

**AN AGGRESSIVE APPROACH TO  
PARAMETER EXTRACTION**

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

SOS-99-20-V

June 1999

© M.H. Bakr, J.W. Bandler and N. Georgieva 1999

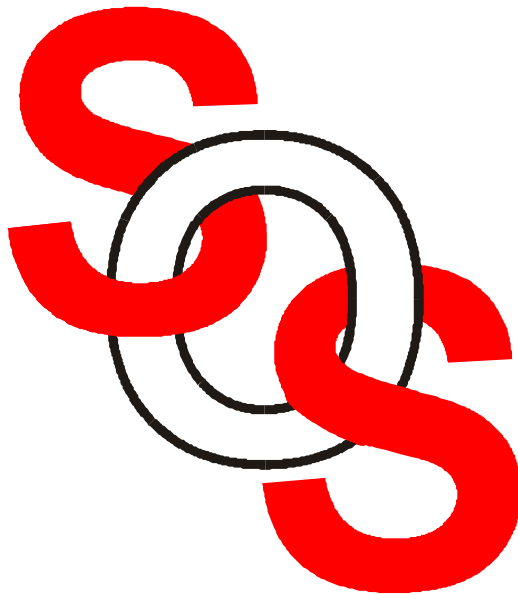
No part of this document may be copied, translated, transcribed or entered in any form into any machine without written permission. Address enquiries in this regard to Dr. J.W. Bandler. Excerpts may be quoted for scholarly purposes with full acknowledgement of source. This document may not be lent or circulated without this title page and its original cover.

# **AN AGGRESSIVE APPROACH TO PARAMETER EXTRACTION**

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

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

[bandler@mcmaster.ca](mailto:bandler@mcmaster.ca)  
[www.sos.mcmaster.ca](http://www.sos.mcmaster.ca)



presented at

1999 IEEE MTT-S International Microwave Symposium, Anaheim, CA, June 14, 1999



## The Parameter Extraction Problem

given a vector of measurements  $\mathbf{R}_m$ , it is required to find a set of parameters of a model whose response matches  $\mathbf{R}_m$

it can be formulated as

$$\mathbf{x}_{os}^e = \arg \left\{ \min_{\mathbf{x}_{os}} \left\| \mathbf{R}_m - \mathbf{R}_{os}(\mathbf{x}_{os}) \right\| \right\}$$

where  $\mathbf{R}_{os}$  is the vector of circuit response and  $\mathbf{x}_{os}^e$  is the vector of extracted parameters

in the context of Space Mapping (SM) the fine model response  $\mathbf{R}_{em}$ , typically from an electromagnetic simulator, at a certain point  $\mathbf{x}_{em}$  supplies the target response  $\mathbf{R}_m$

multi-point parameter extraction enhances the uniqueness of the extraction problem and can be formulated as

$$\mathbf{x}_{os}^e = \arg \left\{ \min_{\mathbf{x}_{os}} \left\| \left[ \mathbf{e}_0^T \quad \mathbf{e}_1^T \quad \cdots \quad \mathbf{e}_{N_p}^T \right]^T \right\| \right\}$$

where

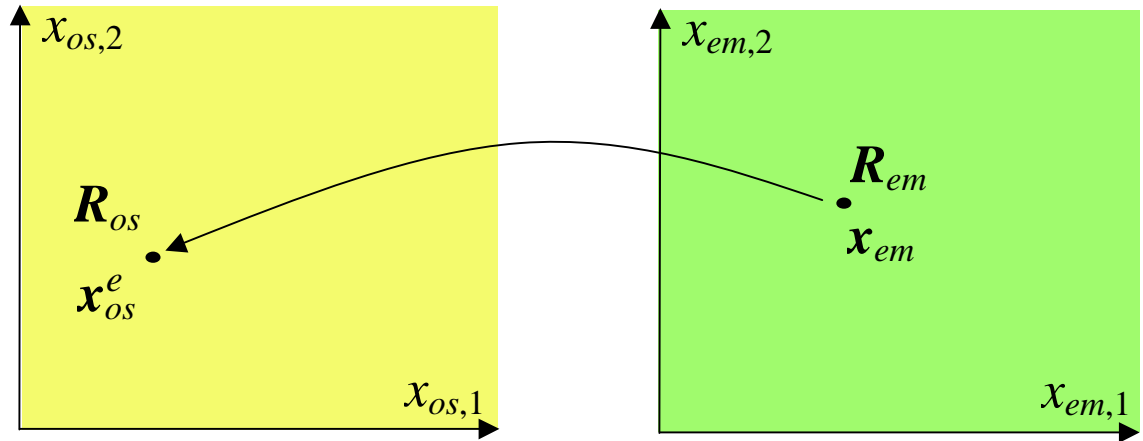
$$\mathbf{e}_0 = \mathbf{R}_{os}(\mathbf{x}_{os}) - \mathbf{R}_{em}(\mathbf{x}_{em})$$

and

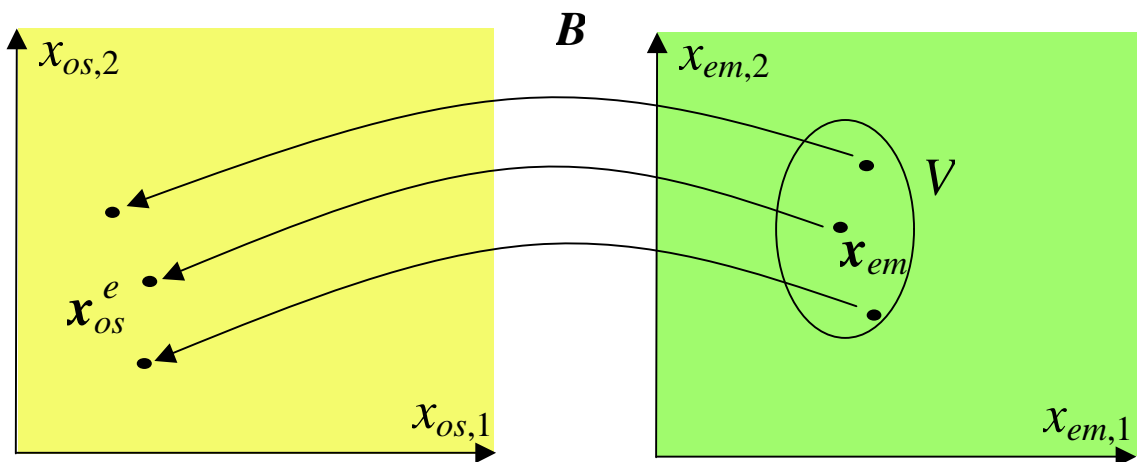
$$\mathbf{e}_i = \mathbf{R}_{os}(\mathbf{x}_{os} + \Delta \mathbf{x}_{os}^{(i)}) - \mathbf{R}_{em}(\mathbf{x}_{em} + \mathbf{B} \Delta \mathbf{x}_{em}^{(i)}), \quad i=1, 2, \dots, N_p$$



## Illustration of Parameter Extraction



single-point extraction



multi-point extraction

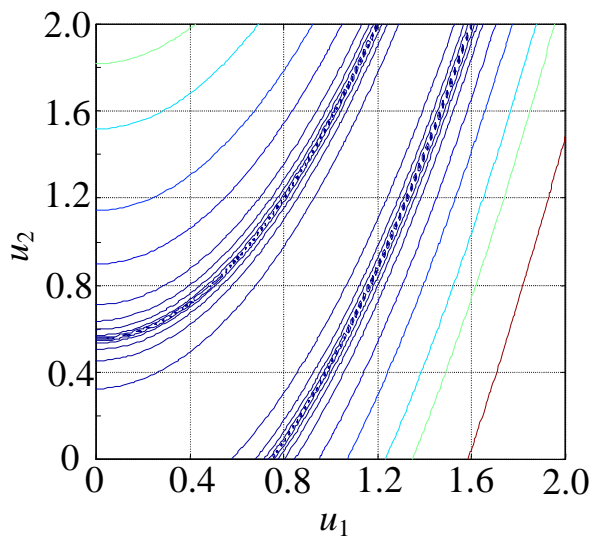


## Classification of the Solution of Parameter Extraction

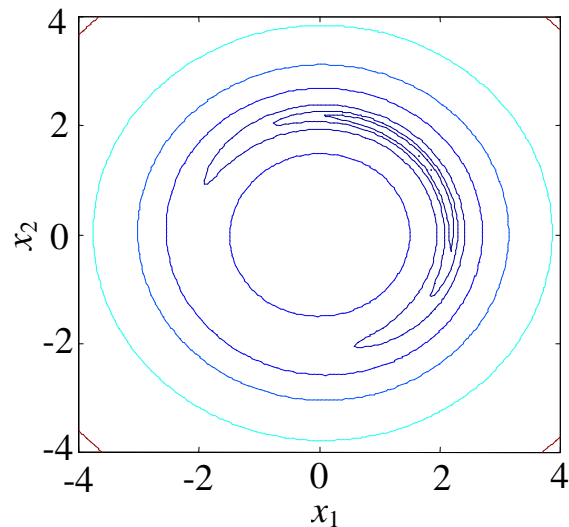
using a vector of matched responses  $\mathbf{R}$ , a solution  $\mathbf{x}_{os}^e$  of the parameter extraction problem is obtained

this solution is labeled locally unique if there exists an open neighborhood of  $\mathbf{x}_{os}^e$  containing no other point  $\mathbf{x}_{os}$  such that  $\mathbf{R}(\mathbf{x}_{os}) = \mathbf{R}(\mathbf{x}_{os}^e)$

the local uniqueness condition is equivalent to the condition that the Jacobian of the vector of matched coarse model responses  $\mathbf{R}$  has rank  $n$ , where  $n$  is the number of optimizable parameters



locally nonunique



locally unique



## Problem Definition

assume that multi-point parameter extraction is carried out at  $\mathbf{x}_{em}$  using  $N_p$  fine model points

then the vector of matched coarse model responses  $\mathbf{R}$  is given by

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{os}(\mathbf{x}_{os}) \\ \mathbf{R}_{os}(\mathbf{x}_{os} + \Delta \mathbf{x}^{(1)}) \\ \cdot \\ \cdot \\ \mathbf{R}_{os}(\mathbf{x}_{os} + \Delta \mathbf{x}^{(N_p-1)}) \end{bmatrix}$$

where  $\Delta \mathbf{x}^{(i)} \in V_p$ ; the set of perturbations utilized

it is required to find the perturbation  $\Delta \mathbf{x}$  that can be added to the set  $V_p$  and significantly enhances the uniqueness of the extraction step



