Celebrating
50 Years of
Microwave Theory
& Techniques

IEEE MTT-S

2002 Microwave Symposium Workshop Notes

Monday, June 3, 2002

Microwave Component Design Using Space Mapping Methodologies

Organizers:

Dr. John Bandler, Bandler Corporation

Sponsors:

MTT-1 Computer-Aided Design
MTT-15 Microwave Field Theory

Seattle, Washington

WMB

2002 IEEE MTT-S INTERNATIONAL MICROWAVE SYMPOSIUM
Seattle, Washington
June 2-7, 2002

WMB: **Microwave Component Design Using Space Mapping Methodologies**

Date: Monday, June 3, 2002
Time: 8:00 am – 5:10 pm

Sponsors: MTT-1 Computer-Aided Design
MTT-15 Microwave Field Theory

Organizer: John W. Bandler, Bandler Corporation, Canada

Authors: J.W. Bandler and Q.S. Cheng
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D. Pelz
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J.-W. Lobeek
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Ke-Li Wu, M. Ehlert and C. Barratt

Microwave engineers have been using optimization techniques for device, component and circuit modeling and CAD for decades. Automatic optimization in modeling, simulation and design is now taken for granted. One of the frontiers that remain is the successful application of optimization procedures in problems for which direct application of traditional optimization approaches is not practical. The recent exploitation of iteratively refined surrogates of "fine" or accurate models, and the implementation of space mapping and related methodologies can be viewed as attempts to address this issue.

Space mapping optimization intelligently links companion "coarse" and "fine" models of different complexities. Examples include full-wave electromagnetic simulations with empirical circuit-theory based simulations, or devices under test with a suitable simulation surrogate. The aim is to accelerate iterative design optimization. It is a simple CAD methodology, which closely follows the traditional experience and intuition of microwave designers, yet can be rigorously grounded mathematically. The exploitation of properly managed space mapped models promises significant efficiency in engineering design optimization practices.

This workshop will bring together the foremost practitioners in these fields including microwave component designers, software developers and academic innovators. They will focus on the state of the art and address designers' needs for effective tools for optimal designs, including yield optimization, exploiting accurate physically based device and component models. Current progress in the development and application of suitable algorithms and software engines will be presented. The concepts address the contradictory challenge of exploitation of device and system models that are both accurate and fast.

WMB: **Microwave Component Design Using Space Mapping Methodologies**

Date: Monday, June 3, 2002

Time: 8:00 am – 5:10 pm

Tentative Workshop Schedule

8:00 am	John Bandler, Welcome: Introductions
8:15 am	John Bandler
9:00 am	José Rayas-Sánchez
9:45 am	Coffee Break
10:30 am	Tony Pavio
11:10 am	Safieddin Safavi-Naeini
11:50 am	Lunch
1:00 pm	Dieter Pelz
1:40 pm	Kaj Madsen
2:20 pm	Jan-Willem Lobeek
3:00 pm	Coffee Break
3:30 pm	Qi-jun Zhang
4:10 pm	Ke-Li Wu
4:50 pm	Discussion Period
5:10 pm	End

Space Mapping Approaches to EM-based Device Modeling and Component Design

J.W. Bandler and Q.S. Cheng

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presented at

WORKSHOP ON MICROWAVE COMPONENT DESIGN USING SPACE MAPPING METHODOLOGIES
2002 IEEE MTT-S International Microwave Symposium, Seattle, WA, June 3, 2002

Space Mapping Approaches to EM-based Device Modeling and Component Design

J.W. Bandler and Q.S. Cheng

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Abstract

The Space Mapping concept intelligently links companion "coarse" and "fine" engineering models of different complexities, e.g., full-wave electromagnetic (EM) simulations and empirical circuit-theory based models. Space mapping optimization closely follows the traditional experience and intuition of designers. Our original 1993 concept and the subsequent Aggressive Space Mapping approach to engineering design optimization will be discussed. Recent developments include neural space mapping and the introduction of the object oriented SMX system to facilitate implementation with commercial simulators. We have developed a comprehensive Space Mapping framework to engineering device modeling. Tableau-based approach, it permits many different practical implementations. The accuracy of available empirical models can be significantly enhanced in selected regions of interest. We present microstrip examples yielding remarkable modeling improvement. It has been reported to be useful in the RF industry for development of new library models. We briefly review the new Implicit Space Mapping (ISM) concept in which we allow preassigned parameters, not used in optimization, to change in some components of the coarse model. Extensive filter design examples, exploiting full wave EM simulators, complement the presentation. Implementation in software such as Agilent Momentum and ADS will be discussed. One of the frontiers that remains in the optimization of large engineering systems is the successful application of optimization procedures in problems where direct optimization is not practical. The recent exploitation of surrogates in conjunction with "true" models, the development of artificial neural network approaches to device modeling and the implementation of space mapping are attempts to address this issue.

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Outline

Space Mapping intelligently links companion "coarse" and "fine" models—full-wave electromagnetic (EM) simulations and empirical models

Space Mapping optimization follows traditional experience of designers

we discuss the 1993 concept and subsequent Aggressive Space Mapping

Outline

object oriented SMX system facilitates commercial simulators

tableau approach enhances accuracy of available empirical models (already used in the RF industry for new library models)

Implicit Space Mapping (ISM), where preassigned parameters change in coarse model

filter design, implementation in Agilent Momentum and ADS

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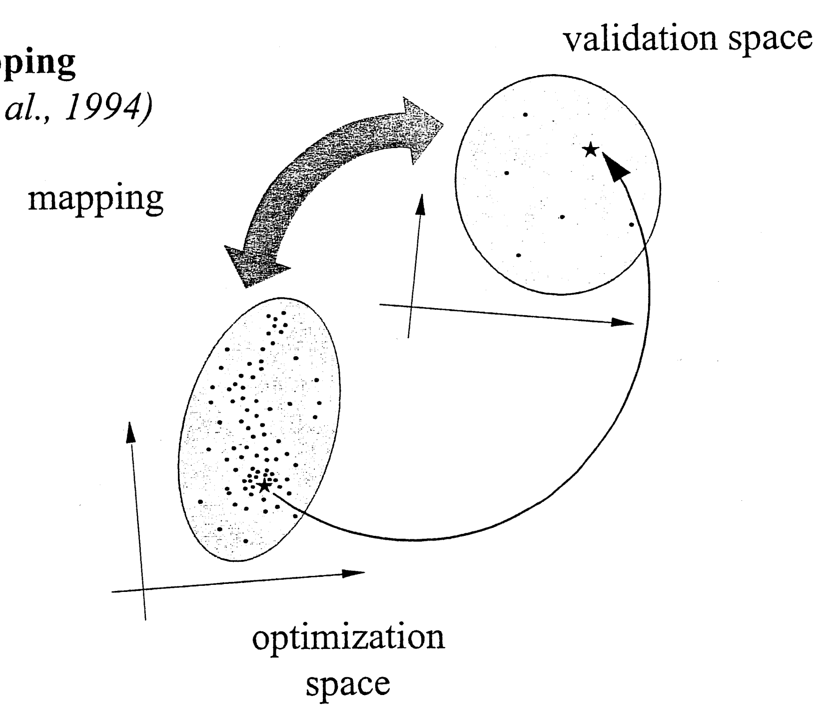
Space Mapping
(Bandler et al., 1994)



Space Mapping: a Glossary of Terms

Space Mapping	transformation, link, adjustment, correction, shift (in parameters or responses)
Coarse Model	simplification or convenient representation, companion to the fine model, auxiliary representation, cheap model
Fine Model	accurate representation of system considered, device under test, component to be optimized, expensive model

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Space Mapping: a Glossary of Terms

Surrogate	model, approximation or representation to be used, or to act, in place of, or as a substitute for, the system under consideration
Surrogate Model	alternative expression for coarse model
Target Response	response the fine model should achieve, (usually) optimal response of a coarse model, enhanced coarse model, or surrogate

Space Mapping: a Glossary of Terms

Companion	coarse
Low Fidelity	coarse
High Fidelity	fine
Empirical	coarse
Physics-based	coarse or fine
Device under Test	fine
Electromagnetic	fine or coarse
Simulation	fine or coarse
Computational	fine or coarse

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Space Mapping: a Glossary of Terms

Parameter (input) Space Mapping	mapping, transformation or correction of design variables
Response (output) Space Mapping	mapping, transformation or correction of responses
Response Surface Approximation	linear/quadratic/polynomial approximation of responses w.r.t. design variables

Space Mapping: a Glossary of Terms

Neuro	implies use of artificial neural networks
Implicit Space Mapping	space mapping when the mapping is not obvious
Not Space Mapping	(usually) space mapping when not acknowledged
Parameter Transformation	space mapping
Predistortion	?

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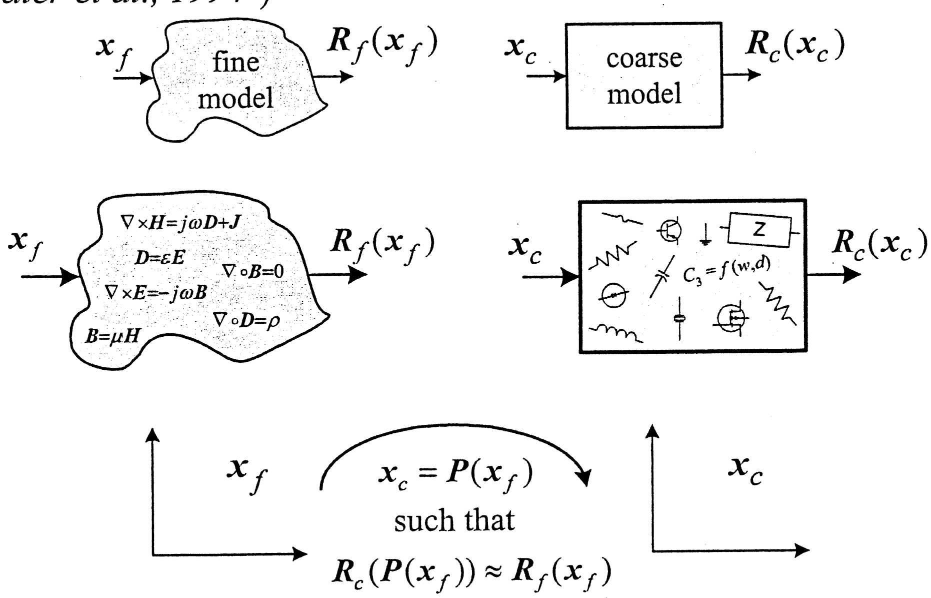
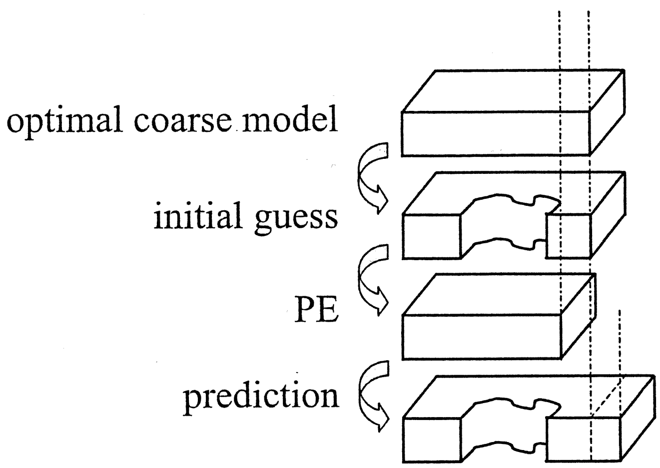
The Space Mapping Concept
(Bandler et al., 1994-)



Space Mapping Practice—Cheese Cutting Problem



$$x_f^{new} = x_f^{old} + P^{-1}(x_c^* - x_c^{new})$$

$$x_f^{new} = x_f^{old} + x_c^* - x_c^{new}$$

The Brain's Automatic Pilot

(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)

[certain brain] circuits are used by the human brain to assess social rewards …

…findings [by neuroscientists] …challenge the notion that people always make conscious choices about what they want and how to obtain it.

Gregory Berns (Emory University School of Medicine):
… most decisions are made subconsciously with many gradations of awareness.

The Brain's Automatic Pilot
(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)

P. Read Montague (Baylor College of Medicine): … how did evolution create a brain that could make … distinctions … [about] …what it must pay conscious attention to?

… the brain has evolved to shape itself, starting in infancy, according to what it encounters in the external world.

… much of the world is predictable: buildings usually stay in one place, gravity makes objects fall …

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The Brain's Automatic Pilot
(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)

As children grow, their brains build internal models of everything they encounter, gradually learning to identify objects …

… as new information flows into it … the brain automatically compares it with what it already knows.

… if there is a surprise …. the mismatch … instantly shifts the brain into a new state.

Drawing on past experience … a decision is made …

Current Space Mapping Milestones

yield driven EM optimization using Space Mapping-based neuromodels (2001)

EM-based optimization exploiting Partial Space Mapping (PSM) and exact sensitivities (2002)

Implicit Space Mapping (ISM) EM-based modeling and design (2002)

introduction of Space Mapping to mathematicians (2002)

Special Issue of *Optimization and Engineering* on Surrogate Modelling and Space Mapping for Engineering Optimization (2002)

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Selected Space Mapping Contributors

Kaj Madsen (Technical University of Denmark, 1993-)
mapping updates, trust region methods

Pavio (Motorola, 1994-)
companion model approach, filter design, LTCC circuits

Shen Ye (ComDev, 1997-)
circuit calibration technique

Mansour (Com Dev, University of Waterloo, 1998-)
Cauchy method and adaptive sampling

Stephane Bila (Limoges, France 1998-)
space mapping, waveguide devices

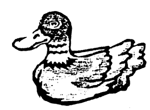
Selected Space Mapping Contributors

Rayas-Sánchez (McMaster University; ITESO, Mexico 1998-)
space mapping through artificial neural networks

Jacob Søndergaard (Technical University of Denmark, 1999-)
space mapping: theory and algorithms

Qi-jun Zhang (Carleton University, 1999-)
knowledge based neural networks, space mapping

Jan Snel (Philips Semiconductors, Netherlands, 2001)
RF component design, library model enhancement



Dan Swanson (Bartley RF Systems, 2001)
combline filter design

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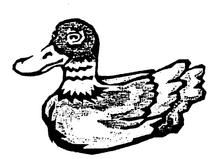
Selected Space Mapping Contributors

Steven Leary (University of Southampton, England, 2000-)
constraint mapping, applications in civil engineering

Lehmensiek (University of Stellenbosch, South Africa, 2000, 2001)
filter design, coupling structures



Frank Pedersen (Technical University of Denmark, 2001-)
space mapping, neural networks

Ke-Li Wu (Chinese University of Hong Kong, 2001-)
knowledge embedded space mapping, LTCC circuits

Pablo Soto (Polytechnic University of Valencia, Spain, 2001)
aggressive space mapping, inductively coupled filters

Hong-Soon Choi (Seoul National University, Korea, 2001)
aggressive space mapping, design of magnetic systems

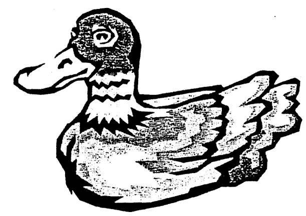
Selected Space Mapping Contributors

Luis Vicente (University of Coimbra, Portugal, 2001-)
mathematics of space mapping: models, sensitivities and trust regions

Marcus Redhe (Linköping University, Sweden, 2001)
sheet metal forming and vehicle crashworthiness design

Dieter Peltz (Radio Frequency Systems, Australia, 2002)
difference matrix approach, coupled resonator filters

Safavi-Naeini (University of Waterloo, 2002)
multi-level generalized space mapping,
multi-cavity microwave structures



Jan-Willem Lobeek (Philips Semiconductors, Netherlands, 2002)
power amplifier design

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Jacobian-Space Mapping Relationship
(Bakr et al., 1999)

through PE we match the responses

$$\boldsymbol{R}_f(\boldsymbol{x}_f) \approx \boldsymbol{R}_c(\boldsymbol{P}(\boldsymbol{x}_f))$$

by differentiation

$$\left(\frac{\partial \boldsymbol{R}_f^T}{\partial \boldsymbol{x}_f}\right)^T \approx \left(\frac{\partial \boldsymbol{R}_c^T}{\partial \boldsymbol{x}_c}\right)^T \cdot \left(\frac{\partial \boldsymbol{x}_c^T}{\partial \boldsymbol{x}_f}\right)^T$$

Jacobian-Space Mapping Relationship

(Bakr et al., 1999)

given coarse model Jacobian J_c and space mapping matrix B we estimate

$$J_f(x_f) \approx J_c(x_c) B$$

given J_c and J_f we estimate (least squares)

$$B \approx (J_c^T J_c)^{-1} J_c^T J_f$$

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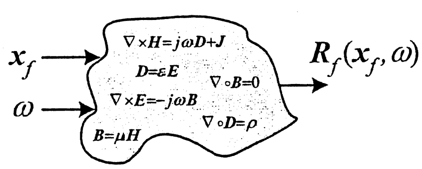
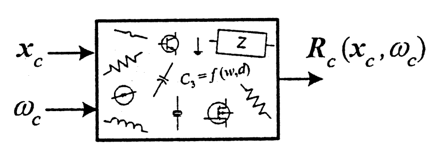
Conventional Space Mapping for Microwave Circuits

(Bandler et al., 1994)

fine model



coarse model



find

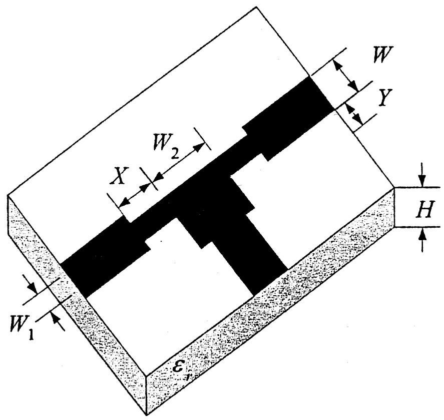
$$\begin{bmatrix} x_c \\ \omega_c \end{bmatrix} = P(x_f, \omega)$$

such that

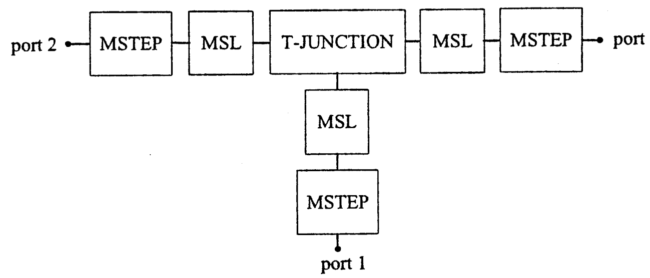
$$R_c(x_c, \omega_c) \approx R_f(x_f, \omega)$$

Microstrip Shaped T-Junction

fine model



coarse model



Microstrip Shaped T-Junction

the region of interest

$$15 \text{ mil} \le H \le 25 \text{ mil}$$
$$2 \text{ mil} \le X \le 10 \text{ mil}$$
$$15 \text{ mil} \le Y \le 25 \text{ mil}$$
$$8 \le \varepsilon_r \le 10$$

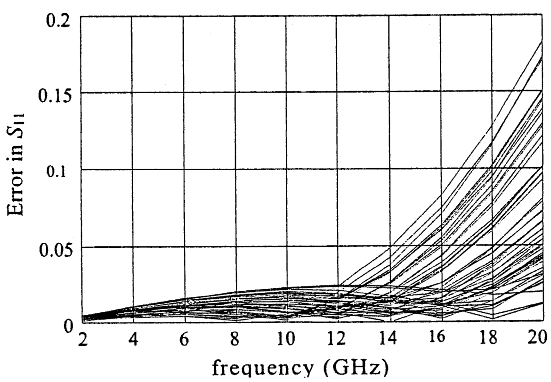
the frequency range is 2 GHz to 20 GHz with a step of 2 GHz
the number of base points is 9, the number of test points is 50

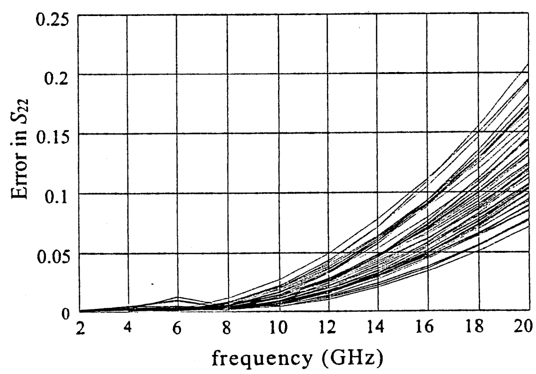
the widths W of the input lines track H so that their characteristic impedance is 50 ohm

$W_1 = W/3$, W_2 is suitably constrained

Microstrip Shaped T-Junction Coarse Model

errors w.r.t. Sonnet's ***em*** at the test points





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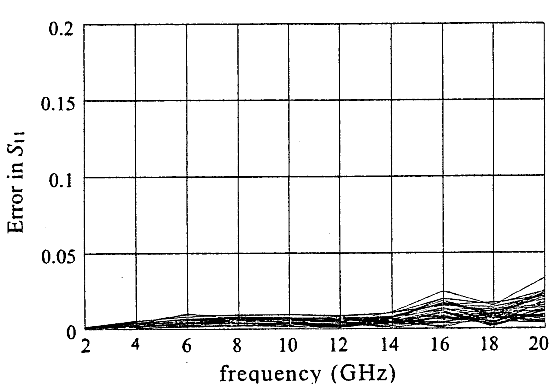
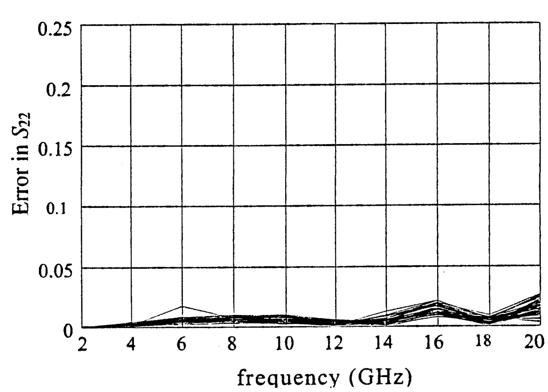
Microstrip Shaped T-Junction Enhanced Coarse Model

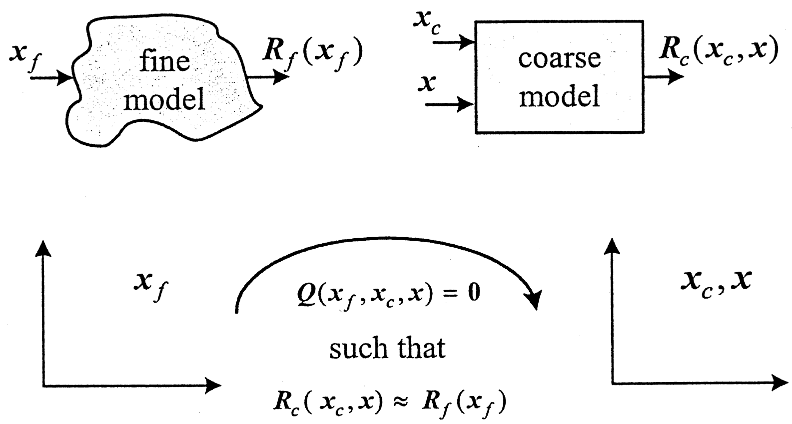
errors w.r.t. Sonnet's ***em*** at the test points





Implicit Space Mapping Theory

(Bandler et al., 2002)



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Implicit Space Mapping Practice

(Bandler et al., 2002)

effective for EM-based microwave modeling and design

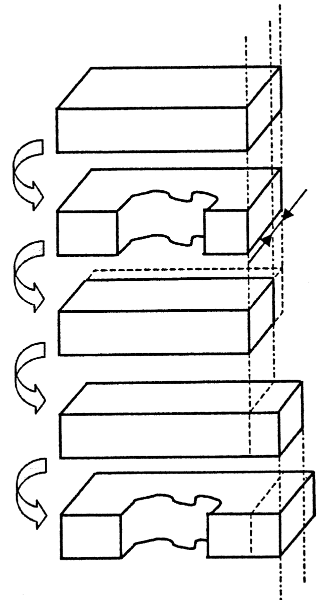
coarse model aligned with EM (fine) model
through preassigned parameters

easy implementation

no explicit mapping involved

no matrices to keep track of

Implicit Space Mapping Practice—Cheese Cutting Problem



optimal coarse model	$x_c^{*(0)} \quad x^{(0)}$
initial guess	$x_f^{(0)} = x_c^{*(0)}$
PE	$x_c^{*(0)} \quad x^{(1)}$
prediction	$x_c^{*(1)} \quad x^{(1)}$
verification	$x_f^{(1)} = x_c^{*(1)}$

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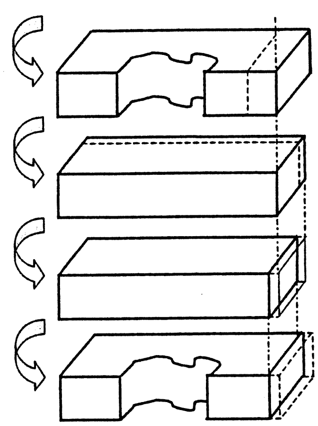
Implicit Space Mapping Practice—Cheese Cutting Problem

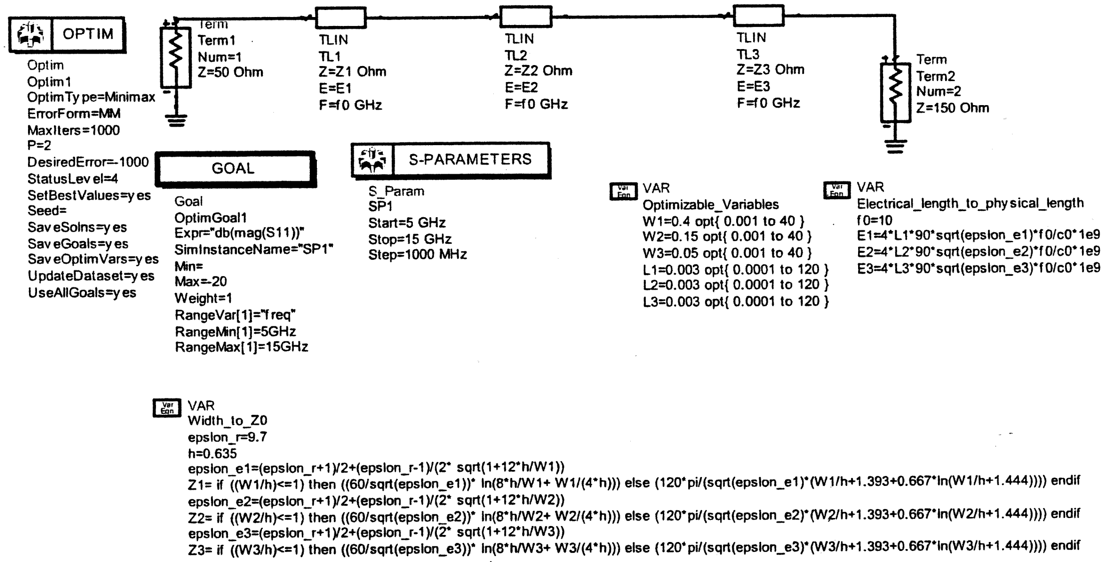


verification	$x_f^{(1)} = x_c^{*(1)}$
PE	$x_c^{*(1)} \quad x^{(2)}$
prediction	$x_c^{*(2)} \quad x^{(2)}$
verification	$x_f^{(2)} = x_c^{*(2)}$

⋮

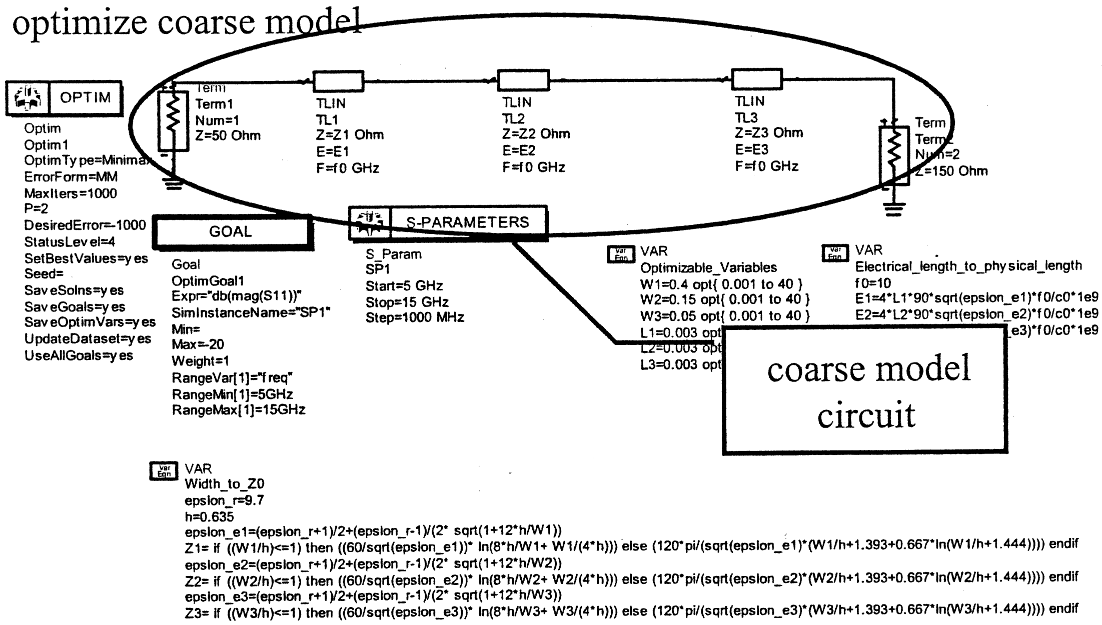
Implicit Space Mapping: Steps 1-3

optimize coarse model



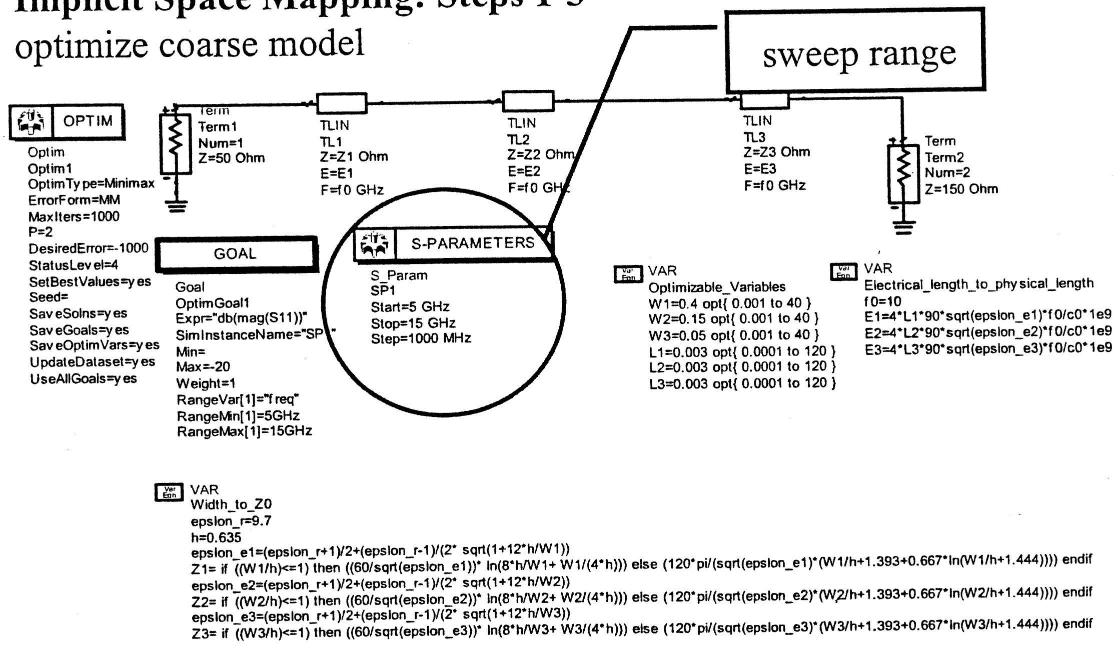
Implicit Space Mapping: Steps 1-3

optimize coarse model



Implicit Space Mapping: Steps 1-3

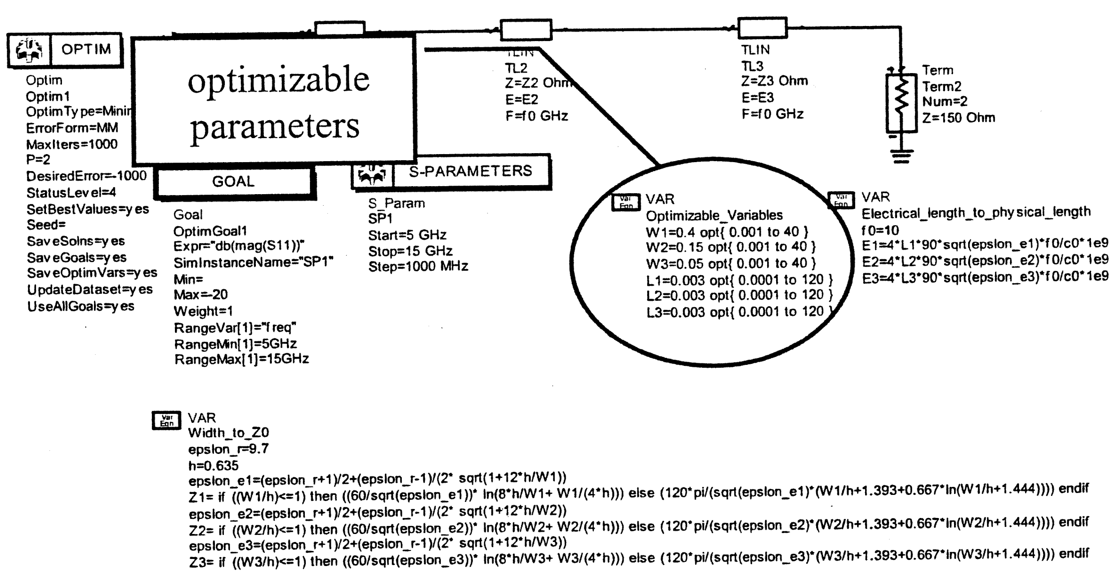
optimize coarse model



ADS/Momentum Implementation

Implicit Space Mapping: Steps 1-3

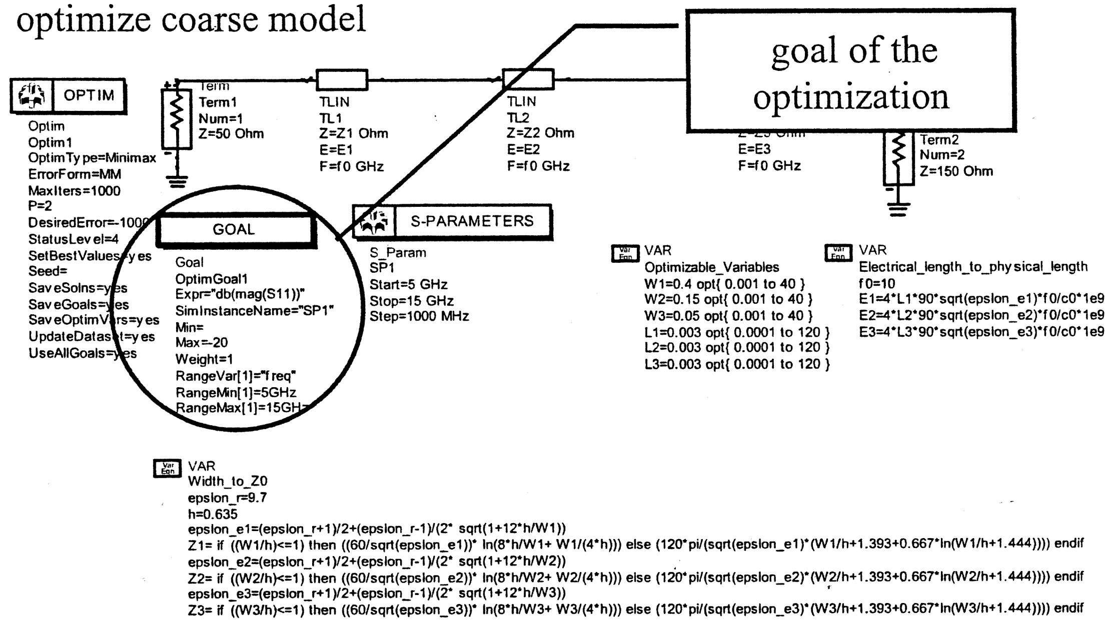
optimize coarse model



ADS/Momentum Implementation

Implicit Space Mapping: Steps 1-3

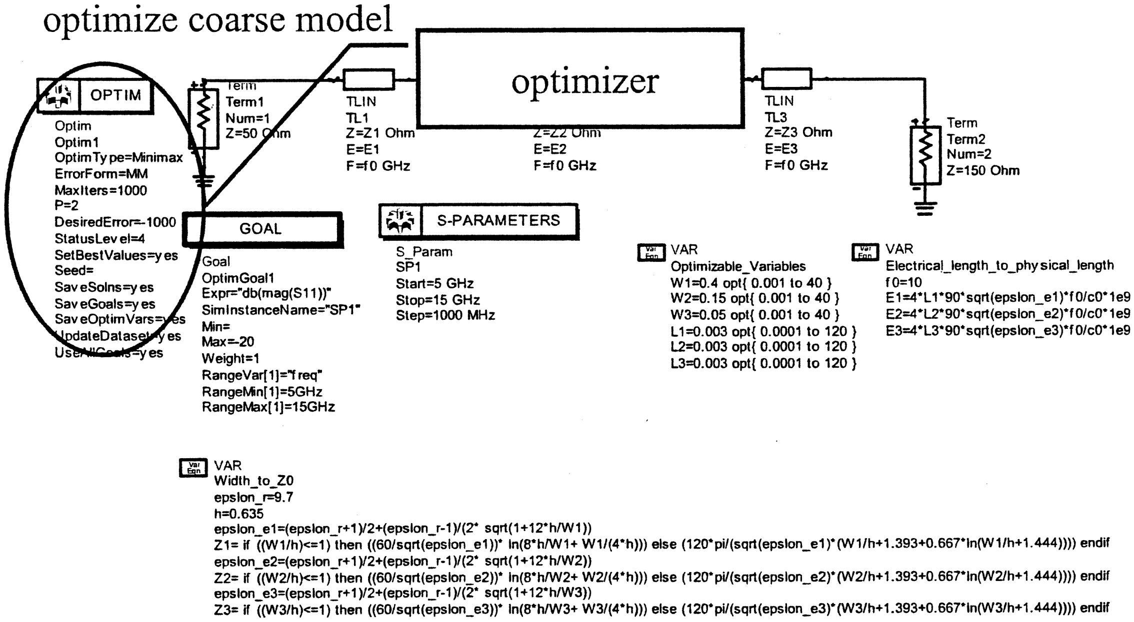
optimize coarse model



ADS/Momentum Implementation

Implicit Space Mapping: Steps 1-3

optimize coarse model



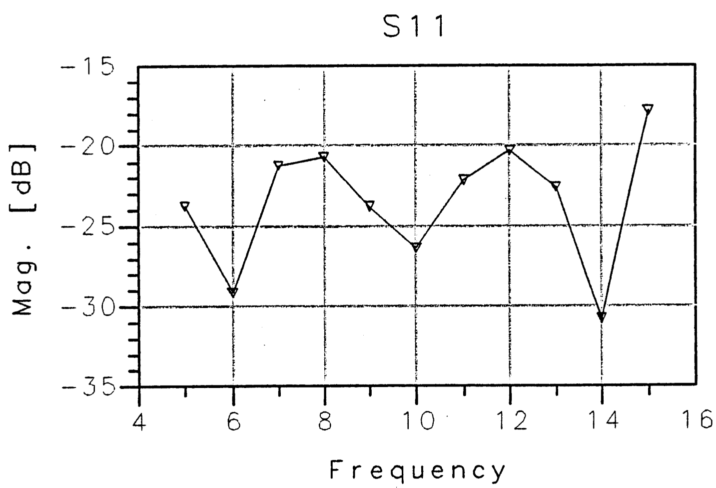
ADS/Momentum Implementation

Implicit Space Mapping: Steps 4-5

simulate fine model using Momentum

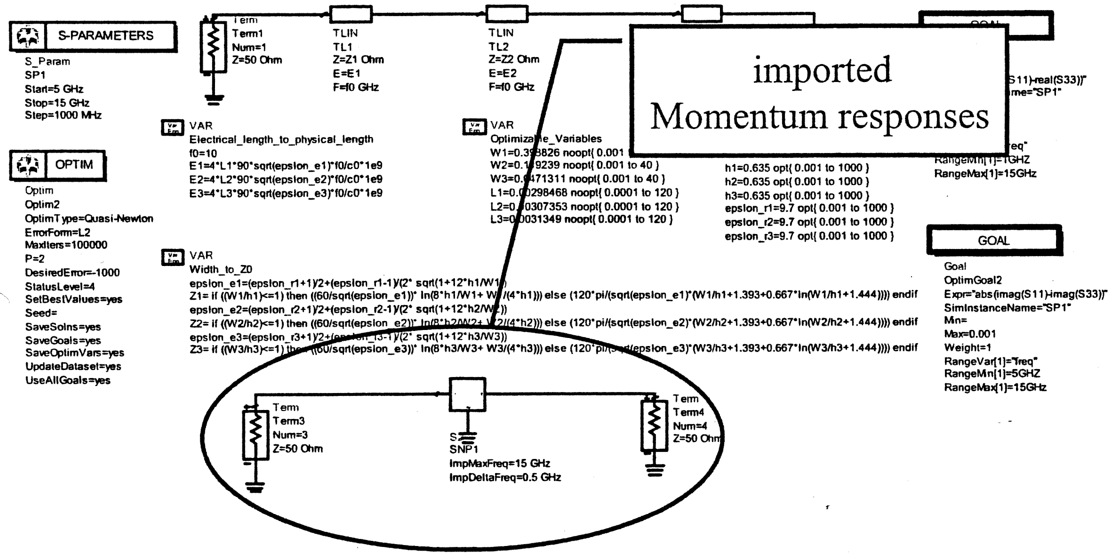
Implicit Space Mapping: Steps 5-6

obtain the fine model result and check stopping criteria



Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



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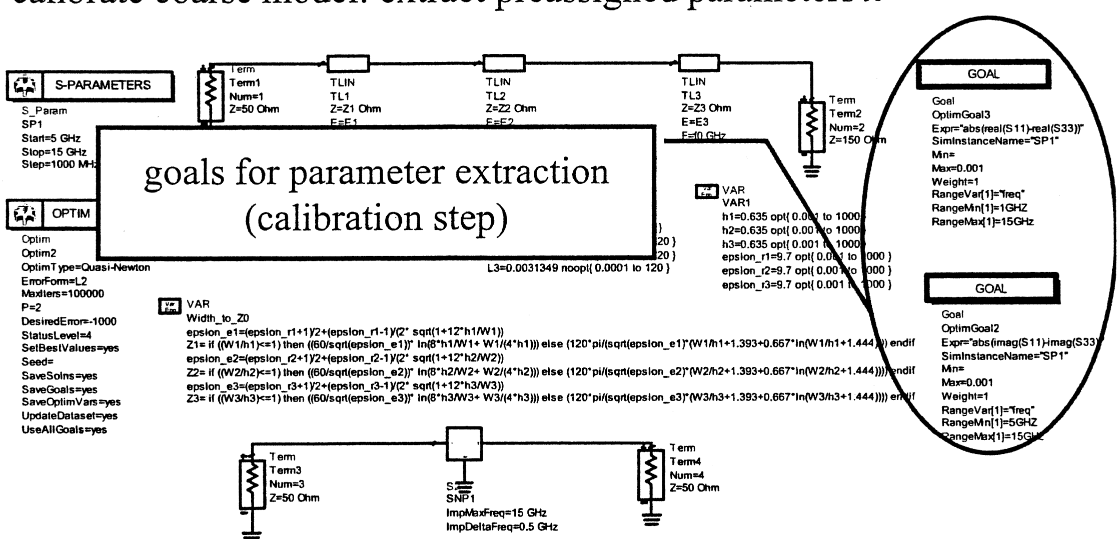
Implicit Space Mapping: Step 7

