Surrogate-based EM Design Methods for Antennas and RF/Microwave Devices

Qingsha Cheng (程庆沙)

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天线理论与技术/天线与电波传播

2024.5.7

Last Week

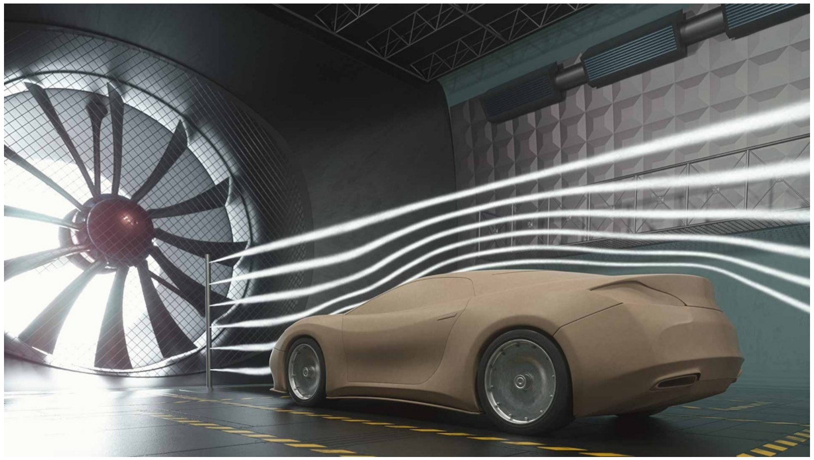
- Introduction
- History of Development of DRA
- Why DRA
- Fundamentals of DRA
- Design Principles
- Performance Improvement Techniques
- Advantages and Disadvantages
- Future Scope
- Conclusions

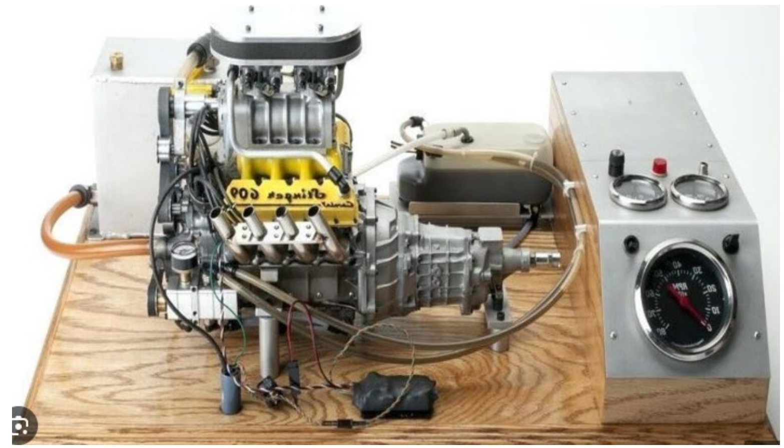
What Is a Model?

- Human model
- Appearance model
- Miniature model
- Physical model

source: Google image

What Is a Model?





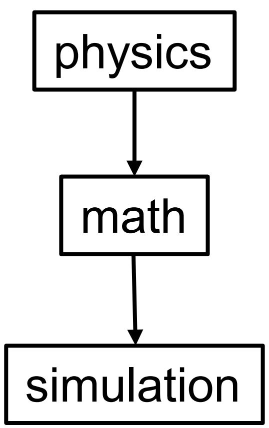
Physics Working model

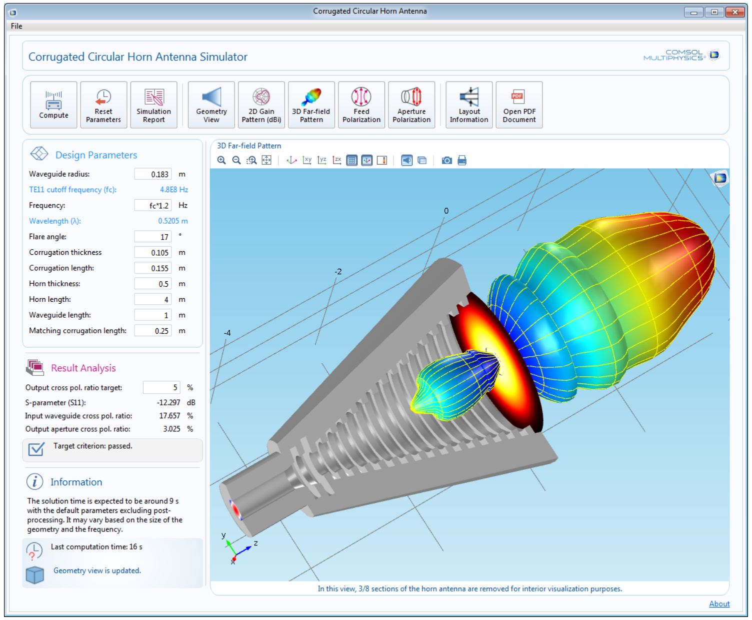
Scale model

source: Google image

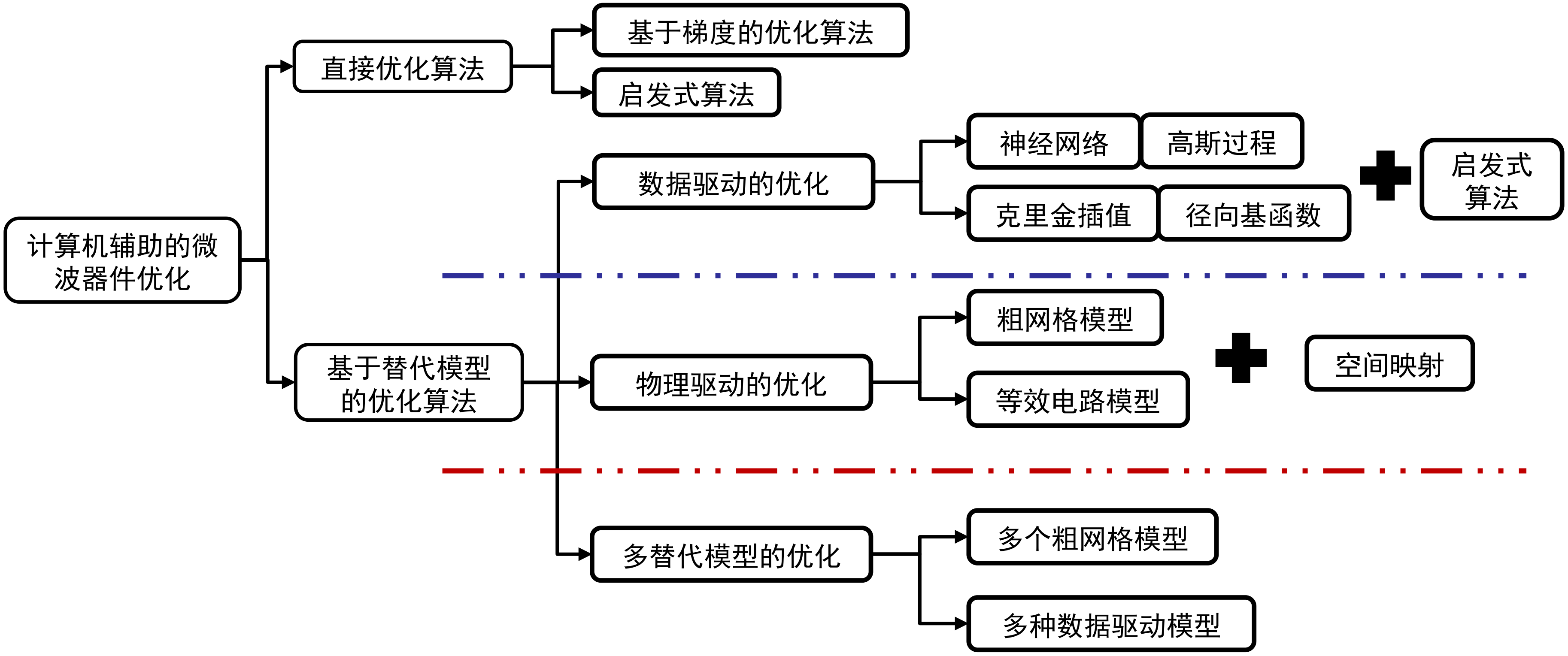
Physics Model/Mathematical Model/Simulation Model

- a **theoretical** or **mathematical** representation of a physical system or phenomenon
- describe and predict how the system or phenomenon behaves based on **known principles of physics**
- a **physics-based model** to predict its performance in the real world

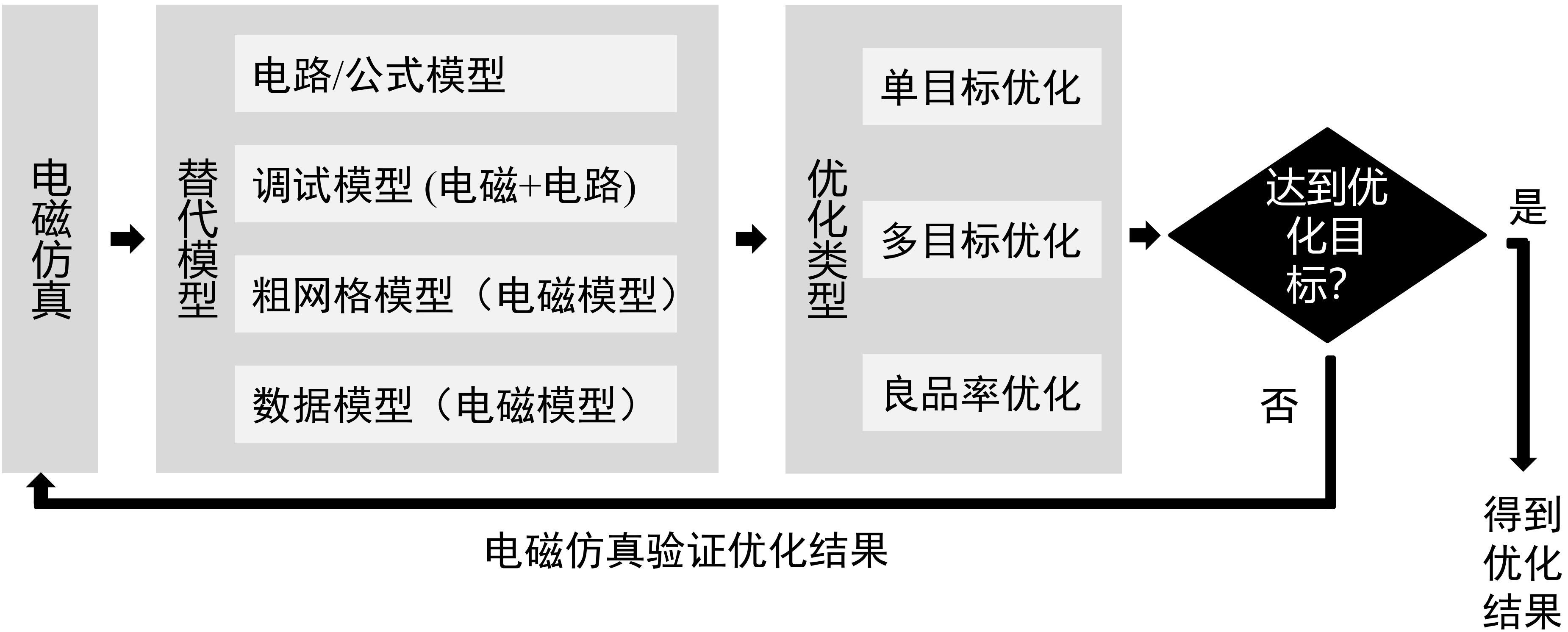




基于电磁仿真的器件设计优化策略

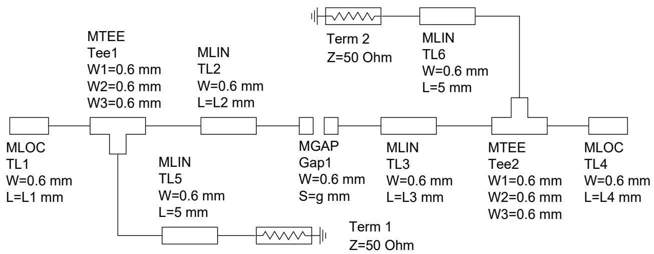


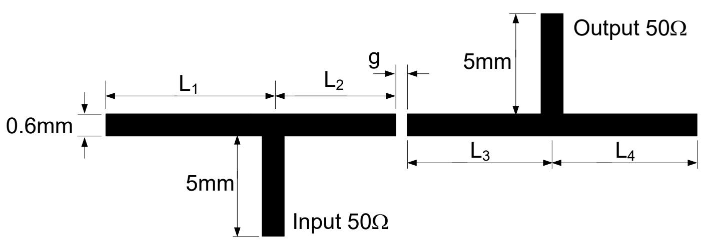
基于替代模型的器件设计优化策略



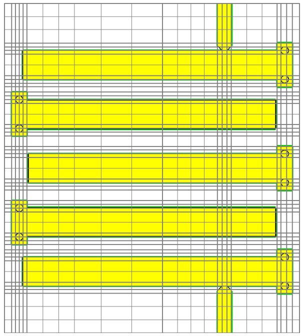
替代模型分类

电路/公式模型

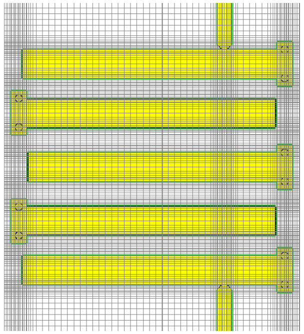




粗网格模型

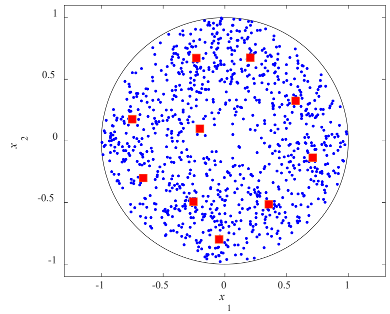


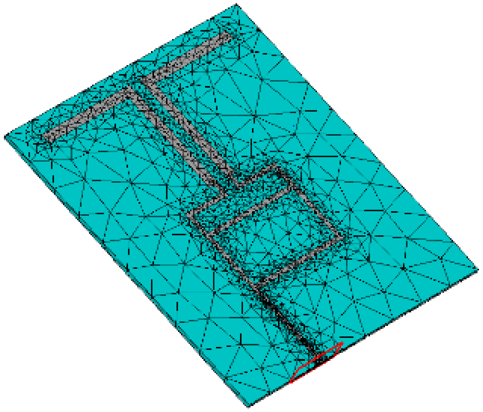
7,500 cells, 18 sec.



216,000 cells, 6 min, 30 sec

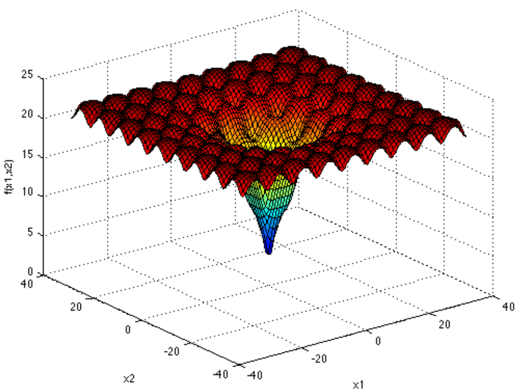
数据模型



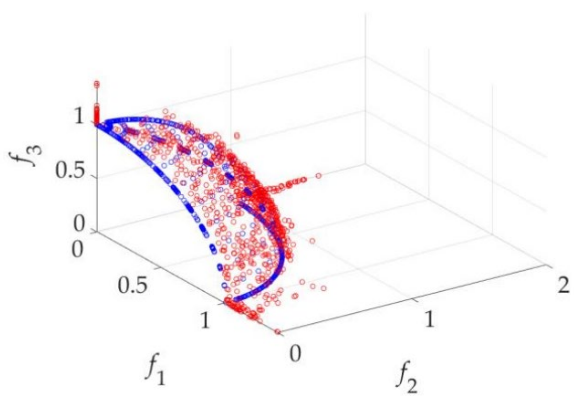


优化类型

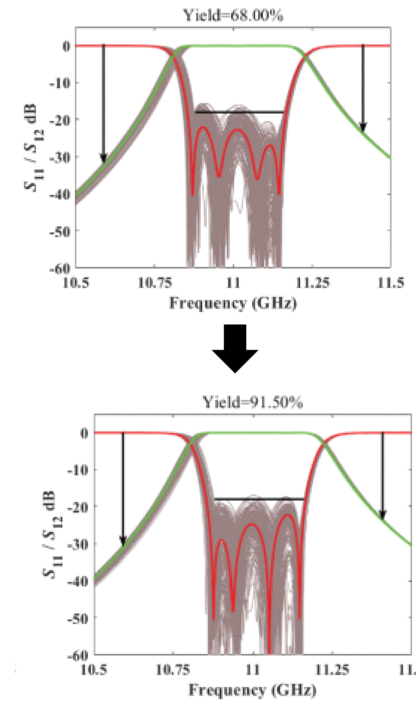
单目标优化



多目标优化



良品率优化



Y. Song, Q.S. Cheng, and S. Koziel, "Multi-fidelity local surrogate model for computationally efficient microwave component design optimization," Sensors, vol. 19, no. 13, July 2019.
Z. Zhang, B. Liu, Y. Yu, M. Imran, Q.S. Cheng, and M. Yu, "A surrogate modeling space definition method for efficient filter yield optimization,"IEEE Microw. and Wirel. Compon. Letters,

Space Mapping: A Physics-based Algorithm
(*Bandler et al., 1994*)

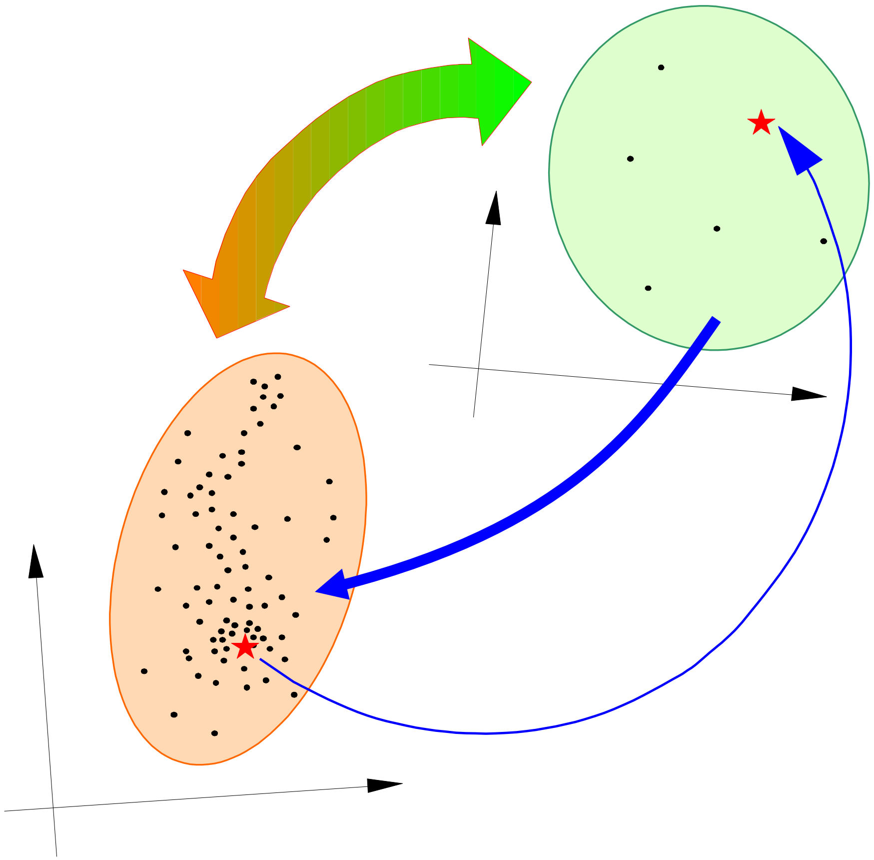
“space mapping” offers a quantitative relation for human intuition

Space Mapping: A Physics-based Algorithm
(*Bandler et al., 1994*)

follows **common sense**
knowledge and experience

exploits the "intuition"
—match and predict
M P

uses an iterative approach
to interact with reality
(uncommon activity)



Space Mapping: A Physics-based Algorithm
(*Bandler et al., 1994*)

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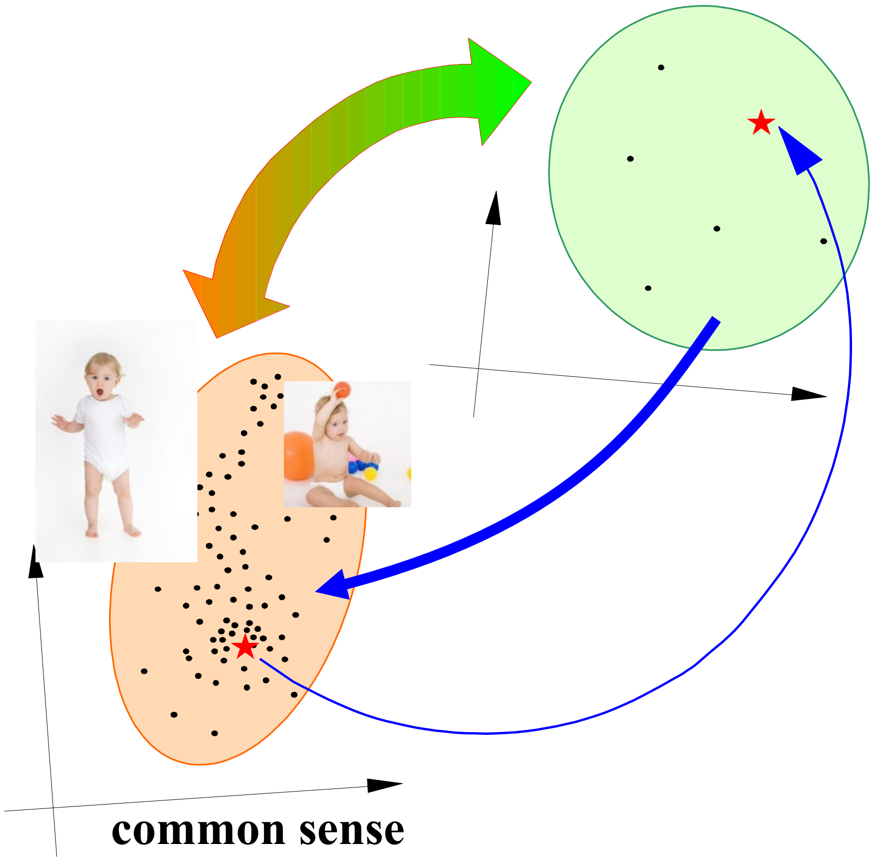

Space Mapping: A Physics-based Algorithm
(*Bandler et al., 1994*)

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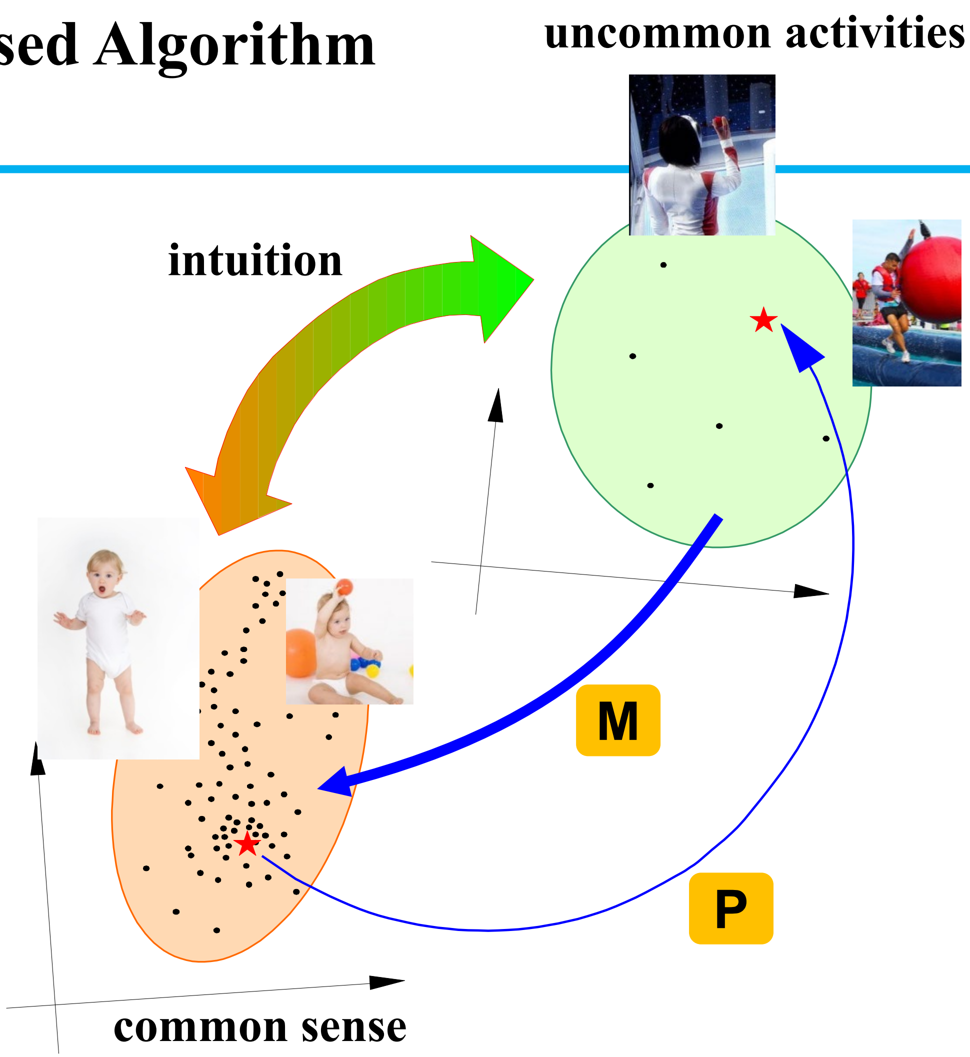


Space Mapping: Engineer's "Feel"

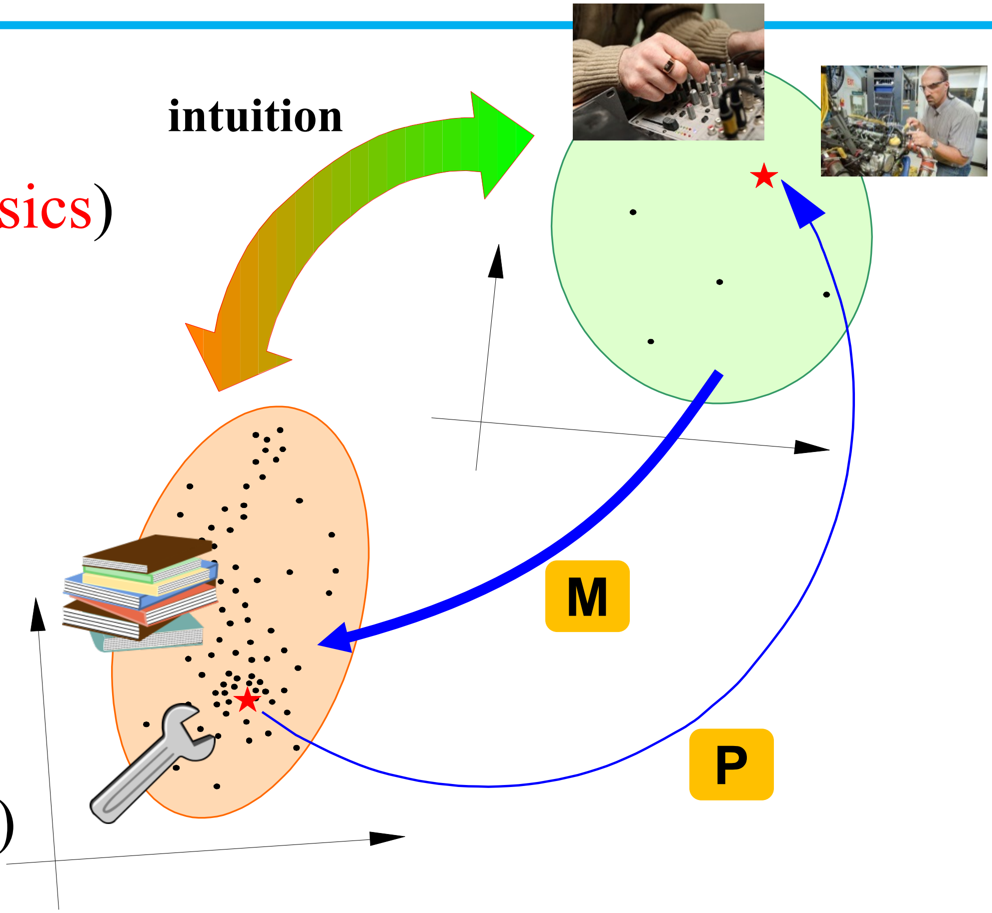
source: Google image

Space Mapping: Engineer's "Feel"

follows the **engineer**'s
knowledge and experience (physics)

exploits the **engineer**'s
"**intuition**"—match and predict
M P

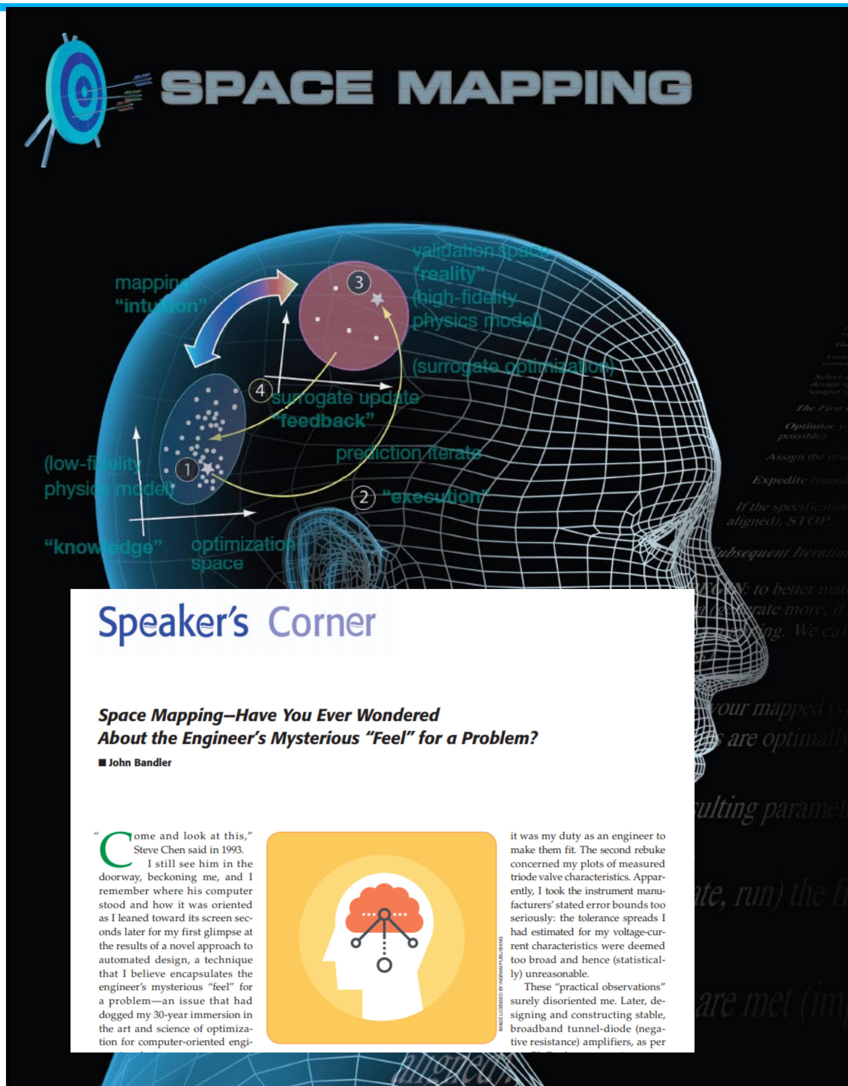
uses an iterative approach
to interact with reality
(complex engineering problems)



Space Mapping: Engineer’s “Feel”

**“space mapping” offers
a quantitative relation for
the engineer’s mysterious “feel” for a
problem**

Space Mapping: The Engineer's Mysterious "Feel"



J.W. Bandler, "Have you ever wondered about the engineer's mysterious 'feel' for a problem?" Feature Article, *IEEE Canadian Review*, no. 70, pp. 50-60, Summer 2013.

