

**NOVEL SPACE MAPPING  
OPTIMIZATION TECHNIQUE  
FOR ELECTROMAGNETIC DESIGN**

J.W. Bandler

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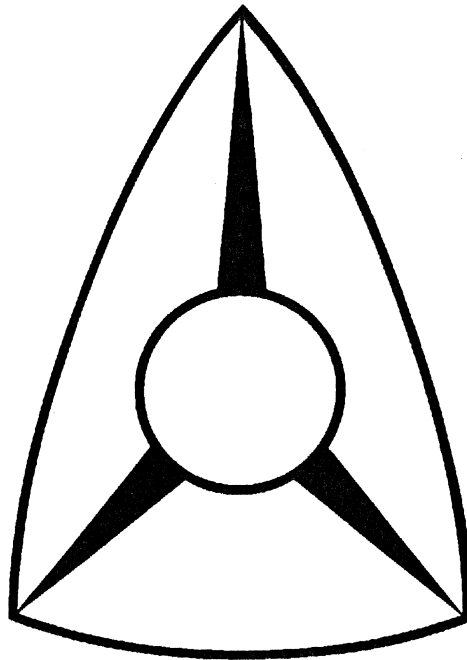
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# **NOVEL SPACE MAPPING OPTIMIZATION TECHNIQUE FOR ELECTROMAGNETIC DESIGN**

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## **Background**

assume that  $X_{os}$  (optimization space) and  $X_{em}$  (EM space) have the same dimensionality, i.e.,

$$x_{os} \in \mathbb{R}^n \quad \text{and} \quad x_{em} \in \mathbb{R}^n,$$

but may not represent the same parameters

the  $X_{os}$ -space model can be comprised of empirical models, or an efficient coarse-grid EM model

the  $X_{em}$ -space model is typically a fine-grid EM model but, ultimately, can represent actual hardware prototypes

we assume that the  $X_{os}$ -space model responses,  $R_{os}(x_{os})$ , are much faster to calculate but less accurate than the  $X_{em}$ -space model responses,  $R_{em}(x_{em})$

we initially perform optimization in  $X_{os}$  to obtain the optimal design  $x_{os}^*$ , for instance in the minimax sense

subsequently, apply SM to find the mapped solution  $\bar{x}_{em}$  in  $X_{em}$  to reproduce the optimal performance predicted by the empirical model



## **The Concept of Space Mapping**

*(Bandler, Biernacki, Chen, Grobelny and Hemmers, 1994)*

our aim is to find an appropriate mapping,  $P$ , from the  $X_{em}$ -space to the  $X_{os}$ -space, i.e.,

$$x_{os} = P(x_{em})$$

such that

$$R_{os}(P(x_{em})) \approx R_{em}(x_{em})$$

we assume that such a mapping exists and is one-to-one within some local modeling region encompassing our SM solution

once the mapping is established, the SM solution is

$$\bar{x}_{em} = P^{-1}(x_{os}^*)$$



## **Original Space Mapping Method**

the mapping is established through an iterative process

to obtain the initial approximation to the mapping,  $P^{(0)}$ , we perform EM analyses at a preselected set of base points in  $X_{em}$  around the starting point

as the first base point we may select the starting point, i.e.,

$$x_{em}^{(1)} = x_{os}^*$$

assuming  $x_{em}$  and  $x_{os}$  represent the same physical parameters, followed by additional base points chosen by perturbation as

$$x_{em}^{(i)} = x_{em}^{(1)} + \Delta x_{em}^{(i-1)}, \quad i = 2, 3, \dots, m$$

this is followed by parameter extraction optimization in  $X_{os}$  to obtain the set of corresponding base points  $x_{os}^{(i)}$  according to

$$\underset{x_{os}^{(i)}}{\text{minimize}} \quad \| R_{os}(x_{os}^{(i)}) - R_{em}(x_{em}^{(i)}) \|$$

for  $i = 1, 2, \dots, m$ , where  $\| \cdot \|$  indicates a suitable norm



### **Original Space Mapping Method (continued)**

at the  $j$ th iteration, both sets may be expanded to contain  $m_j$  points which are used to establish the updated mapping  $P^{(j)}$

the current approximation  $P^{(j)}$  is used to estimate  $\bar{x}_{em}$  as

$$x_{em}^{(m_j+1)} = P^{(j)-1}(x_{os}^*)$$

the process continues until the termination condition

$$\| R_{os}(x_{os}^*) - R_{em}(x_{em}^{(m_j+1)}) \| \leq \epsilon$$

is satisfied, where  $\epsilon$  is a small positive constant, then  $P^{(j)}$  is our desired  $P$

if not, the set of base points in  $X_{em}$  is augmented by  $x_{em}^{(m_j+1)}$  and correspondingly,  $x_{os}^{(m_j+1)}$  determined by parameter extraction augments the set of base points in  $X_{os}$

upon termination, we set  $\bar{x}_{em} = x_{em}^{(m_j+1)} = P^{(j)-1}(x_{os}^*)$  as the SM solution

