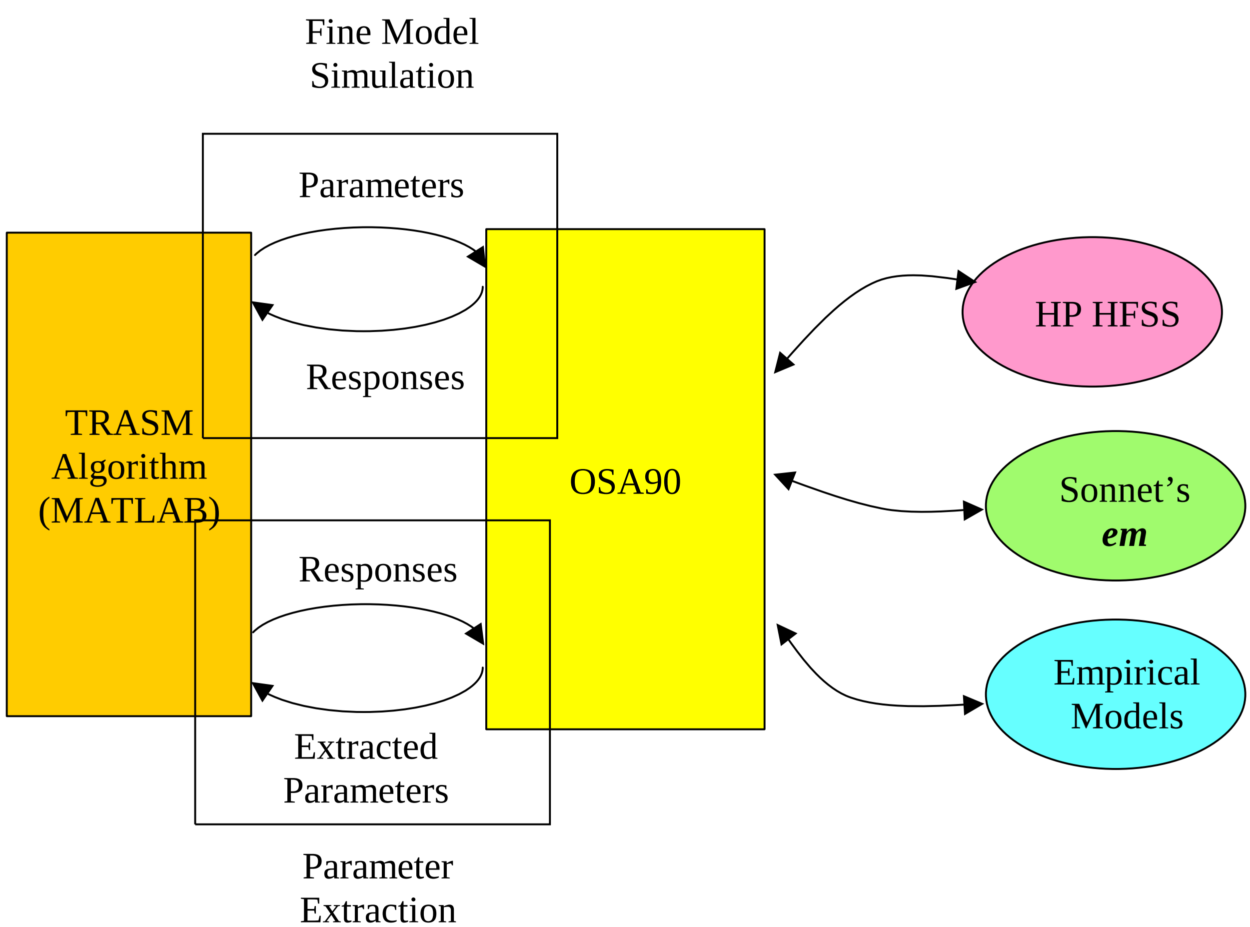
$$\underset{\boldsymbol{x}_c}{minimize} \left\| \boldsymbol{R}_c(\boldsymbol{x}_c + \boldsymbol{B}^{(i)}(\boldsymbol{x} - \boldsymbol{x}_f^{(i+1)})) - \boldsymbol{R}_f(\boldsymbol{x}) \right\|$$