J.W. Bandler, "Space mapping—have you ever wondered about the engineer's mysterious 'feel' for a problem?" Feature Article, IEEE Canadian Review, no. 70, pp. 50-60, Summer 2013. Reprinted in *IEEE Microwave Magazine*, vol. 19, no. 2, Mar./Apr. 2018.

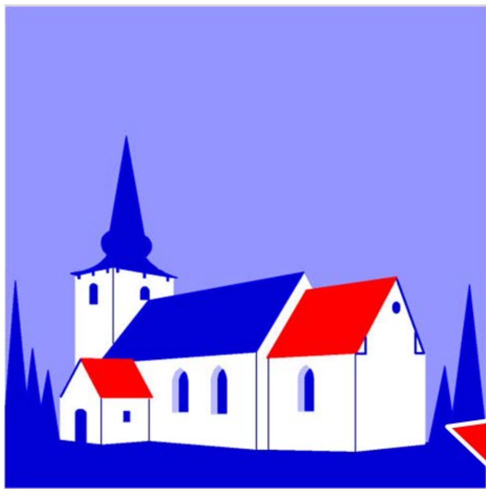
Origin of Space Mapping

John and Kaj were discussing a church

Kaj Madsen (Prof. and Mathematician)

John Bandler (Prof. and Engineer)

Origin of Space Mapping



Korning Kirke, Denmark
—Asbjorn Lonvig, artist

space mapping

The cathedral, Cologne
—historyfish.net

Kaj Madsen (Prof. and Mathematician)

John Bandler (Prof. and Engineer)

A simplified church and an elaborated cathedral symbolize a “coarse” model and a “fine” model.

Origin of Space Mapping


电子与电气工程系讲座

Trends and Innovations in Electronic Design Automation Software

Dr. Steve Chen（陈少华博士)

时间：2016年4月20日 下午2:30-3:30 地点：第一教学楼 107

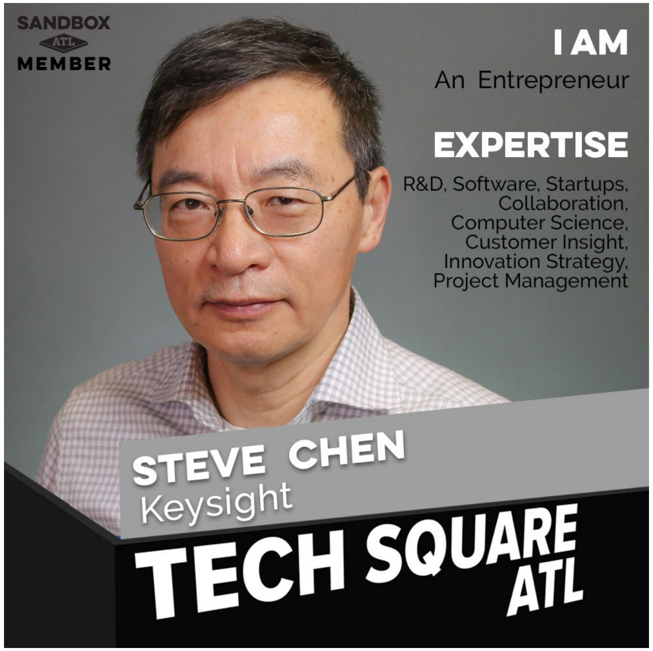
电子仿真与自动化设计软件(EDA)领域资深专家、美国是德科技EDA产品研发总监陈少华博士将为同学们介绍EDA领域及其最新进展，并与大家分享云计算、大数据、物联网及5G对仿真与测量技术的推动，以及成功进入该行业工作所需具备的核心技能。

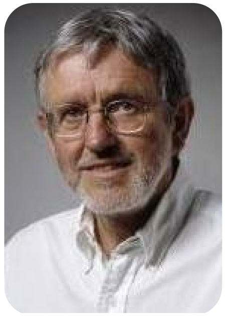
Steve Chen is an R&D Section Manager in the EEsof EDA division at Keysight Technologies. He leads R&D teams at several global sites responsible for developing simulation software for circuit design, electromagnetic and electrothermal verification. He is also the R&D leader for EEsof's high-speed digital EDA business segment. Steve received his B.S. degree in EE from South China Institute of Technology and his Ph.D. degree in EE from McMaster University in Canada. He held positions in academia and a small start-up before joining Hewlett-Packard in Santa Rosa in 1997. Dr. Chen has broad experience in both academic research and engineering management. He has technical expertise in semiconductor device modeling, optimization and statistical analysis, RF microwave circuits and systems.

报告摘要:

In this presentation, Dr. Chen will share his view of how the trends of Cloud, Big Data, IoT and 5G drive demands in electronic design. Key technological enablers will be highlighted and the rapidly increasing technical complexity and challenges faced by electronic designers will be discussed. An overview of Electronic Design Automation (EDA) will be provided at various levels of abstraction. Emphasis will be on how EDA innovations help designers address technical challenges. A number of specific and current engineering case studies will be illustrated. The talk will conclude with a discussion of core skills for a successful career in EDA software industry.

主办单位：电子系、树德书院





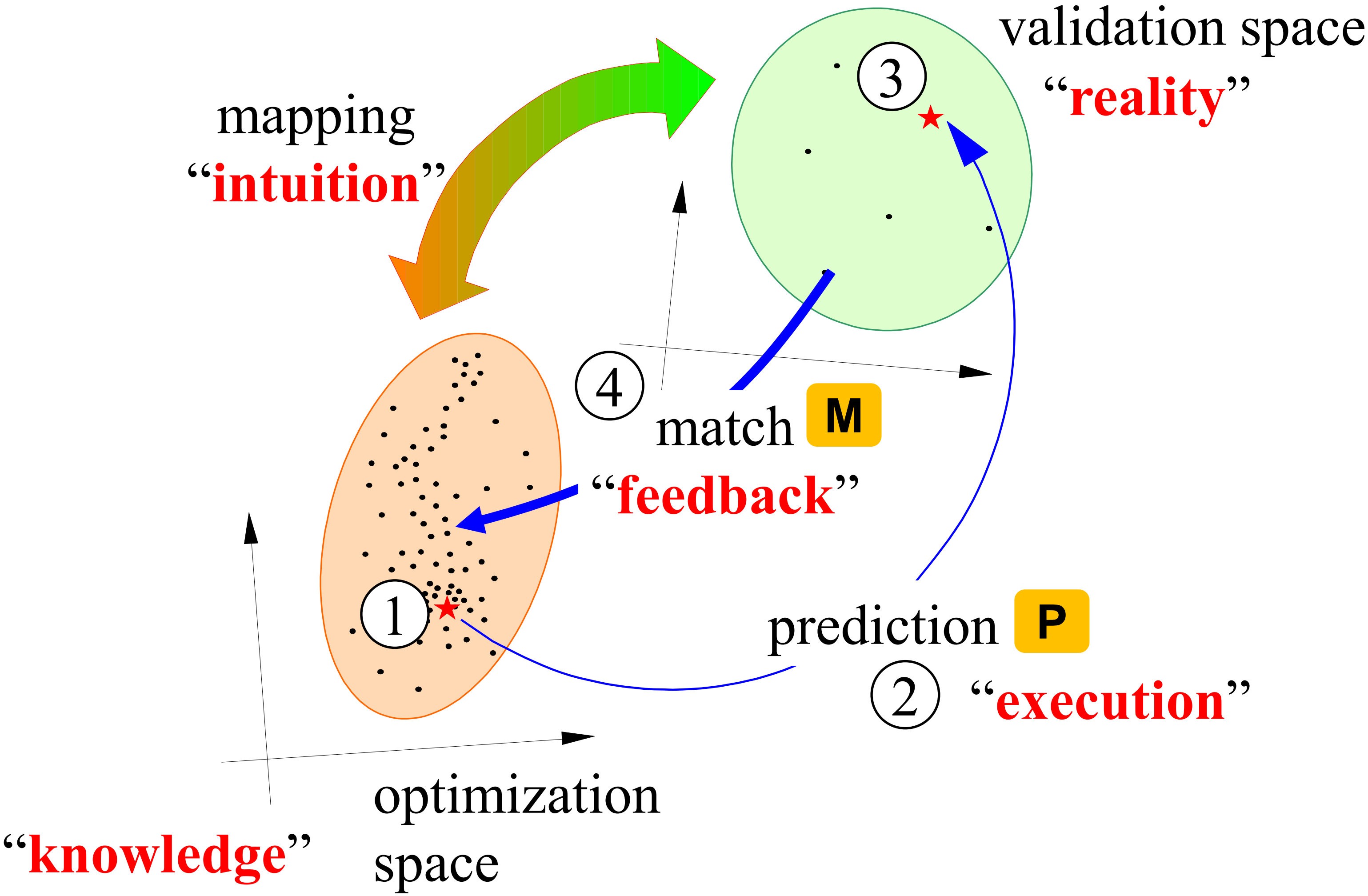
Kaj Madsen
Professor/
Mathematician
DTU, Denmark

John Bandler
1941-2023
Professor/
Engineer
McMaster
University, Canada

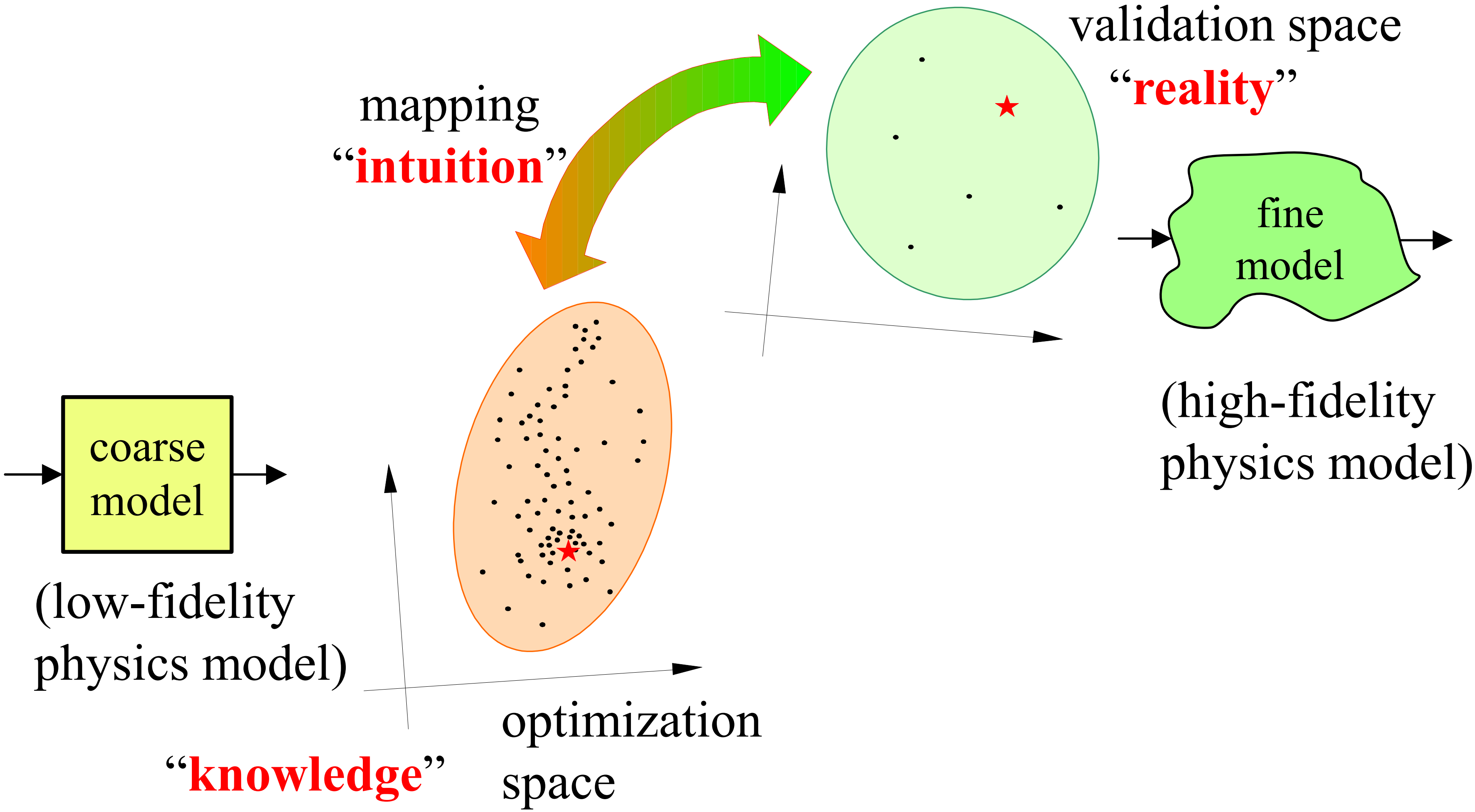
“Come and look at this,” Steve Chen said in 1993. I still see him in the doorway, beckoning me, and I remember where his computer stood and how it was oriented as I leaned toward its screen seconds later for my first glimpse at the results of a novel approach to automated design, a technique that I believe encapsulates the engineer's mysterious “feel” for a problem-an issue that had dogged my 30-year immersion in the art and science of optimization for computer-oriented engineering design.

John Bandler

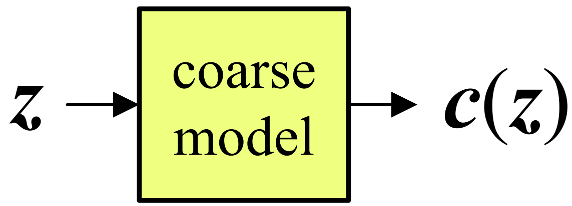
The Space Mapping Concept-Four Steps
(*Bandler et al., 1994-*)

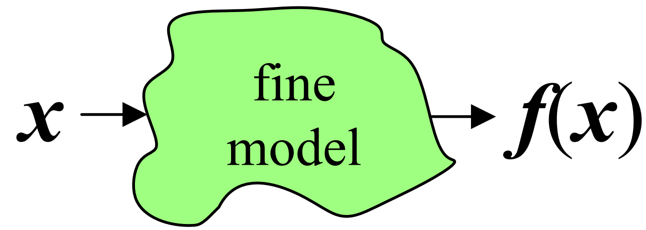


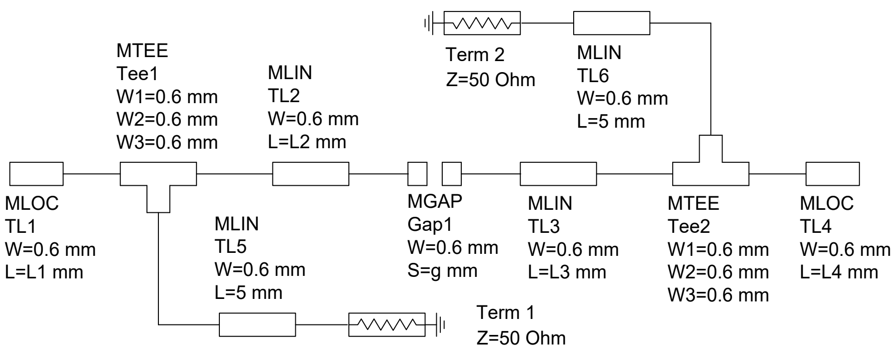
The Space Mapping Concept: Coarse Model and Fine Model
(*Bandler et al., 1994-*)

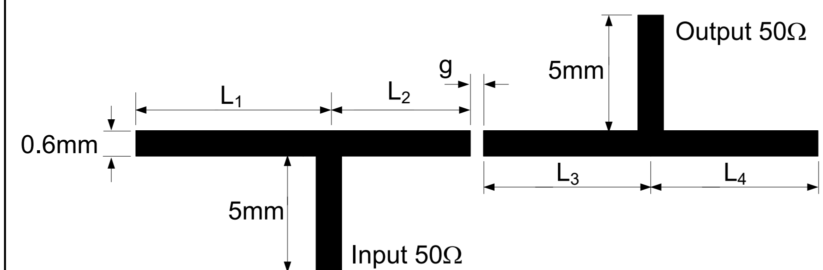


The Space Mapping Concept: Coarse Model and Fine Model
(image source: S. Koziel, Reykjavik University)







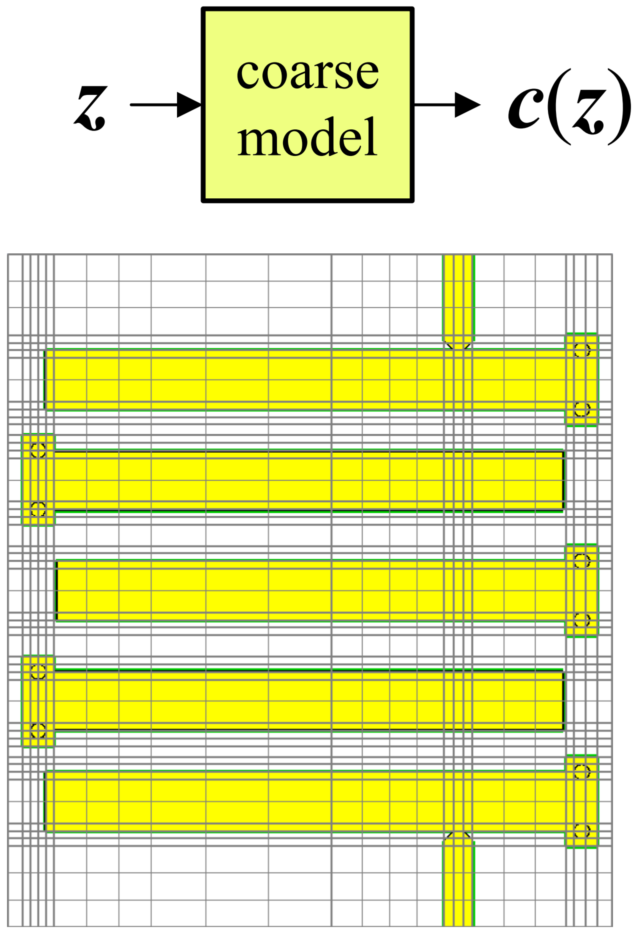


fast but may not accurate

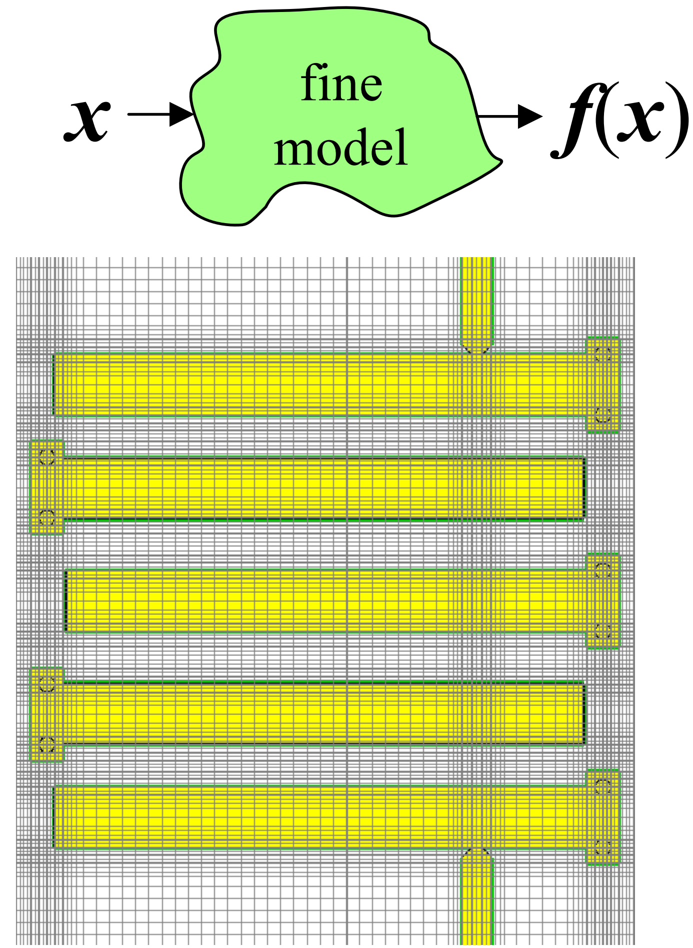
expensive but accurate

The Space Mapping Concept: Coarse Model and Fine Model

(image source: Peter Thoma, CST)



7,500 cells, 18 sec.

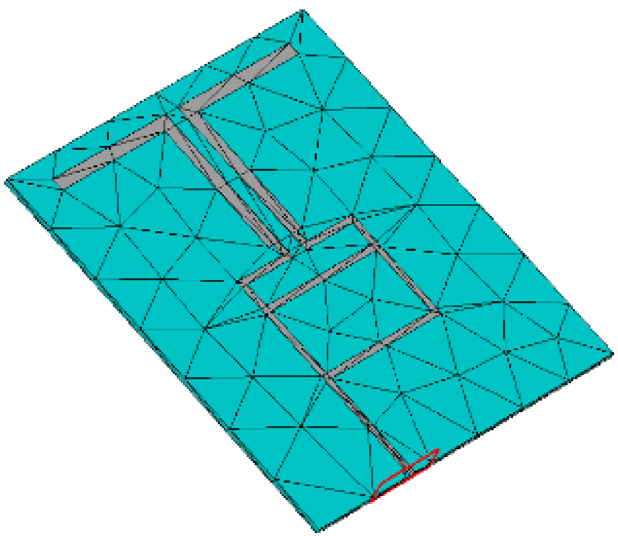


216,000 cells, 6 min, 30 sec

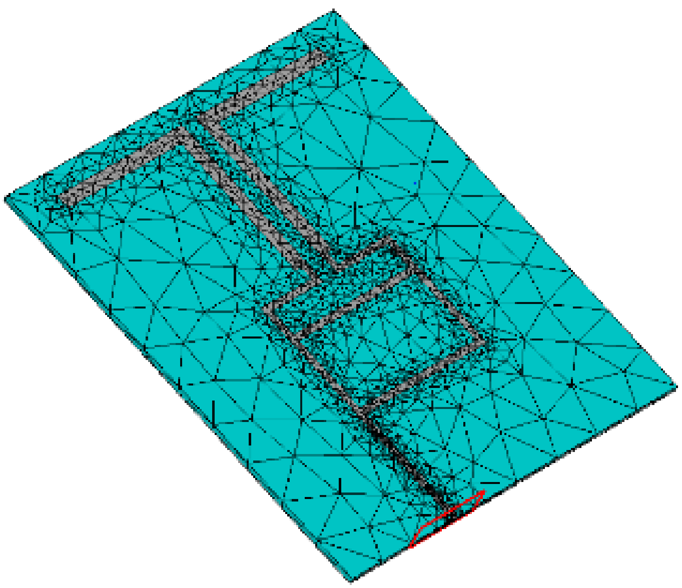
The Space Mapping Concept: Coarse Model and Fine Model

$z \rightarrow$ coarse model $\rightarrow c(z)$

$x \rightarrow$ fine model $\rightarrow f(x)$

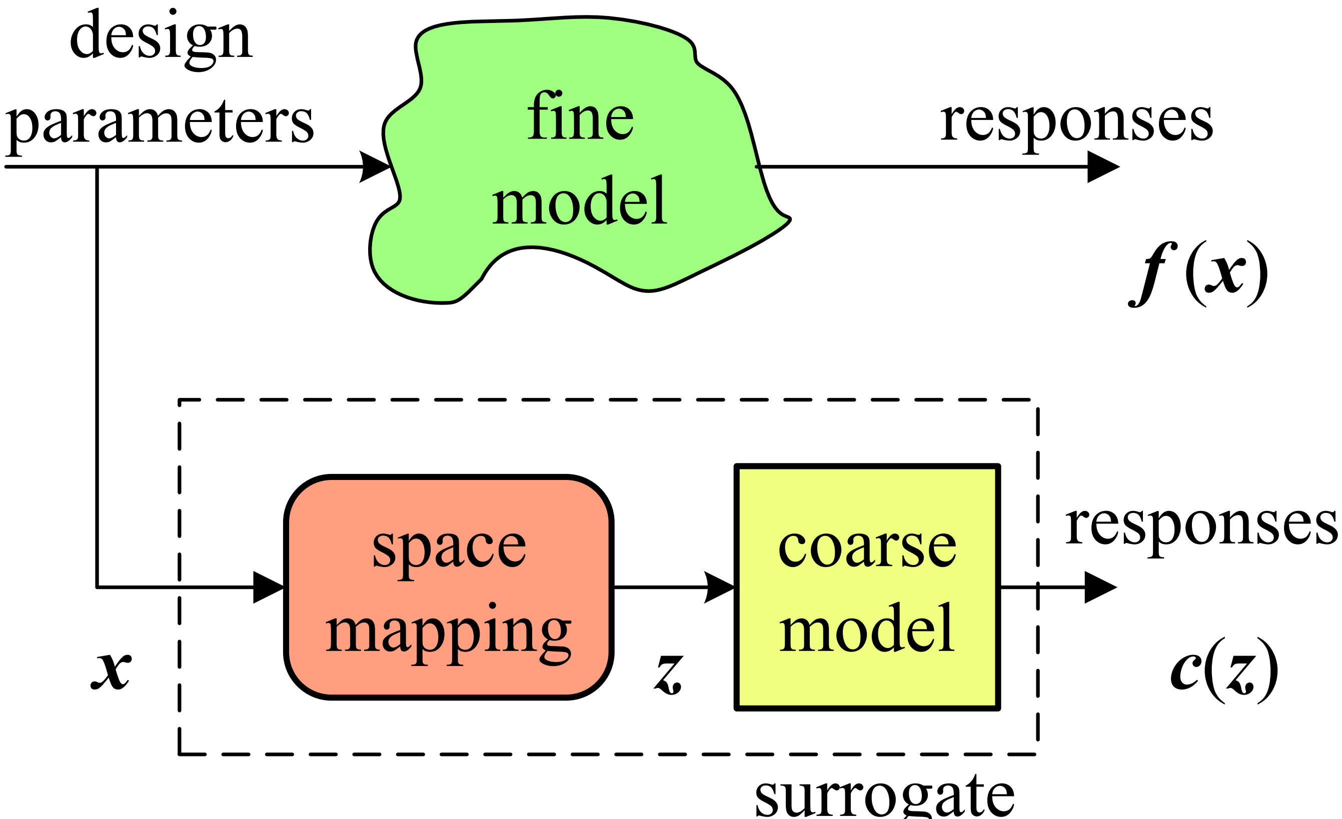


粗网格的EM模型
仿真时间约**40秒**



细网格的EM模型
仿真时间约**207秒**

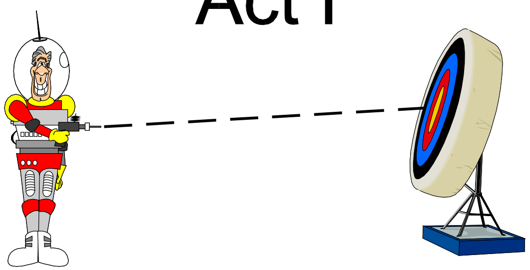
The Space Mapping Concept: A Diagram
(Bandler et al., 1994-)