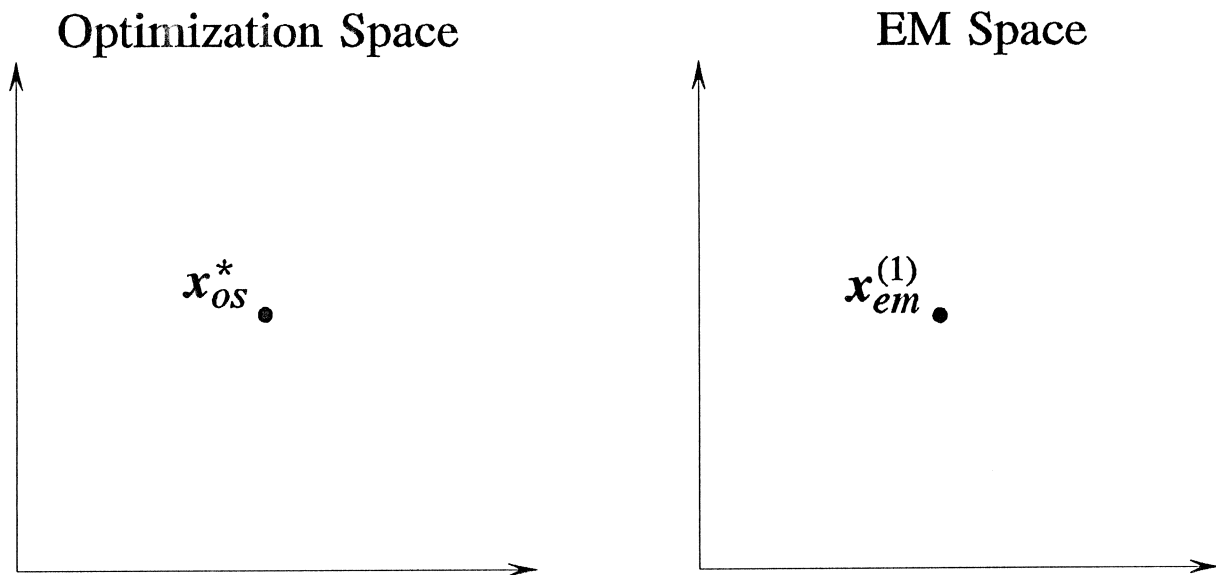


## Illustration of Space Mapping Optimization

*Step 0*

find the optimal design  $x_{os}^*$  in Optimization Space

*Step 1*



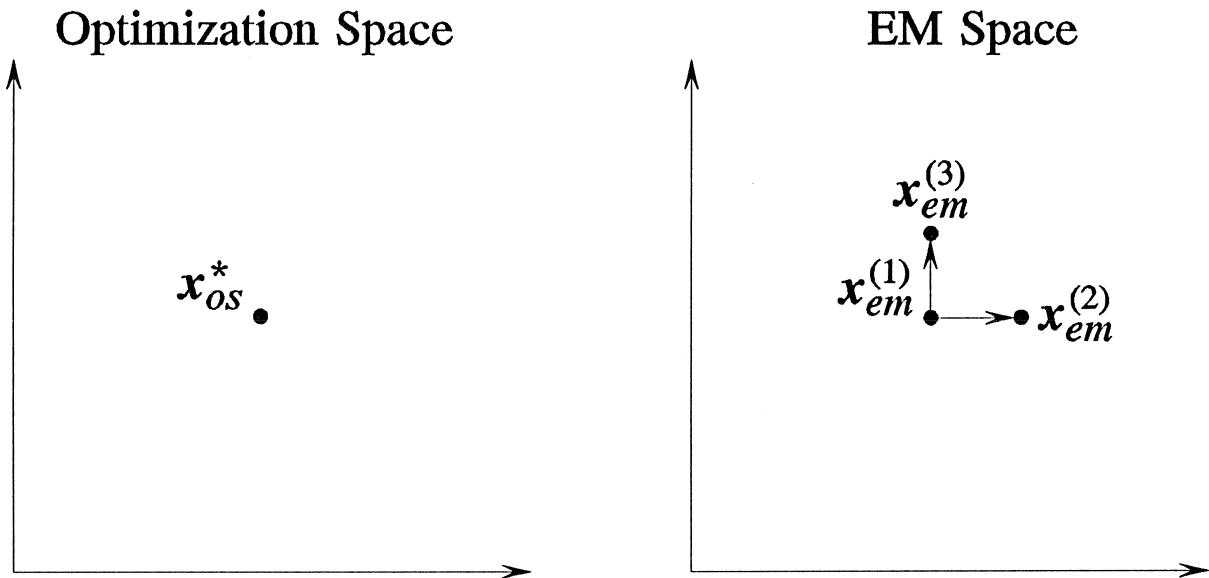
set  $x_{em}^{(1)} = x_{os}^*$  assuming  $x_{em}$  and  $x_{os}$  represent the same physical parameters