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

The Current Implementation

the algorithm is currently implemented in MATLAB

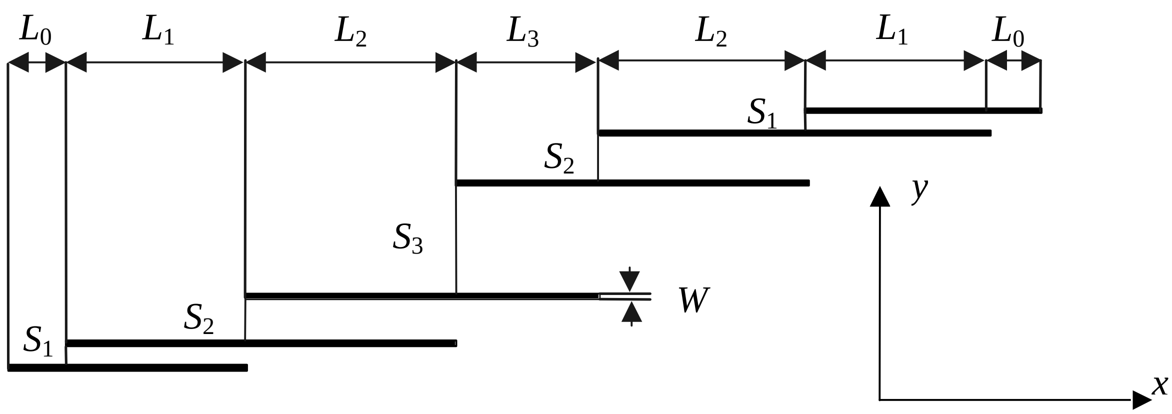
OSA90 is used as a platform for the multi-point parameter extraction and for the fine model simulations



TRASM: Trust Region Aggressive Space Mapping

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

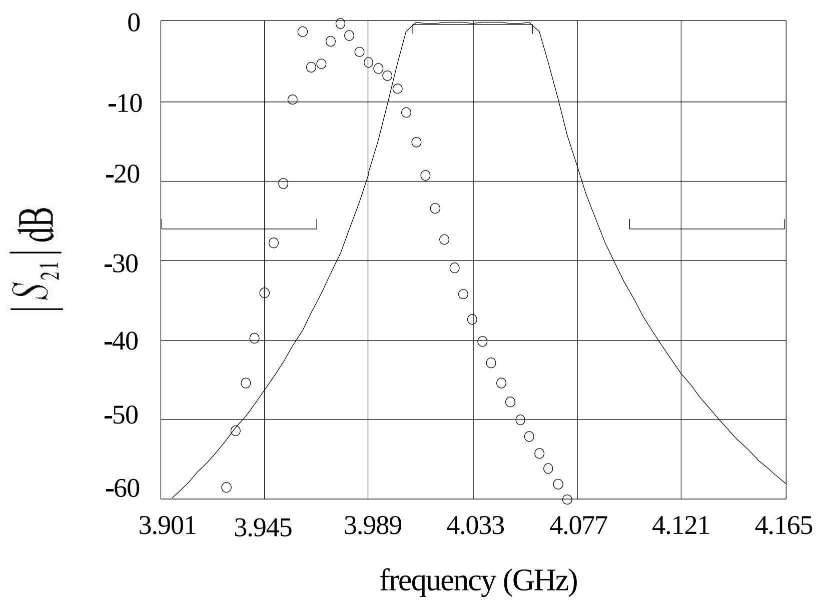
100 elapsed minutes are needed for ***em*** analysis at single frequency on a Sun SPARCstation 10