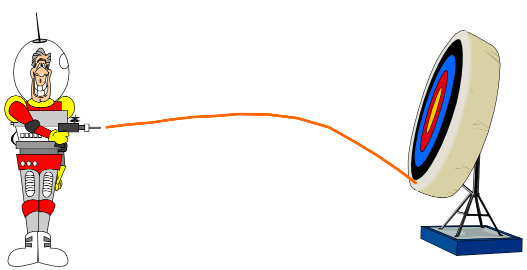
$$\boldsymbol{z} = \boldsymbol{P}(\boldsymbol{x}) \equiv \arg\min_{\boldsymbol{z}} \left\| \boldsymbol{f}(\boldsymbol{x}) - \boldsymbol{c}(\boldsymbol{z}) \right\|$$

Aggressive Space Mapping Optimization Interpretation

Space Mapping
Act I

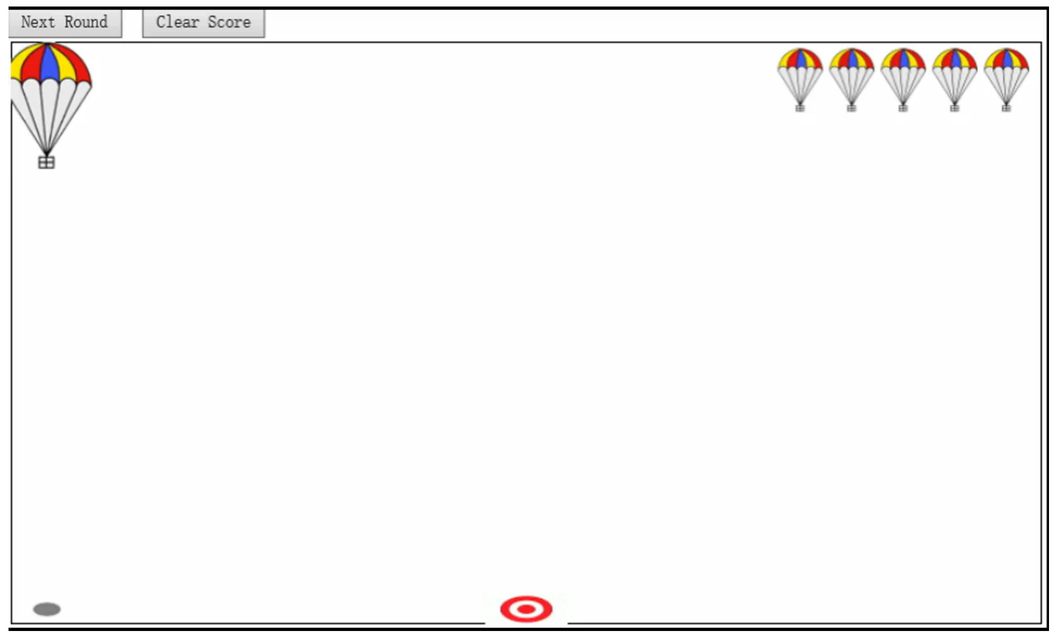


ideal aim



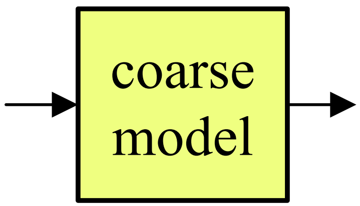
reality check ... oops

(*Bandler et al., 2001*)



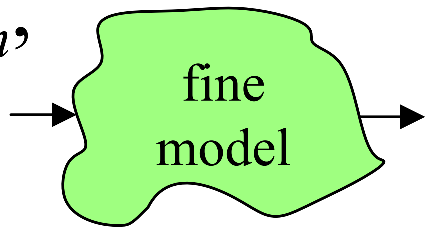
Space Mapping Notation Change

ϕ_c, $\mathbf{x}_{os}$, z, $\boldsymbol{x}_c$



$\mathbf{R}_c(\phi_c)$, $\boldsymbol{c}(\boldsymbol{z})$, $\mathbf{R}_{os}(\mathbf{x}_{os})$, $\boldsymbol{R}_c(\boldsymbol{x}_c)$

ϕ_f , $\mathbf{x}_{em}$, z, $\boldsymbol{x}_f$



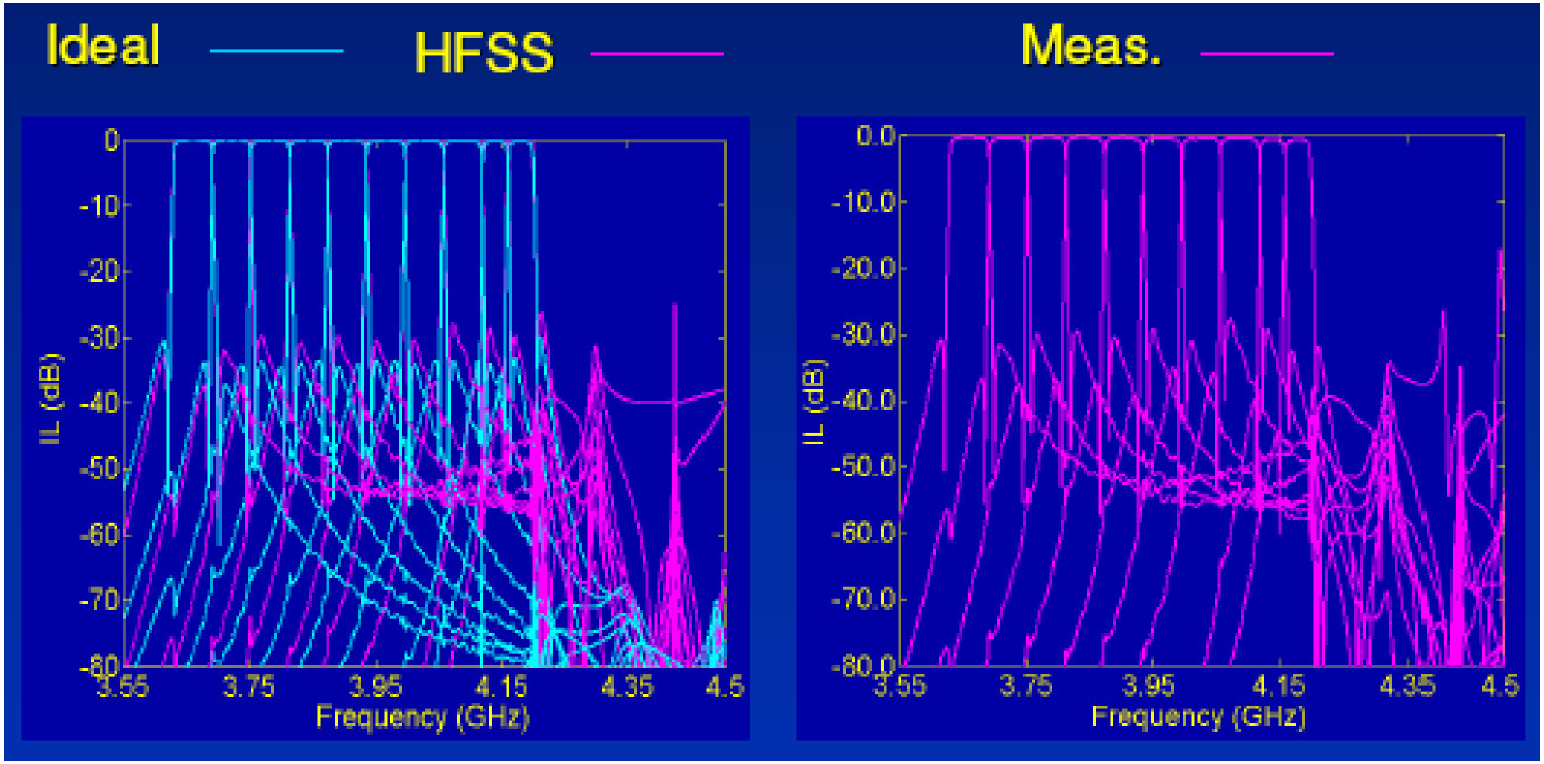
$\mathbf{R}_c(\phi_c)$, $\boldsymbol{f}(\boldsymbol{x})$, $\mathbf{R}_{em}(\mathbf{x}_{em})$, $\boldsymbol{R}_f(\boldsymbol{x}_f)$

$$\boldsymbol{R}_c : X_c \to R^m,\ X_c \subseteq R^n$$
$$\boldsymbol{x}_c \in X_c$$

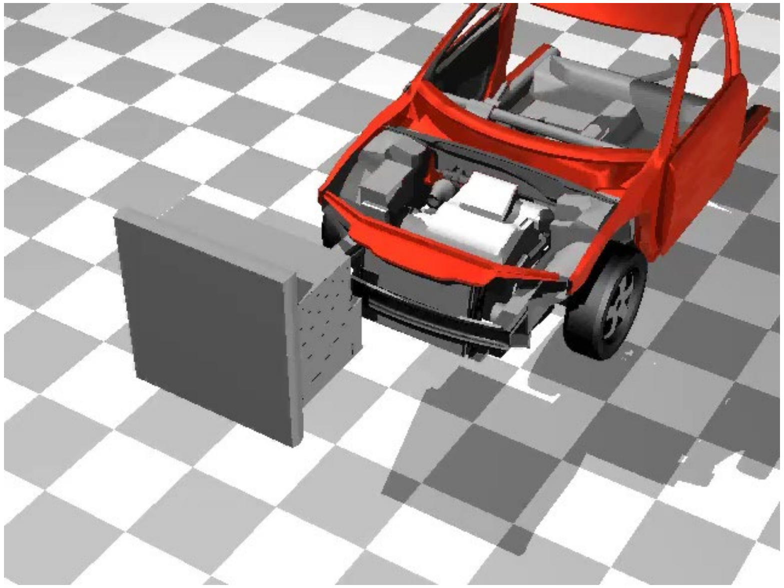
$$\boldsymbol{R}_f : X_f \to R^m,\ X_f \subseteq R^n$$
$$\boldsymbol{x}_f \in X_f$$

ASM Design Of Dielectric Resonator Multiplexers
(*Ismail et al., 2003, Com Dev, Canada*)

10-channel output multiplexer, 140 variables



Space Mapping Applications



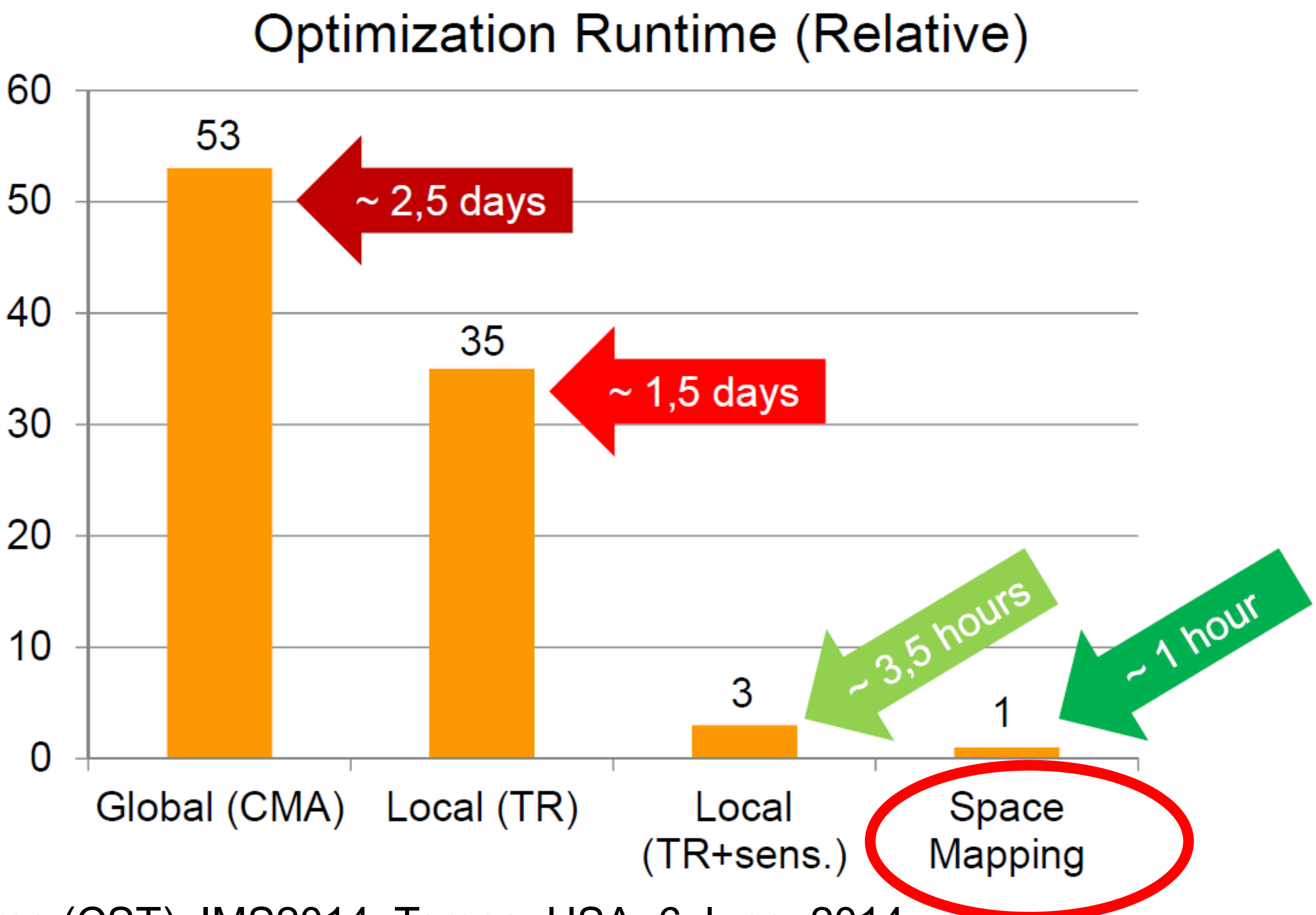
autonomous underwater vehicle design
(*Leifsson et al., 2011, Iceland*)

car crashworthiness design
(*Nilsson and Redhe, 2005, Sweden*)

Space Mapping Applications

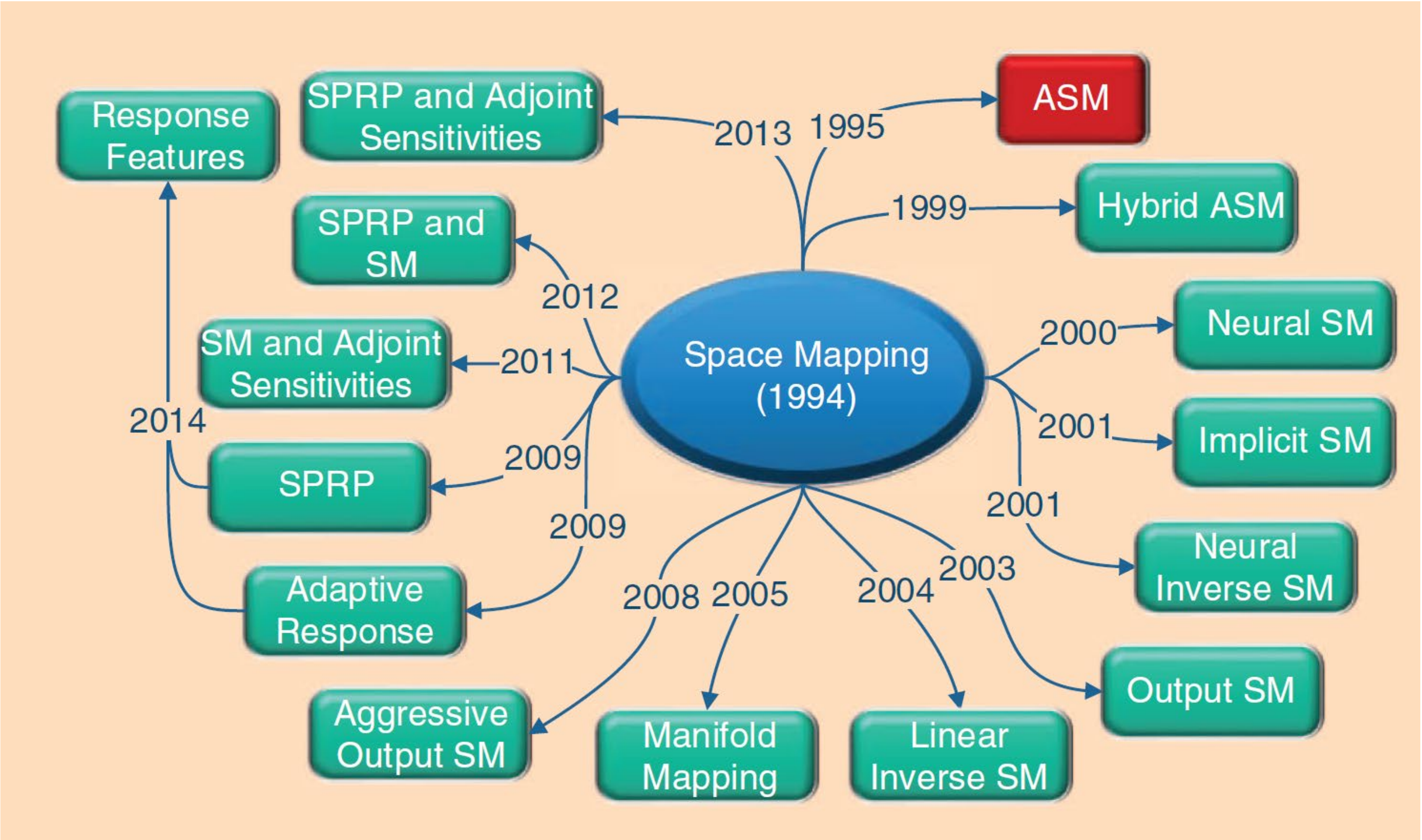
- SM application to PDE constrained shape optimization (Blauth, Germany, 2023)
- SM application to interacting particle systems (Weißen et al., Germany, 2021)
- SM application to wing aerodynamic shape optimization (Leifsson et al., Iceland, 2013, 2014).
- SM application to statistical modeling of passive components (Zhang et al., Freescale Semiconductor Inc., USA, 2012).
- SM application to optimization of a marine ecosystem model (Prieß and Slawig, Germany, 2012).
- SM application to a feasibility study for transport processes coming from the fields of fluid dynamics, semiconductors and radiation (Marheineke and Pinnau, Germany, 2012).
- SM application to EGG source analysis (Crevecoeur et al., Belgium, 2008).
- SM application to development of new library models for wireless components (Philips, The Netherlands, 2001-).

Space Mapping Achieves Fast Optimization and Design



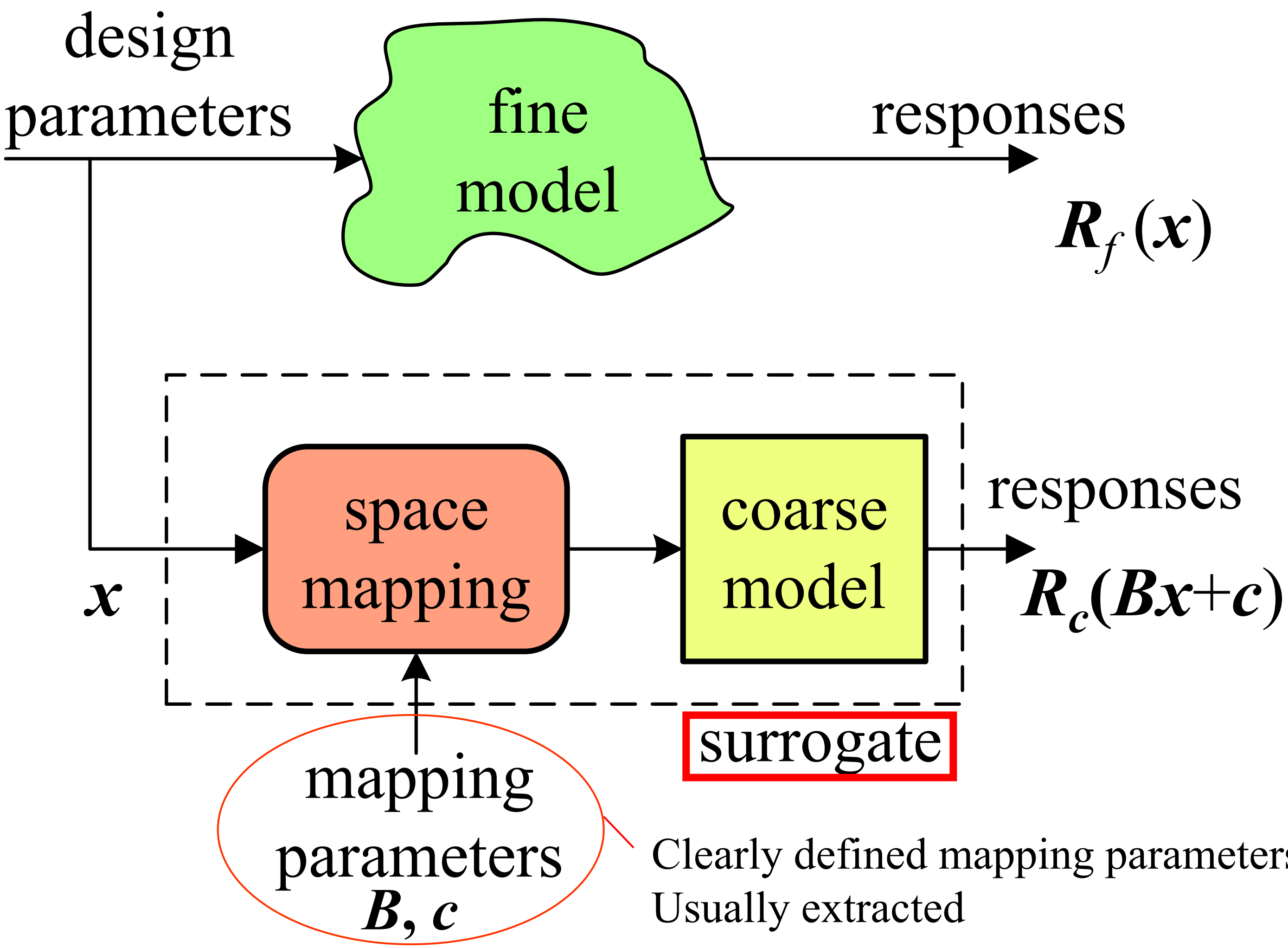
Peter Thoma (CST), IMS2014, Tampa, USA, 6 June, 2014

History of Space Mapping



José E. Rayas-Sánchez, Microwave Magazine, April, 2016

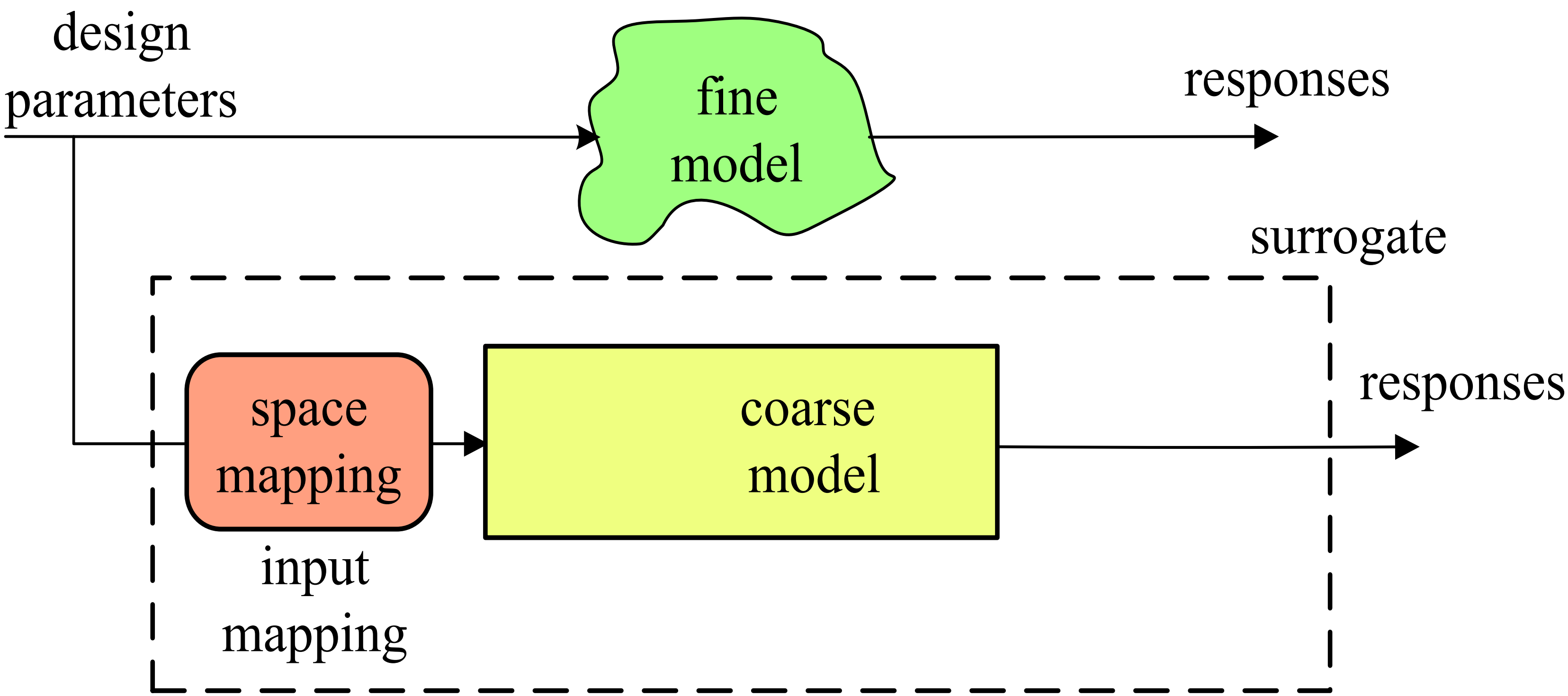
The Space Mapping (Surrogate) Concept
(Bandler et al., 2004-)