## **Problem Assumptions**

the coarse model is assumed to be much faster than the fine model

few extra coarse model simulations add negligible overhead to the computational time of the problem

the first and second order derivatives of the coarse model responses can be obtained

in the absence of information about the mapping between the two spaces we take  $\mathbf{B}=\mathbf{I}$

the mapping  $\mathbf{B}$  can be integrated with the algorithm if it is available



## The Locally Nonunique Case

assume that the rank of the Jacobian of matched coarse model responses at  $\mathbf{x}_{os}^e$  is  $k < n$

we impose the condition that the gradients of  $n-k$  of the responses generated by the new coarse model point  $\mathbf{x}_{os}^e + \Delta\mathbf{x}$  be normal to the gradients of a linearly independent set of gradients of cardinality  $k$  of the responses in the vector  $\mathbf{R}$

define the set of linearly independent gradients by

$$S = \{ \mathbf{g}^{(1)}, \dots, \mathbf{g}^{(k)} \}$$

the gradient of each of the  $n-k$  selected responses can be approximated by

$$\mathbf{g}_a^{(i)} = \mathbf{g}^{(i)} + \mathbf{G}^{(i)} \Delta\mathbf{x}, \quad i=k+1, \dots, n$$

where  $\mathbf{g}^{(i)}$  is the gradient of the  $i$ th response at  $\mathbf{x}_{os}^e$  and  $\mathbf{G}^{(i)}$  is the corresponding Hessian





## The Locally Nonunique Case

the perturbation  $\Delta \mathbf{x}$  that satisfies the orthogonality condition is obtained by solving

$$\mathbf{A}^T \Delta \mathbf{x} = -\mathbf{c}$$

where

$$\mathbf{A} = [\mathbf{G}^{(k+1)} \mathbf{g}^{(1)} \dots \mathbf{G}^{(n)} \mathbf{g}^{(1)} \dots \mathbf{G}^{(n)} \mathbf{g}^{(k)}]$$

and

$$\mathbf{c} = \begin{bmatrix} \mathbf{g}^{(k+1)T} \mathbf{g}^{(1)} \\ \vdots \\ \mathbf{g}^{(n)T} \mathbf{g}^{(1)} \\ \vdots \\ \mathbf{g}^{(n)T} \mathbf{g}^{(k)} \end{bmatrix}$$

this system of linear equations may be under-determined, over-determined or well-determined

the pseudoinverse of  $\mathbf{A}^T$  is used to find the solution of minimum length in all cases

$\Delta \mathbf{x}$  is rescaled to satisfy a certain trust region condition



## The Locally Unique Case

a perturbation of  $\Delta \mathbf{x}$  results in a perturbation of the coarse model response at the two minima by

$$\Delta \mathbf{R}_1 = \mathbf{J}_{os}(\mathbf{x}_{os,1}^e) \Delta \mathbf{x}$$

and

$$\Delta \mathbf{R}_2 = \mathbf{J}_{os}(\mathbf{x}_{os,2}^e) \Delta \mathbf{x}$$

we impose the condition that the difference between the  $\ell_2$  norms of these two response perturbations be maximized subject to certain trust region size

it follows that the following Lagrangian can be formed

$$L(\Delta \mathbf{x}, \lambda) = \Delta \mathbf{x}^T \mathbf{J}_{os}(\mathbf{x}_{os,1}^e)^T \mathbf{J}_{os}(\mathbf{x}_{os,1}^e) \Delta \mathbf{x} - \Delta \mathbf{x}^T \mathbf{J}_{os}(\mathbf{x}_{os,2}^e)^T \mathbf{J}_{os}(\mathbf{x}_{os,2}^e) \Delta \mathbf{x} + \lambda(\Delta \mathbf{x}^T \Delta \mathbf{x} - \delta^2)$$

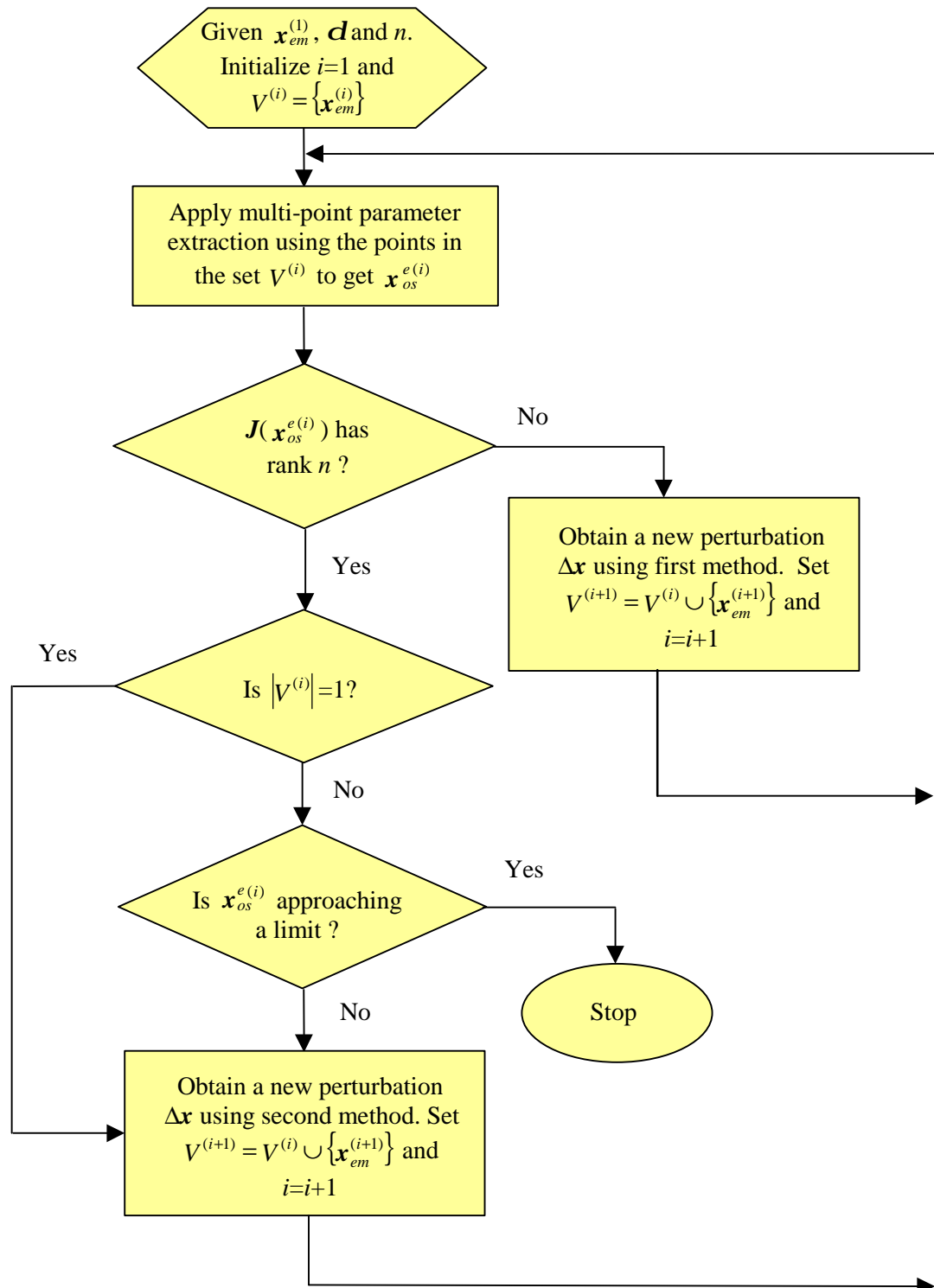
it can be shown that the perturbation  $\Delta \mathbf{x}$  is an eigenvector for the matrix  $\mathbf{J}_{os}(\mathbf{x}_{os,1}^e)^T \mathbf{J}_{os}(\mathbf{x}_{os,1}^e) - \mathbf{J}_{os}(\mathbf{x}_{os,2}^e)^T \mathbf{J}_{os}(\mathbf{x}_{os,2}^e)$

the perturbation is then scaled to satisfy the length condition

we make the assumption that  $\mathbf{J}_{os}(\mathbf{x}_{os,2}^e)^T \mathbf{J}_{os}(\mathbf{x}_{os,2}^e) = \mathbf{I}$  because of lack of information about other minima