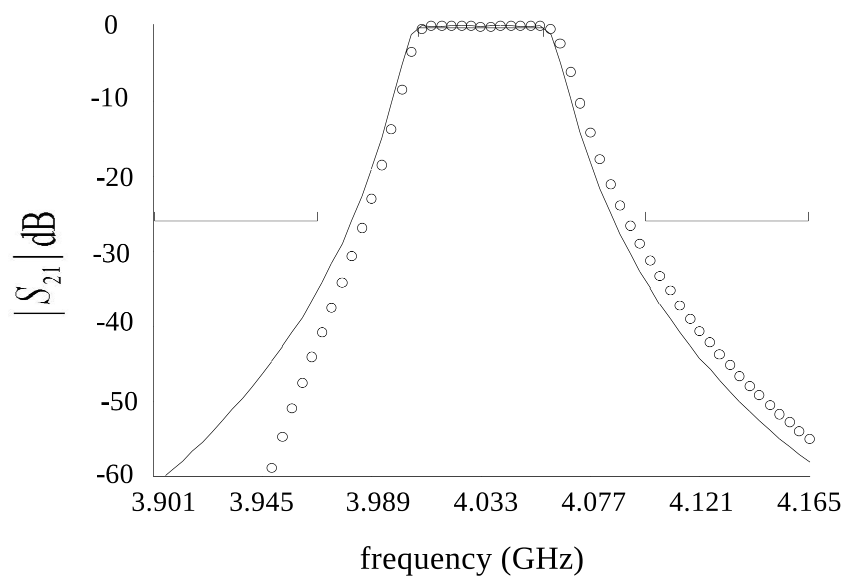
final design is obtained in 5 TRASM iterations, requiring 8 ***em*** simulations

15 frequency points are used per ***em*** simulation

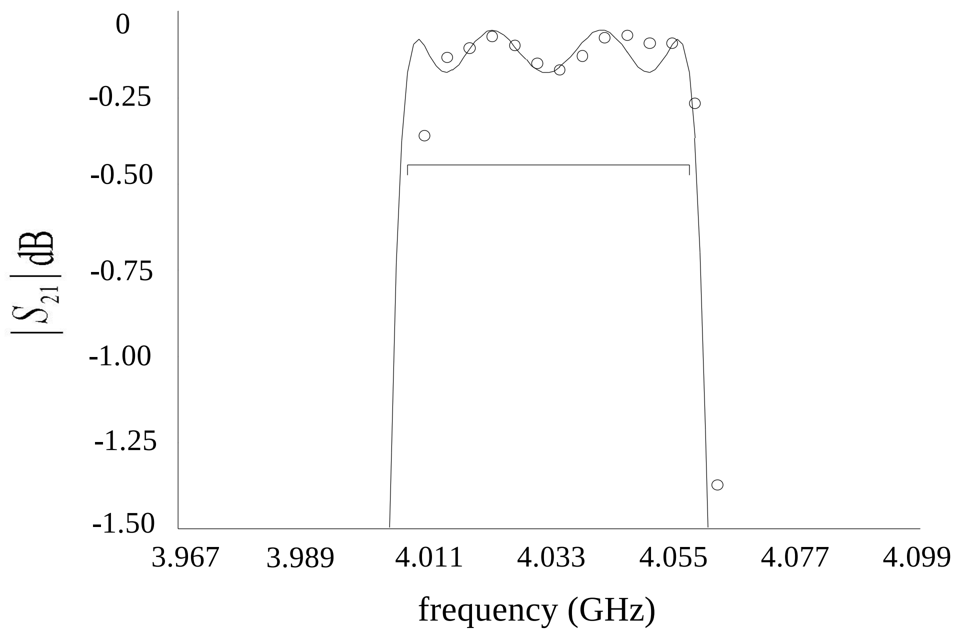
High-Temperature Superconducting Filter Responses