Clearly defined mapping parameters
Usually extracted

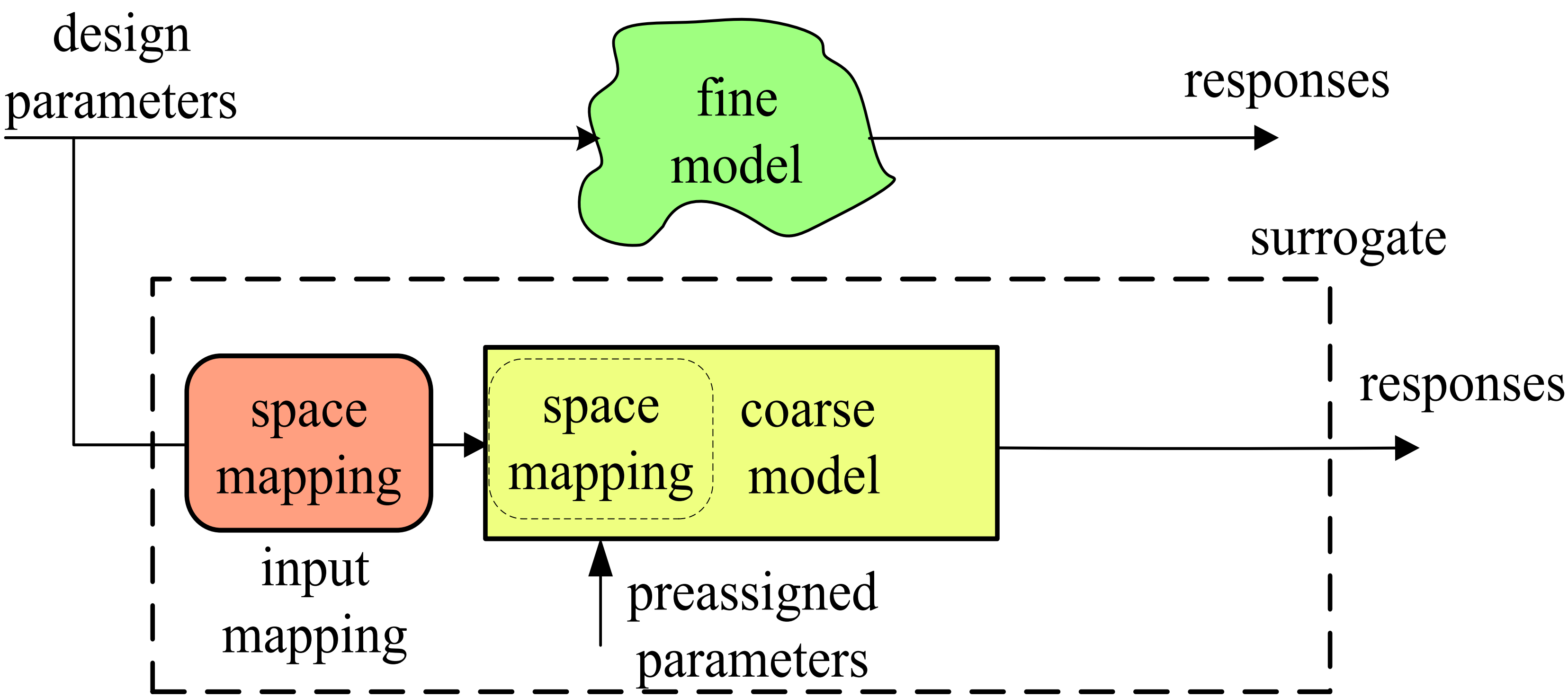
Input Space Mappings (Surrogate)

(*Bandler et al., 1994-*)



expert engineering
knowledge helpful
(few designable
variables)

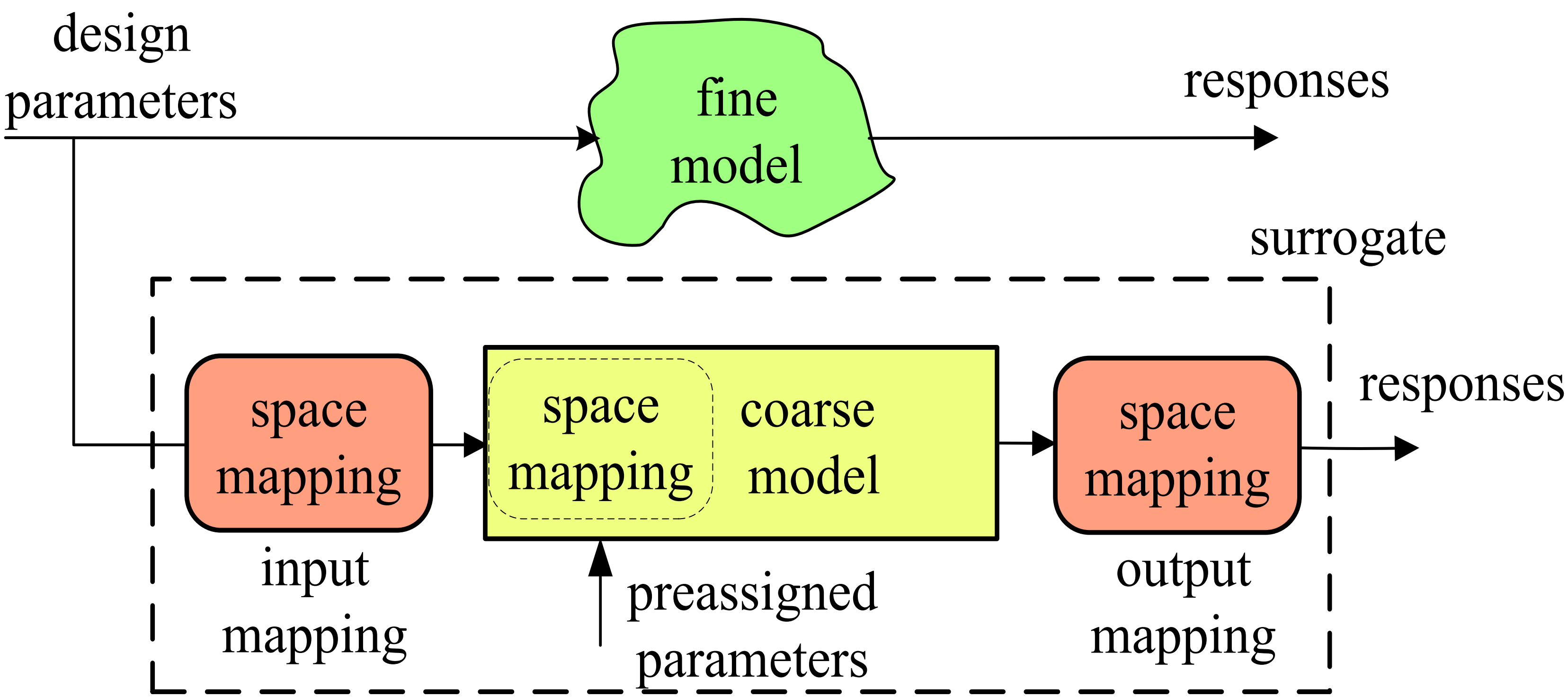
Implicit and Input Space Mappings (Surrogate) *(Bandler et al., 2003-)*



expert engineering knowledge helpful (few designable variables)

expertise helpful in “tuning the surrogate” (many possibilities, e.g., dielectric constant)

Implicit, Input and Output Space Mappings (Surrogate)
(Bandler et al., 2003-)

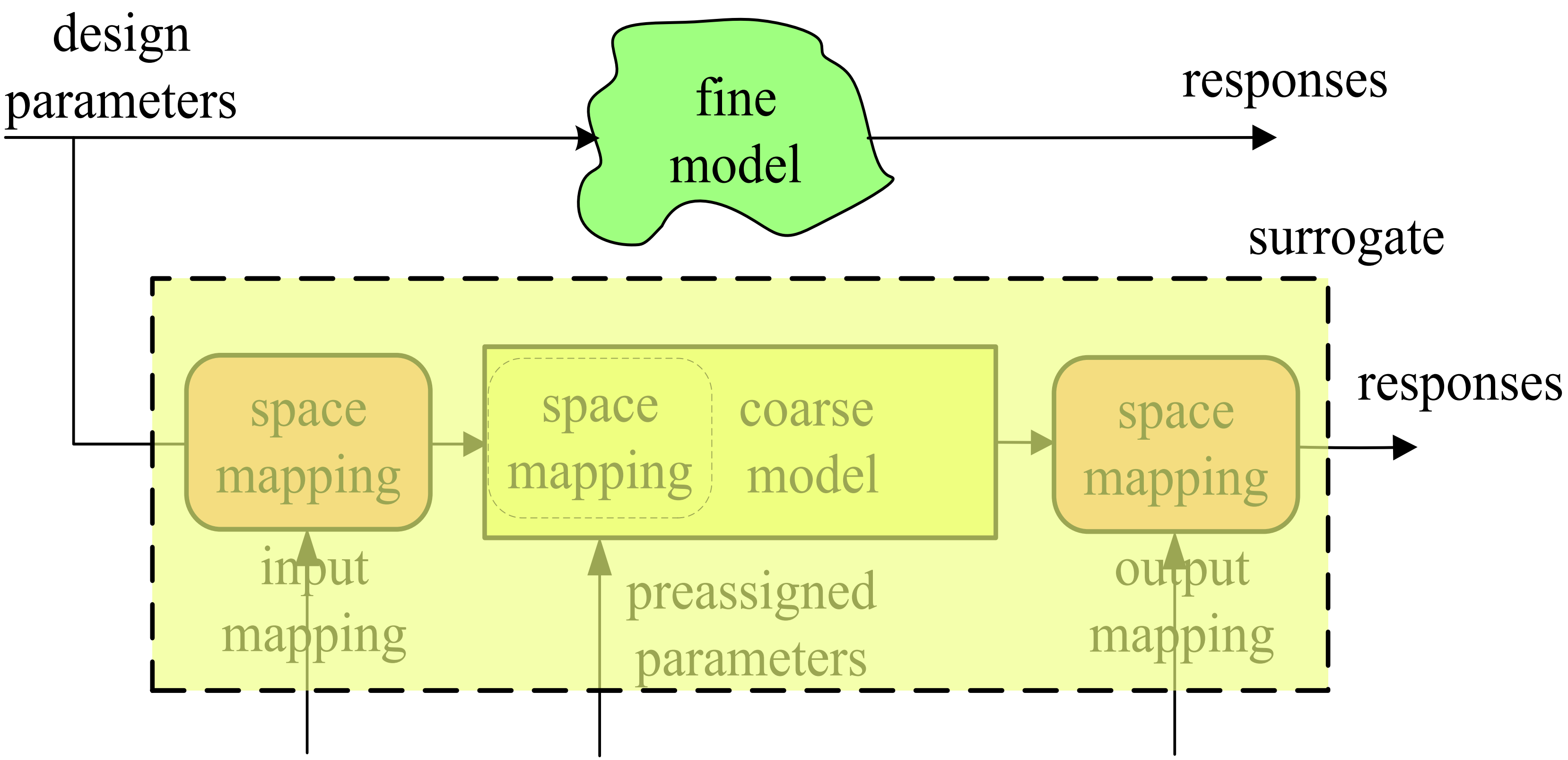


expert engineering knowledge helpful (few designable variables)

expertise helpful in "tuning the surrogate" (many possibilities, e.g., dielectric constant)

engineering expertise perhaps less necessary (many output variables)

Implicit, Input and Output Space Mappings (Surrogate)
(*Bandler et al., 2004-*)



but all types of space mapping can be viewed as special cases of <u>implicit</u> space mapping

Generalized Implicit Space Mapping (Surrogate)
(*Koziel, Bandler, and Madsen, 2006*)

define the *i*th surrogate $\boldsymbol{R}_s^{(i)}$ as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}) + \boldsymbol{d}^{(i)} + \boldsymbol{E}^{(i)} \cdot (\boldsymbol{x} - \boldsymbol{x}^{(i)})$$

with $\boldsymbol{A}^{(i)}$, $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ and $\boldsymbol{G}^{(i)}$ determined using parameter extraction

$$(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}, \boldsymbol{G}^{(i)}) =$$

$$\arg \min_{(\boldsymbol{A},\boldsymbol{B},\boldsymbol{c},\boldsymbol{x}_p)} \Big(\sum_{k=0}^{i} w_k \| \boldsymbol{R}_f(\boldsymbol{x}^{(k)}) - \boldsymbol{A} \cdot \boldsymbol{R}_c(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \|$$

$$+ \sum_{k=0}^{i} v_k \| \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(k)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \| \Big)$$

and

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

$$\boldsymbol{E}^{(i)} = \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(i)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

Generalized Implicit Space Mapping (Surrogate)

(*Koziel, Bandler, and Madsen, 2006*)

define the ith surrogate $\boldsymbol{R}_s^{(i)}$ as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\underbrace{\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}}_{\text{input mapping}}) + \boldsymbol{d}^{(i)} + \boldsymbol{E}^{(i)} \cdot (\boldsymbol{x} - \boldsymbol{x}^{(i)})$$

with $\boldsymbol{A}^{(i)}$, $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ and $\boldsymbol{G}^{(i)}$ determined using parameter extraction

$$(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}, \boldsymbol{G}^{(i)}) =$$

$$\arg \min_{(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{c}, \boldsymbol{x}_p)} \Big(\sum_{k=0}^{i} w_k \| \boldsymbol{R}_f(\boldsymbol{x}^{(k)}) - \boldsymbol{A} \cdot \boldsymbol{R}_c(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \|$$

$$+ \sum_{k=0}^{i} v_k \| \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(k)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \| \Big)$$

and

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

$$\boldsymbol{E}^{(i)} = \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(i)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

SUSTech

Generalized Implicit Space Mapping (Surrogate)

(*Koziel, Bandler, and Madsen, 2006*)

define the ith surrogate $\boldsymbol{R}_s^{(i)}$ as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boxed{\boldsymbol{A}^{(i)}} \cdot \boldsymbol{R}_c(\underbrace{\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}}_{\textbf{input mapping}}) + \underbrace{\boldsymbol{d}^{(i)} + \boldsymbol{E}^{(i)} \cdot (\boldsymbol{x} - \boldsymbol{x}^{(i)})}_{\textbf{output mapping}}$$

with $\boldsymbol{A}^{(i)}$, $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ and $\boldsymbol{G}^{(i)}$ determined using parameter extraction

$$(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}, \boldsymbol{G}^{(i)}) =$$

$$\arg \min_{(\boldsymbol{A},\boldsymbol{B},\boldsymbol{c},\boldsymbol{x}_p)} \Big(\sum_{k=0}^{i} w_k \, \| \boldsymbol{R}_f(\boldsymbol{x}^{(k)}) - \boldsymbol{A} \cdot \boldsymbol{R}_c(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \|$$

$$+ \sum_{k=0}^{i} v_k \, \| \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(k)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \| \Big)$$

and

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

$$\boldsymbol{E}^{(i)} = \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(i)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

Generalized Implicit Space Mapping (Surrogate)

(*Koziel, Bandler, and Madsen, 2006*)

define the ith surrogate $\boldsymbol{R}_s^{(i)}$ as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\underbrace{\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}}_{\text{input mapping}}) + \underbrace{\boldsymbol{d}^{(i)} + \boldsymbol{E}^{(i)}(\boldsymbol{x} - \boldsymbol{x}^{(i)})}_{\text{output mapping}}$$

with $\boldsymbol{A}^{(i)}$, $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ and $\boldsymbol{G}^{(i)}$ determined using parameter extraction

$$(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}, \boldsymbol{G}^{(i)}) =$$

$$\arg \min_{(\boldsymbol{A},\boldsymbol{B},\boldsymbol{c},\boldsymbol{x}_p)} \Big(\sum_{k=0}^{i} w_k \, \| \underbrace{\boldsymbol{R}_f(\boldsymbol{x}^{(k)}) - \boldsymbol{A} \cdot \boldsymbol{R}_c(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)})}_{\text{matching function value}} \|$$

$$+ \sum_{k=0}^{i} v_k \, \| \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(k)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)}) \| \Big)$$

and

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

$$\boldsymbol{E}^{(i)} = \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(i)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

Generalized Implicit Space Mapping (Surrogate)

(*Koziel, Bandler, and Madsen, 2006*)

define the ith surrogate $\boldsymbol{R}_s^{(i)}$ as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\underbrace{\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}}_{\text{input mapping}}) + \underbrace{\boldsymbol{d}^{(i)} + \boldsymbol{E}^{(i)} \cdot (\boldsymbol{x} - \boldsymbol{x}^{(i)})}_{\text{output mapping}}$$

with $\boldsymbol{A}^{(i)}$, $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ and $\boldsymbol{G}^{(i)}$ determined using parameter extraction

$$(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}, \boldsymbol{G}^{(i)}) =$$

$$\arg \min_{(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{c}, \boldsymbol{x}_p)} \Big(\sum_{k=0}^{i} w_k \, \| \underbrace{\boldsymbol{R}_f(\boldsymbol{x}^{(k)}) - \boldsymbol{A} \cdot \boldsymbol{R}_c(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)})}_{\text{matching function value}} \|$$

$$+ \sum_{k=0}^{i} v_k \, \| \underbrace{\boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(k)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}, \boldsymbol{x}_p + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(k)})}_{\text{matching derivatives}} \| \Big)$$

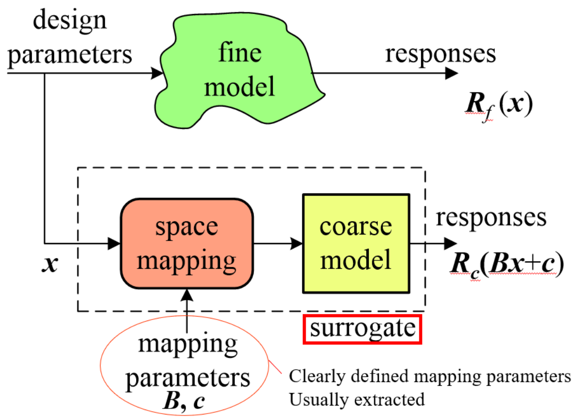
and

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

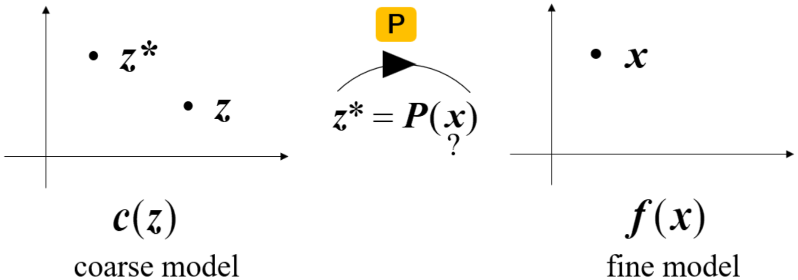
$$\boldsymbol{E}^{(i)} = \boldsymbol{J}_{\boldsymbol{R}_f}(\boldsymbol{x}^{(i)}) - \boldsymbol{J}_{\boldsymbol{R}_s}(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)} + \boldsymbol{G}^{(i)} \cdot \boldsymbol{x}^{(i)})$$

Surrogate-Based SM vs. Original or Aggressive SM

Surrogate-based SM:
- A **surrogate** model is available always.
- Optimization of surrogate may be necessary.



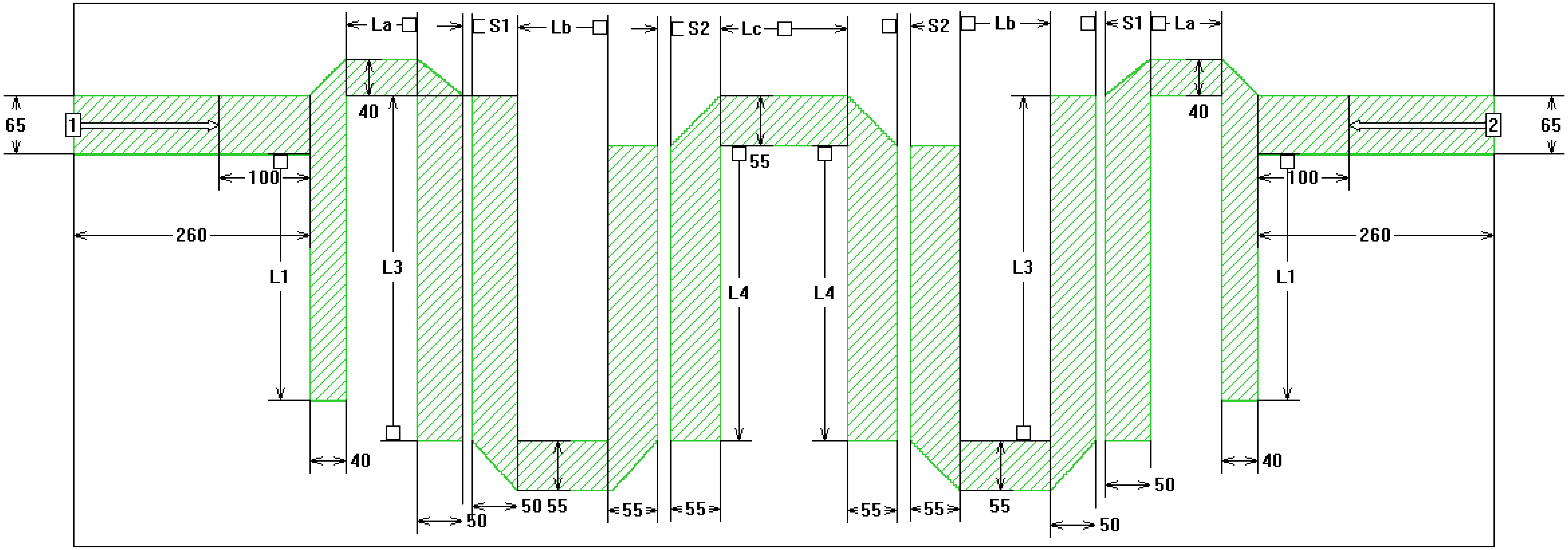
Original or Aggressive SM:
- No surrogate.
- Surrogate optimization is not necessary.



if we find the mapping P, using its inverse, we can find an x corresponding to z^*

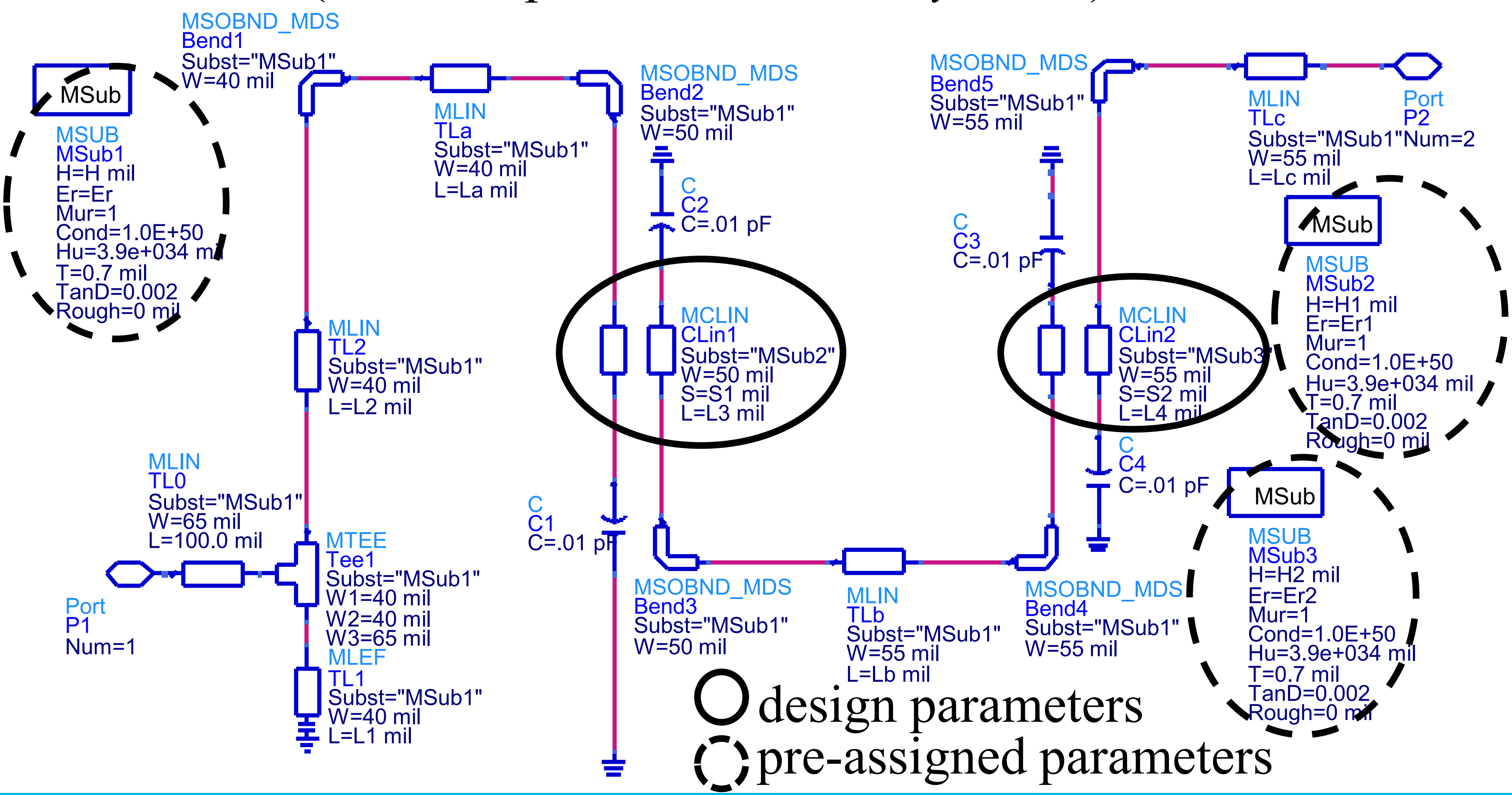
Microstrip Hairpin Filter: Implicit Space Mapping (Surrogate) (*Cheng et al., 2008*)

fine model represented electromagnetically in Sonnet ***em***



Microstrip Hairpin Filter: Implicit Space Mapping (Surrogate) (*Cheng et al., 2008*)

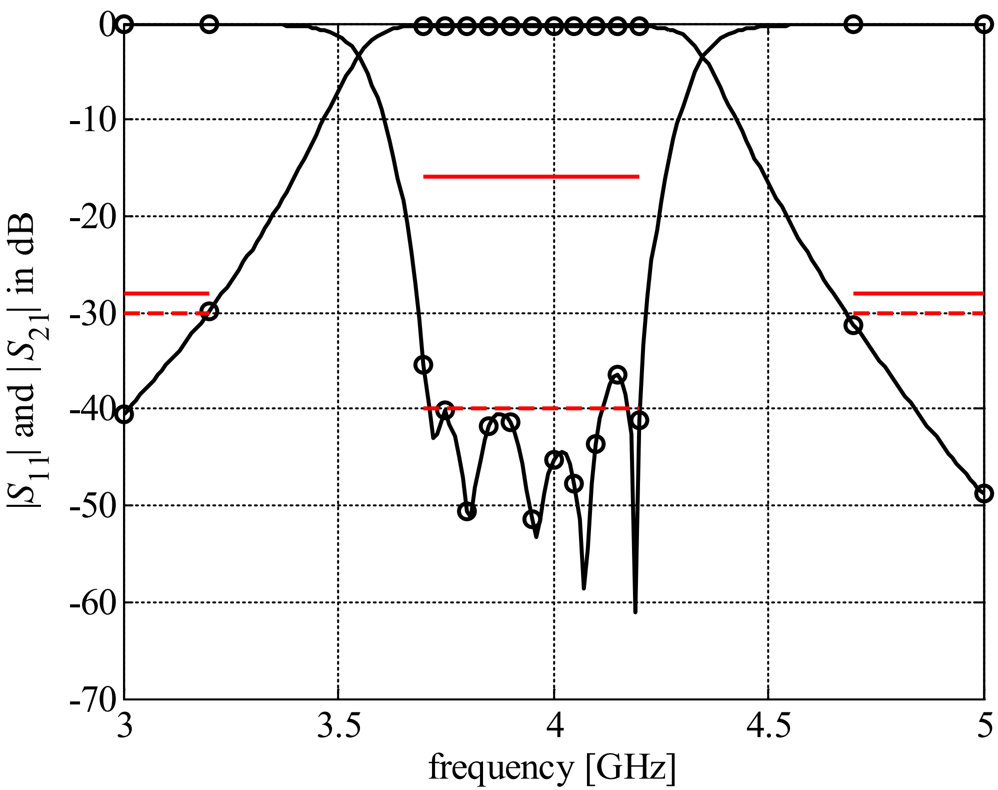
coarse model ("half" implementation, *Brady, 2002*)



Microstrip Hairpin Filter: Implicit SM (Surrogate)

(*Cheng et al., 2008*)

fine model after 3 implicit SM iterations and one output SM

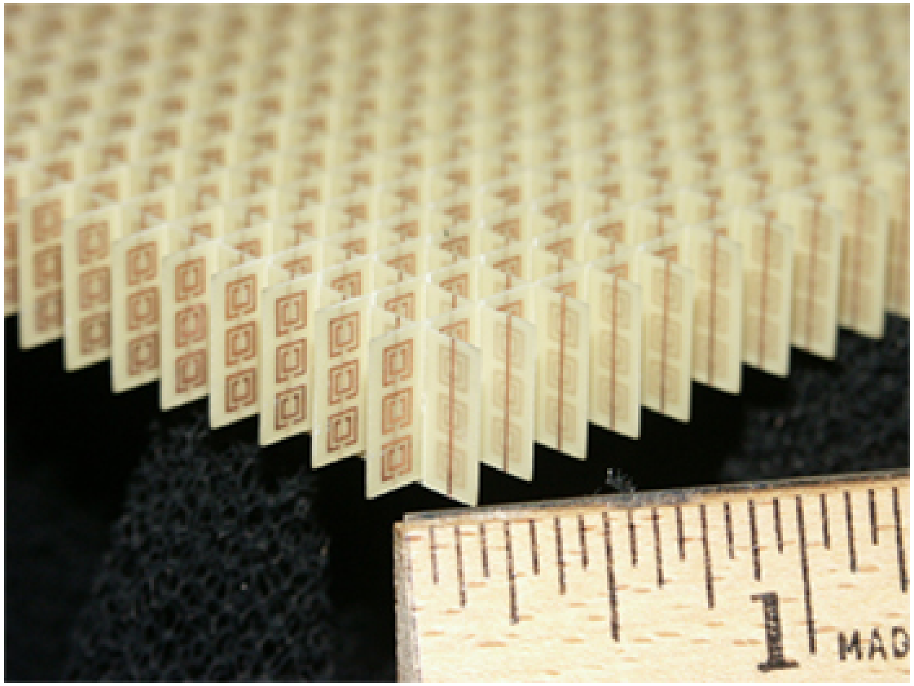


desired specification (—) and the tightened specification (---)