## Illustration of Space Mapping Optimization

*Step 2*

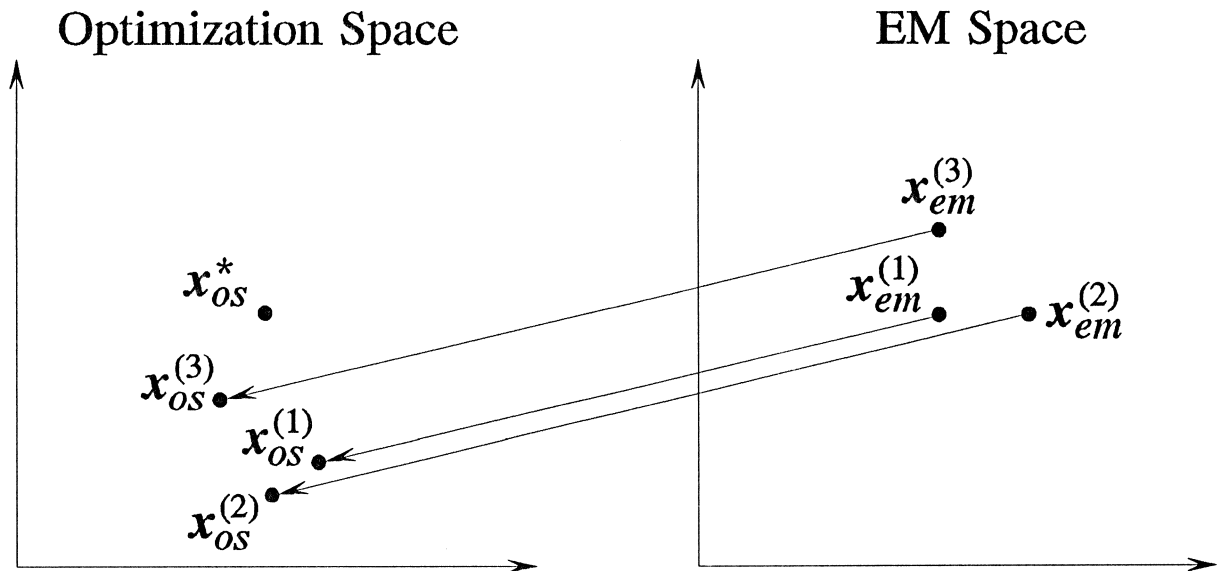


generate additional base points around  $x_{em}^{(1)}$



## Illustration of Space Mapping Optimization

### Step 3



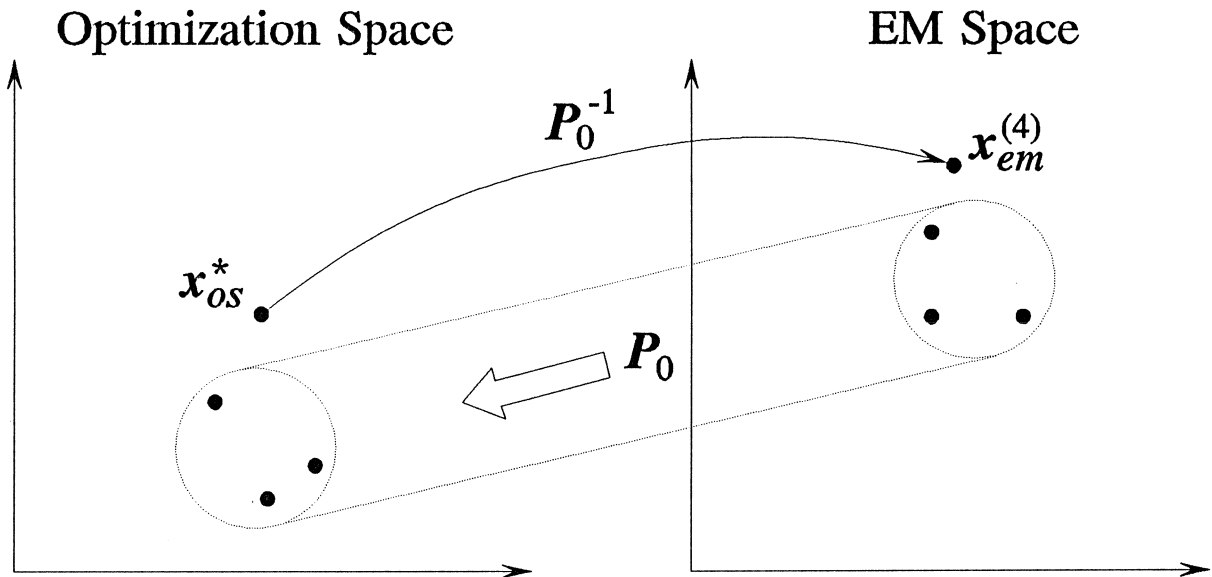
perform  $X_{os}$ -space model parameter extraction for each of the base points to match the EM and OS responses