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

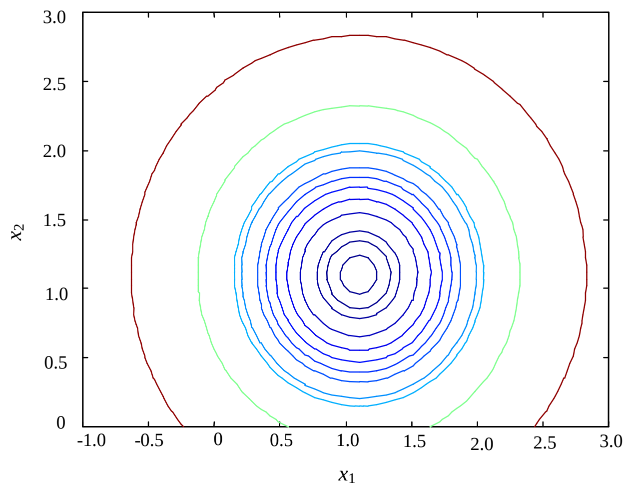
the optimal coarse model design is $\boldsymbol{x}_c^* = [1.0 \quad 1.0]^T$

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

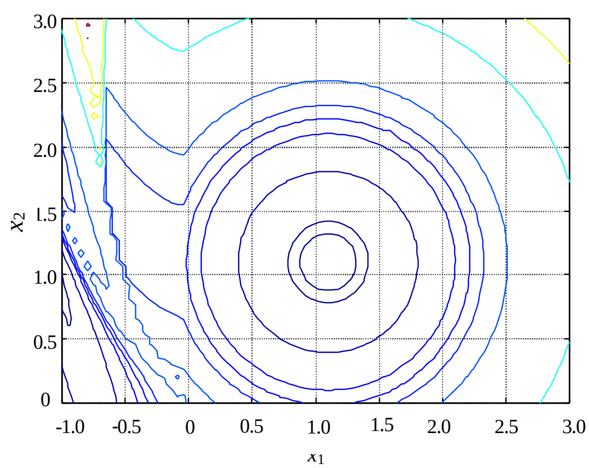
the misalignment between the two models is thus given by the two shifts α_1 and α_2

Illustrative Example: A Rosenbrock Function

consider the case $a_1 = a_2 = -0.1$



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

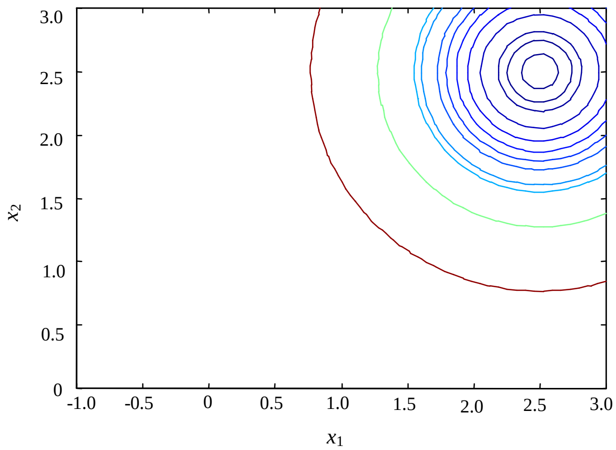


actual contour plot of $\left\| \boldsymbol{P}(\boldsymbol{x}_f) - \boldsymbol{x}_c^* \right\|_2^2$