Space Mapping Design of Novel Material

many sub-wavelength cells

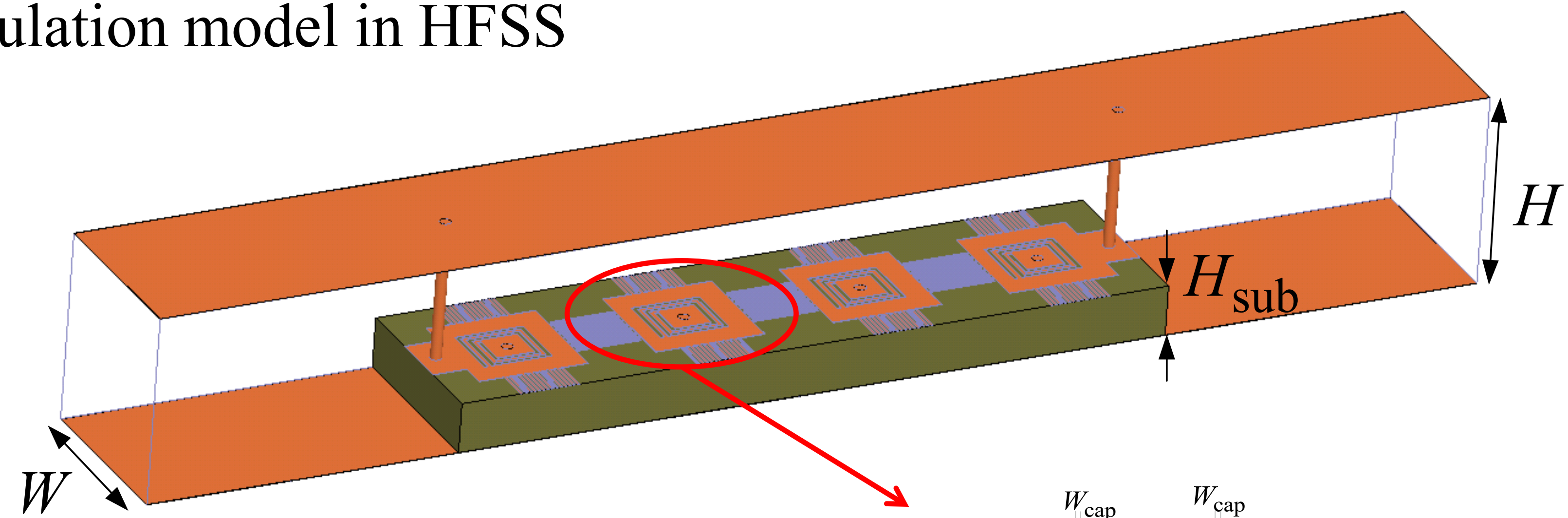
electrically large arrays

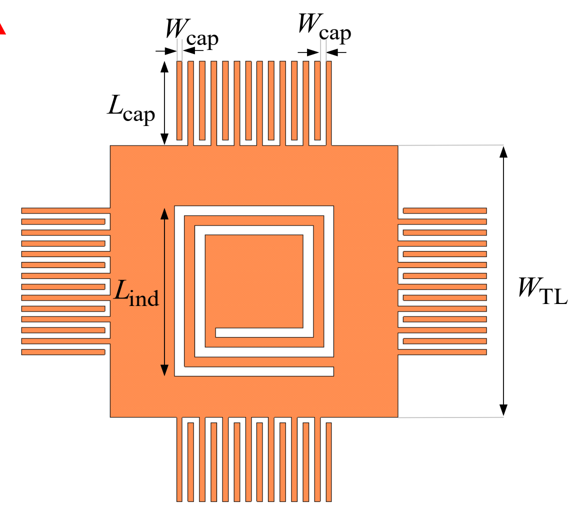


https://en.wikipedia.org/wiki/Metamaterial

Transmission-Line-Based Negative Refractive Index Lens
(*Zhu and Eleftheriades, 2008*)

simulation model in HFSS

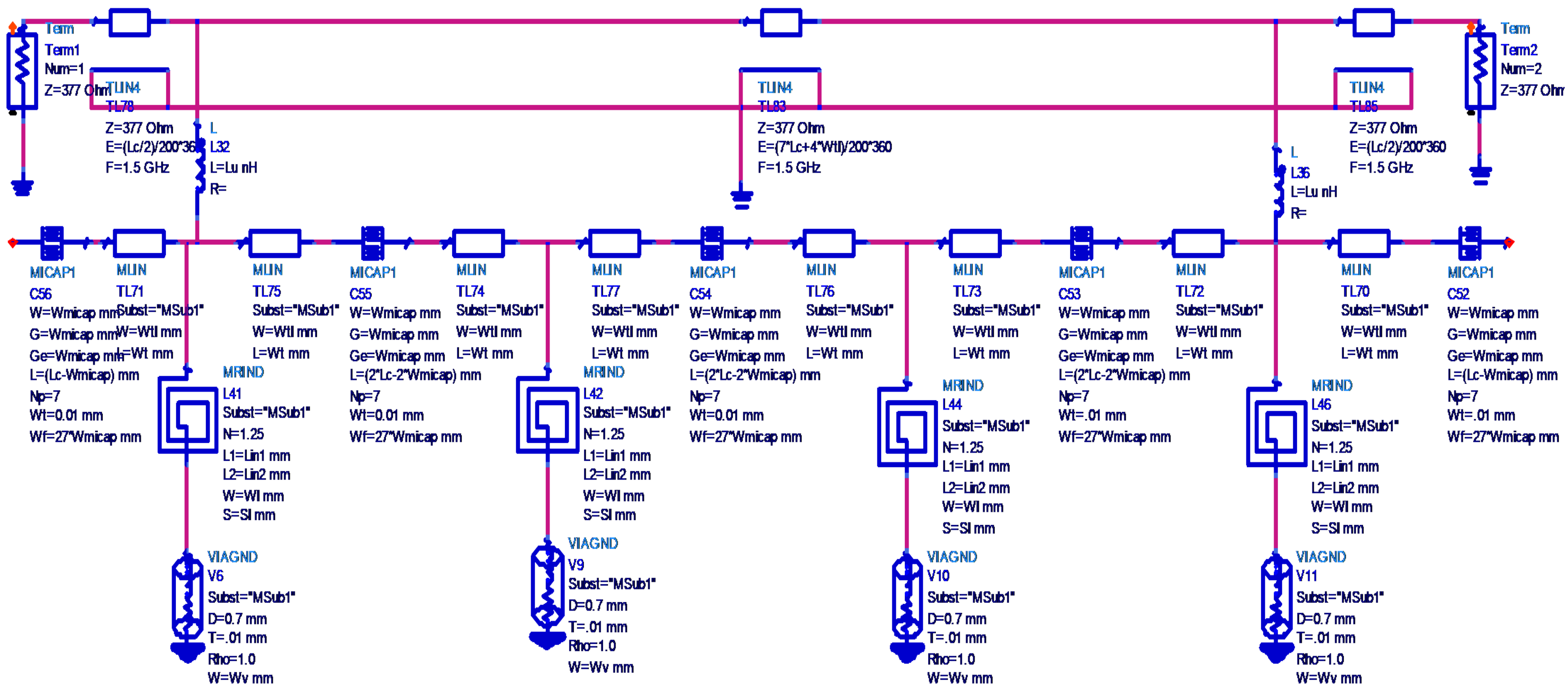




PEC walls on top and bottom
PMC walls on both sides
(infinitely large structure
in the transverse direction)

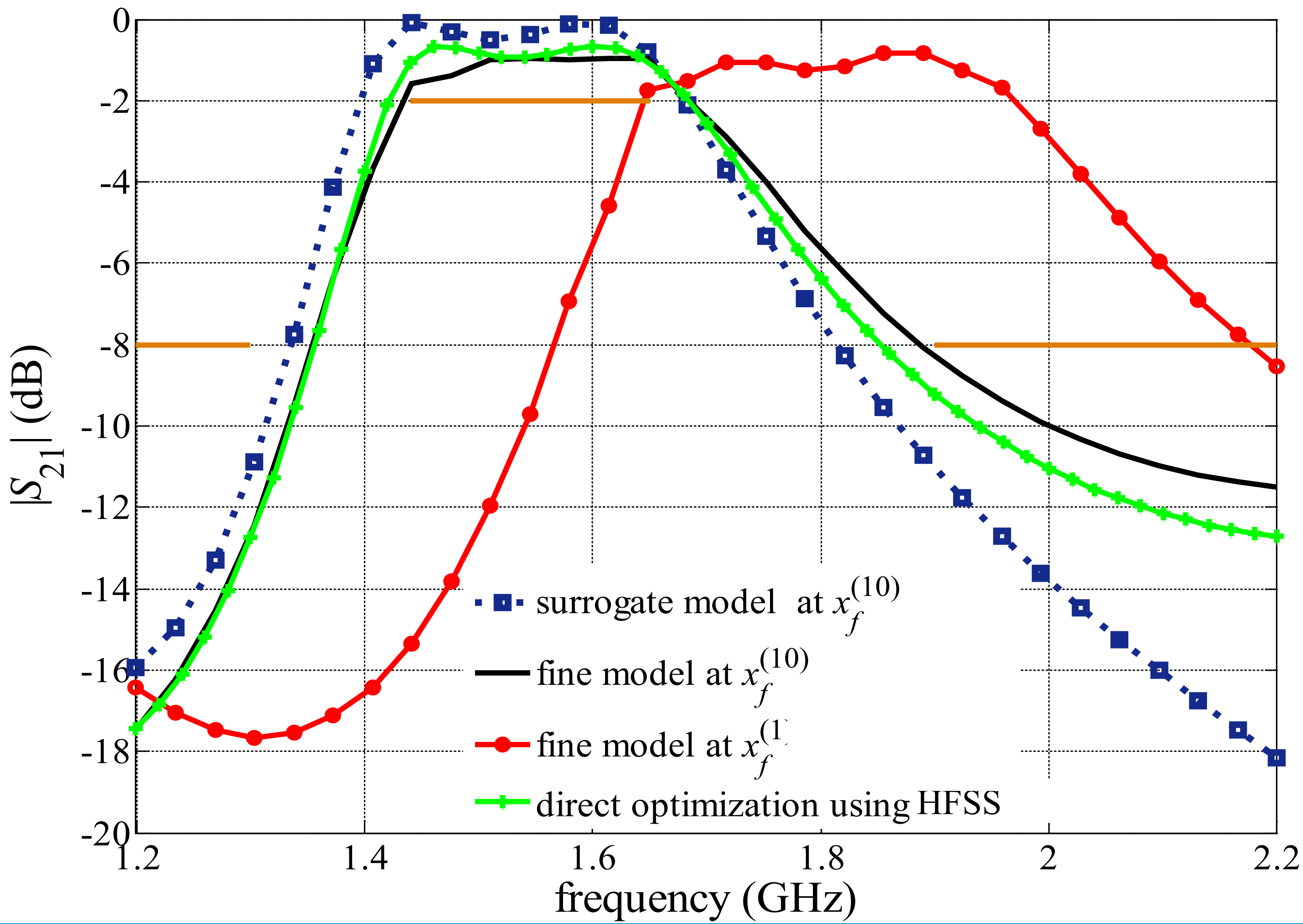
Transmission-Line-Based Negative Refractive Index Lens Coarse Model *(Khalatpour et al., 2011)*

Agilent ADS schematic



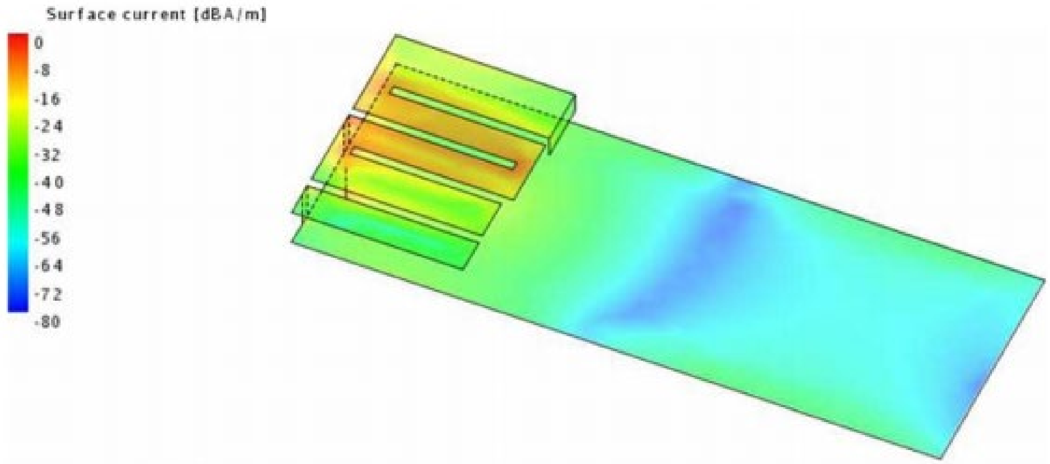
Responses Obtained After Design Framework Terminates

(Khalatpour et al., 2011)

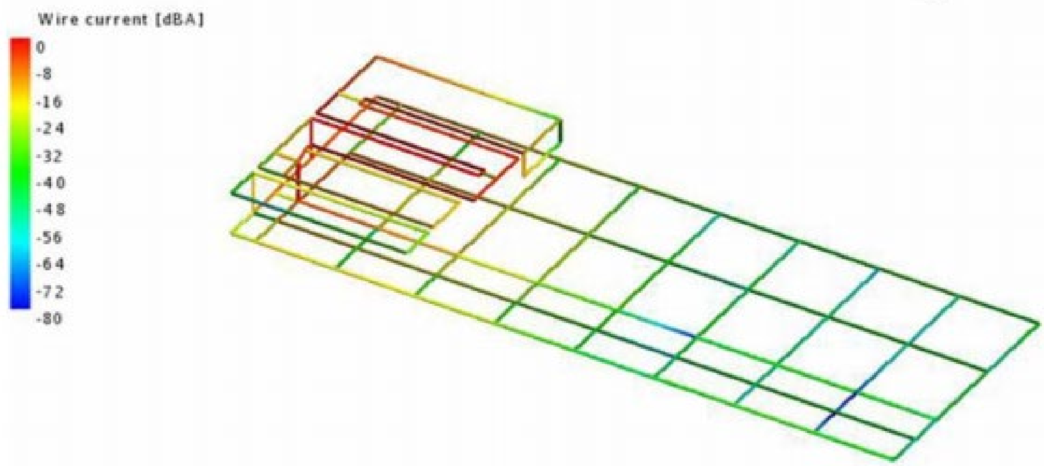


Space Mapping Design of Handset Antennas
(*Tu et al., 2013*)

internal dual-band patch antenna



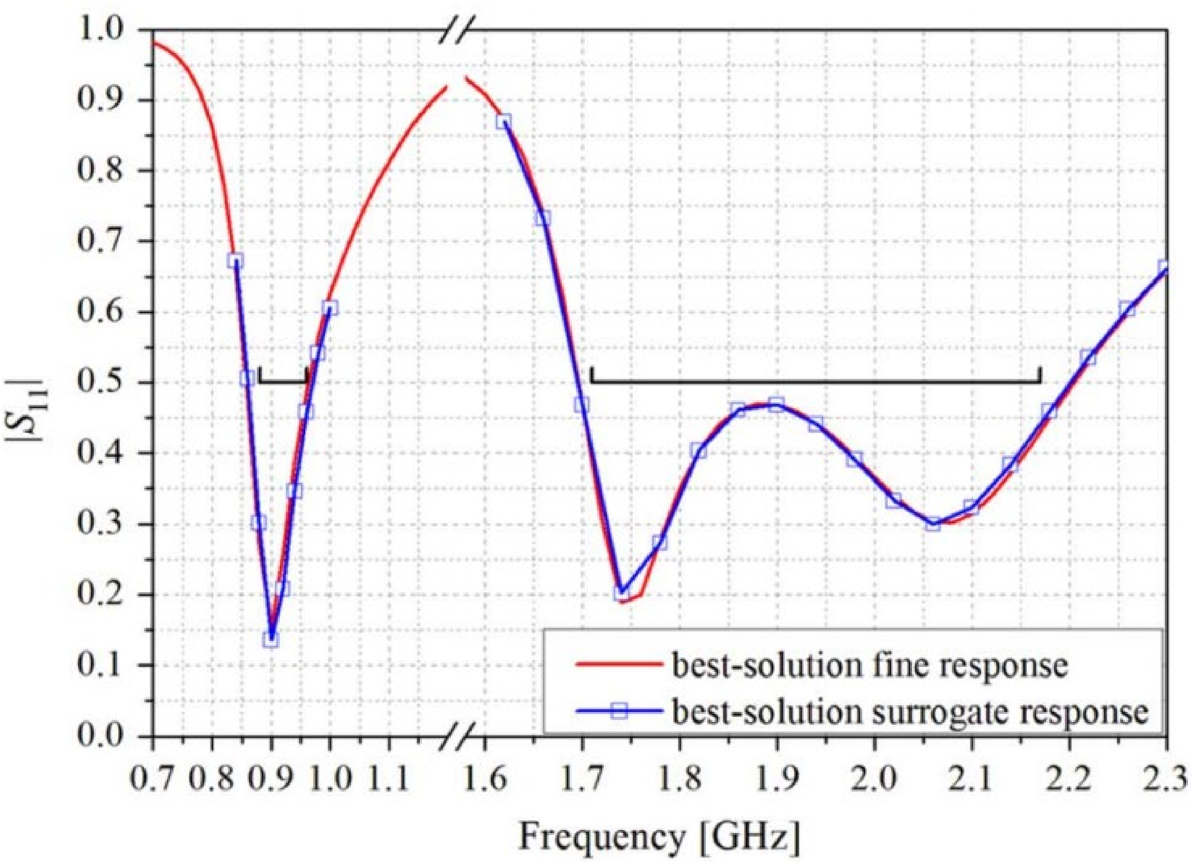
fine model：
fine mesh
simulation time:
9 min 40 sec



coarse model:
thin-wire model and
coarse mesh ground
simulation time:
17 secs

Space Mapping Design of Handset Antennas
(*Tu et al., 2013*)

internal dual-band patch antenna



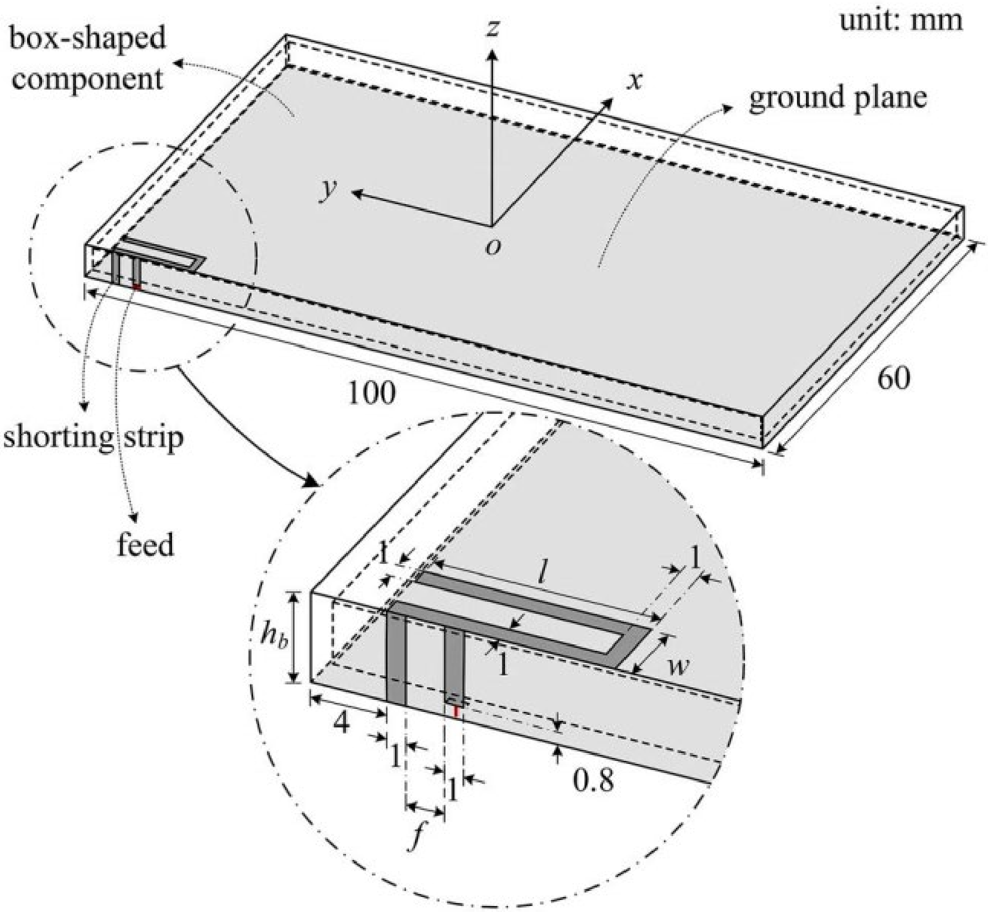
implicit and output space mapping algorithm

6 iterations

7 fine model evaluations

Space Mapping Design of Handset Antennas
(*Tu et al., 2013*)

arm-folded PIFA

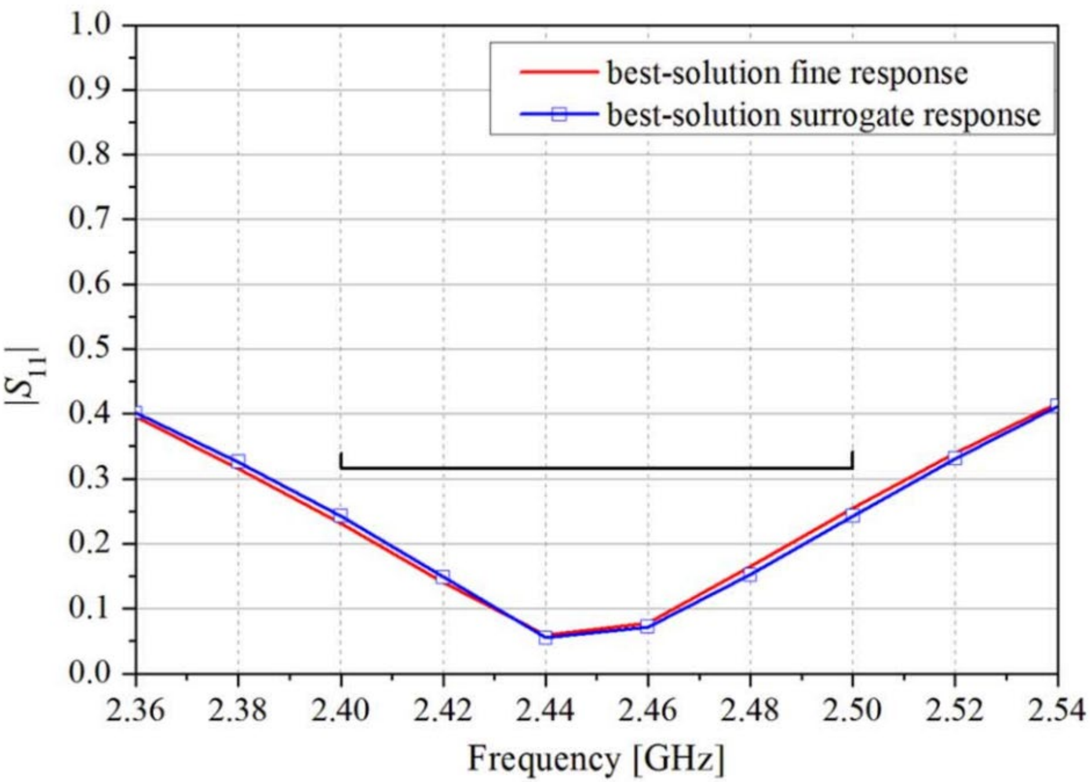


fine model：
fine mesh
simulation time:
35 min

coarse model:
thin-wire model and
infinite ground plane
without substrate
simulation time：
3 secs

Space Mapping Design of Handset Antennas
(*Tu et al., 2013*)

arm-folded PIFA



implicit and output space mapping algorithm
2 iterations
3 fine model evaluations

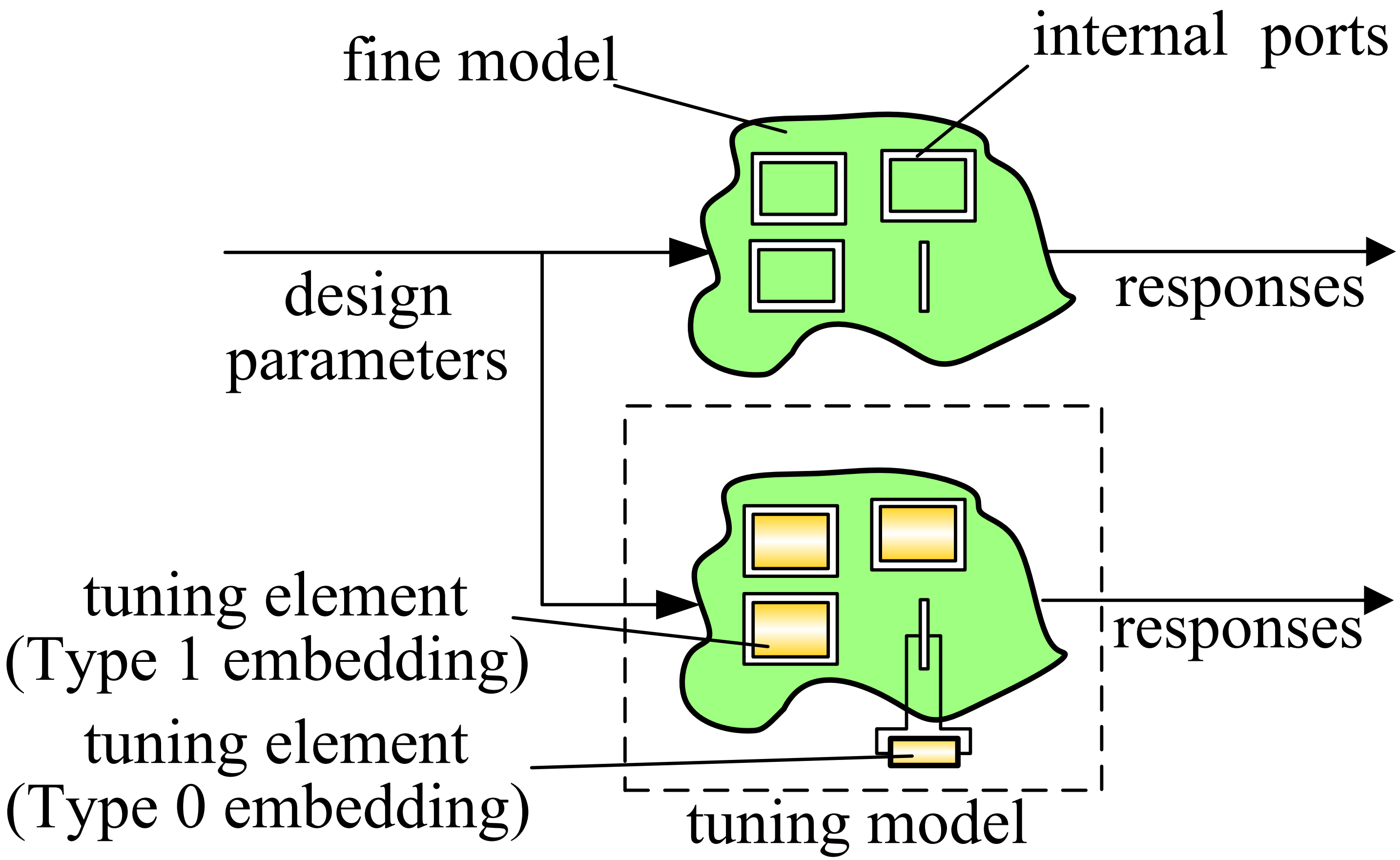
Space Mapping Design of Handset Antennas

"By using a space-mapping-based modeling and design technique for handset antennas, it is possible to achieve significant time savings over direct EM-based optimization."