a set of OS points corresponding to the EM base points is established



## Illustration of Space Mapping Optimization

Step 4



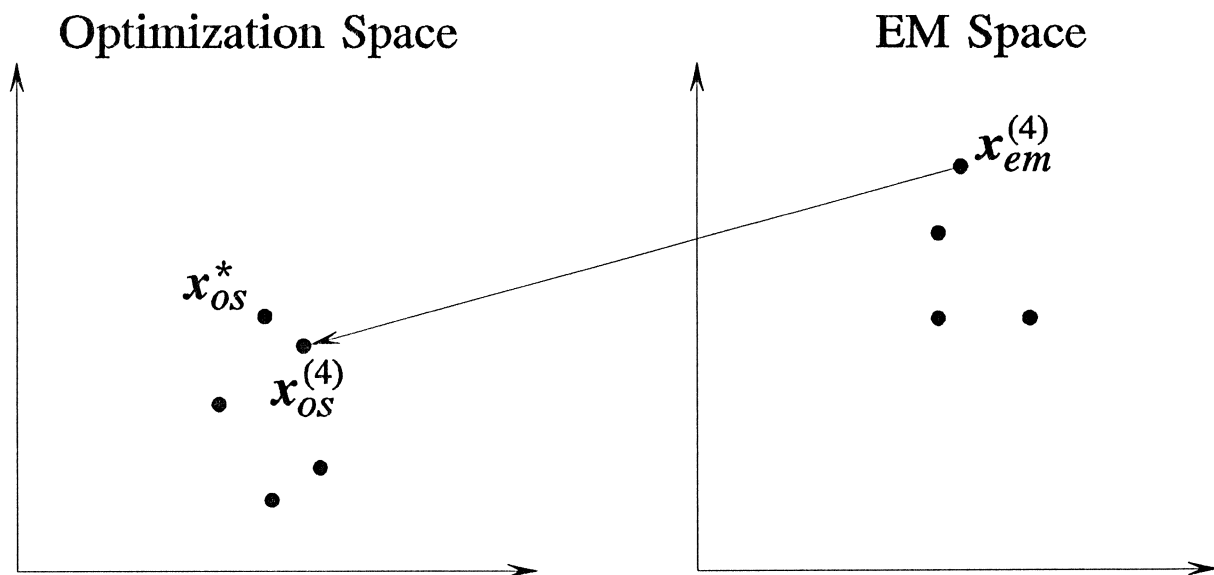
determine the initial mapping  $P_0$

use the inverse mapping to obtain  $x_{em}^{(4)}$



## Illustration of Space Mapping Optimization

*Step 5*

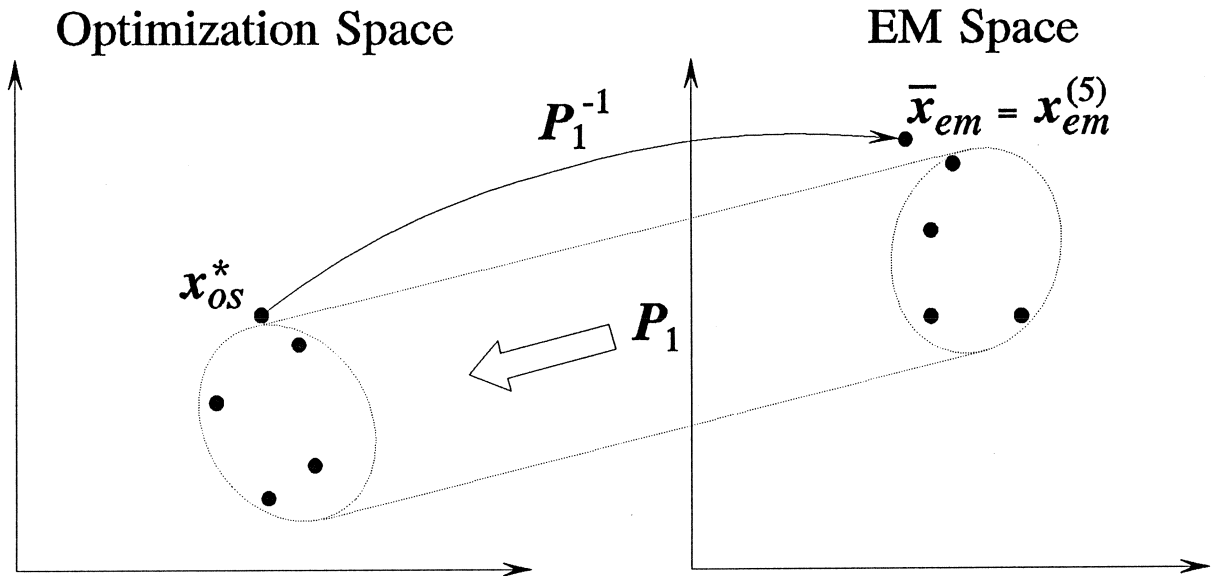


perform  $X_{os}$ -space model parameter extraction to obtain  $x_{os}^{(4)}$



## Illustration of Space Mapping Optimization

Step 6



use the additional pair of points to update the mapping to  $P_1$

apply the updated inverse mapping to obtain  $x_{em}^{(5)}$

if  $\|R_{os}(x_{os}^*) - R_{em}(x_{em}^{(5)})\| \leq \epsilon$  then  $\bar{x}_{em} = x_{em}^{(5)}$  is considered as the SM solution



### **Aggressive Approach to Space Mapping**

*(Bandler, Biernacki, Chen, Hemmers and Madsen, 1995)*

at the SM solution,  $R_{em}(x_{em}^{(M)})$  will closely match  $R_{os}(x_{os}^*)$ ,

$$\|R_{os}(x_{os}^*) - R_{em}(x_{em}^{(M)})\| \leq \epsilon$$

where  $M$  is the number of iterations needed to converge to an SM solution

hence, after an additional parameter extraction optimization in  $X_{os}$ , the resulting point

$$x_{os}^{(M)} = P(x_{em}^{(M)})$$

approaches the point  $x_{os}^*$  (optimal solution in  $X_{os}$ ), or

$$\|x_{os}^{(M)} - x_{os}^*\| \leq \eta \text{ as } j \rightarrow M$$

where  $\eta$  is a small positive constant

by setting  $\eta$  to 0, we consider the set of  $n$  nonlinear equations

$$f(x_{em}) = \mathbf{0}$$

of the form

$$f(x_{em}) = P(x_{em}) - x_{os}^*$$

where  $x_{os}^*$  is a given vector



## **Aggressive Space Mapping - Quasi-Newton Iteration**

let  $x_{em}^{(j)}$  be the  $j$ th approximation to the solution and  $f^{(j)}$  written for  $f(x_{em}^{(j)})$

the next iterate is found by a quasi-Newton iteration

$$x_{em}^{(j+1)} = x_{em}^{(j)} + h^{(j)}$$

by solving the linear system

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

$B^{(j)}$  is an approximation to the Jacobian matrix

$$J(x_{em}^{(j)}) = \left( \frac{\partial f^T(x_{em})}{\partial x_{em}} \right)^T \bigg|_{x_{em} = x_{em}^{(j)}}$$

in our implementation,  $B^{(1)}$  is set to the identity matrix

the approximation to the Jacobian matrix is updated by the classic Broyden formula (*Broyden, 1965*)

$$B^{(j+1)} = B^{(j)} + \frac{f(x_{em}^{(j)} + h^{(j)}) - f(x_{em}^{(j)}) - B^{(j)} h^{(j)}}{h^{(j)T} h^{(j)}} h^{(j)T}$$



## **Aggressive Space Mapping - Implementation**

begin with a point,  $x_{os}^* \triangleq \arg \min \{H(x_{os})\}$ , representing the optimal design in  $X_{os}$  where  $H(x_{os})$  is some appropriate objective function

*Step 0.* initialize  $x_{em}^{(1)} = x_{os}^*$ ,  $B^{(1)} = \mathbf{1}$ ,  $f^{(1)} = P(x_{em}^{(1)}) - x_{os}^*$ ,  
 $j = 1$ ; stop if  $\|f^{(1)}\| \leq \eta$

*Step 1.* solve  $B^{(j)}h^{(j)} = -f^{(j)}$  for  $h^{(j)}$

*Step 2.* set  $x_{em}^{(j+1)} = x_{em}^{(j)} + h^{(j)}$

*Step 3.* evaluate  $P(x_{em}^{(j+1)})$

*Step 4.* compute  $f^{(j+1)} = P(x_{em}^{(j+1)}) - x_{os}^*$ ; if  $\|f^{(j+1)}\| \leq \eta$ ,  
stop