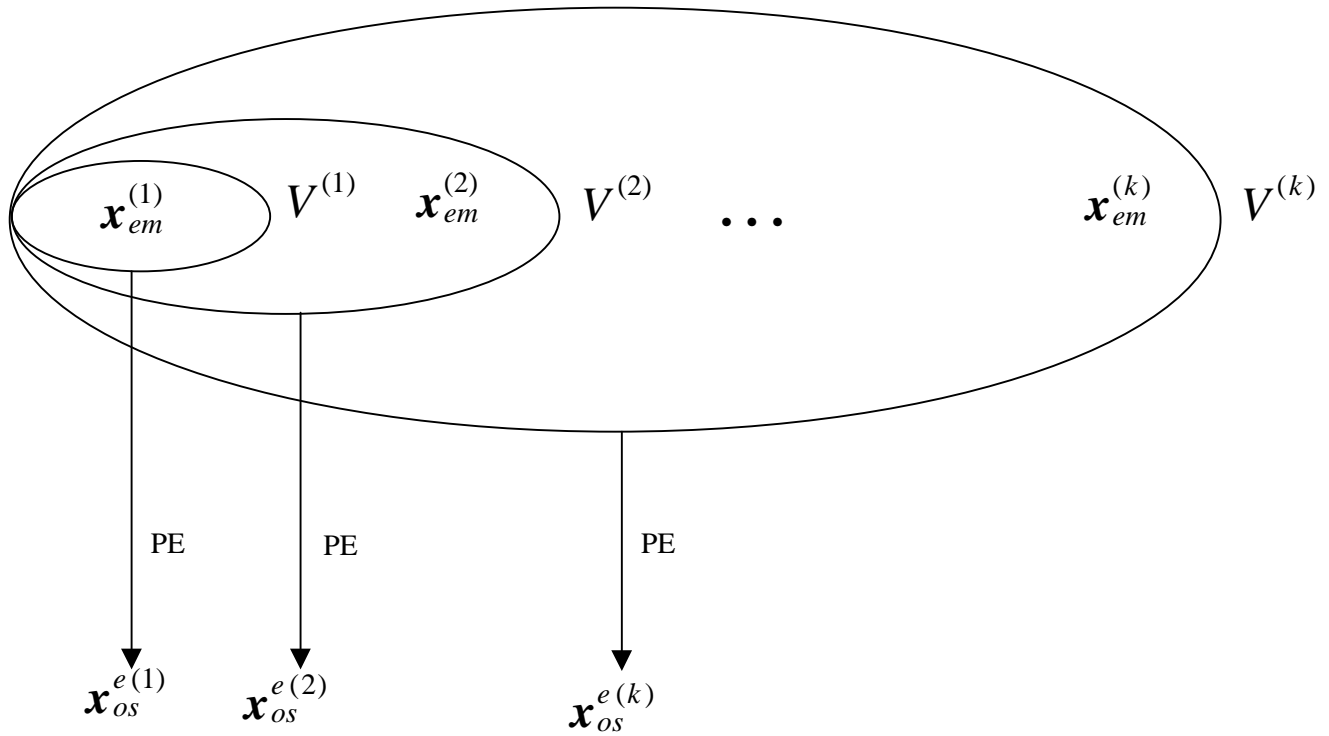


## The Algorithm Flowchart





## An Illustration of the Algorithm





## **A Quadratic Function**

the coarse model is

$$R_{os} = x_1^2 + x_2^2$$

the fine model is taken as

$$R_{em} = (0.9x_1 + 0.1x_2)^2 + (0.1x_1 + 0.9x_2)^2$$

it is required to extract the coarse model parameters corresponding to  $\mathbf{x}_{em} = [2.0 \quad 1.0]^T$

4 fine model points were needed to ensure the uniqueness of the extracted parameters



## The Variation of the Extracted Parameters with the Number of Fine Model Points for the Quadratic Function

---

Number of Points	$x_{os,1}$	$x_{os,2}$
1	1.95724	0.99458
2	2.10283	0.63094
3	1.92787	1.05337
4	1.89571	1.10868

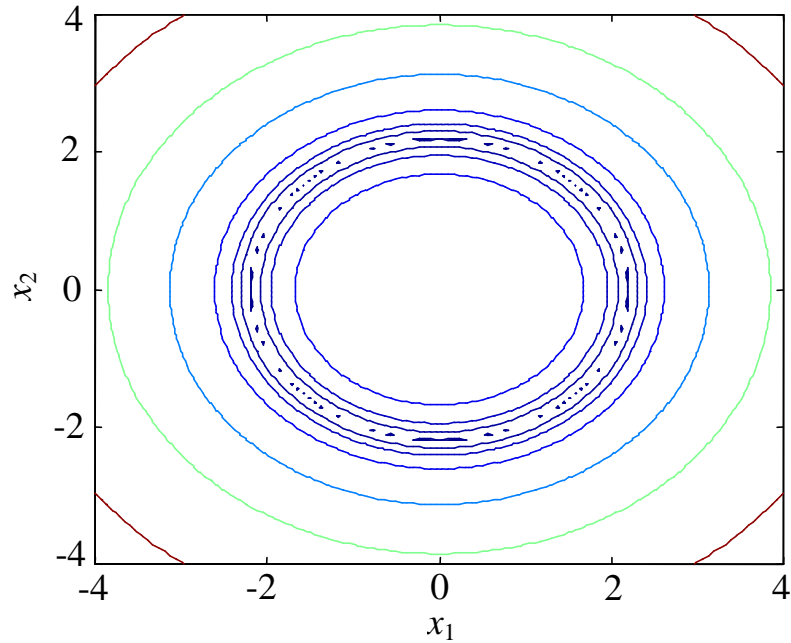
---

the exact solution for the parameter extraction problem is

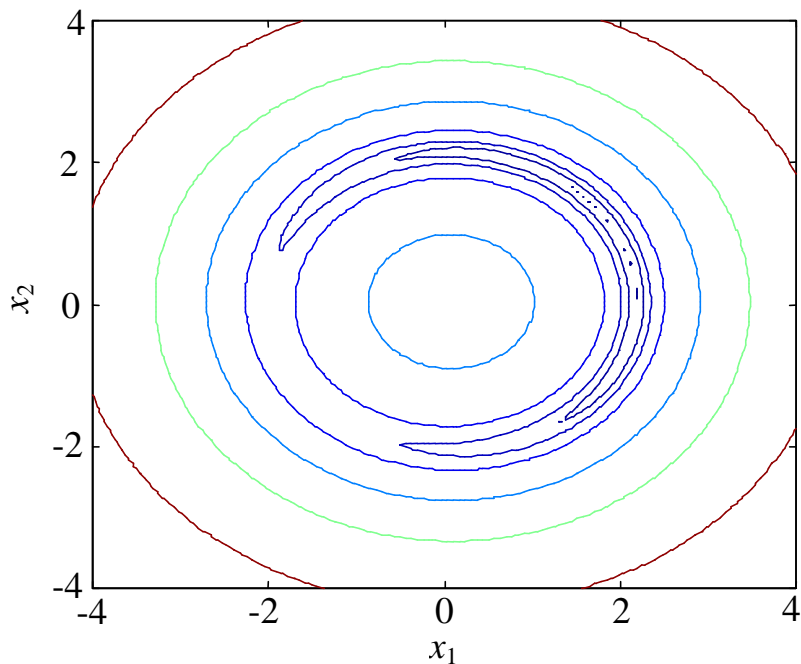
$$\mathbf{x}_{os}^e = [1.9 \quad 1.1]^T$$



## Contours of the $l_2$ Objective Function for the Quadratic Function



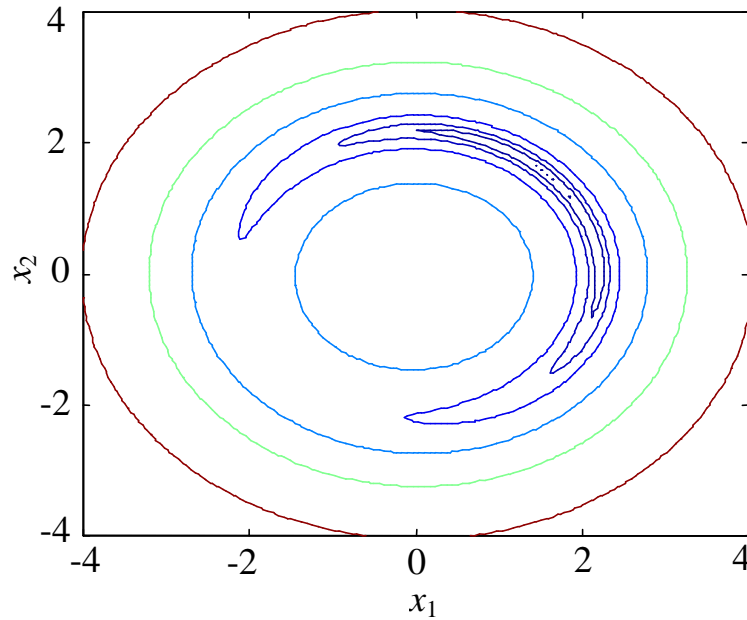
single-point extraction



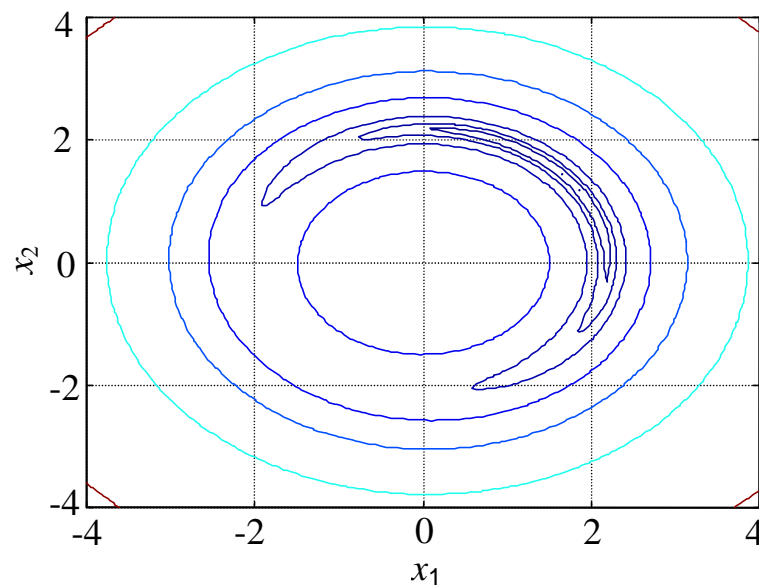
two-point extraction



## Contours of the $l_2$ Objective Function for the Quadratic Function



three-point extraction



four-point extraction





## The Rosenbrock Function

the coarse model is

$$R_{os} = 100(u_2 - u_1^2)^2 + (1 - u_1)^2$$

the fine model is

$$R_f = 100((u_2 + 0.2) - (u_1 - 0.2)^2)^2 + (1 - (u_1 - 0.2))^2$$

it is required to extract the vector of coarse model parameters at the point  $[1.0 \ 1.0]^T$

3 fine model points were needed for the algorithm to terminate

the variation of the extracted parameters with the number of fine model points is shown in the table