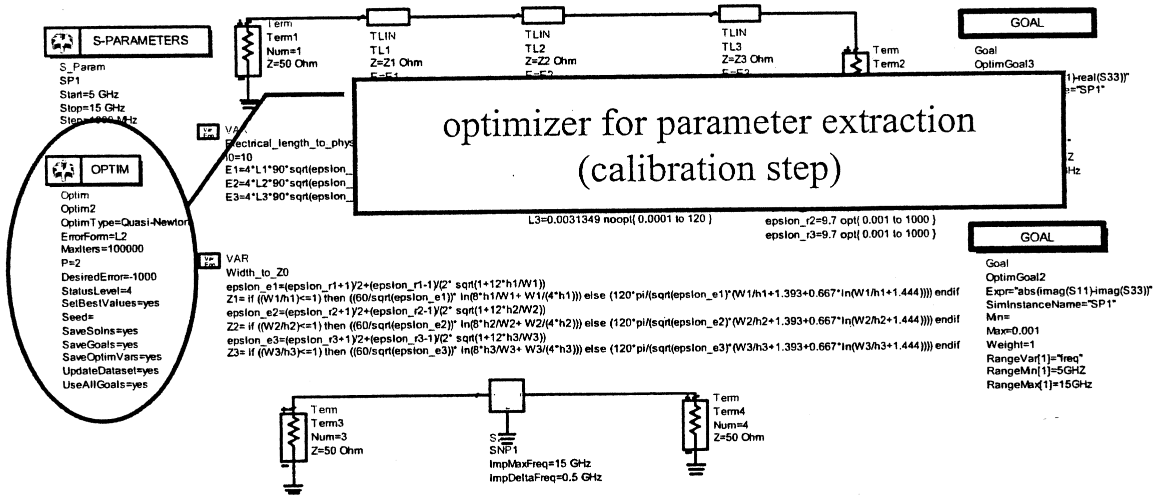
calibrate coarse model: extract preassigned parameters x



ADS/Momentum Implementation

Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



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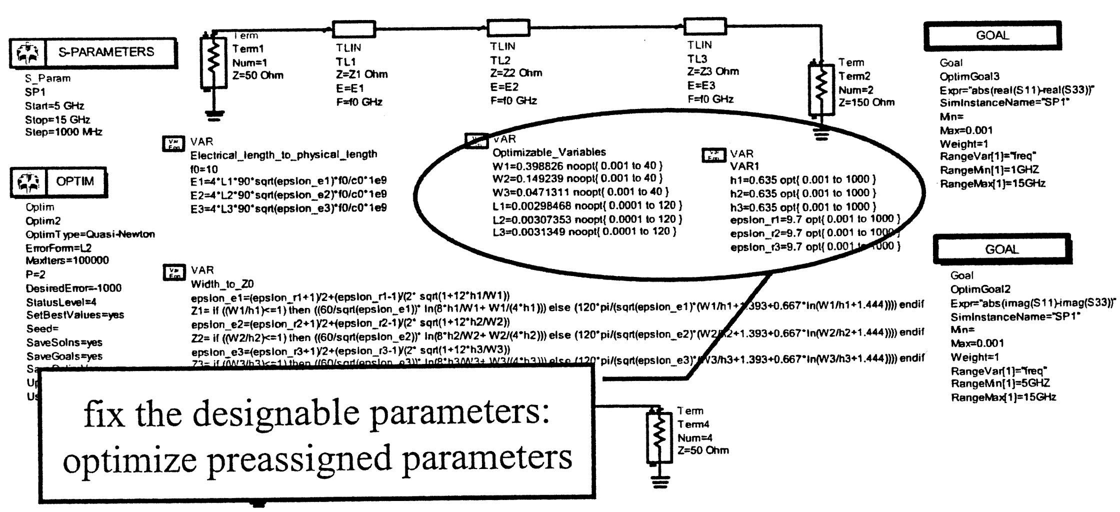
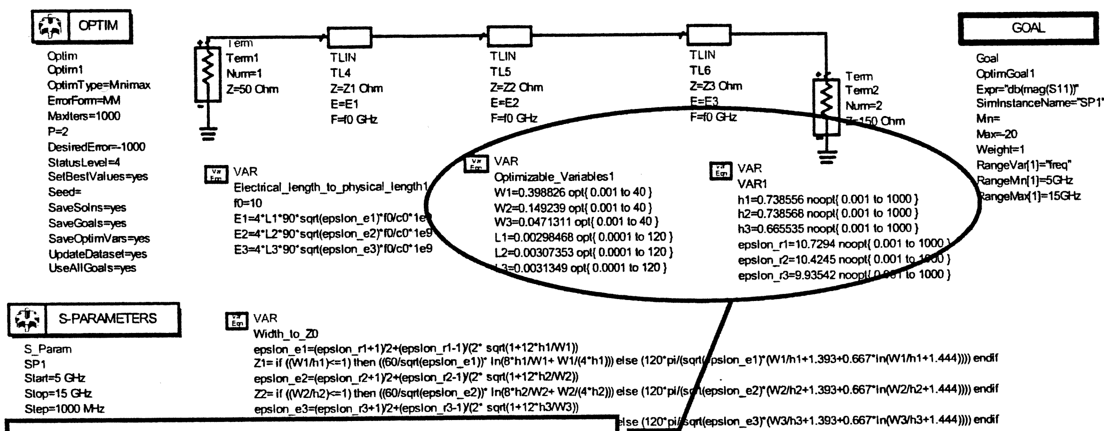
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



Implicit Space Mapping: Steps 8-3

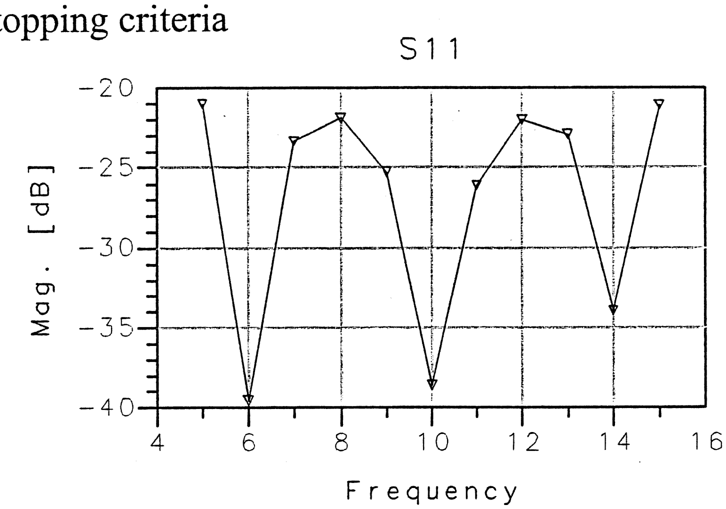
fix preassigned parameters: reoptimize calibrated coarse model



fix preassigned parameters:
reoptimize calibrated coarse model

Implicit Space Mapping: Steps 4-6

simulate fine model using Momentum,
satisfy stopping criteria



Conclusions

Space Mapping intelligently links companion "coarse" or "surrogate" models with "fine" models—physical, empirical, electromagnetic

Space Mapping optimization follows traditional experience of designers

researchers and practitioners attracted to Aggressive Space Mapping

Space Mapping already used in the RF industry
for enhanced (mapped) library (surrogate) models

Implicit Space Mapping (ISM), where preassigned parameters change in coarse model—novel approach

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References

J.W. Bandler, R.M. Biernacki, S.H. Chen, P.A. Grobelny and R.H. Hemmers, "Space mapping technique for electromagnetic optimization," *IEEE Trans. Microwave Theory Tech.*, vol. 42, 1994, pp. 2536-2544.

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Space Mapping Approaches to EM-based Device Modeling and Component Design

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presented at

WORKSHOP ON MICROWAVE COMPONENT DESIGN USING SPACE MAPPING METHODOLOGIES
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Space Mapping Approaches to EM-based Device Modeling and Component Design

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Abstract

The Space Mapping concept intelligently links companion "coarse" and "fine" engineering models of different complexities, e.g., full-wave electromagnetic (EM) simulations and empirical circuit-theory based models. Space mapping optimization closely follows the traditional experience and intuition of designers. Our original 1993 concept and the subsequent Aggressive Space Mapping approach to engineering design optimization will be discussed. Recent developments include neural space mapping and the introduction of the object oriented SMX system to facilitate implementation with commercial simulators. We have developed a comprehensive Space Mapping framework to engineering device modeling. Tableau-based approach, it permits many different practical implementations. The accuracy of available empirical models can be significantly enhanced in selected regions of interest. We present microstrip examples yielding remarkable modeling improvement. It has been reported to be useful in the RF industry for development of new library models. We briefly review the new Implicit Space Mapping (ISM) concept in which we allow preassigned parameters, not used in optimization, to change in some components of the coarse model. Extensive filter design examples, exploiting full wave EM simulators, complement the presentation. Implementation in software such as Agilent Momentum and ADS will be discussed. One of the frontiers that remains in the optimization of large engineering systems is the successful application of optimization procedures in problems where direct optimization is not practical. The recent exploitation of surrogates in conjunction with "true" models, the development of artificial neural network approaches to device modeling and the implementation of space mapping are attempts to address this issue.

Outline

Space Mapping intelligently links companion "coarse" and "fine" models—full-wave electromagnetic (EM) simulations and empirical models

Space Mapping optimization follows traditional experience of designers

we discuss the 1993 concept and subsequent Aggressive Space Mapping

Outline

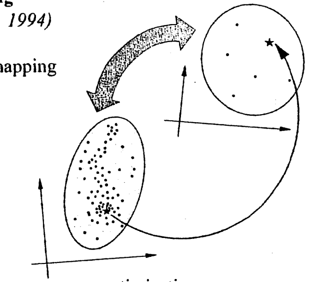
object oriented SMX system facilitates commercial simulators

tableau approach enhances accuracy of available empirical models (already used in the RF industry for new library models)

Implicit Space Mapping (ISM), where preassigned parameters change in coarse model

filter design, implementation in Agilent Momentum and ADS

Space Mapping
(Bandler et al., 1994)



Space Mapping: a Glossary of Terms

Space Mapping	transformation, link, adjustment, correction, shift (in parameters or responses)
Coarse Model	simplification or convenient representation, companion to the fine model, auxiliary representation, cheap model
Fine Model	accurate representation of system considered, device under test, component to be optimized, expensive model

Space Mapping: a Glossary of Terms

Surrogate	model, approximation or representation to be used, or to act, in place of, or as a substitute for, the system under consideration
Surrogate Model	alternative expression for coarse model
Target Response	response the fine model should achieve, (usually) optimal response of a coarse model, enhanced coarse model, or surrogate

Space Mapping: a Glossary of Terms

Companion	coarse
Low Fidelity	coarse
High Fidelity	fine
Empirical	coarse
Physics-based	coarse or fine
Device under Test	fine
Electromagnetic	fine or coarse
Simulation	fine or coarse
Computational	fine or coarse

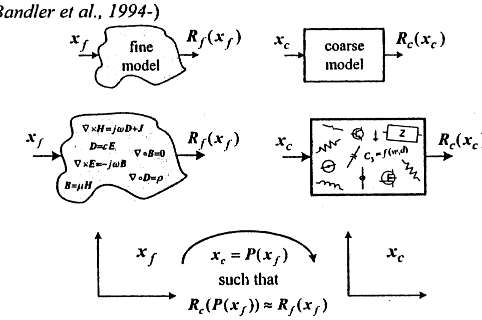
Space Mapping: a Glossary of Terms

Parameter (input) Space Mapping	mapping, transformation or correction of design variables
Response (output) Space Mapping	mapping, transformation or correction of responses
Response Surface Approximation	linear/quadratic/polynomial approximation of responses w.r.t. design variables

Space Mapping: a Glossary of Terms

Neuro	implies use of artificial neural networks
Implicit Space Mapping	space mapping when the mapping is not obvious
Not Space Mapping	(usually) space mapping when not acknowledged
Parameter Transformation	space mapping
Predistortion	?

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



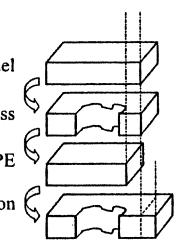
Space Mapping Practice—Cheese Cutting Problem

optimal coarse model

initial guess

PE

prediction



$$x_f^{new} = x_f^{old} + P^{-1}(x_c^* - x_c^{new})$$

$$x_f^{new} = x_f^{old} + x_c^* - x_c^{new}$$

The Brain's Automatic Pilot
*(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)*

[certain brain] circuits are used by the human brain
to assess social rewards …

…findings [by neuroscientists] …challenge the notion
that people always make conscious choices
about what they want and how to obtain it.

Gregory Berns (Emory University School of Medicine):
… most decisions are made subconsciously
with many gradations of awareness.

The Brain's Automatic Pilot
*(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)*

P. Read Montague (Baylor College of Medicine): … how did
evolution create a brain that could make … distinctions …
[about] …what it must pay conscious attention to?

… the brain has evolved to shape itself, starting in infancy,
according to what it encounters in the external world.

… much of the world is predictable: buildings usually stay
in one place, gravity makes objects fall …

The Brain's Automatic Pilot
*(Sandra Blakeslee, The New York Times,
International Herald Tribune, February 21, 2002, p.7)*

As children grow, their brains build internal models
of everything they encounter, gradually learning to identify objects …

… as new information flows into it … the brain automatically
compares it with what it already knows.

… if there is a surprise …. the mismatch … instantly shifts
the brain into a new state.

Drawing on past experience … a decision is made …

Current Space Mapping Milestones

yield driven EM optimization using Space Mapping-based
neuromodels (2001)

EM-based optimization exploiting Partial Space Mapping (PSM)
and exact sensitivities (2002)

Implicit Space Mapping (ISM) EM-based modeling and design (2002)

introduction of Space Mapping to mathematicians (2002)


Special Issue of *Optimization and Engineering*
on Surrogate Modelling and Space Mapping
for Engineering Optimization (2002)

Selected Space Mapping Contributors

Kaj Madsen (Technical University of Denmark, 1993-)
mapping updates, trust region methods

Pavio (Motorola, 1994-)
companion model approach, filter design, LTCC circuits

Shen Ye (ComDev, 1997-)
circuit calibration technique

Mansour (Com Dev, University of Waterloo, 1998-)
Cauchy method and adaptive sampling

Stephane Bila (Limoges, France 1998-)
space mapping, waveguide devices

Selected Space Mapping Contributors

Rayas-Sánchez (McMaster University; ITESO, Mexico 1998-)
space mapping through artificial neural networks

Jacob Søndergaard (Technical University of Denmark, 1999-)
space mapping: theory and algorithms

Qi-jun Zhang (Carleton University, 1999-)
knowledge based neural networks, space mapping

Jan Snel (Philips Semiconductors, Netherlands, 2001)
RF component design, library model enhancement

Dan Swanson (Bartley RF Systems, 2001)
combline filter design

Selected Space Mapping Contributors

Steven Leary (University of Southampton, England, 2000-)
constraint mapping, applications in civil engineering

Lehmensiek (University of Stellenbosch, South Africa, 2000, 2001)
filter design, coupling structures

Frank Pedersen (Technical University of Denmark, 2001-)
space mapping, neural networks

Ke-Li Wu (Chinese University of Hong Kong, 2001-)
knowledge embedded space mapping, LTCC circuits

Pablo Soto (Polytechnic University of Valencia, Spain, 2001)
aggressive space mapping, inductively coupled filters

Hong-Soon Choi (Seoul National University, Korea, 2001)
aggressive space mapping, design of magnetic systems

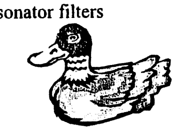
Selected Space Mapping Contributors

Luis Vicente (University of Coimbra, Portugal, 2001-)
mathematics of space mapping: models, sensitivities and trust regions

Marcus Redhe (Linköping University, Sweden, 2001)
sheet metal forming and vehicle crashworthiness design

Dieter Peltz (Radio Frequency Systems, Australia, 2002)
difference matrix approach, coupled resonator filters

Safavi-Naeini (University of Waterloo, 2002)
multi-level generalized space mapping,
multi-cavity microwave structures



Jan-Willem Lobeek (Philips Semiconductors, Netherlands, 2002)
power amplifier design

Jacobian-Space Mapping Relationship
(Bakr et al., 1999)

through PE we match the responses

$$R_f(x_f) \approx R_c(P(x_f))$$

by differentiation

$$\left(\frac{\partial R_f^T}{\partial x_f}\right)^T \approx \left(\frac{\partial R_c^T}{\partial x_c}\right)^T \cdot \left(\frac{\partial x_c^T}{\partial x_f}\right)^T$$

Jacobian-Space Mapping Relationship
(Bakr et al., 1999)

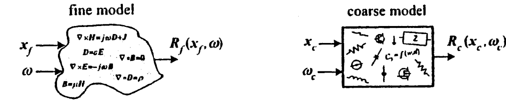
given coarse model Jacobian J_c and space mapping matrix B we estimate

$$J_f(x_f) \approx J_c(x_c)B$$

given J_c and J_f we estimate (least squares)

$$B \approx (J_c^T J_c)^{-1} J_c^T J_f$$

Conventional Space Mapping for Microwave Circuits
(Bandler et al., 1994)



find

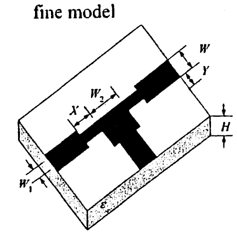
$$\begin{bmatrix} x_c \\ \omega_c \end{bmatrix} = P(x_f, \omega)$$

such that

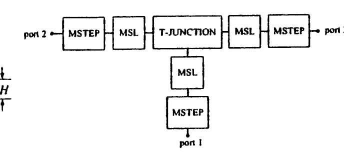
$$R_c(x_c, \omega_c) \approx R_f(x_f, \omega)$$

Microstrip Shaped T-Junction

fine model



coarse model



Microstrip Shaped T-Junction

the region of interest

$$15 \text{ mil} \le H \le 25 \text{ mil}$$
$$2 \text{ mil} \le X \le 10 \text{ mil}$$
$$15 \text{ mil} \le Y \le 25 \text{ mil}$$
$$8 \le \varepsilon_r \le 10$$

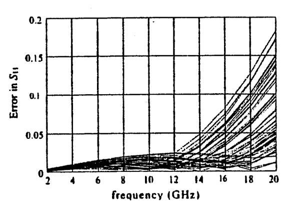
the frequency range is 2 GHz to 20 GHz with a step of 2 GHz
the number of base points is 9, the number of test points is 50

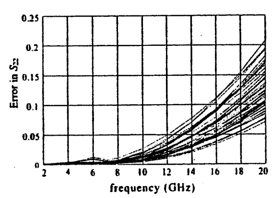
the widths W of the input lines track H so that their characteristic impedance is 50 ohm

$W_1 = W/3$, W_2 is suitably constrained

Microstrip Shaped T-Junction Coarse Model

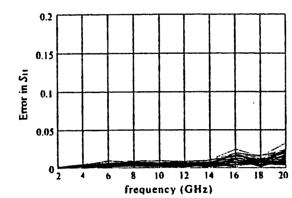
errors w.r.t. Sonnet's ***em*** at the test points

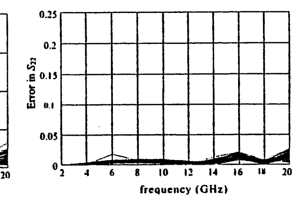




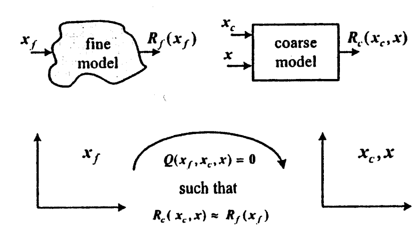
Microstrip Shaped T-Junction Enhanced Coarse Model

errors w.r.t. Sonnet's ***em*** at the test points





Implicit Space Mapping Theory
(Bandler et al., 2002)



Implicit Space Mapping Practice

(Bandler et al., 2002)

effective for EM-based microwave modeling and design

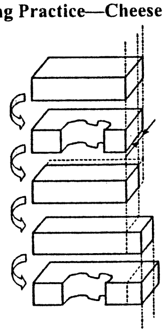
coarse model aligned with EM (fine) model
through preassigned parameters

easy implementation

no explicit mapping involved

no matrices to keep track of

Implicit Space Mapping Practice—Cheese Cutting Problem



optimal coarse model — $x_c^{*(0)}$ $x^{(0)}$

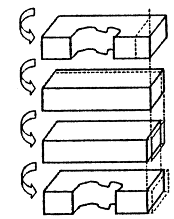
initial guess — $x_f^{(0)} = x_c^{*(0)}$

PE — $x_c^{*(0)}$ $x^{(1)}$

prediction — $x_c^{*(1)}$ $x^{(1)}$

verification — $x_f^{(1)} = x_c^{*(1)}$

Implicit Space Mapping Practice—Cheese Cutting Problem



verification — $x_f^{(1)} = x_c^{*(1)}$

PE — $x_c^{*(1)}$ $x^{(2)}$

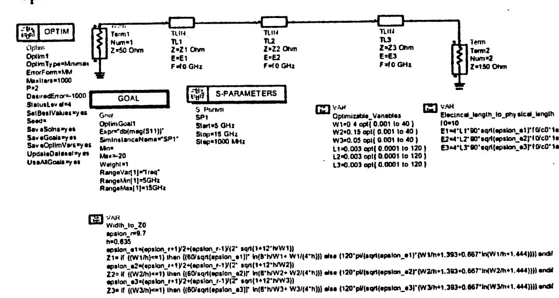
prediction — $x_c^{*(2)}$ $x^{(2)}$

verification — $x_f^{(2)} = x_c^{*(2)}$

⋮

Implicit Space Mapping: Steps 1-3

optimize coarse model

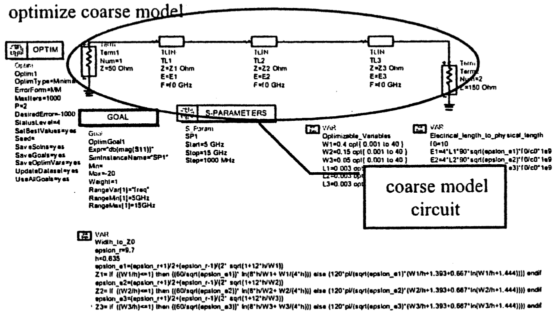


Agilent Technologies

ADS/Momentum Implementation

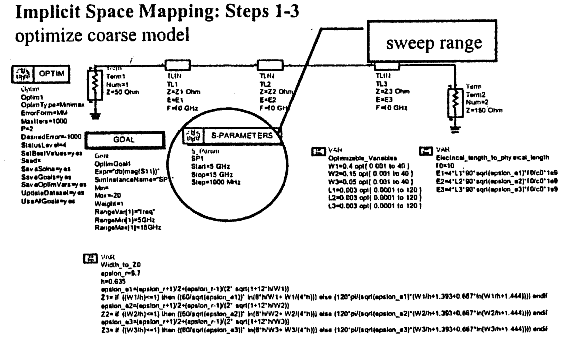
Implicit Space Mapping: Steps 1-3

optimize coarse model



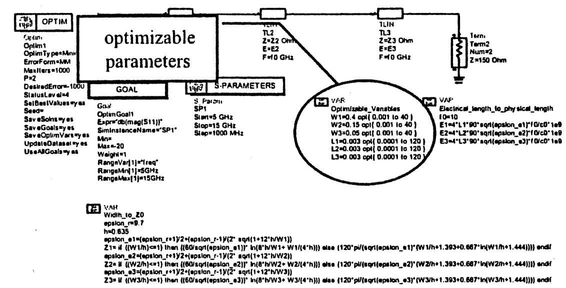
Implicit Space Mapping: Steps 1-3

optimize coarse model



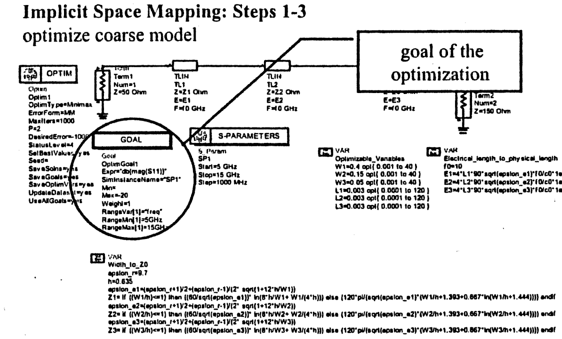
Implicit Space Mapping: Steps 1-3

optimize coarse model



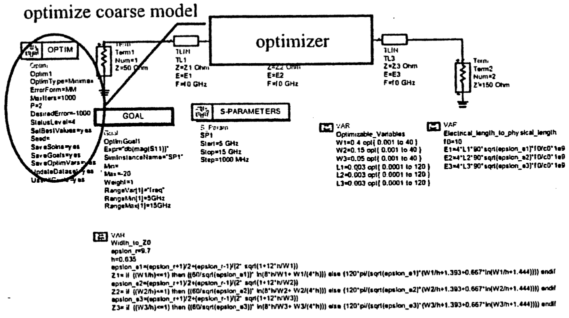
Implicit Space Mapping: Steps 1-3

optimize coarse model



Implicit Space Mapping: Steps 1-3

optimize coarse model

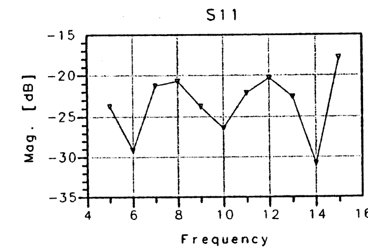


Implicit Space Mapping: Steps 4-5

simulate fine model using Momentum

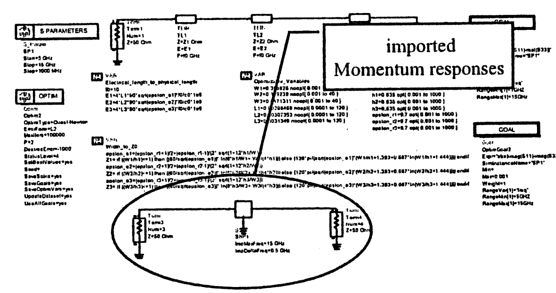
Implicit Space Mapping: Steps 5-6

obtain the fine model result and check stopping criteria



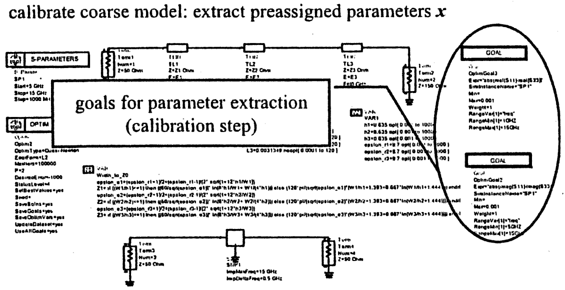
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters $\boldsymbol{x}$



Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



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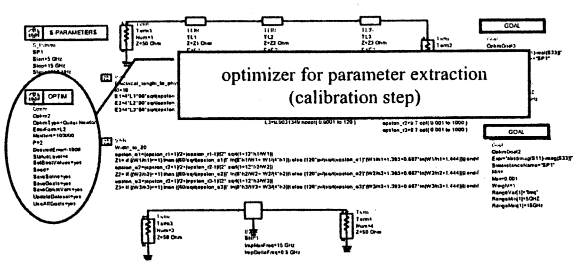
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



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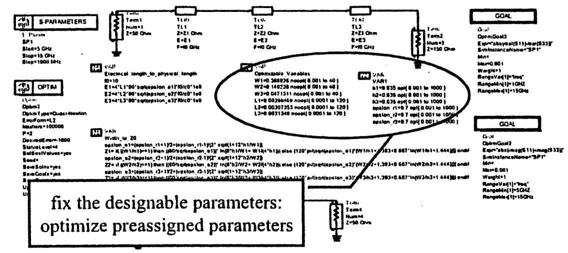
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters x



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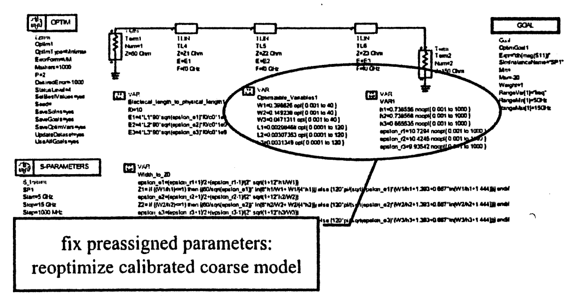
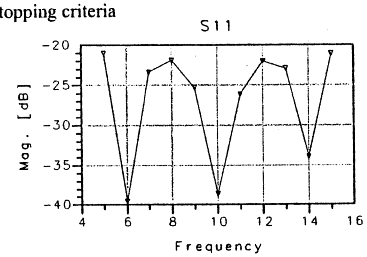
Implicit Space Mapping: Steps 8-3

fix preassigned parameters: reoptimize calibrated coarse model



Implicit Space Mapping: Steps 4-6

simulate fine model using Momentum,
satisfy stopping criteria



ADS/Momentum Implementation

Conclusions

Space Mapping intelligently links companion "coarse" or "surrogate" models with "fine" models—physical, empirical, electromagnetic

Space Mapping optimization follows traditional experience of designers

researchers and practitioners attracted to Aggressive Space Mapping

Space Mapping already used in the RF industry
for enhanced (mapped) library (surrogate) models

Implicit Space Mapping (ISM), where preassigned parameters change in coarse model—novel approach

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EM-Based Design through Neural Space Mapping Methods

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McMaster University

presented at

WORKSHOP ON MICROWAVE COMPONENT DESIGN USING SPACE MAPPING METHODOLOGIES
2002 IEEE MTT-S International Microwave Symposium, Seattle, WA, June 3, 2002

1

EM-Based Design through Neural Space Mapping Methods

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Abstract

Artificial Neural Networks (ANN) and Space Mapping (SM) are eficiently combined to formulate EM-based design algorithms. Neural Space Mapping (NSM) optimization and Neural Inverse Space Mapping (NISM) optimization are reviewed.

NSM optimization exploits the SM-based neuromodeling techniques to efficiently approximate the mapping. The next point is predicted avoiding parameter extraction (PE). The initial mapping is established by performing upfront fine model analyses at a reduced number of base points. Coarse model sensitivities are exploited to select those base points. Huber optimization is used to train, without testing points, simple SM-based neuromodels at each NSM iteration. EM-based yield optimization is efficiently realized after NSM optimization.

NISM optimization is the first space mapping algorithm that explicitly makes use of the inverse of the mapping from the fine to the coarse model parameter spaces. NISM follows an aggressive formulation by not requiring a number of up-front fine model evaluations to start building the mapping. An statistical procedure to PE avoids the need for multipoint matching and frequency mappings. It can also overcome poor local mimima during PE. An ANN whose generalization performance is controlled through a network growing strategy approximates the inverse mapping at each iteration. In this manner, the ANN always starts from a 2-layer perceptron and automatically migrates to a 3-layer perceptron only if the amount of nonlinearity found in the inverse mapping becomes significant. The NISM step consists of evaluating the current neural network at the optimal coarse solution. This step is equivalent to a quasi-Newton step while the inverse mapping is essentially linear, and gradually departs from a quasi-Newton step as the amount of nonlinearity in the inverse mapping grows.

Contrast is made between neural space mapping design methods. A number of industrially relevant microwave design problems are efficiently solved.