Nancy Friedrich

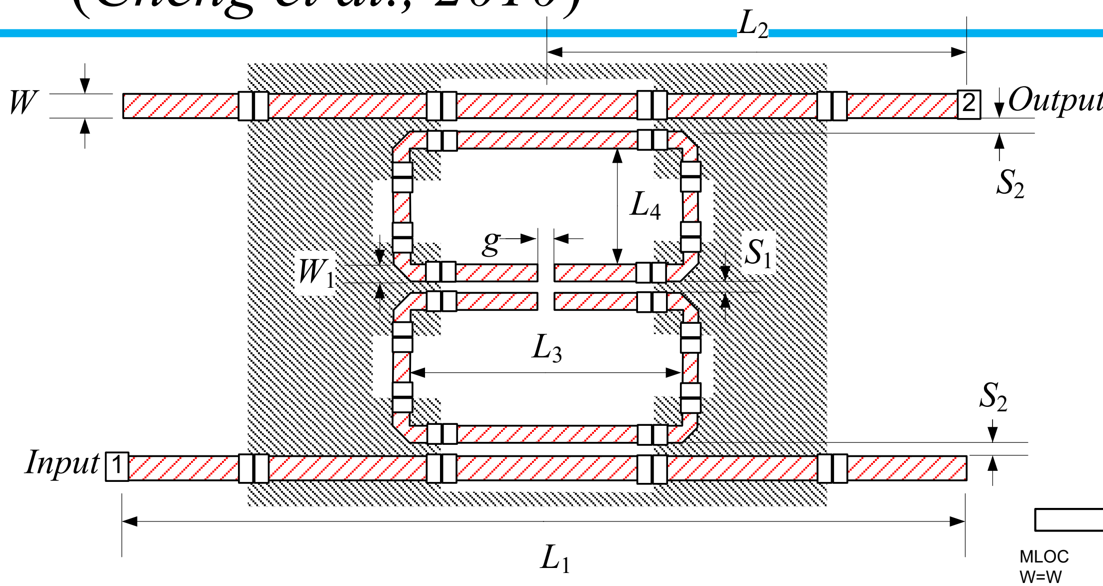
Editor-in-Chief, Microwaves & RF

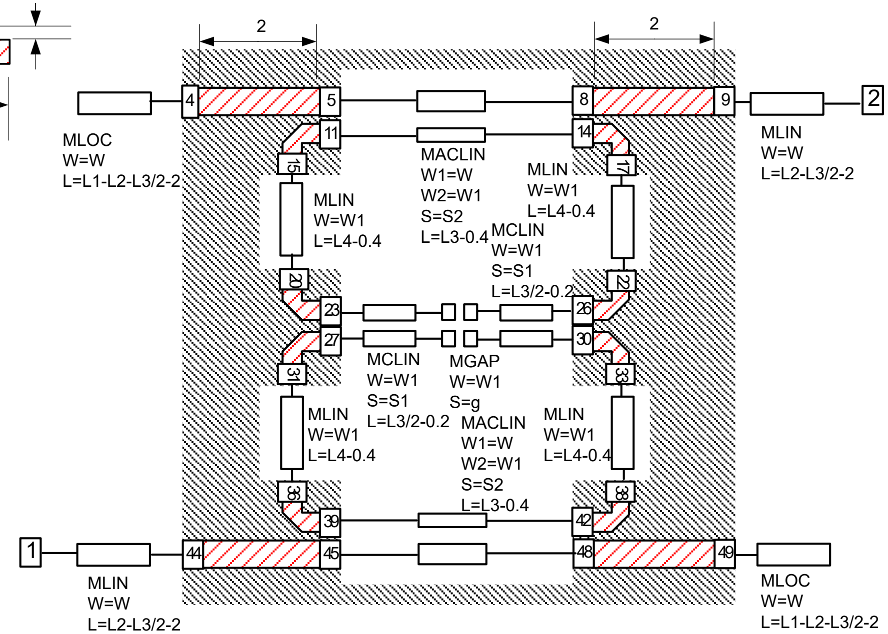
Tuning Space Mapping (TSM): Type 1 and Type 0 Embedding
(*Cheng et al., 2010*)



Open-loop Ring Resonator Bandpass Filter (Type 1)

(*Cheng et al., 2010*)





design parameters

$\boldsymbol{x} = [L_1 \;\; L_2 \;\; L_3 \;\; L_4 \;\; S_1 \;\; S_2 \;\; g]^T$ mm

specifications

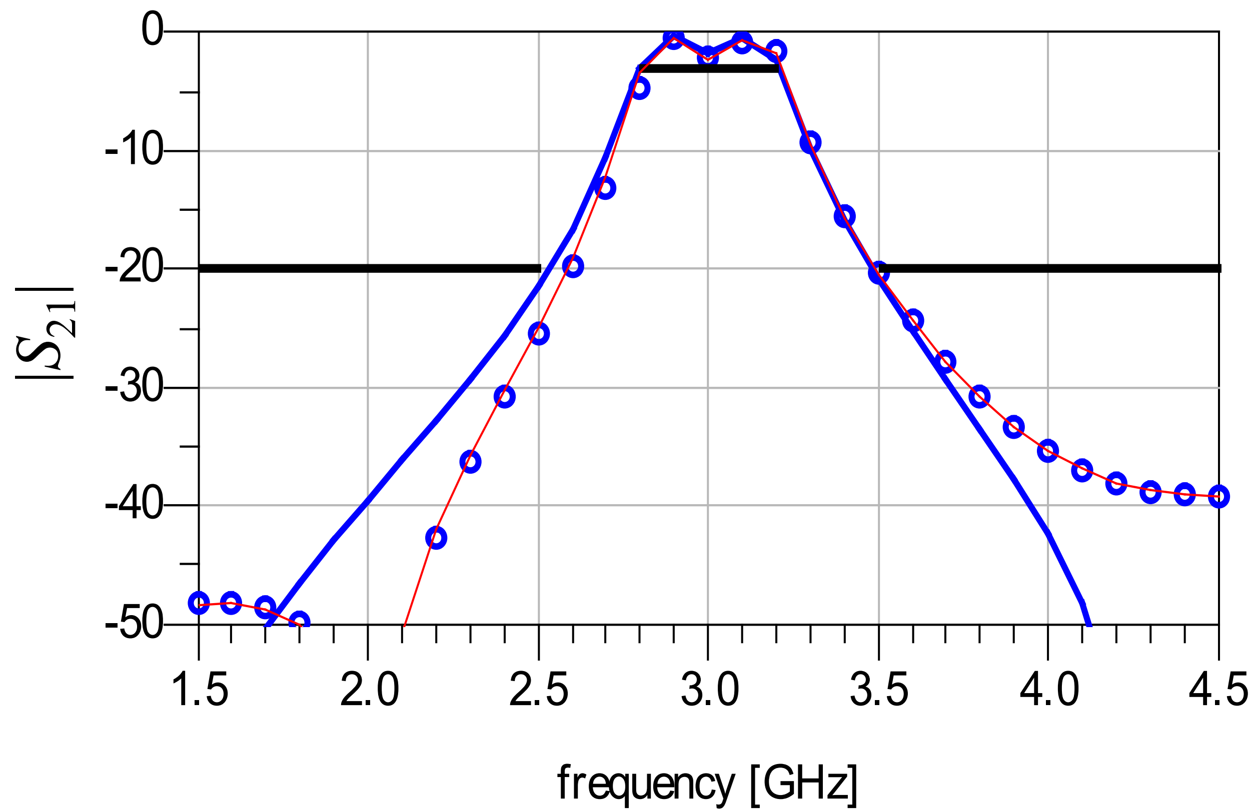
$|S_{21}| \geq -3$ dB for 2.8–3.2 GHz

$|S_{21}| \leq -20$ dB for 1.5–2.5 GHz

$|S_{21}| \leq -20$ dB for 3.5–4.5 GHz

Open-loop Ring Resonator Bandpass Filter (Type 1)
(*Cheng et al., 2010*)

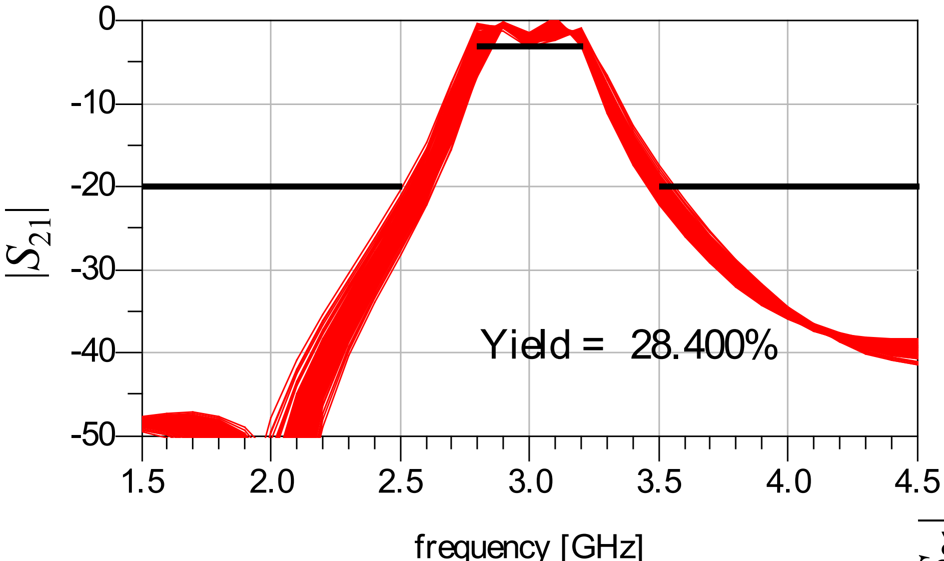
tuning model after two iterations (—), fine model (○), response corrected surrogate (—)



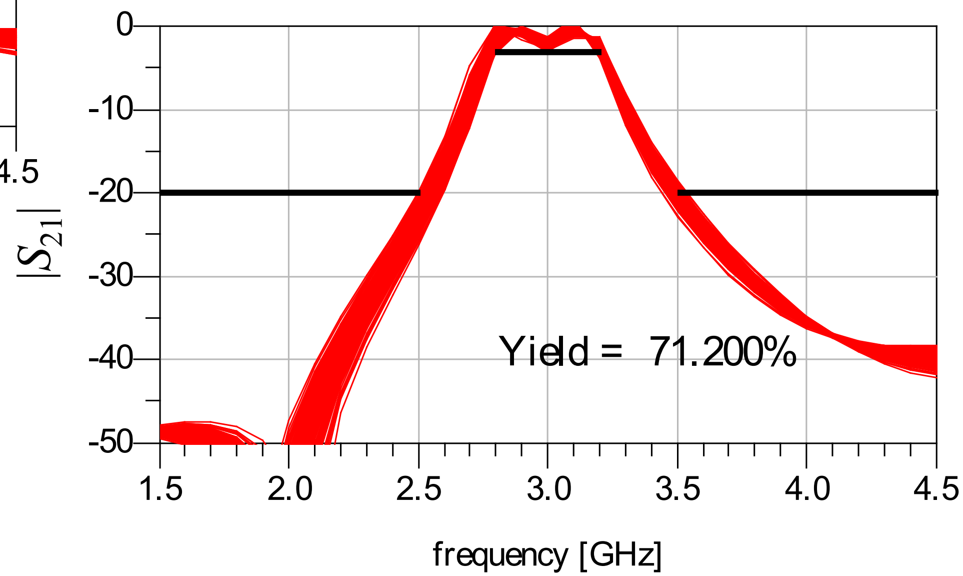
Open-loop Ring Resonator Bandpass Filter (Type 1)

(*Cheng et al., 2010*)

response corrected surrogate
before yield optimization



response corrected surrogate
after yield optimization

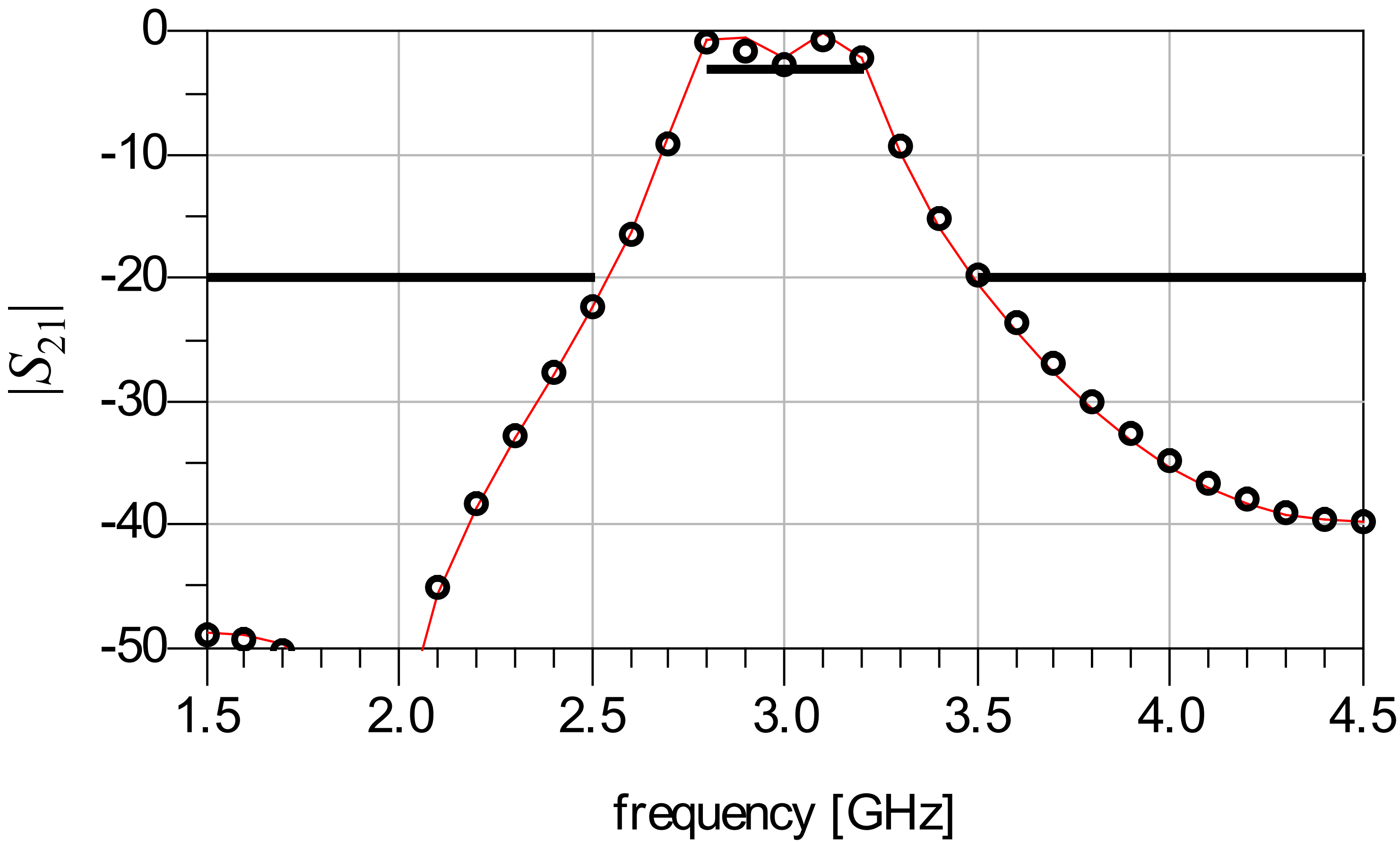


0.2% of variation
for the dielectric constant
20 micron of standard deviation
for the physical dimensions

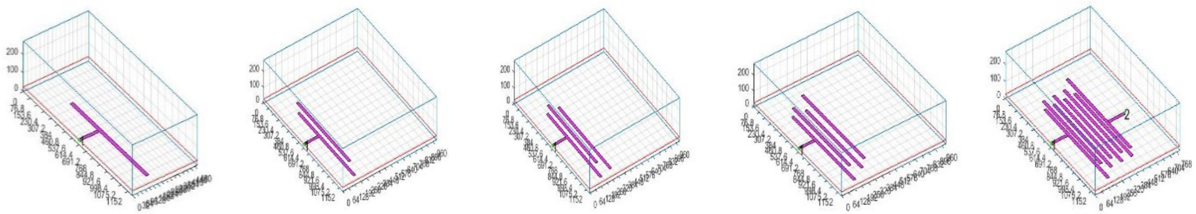
Open-loop Ring Resonator Bandpass Filter (Type 1)

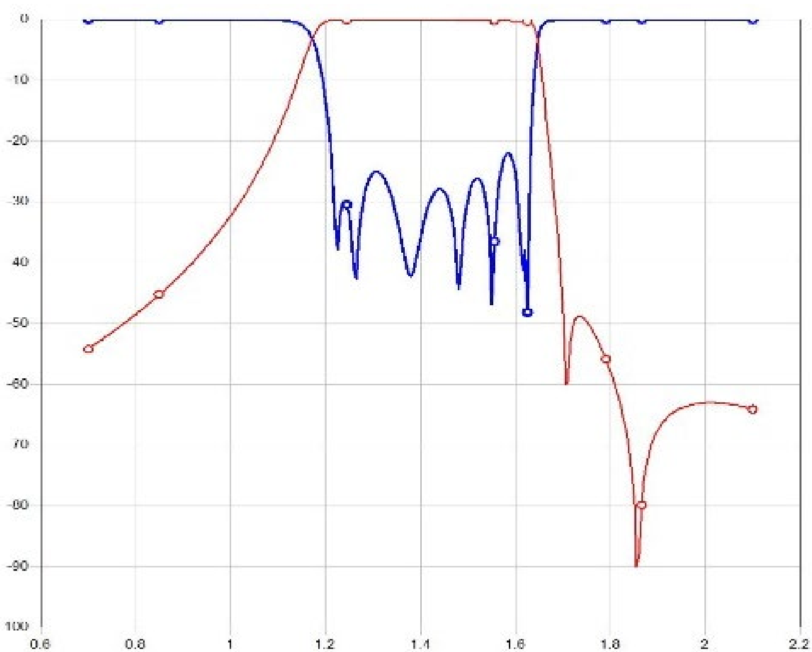
(*Cheng et al., 2010*)

response corrected surrogate at design center (—)
and final validation on a finer grid (○)

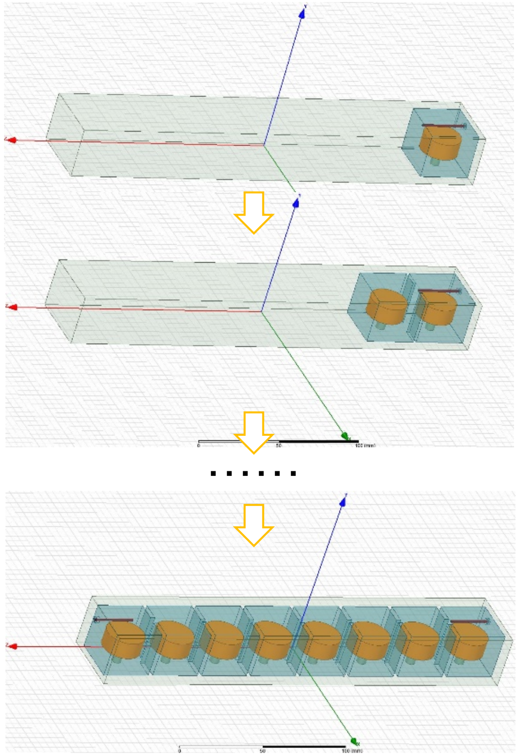


Progressive Space Mapping
(*Fan et al., 2017*)





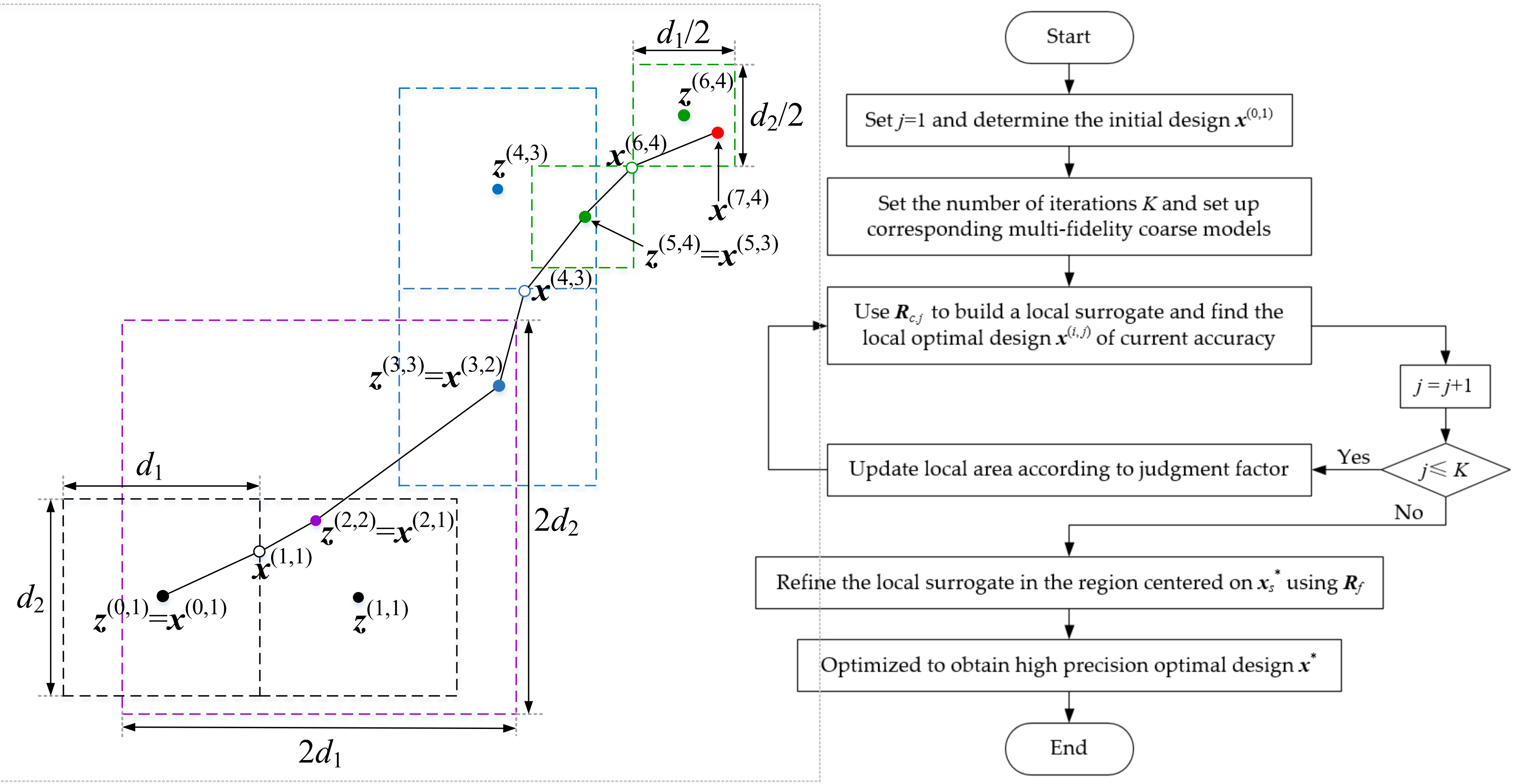
8th order Interdigital



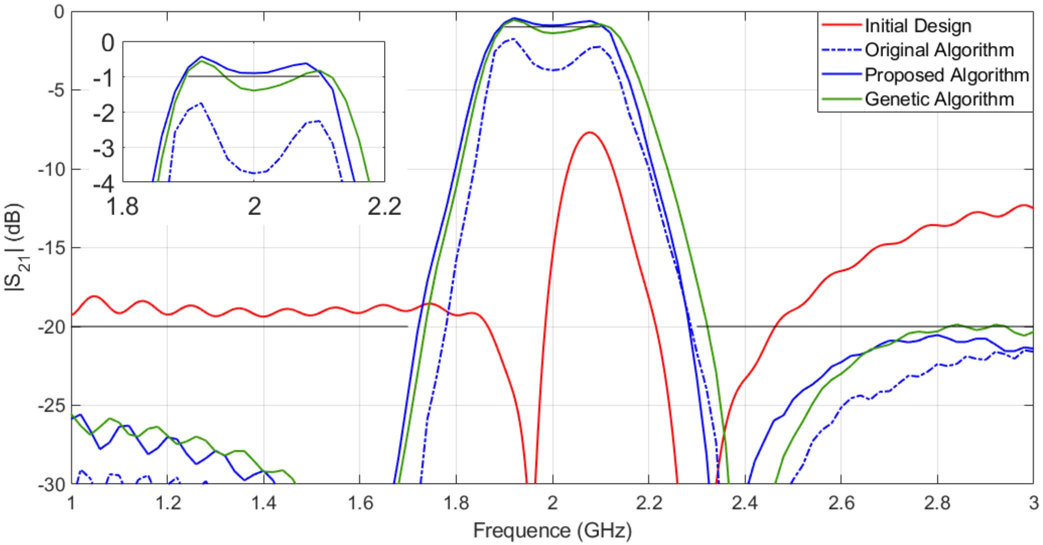
dielectric resonator

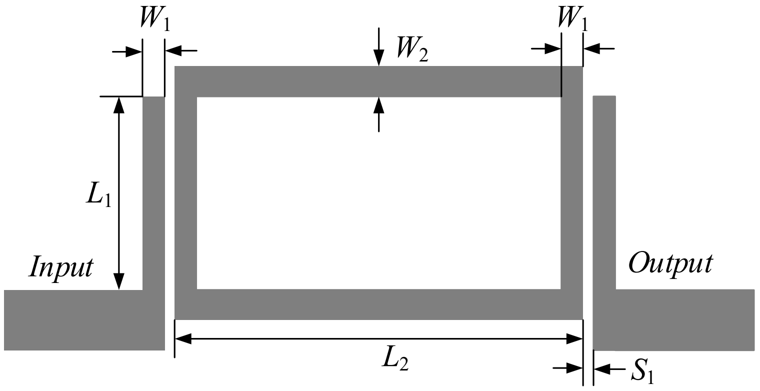
Multi-fidelity Local Surrogates and Space Mapping

(Song et al., 2019)



Multi-fidelity Local Surrogates: Microstrip Filter Design *(Song et al., 2019)*

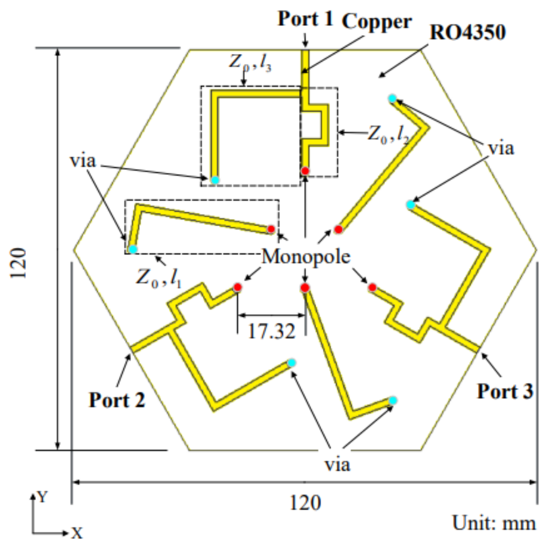




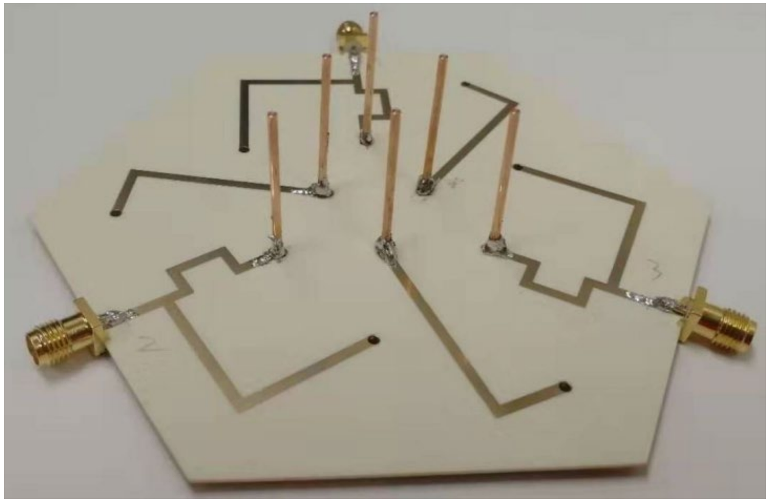
The computational saving of the proposed method is 95%

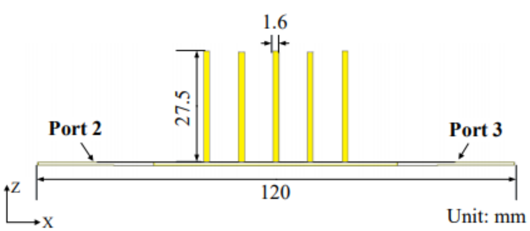
Method	Required model evaluation	Number of model evaluations	Optimization time: Absolute (min)	Optimization time: Relative to fine model time	Specifications satisfied
Direct optimization	Fine model	397	1985	397	No
Original algorithm	Coarse model Fine model Total optimization time	55 2 N/A	71.5 10 81.5	14.3 2 16.3	No
Proposed algorithm	Coarse model 1 Coarse model 2 Fine model Total optimization time	22 44 2 N/A	13.2 57.2 10 **80.4**	2.6 11.4 2 **16**	**Yes**