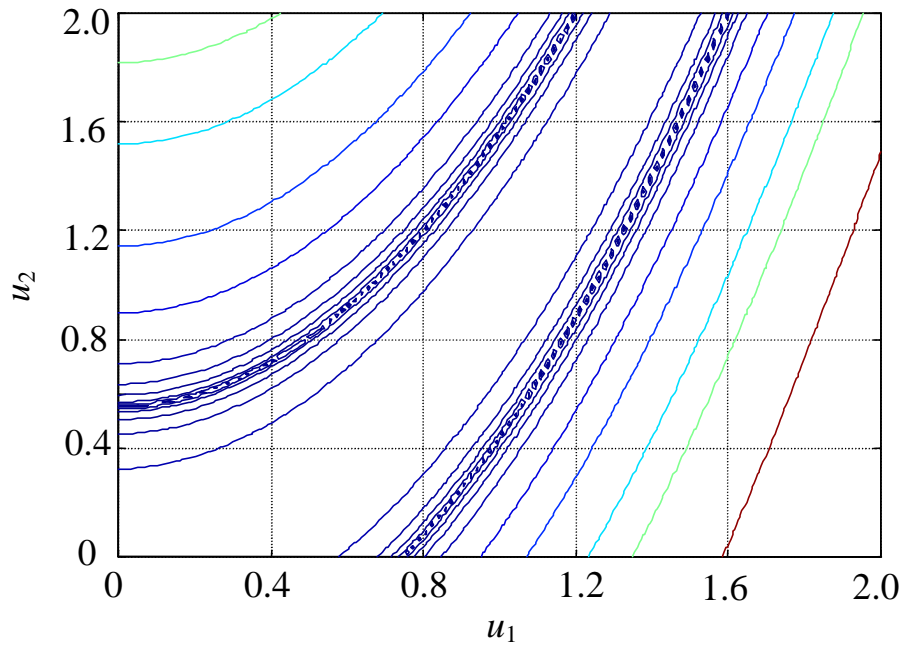
---

Number of Points	$x_{os,1}^e$	$x_{os,2}^e$
1	1.21541	0.91728
2	0.80008	1.20012
3	0.80008	1.20014

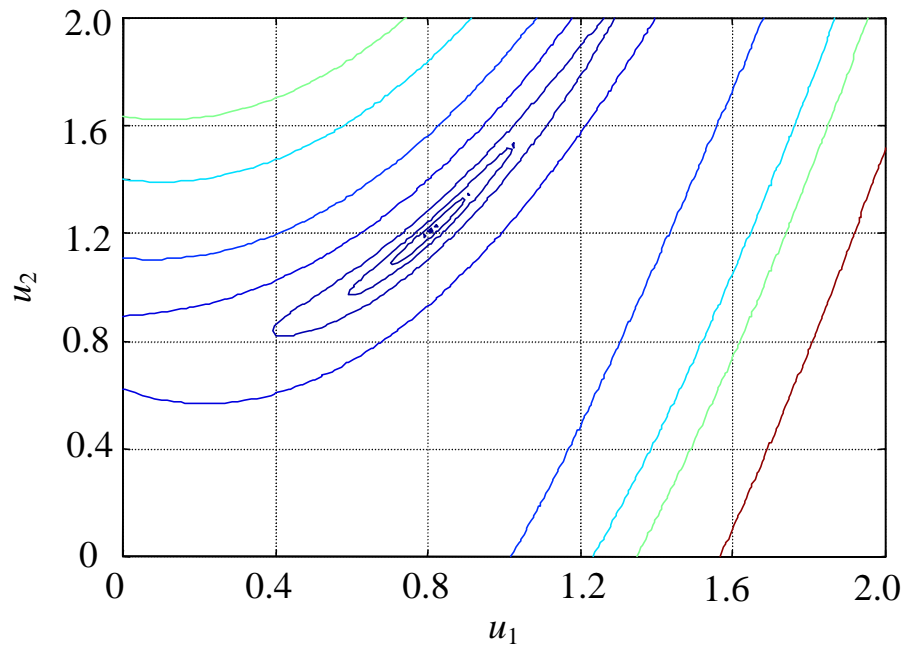
---



## Contours of the $l_2$ Objective Function for the Rosenbrock Function



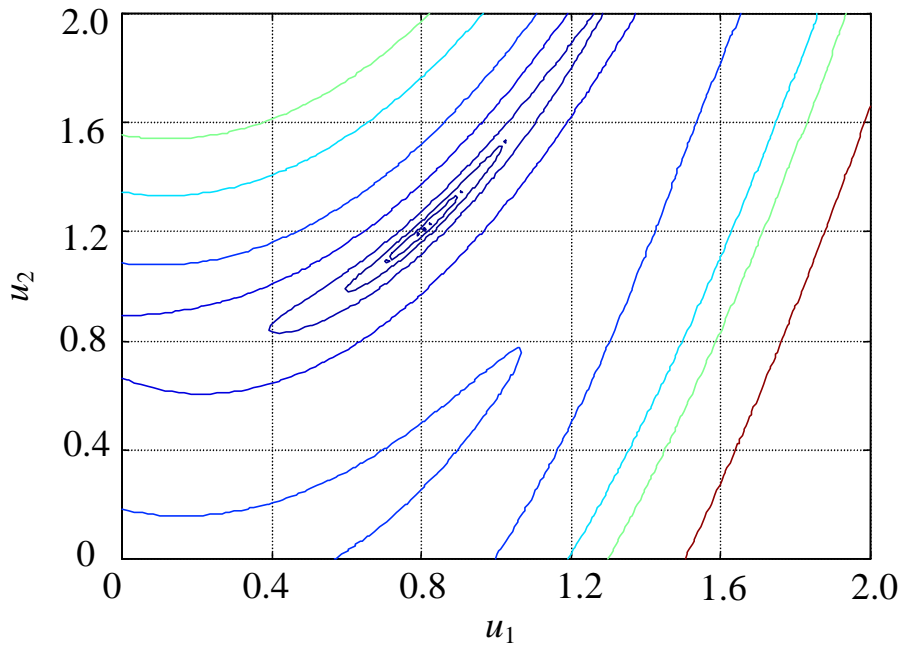
single-point extraction



two-point extraction



## Contours of the $\ell_2$ Objective Function for the Rosenbrock Function



three-point extraction



## **10:1 Impedance Transformer**

the design parameters are the characteristic impedances of the two transmission lines

the lengths of both lines are kept fixed at their optimal values (quarter wavelength)

the coarse model is an ideal 10:1 impedance transformer

the fine model scales each of the two impedances by 1.6

the responses of both models at 11 different frequencies in the frequency band  $0.5 \text{ GHz} \leq f \leq 1.5 \text{ GHz}$  were used to match the two models

it is required to extract the coarse model parameters corresponding to the fine model point  $[2.2628 \quad 4.5259]^T$

3 fine model points were needed to improve uniqueness

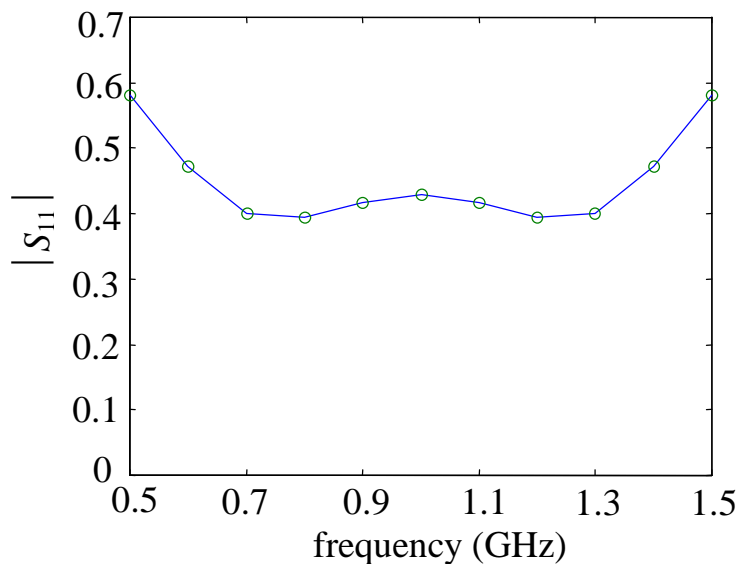


## The Matched Responses for the 10:1 Transformer (Single-Point Extraction)

the set of fine model points utilized in parameter extraction is

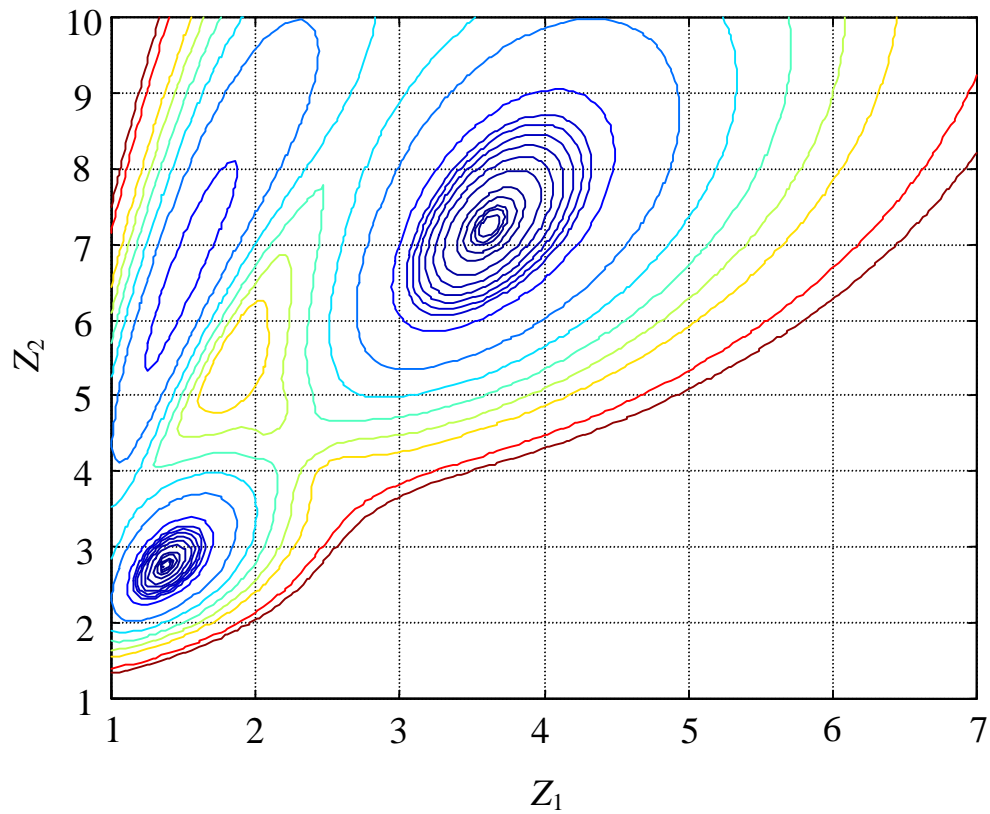
$$V = \left\{ \begin{bmatrix} 2.26277 \\ 4.52592 \end{bmatrix} \right\}$$

the extracted parameters are  $\mathbf{x}_{os}^{e(1)} = \begin{bmatrix} 3.62043 \\ 7.24147 \end{bmatrix}$