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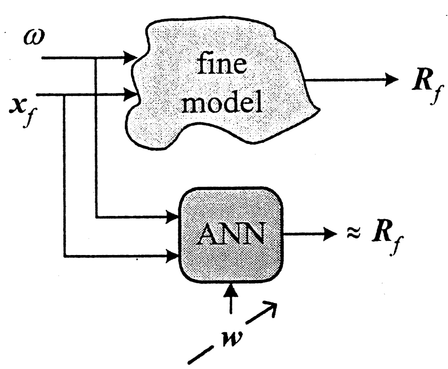
Outline

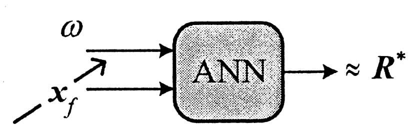
- Conventional ANN optimization
- Neural Space Mapping (NSM) optimization
- Yield optimization using neuromodels
- Neural Inverse Space Mapping (NISM) optimization
- Conclusions

Conventional ANN-Based Optimization

Step 1



Step 2



Many fine model simulations are needed

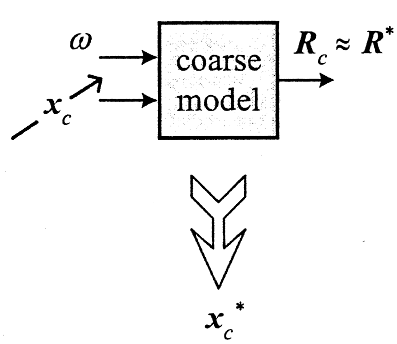
Solutions predicted outside the training region are unreliable

Neural Space Mapping (NSM) Optimization

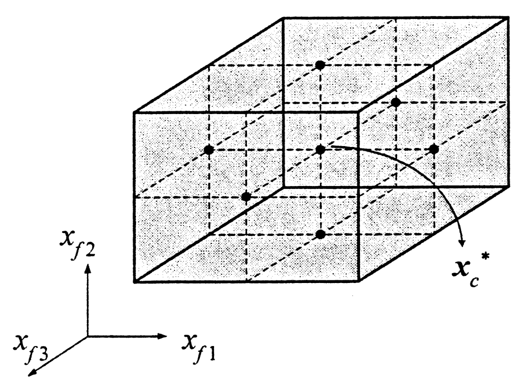
- Exploits the SM-based neuromodeling techniques *(Bandler et al., 1999)*
- Coarse models reduce the amount of learning data and improve the generalization and extrapolation performance
- NSM requires a reduced set of upfront learning base points
- The initial learning base points are selected through sensitivity analysis using the coarse model
- A network growing strategy is employed

NSM Optimization Concept

Step 1

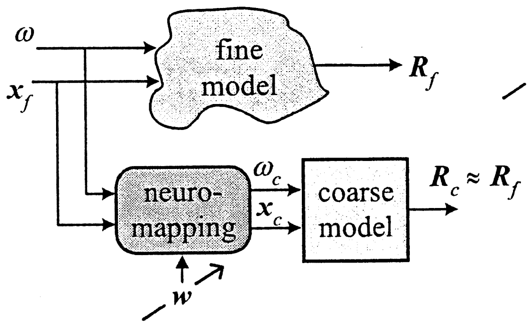


Step 2

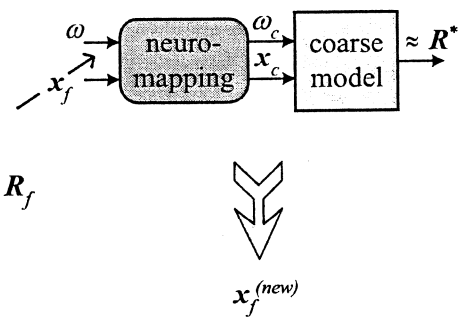


NSM Optimization Concept (cont)

Step 3

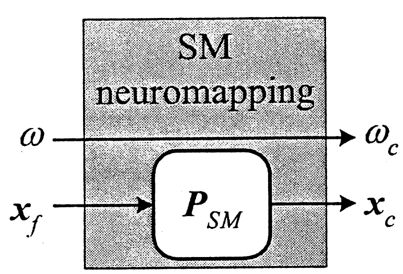


Step 4

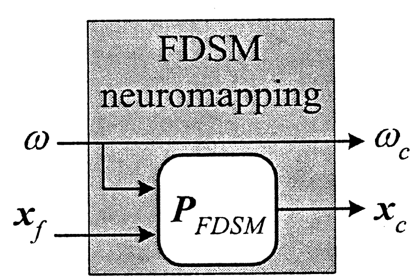


Neuromappings

Space Mapped neuromapping

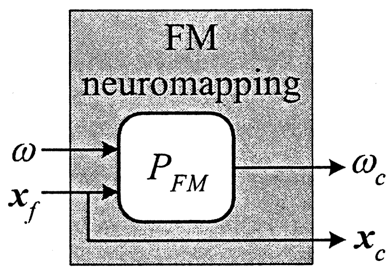


Frequency-Dependent Space Mapped neuromapping

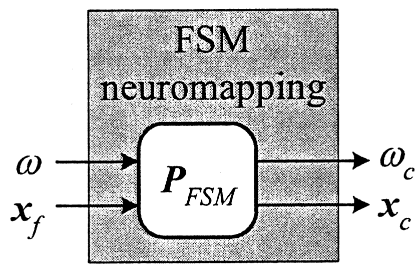


Neuromappings (cont)

Frequency Mapped neuromapping

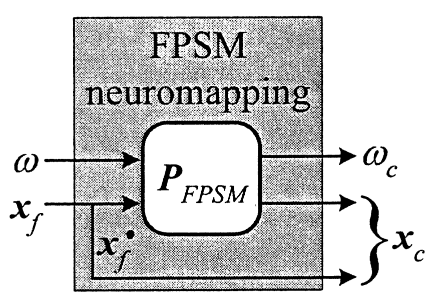


Frequency Space Mapped neuromapping



Neuromappings (cont)

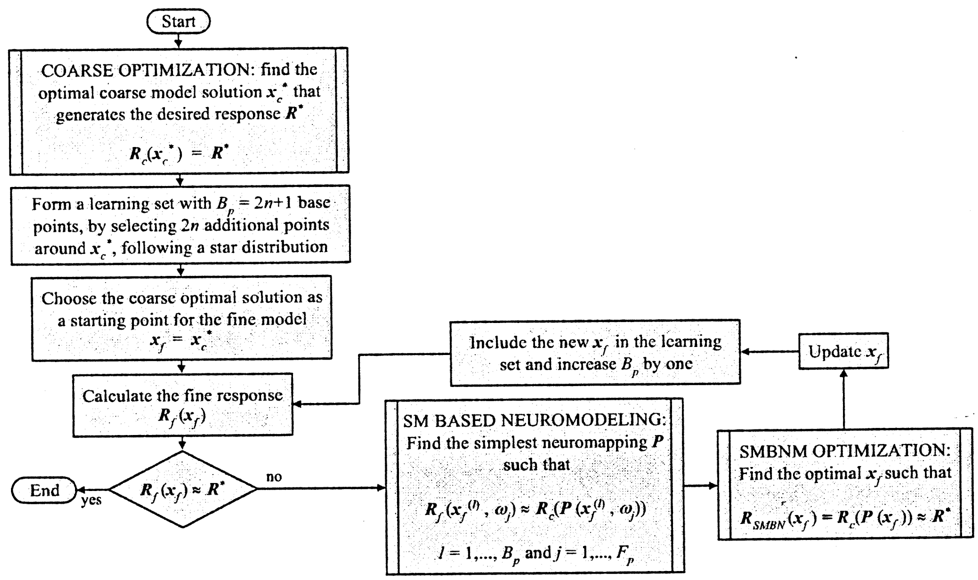
Frequency Partial-Space Mapped neuromapping



It is not always necessary to map the whole set of design parameters

Coarse model sensitivities can be used to select the mapped parameters

NSM Optimization Algorithm



Coarse Optimization Phase

$$R_c(x_c) = [R_c^1(x_c)^T \quad \ldots \quad R_c^r(x_c)^T]^T$$

$$R_c^k(x_c) = [R_c^k(x_c, \omega_1) \quad \ldots \quad R_c^k(x_c, \omega_{F_p})]^T \qquad k = 1, \ldots, r$$

Circuit design using the coarse model is formulated as

$$x_c^* = \arg\min_{x_c} U(R_c(x_c))$$

where U is a suitable objective function

Training the SM-Based Neuromodel

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\cdots \quad \boldsymbol{e}_s^T \quad \cdots]^T \right\|$$

$$\boldsymbol{e}_s = \boldsymbol{R}_f(\boldsymbol{x}_f^{(l)}, \omega_j) - \boldsymbol{R}_c(\boldsymbol{x}_{c_j}^{(l)}, \omega_{c_j}) \qquad \boldsymbol{e}_s \in \Re^r$$

$$\begin{bmatrix} \boldsymbol{x}_{c_j}^{(l)} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f^{(l)}, \omega_j, \boldsymbol{w})$$

$$j = 1, \ldots, F_p \qquad s = j + F_p(l-1) \qquad l = 1, \ldots, 2n+i$$

r is the number of responses in the model

$\boldsymbol{P}$ is the ANN function and $\boldsymbol{w}$ contains its weights

$2n$+1 is the number of training base points and F_p is the number of frequency points

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SM-Based Neuromodel Optimization

We use an SM-based neuromodel as an enhanced coarse model

$$\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f) = [\boldsymbol{R}_{SMBN}^1(\boldsymbol{x}_f)^T \quad \ldots \quad \boldsymbol{R}_{SMBN}^r(\boldsymbol{x}_f)^T]^T$$

$$\boldsymbol{R}_{SMBN}^k(\boldsymbol{x}_f) = [R_c^k(\boldsymbol{x}_{c1}, \omega_{c1}) \quad \ldots \quad R_c^k(\boldsymbol{x}_{cF_p}, \omega_{cF_p})]^T \qquad k = 1, \ldots, r$$

$$\begin{bmatrix} \boldsymbol{x}_{c_j} \\ \omega_{c_j} \end{bmatrix} = \boldsymbol{P}^{(i)}(\boldsymbol{x}_f, \omega_j, \boldsymbol{w}^*) \qquad j = 1, \ldots, F_p$$

The next iterate is obtained by solving

$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_{SMBN}(\boldsymbol{x}_f))$$

If an SMN is used to implement $\boldsymbol{P}(i)$

$$\boldsymbol{x}_f^{(2n+i+1)} = \arg\min_{\boldsymbol{x}_f} \| \boldsymbol{P}_{SM}^{(i)}(\boldsymbol{x}_f, \boldsymbol{w}^*) - \boldsymbol{x}_c^* \|$$

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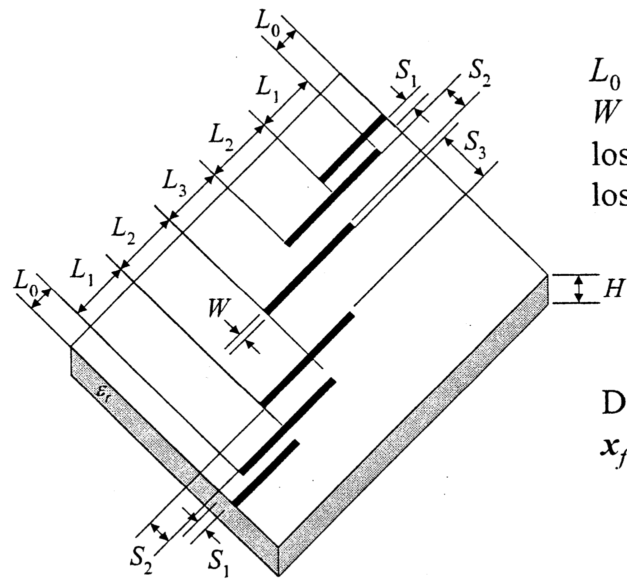
HTS Filter *(Westinghouse, 1993)*



L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; lossless metalization

Design parameters
$x_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$

NSM Optimization of the HTS Microstrip Filter

Specifications

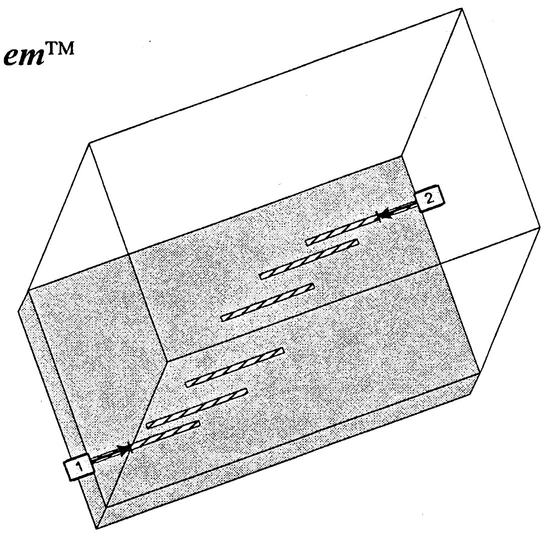
$|S_{21}| \geq 0.95$ for 4.008 GHz $\leq f \leq$ 4.058 GHz

$|S_{21}| \leq 0.05$ for $f \leq$ 3.967 GHz and $f \geq$ 4.099 GHz

NSM Optimization of the HTS Microstrip Filter

Fine model

Sonnet's ***em***™



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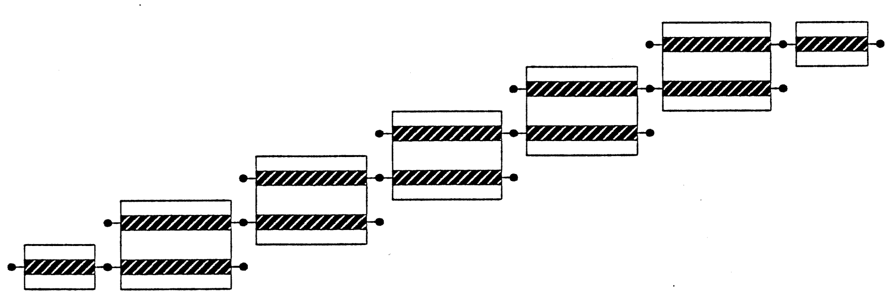
NSM Optimization of the HTS Microstrip Filter

Coarse model

OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines



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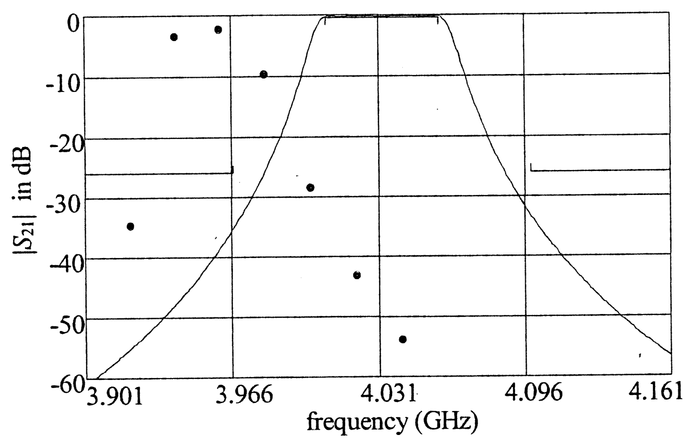
NSM Optimization of the HTS Microstrip Filter

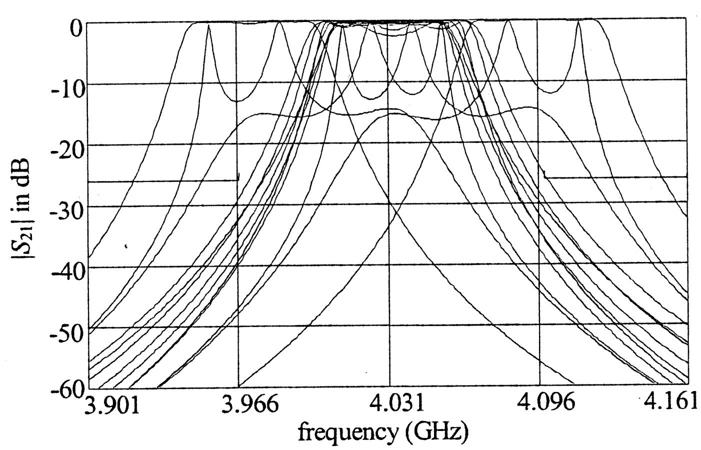
Starting point

OSA90/hope™ (–) and *em*™ (•)



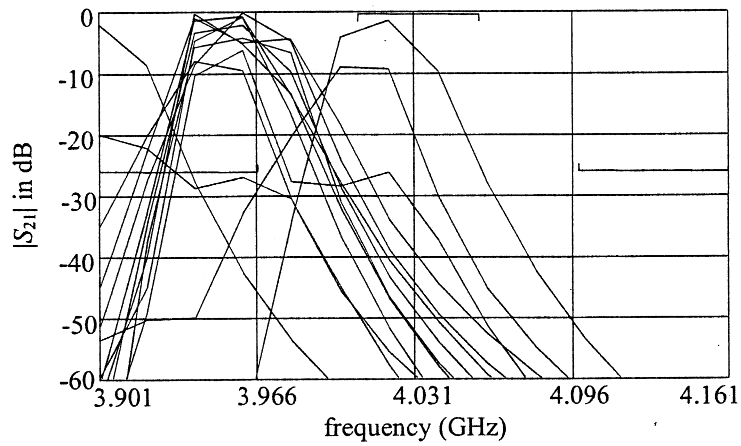
NSM Optimization of the HTS Microstrip Filter

Coarse model responses at the initial $2n+1$ points



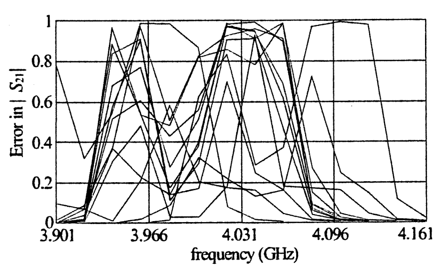
NSM Optimization of the HTS Microstrip Filter

Fine model responses at the initial $2n+1$ points

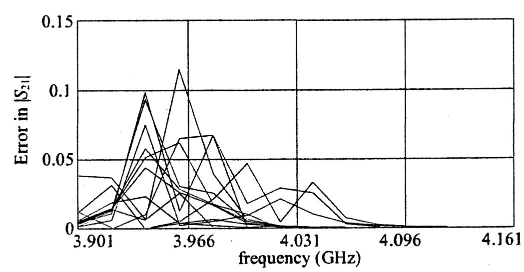


NSM Optimization of the HTS Microstrip Filter

Errors before and after neuromapping

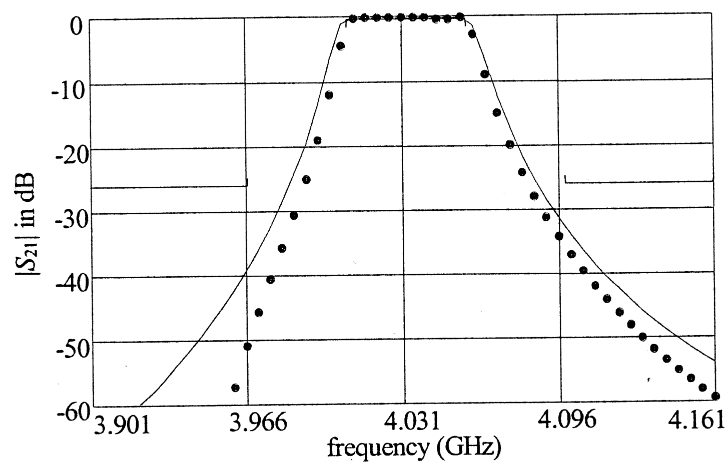


(mapping w, $L1$ and $S1$ with a 3LP:7-5-3)



NSM Optimization of the HTS Microstrip Filter

em™ (•) and FPSM 7-5-3 (–) model responses at the next point predicted after the first NSM iteration



Yield Optimization with SM-based Neuromodels

$$\boldsymbol{R}_f(\boldsymbol{x}_f, \omega) \approx \boldsymbol{R}_{SMBN}(\boldsymbol{x}_f, \omega)$$

for all $\boldsymbol{x}_f$ and ω in the training region

We can show that

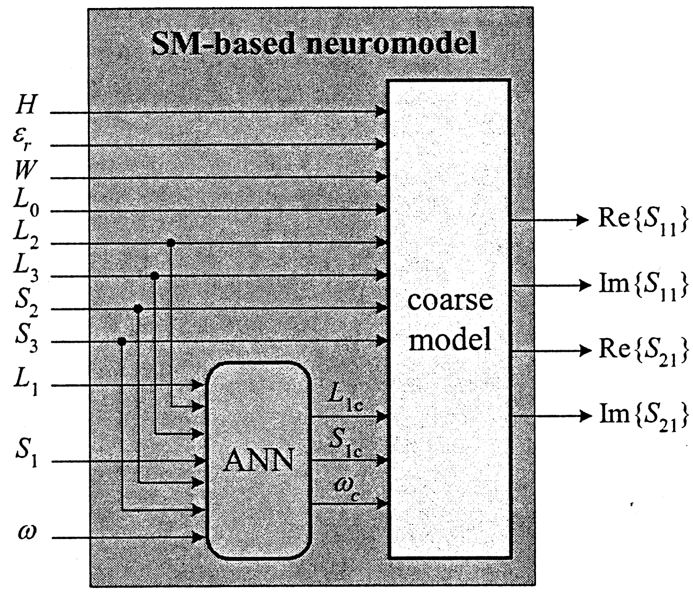
$$\boldsymbol{J}_f \approx \boldsymbol{J}_c \, \boldsymbol{J}_P$$

$\boldsymbol{J}_f \in \Re^{r \times n}$ Jacobian of the fine model responses w.r.t. the fine model parameters

$\boldsymbol{J}_c \in \Re^{r \times (n+1)}$ Jacobian of the coarse model responses w.r.t. the coarse model parameters and mapped frequency

$\boldsymbol{J}_P \in \Re^{(n+1) \times n}$ Jacobian of the mapping function w.r.t. the fine model parameters

SM-based Neuromodel of the HTS Filter



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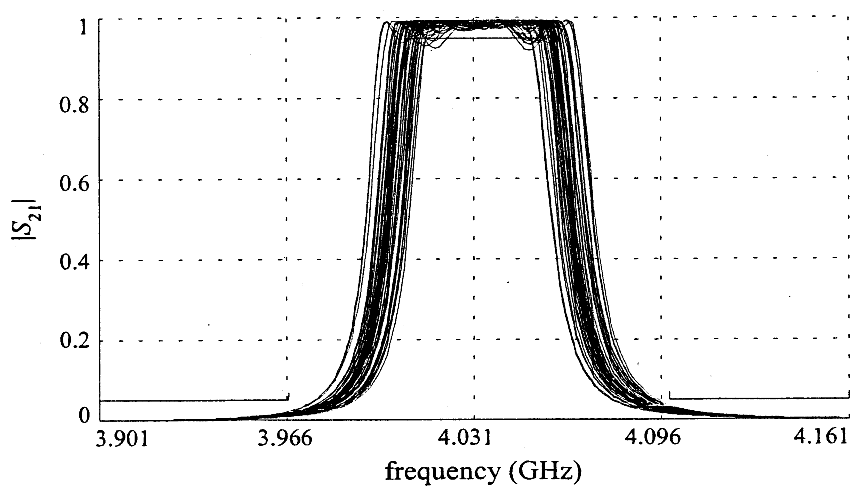
Yield Analysis of the HTS Filter (cont)

At the nominal SM-solution: yield = 18.4%



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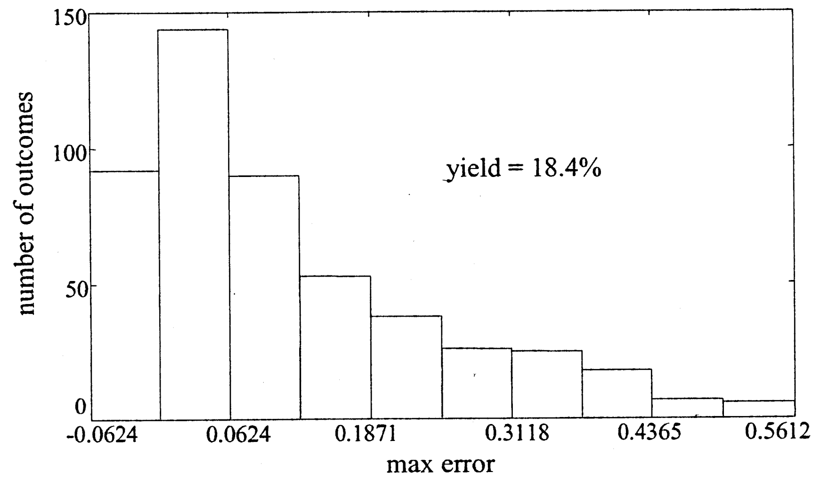
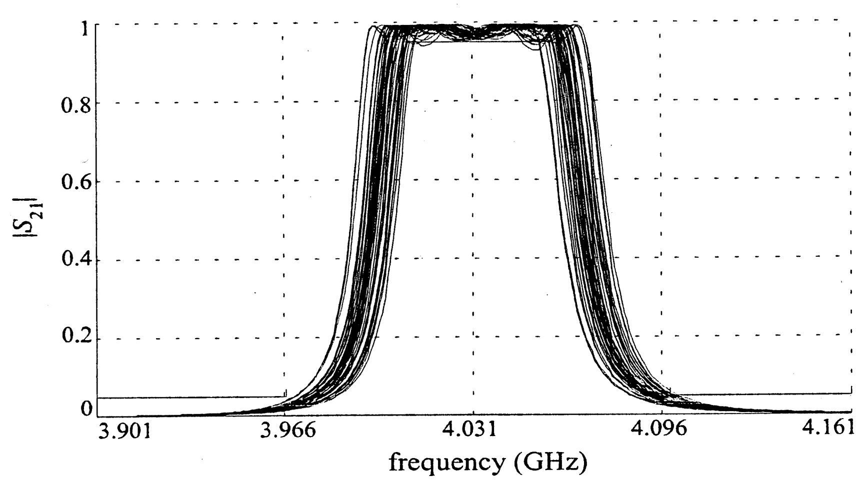
Yield Analysis of the HTS Filter (cont)

At the nominal SM-solution: yield = 18.4%



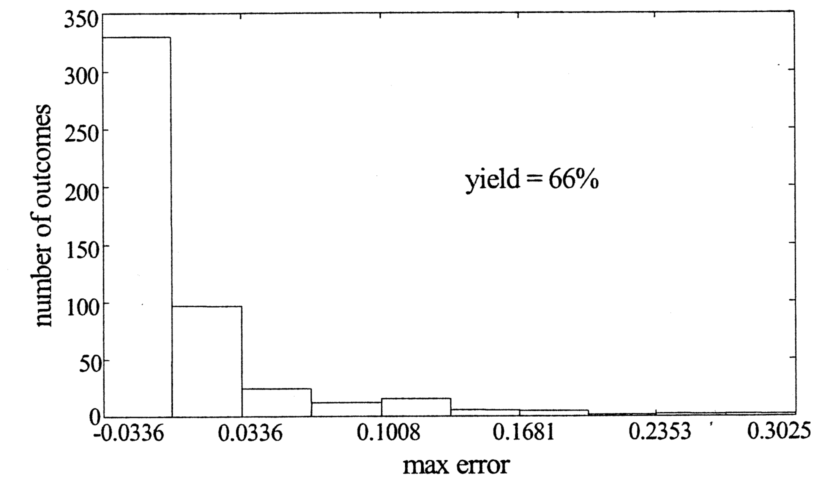
Yield Optimization of the HTS Filter

At the optimal yield SM-solution: yield = 66%



Yield Optimization of the HTS Filter (cont)

At the optimal yield SM-solution: yield = 66%



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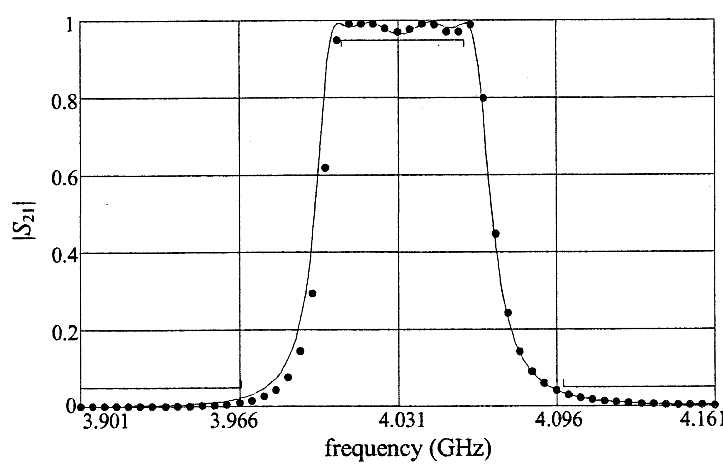
Yield Optimization of the HTS Filter (cont)

em™ (•) response and SM-based neuromodel (–) response at the optimal yield SM-solution



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Neural Inverse Space Mapping Optimization

Objectives

Develop an aggressive ANN-based space mapping optimization algorithm

Avoid multipoint parameter extraction and frequency mappings

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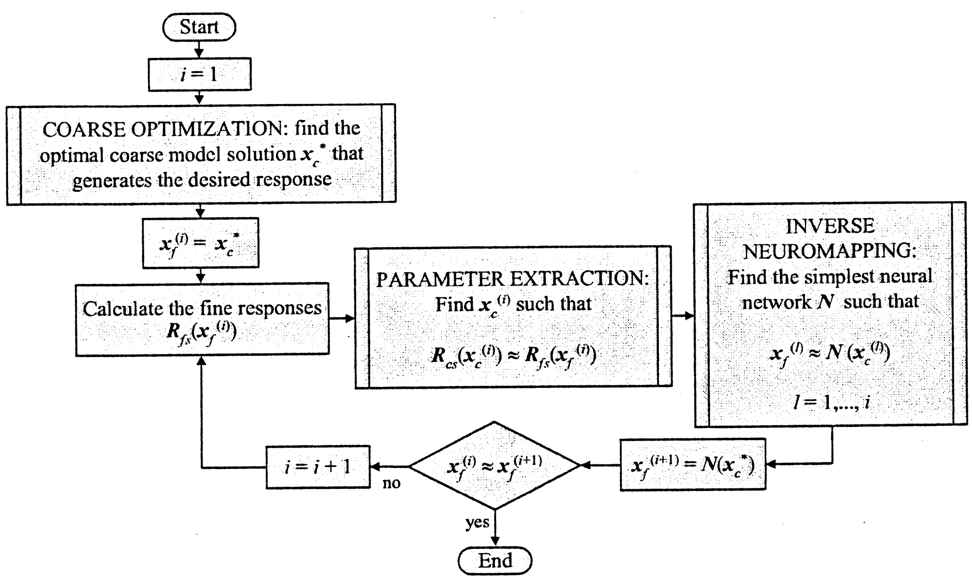
Neural Inverse Space Mapping Optimization



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Statistical Parameter Extraction

(1)

$$x_c^{(i)} = \arg\min_{x_c} U_{PE}(x_c)$$

$$U_{PE}(x_c) = \| e(x_c) \|_2^2$$

$$e(x_c) = R_{fs}(x_f^{(i)}) - R_{cs}(x_c)$$

(2)

$$\Delta_{\max} = \frac{\delta_{PE}}{\| \nabla U_{PE}(x_c^*) \|_\infty}$$

(3)

$$\Delta x_k = \Delta_{\max}(2 rand_k - 1)$$

$$k = 1 \ldots n$$

begin
solve (1) using x_c^* as starting point
while $\| e(x_c^{(i)}) \|_\infty > \varepsilon_{PE}$
calculate Δx using (2) and (3)
solve (1) using $x_c^* + \Delta x$ as starting point
end

Inverse Neuromapping

(4)

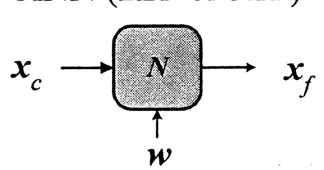
$$w^* = \arg\min_{w} U_N(w)$$

$$U_N(w) = \left\| [\cdots \quad e_l^T \quad \cdots]^T \right\|_2^2$$

$$e_l = x_f^{(l)} - N(x_c^{(l)}, w)$$

$$l = 1, \ldots, i$$

ANN (2LP or 3LP)



begin
solve (4) using a 2LP
$h = n$
while $U_N(w^*) > \varepsilon_L$
solve (4) using a 3LP
$h = h + 1$
end

Nature of the NISM Step

- Evaluates the current ANN at the optimal coarse solution

$$\boldsymbol{x}_f^{(i+1)} = \boldsymbol{N}(\boldsymbol{x}_c^{*})$$

- Is equivalent to a quasi-Newton step
- Departs from a quasi-Newton step as the nonlinearity in the inverse mapping increases
- Does not use classical updating formulas to approximate the Jacobian inverse

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Termination Condition for NISM Optimization

$$\left\|\boldsymbol{x}_f^{(i+1)} - \boldsymbol{x}_f^{(i)}\right\|_2 \le \varepsilon_{end}(\varepsilon_{end} + \left\|\boldsymbol{x}_f^{(i)}\right\|_2) \quad \vee \quad i = 3n$$

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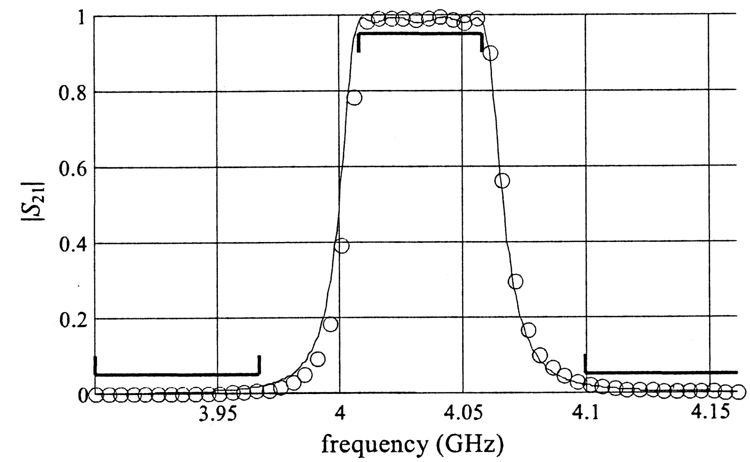
NISM Optimization of the HTS Filter (cont)

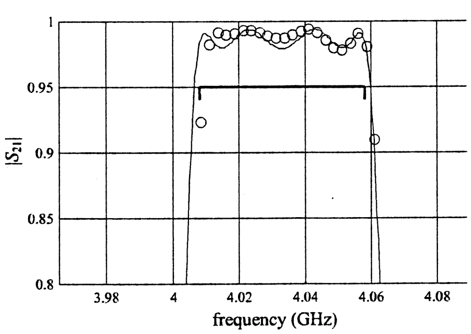
Responses using OSA90/hope™ (–) at x_c^* and
em™ (○) at the NISM solution (after 3 NISM iterations)

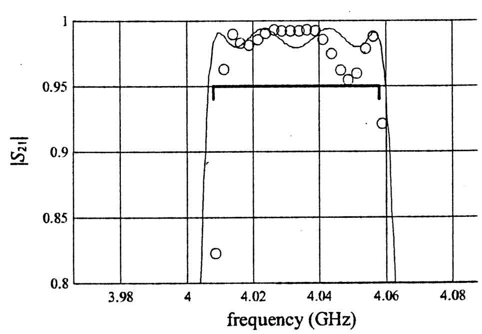


NISM vs. NSM Optimization

HTS filter optimal responses in the passband

NISM (3 fine simulations) NSM (14 fine simulations)





Conclusions

- A number of neural space mapping methods are reviewed
- NSM optimization creates an initial mapping with an ANN, and refines it at each iteration
- After NSM, inexpensive yield optimization can be realized
- NISM optimization implements the inverse mapping with an ANN at each iteration (aggressive approach)
- A statistical procedure overcomes poor local minima during parameter extraction in NISM optimization
- NISM optimization has superior performance to NSM optimization

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The Optimization of Complex Multi-Layer Microwave Circuits Using Companion Models and Space Mapping Techniques

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Abstract — **A novel approach for the optimization of high density, multi-layer circuits for both RF and microwave applications will be presented. The method employs the use of "companion" or "coarse models" coupled with conventional circuit analysis and electromagnetic simulation to yield an optimum component solution with a minimal amount of EM analysis. Limitations on model structure, mapping requirements, simulation accuracy and computation time will be included.**

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7700 S. River Parkway, Tempe, AZ 85284

MTT-S 2002 Workshop "Microwave Component Design Using Space Mapping Methodologies"

Overview

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- *Introduction*
- *Method Outline*
- *Simplified Design Example*
- *Companion Model Formation and Limitations*
- *Design Examples*
- *Conclusion*

Method Outline

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- THE CIRCUIT IS ANALYZED USING STANDARD LINEAR/NONLINEAR SIMULATION TECHNIQUES.
- THE OPTIMIZED CIRCUIT VALUES (COMPANION MODEL) ARE MAPPED (space mapping) TO THE EM SIMULATOR.
- THE CIRCUIT MODEL VALUES ARE THEN ADJUSTED SO THAT THE SIMULATED PERFORMANCE MATCHES THAT OF THE FIRST PASS EM SIMULATION.
- THE CHANGE IN VALUES FROM THE COMPANION CIRCUIT MODEL ARE THEN USED TO UPDATE THE EM SIMULATOR FOR THE NEXT ITERATION STEP.
- THE ITERATION PROCEDURE IS REPEATED UNTILL THE DESIRED PERFORMANCE IS OBTAINED.

Simplified Example

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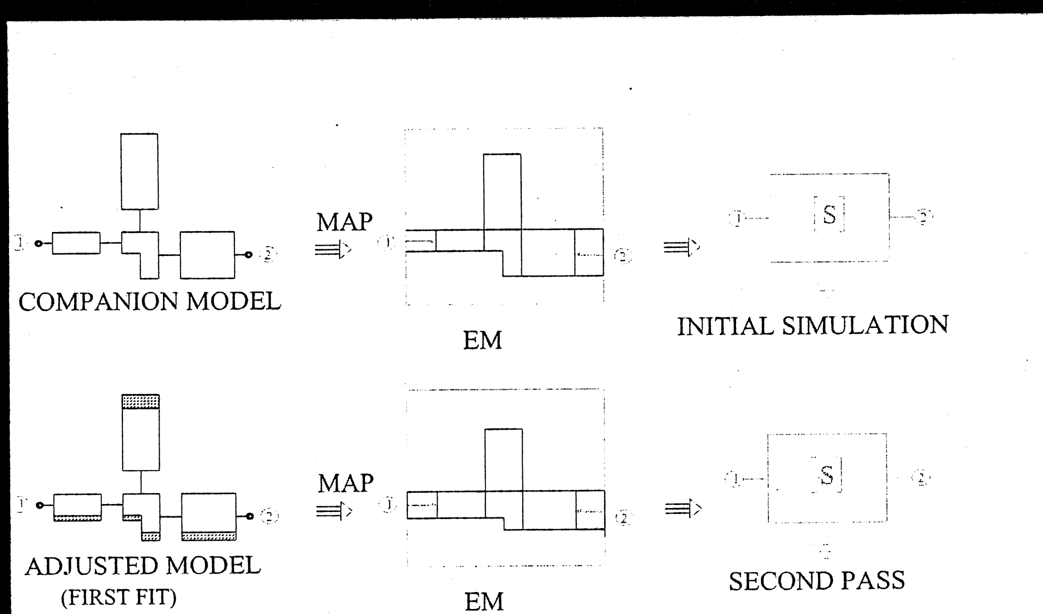

Simplified Band Stop Filter

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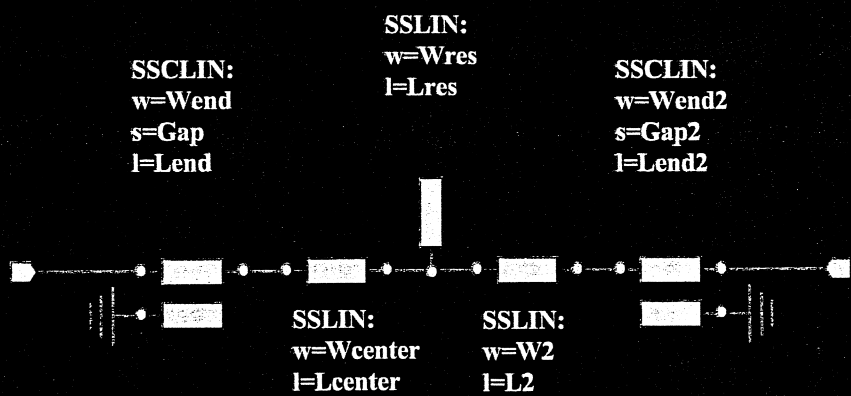
Companion Model for Three-Pole Band Stop Filter



Simplified Band Stop Filter

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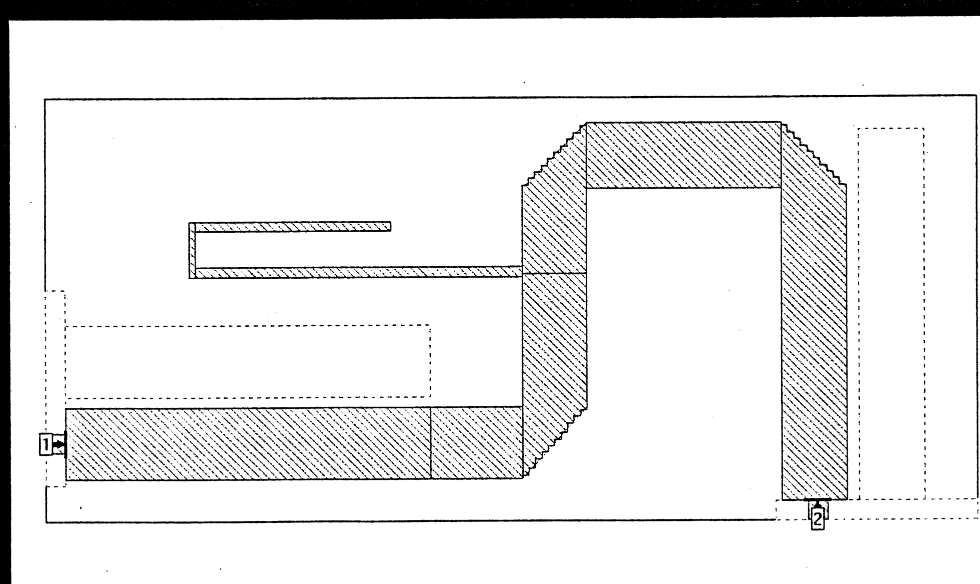
Sonnet Filter Layout for Three-Pole Band Stop Filter



Simplified Band Stop Filter

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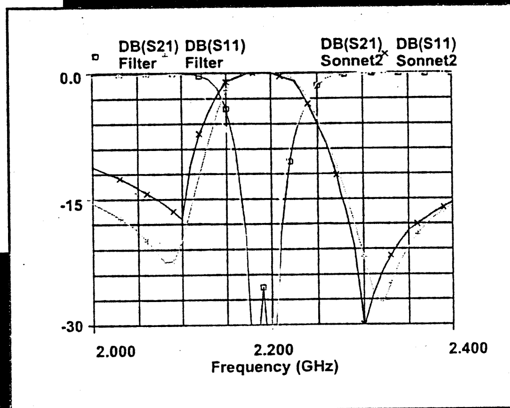
ITERATION MATRIX

	MODEL	FIT # 1	DELTA1	FIT # 2	DELTA2
WEND	220	220	0	220	0
LEND	1185	1160	25	1187	-2
GAP	29	23	6	29	0
WEND2	200	200	0	200	0
LEND2	1200	1192	8	1201	-1
GAP2	38	28	10	38	0
LCENTER	975	1008	-33	979	-4
LRES	1770	1754	16	1770	0
L2	960	957	13	958	2

Model Values During Optimization



"Coarse" Companion Model versus EM Simulation

LTCC Capacitor Model

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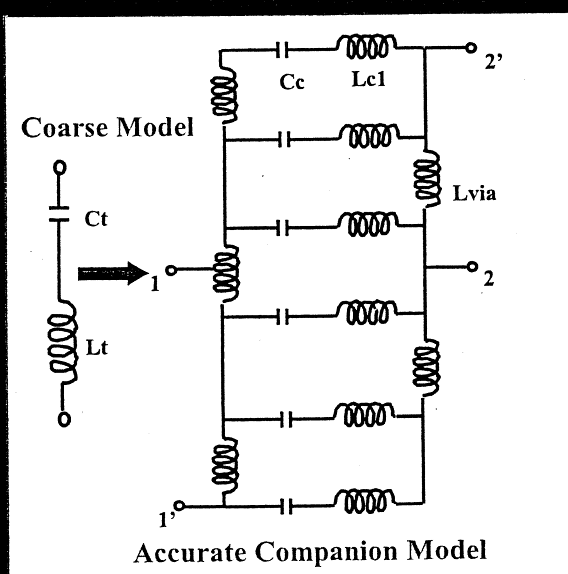
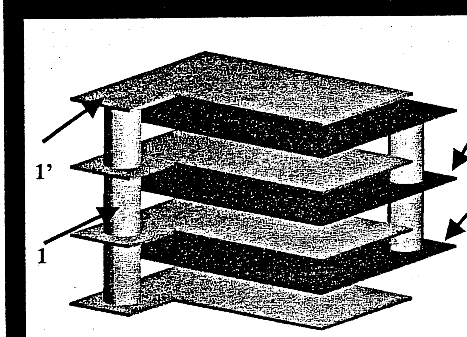
Models





Physical LTCC Capacitor

LTCC Band Stop Filter

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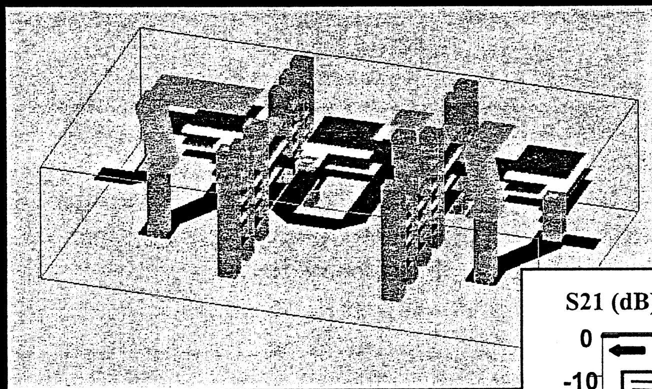
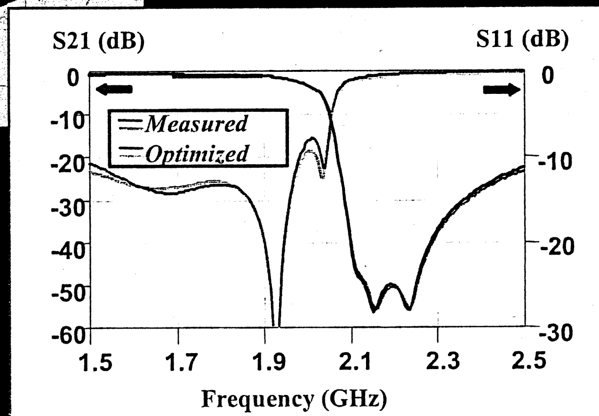


Physical LTCC Three Section Filter



Measured versus EM Optimized Band Stop Filter Response

LTCC Broadband Tapered Transformer

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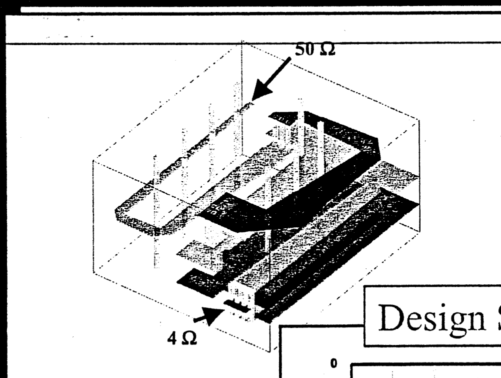
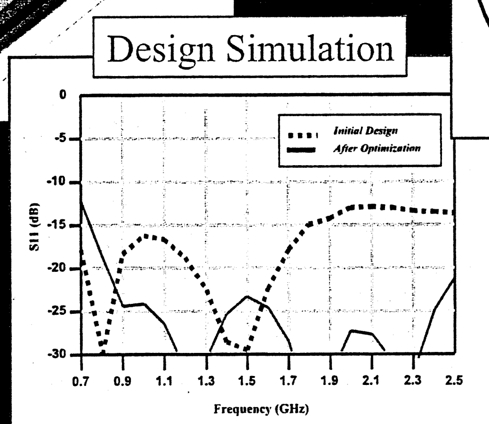
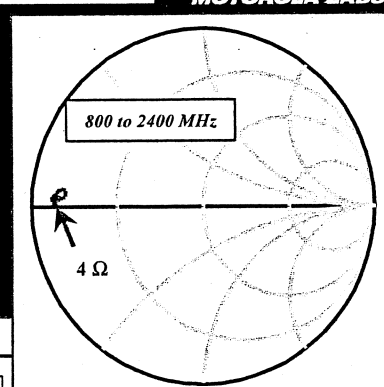


Physical LTCC Transformer





Transformer Performance (Measured)

Summary

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- METHOD IS EASY TO APPLY USING MANUAL TECHNIQUES.
- COARSE MODELS CAN ONLY BE USED FOR SIMPLE CIRCUITS.
- HIGH DENSITY CIRCUITS REQUIRE COMPLEX MODELS.
- SPECIAL STRUCTURES SUCH AS HIGH "Q" FILTERS AND DELAY LINES CAN BE RAPIDLY OPTIMIZED.
- ACTIVE DEVICES CAN BE ADDED TO SIMULATION.
- METHOD IS NOT EASILY AUTOMATED.
- LARGE CIRCUITS SHOULD BE SEGMENTED AND SOLVED USING MULTIPLE PROCESSORS.