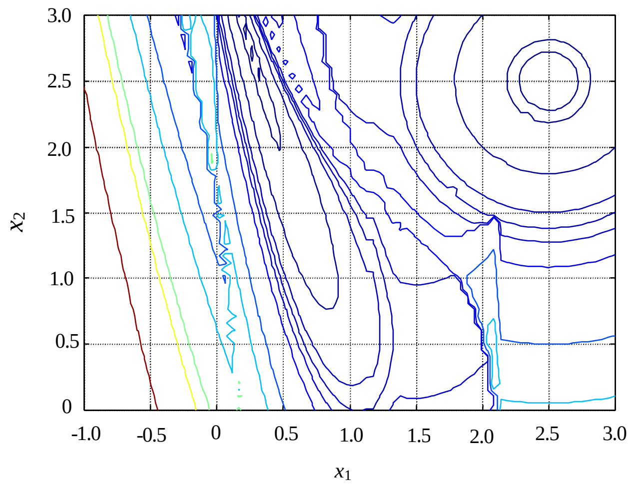
the TRASM algorithm is likely to converge

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 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

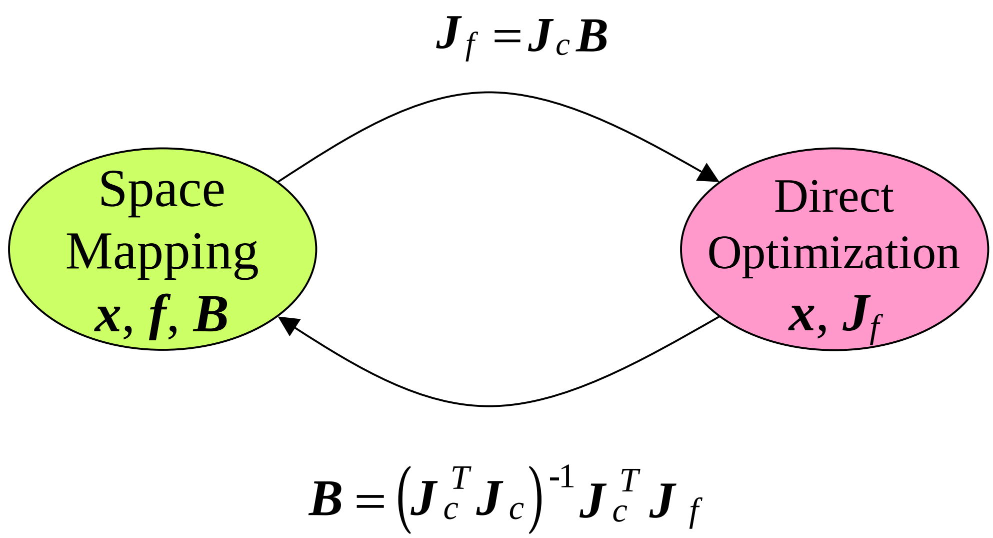
the second phase applies direct optimization to match the fine model response to the optimal coarse model response

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 $\boldsymbol{B}$

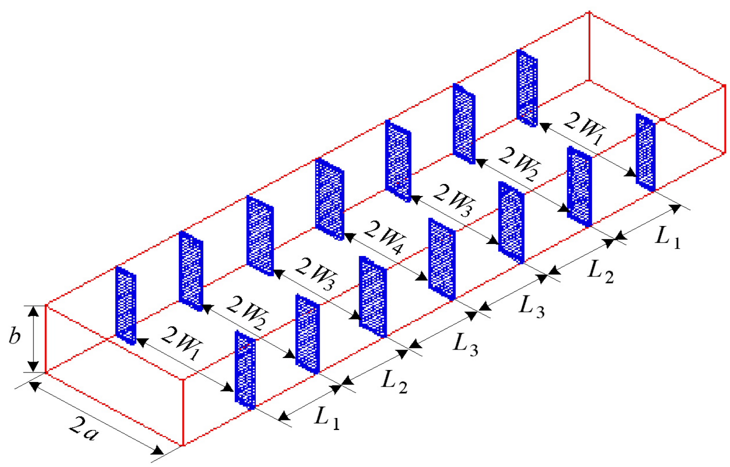
several switches can take place between the two phases