*Step 5.* update  $B^{(j)}$  to  $B^{(j+1)}$

*Step 6.* set  $j = j + 1$ ; go to *Step 1*

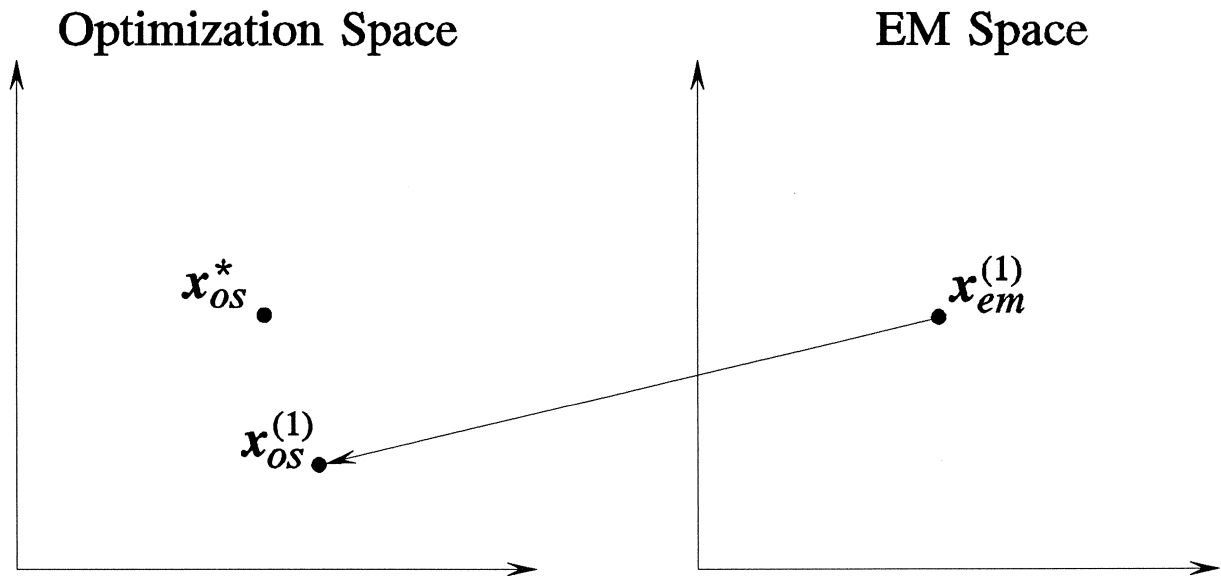






## **Illustration of Aggressive Space Mapping Optimization**

*Step 2*



perform  $X_{os}$ -space model parameter extraction

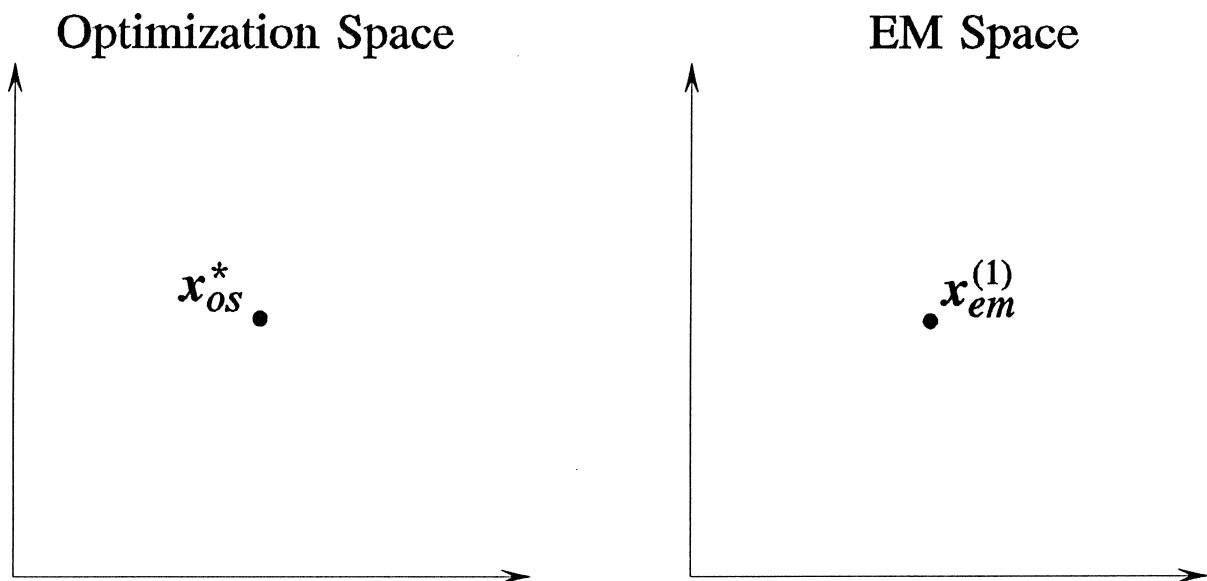


## Illustration of Aggressive Space Mapping Optimization

*Step 0*

find the optimal design  $x_{os}^*$  in Optimization Space

*Step 1*

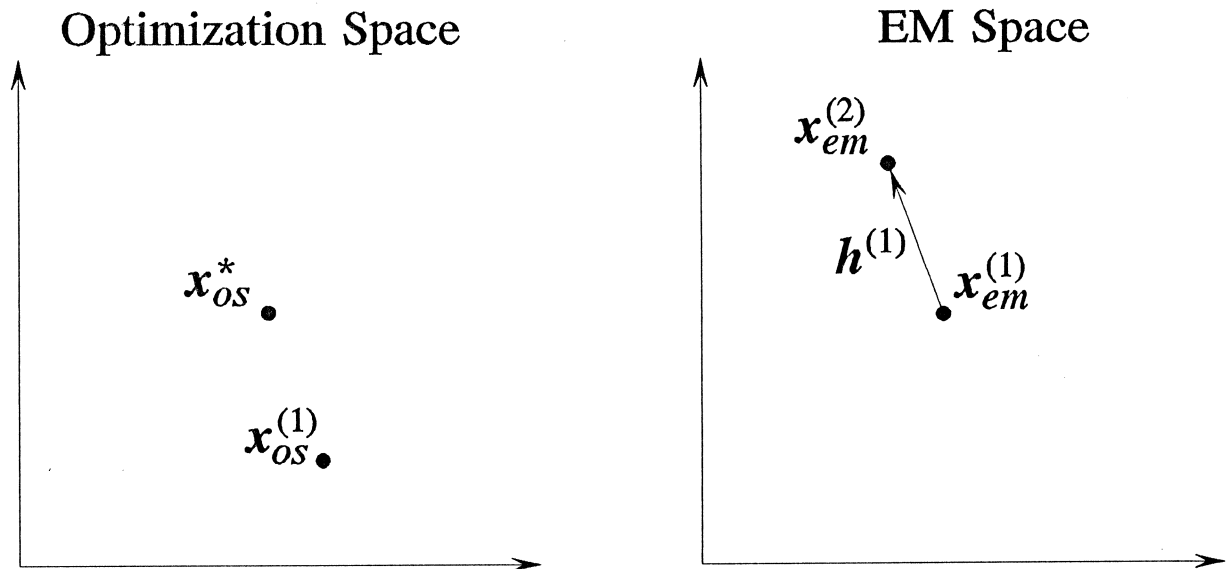


set  $x_{em}^{(1)} = x_{os}^*$  assuming  $x_{em}$  and  $x_{os}$  represent the same physical parameters