A Multi-level Design Optimization Strategy for Complex RF/Micorwave Structures

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Abstract

A multi-level hybrid design optimization and computer diagnosis method using three classes of models: 1) circuit models; 2) approximate (corrected quasi-static) models; and 3) electromagnetic (EM) field theoretical models will be presented. The method is based on a generalized "space mapping" concept.

Design optimization of RF/microwave circuits currently uses well-established synthesis methods that are entirely based on lumped or distributed circuit models and RLC and/or transmission line parameters (class 1 models). To link the circuit parameters with physical parameters used in rigorous EM field numerical solvers, we use an intermediate class of approximate models (class 2 models). These are constructed from quasi-static semi-analytical theories, parametric modeling approaches such a Cauchy method and asymptotic matching, and neural models. The approximate model parameters are extracted and adjusted in such a way that output from these models match those from rigorous numerical algorithms, over the prescribed range of design parameters. Although the proposed method can essentially use any commercially available EM simulator, an efficient surface integration equation algorithm is also under investigation for class 3 models.

The main advantages of the proposed approach are: 1) the number of calls to the rigorous EM solver (class 3 models) is significantly reduced because these models are only used to calibrate the approximate (class 2) models which are already reasonably accurate; 2) The actual design optimization process essentially involves fast circuit (class 1) and approximate (class 2) models. These features make the developed design optimization scheme very fast and applicable to complex RF/microwave multi-cavity structures.

The proposed method has been implemented in a CAD software, *WATML-MiCAD* (Waterloo Multi-Level Microwave CAD), for design optimization and computer diagnosis of complex coupled cavity filters and multiplexers. The circuit model (class 1) used for RF/Microwave multi-cavity filter uses coupling matrix formulation and pole-zero location estimation. The architecture of the software, circuit model, optimization algorithm, approximate model generation, as well as some design and diagnosis examples will be presented.

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June 2002

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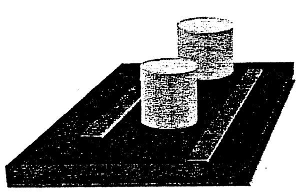
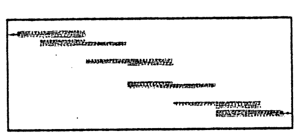
Contents

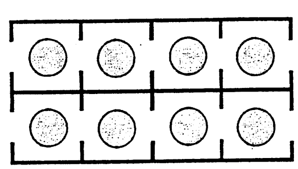
- Introduction
- EM-Based Approximate Modeling Schemes
- Optimization Methods
- Architecture of ***WATML-MiCAD***
- Conclusions

Introduction

- Computational complexity of field-theoretical methods for design of microwave structures
- Circuit models are fast but inaccurate
- Design optimization issues







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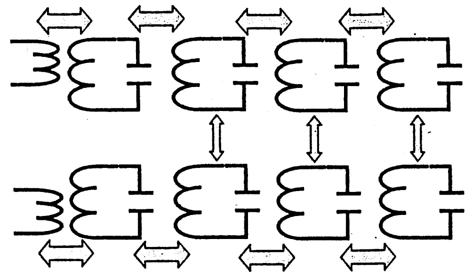
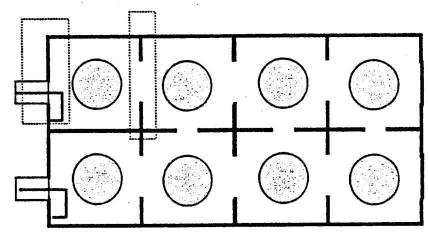
2-level Space Mapping
Example: Coupled cavity structures





Coarse Model

$$R_c(x_c) = \mathbf{S}\{\omega, R(\vec{p}), L(\vec{p}), , C(\vec{p}), \mathbf{M}(\vec{p})\}$$

Fine Model

$$R_f(x_f) = \mathbf{S}\{\omega, \vec{p}\}$$

$\vec{p}$ = physical parameters

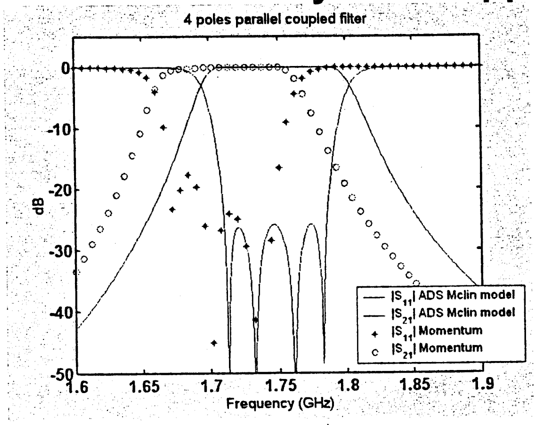
$$R(\vec{p}), L(\vec{p}), C(\vec{p}), \mathbf{M}(\vec{p}) = ?$$

Essential requirement:
Accurate electromagnetic (EM)-based coarse models

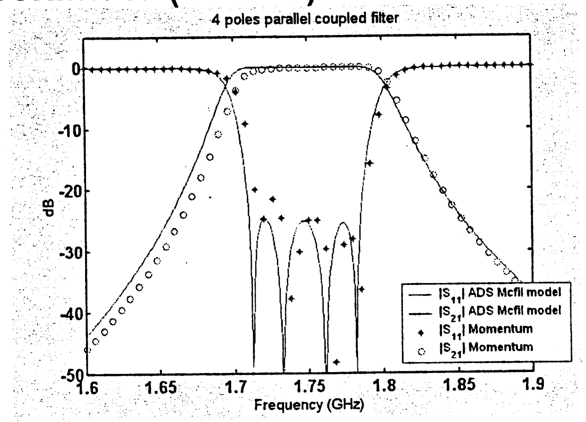
- Method may not yield accurate results if the coarse model does not correlate with physical reality

- Use of electromagnetic based approximate (coarse) models can guarantee the existence of a physically realizable solution

Example: Parallel coupled line filter, the significance of the accuracy of the approximate (coarse) model

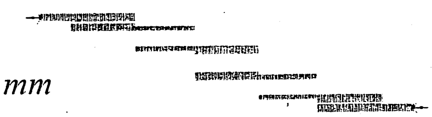


Coarse model 1: cascade of coupled line sections without any discontinuity effects.

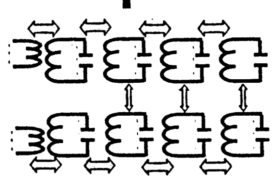


Coarse model 2: cascade of coupled line sections with inclusion of step and end effect discontinuities (*Mcfil* model in ADS)

Four poles coupled line filter at 1800 MHz
Substrate: $\varepsilon_r = 10.5, \quad h = 1.27 \ mm$



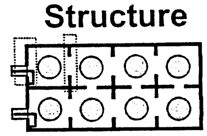
Proposed Approach



Class I Models

Coarse Models (Circuit)

Physical Structure



Class III Models

Fine Models (EM)

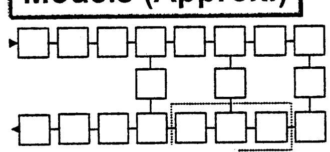
Final check if required

Model verification
Parameter extract.
Training (**Off-line**)

Synthesis
Design optimization
Diagnosis
Tolerance/sensitivity
Analysis (**On-line**)

Class II Models

Intermediate Models (Approx.)



Main Steps

1. Synthesis, performance optimization, tolerance/sensitivity analysis, and diagnosis using circuit (class I) models
2. Physical design/realization of the above circuit models and their structural analysis using EM-based approximate (Class II) models
3. Verification/validation and training of approximate models using ***fast and rigorous*** EM-solver (Class III), developed for particular group of structures

Major Challenges

- Accurate and fast EM-based approximate models relating circuit parameters to physical parameters
- Robust (*Global*) optimization algorithms
- Fast parameter identification methods

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EM-based Approximate (Class II) Modeling Schemes

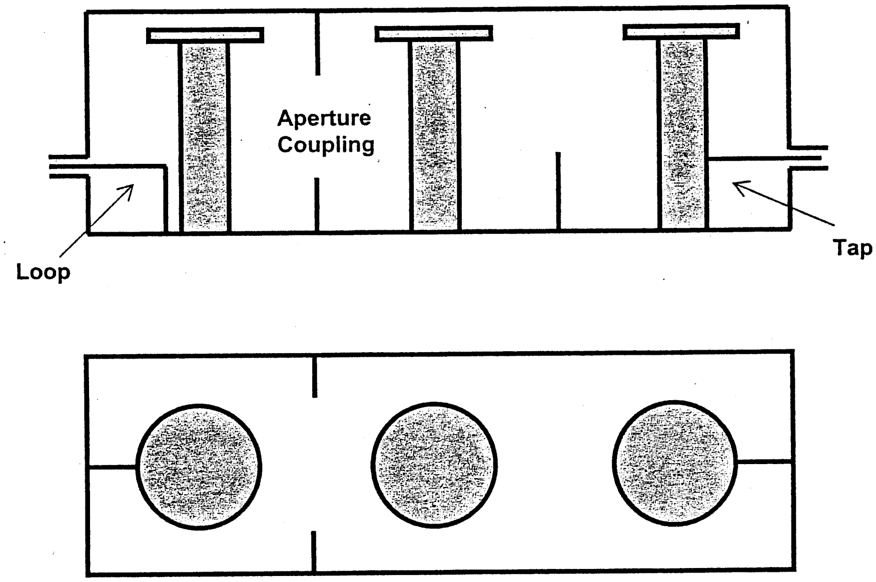
- Quasi-static models, TEM models, numerical and analytical approximations
- Wideband modified quasi-static models
- Multidimensional parametric models (Cauchy method, ...)
- Neural models, hybrid techniques

Example: Combline-type Filters

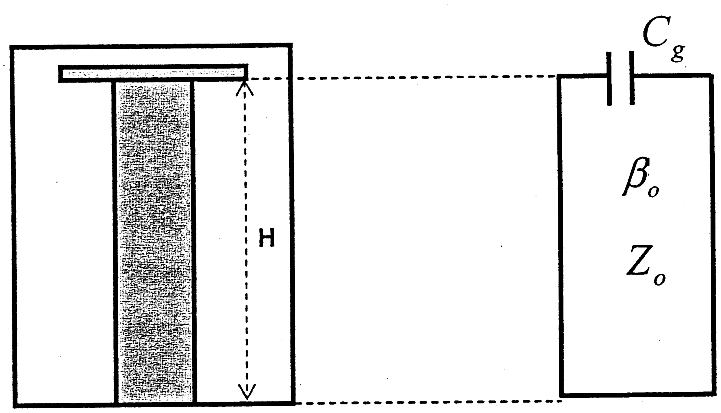
Approximate EM-based models for:

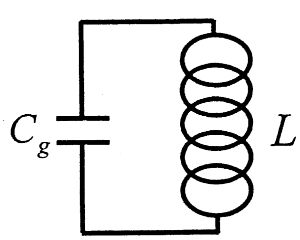
- Inductance and capacitance for resonator
- Coupling through rectangular loops and taps
- Coupling through rectangular apertures
- Parasitic effects

Combline-type Filters



Combline Resonator





$$C_g = \frac{1}{Z_o \omega_o} \cot(\omega_o \frac{H}{v})$$

$$\omega_o = \frac{1}{\sqrt{L C_g}}$$

Gap Capacitance

- Closed form formula for small gap
- Static solution
- Accuracy better than %5

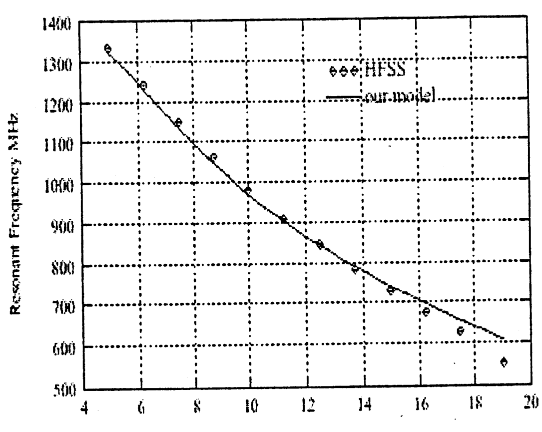
$$C_g = C_{go} + C_d$$

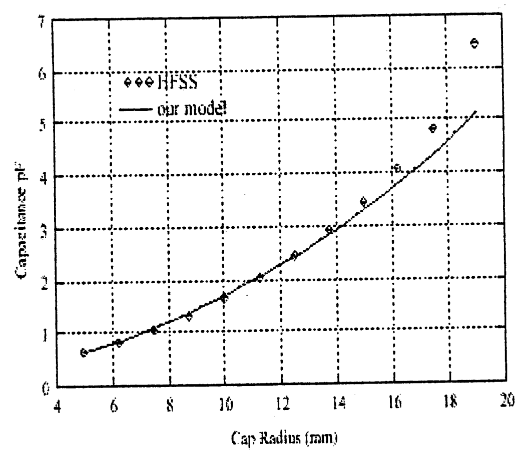
$$C_{go} = \varepsilon_o \left(\frac{\pi R_c^2}{g} + 4R_c \log \frac{R_{eff} - R_c}{g} \right)$$

$$C_d = 2\varepsilon_o R_{eff} \left\{ \left(\frac{\alpha^2 + 1}{\alpha^2} \log \frac{1+\alpha}{1-\alpha} - 2\log \frac{4\alpha}{1-\alpha^2} \right) + 0.111(1-\alpha)(\tau - 1) \right\}$$

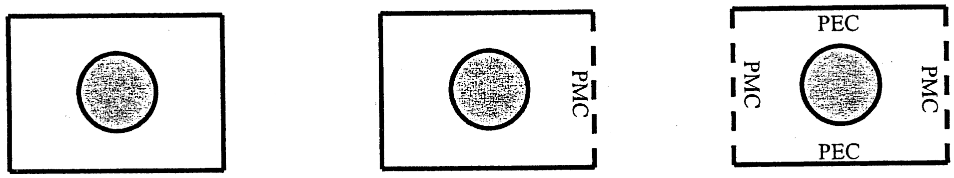
$$\alpha = \frac{R_{eff} - R_c}{R_{eff} - \tau} \qquad \tau = \frac{R_{eff}}{R_c} \qquad R_{eff} = \sqrt{\frac{ab}{\pi}}$$

Comparison with HFSS





Circular Rods in Rectangular Enclosure



Applications:

- Characteristic impedance of combline resonator
- Field distribution of TEM mode
- Even and odd mode impedances for aperture couplings

MoM Formulation

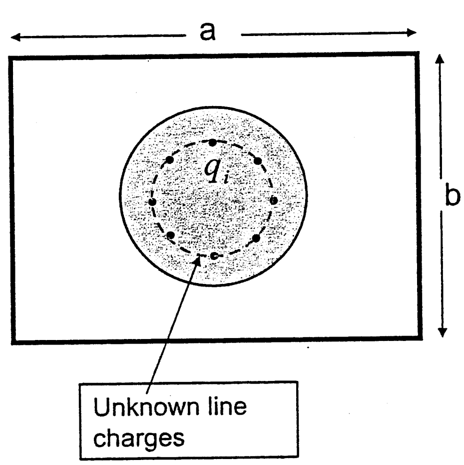
Fast, Flexible, and Accurate

$$Z_0 = \frac{\sqrt{\mu\varepsilon}}{C}$$

$$C = \sum_{i=1}^{N} q_i$$

$$\sum_{i=1}^{N} G_{ji} q_i = 1 \qquad j = 1,2,\dots, M$$

$$M \geq N$$



- Very fast convergent Green's function

Fast Convergent Green's Function

- Infinite summation of images
- Logarithm of ϑ function

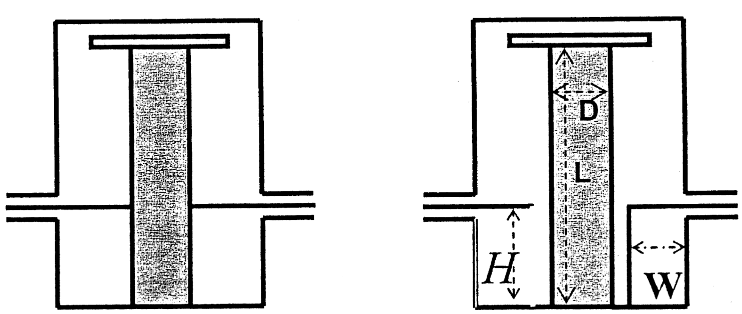
$$G(z,z') = \mathrm{Re}\{W(z,z')\}$$

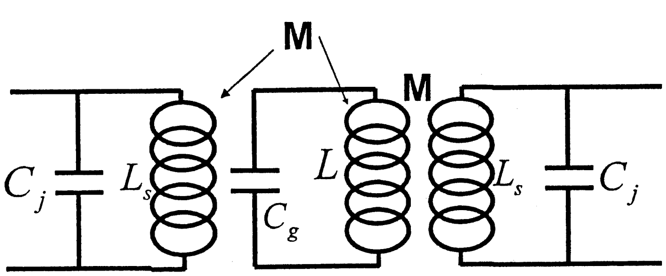
$$W(z,z') = -\frac{1}{2\pi}\left\{\ln\vartheta_1\left(\frac{z-z'}{2a}\right) + \ln\vartheta_1\left(\frac{z+z'}{2a}\right) - \ln\vartheta_1\left(\frac{z-\bar{z}'}{2a}\right) - \ln\vartheta_1\left(\frac{z+\bar{z}'}{2a}\right)\right\}$$

$$\vartheta_1(z) = 2\sum_{m=0}^{\infty} e^{-\pi\frac{b}{a}\left(m+\frac{1}{2}\right)^2}(-1)^m \sin[(2m+1)\pi z]$$

6 terms is enough!

Rectangular Loops and Taps





$$M = \mu_o \iint_{S_{loop}} \vec{H}_{TEM} . \vec{ds}$$

$$\vec{H}_{TEM} = \frac{1}{\eta_o}\hat{z}\times\vec{E}_{TEM}$$

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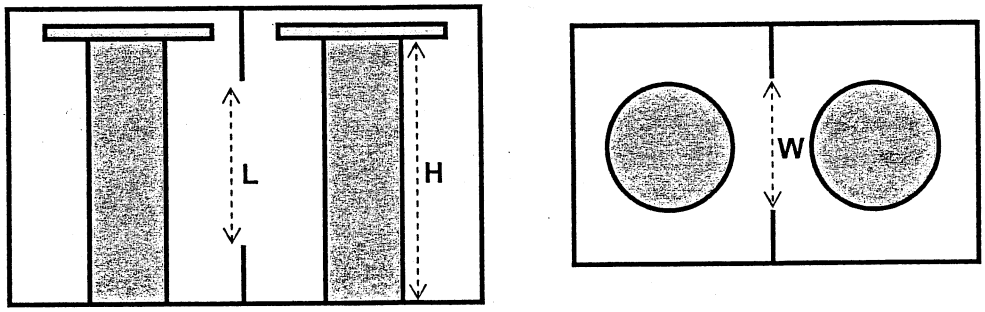
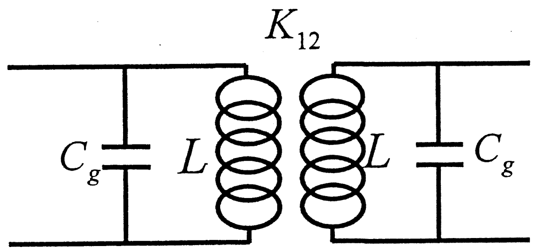
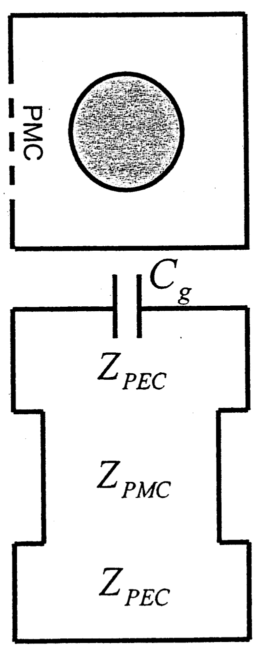
Rectangular Apertures



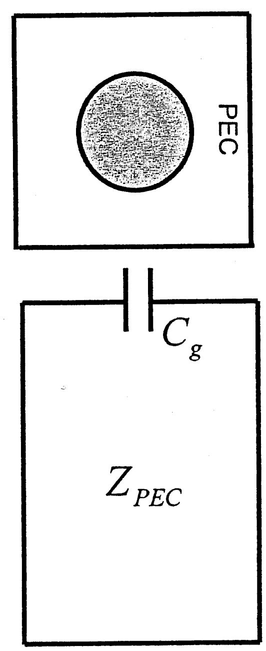


Coupling Factor



Even mode

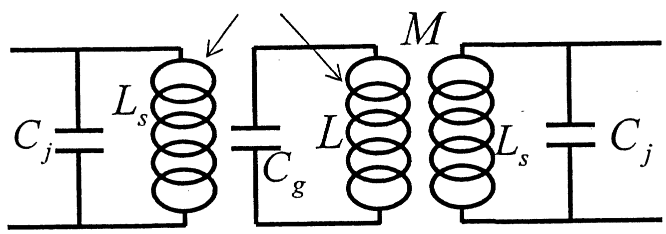
$$k_{12} = \frac{f_e^2 - f_m^2}{f_e^2 + f_m^2}$$



Odd mode

Parasitic Elements: Neural Modeling

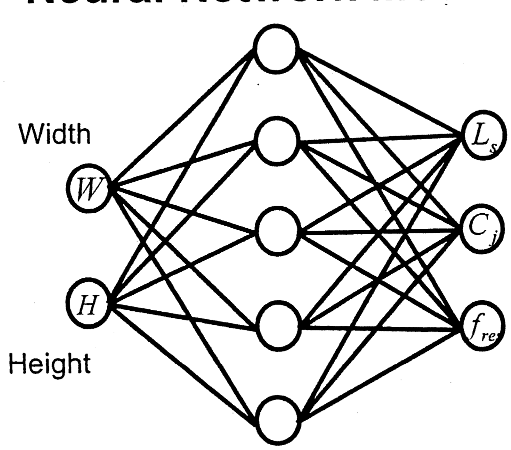
Example: Tap Coupling

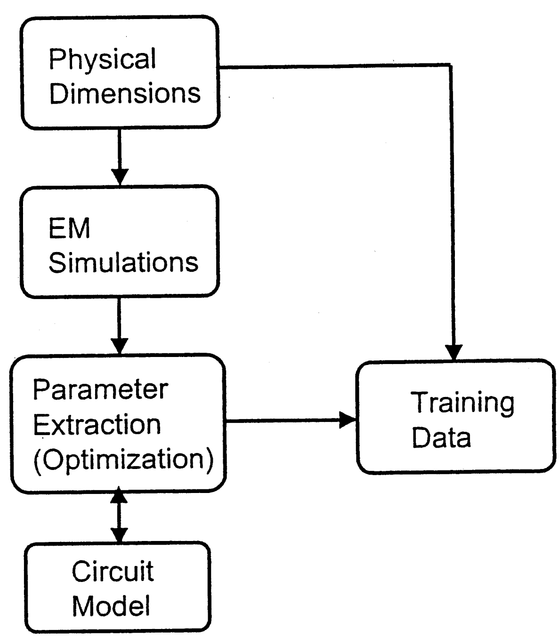


- Analytic models for L, M, C_g
- Neural network model for L_s, C_j

Training and Validation

Neural Network Model





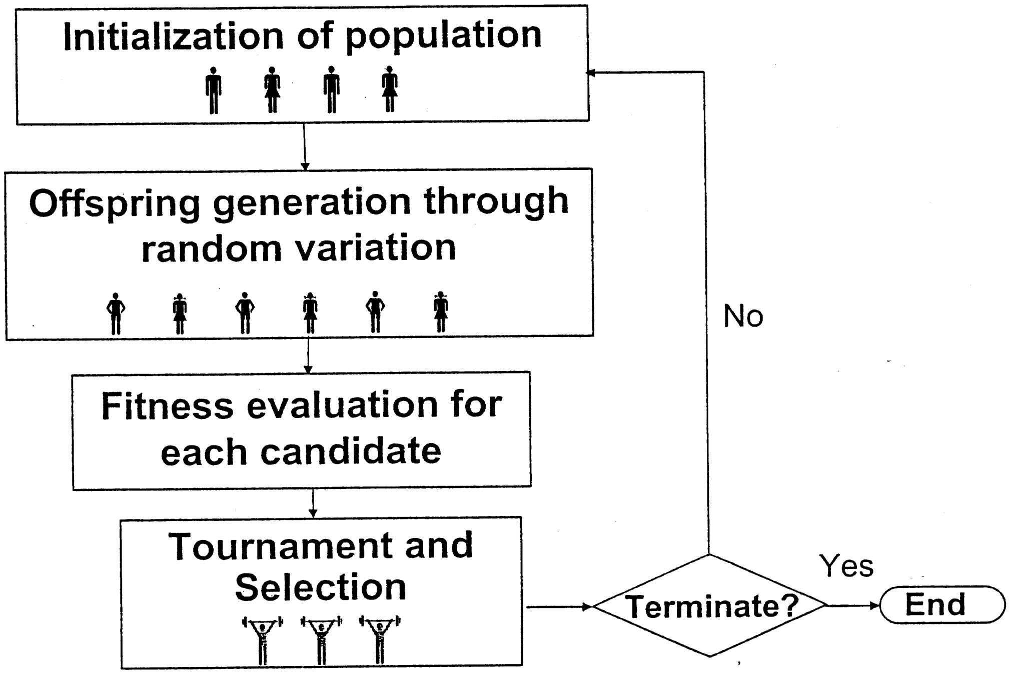
Optimization Methods

- Design optimization of circuit (class I) models and approximate (class II) models
- Parameter extraction and/or model calibration process
- *Multimodal* problems
- Global optimization

Examples of Optimization Methods

Deterministic Methods	Stochastic Methods
• Fast	• Slow
• Need initial guess	• Don't need initial guess
• May trap into local min	• Can perform global search
• Examples:	• Examples:
➢ Gradient	➢ Random
➢ Quasi-Newton	➢ Simulated Annealing
➢ SQP	➢ Evolutionary Algorithm

Evolutionary Algorithm



Evolutionary Programming vs. GA

EP

- Works with real coded parameters
- Asexual recombination
- Only mutation is used
- Adaptive evolution

GA

- Works with binary coded parameters
- Bisexual recombination
- Both mutation and crossover are used
- No Adaptive evolution

EP + Niching technique

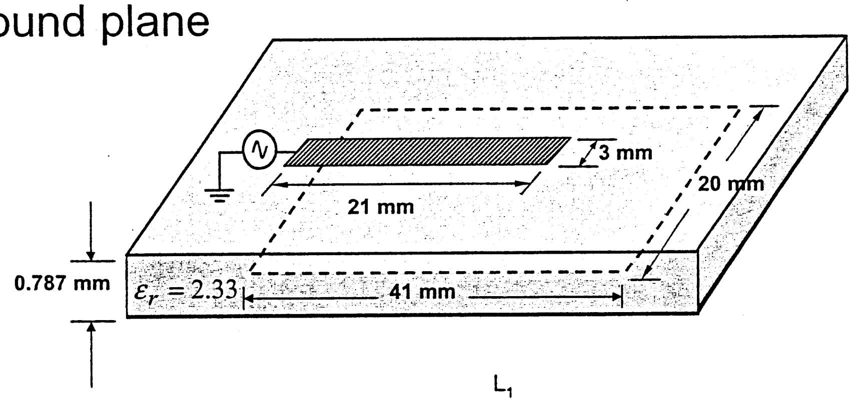
- Simple EP or GA cannot keep stable subpopulations at a number of peaks
- Use fitness sharing to prevent the overcrowding of population

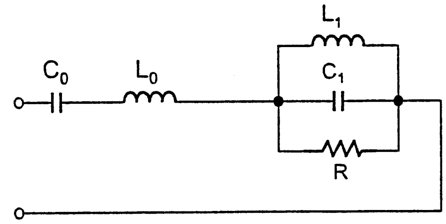
define $$sh(d)=\begin{cases} 1-\left(\dfrac{d}{\sigma_{share}}\right)^{\alpha} & \text{, if } d<\sigma_{share} \\ 0, & \text{otherwise} \end{cases}$$

New Obj. func. : $(f_i)_{shared}=f_i+w\sum_{j=1}^{n} sh(d_{ij})$ *or* $(f_i)_{shared}=\dfrac{f_i}{\sum_{j=1}^{n} sh(d_{ij})}$

Example 2

Microstrip monopole with aperture in the ground plane



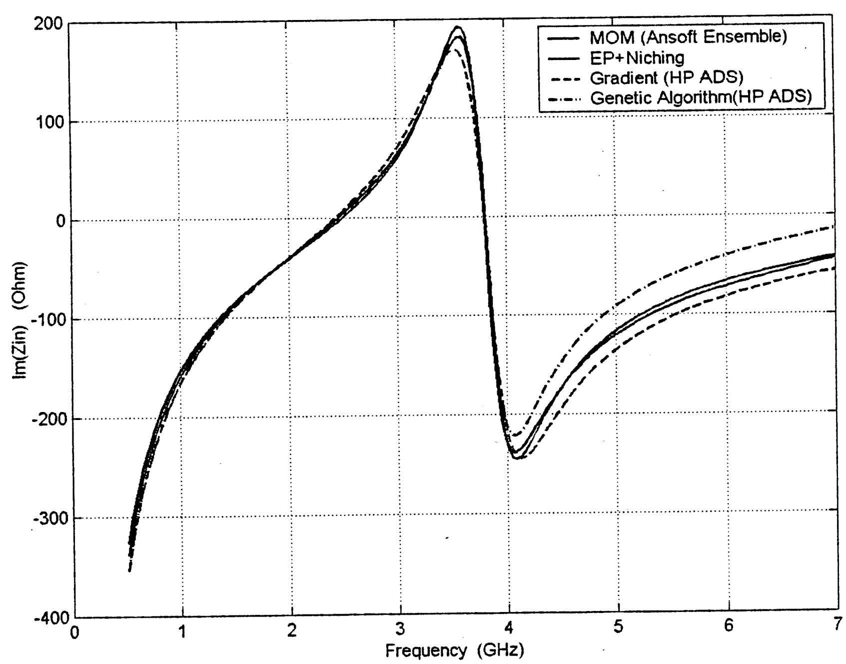


Example 2: results

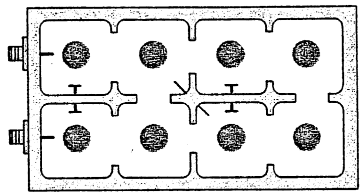
$$Errf = \sum_{j=1}^{200}\left[\left|\mathrm{Re}(Z_{in\_MoM}) - \mathrm{Re}(Z_{in\_Model})\right|^2 + \left|\mathrm{Im}(Z_{in\_MoM}) - \mathrm{Im}(Z_{in\_Model})\right|^2\right]_{f_j}$$

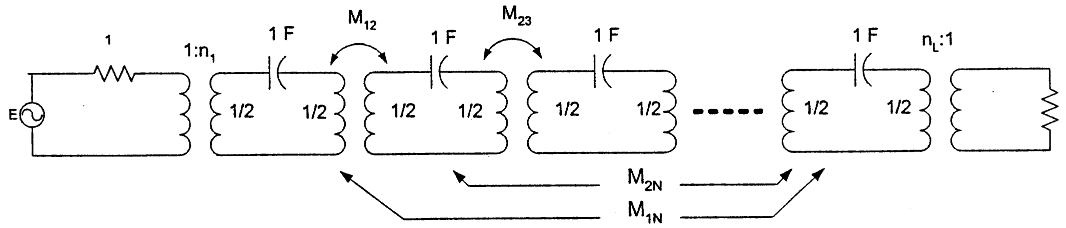
Optimization method	C_0 (PF)	L_0 (nH)	C_1 (PF)	L_1 (nH)	R (Ohm)	*Errf*
EP+Niching ($\mu = 20, q = 6, \sigma_{sh} = 0.8$)	0.8829	0.65125	0.713	2.435	435	20.356
Gradient (HP-ADS)	0.8431	0.499	0.692	2.52	423	33.43
Genetic Algorithm (HP-ADS)	0.8721	0.704	0.775	2.241	424.5	35.3

Example 2: results



Example 3: Multiple-Coupled Cavity Filters





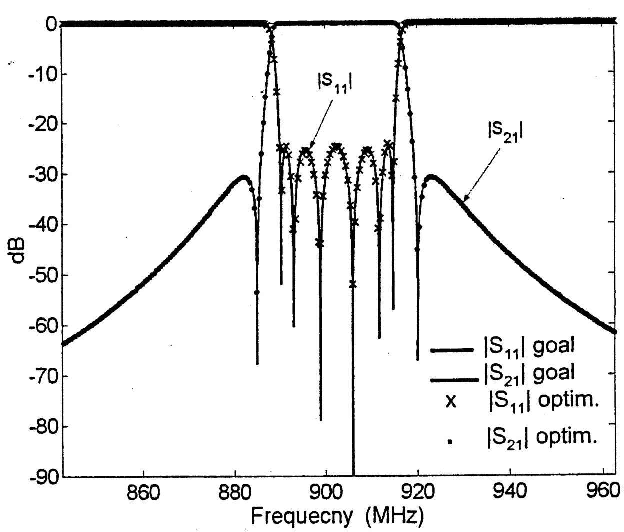
$$S_{11}(\omega) = \frac{F_N(\omega)}{E_N(\omega)}, \quad S_{21}(\omega) = \frac{P_N(\omega)}{\varepsilon E_N(\omega)}$$

$$errf\ (\tilde{M}) = \sum^{N} |F_N(P_i)|^2 + \sum_{j=1}^{M} |P_N(Q_j)|^2$$

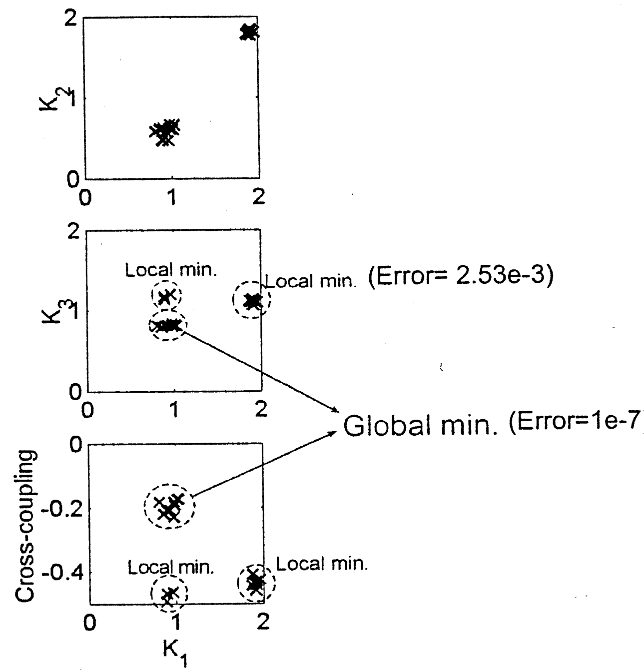
Example 3: cont.