The Hybrid Aggressive Space Mapping (HASM) Algorithm

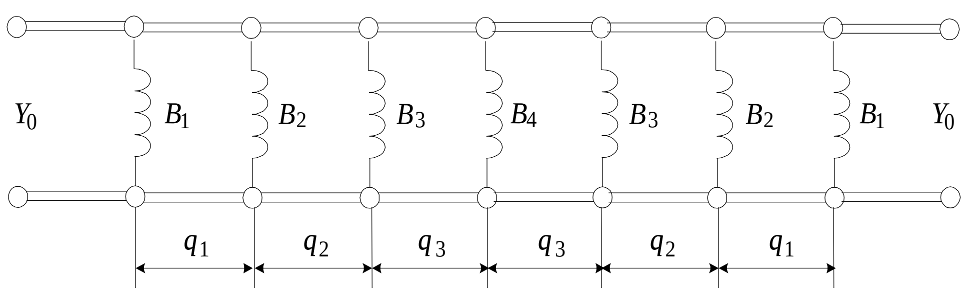


to ensure optimality of the final design, minimax optimization is applied from the final solution reached by the second phase

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 $5.4 \text{ GHz} \leq f \leq 9.0 \text{ GHz}$
$|S_{11}| \geq 0.85$ for $f \leq 5.2 \text{ GHz}$ and $|S_{11}| \geq 0.5$ for $9.5 \text{ GHz} \leq f$

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

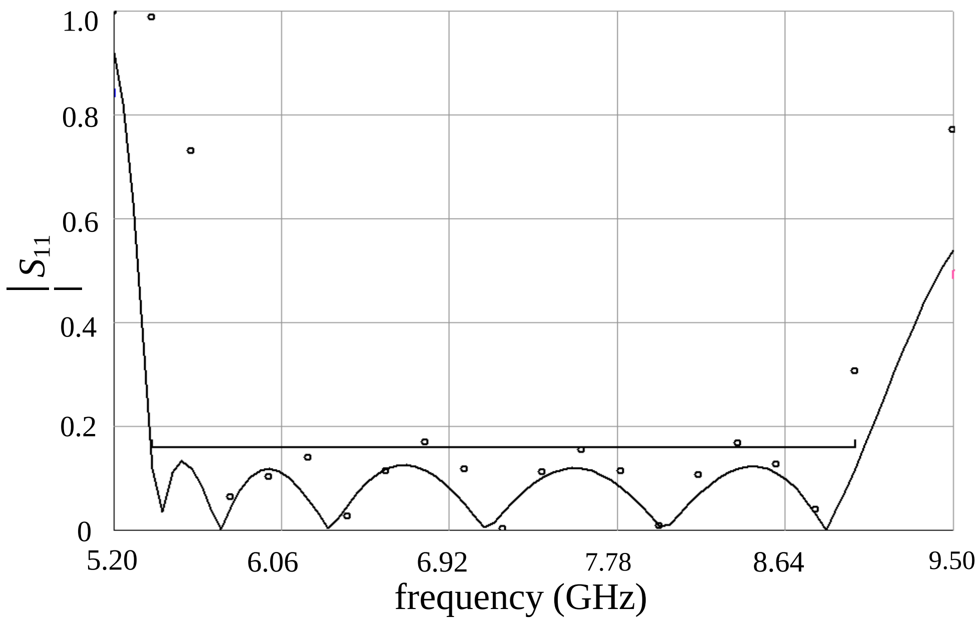
the first phase executed 4 iterations requiring a total of 5 fine model simulations