## Contours of the $l_2$ Objective Function for the 10:1 Transformer (Single-Point Extraction)



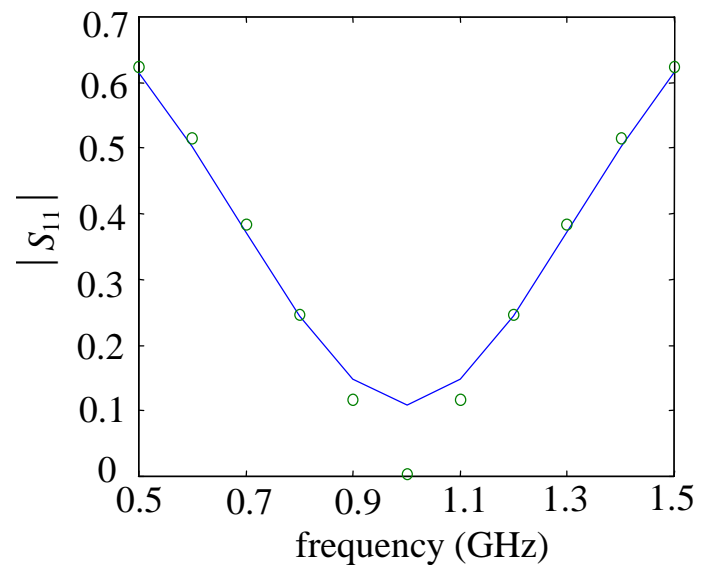
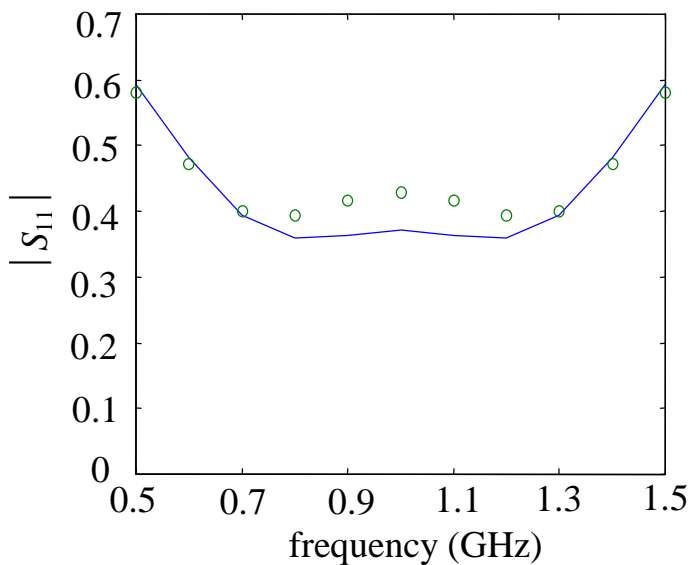


## The Matched Responses for the 10:1 Transformer (Two-Point Extraction)

the set of fine model points utilized in parameter extraction is

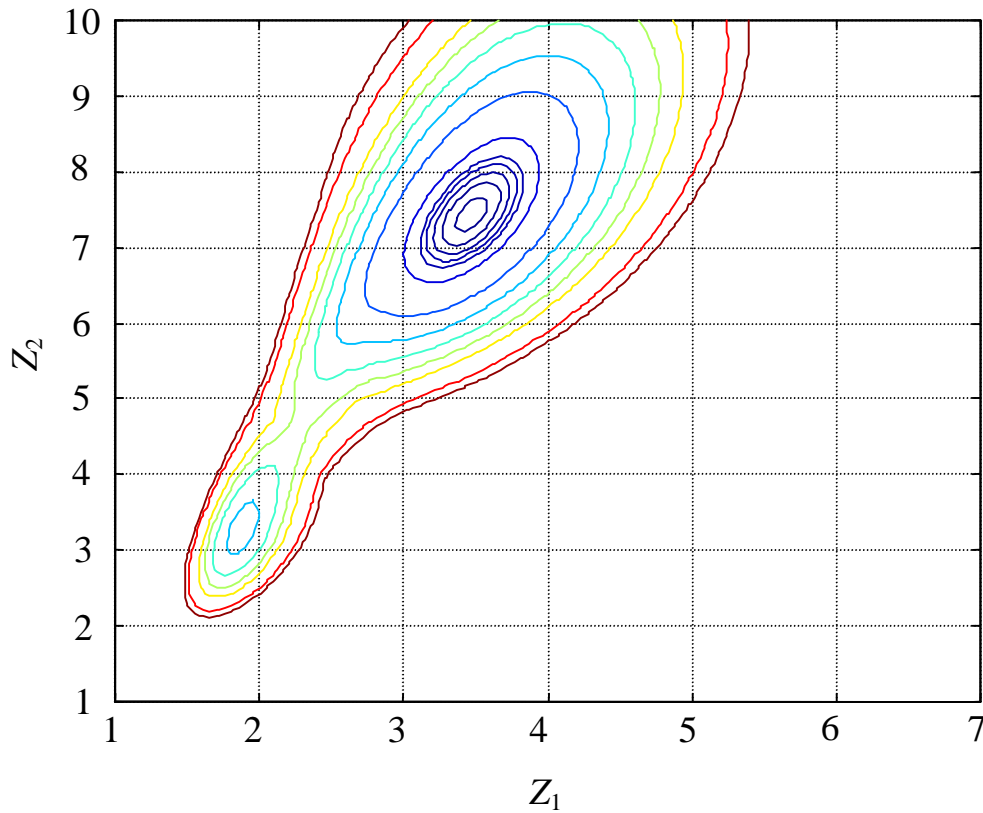
$$V = \left\{ \begin{bmatrix} 2.26277 \\ 4.52592 \end{bmatrix}, \begin{bmatrix} 1.49975 \\ 4.76634 \end{bmatrix} \right\}$$

the extracted parameters are  $\mathbf{x}_{os}^{e(2)} = \begin{bmatrix} 3.47160 \\ 7.43214 \end{bmatrix}$





## Contours of the $\ell_2$ Objective Function for the 10:1 Transformer (Two-Point Extraction)





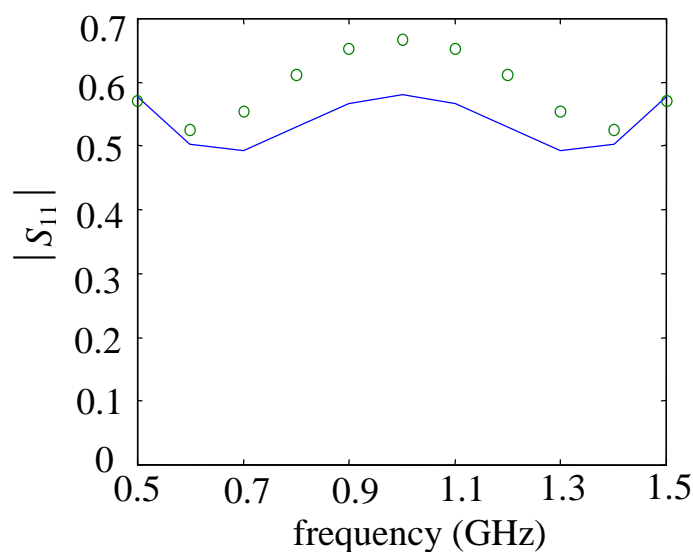
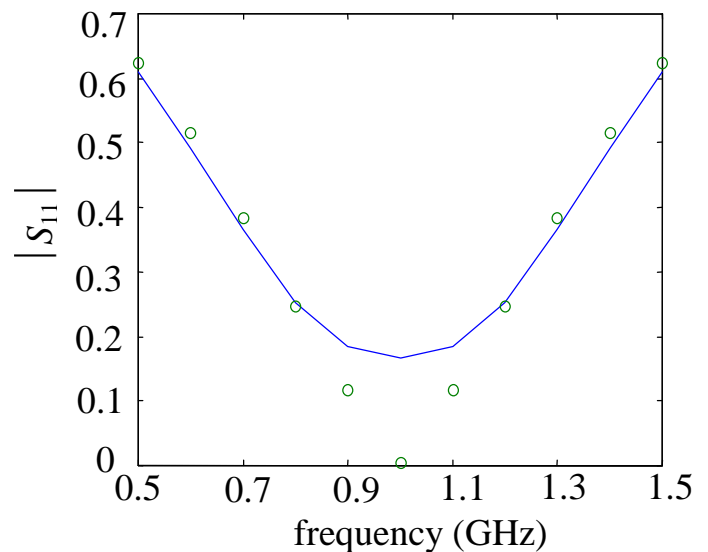
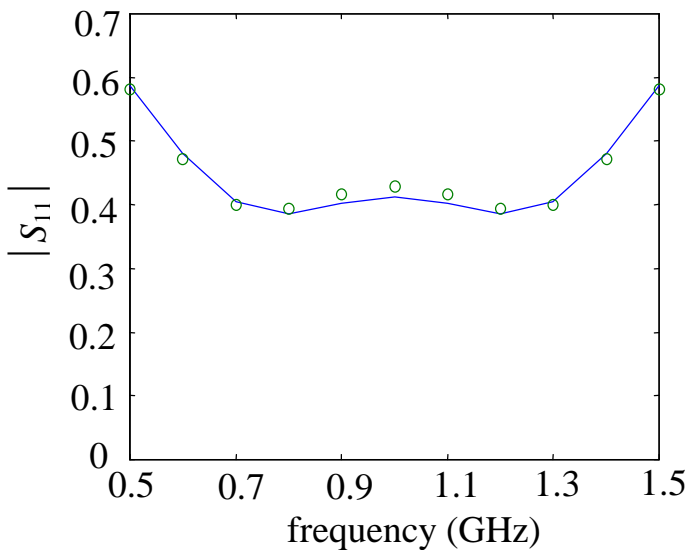