- Six pole filter with two transmission zeros
- Coupling matrix:

$$\tilde{M} = \begin{bmatrix} 0 & K_1 & 0 & 0 & 0 & 0 \\ K_1 & 0 & K_2 & 0 & X_1 & 0 \\ 0 & K_2 & 0 & K_3 & 0 & 0 \\ 0 & 0 & K_3 & 0 & K_4 & 0 \\ 0 & X_1 & 0 & K_4 & 0 & K_5 \\ 0 & 0 & 0 & 0 & K_5 & 0 \end{bmatrix}$$

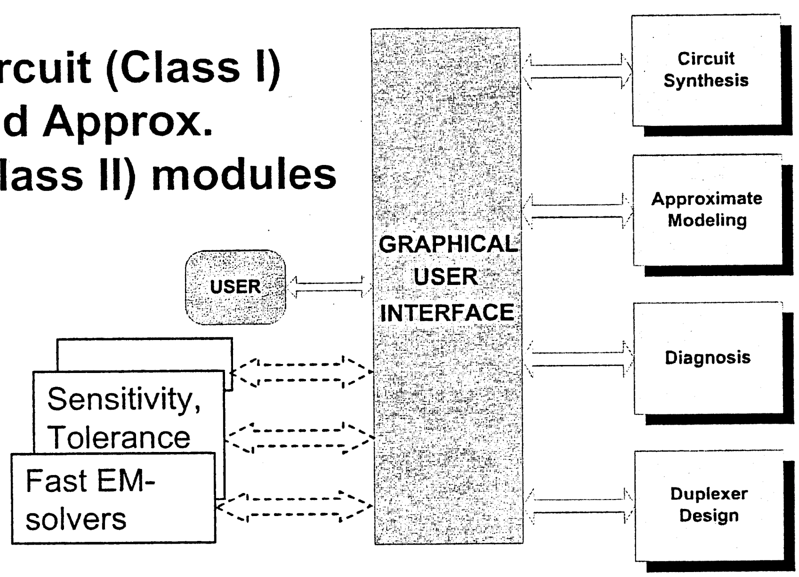


Example 3: results

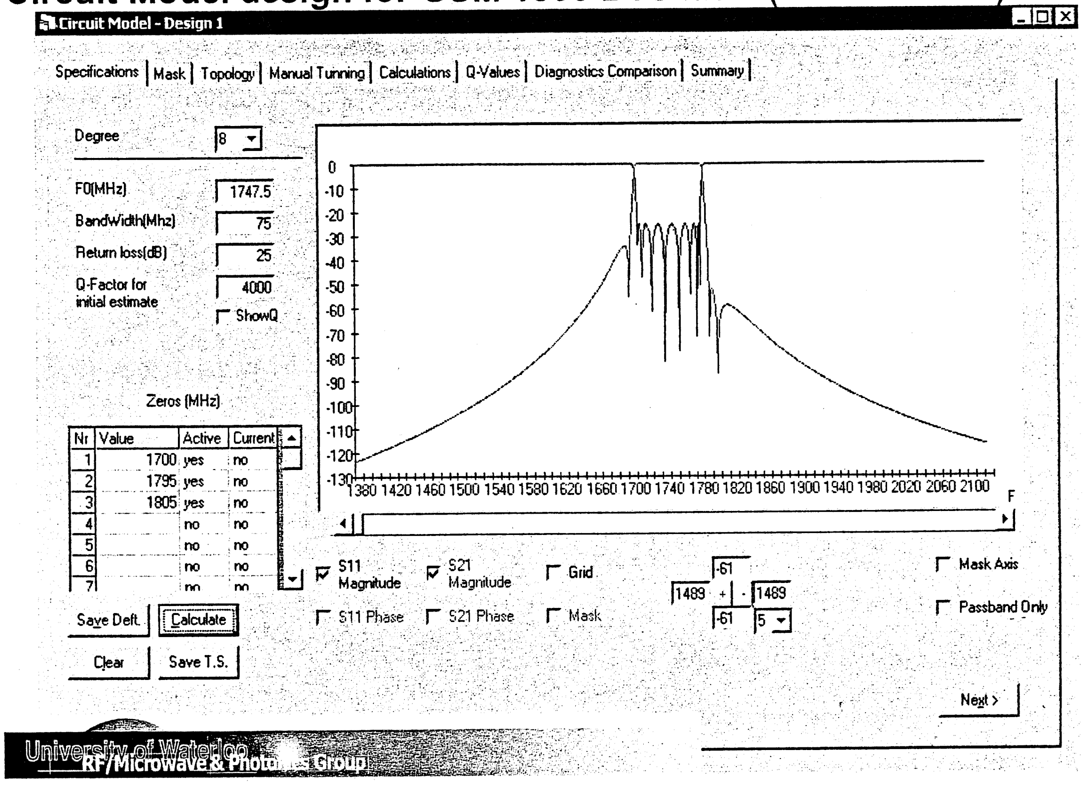


Architecture of *WATML-MiCAD* (Waterloo Multi-Level Microwave CAD)

Circuit (Class I) and Approx. (Class II) modules

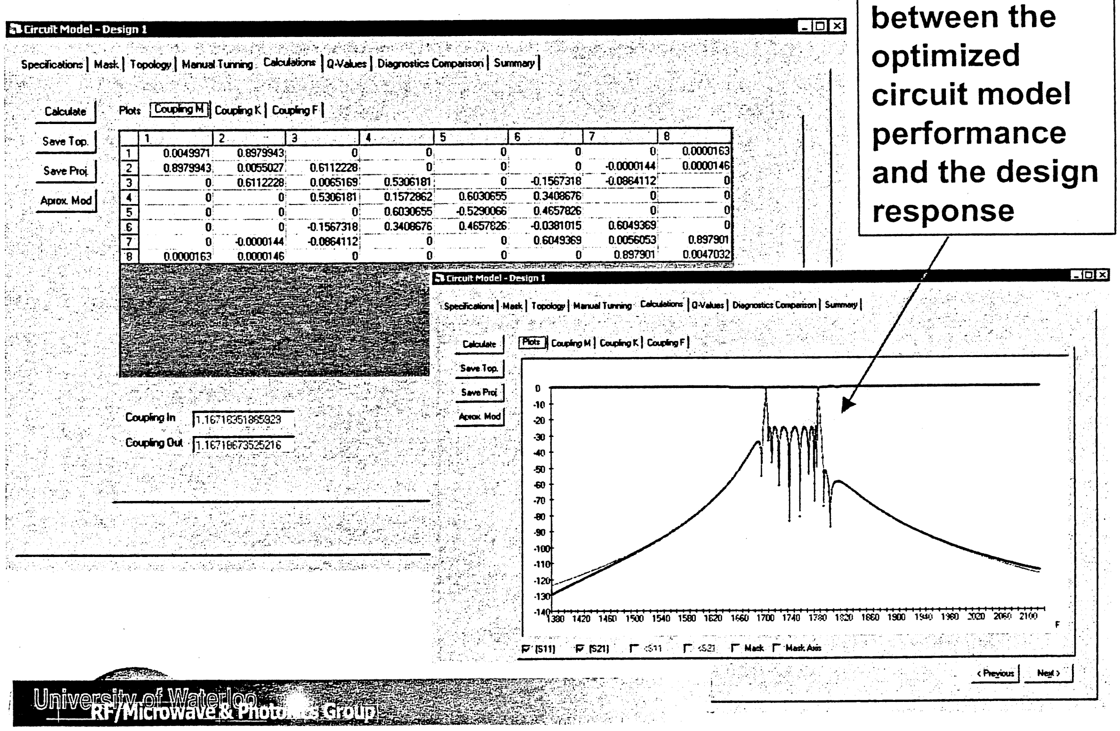


Circuit Model design for GSM 1800 BTS filter (receive band)



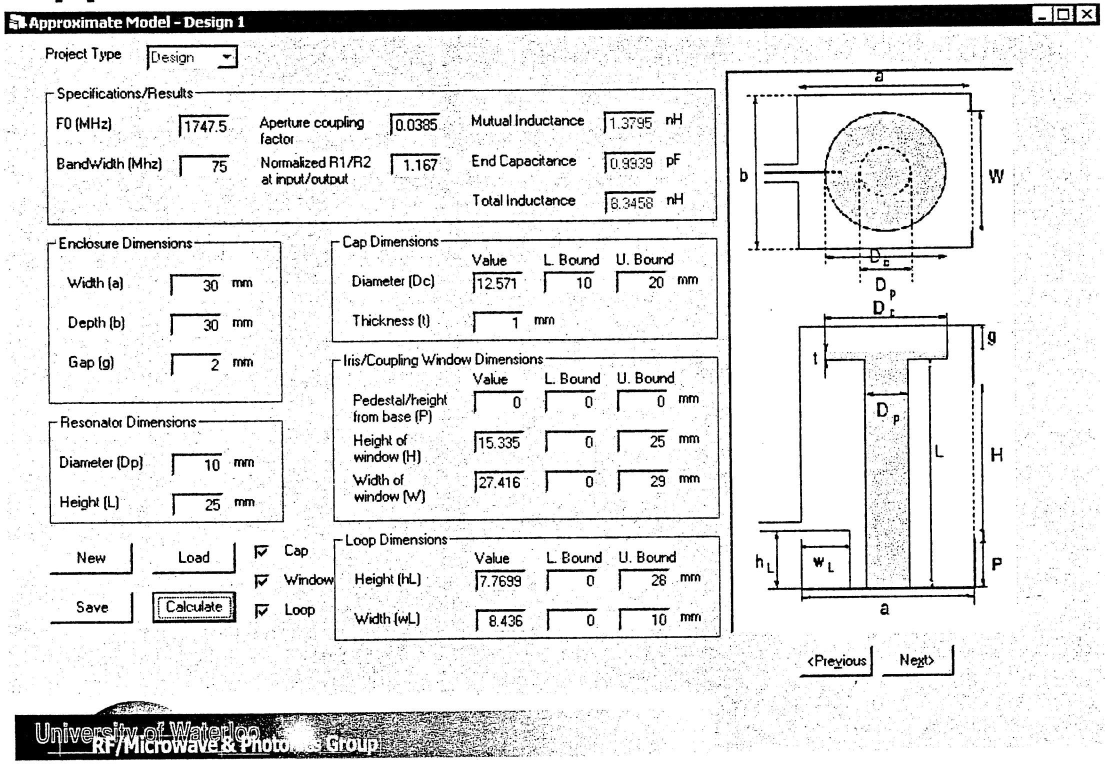
Coupling matrix synthesis

Comparison between the optimized circuit model performance and the design response

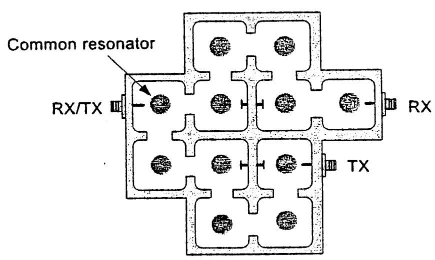


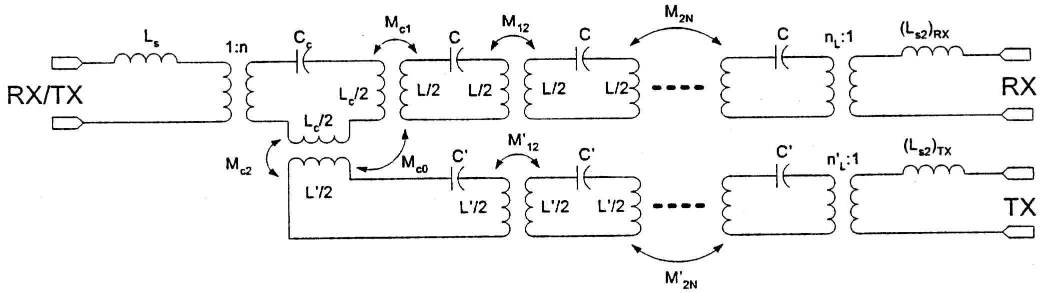
	1	2	3	4	5	6	7	8
1	0.0049971	0.8979943	0	0	0	0	0	0.0000163
2	0.8979943	0.0055027	0.6112228	0	0	0	-0.0000144	0.0000146
3	0	0.6112228	0.0065169	0.5306181	0	-0.1567318	-0.0864112	0
4	0	0	0.5306181	0.1572862	0.6030655	0.3408676	0	0
5	0	0	0	0.6030655	-0.5290066	0.4657826	0	0
6	0	0	-0.1567318	0.3408676	0.4657826	-0.0381015	0.6049369	0
7	0	-0.0000144	-0.0864112	0	0	0.6049369	0.0056053	0.897901
8	0.0000163	0.0000146	0	0	0	0	0.897901	0.0047032

Approximate modeling

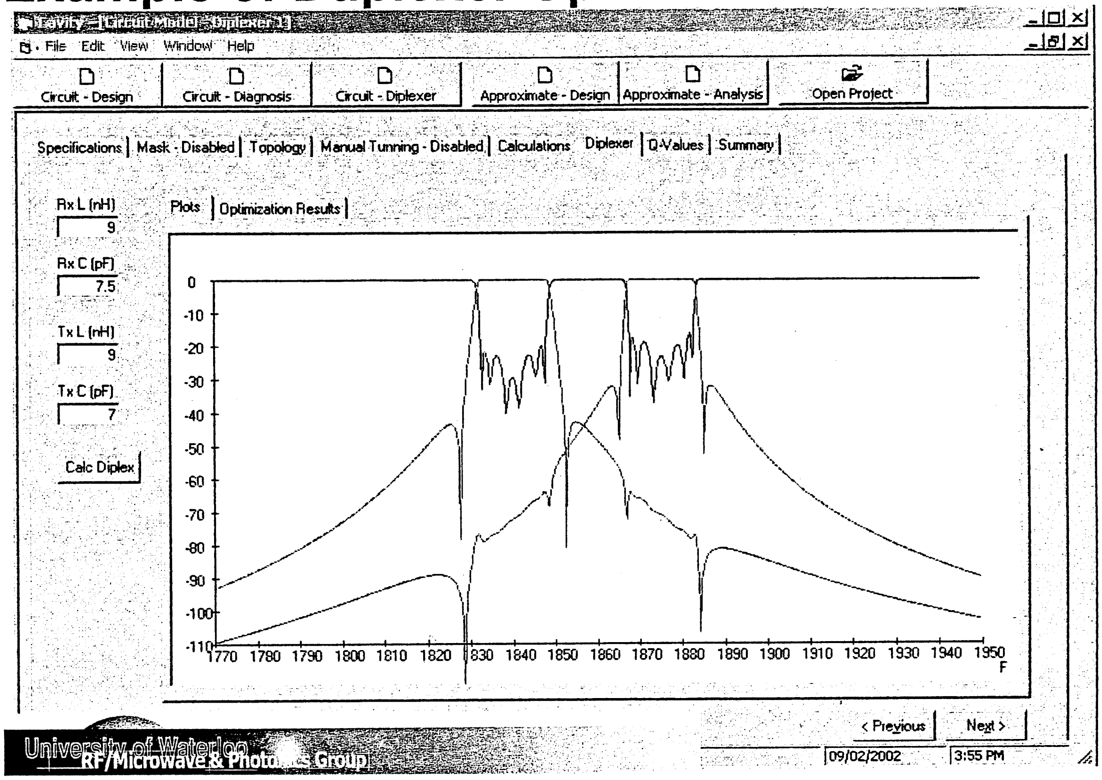


Duplexer Modeling and Design





Example of Duplexer Optimization



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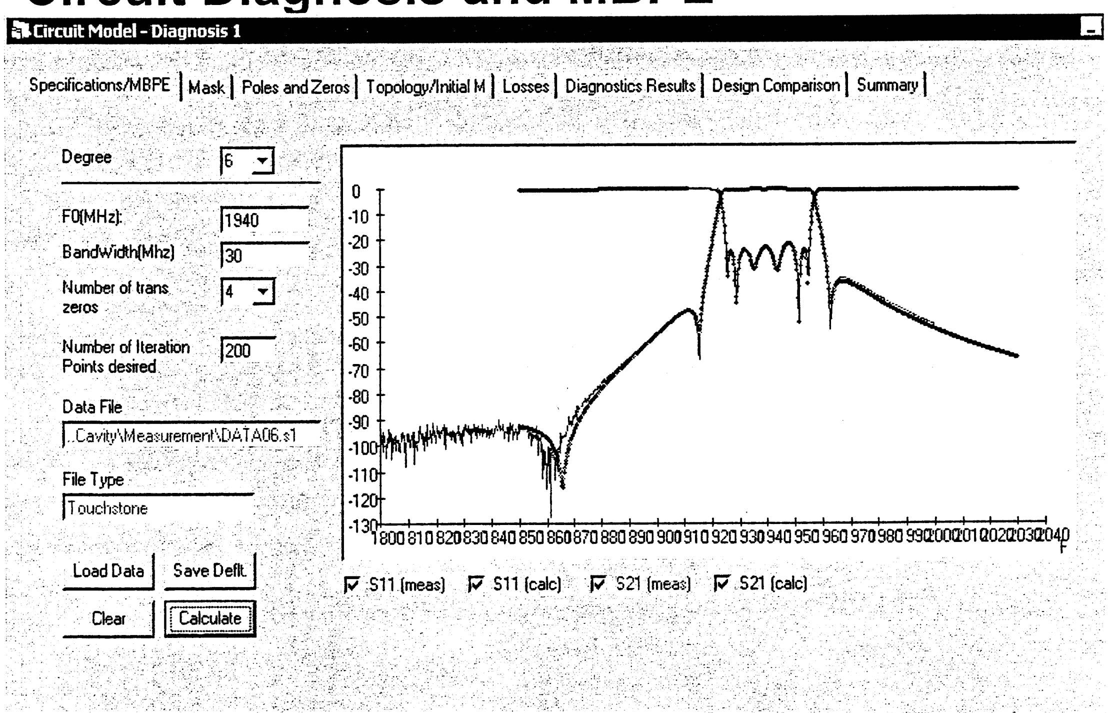
Circuit Diagnosis and MBPE



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Conclusion

- A 3-level design strategy for microwave circuit was described.
- Efficient EM-based approximate modeling schemes were presented.
- Robust optimization algorithms for design optimization and parameter identification were discussed.
- Architecture of ***WATML-MiCAD*** was described

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1. M. Kahrizi, S. Safavi-Naeini, S. K. Chaudhuri, and R. Sabry, "Computer Diagnosis and Tuning of RF and Microwave Filters Using Model-Base Parameter Estimation", to be published in IEEE Trans. Circuit PART I, 2002.
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3. N.Damavandi, S.Safavi-Naeini, "Evolutionary programming with niching technique for efficient model parameter extraction," IEEE-APS Int. Symp., Boston, MA, USA, vol. 4, 2001, pp. 680-683.
4. N.Damavandi, S. Safavi-Naeini, "A Robust Model Parameter Extraction Technique Based on Meta-Evolutionary Programming for High Speed/High Frequency Package Interconnects," Canadian Conference on Electrical and Computer Engineering - IEEE-CCECE, Toronto, Ontario, Canada, vol. 2, 2001, pp. 1151 –1155.
5. Amir Borji, S.Safavi-Naeini, S.K.Chaudhuri, "Mutual Coupling Factor of Rectangular Loops in Rectangular Coaxial Cavities", Proceedings of 8th Symposium on Antenna Technology and Applied Electromagnetics, Winnipeg, Manitoba, Jul. 31-Aug. 2, 2000, pp.133-136
6. Amir Borji, S.Safavi-Naeini, S.K.Chaudhuri, "TEM Properties of Shielded Homogeneous Multiconductor Transmission Lines with PEC and PMC Walls", IEEE MTT-S 2001 International Microwave Symposium Digest, Phoenix, Arizona, May 20-25, 2001, Vol. 2, pp.731-734.
7. Amir Borji, Dan Busuioc, S.Safavi-Naeini, S.K.Chaudhuri, "ANN and EM Based Models for Fast and Accurate Modeling of Excitation Loops in Combline-type Filters", Accepted to 2002 IEEE MTT-S International Microwave Symposium, Seattle, Washington, June 2-7, 2002sing

Coupled Resonator Filter Realization by 3D-EM Analysis and Space Mapping

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IMS2002

01/31/02 v1.0

Abstract

The realization of narrowband coupled resonator filter structures involves relatively complex resonator topologies to be designed in such a way that a given coupling matrix [1] is realized by physical couplings, such as apertures between resonators. 3D EM analysis of filter structures and manual response optimization is elaborate, time consuming and demands accurate resonator tuning. Coarse mesh model (fast model) 3D EM simulation [S]-matrix data - while limited in its absolute accuracy - contains valid information on the couplings between resonators. Minor resonator tuning offsets have no bearing on the coupling matrix of a given structure. A space mapping technique [2] linking a subset of the physical model parameter space to the coupling matrix of an equivalent LC network is used in a fast-converging iterative process for properly adjusting the physical parameters.

Purpose

- To minimize the number of EM analysis cycles during physical filter design
- To exploit coarse mesh 3D EM analysis data (fast model)
- To ensure rapid convergence of an iterative design process

Outline

- Description of design problem
- Circuit model and coarse mesh 3D EM model
- Application of space mapping technique
- Example
- Outlook

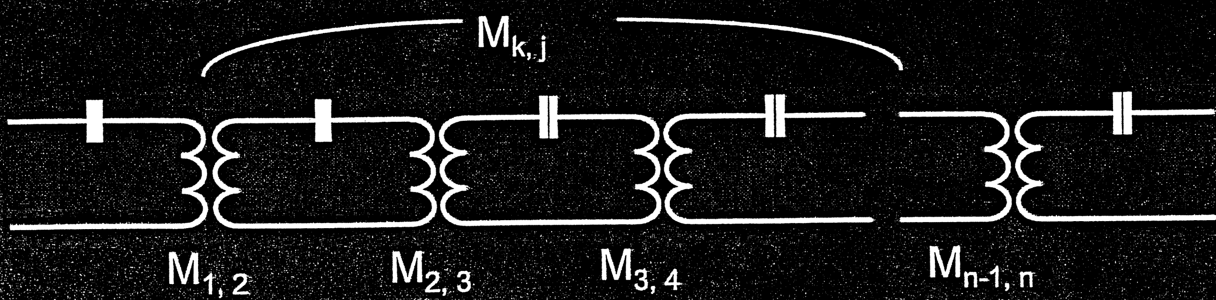
Design Problem

- A given physical coupled resonator bandpass filter structure has to correspond to a particular equivalent LC - network coupling matrix
- The physical dimensions of apertures between resonators need to be determined

Design Problem Scenario

- Coupling aperture dimensions for a chosen physical filter structure cannot be calculated directly
- Strong interaction between physical couplings can exist
- Natural frequencies of the structure are sensitive to 3D mesh resolution
- Fine mesh 3D EM analysis is time consuming

Circuit Model of Coupled Resonator Bandpass Filter



Coupling matrix

$$[M]_n = \begin{bmatrix} 0 & M_{12} & 0 & M_{14} & 0 \\ M_{12} & 0 & M_{23} & 0 & \cdots \\ 0 & M_{23} & 0 & \cdots & 0 \\ M_{14} & 0 & \cdots & 0 & M_{n-1,n} \\ 0 & \cdots & 0 & M_{n-1,n} & 0 \end{bmatrix}$$

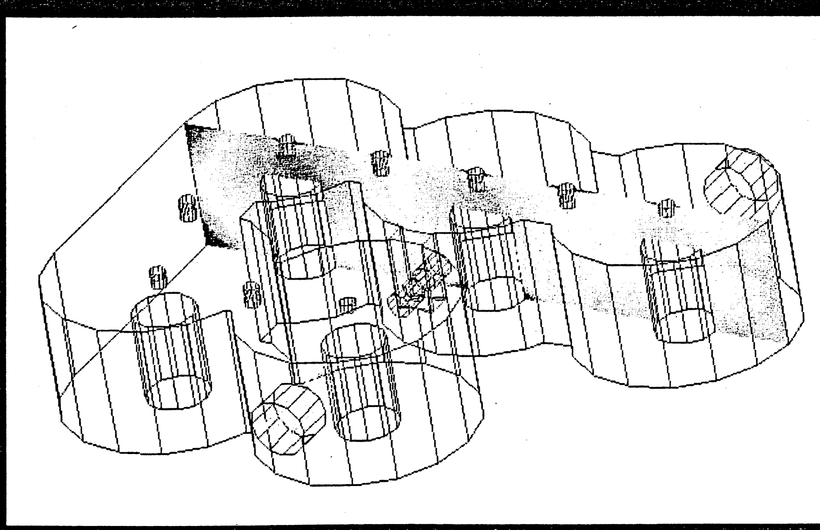
$$[k] = \frac{[M]}{L_{Loop}}$$

Loop Current Analysis of LC Circuit Model

$$[I(f)] = [Z(f)]^{-1} * [V]$$

$$[Z(f)] = j * \left[[M] + [X] + [I] * \lambda(f) \right] + [R]$$

3D EM Model (HFSS)



3D EM Model (HFSS)

- minimum number of geometry faces
- coarse line approximation of circular shapes
- avoid structure details in areas of low field variation
- fast frequency sweep (rational function fitting) can be used

Application of Space Mapping

- Nominal coupling matrix of equivalent LC - network is known (synthesis)
- Space mapping relates 3D EM model dimension data subset to coupling matrix
- Coupling matrix of 3D EM model is adjusted iteratively by modification of dimension data subset

Variable Subsets

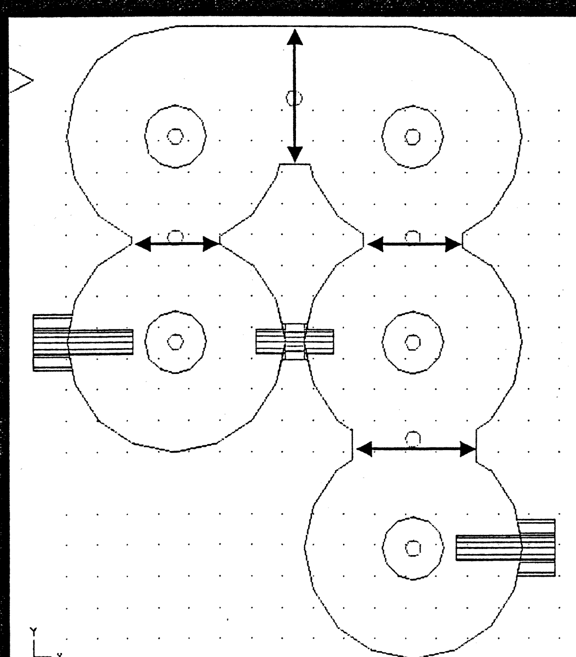
3D EM model variable subset

$$x_{CMM} = [w_{12}, w_{23}, \ldots w_{k,\,k+1}, w_{k,\,k+j}, \ldots w_{n-1,\,n}]^T$$

Circuit network model variable subset

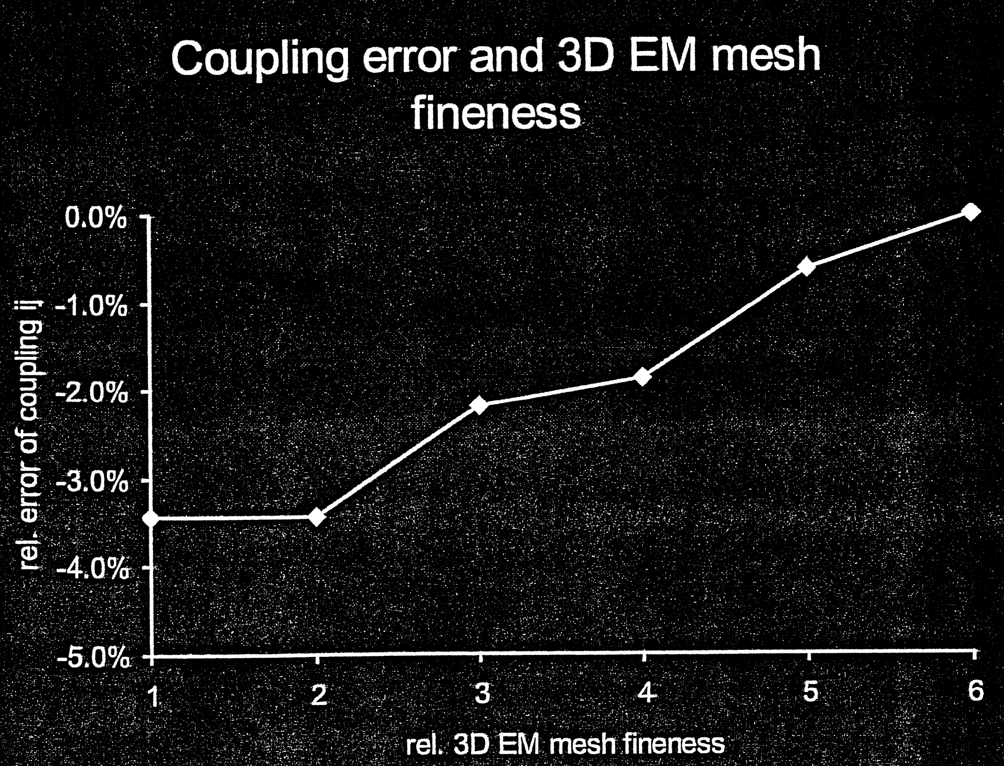
$$x_{CNM} = [M_{12}, M_{23}, \ldots M_{k,\,k+1}, M_{k,\,k+j}, \ldots M_{n-1,\,n}]^T$$

Example of 3D EM Model Parameter Subset

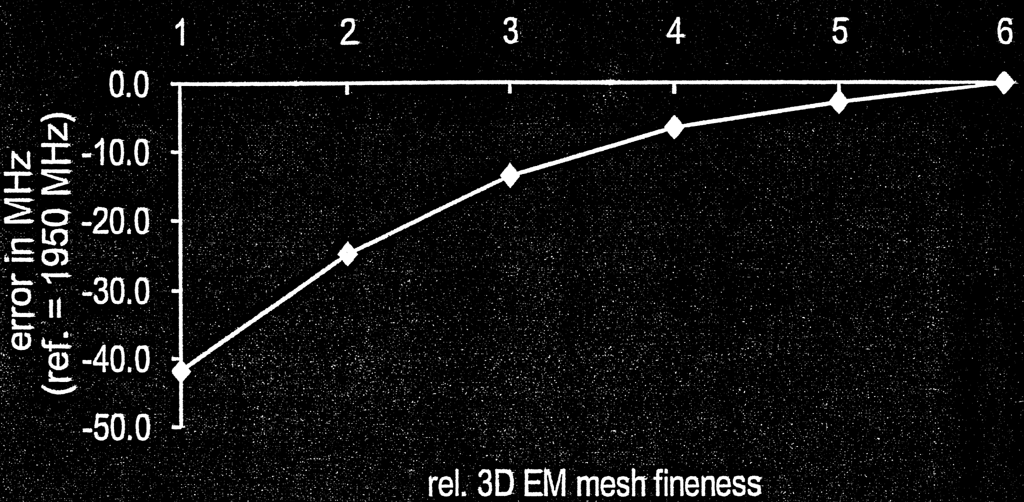


Exploiting the Coarse Mesh Model

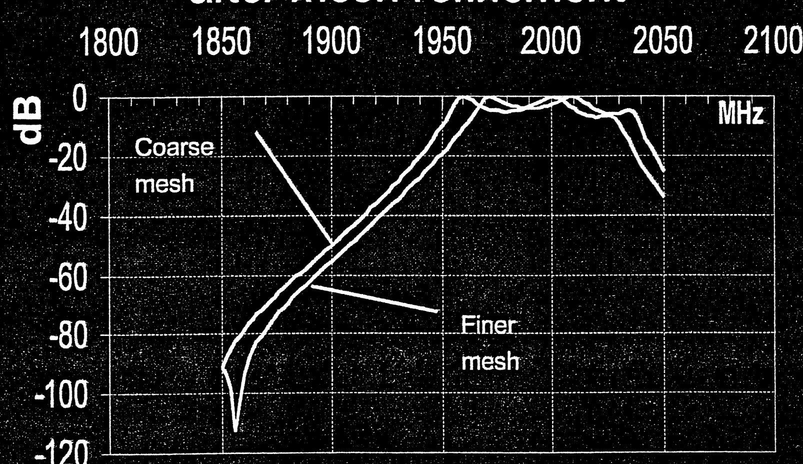
- Coarse mesh 3D EM analysis is sufficiently accurate with respect to the couplings between resonators
- A very coarse mesh can be used for the initial iterations
- The coarse mesh simulation response is offset in frequency



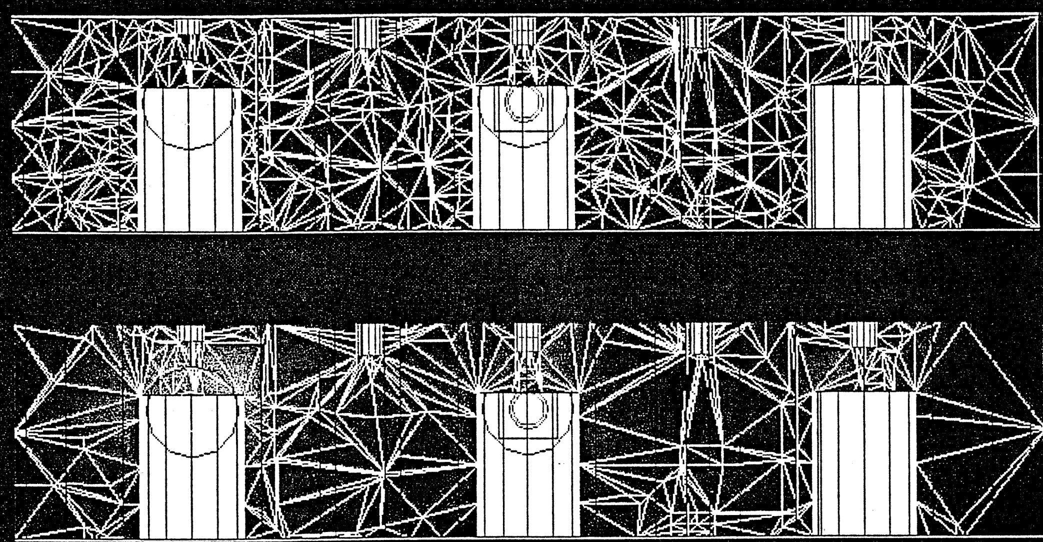
Extracted natural resonance of i-th resonator vs mesh fineness



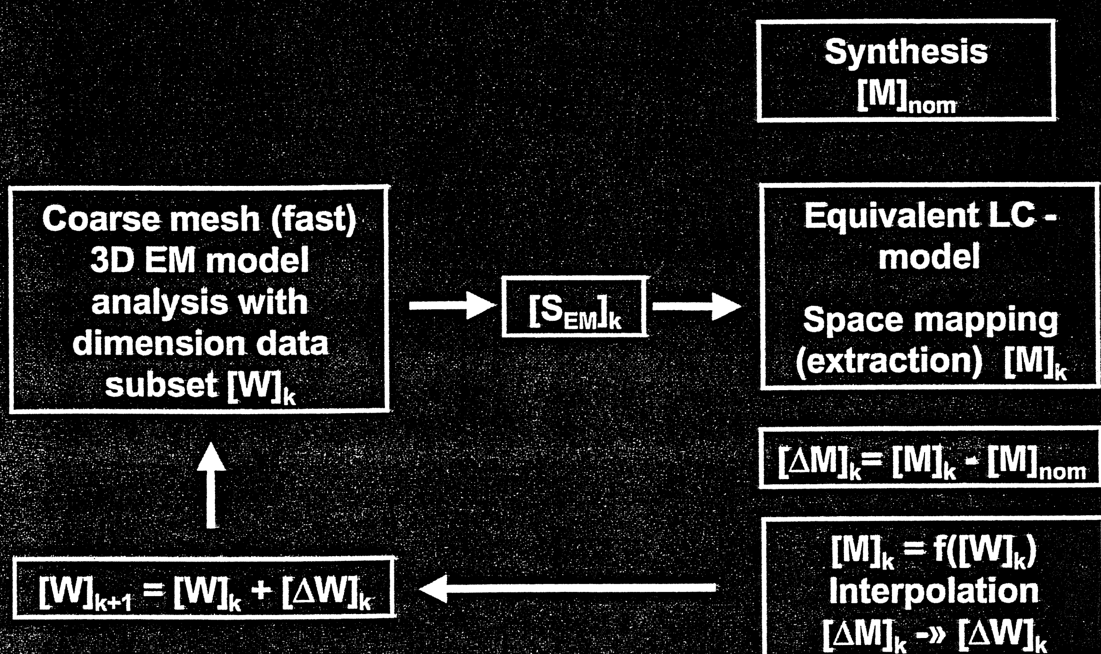
Frequency response offset after mesh refinement



Fine and coarse 3D EM simulation mesh (HFSS)



Block Diagram of the Process



From physical model variable space to electrical model variable space

$$x_{CNM}^{(i)} = \arg \min_{x_{CNM}} \left\| \left[S(f, x_{CMM}^{(i)}) \right] - \left[S(f, x_{CNM}^{(i)}) \right] \right\|$$

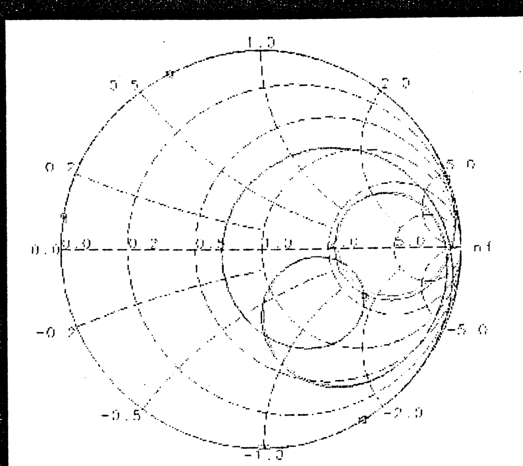
Extraction of Circuit Model Parameters from EM Simulation Data

$$[S]_{EM}{}^{k} \longrightarrow \boxed{\text{LC network model}} \longrightarrow [M]_k$$

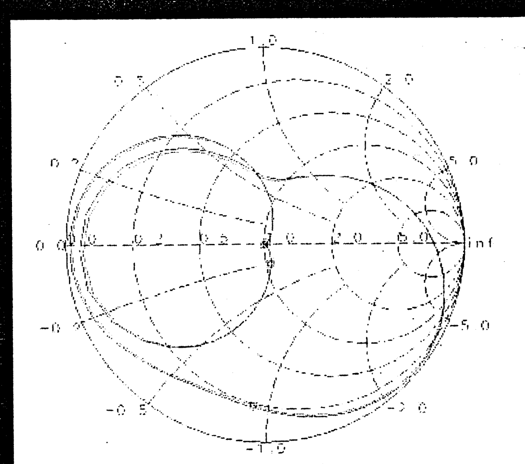
Circuit model

- Real-world effects must be represented adequately
- "electrically long" coupling structures require suitable circuit model representation
- insufficient circuit detail can lead to wrong accommodation of real-world effects