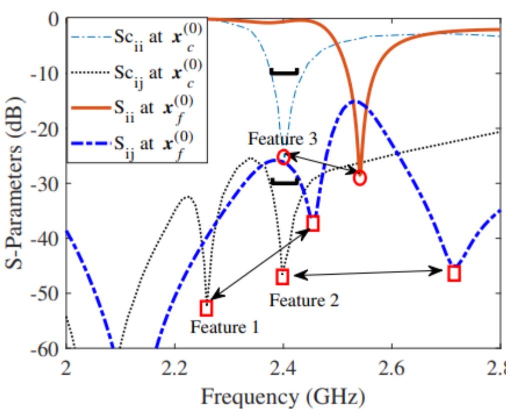
MIMO Antenna Decoupling Network Design using Space Mapping *(Jiang et al., 2021)*

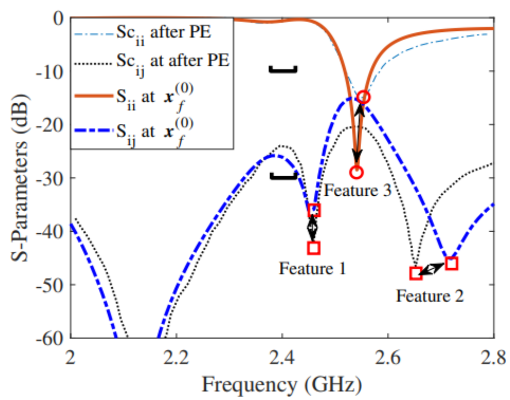


(a)





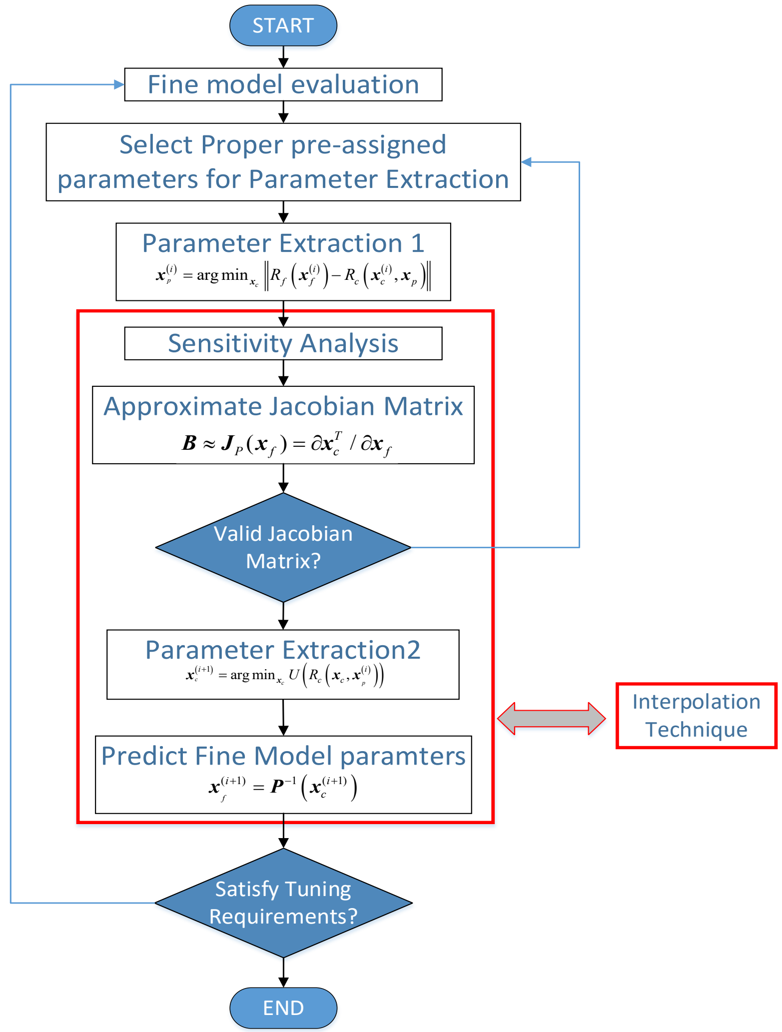




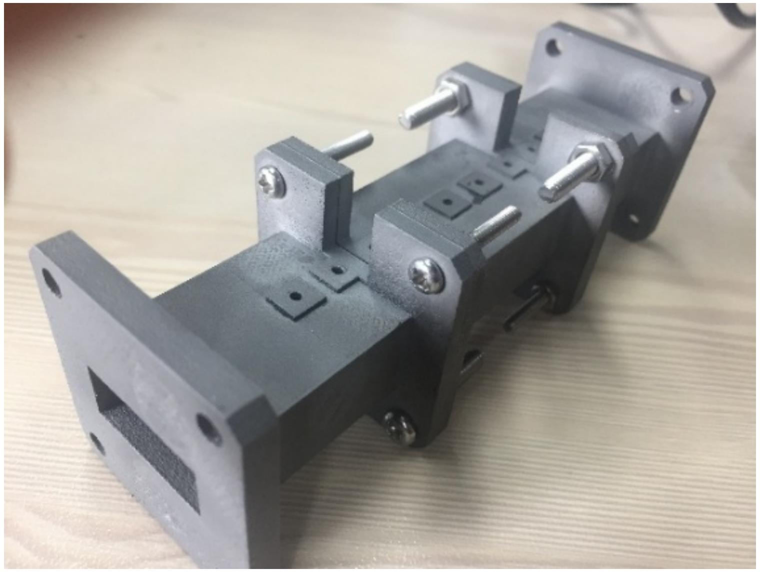
F. Jiang, Z. Zhang, Q.S. Cheng, S. Shen, C.-Y. Chiu, and R. Murch, "An efficient optimization scheme for MIMO antenna decoupling networks using space mapping techniques" IEEE Journal on Multiscale and Multiphysics Computational Techniques, vol. 6, pp. 56-61, May 2021.

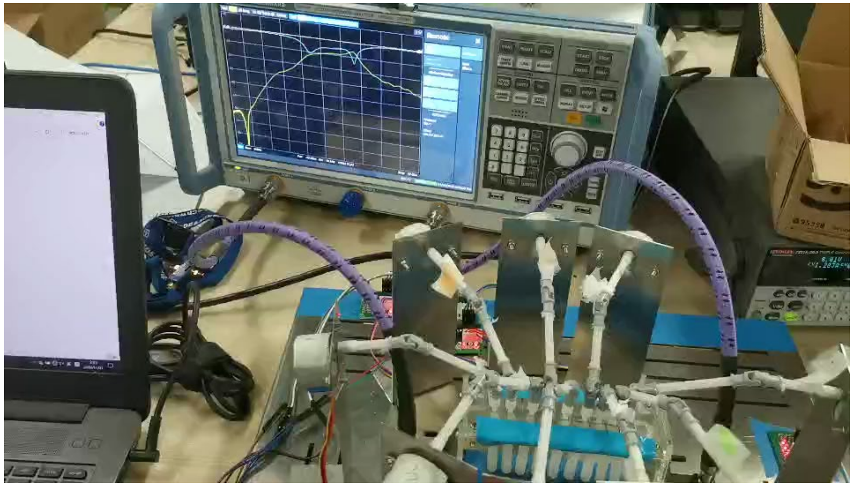
Space Mapping Post-Production Tuning Method
(Li et al., 2020)

- Surrogate model
  - A qualified surrogate model should be able to approximate the physical phenomenon of the fine model
- Parameters
  - Tuning parameters
  - Pre-assigned parameters
- Fine model
  - Tunable waveguide

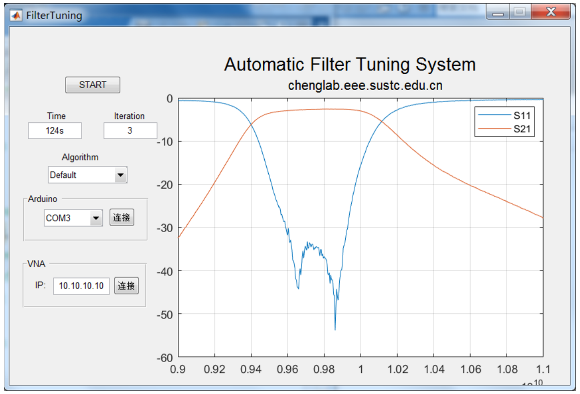


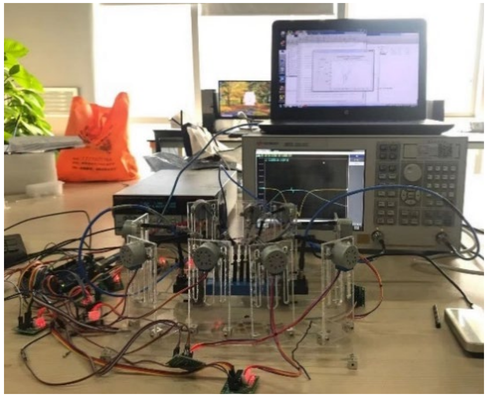
Space Mapping Design and Tuning of Waveguide Filter
(Li et al., 2020)



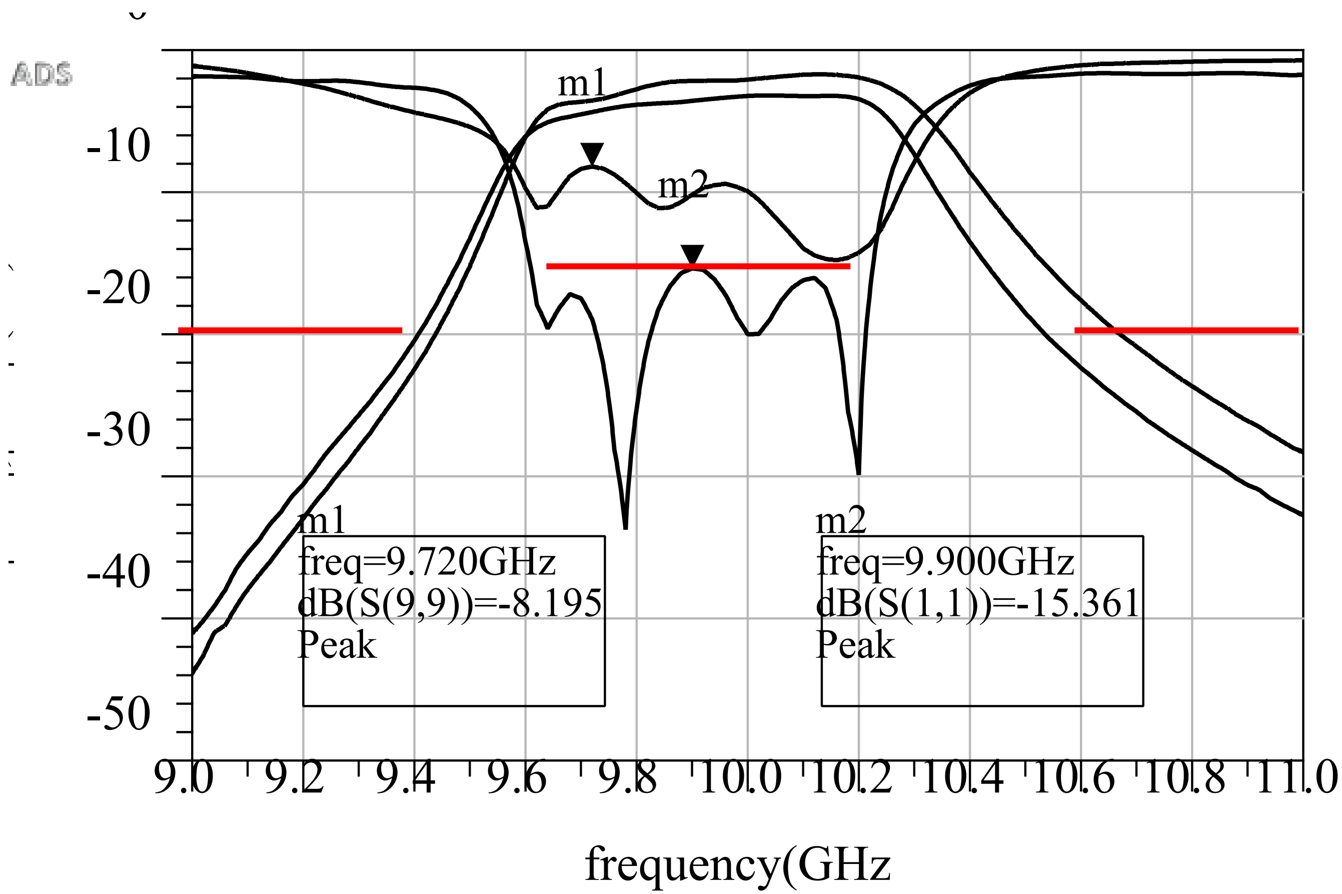


3D-printed 4-pole air-filled X-band filter



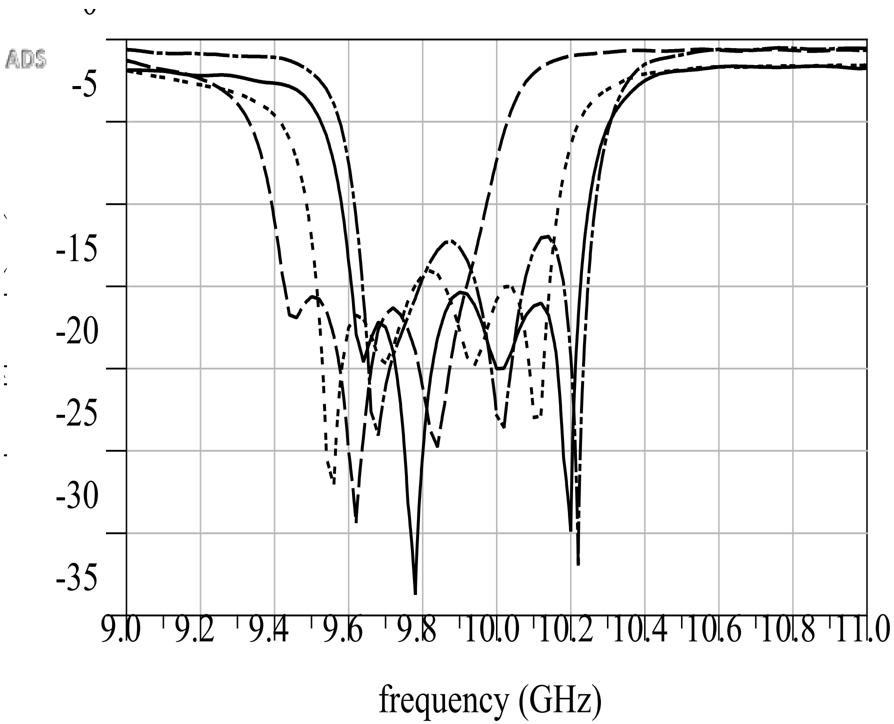


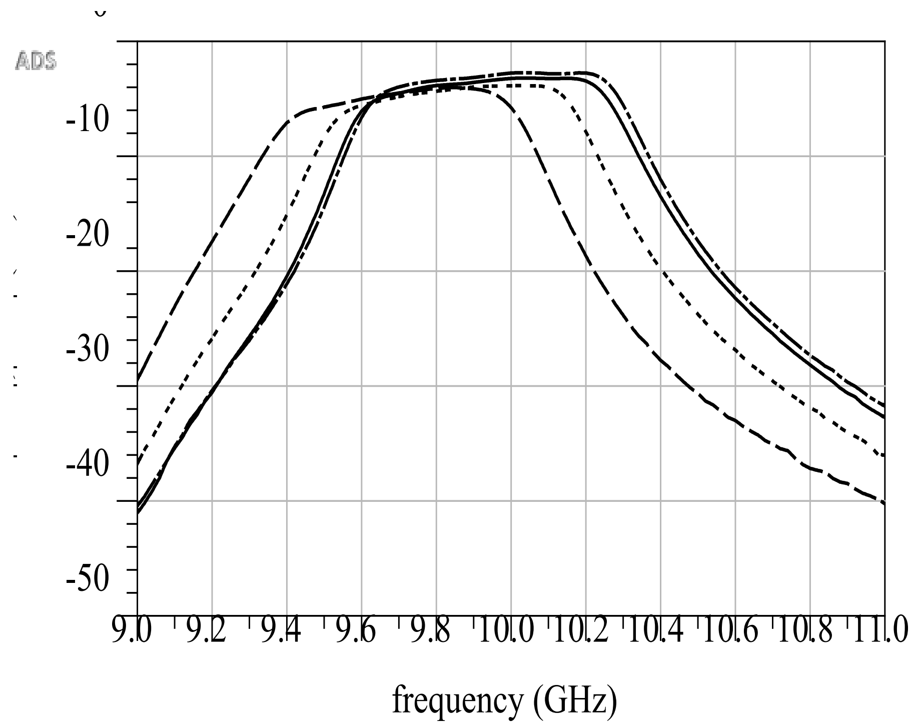
Space Mapping Design and Tuning of Waveguide Filter
(Li et al., 2020)



3D-printed 4-pole air-filled X-band filter before and after tuning

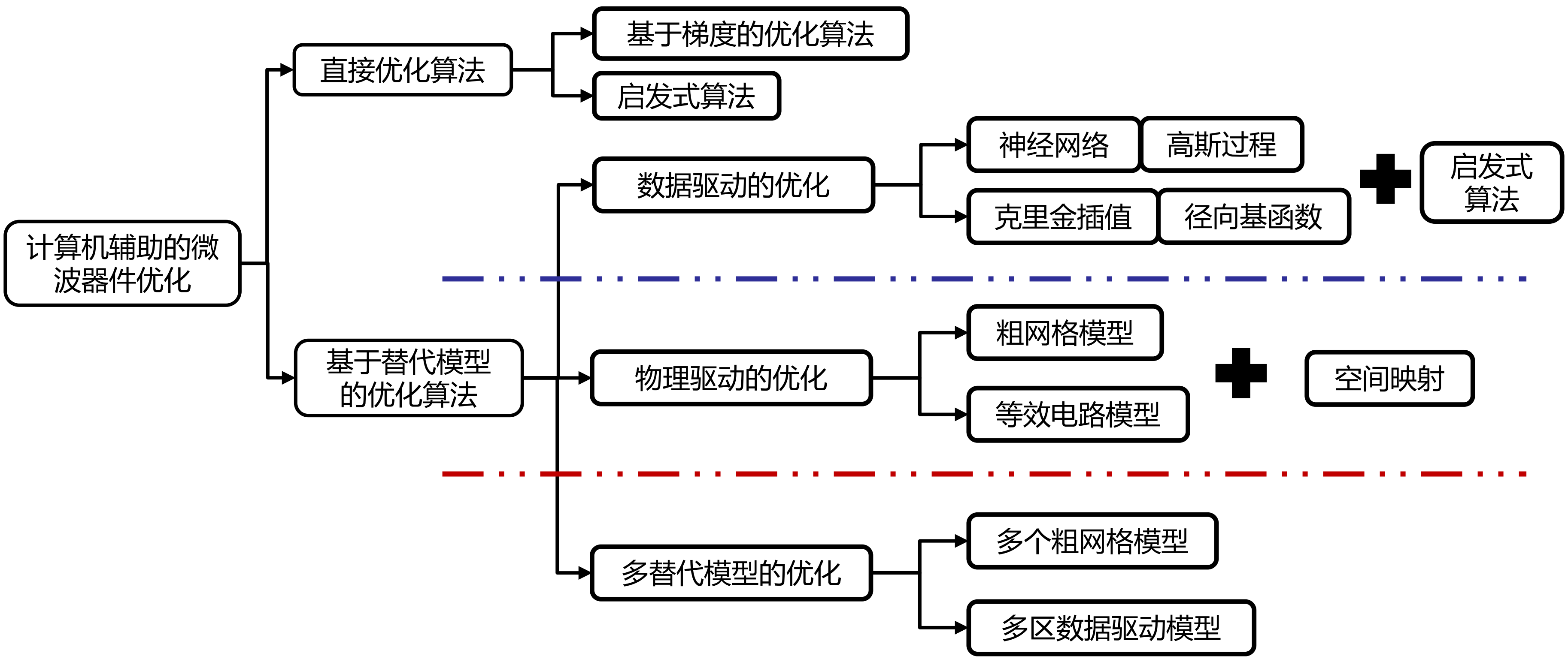
Space Mapping Design and Tuning of Waveguide Filter
(Li et al., 2020)



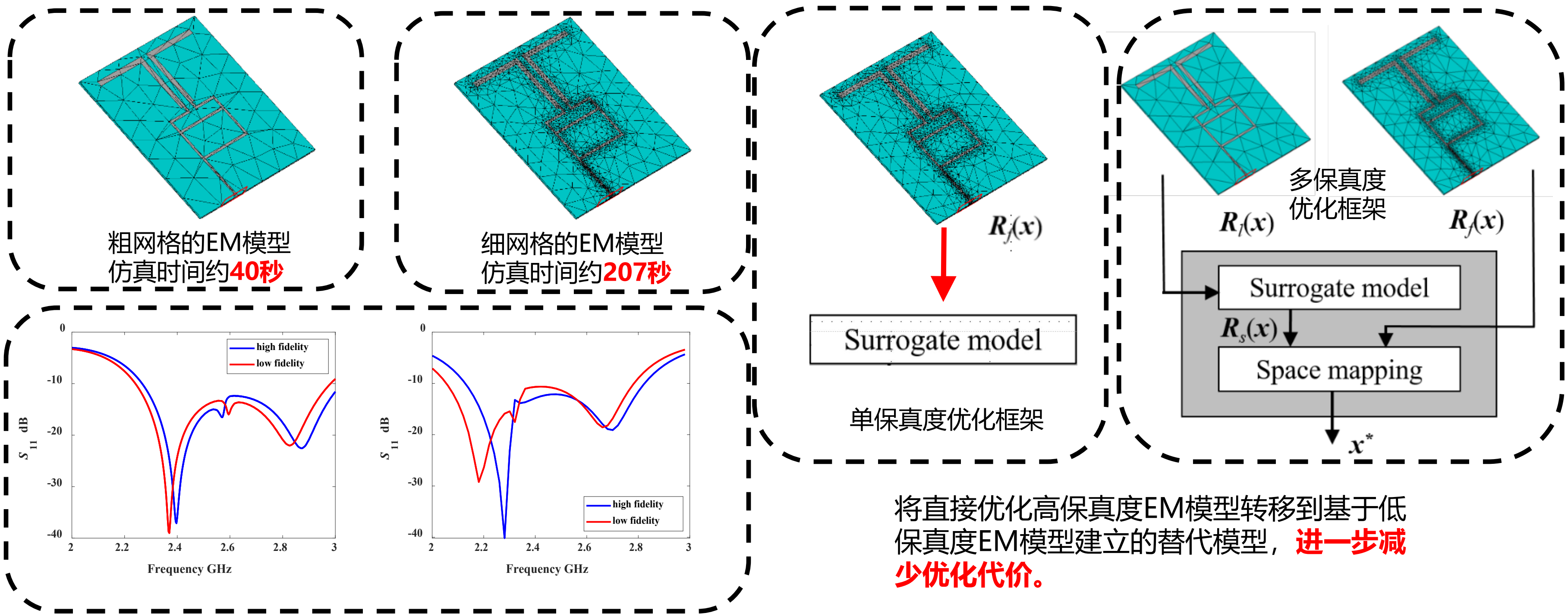


tuning of center frequency: 3D-printed 4-pole air-filled X-band filter

Multi-Surrogate Framework



Physics-based Surrogate
(Zhang et. al., 2021)

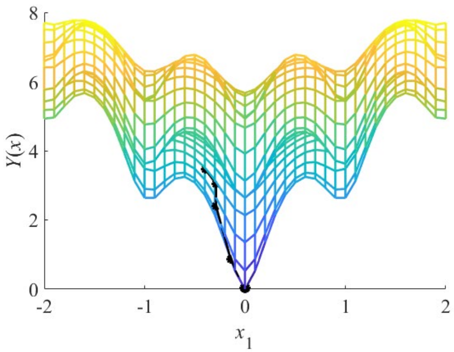


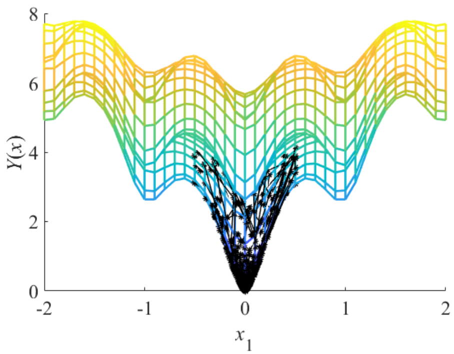
将直接优化高保真度EM模型转移到基于低保真度EM模型建立的替代模型，**进一步减少优化代价。**

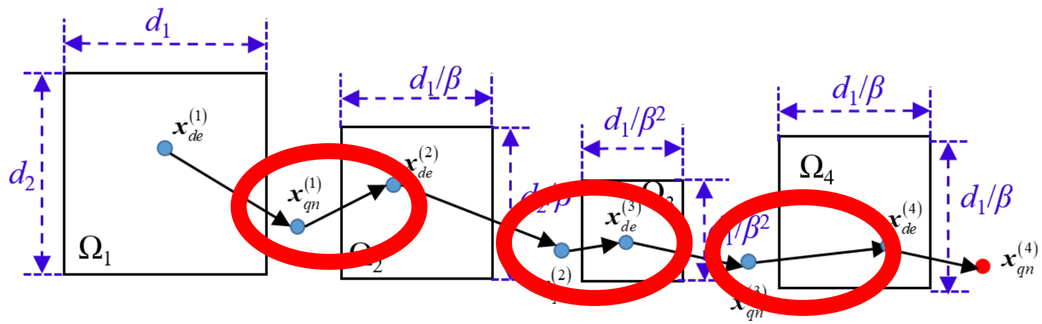
Z. Zhang, H.C. Chen, and Q.S. Cheng, "Surrogate-Assisted Quasi-Newton Enhanced Global Optimization of Antennas Based on a Heuristic Hypersphere Sampling," **IEEE Transactions on Antennas and Propagation,** 2021,69(5):2993-2998.

Physics-based Surrogate
(Zhang et. al., 2021)

拟牛顿增强型差分进化算法







$$\alpha = \log_{10}\left(\max\left(\left(obj_{de} - obj_{g}\right),0\right)\right)$$

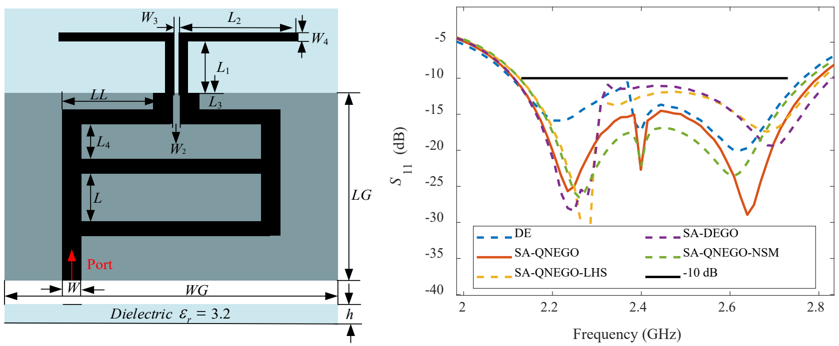
决定着何时两种算法执行转换

$$\Omega_{k+1} = \begin{cases} \beta\cdot\Omega_k & \text{if } obj_{qn} < obj_{de} \\ \dfrac{\Omega_k}{\beta} & \text{otherwise} \end{cases}$$

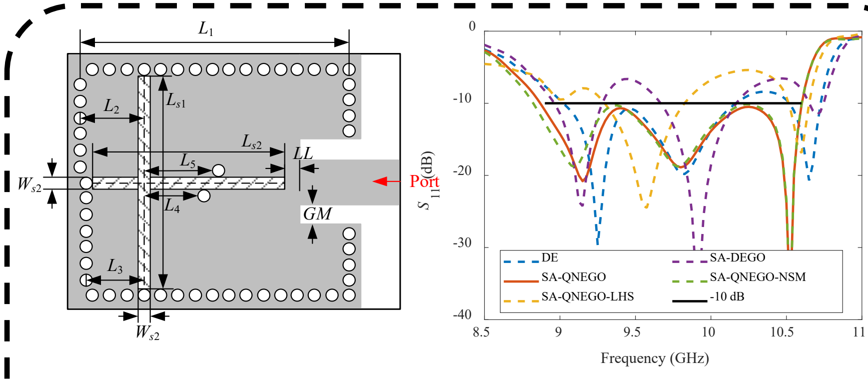
优化空间的实时变换

Z. Zhang, H.C. Chen, and Q.S. Cheng, "Surrogate-Assisted Quasi-Newton Enhanced Global Optimization of Antennas Based on a Heuristic Hypersphere Sampling," **IEEE Transactions on Antennas and Propagation,** 2021,69(5):2993-2998.