## The Matched Responses for the 10:1 Transformer (Three-Point Extraction)

the set of fine model points is

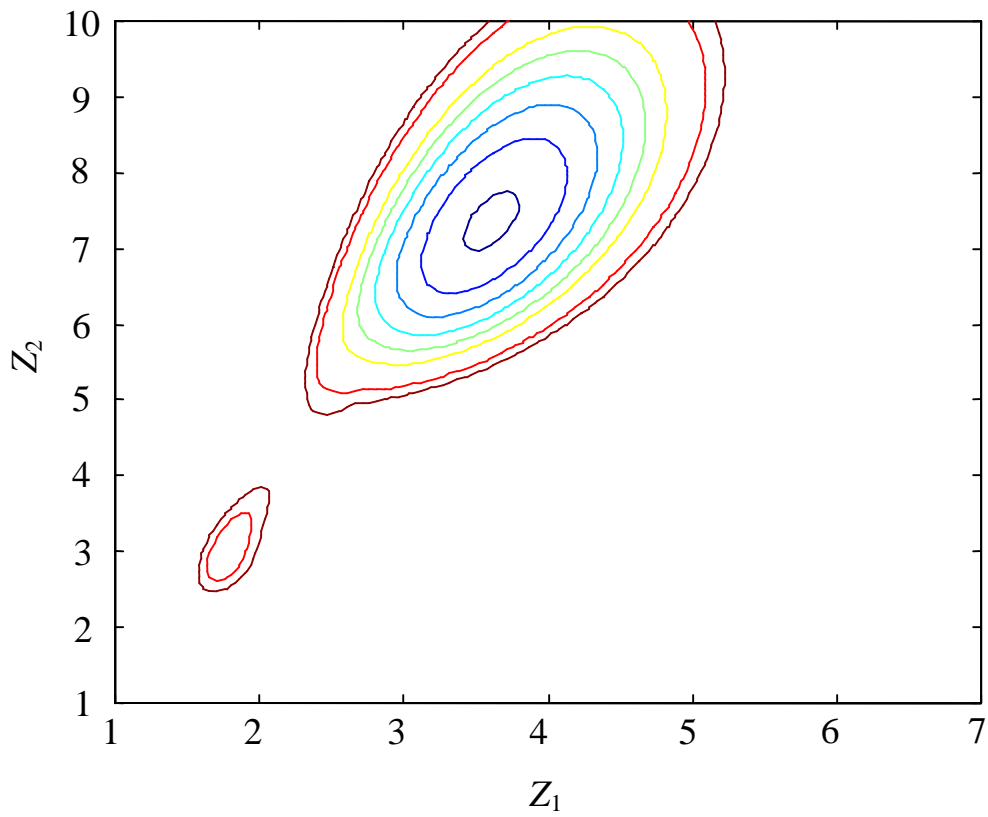
$$V = \left\{ \begin{bmatrix} 2.26277 \\ 4.52592 \end{bmatrix}, \begin{bmatrix} 1.49975 \\ 4.76634 \end{bmatrix}, \begin{bmatrix} 3.02024 \\ 4.26855 \end{bmatrix} \right\}$$

the extracted parameters are  $\mathbf{x}_{os}^{e(3)} = \begin{bmatrix} 3.60357 \\ 7.35052 \end{bmatrix}$





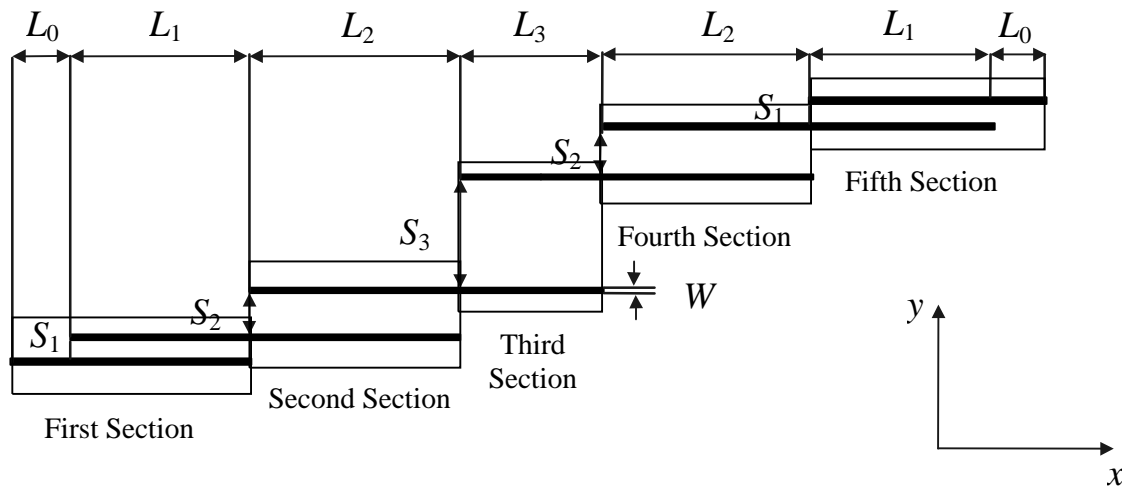
## Contours of the $\ell_2$ Objective Function for the 10:1 Transformer (Three-Point Extraction)





## HTS Filter

(Westinghouse, 1993, Bandler et al., 1995)



the fine model simulates the filter as a whole

the coarse model is a decomposed version of the fine model with coarser grid size

both models exploit Sonnet's *em*

it is required to extract the coarse model point corresponding to

$$\mathbf{x}_f = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ S_1 \\ S_2 \\ S_3 \end{bmatrix} = \begin{bmatrix} 181.00 \\ 201.59 \\ 180.97 \\ 20.12 \\ 67.89 \\ 66.85 \end{bmatrix}$$



## HTS Filter

4 fine model points are needed to trust the extracted parameters

---

Parameter	$\mathbf{x}_f^{(1)}$	$\mathbf{x}_f^{(2)}$	$\mathbf{x}_f^{(3)}$	$\mathbf{x}_f^{(4)}$
$L_1$	181.00	182.55	181.34	179.86
$L_2$	201.59	205.64	205.38	197.74
$L_3$	180.97	183.36	184.20	178.08
$S_1$	20.12	20.05	20.07	20.46
$S_2$	67.89	68.40	68.08	67.35
$S_3$	66.85	67.25	66.98	66.46

---

all values are in mils

---

---

Parameter	1	2	3	4
$L_1$	188.31	179.99	176.67	178.50
$L_2$	197.69	204.52	208.52	206.78
$L_3$	189.72	181.230	178.00	179.09
$S_1$	19.34	17.13	17.21	18.99
$S_2$	52.67	63.44	56.52	57.99
$S_3$	52.06	53.18	53.47	56.77

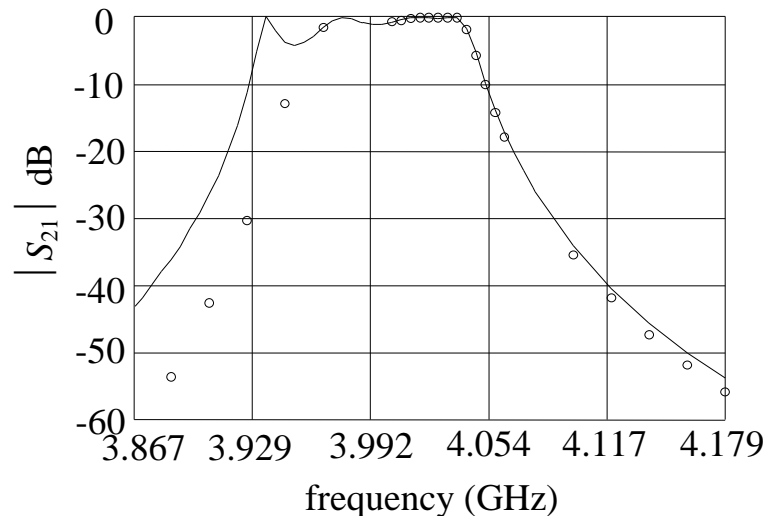
---

all values are in mils

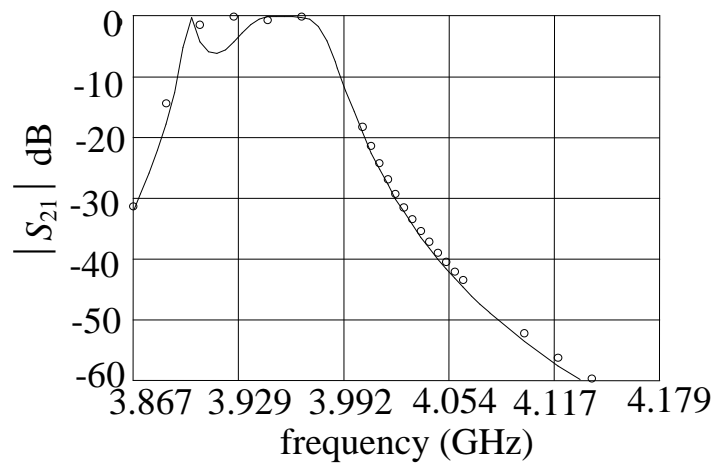
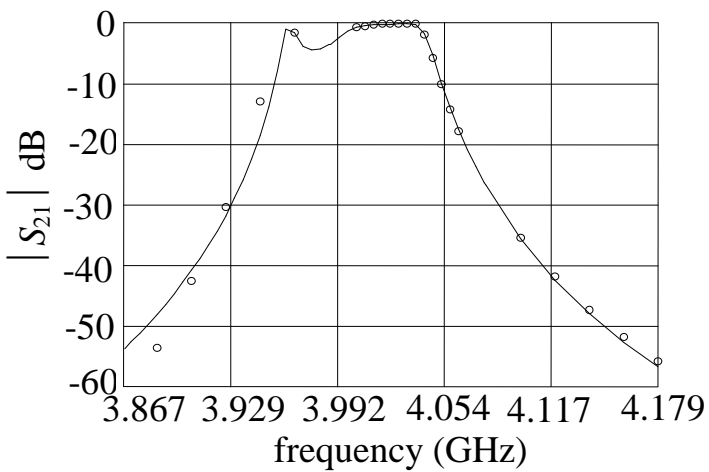
---