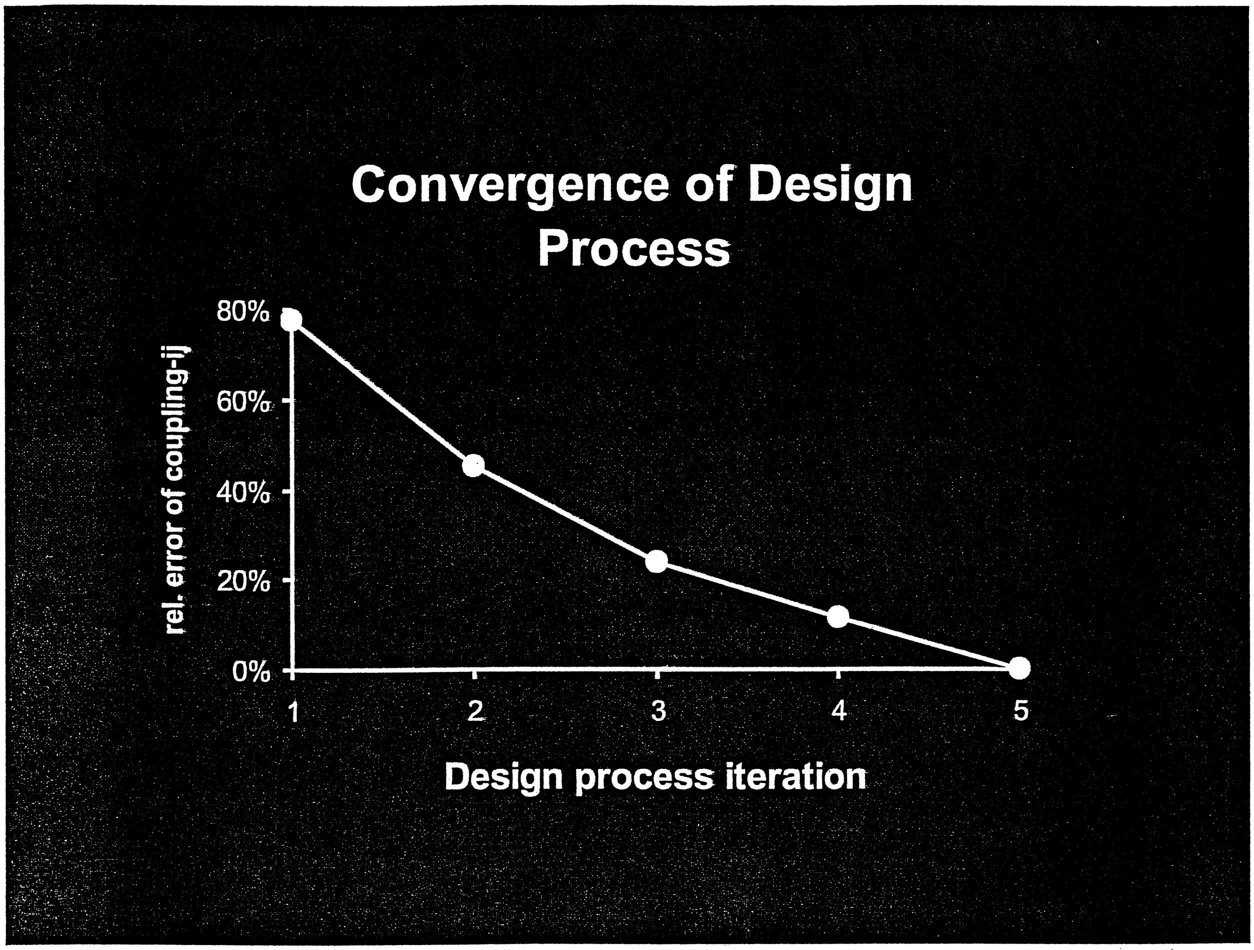
LC Model Extraction accuracy

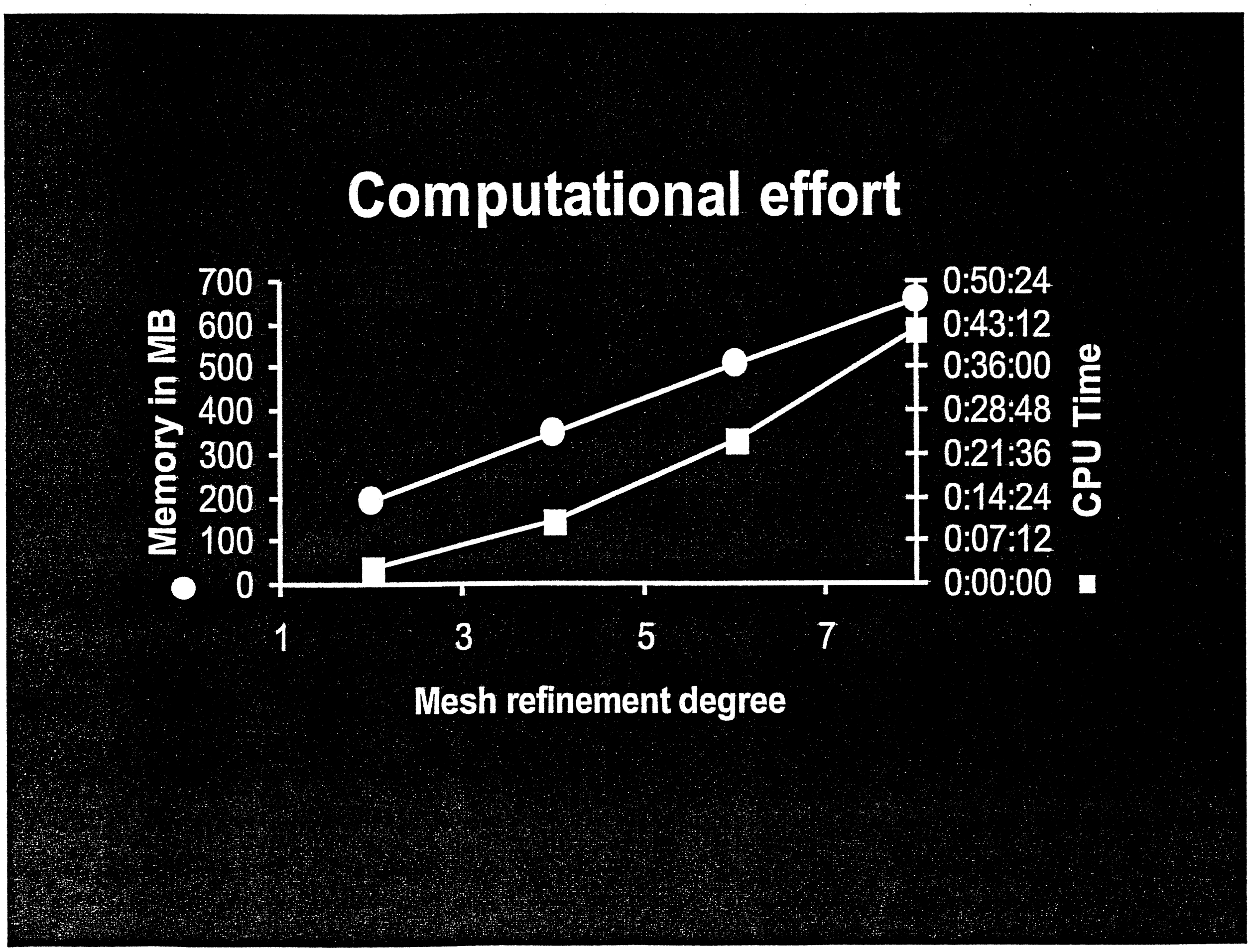


S_{11}

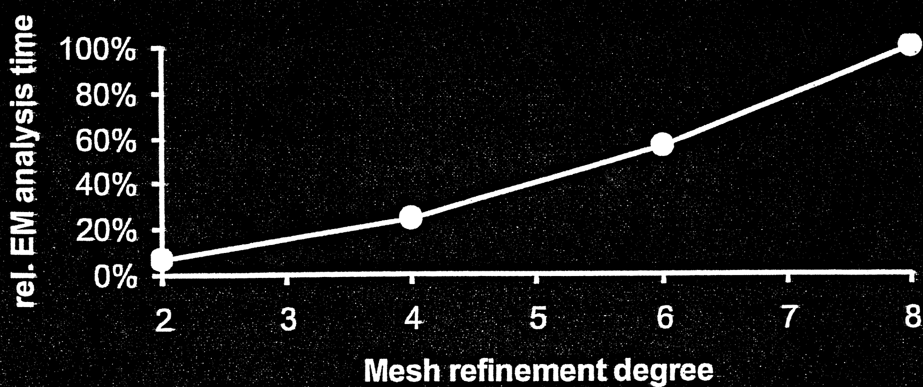


S_{21}


Convergence of Design Process
rel. error of coupling-ij
80%
60%
40%
20%
0%
1
2
3
4
5
Design process iteration


Computational effort
Memory in MB
700
600
500
400
300
200
100
0
0:50:24
0:43:12
0:36:00
0:28:48
0:21:36
0:14:24
0:07:12
0:00:00
CPU Time
1
3
5
7
Mesh refinement degree

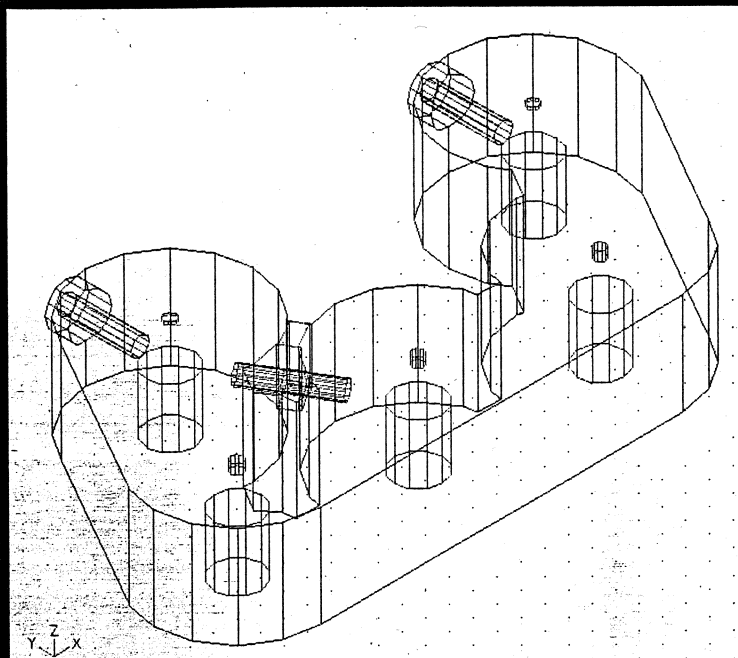
EM Analysis Time



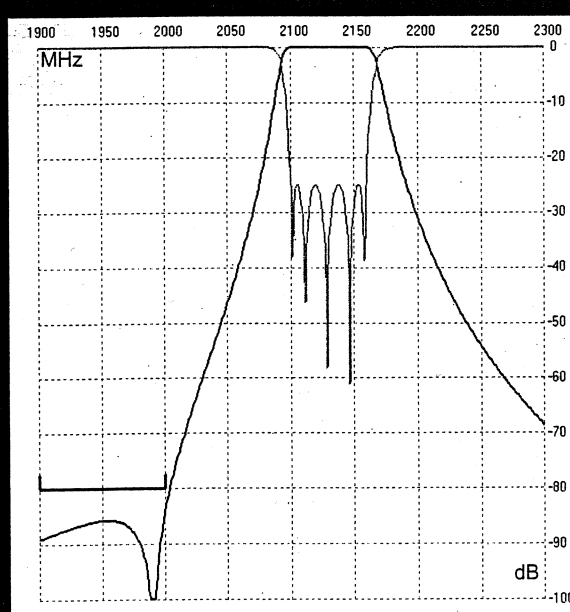
Example: 5-pole filter

		Nominal values		Iteration 1	Iteration 2	Iteration 3	Iteration 4
	k_{12}	0.0274		0.0116	0.0164	0.0272	0.0273
	k_{23}	0.0195		0.0329	0.0302	0.0225	0.0196
	k_{34}	0.0199		0.0303	0.0244	0.0224	0.0190
	k_{45}	0.0290		0.0112	0.0162	0.0291	0.0291
	w_{12}			30.0	33.0	38.9	39.0
	w_{23}			42.0	40.0	36.2	34.7
	w_{34}			41.0	38.0	36.6	34.8
	w_{45}			30.0	33.0	40.3	40.2
w_{ij} in mm				k_{ij} error			
				-57.7%	-40.1%	-0.7%	-0.4%
				68.7%	54.9%	15.4%	0.5%
				52.3%	22.6%	12.6%	-4.5%
				-61.4%	-44.1%	0.3%	0.3%

Example: 5-pole filter



Example: 5-pole filter



Outlook

- Classical space mapping can be applied to further increase the accuracy of coarse mesh simulation derived coupling matrix data
- 3D EM simulation and linear circuit simulation could be combined

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[2] J.W. Bandler, et. al., "Space Mapping Technique for Electromagnetic Optimization", IEEE MTT Vol. 42, No. 12, Dec. 1994

[3] M.H. Bakr, J.W. Bandler, K. Madsen, J. Sondergaard, "Review of the Space Mapping Approach to Engineering Optimization and Modeling", Optimization and Engineering, vol.1 2000, pp. 241 - 276 (available at www.bandler.com)

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Theory and Applications of the Space Mapping Technique

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K. Madsen J. Søndergaard

IMS2002

Purpose

Optimization of very expensive models

we assume two models of a physical object are available:

- an accurate fine model (expensive)
- a simpler coarse model (cheap)

Outline

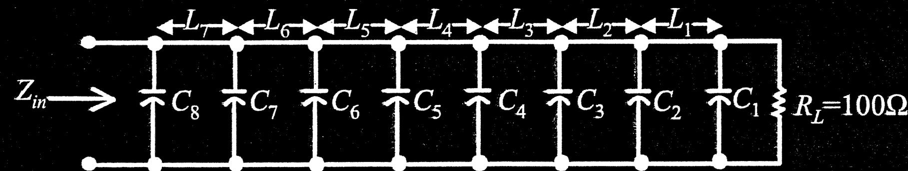
- Motivate the Space Mapping
- Define the Space Mapping
- Transmission-line example
- Compare with traditional methods

Example

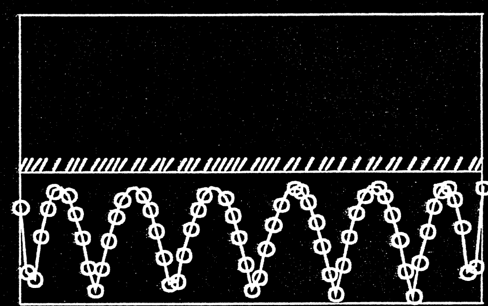
7 section capacitively loaded transmission-line transformer (TLT) to be optimized

- capacitances are fixed at 0.025 pF
- characteristic impedances are kept fixed
- optimize only the lengths
- synthetic example

7 Section TLT



Optimal response:



Type of problem considered

Minimize w.r.t. x the absolute values of the deviations between response $r(x;t_i)$ and specifications y_i

$$f_i(x) = r(x;t_i) - y_i,\ i = 1, \dots, m$$

Traditional methods:
Based on local information

Least squares formulation

$$F(x) = \sum_{i=1}^{m} f_i^2(x)$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \sum_{i=1}^{m} \hat{l}_i^2(x)$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

Minimax formulation

$$F(x) = \max_i |f_i(x)|$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \max_i \left|\hat{l}_i(x)\right|$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

L_1 formulation

$$F(x) = \sum_{i=1}^{m} |f_i(x)|$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \sum_{i=1}^{m} \left|\hat{l}_i(x)\right|$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

General formulation

Minimize

$$F(x) = H(f(x))$$

At the iterate $\hat{x}$:

$$\hat{L}(x) = H(\hat{l}(x))$$

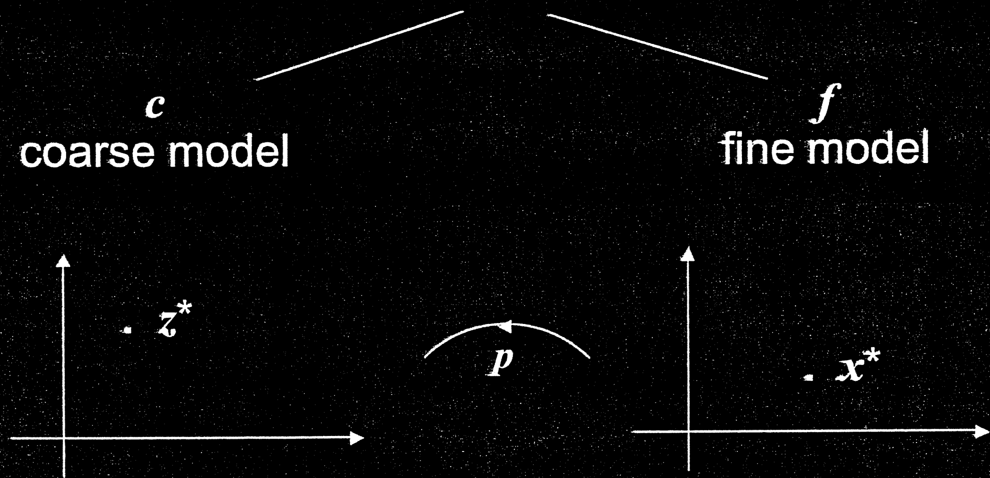
$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T(x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

Space Mapping

Space Mapping

Physical problem



Connect similar responses

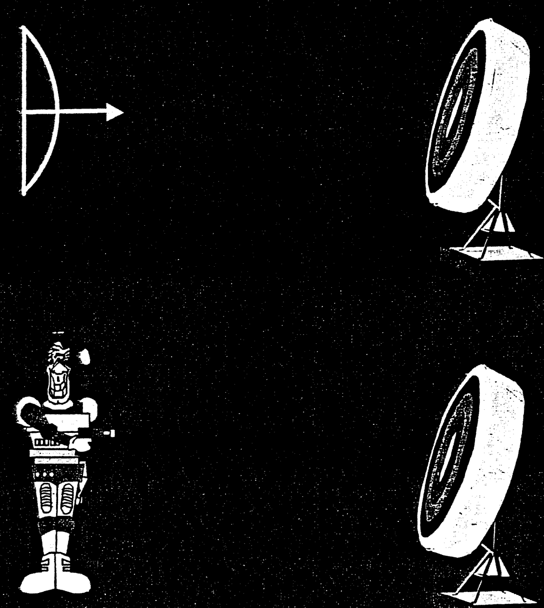
Archery example

Coarse model:

no wind, no gravity, etc.

Fine model:

reality



Archery example

First aim:

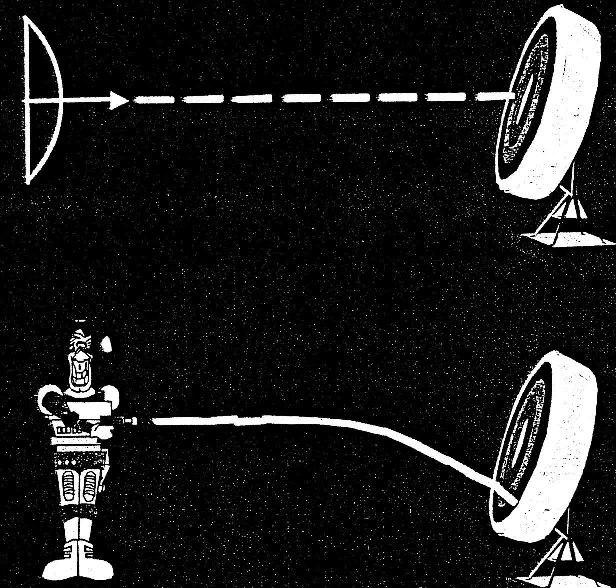
(z^* in coarse model)

First shot:

"Calculate" $f(x_0)$

(fine model)

$x_0 = z^*$



Parameter extraction

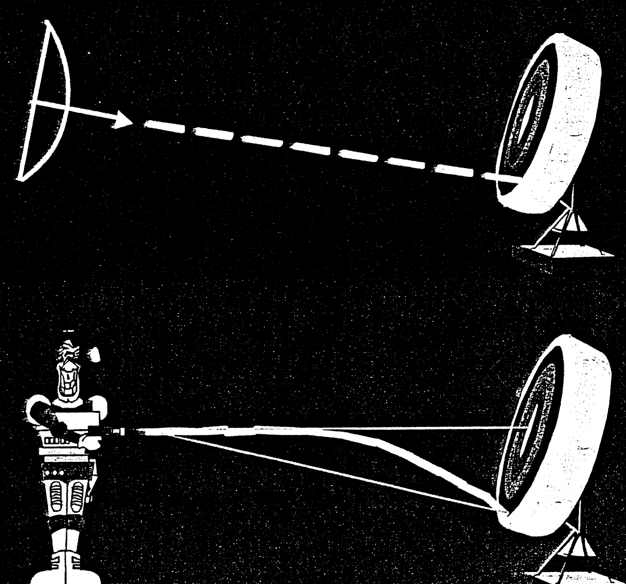
Match first shot: z_0

(coarse model)

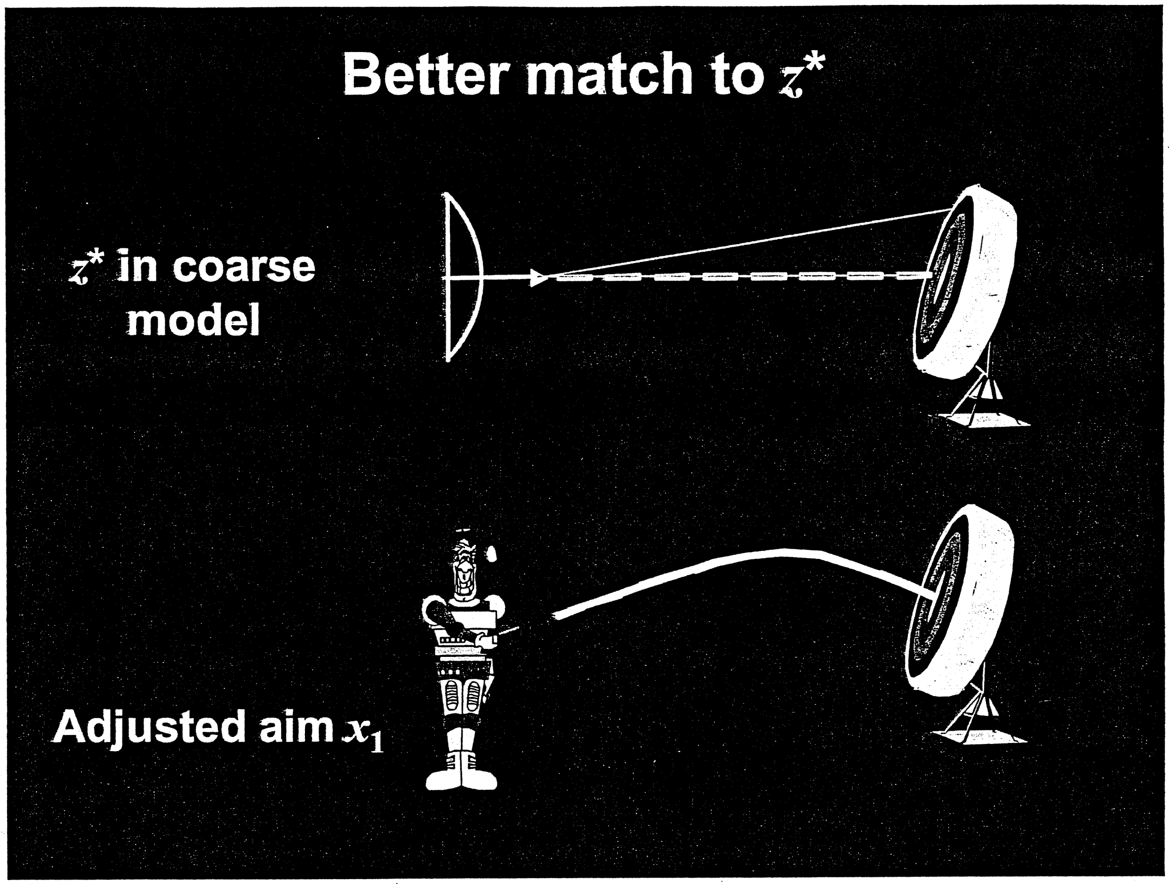
First shot:

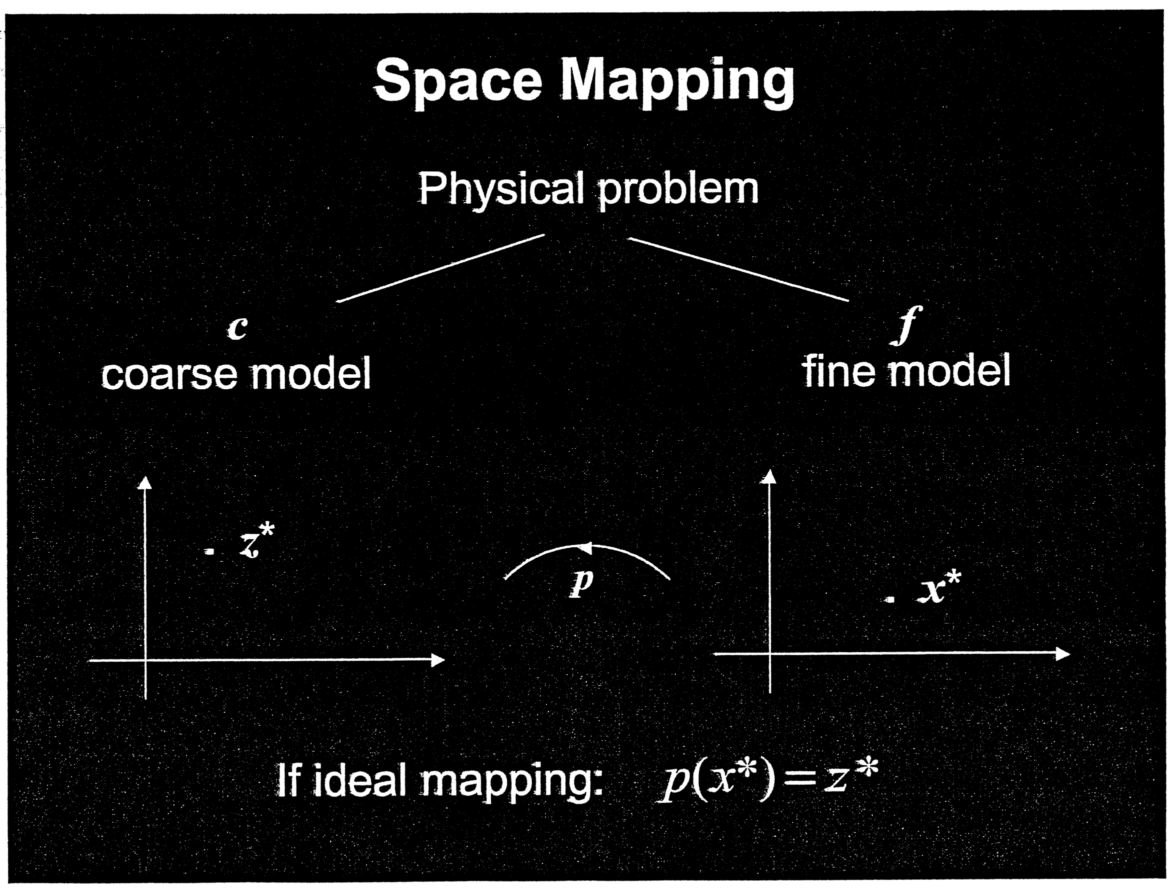
x_0

(fine model)



$$p(x_0) = z_0$$


Better match to z^*
z^* in coarse model
Adjusted aim x_1


Space Mapping
Physical problem
c
coarse model
f
fine model
z^*
p
x^*
If ideal mapping: $p(x^*) = z^*$

k'th iteration

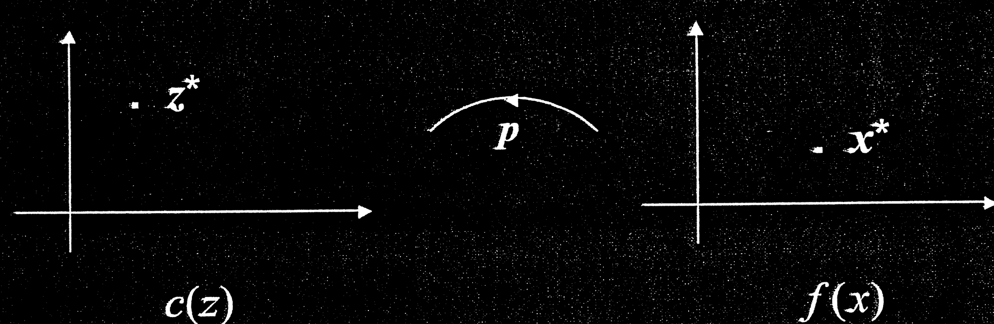
Assume p has been computed at $x_0, x_1, \ldots, x_k$

$$\begin{aligned} p(x) &\approx p(x_k) + p'(x_k)(x - x_k) \\ &\approx p(x_k) + B_k(x - x_k) \\ &\equiv p_k(x) \end{aligned}$$

where $B_k \approx p'(x_k)$ is, e.g., a Broyden update

Approximate aim: $p_k(x) = z^* \rightarrow x_{k+1}$

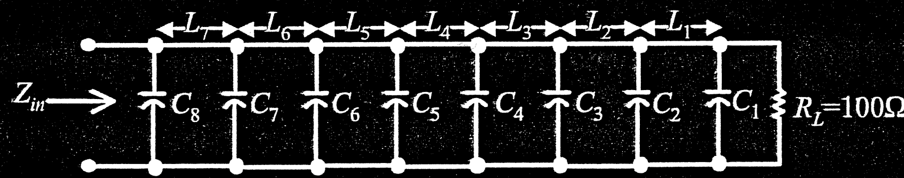
Parameter extraction: Define $p(x)$



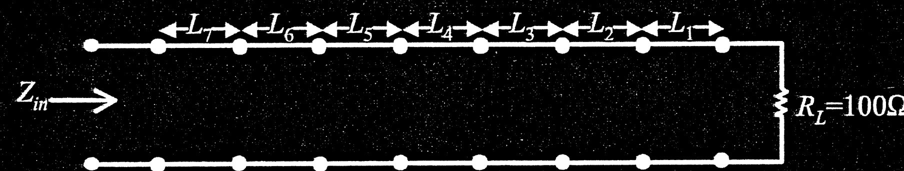
$$p(x) \equiv \arg\min_z \{ \| f(x) - c(z) \| \}$$

7 Section TLT

Fine model



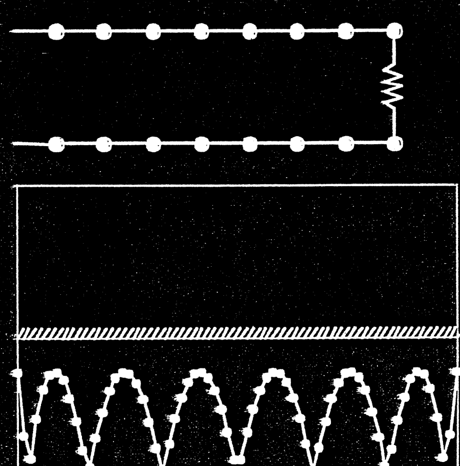
Coarse model

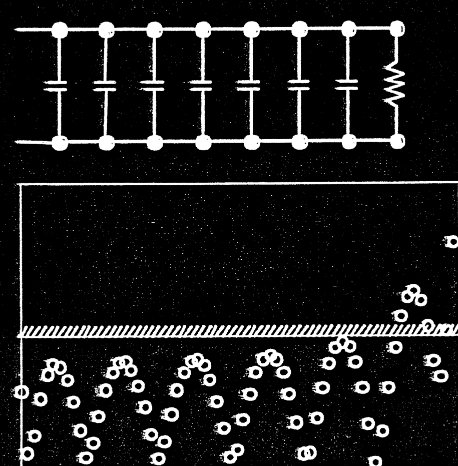


Initial value x_0

coarse model optimum: z^*

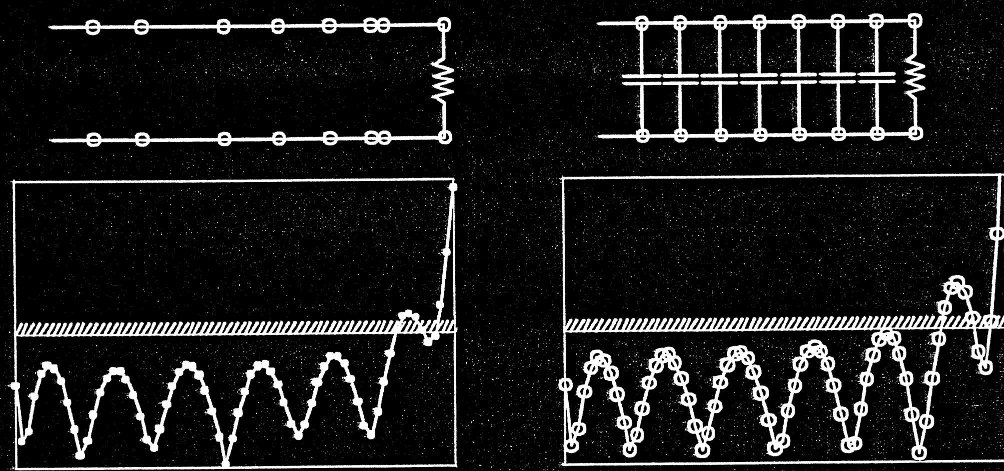
fine model at $x_0 = z^*$





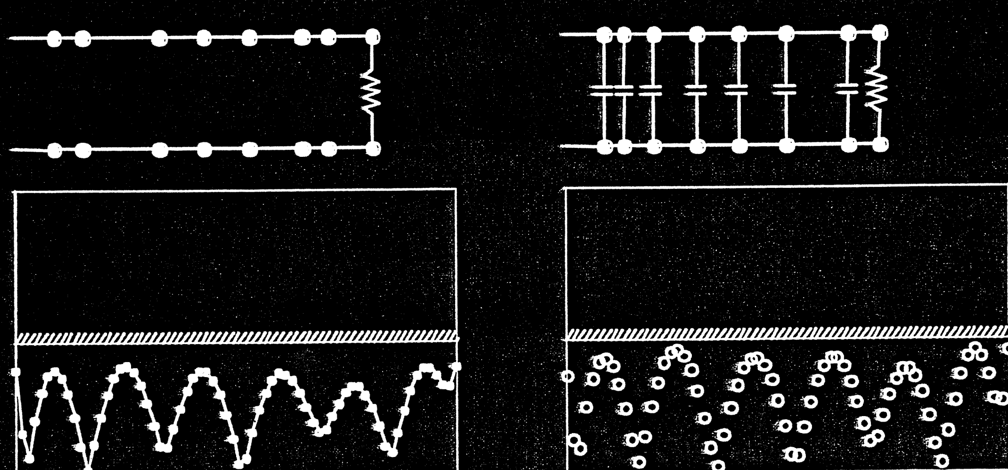
Parameter extraction: Find $p(x_0)$

coarse model at $z_0 = p(x_0)$ fine model at x_0



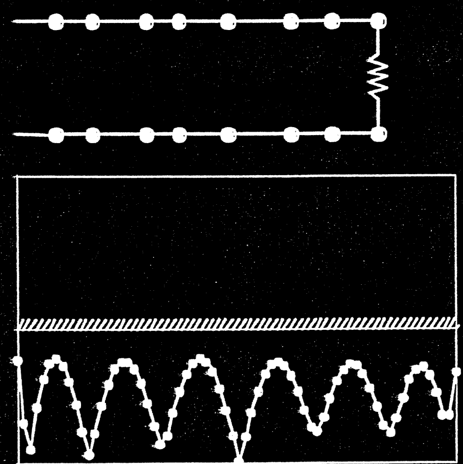
Find x_1 and z_1

coarse model at $z_1 = p(x_1)$ fine model at x_1

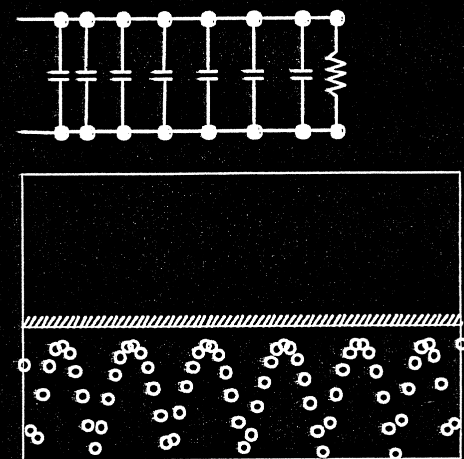


Find x_2 and z_2

coarse model at $z_2=p(x_2)$

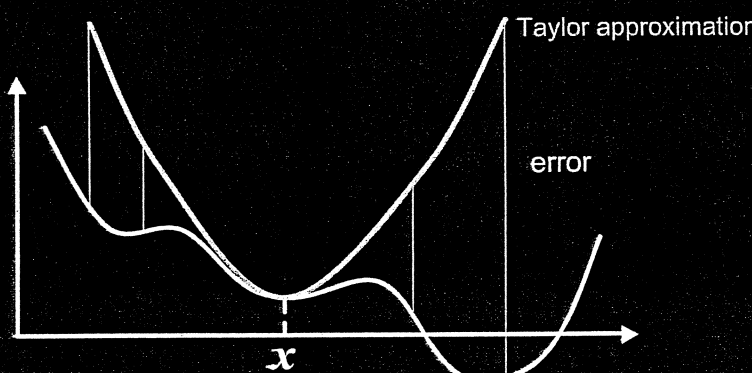


fine model at x_2

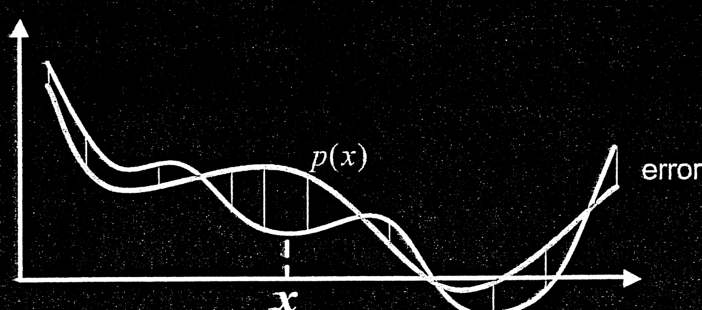


Optimization methodologies

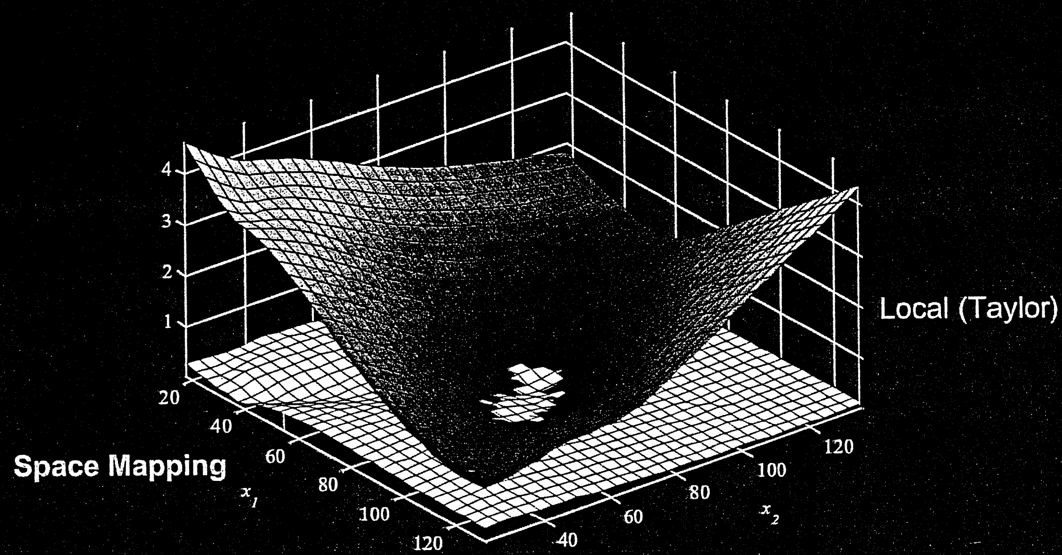
Local



Space Mapping



Approximation errors



Conclusion

**Use of coarse model
may provide large iteration steps**

**Space Mapping may provide a good
approximate solution in few iteration steps**

- **Small iteration steps: Taylor best**
- **Large iteration steps: Space Mapping best**

Theory and Applications of the Space Mapping Technique

M.Bakr J.W. Bandler

K. Madsen J. Søndergaard

IMS2002

Purpose

Optimization of very expensive models

we assume two models of a physical object are available:

- an accurate fine model (expensive)
- a simpler coarse model (cheap)

Outline

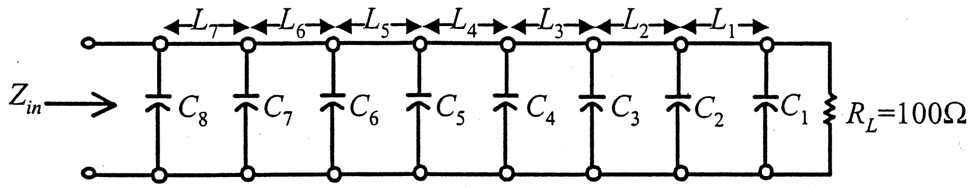
- Motivate the Space Mapping
- Define the Space Mapping
- Transmission-line example
- Compare with traditional methods

Example

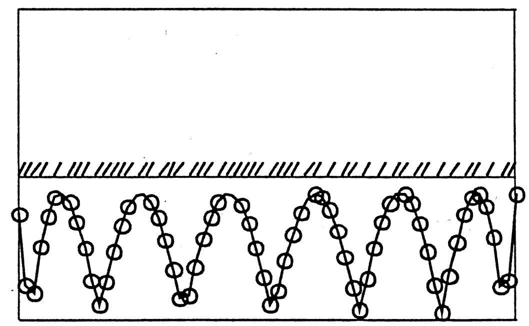
7 section capacitively loaded transmission-line transformer (TLT) to be optimized

- capacitances are fixed at 0.025 pF
- characteristic impedances are kept fixed
- optimize only the lengths
- synthetic example

7 Section TLT



Optimal response:



Type of problem considered

Minimize w.r.t. x the absolute values of the deviations between response $r(x;t_i)$ and specifications y_i

$$f_i(x) = r(x;t_i) - y_i,\ i = 1,\ \ldots,\ m$$

Traditional methods:

Based on local information

Least squares formulation

$$F(x) = \sum_{i=1}^{m} f_i^2(x)$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \sum_{i=1}^{m} \hat{l}_i^2(x)$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

Minimax formulation

$$F(x) = \max_i |f_i(x)|$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \max_i |\hat{l}_i(x)|$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

L_1 formulation

$$F(x) = \sum_{i=1}^{m} |f_i(x)|$$

Local approximation at $\hat{x}$:

$$\hat{L}(x) = \sum_{i=1}^{m} |\hat{l}_i(x)|$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

General formulation

Minimize

$$F(x) = H(f(x))$$

At the iterate $\hat{x}$:

$$\hat{L}(x) = H(\hat{l}(x))$$

$$\hat{l}_i(x) = f_i(\hat{x}) + f_i'(\hat{x})^T (x - \hat{x})$$

Minimize $\hat{L}$ subject to some trust region

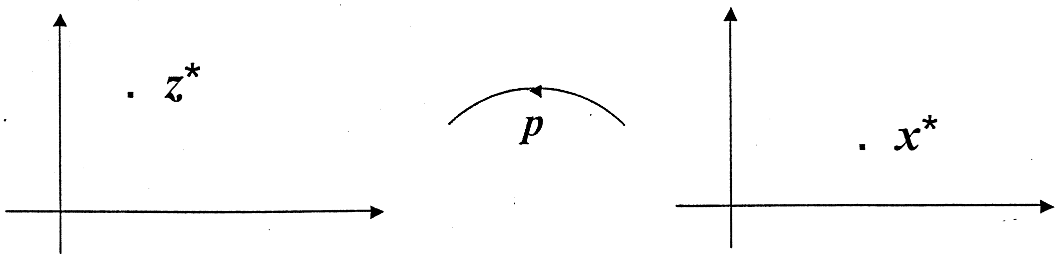
Space Mapping

Space Mapping

Physical problem

c
coarse model

f
fine model

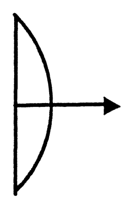


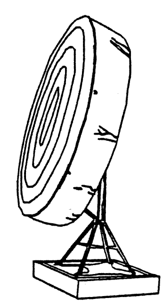
Connect similar responses

Archery example

Coarse model:

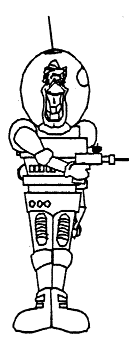
no wind, no gravity, etc.