## Illustration of Aggressive Space Mapping Optimization

*Step 3*



initialize Jacobian approximation  $B^{(1)} = 1$

obtain  $x_{em}^{(2)}$  by solving

$$B^{(1)}h^{(1)} = -f^{(1)}$$

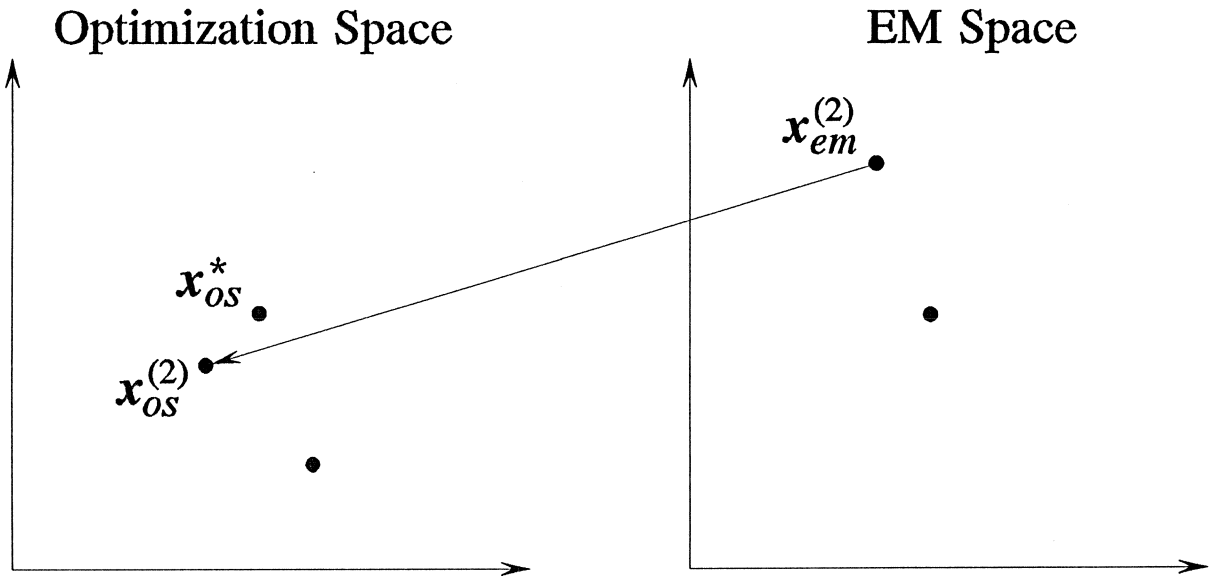
where

$$f^{(1)} = x_{os}^{(1)} - x_{os}^*$$



## Illustration of Aggressive Space Mapping Optimization

*Step 4*

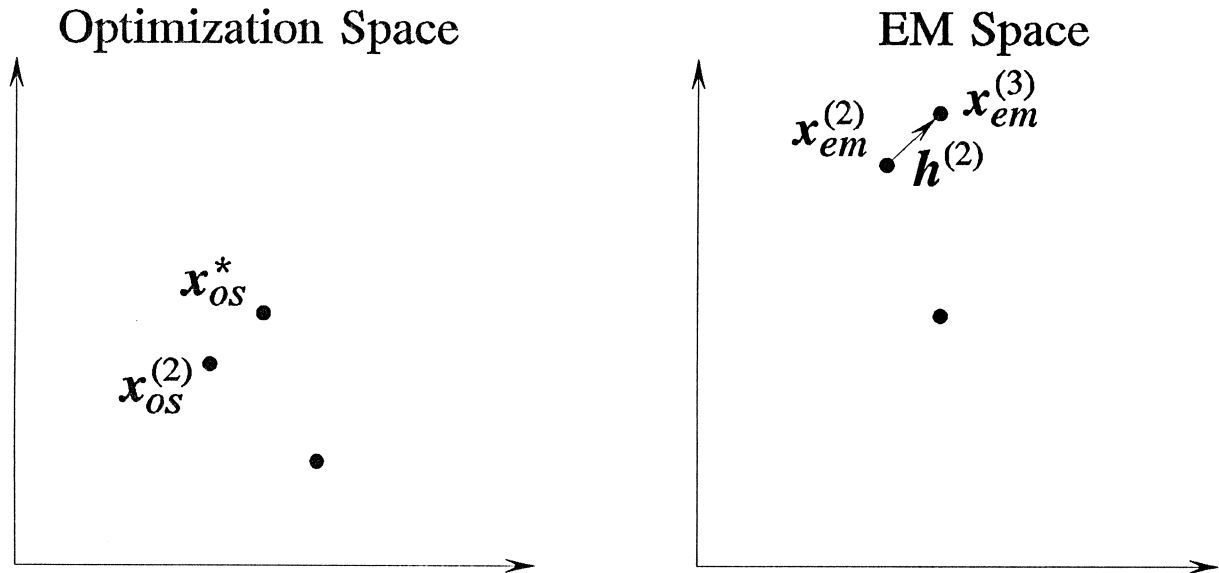


perform  $X_{os}$ -space model parameter extraction



## Illustration of Aggressive Space Mapping Optimization

Step 5



update Jacobian approximation from  $B^{(1)}$  to  $B^{(2)}$

obtain  $x_{em}^{(3)}$  by solving

$$B^{(2)}h^{(2)} = -f^{(2)}$$

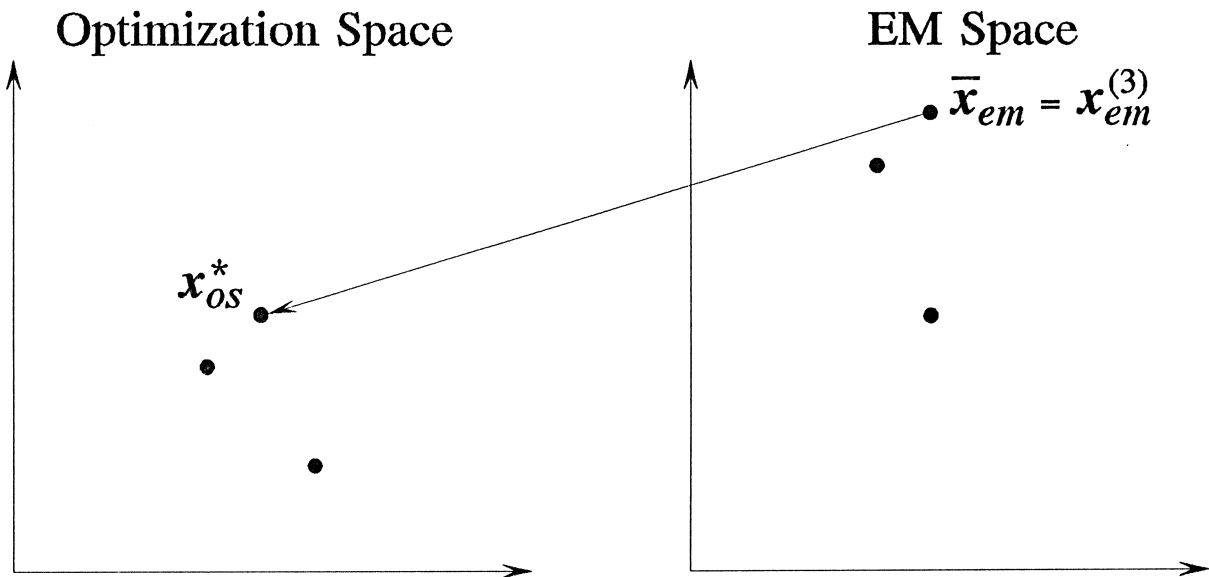
where