the second phase did not produce successful iterations

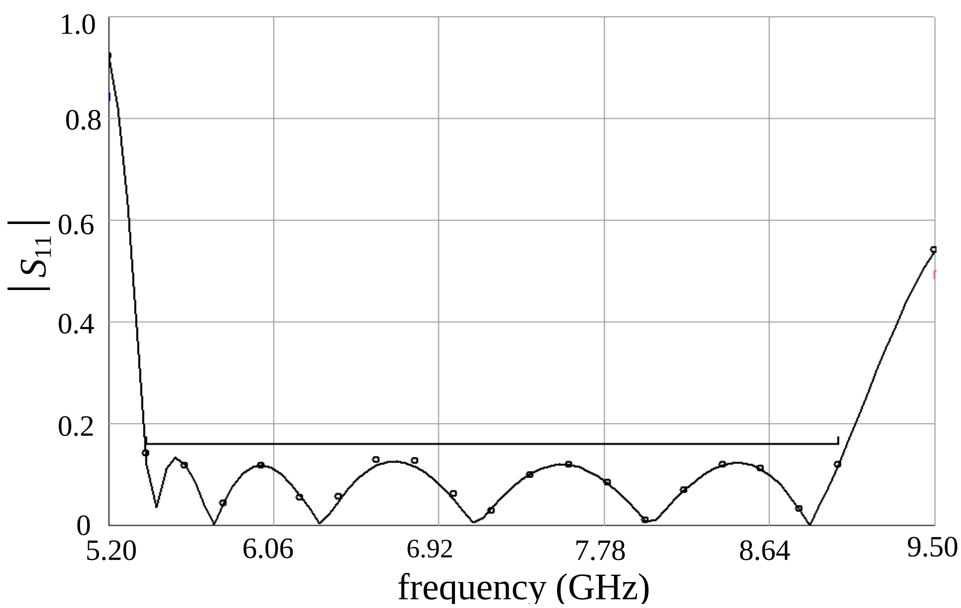
the optimal fine model design is obtained using minimax optimization

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

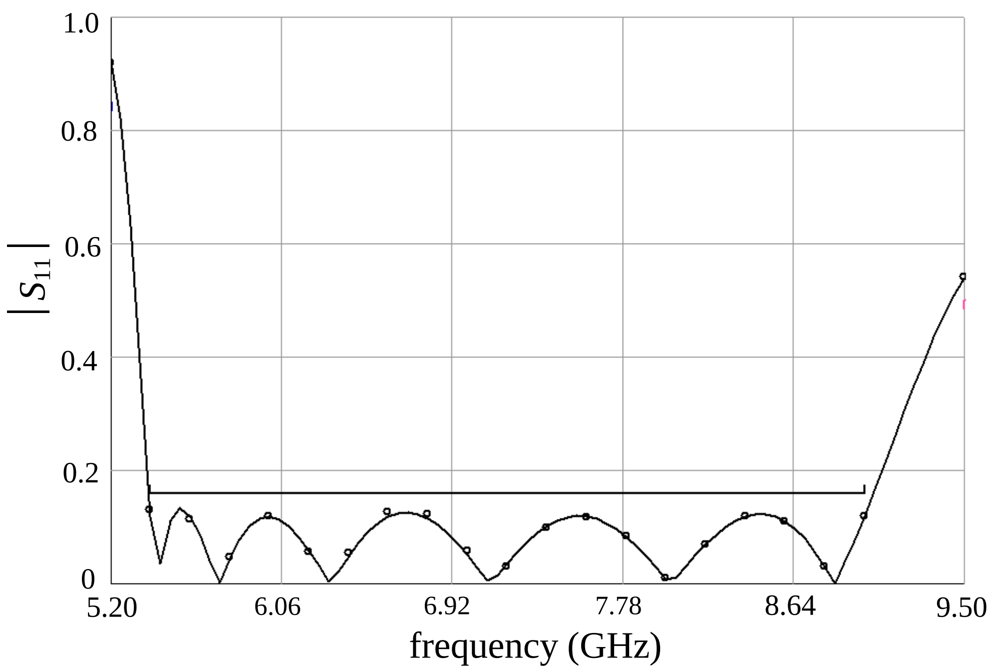


the initial fine model design



the second phase design

Six-Section H-plane Waveguide Filter



the optimal fine model design

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