Physics-based Surrogate
(Zhang et. al., 2021)



算法	Y (dB)	时间代价 (s)	电磁仿真次数
DE	−10.50	41400	200 (h)
SA-QNEGO-NSM	−10.24	7454	36 (h)
SA-DEGO	−10.84	6683	126(l)+1(h)
SA-QNEGO-LHS	−10.18	3464	75(l)+13(h)
SA-QNEGO	**−11.10**	**1835**	**38(l)+1(h)**

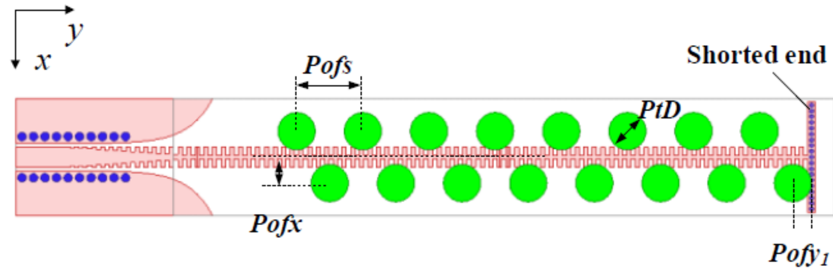


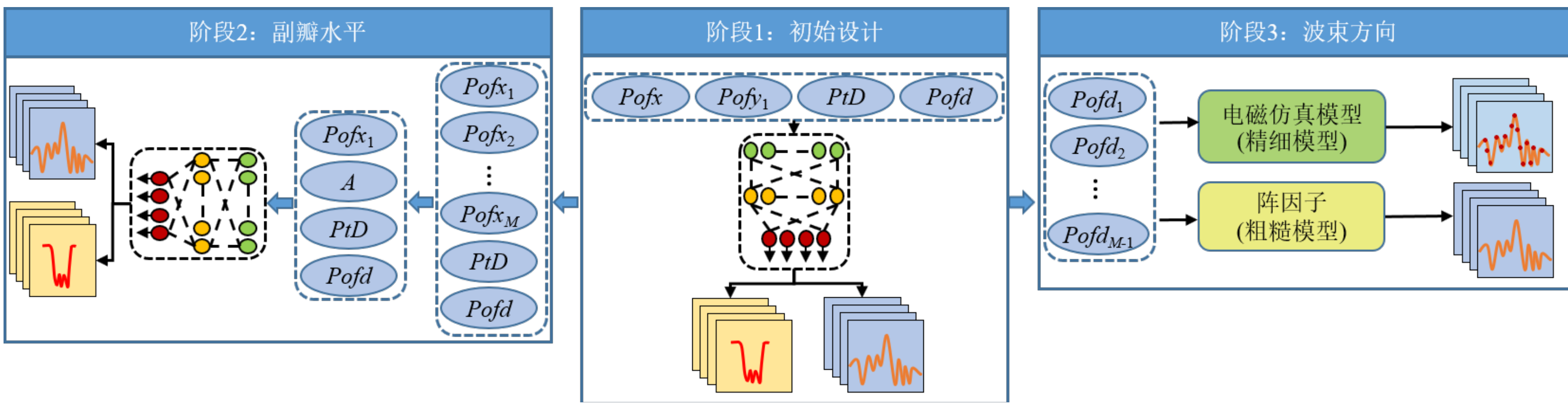
算法	Y (dB)	时间代价 (s)	仿真次数
DE	−7.56	75250	250(h)
SA-QNEGO-NSM	−10.12	59184	197(h)
SA-DEGO	−6.56	59960	250(l)+16(h)
SA-QNEGO-LHS	−5.39	62750	250(l)+25(h)
SA-QNEGO	**−10.24**	**42426**	**227(l)+9(h)**

Z. Zhang, H.C. Chen, and Q.S. Cheng, "Surrogate-Assisted Quasi-Newton Enhanced Global Optimization of Antennas Based on a Heuristic Hypersphere Sampling," **IEEE Transactions on Antennas and Propagation,** 2021,69(5):2993-2998.

Multi-Surrogate Framework For SSPP Antenna Array

(Jiao et al., 2022)





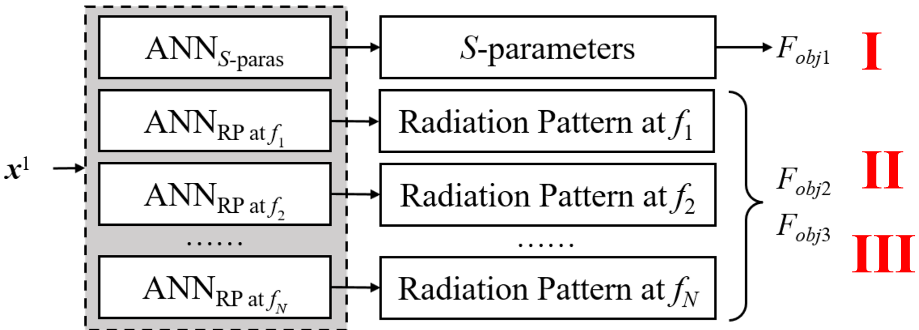
阶段	阶段变量 *	目标函数
阶段 1	$Pofd, Pofx, Pofy_1, PtD$	S 参数、增益、副瓣水平
阶段 2	$Pofx_1, A, Pofd, PtD$	S 参数、增益、副瓣水平
阶段 3	$Pofd_1, Pofd_2, Pofd_3, \ldots, Pofd_M$	增益、副瓣水平、主瓣方向、零点

阶段变量是每个阶段待优化的变量

Multi-Surrogate Framework For SSPP Antenna Array
(Jiao et al., 2022)

阶段1：初始设计

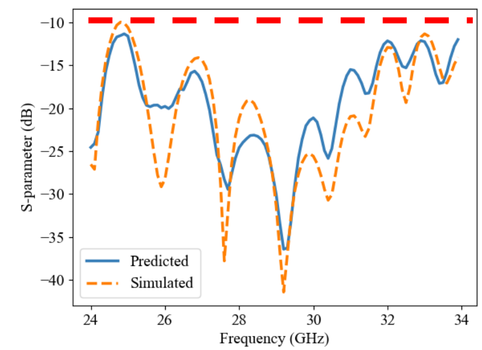
- 设计参数：$x^1 = [Pofx, Pofd, Pofy_1, PtD]^T$
- 采样：Python-CST联合仿真实现自动化采样
- 人工神经网络建模：

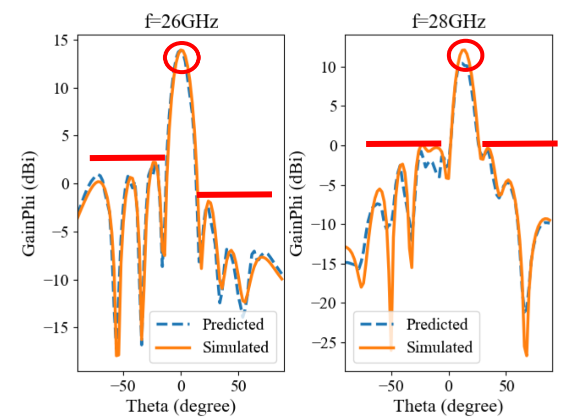


替代模型

- **优化目标函数：**

$$\boldsymbol{x}^{1*} = \arg\min_{\boldsymbol{x}^1}(w_1 \cdot F_{obj1}(\boldsymbol{x}^1) + w_2 \cdot F_{obj2}(\boldsymbol{x}^1) + w_3 \cdot F_{obj3}(\boldsymbol{x}^1))$$

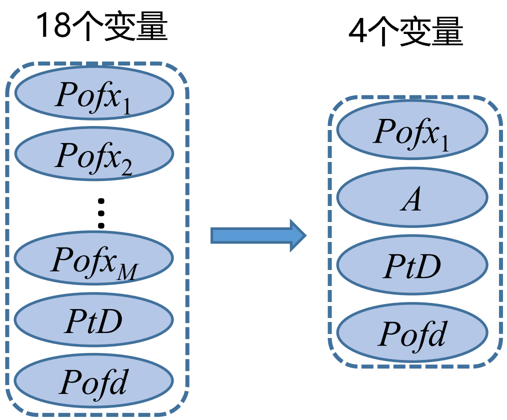




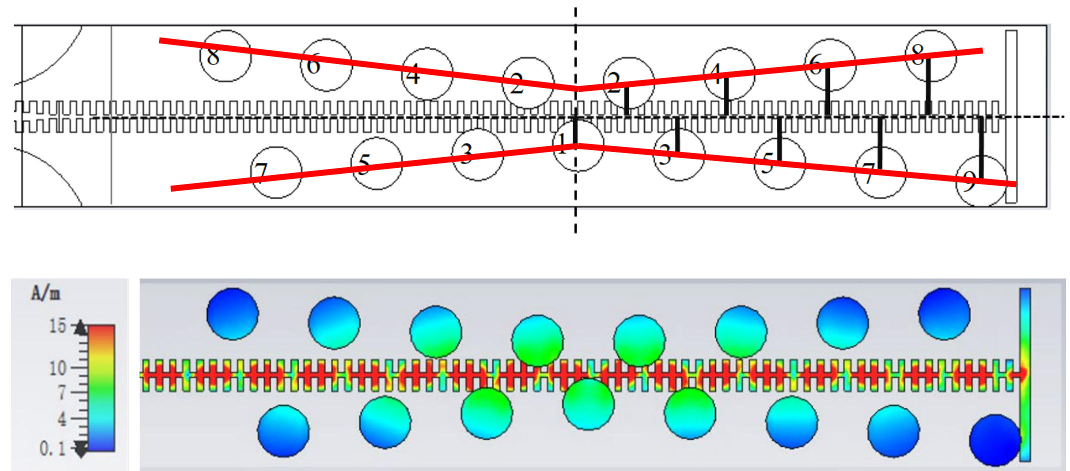
Multi-Surrogate Framework For SSPP Antenna Array
(Jiao et al., 2022)

阶段2：基于副瓣水平的建模与优化

- 缩减设计变量值：



$$Pofx = A\cdot(i-1)+Pofx_1$$



- 设计参数：$x^2 = [Pofx_1, A, Pofd, PtD]^T$

X形分布

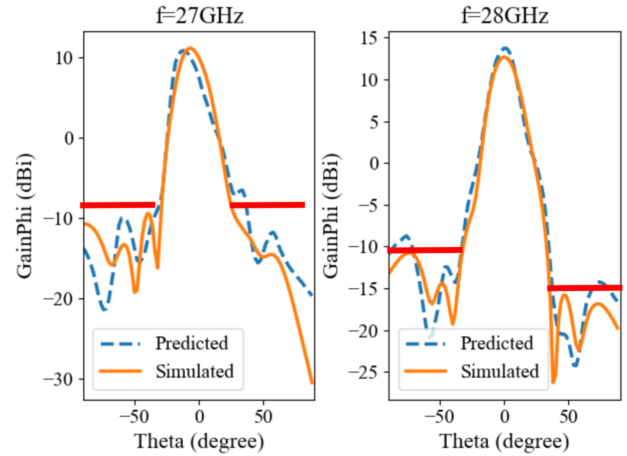
Multi-Surrogate Framework For SSPP Antenna Array *(Jiao et al., 2022)*

阶段2：基于副瓣水平的建模与优化

- 拉丁超立方采样
  Python-CST联合仿真实现自动化采样
- 人工神经网络建模：
  Pytorch框架
- 优化目标函数：

$$\boldsymbol{x}^{2*} = \arg\min_{\boldsymbol{x}^2}(\underbrace{w_1 \cdot F_{obj1}(\boldsymbol{x}^2)}_{\mathrm{I}} + \underbrace{w_2 \cdot F_{obj2}(\boldsymbol{x}^2)}_{\mathrm{II}} + \underbrace{w_3 \cdot F_{obj3}(\boldsymbol{x}^2)}_{\mathrm{III}})$$

- 最优解为 $x^{2*}= [1.30, 0.20, 2.26, 2.31]^T$
  EM仿真验证后与神经网络预测结果对比



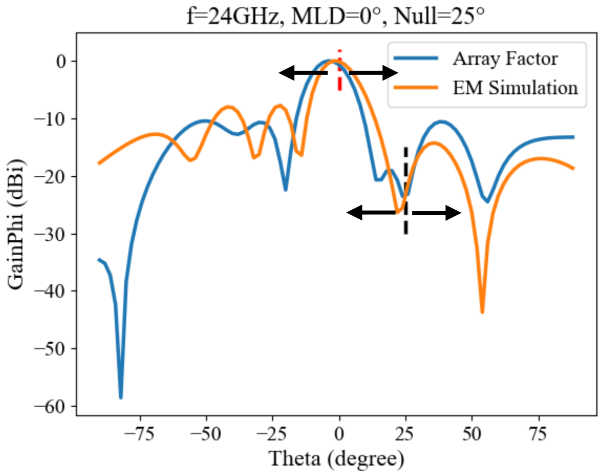
频率 [GHz]	24	25	26	27	28	29	30
S 参数	-10.9	-8.0	-6.4	-5.3	-12.1	-13.6	-9.0
增益	10.6	10.4	9.87	11.2	12.7	7.90	8.23
副瓣水平	-4.9	-4.8	-19.8	-20.5	-20.9	-5.2	-5.6
方向角	-27	-19	-16	-7	0	11	11

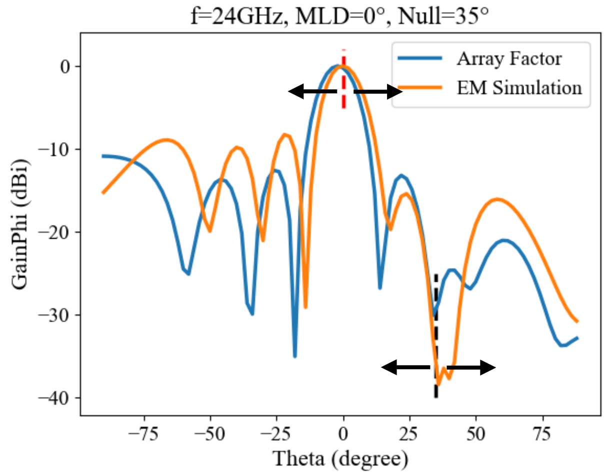
Multi-Surrogate Framework For SSPP Antenna Array
(Jiao et al., 2022)

阶段3：基于波束方向的建模与优化

- 设计参数：$x^3 = [Pofd_1, Pofd_2, \ldots, Pofd_3, Pofd_{M\text{-}1}]^T$　　15个变量
- 优化目标函数：

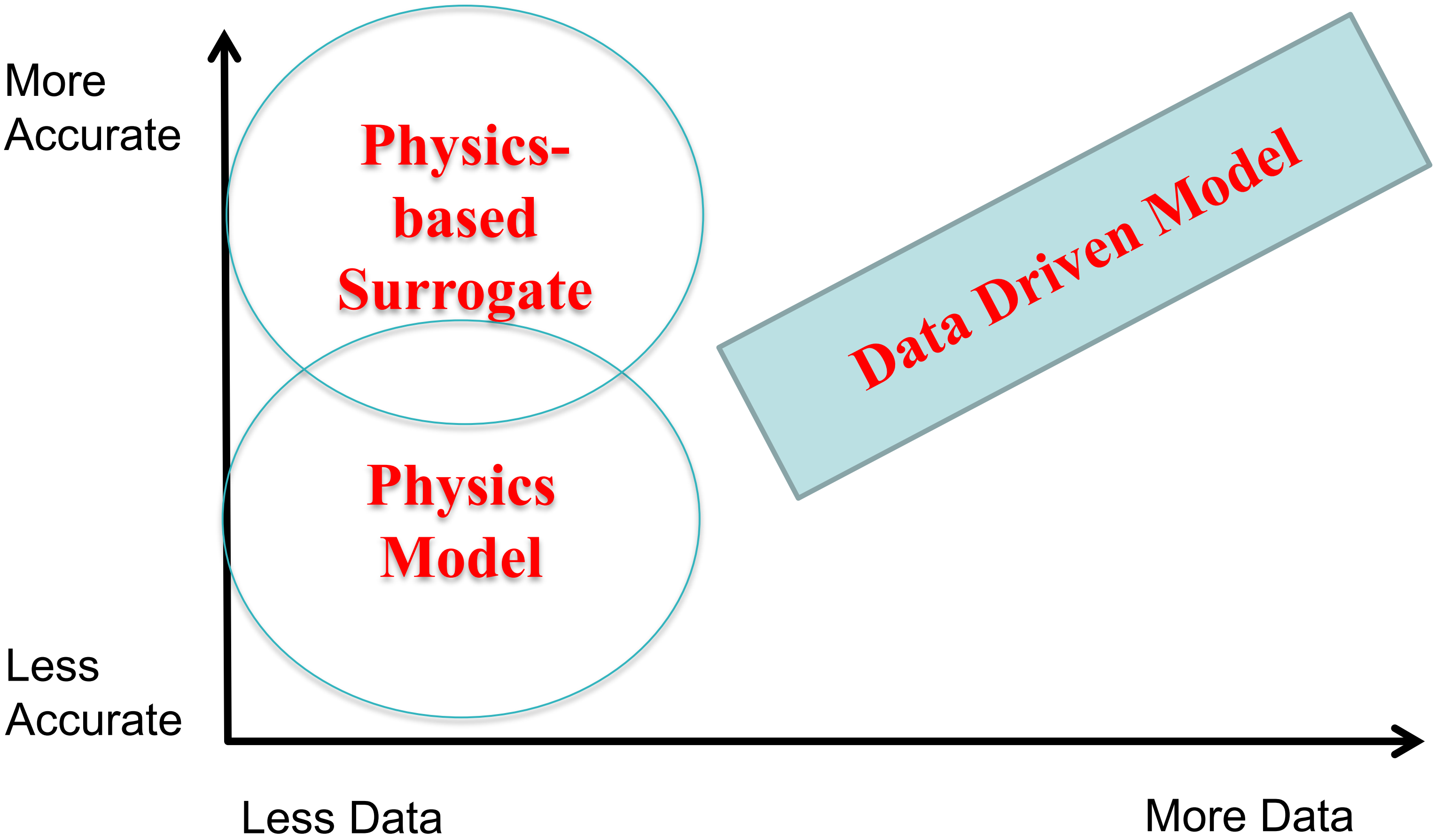
$$\boldsymbol{x}^{3*} = \arg\min_{\boldsymbol{x}^3}(w_1 \cdot \underbrace{F_{obj2}(\boldsymbol{x}^3)}_{\mathrm{II}} + w_2 \cdot \underbrace{F_{obj3}(\boldsymbol{x}^3)}_{\mathrm{III}} + w_3 \cdot \underbrace{F_{obj4}(\boldsymbol{x}^3)}_{\mathrm{IV}} + w_4 \cdot \underbrace{F_{obj5}(\boldsymbol{x}^3)}_{\mathrm{V}})$$





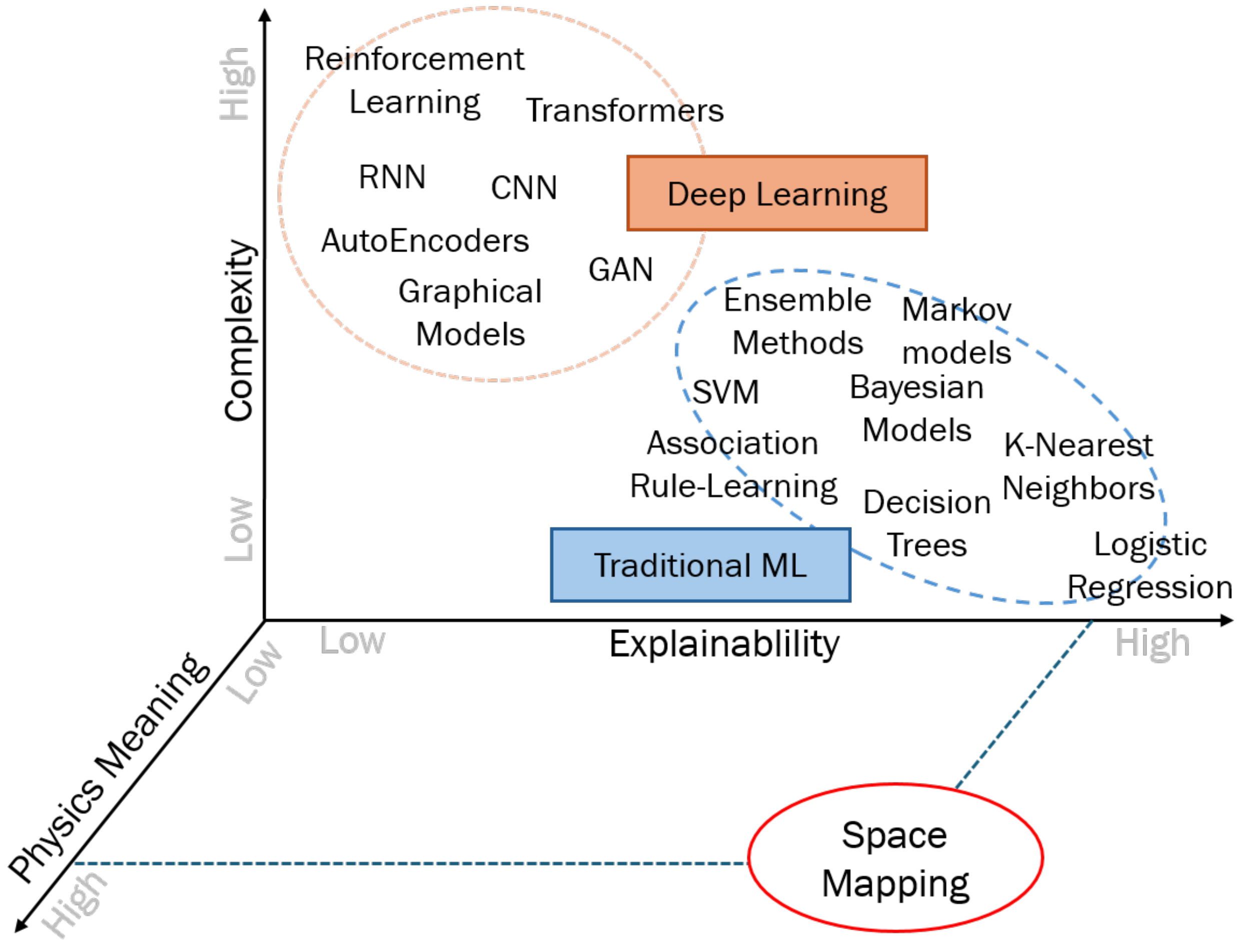
SUSTech

Physics Driven and Data Driven



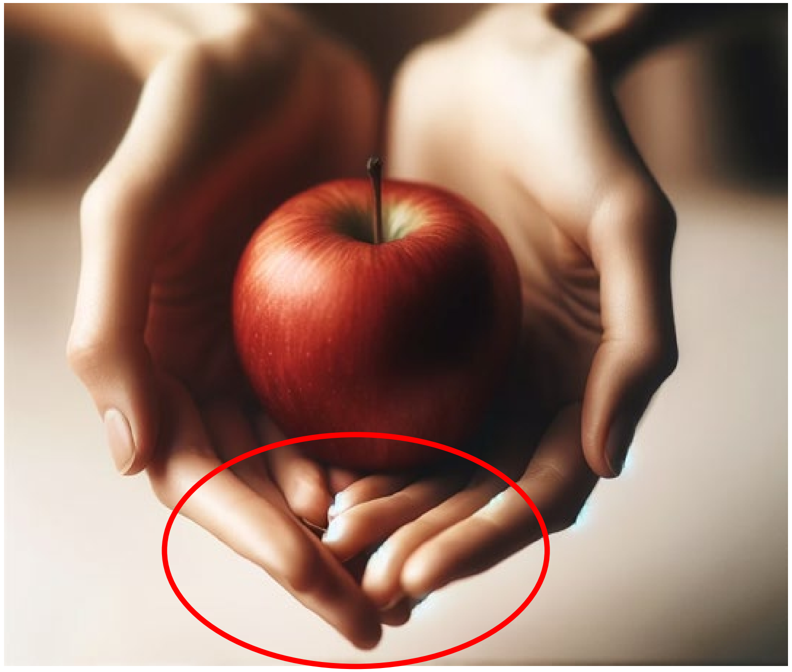
AI versus Space Mapping

➢ Complexity, explainability, and physics meaning.



AI Works but Not Exactly

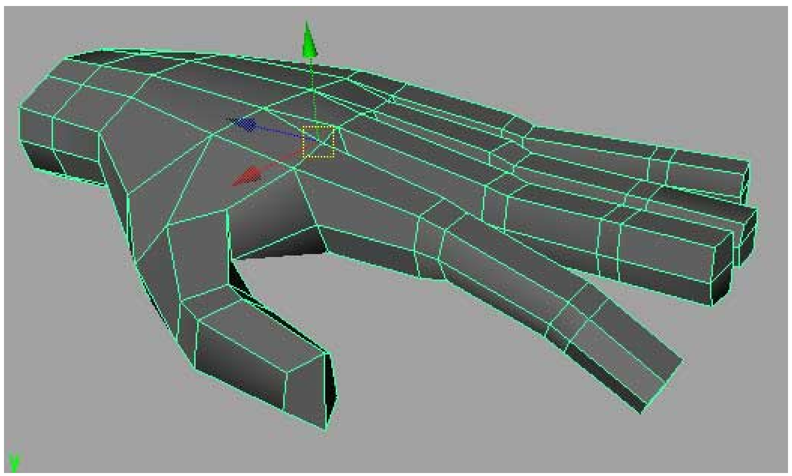
➢ AI Struggles With Drawing Hands



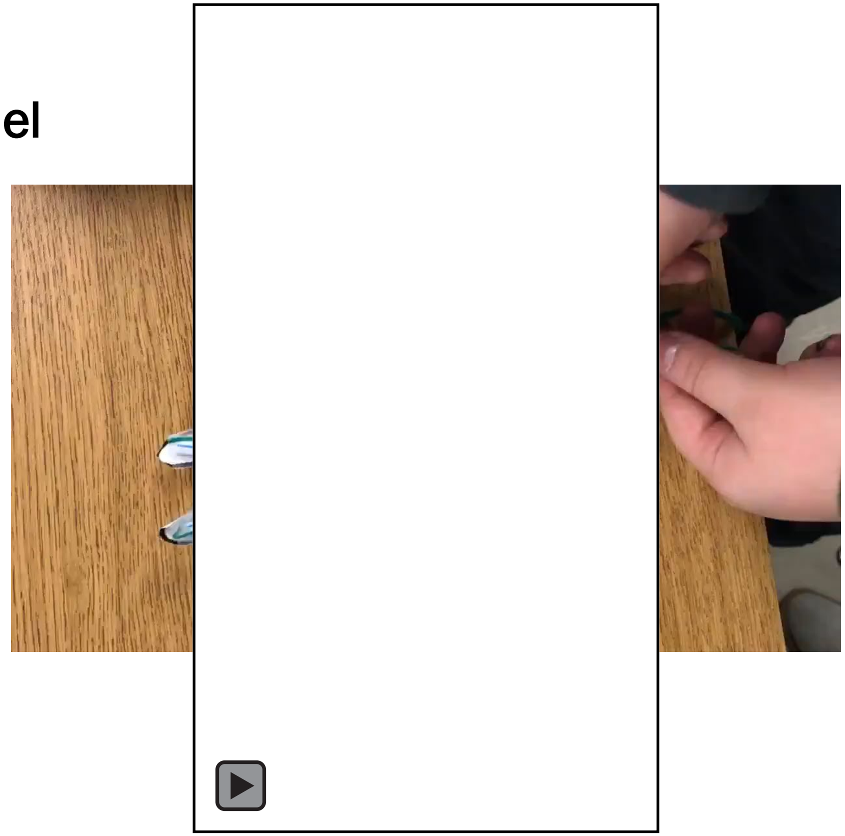
Wrong number, posture, shape of fingers.

AI Works but Not Exactly

- Not enough data?
- Simple physics not included in AI model



Source: Google image



The Essence of Space Mapping and Surrogate: Less is More

build a thin, minimally complex layer around existing physics model

existing physics-based model is generated through various methods

for model enhancement, the sample number required is small; for design optimization, the iteration count is small

manual implementation is often possible (easy automation)

the enhanced model can be astonishingly good

can be applied in many fields

Future Research

Human Brain/Cognition and Space Mapping
(Behavior Model, MRI Brain image, EEG)

3D Printing/Fabrication Fast Prototyping
(Fine model: Printed or Fabricated Structures)

Tuning Robot
(Post-production Tuning of Filters)

mmWave and Terahertz devices
(Modeling and Optimization)

Future Research

Novel Antenna Design
(Cellphone, Embroidered Antennas)

On-Chip Component Design
(CMOS High Frequency Component)

Antenna in Packaging

Multi-objective Optimization of Microwave and RF Devices

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