$$f^{(2)} = x_{os}^{(2)} - x_{os}^*$$



## Illustration of Aggressive Space Mapping Optimization

Step 6



perform  $X_{os}$ -space model parameter extraction

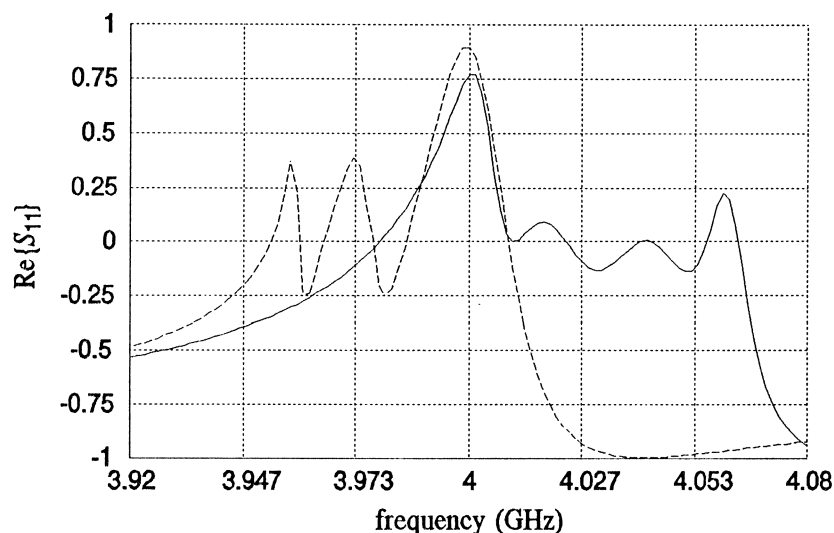
if  $\|x_{os}^{(3)} - x_{os}^*\| \leq \epsilon$  then  $\bar{x}_{em} = x_{em}^{(3)}$  is considered as the SM solution



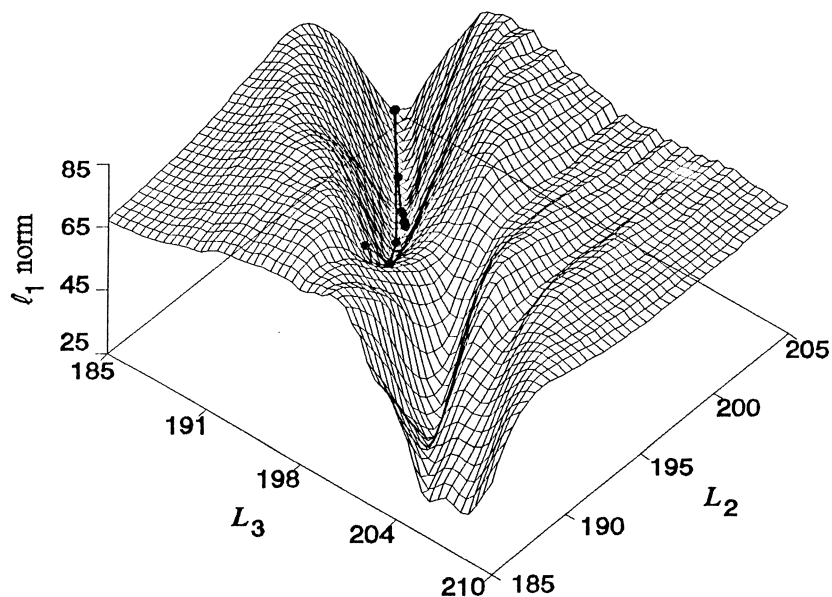
## Frequency Space Mapping for Parameter Extraction

parameter extraction can be a serious challenge, especially at the starting point, if the model responses are misaligned

$\text{Re}\{S_{11}\}$  using OSA90/hope (—) and *em* (---) at  $x_{os}^*$



straightforward optimization from such a starting point can lead to a local minimum