## The Matched Responses for the HTS Filter



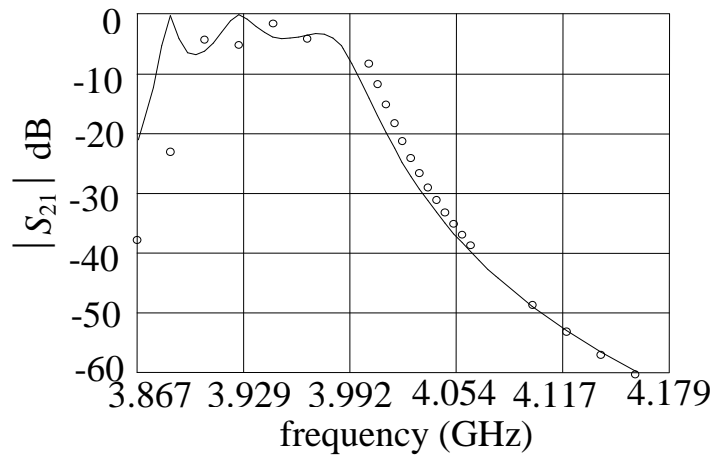
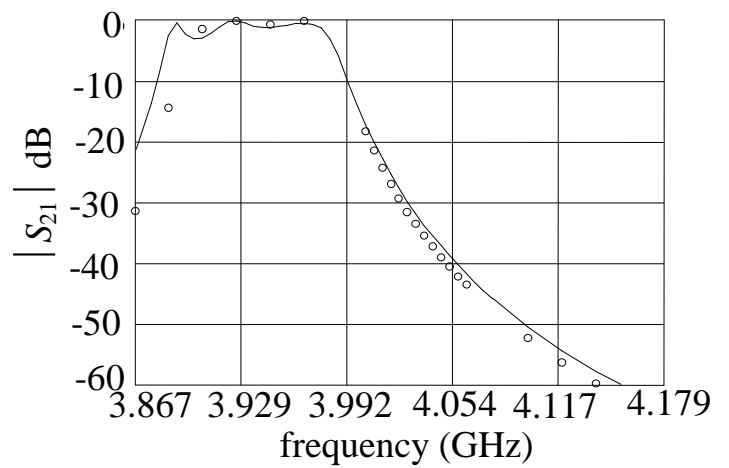
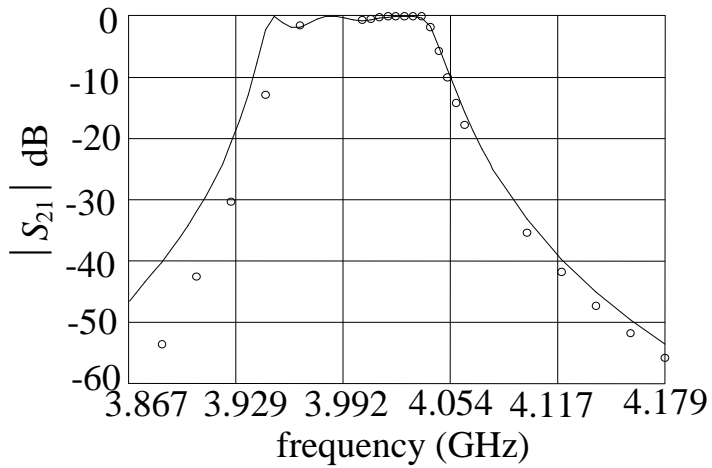
single point extraction



two-point extraction



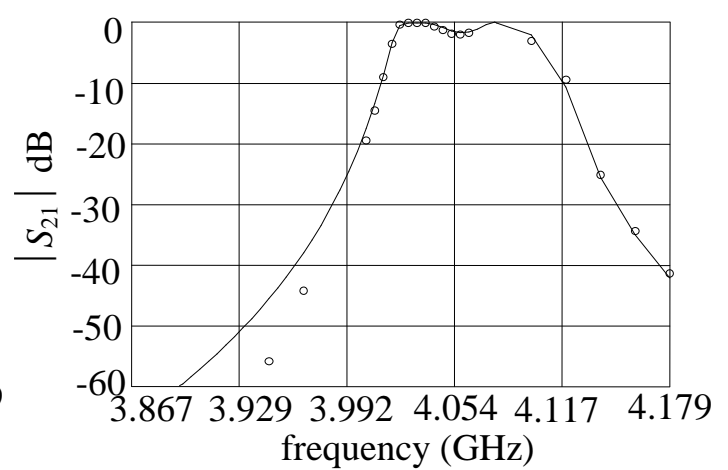
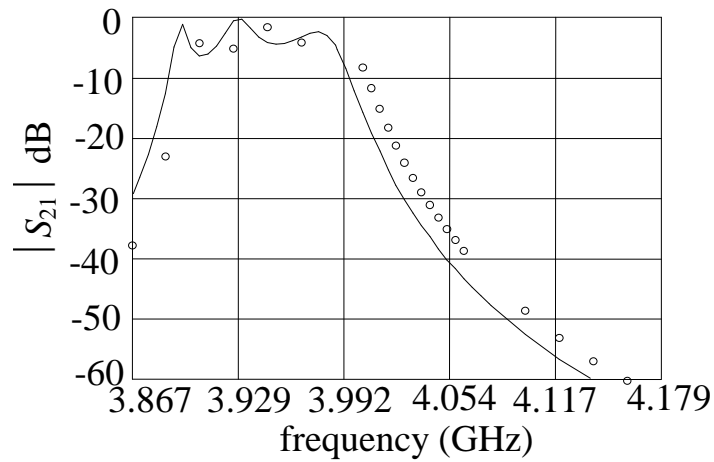
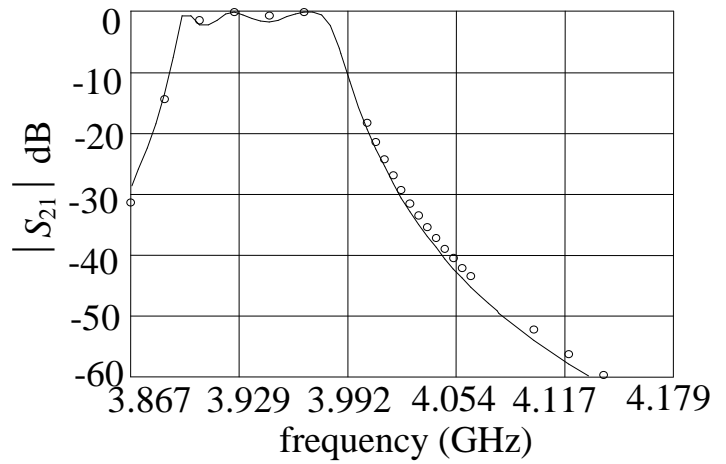
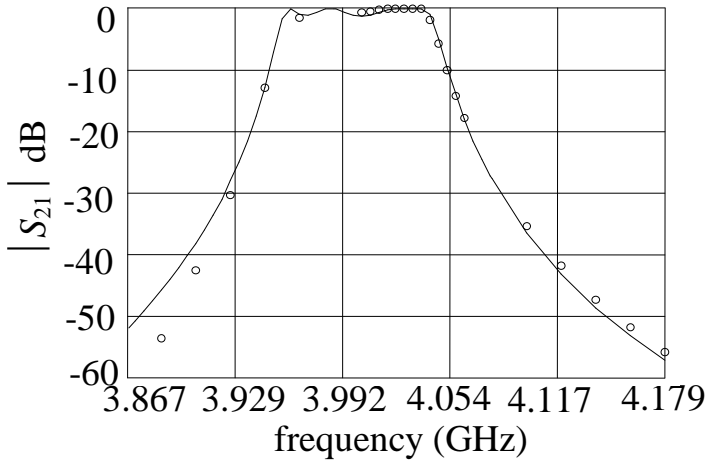
## The Matched Responses for the HTS Filter



three-point extraction



## The Matched Responses for the HTS Filter

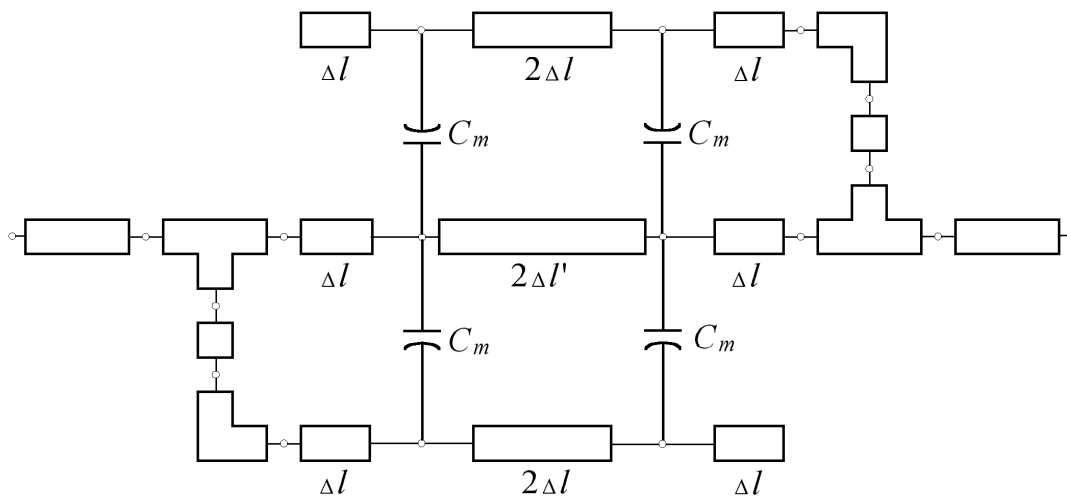
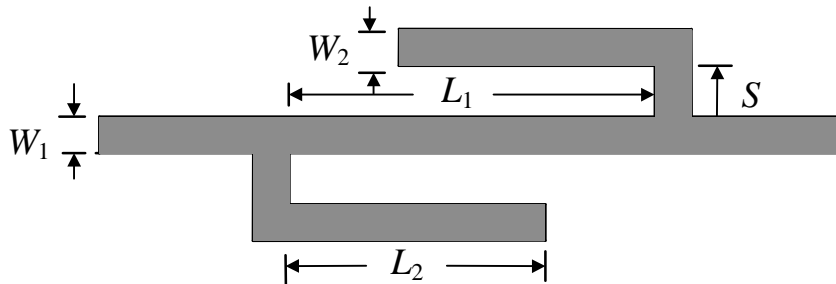


four-point extraction



## 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*)

$W_1$  and  $W_2$  are fixed at 4.8 mil

it is required to extract the coarse model parameters  
corresponding to the fine model point

$$[L_1 \ L_2 \ S]^T = [66.73 \ 60.23 \ 9.59]^T \text{ mils}$$



## Double-Folded Stub Microstrip Filter

9 fine model points are needed to ensure the uniqueness of the extracted parameters