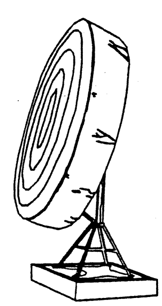




Fine model:

reality

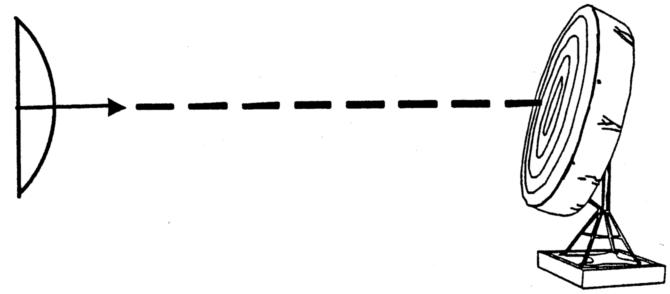




Archery example

First aim:

(z^* in coarse model)

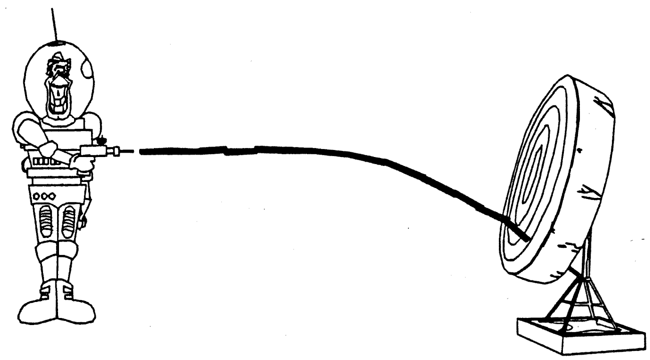


First shot:

”Calculate” f(x_0)

(fine model)

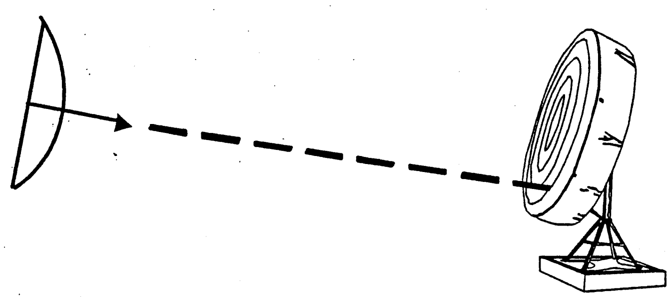
$x_0 = z^*$



Parameter extraction

Match first shot: z_0

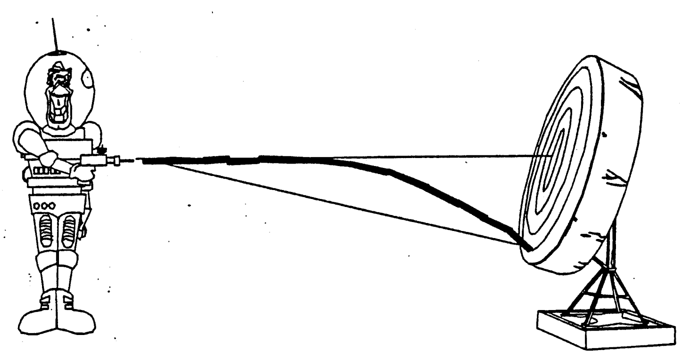
(coarse model)



First shot:

x_0

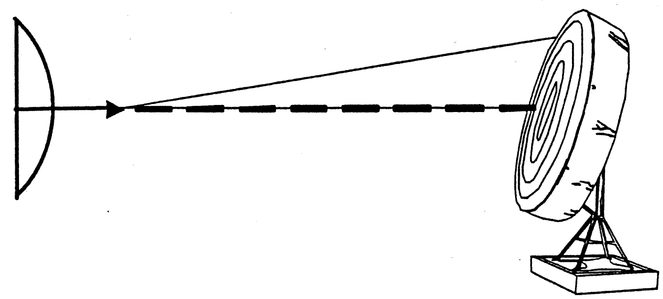
(fine model)

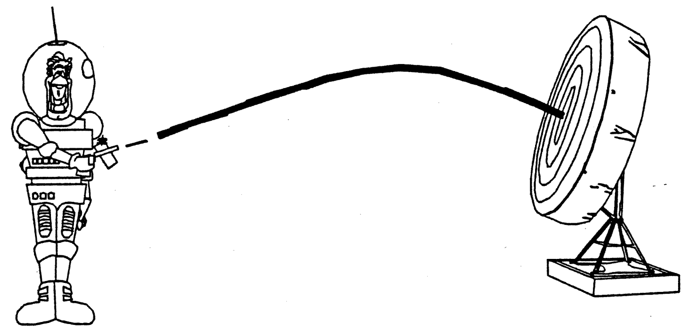


$$p(x_0) = z_0$$

Better match to z^*

z^* in coarse model





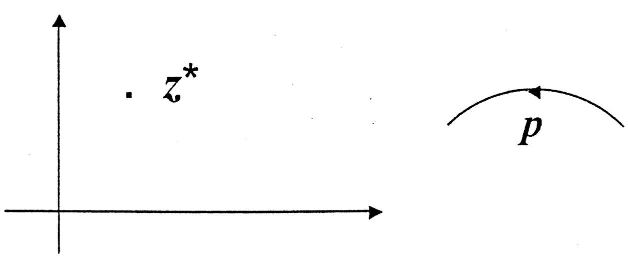
Adjusted aim x_1

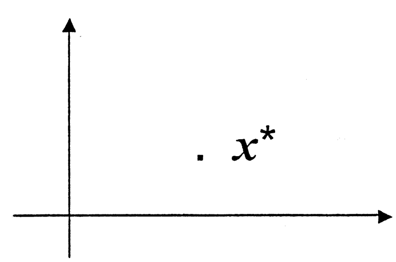
Space Mapping

Physical problem

c
coarse model

f
fine model





If ideal mapping: $p(x^*) = z^*$

k'th iteration

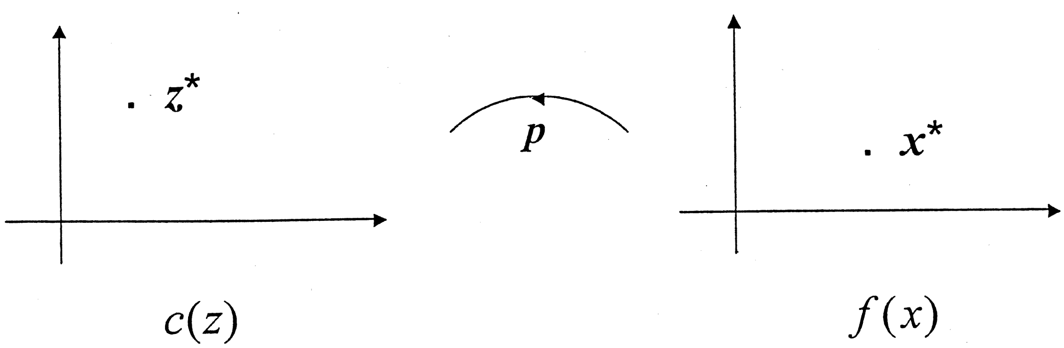
Assume p has been computed at

$$\begin{aligned} p(x) &\approx p(x_k) + p'(x_k)(x - x_k) \\ &\approx p(x_k) + B_k(x - x_k) \\ &\equiv p_k(x) \end{aligned}$$

where $B_k \approx p'(x_k)$ is, e.g., a Broyden update

Approximate aim: $p_k(x) = z^* \quad \rightarrow \quad x_{k+1}$

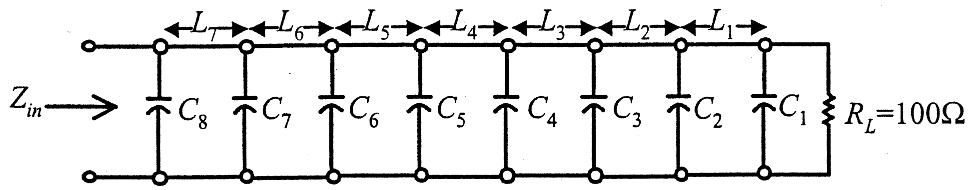
Parameter extraction: Define $p(x)$



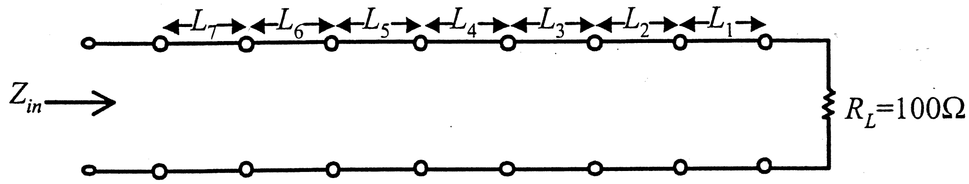
$$p(x) \equiv \arg\min_z \{ \| f(x) - c(z) \| \}$$

7 Section TLT

Fine model

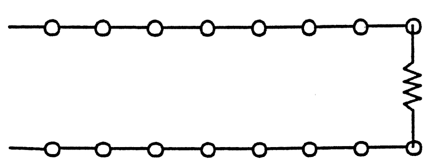


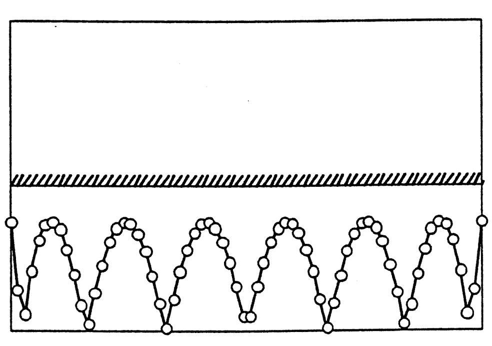
Coarse model



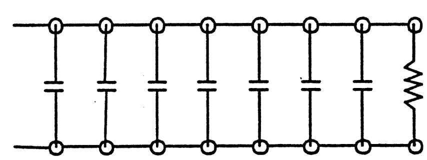
Initial value x_0

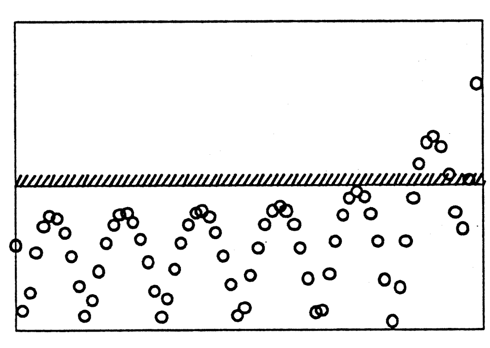
coarse model optimum: z^*





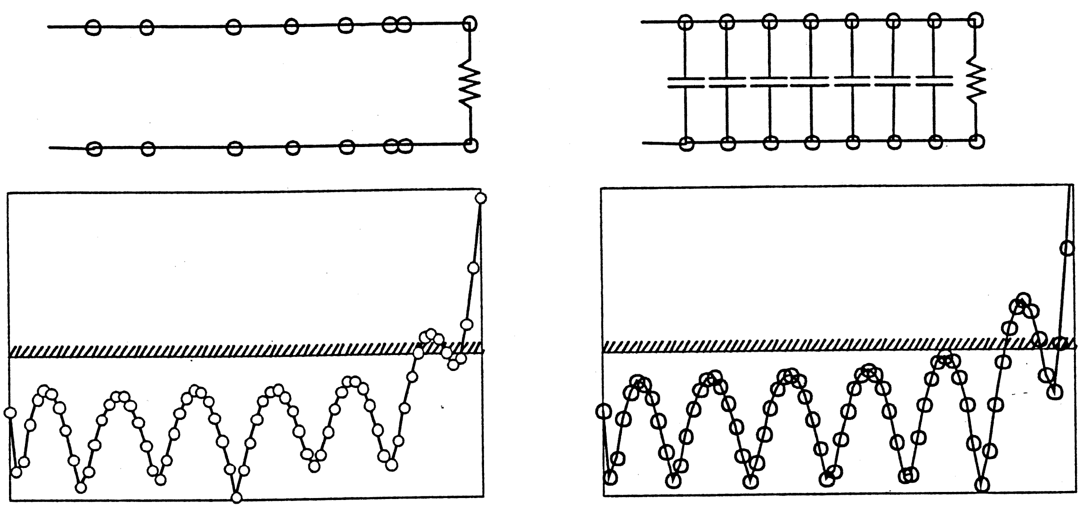
fine model at $x_0 = z^*$





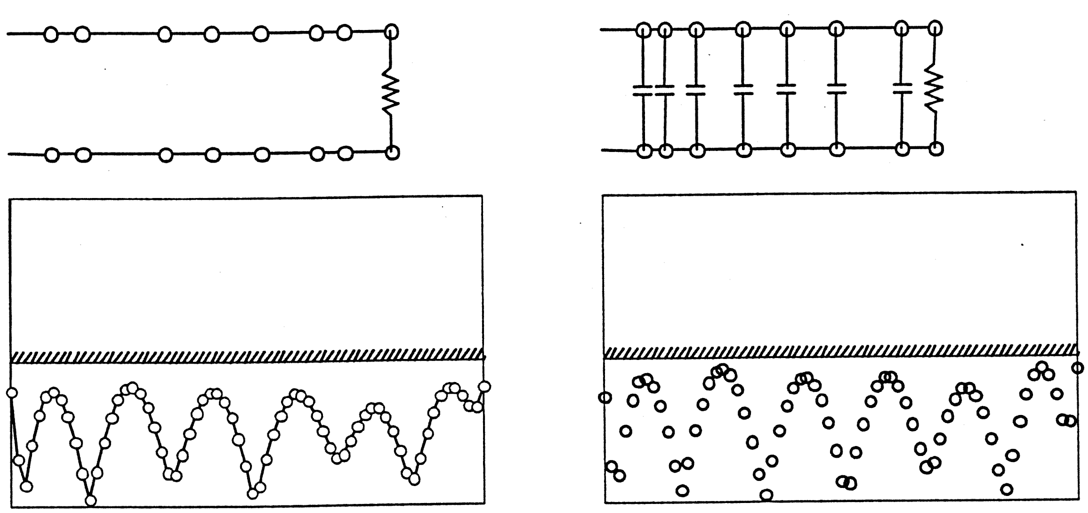
Parameter extraction: Find $p(x_0)$

coarse model at $z_0=p(x_0)$ | **fine model at x_0**



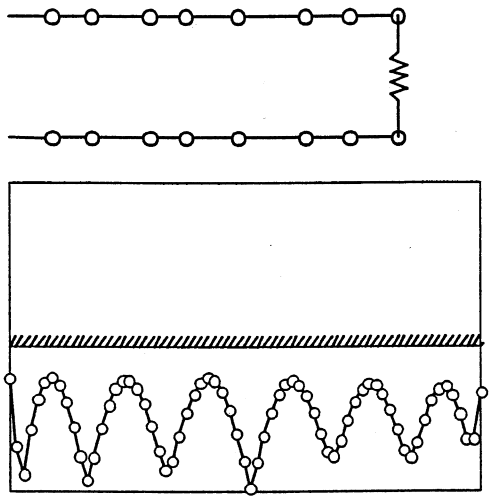
Find x_1 and z_1

coarse model at $z_1=p(x_1)$ | **fine model at x_1**

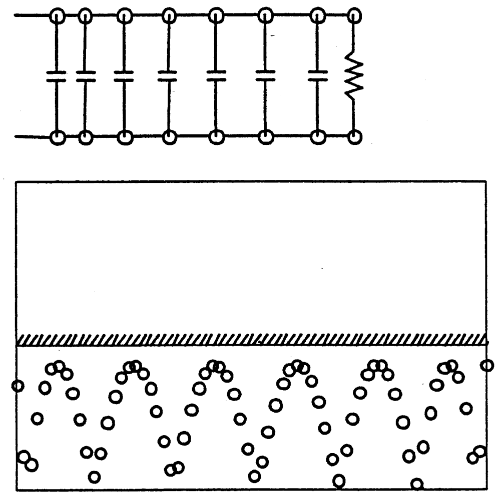


Find x_2 and z_2

coarse model at $z_2=p(x_2)$

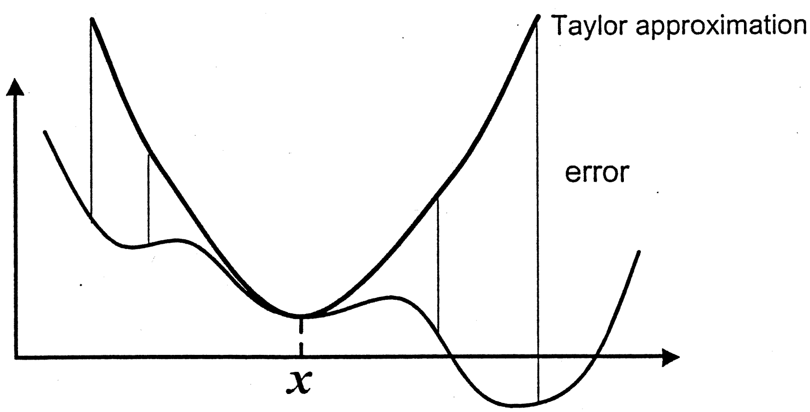


fine model at x_2

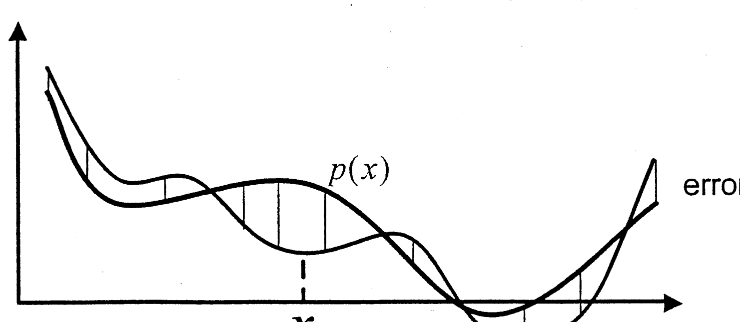


Optimization methodologies

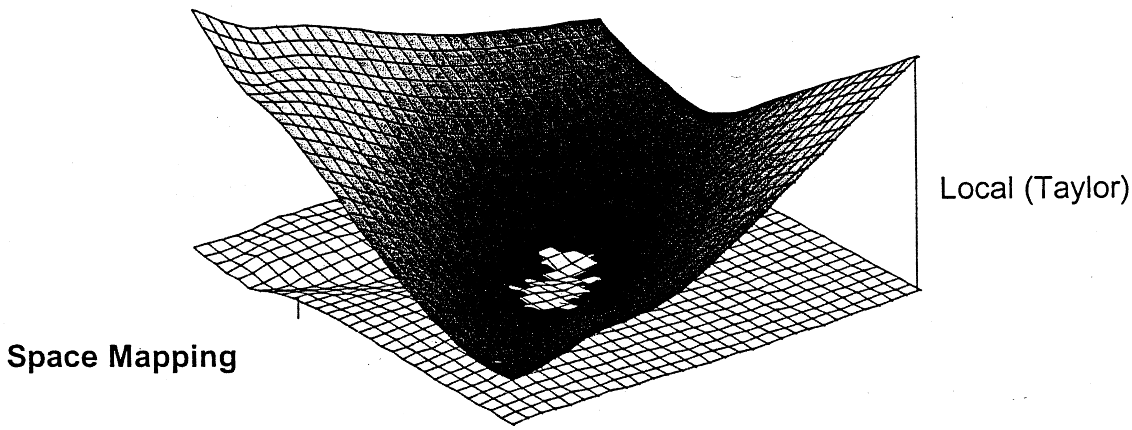
Local



Space Mapping



Approximation errors



Conclusion

Use of coarse model may provide large iteration steps

Space Mapping may provide a good approximate solution in few iteration steps

- **Small iteration steps: Taylor best**
- **Large iteration steps: Space Mapping best**

Space Mapping in the Design of Cellular PA Output Matching Circuits

Jan-Willem Lobeek
Philips Semiconductors
BL RF Modules
The Netherlands
jan-willem.lobeek@philips.com

Time to market is a key factor in the design and manufacturing of power amplifiers. Hereto, designers should be equipped with parameterised fast and accurate models, with which they quickly can build their circuits. However, often these archetype models are not available because of the great design freedom designers wish to have. This forces the designers to use EM simulation, which is a time consuming tool and not very suitable for circuit synthesis. Within BL RF Modules at Philips Semiconductors Space Mapping is used to speed up the design cycle for power amplifiers.

In this presentation Space Mapping is demonstrated for the design of a DCS/PCS output match of a cellular power amplifier. In the design of power amplifiers several different technologies are used on a multi-layer substrate carrier. Even for a single block such as the output match, different technologies are used to achieve the best and cheapest concept.

In the design process of a multi-technology output match, the functional circuits in the different technologies are calculated individually with EM and connected together on a circuit level. The discussed design uses a 6-layer LTCC substrate, a silicon Passive Integration die, discrete SMD's as well as bondwires. For this design a Space Mapping model is derived for the silicon Passive Integration die, which is mainly used to integrate capacitors and low value inductors.

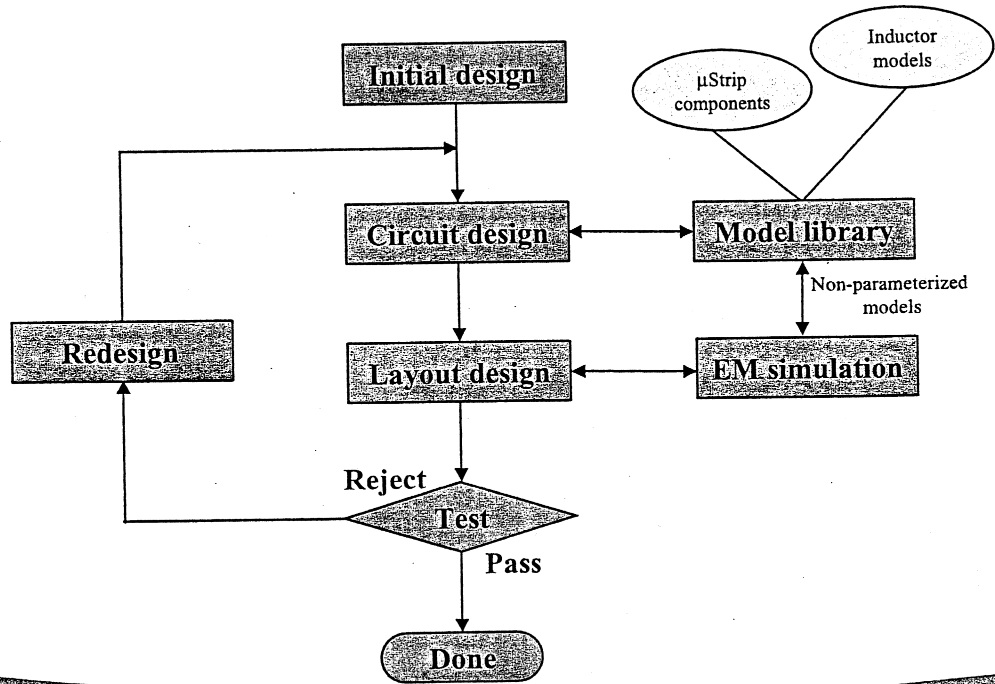
The functional circuits of the output match can be optimised separately. However, an optimisation of the complete circuit is not possible or very difficult. This problem is addressed with a Space Mapping model of the silicon die, which results in fast and accurate circuit models. These models can be used to optimise the overall circuit response in a fast and accurate manner.

Space Mapping models at the BL RF Modules are used for nominal optimisation of circuit performance. In addition, because the physical parameters and parasitics, which are captured in the EM are also absorbed into the Space Mapped model, Space Mapping can also be used to monitor the statistical behaviour of the design over a change in parameter value. To this end Monte Carlo analysis can be used to monitor the performance of the output match circuit over a range of parameter values encountered during manufacturing. In this talk we will show the results of a Monte Carlo analysis with EM accuracy based on a Space Mapped model and compared with manufactured data. This comparison shows immediately the strength of fast and accurate Space Mapping models.

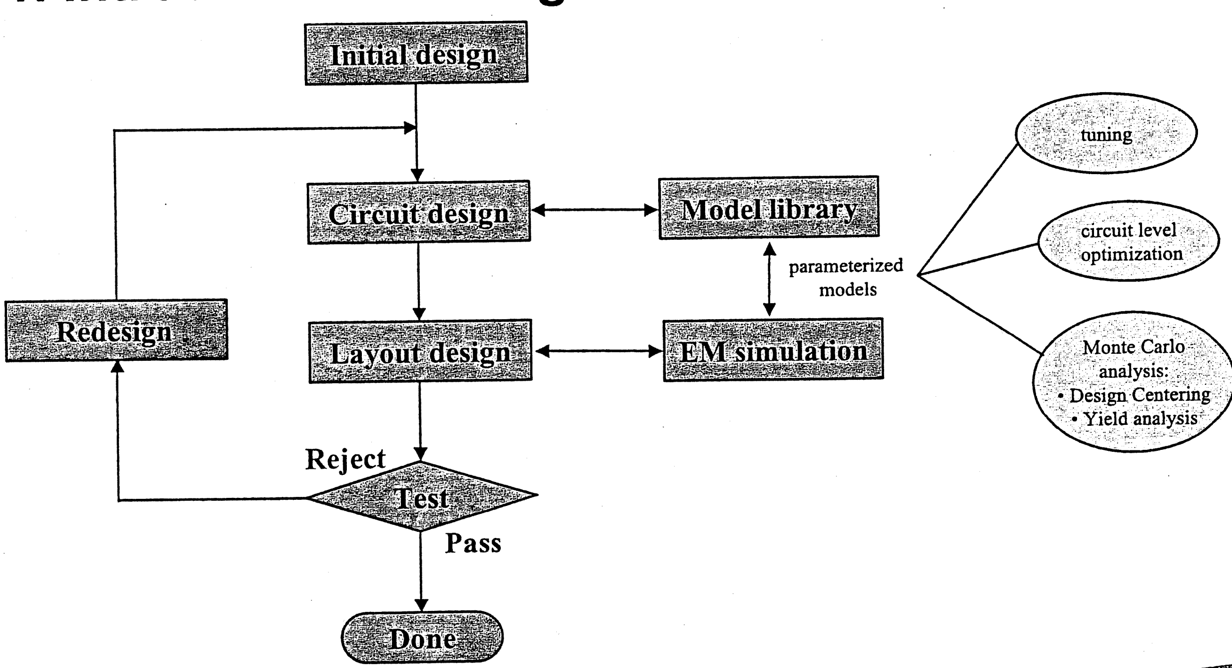
Summary

1. Introduction
2. DCS/PCS Output Match
3. Space Mapping model
4. Simulation versus measurement
5. Statistical analysis of Output Match
6. Statistical Analysis of module performance
7. Comparison between simulated and manufactured

1. Introduction - Design flow



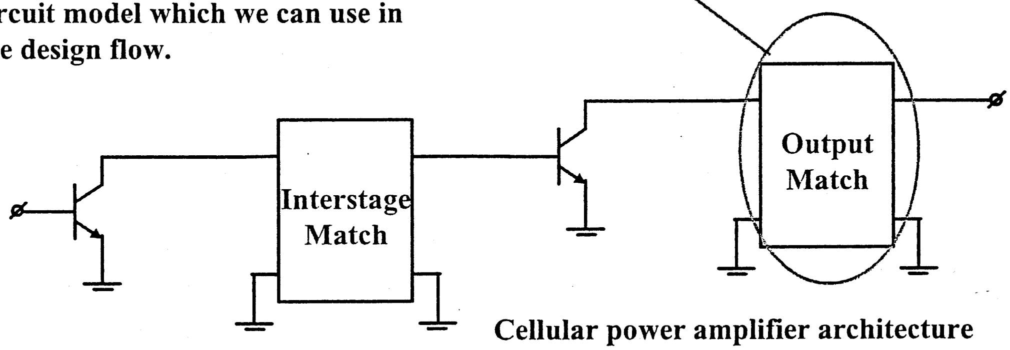
1. Introduction - Design flow



2. Design Strategy

■ Multi-technology Output match
- multi-layer LTCC substrate carrier
- High Ohmic silicon passive integration technology to integrate capacitors in
- SMD's
- Bondwires as interconnect

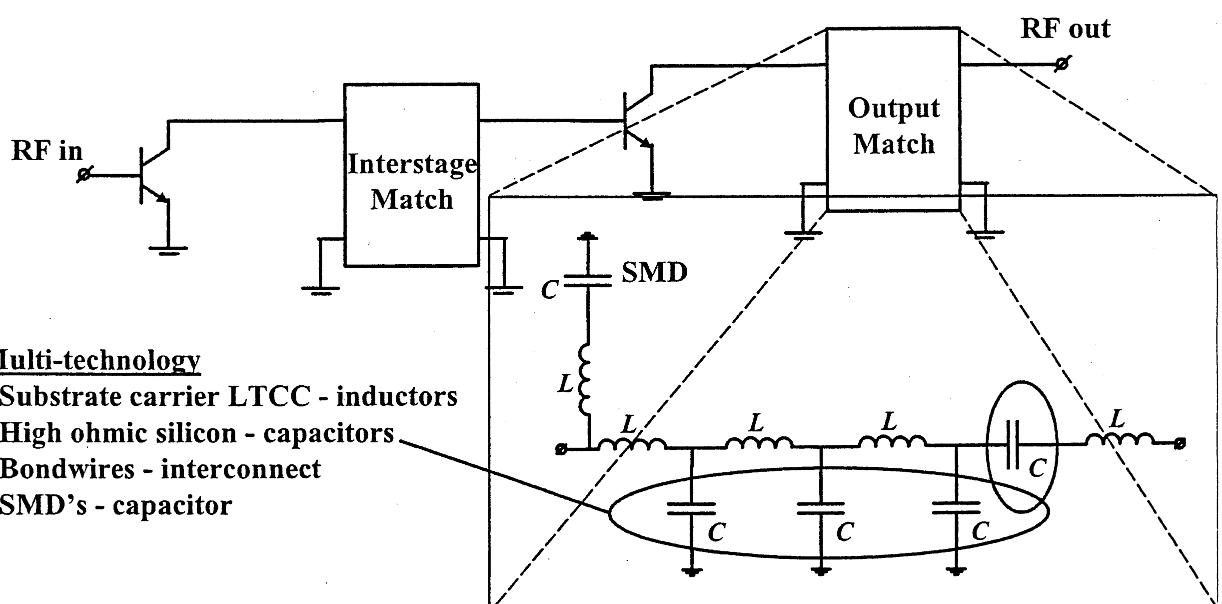
■ <u>Design Strategy:</u>
We will try to generate a parameterized circuit model which we can use in the design flow.