## Frequency Space Mapping - Mapping and Alignment

to better condition the parameter extraction subproblem

first, we align  $R_{os}$  and  $R_{em}$  along the frequency axis using

$$\omega_{os} = P_{\omega}(\omega)$$

this frequency space mapping can be as simple as

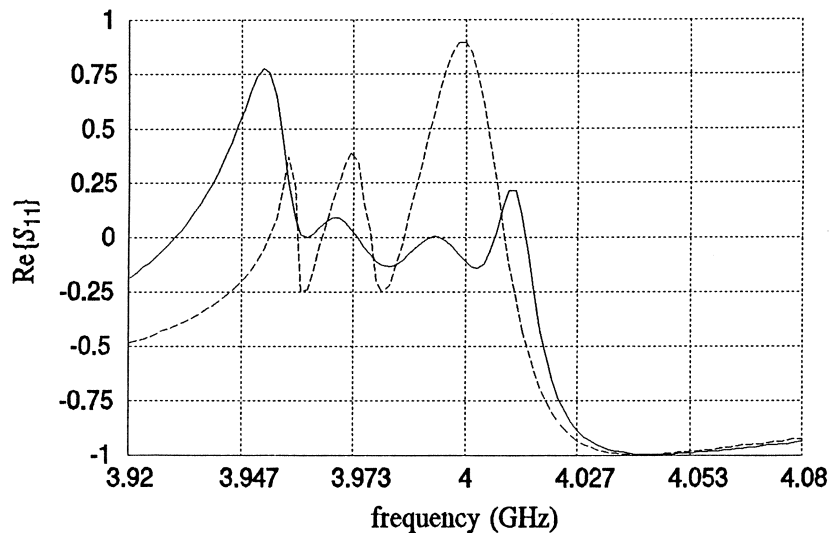
$$\omega_{os} = \sigma \omega + \delta$$

at the starting point, we determine  $\sigma_0$  and  $\delta_0$  by

$$\underset{\sigma_0, \delta_0}{\text{minimize}} \quad \| R_{os}(x_{os}, \sigma_0, \delta_0) - R_{em}(x_{em}) \|$$

where  $x_{os}$  and  $x_{em}$  are fixed and  $x_{os} = x_{em}$

resulting alignment between OSA90/hope (—) and *em* (---):





## **Frequency Space Mapping: Sequential FSM (SFSM) Algorithm**

we perform a sequence of optimizations to gradually achieve the identity Frequency Space Mapping

we optimize  $x_{os}$  to match  $R_{os}$  and  $R_{em}$ :

$$\underset{x_{os}^{(j)}}{\text{minimize}} \quad \| R_{os}(x_{os}^{(j)}, \sigma^{(j)}, \delta^{(j)}) - R_{em}(x_{em}) \|$$

the values  $\sigma^{(j)}$  and  $\delta^{(j)}$  are updated according to

$$\sigma^{(j)} = 1 + (\sigma_0 - 1) \frac{(K - j)}{K}$$

and

$$\delta^{(j)} = \delta_0 \frac{(K - j)}{K},$$

respectively, for  $j = 0, 1, \dots, K$

$K$  determines the number of steps in the sequence

larger values of  $K$  increase the probability of success in the parameter extraction subproblem at the expense of longer optimization time



## **Frequency Space Mapping: Exact Penalty Function (EPF) Algorithm**

we perform only one optimization to achieve the identity Frequency Space Mapping and optimize  $x_{os}$  to match  $R_{os}$  to  $R_{em}$

the  $\ell_1$  norm version of the EPF formulation is given by

$$\underset{x_{os}, \sigma, \delta}{\text{minimize}} \quad \{ \|R_{os}(x_{os}, \sigma, \delta) - R_{em}(x_{em})\|_1 + \alpha_1 |\sigma - 1| + \alpha_2 |\delta| \}$$

the minimax version is given by

$$\underset{x_{os}, \sigma, \delta}{\text{minimize}} \quad \left\{ \max_{1 \leq i \leq 4} [U(x_{os}, \sigma, \delta), U(x_{os}, \sigma, \delta) - \alpha_i g_i] \right\}$$

where

$$U(x_{os}, \sigma, \delta) = \|R_{os}(x_{os}, \sigma, \delta) - R_{em}(x_{em})\|$$

and

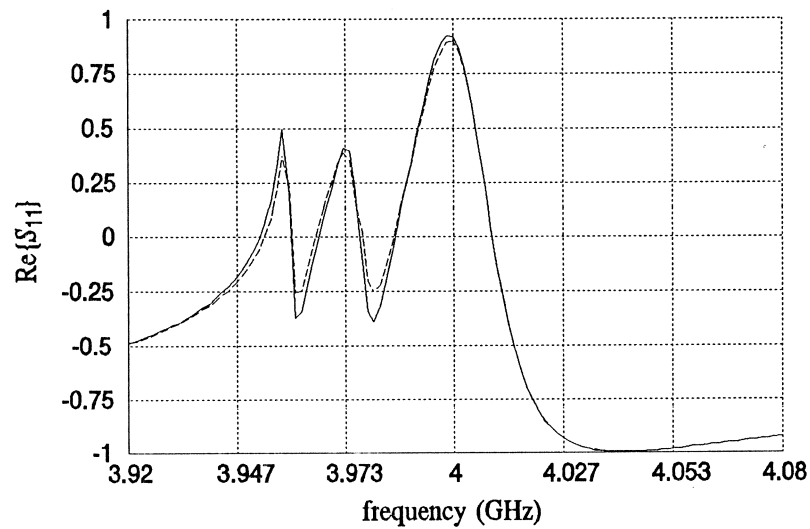
$$g(\sigma, \delta) = \begin{bmatrix} \sigma - 1 \\ 1 - \sigma \\ \delta \\ -\delta \end{bmatrix}$$

in both EPF formulations,  $\alpha_i$  are kept fixed and must be sufficiently large to obtain the identity mapping and hence the solution to the parameter extraction problem



## Frequency Space Mapping - Results

$\text{Re}\{S_{11}\}$  using OSA90/hope (—) and *em* (---)



resulting match after applying the FSM algorithm