---

Parameter	$\mathbf{x}_{em}^{(1)}$	$\mathbf{x}_{em}^{(2)}$	$\mathbf{x}_{em}^{(3)}$	$\mathbf{x}_{em}^{(4)}$	$\mathbf{x}_{em}^{(5)}$	$\mathbf{x}_{em}^{(6)}$	$\mathbf{x}_{em}^{(7)}$	$\mathbf{x}_{em}^{(8)}$	$\mathbf{x}_{em}^{(9)}$
$L_1$	66.73	67.72	67.32	66.15	70.60	67.66	62.82	65.80	66.57
$L_2$	60.23	63.58	64.13	56.33	59.48	64.10	60.88	56.36	59.85
$S$	9.59	9.27	9.48	9.71	9.71	9.66	9.50	9.52	10.26

---

all values are in mils

---

---

Parameter	$\mathbf{x}_{os}^{e(1)}$	$\mathbf{x}_{os}^{e(2)}$	$\mathbf{x}_{os}^{e(3)}$	$\mathbf{x}_{os}^{e(4)}$	$\mathbf{x}_{os}^{e(5)}$	$\mathbf{x}_{os}^{e(6)}$	$\mathbf{x}_{os}^{e(7)}$	$\mathbf{x}_{os}^{e(8)}$	$\mathbf{x}_{os}^{e(9)}$
$L_1$	58.01	67.05	66.11	64.36	56.46	66.10	56.50	56.39	56.59
$L_2$	38.40	40.47	40.40	43.28	42.94	42.02	42.81	43.00	43.02
$S$	3.24	6.86	6.64	8.83	18.10	7.99	18.25	17.93	17.87

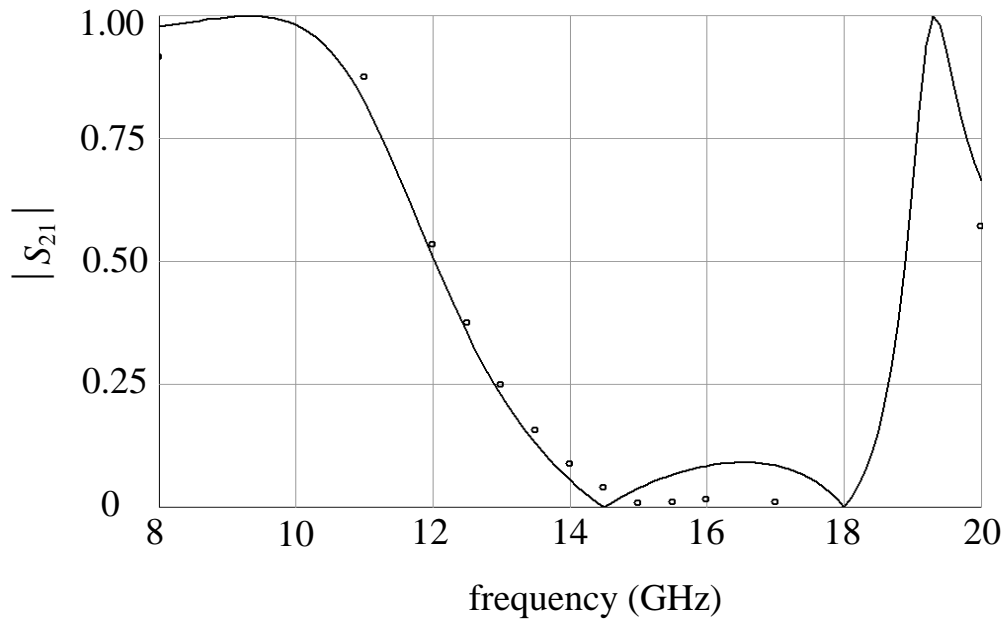
---

all values are in mils

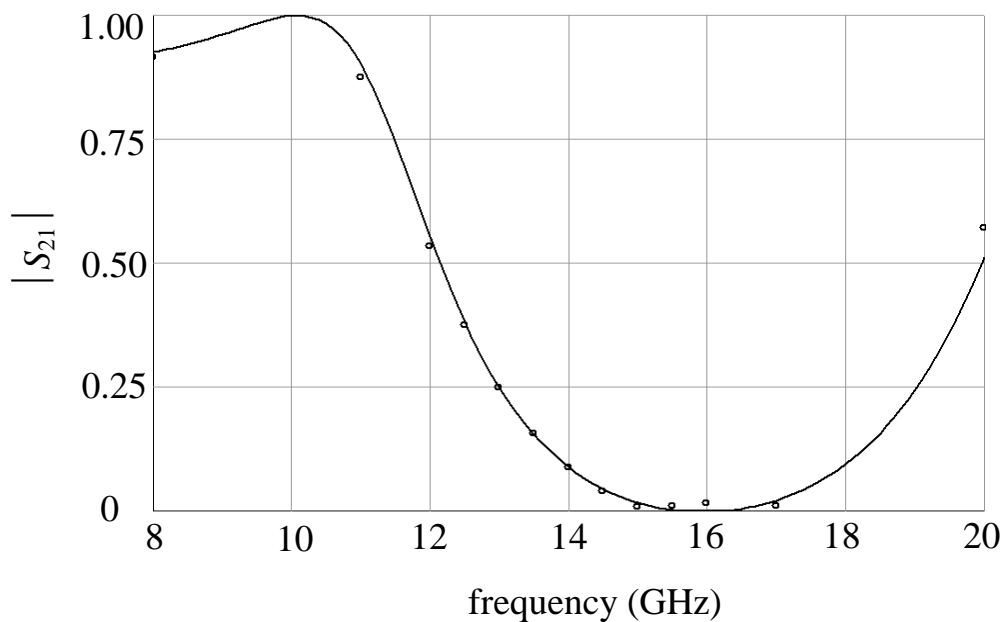
---



## Matched Responses of the Coarse and Fine Models



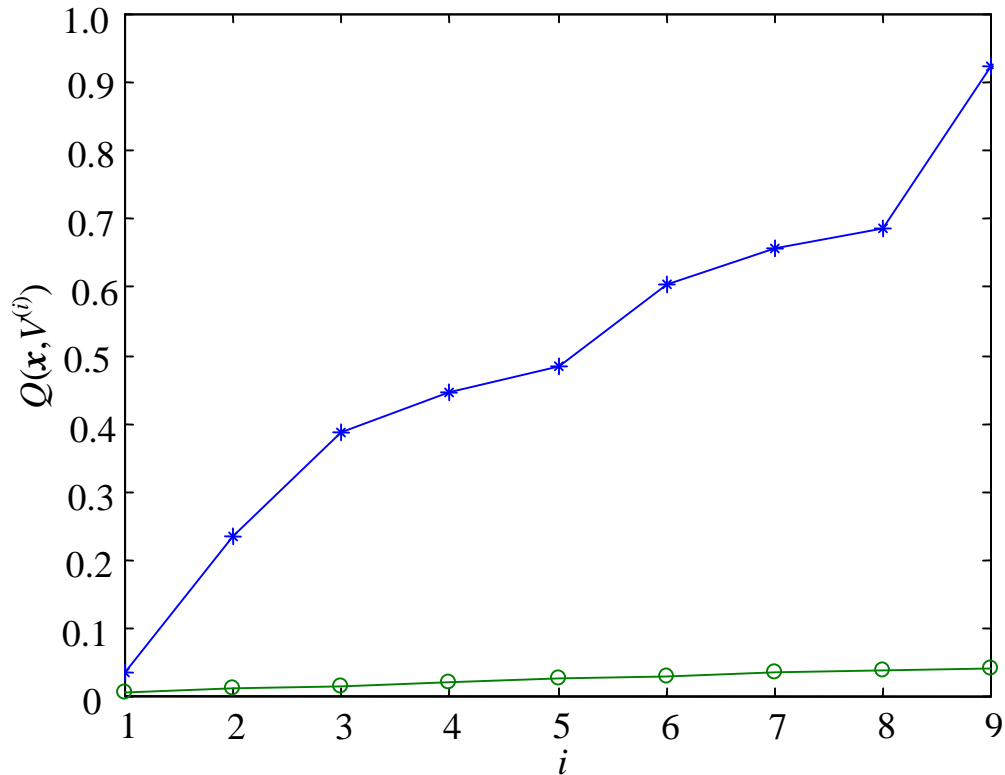
the given fine model response and the coarse  
model response at  $\mathbf{x}_{os}^{e(1)}$



the given fine model response and the coarse  
model response at  $\mathbf{x}_{os}^{e(9)}$



## The Variation of the Objective Function with the Number of Fine Model Points



at the point  $x_{os}^{e(1)}$  (— \* —) and at the point  $x_{os}^{e(9)}$  (— o —)



## **Conclusions**

we present an Aggressive Parameter Extraction (APE) algorithm

the APE algorithm addresses optimal selection of parameter perturbations to improve the sharpness of a multi-point parameter extraction procedure

new parameter perturbations are generated based on the nature of the minimum reached in the previous iteration

we consider possibly locally unique and locally nonunique minima

the APE algorithm continues until the extracted coarse model parameters can be trusted

the algorithm is demonstrated through a number of examples