Cellular power amplifier architecture

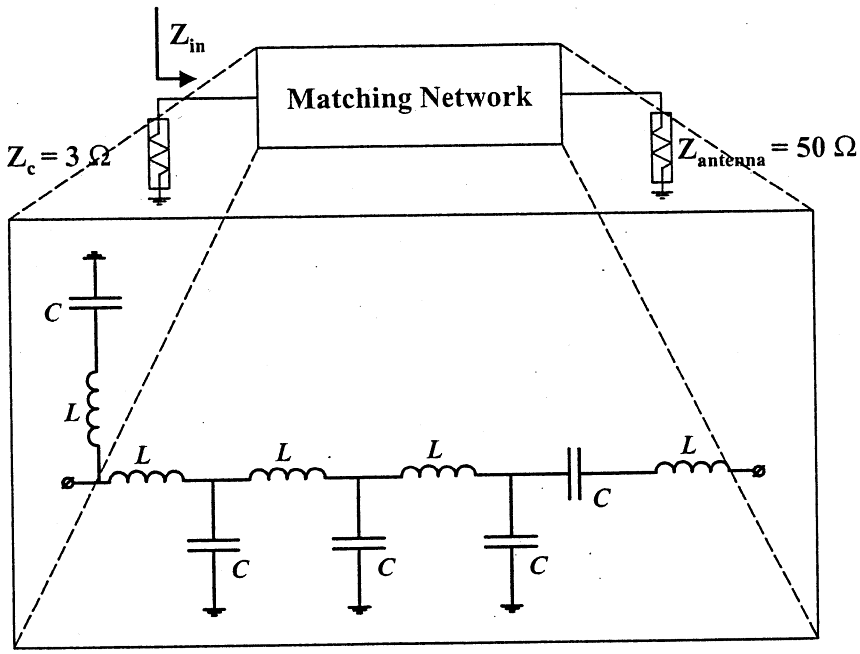
2. DCS/PCS Output Match

Cellular power amplifier architecture

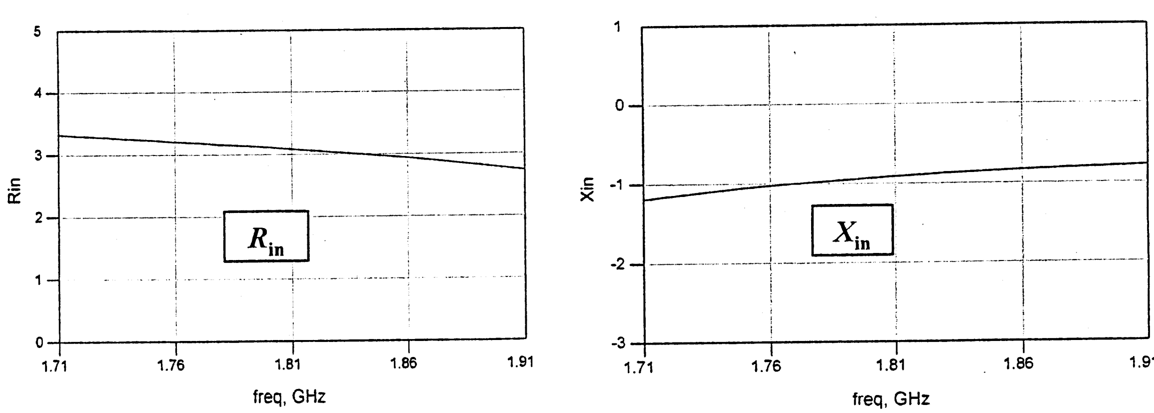


<u>Multi-technology</u>
- Substrate carrier LTCC - inductors
- High ohmic silicon - capacitors
- Bondwires - interconnect
- SMD's - capacitor

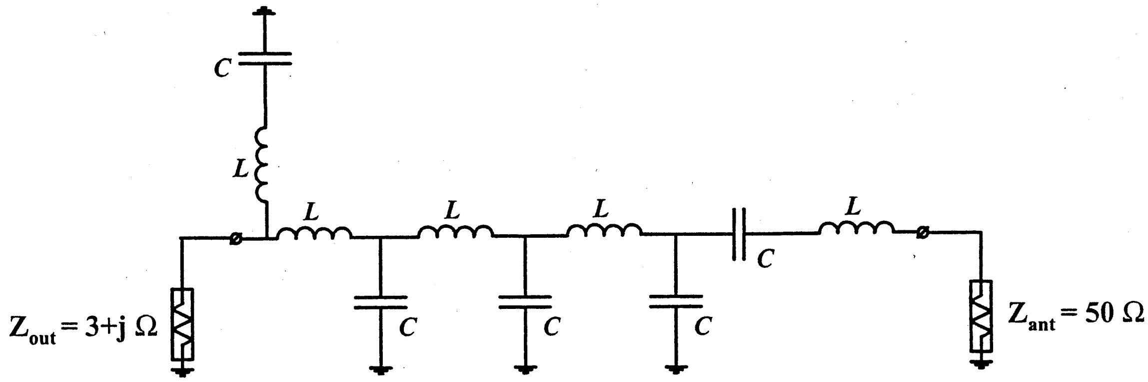
2. Circuit design - DCS/PCS Output Match



2. Circuit design - DCS/PCS Output Match

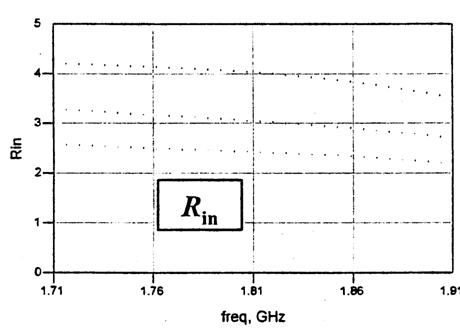


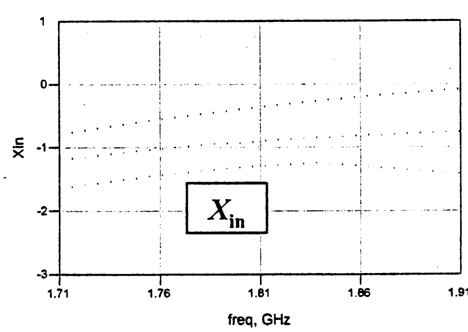
2. DCS/PCS Output Match
Yield Analysis after Nominal Optimization



Tolerances on component values

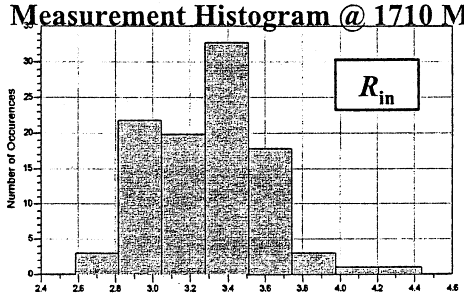
2. After Optimization (Yield Analysis)



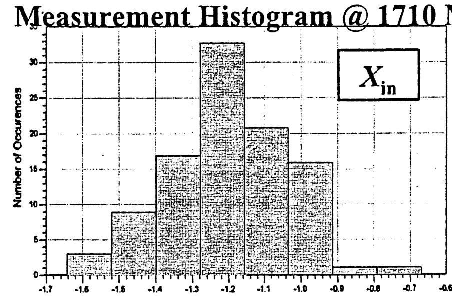


— mean value
— max value
— min value

Measurement Histogram @ 1710 MHz

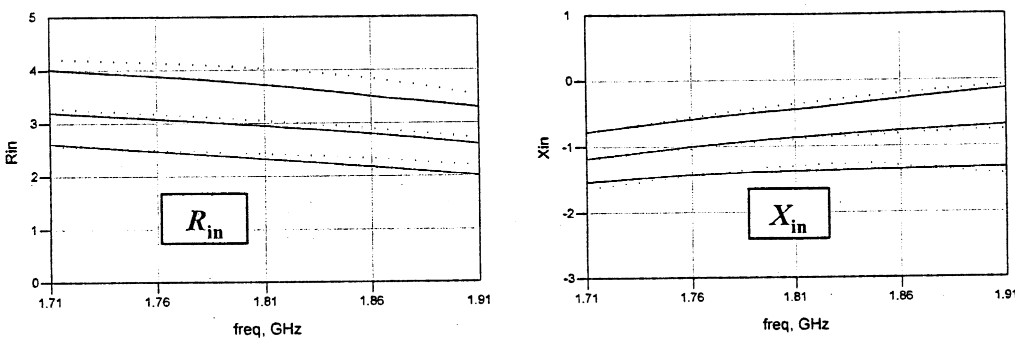


Measurement Histogram @ 1710 MHz



Yield = 13 %

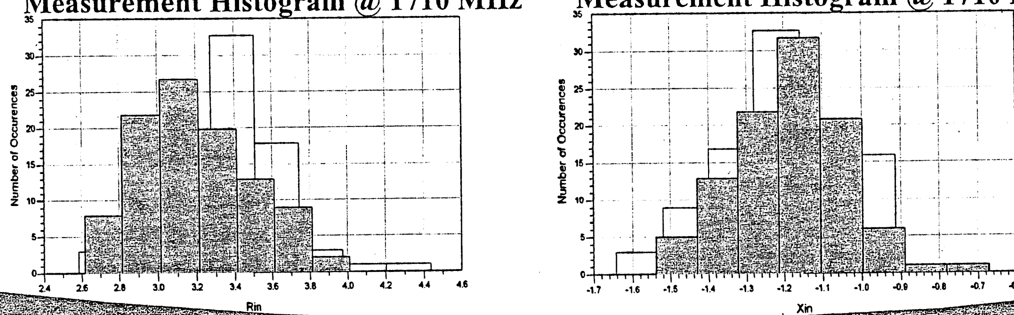
2. After Yield Optimization (Yield Analysis)



— mean value
— max value
— min value
- - after nominal optimization
— after yield optimization

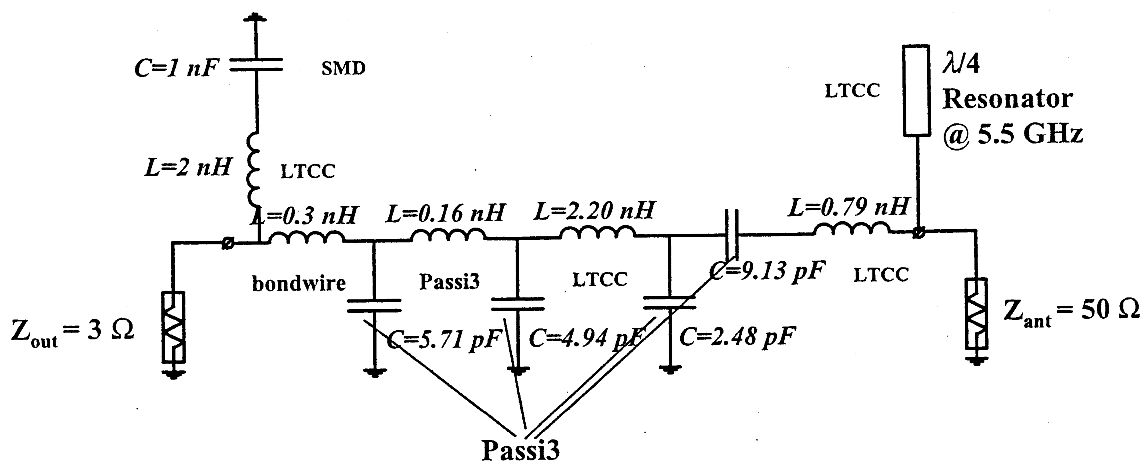
Measurement Histogram @ 1710 MHz

Measurement Histogram @ 1710 MHz

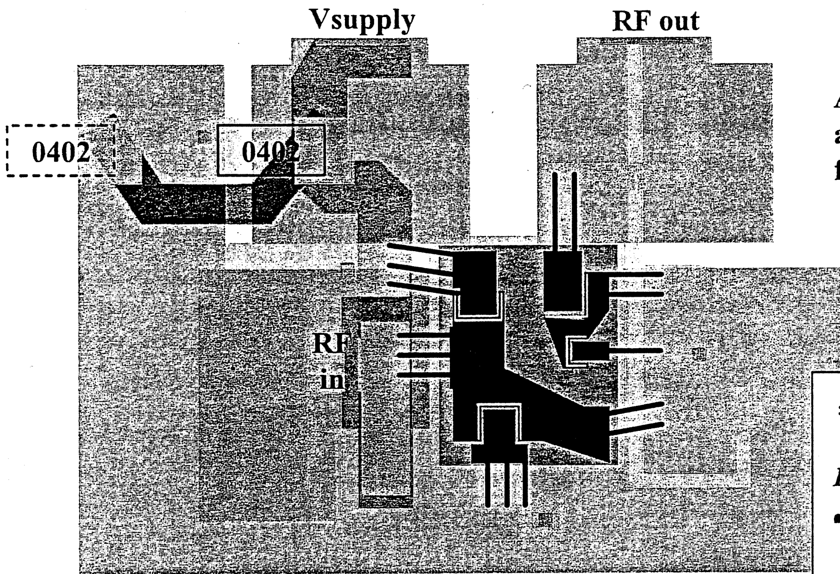


Yield = 28 %
— after nomin[a]
optimization
— after yield
optimization

2. DCS/PCS Output Match

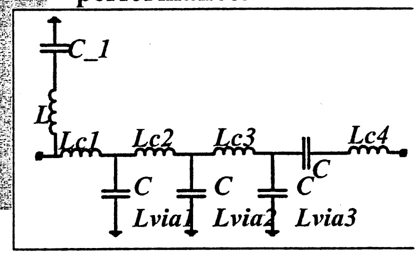


2. DCS/PCS Output Match

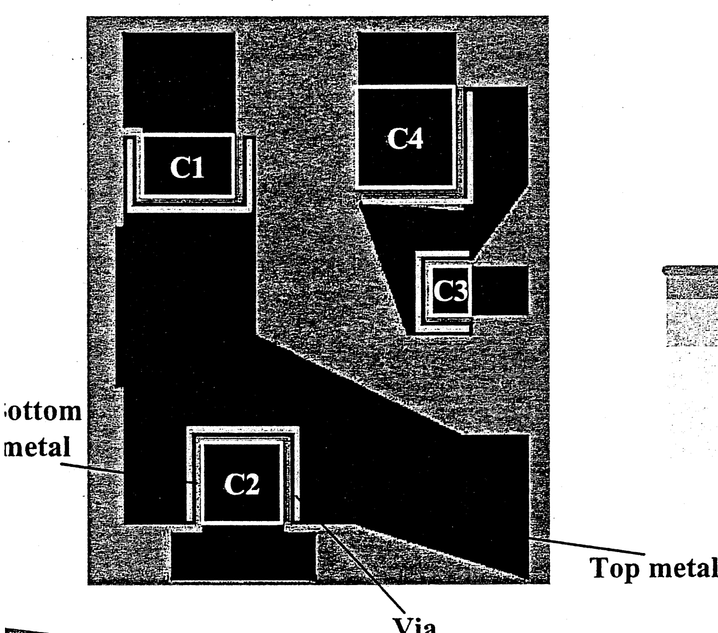


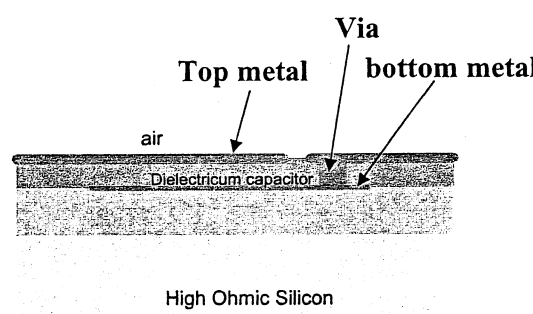
All sub-circuit simulations are connected on schematic for complete simulation.

Capacitors and Inductors are tuned for optimum performance.

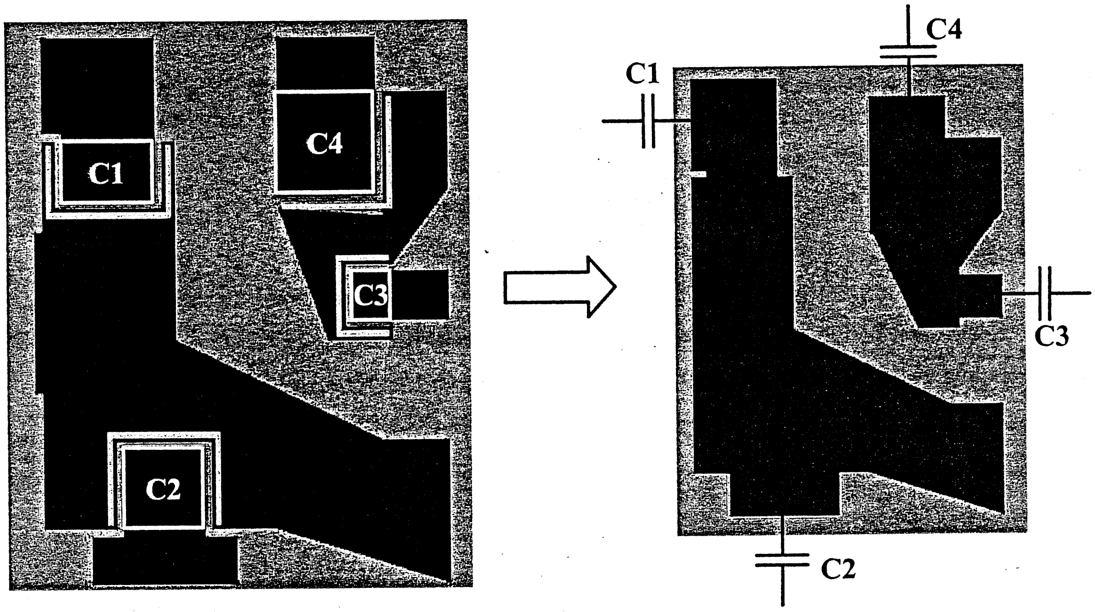


3. Parameterized model of the Passi die





3. Parameterized model of the Passi die



3. Parameterized model of the Passi die

$$\begin{pmatrix} C_{c1} \\ C_{c2} \\ C_{c3} \\ C_{c4} \end{pmatrix} = \begin{pmatrix} \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \end{pmatrix} \begin{pmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \end{pmatrix}$$

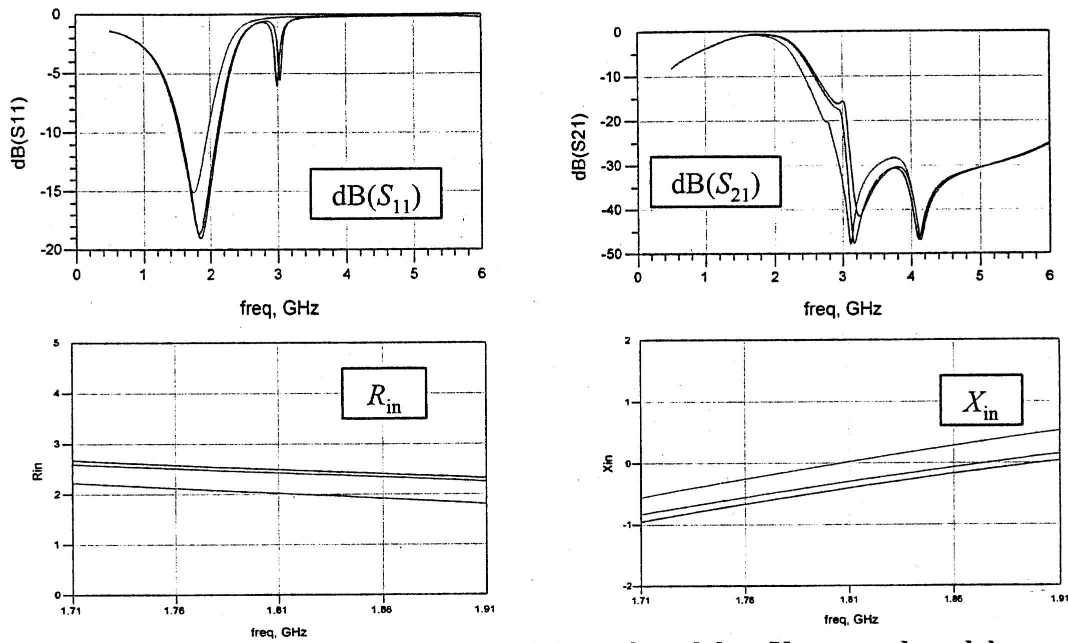
$$\mathrm{A} = \left[\left(\mathrm{DT} \cdot \mathrm{DT}^{\mathrm{T}} \right)^{-1} \cdot \mathrm{DT} \cdot \mathrm{CT}^{\mathrm{T}} \right]^{\mathrm{T}}$$

DT = real parameters
CT = Circuit parameters

Modeled region:
C1 = 5 ± 1 pF
C2 = 4 ± 1 pF
C3 = 1.5 ± 0.5 pF
C4 = 9 ± 1 pF

$$\boxed{C_{c1} = -0.33 + 1.26\,C_1 - 0.22\,C_2 + 0.10\,C_3 - 0.05\,C_4}$$

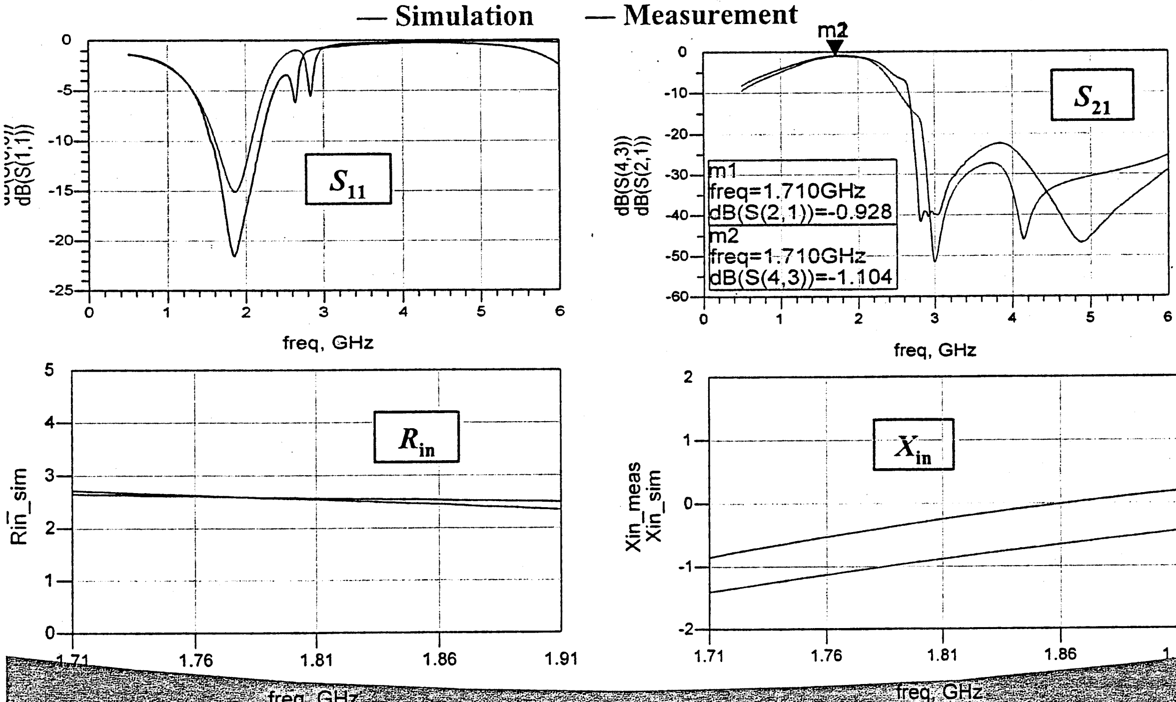
3. Parameterized model of the Passi die



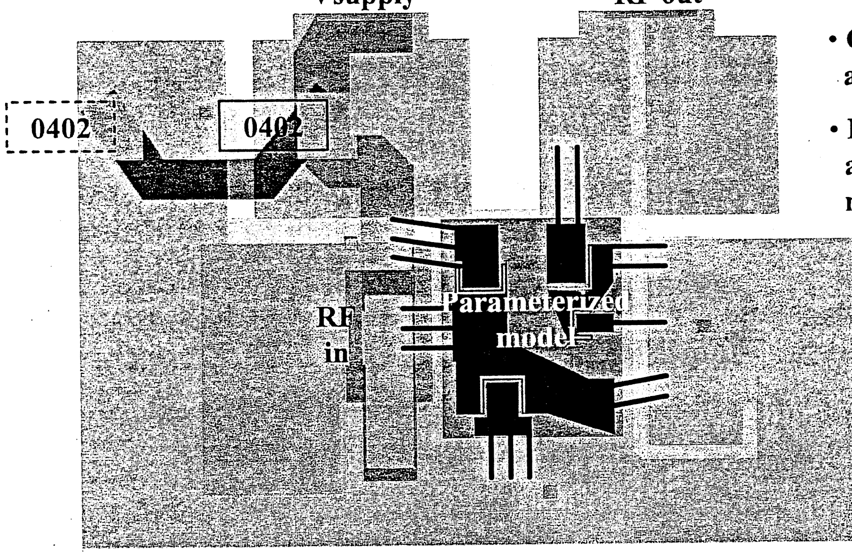
– EM simulation – Space Mapped model – Unmapped model

4. Simulation versus Measurement

— Simulation — Measurement



5. DCS/PCS Output Match



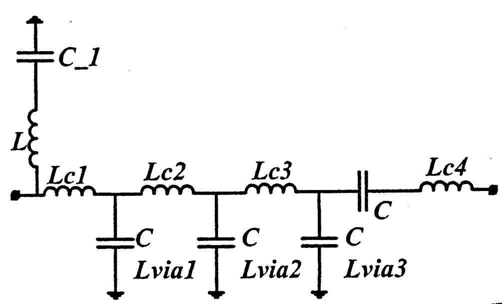
- Circuit can now be optimizec and tuned to meet spec.
- For Monte Carlo based analysis the EM simulations need to be parameterized.

5. Statistical Analysis

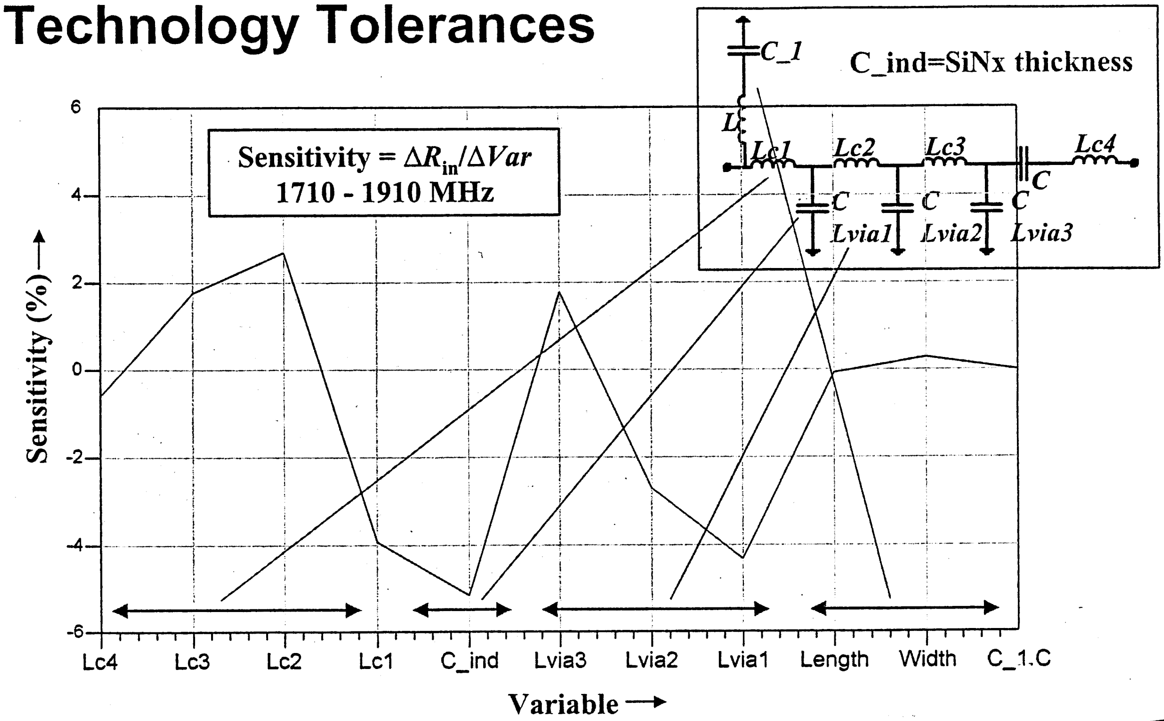
We will construct our statistical model based on:

- ■ Technology and Assembly tolerances
- • LTCC: Line width, dielectric thickness, Rsheet, etc..
- • Passive integration: dielectric thickness of capacitor, Rsheet, etc..
- • Bondwires: Loop height, etc..
- • SMD's

- ■ Sensitivity analysis
- • Which components have to be incorporated in the statistical analysis

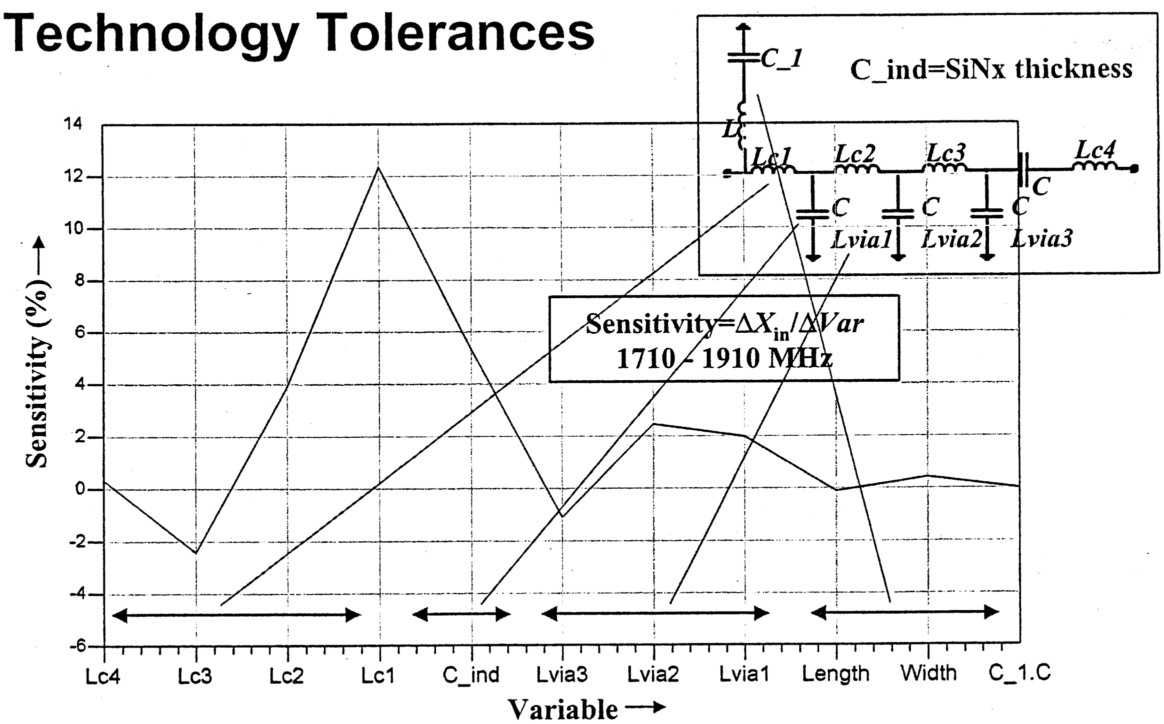


5. Technology Tolerances

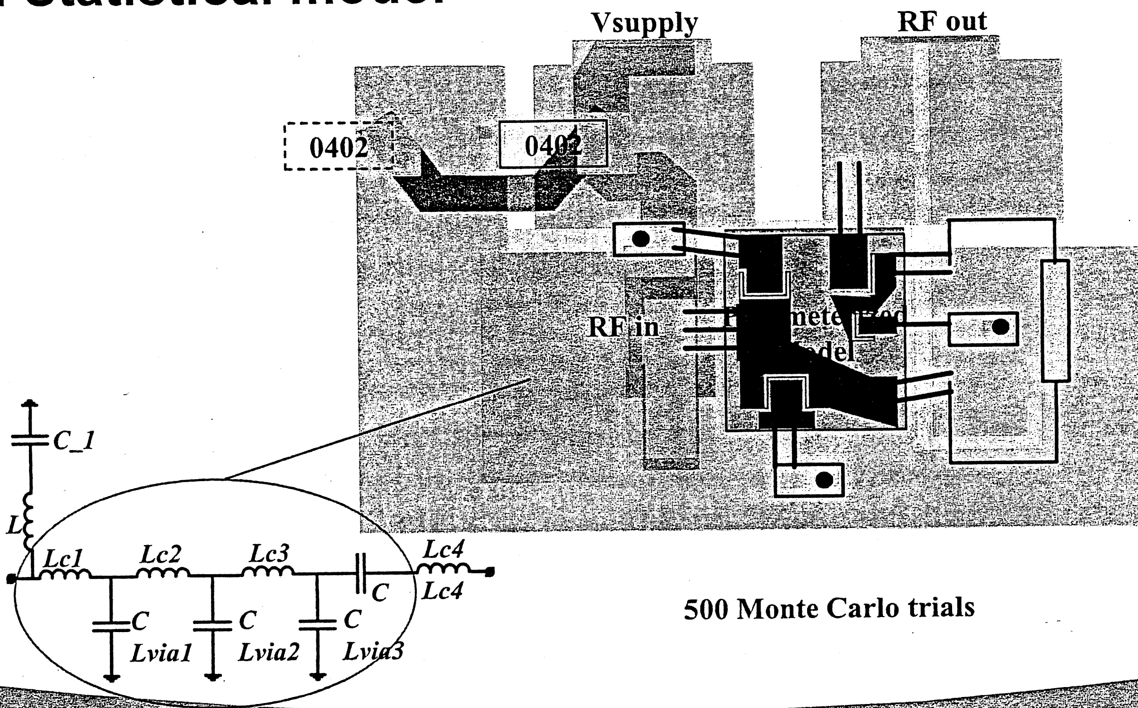


Philips Semiconductors

5. Technology Tolerances

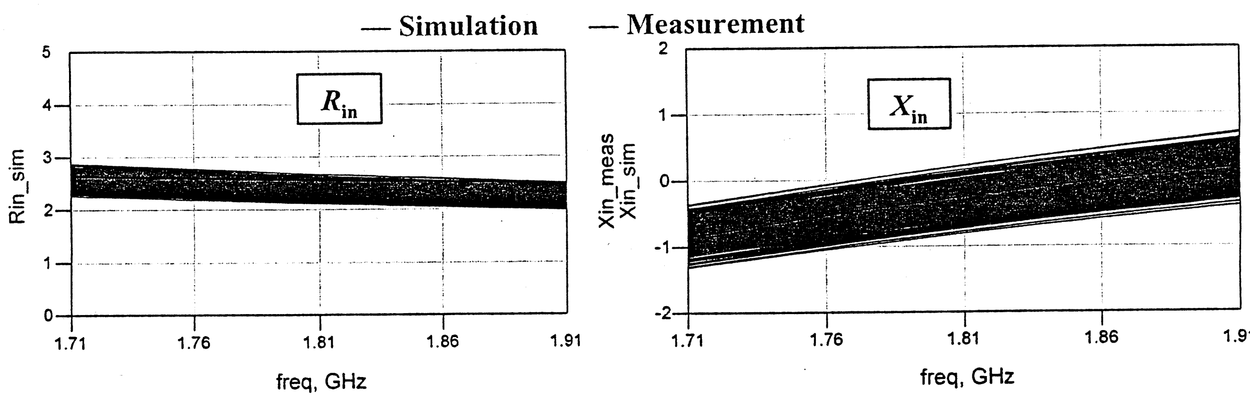


5. Statistical model



500 Monte Carlo trials

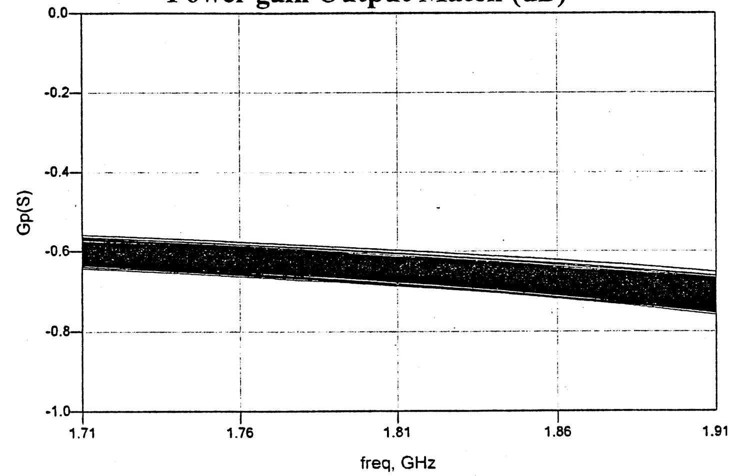
5. Statistical Simulation Results



Mean ± stddev \ freq	1710 MHz	1785 MHz
R_{in}	2.54 ± 0.10	2.40 ± 0.09
X_{in}	-0.84 ± 0.16	-0.39 ± 0.17

5. Statistical Simulation Results

Power gain Output Match (dB)



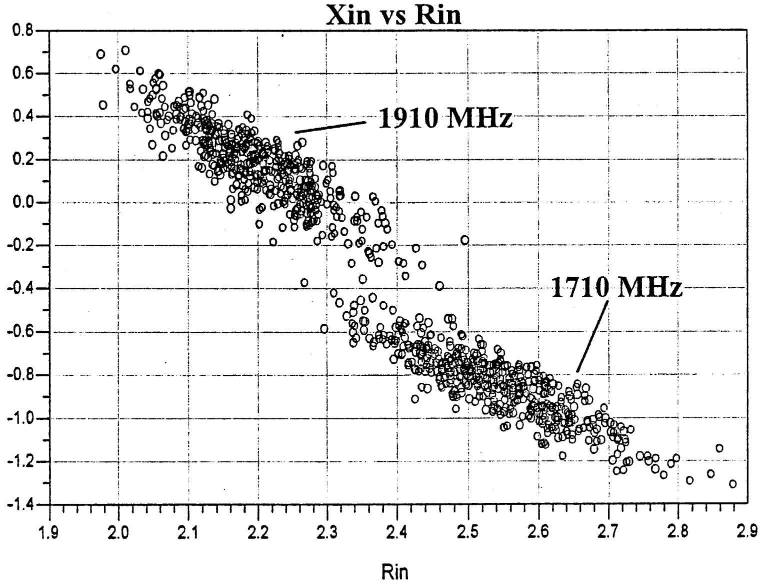
Gp @ 1710 MHz
Mean = - 0.601 dB
stddev = 0.013 dB
Max = -0.555 dB
Min = -0.643 dB

Spread in power gain is < 0.04 dB

Philips Semiconductors

5. Statistical Simulation Results

Scatter plot (Zload)
Xin vs Rin

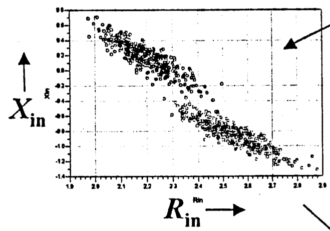


The input impedance of the matching network is the load impedance which is seen by the power amplifier.
Thus the simulated spread in the input impedance pairs can be used to calculate the spread in the output power and efficiency of the power amplifier.

6. Statistical Simulation of Module Performance

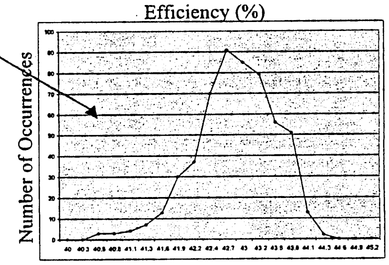
Efficiency = Eff(*Rin,Xin*)
Pout = Pout(*Rin,Xin*)

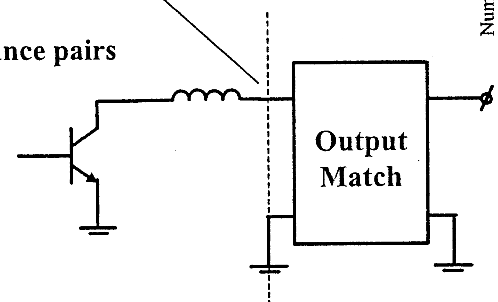
Simulation Results



- Input impedance pairs

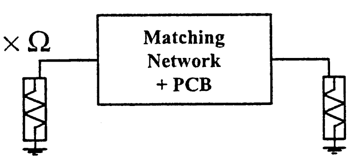
Manufacturing Results





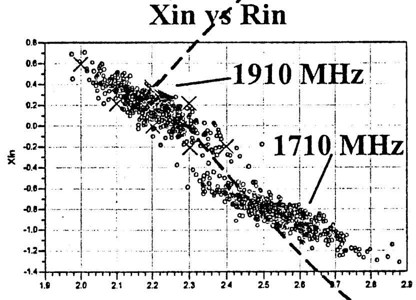
- Efficiency
- Output power
- H2
- H3

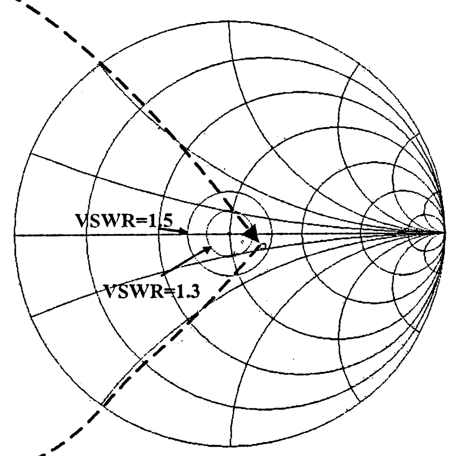
6. Statistical Simulation of Module Performance



Z_{out} is optimized to the want input impedance (×).

Xin vs Rin





° Monte Carlo simulation
× Points needed for prediction of Load Pull surface

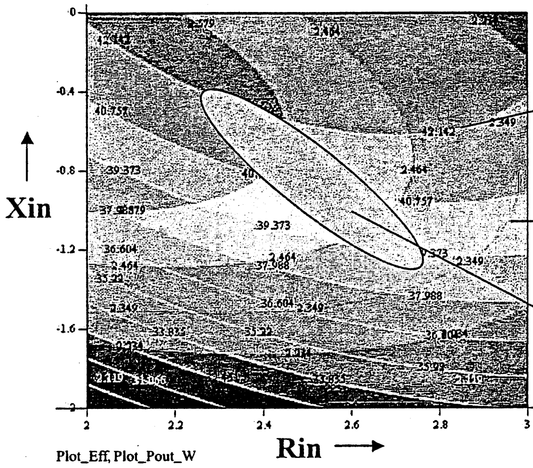
Efficiency
Pout

° Corresponding Z_{out} to input impedance (×)

6. Statistical Simulation of Module Performance

Example of a contour plot of output power and efficiency @ 1710 MHz and Vs = 3.5 V.

Circuit can now be (yield) optimized wrt to:
- Efficiency
- Output power



Contour line efficiency (%)

Contour line Pout (W)

Simulated spread in load impedance

7. Comparison between Simulated and Manufactured

Comparison between measured data from manufactured units and simulated data.

Manufacturing environment
- measured in test jig
- 560 samples

Simulation environment
- based on load pull measurements on demo board
- 500 Monte Carlo runs

We need to know the deviation of the jig to the simulation (or Demoboard measurements)

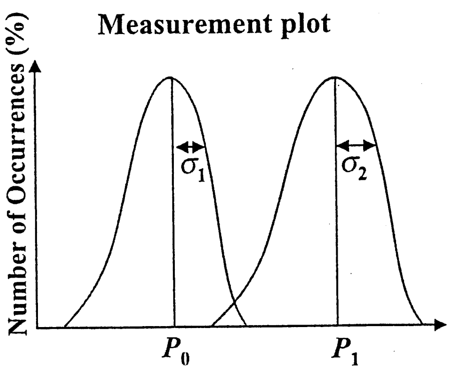
7. Example: Simulated vs Manufactured

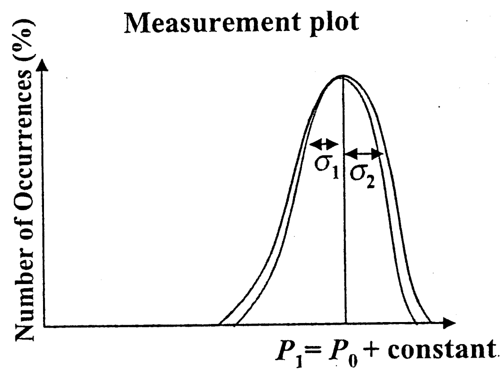
$$E(P) = P_0 = \text{mean} \qquad E\{(P-P_0)^2\} = \sigma^2 = \text{variance}$$

$$E(P+\text{constant}) = E(P) + \text{constant} \qquad E\{(P^*-P_o^*)^2\} = E\{(P-P_0)^2\} \text{ where } P^* = P + \text{constant}$$

— Measured

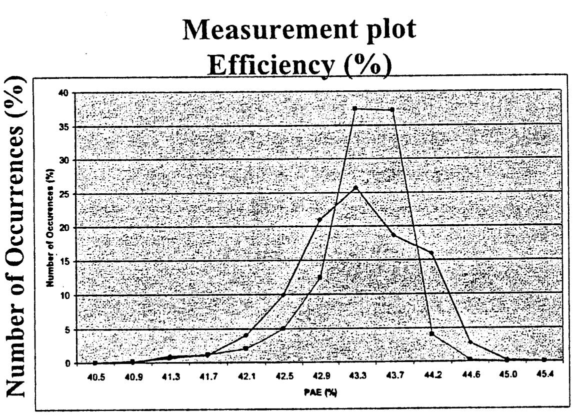
— Simulated





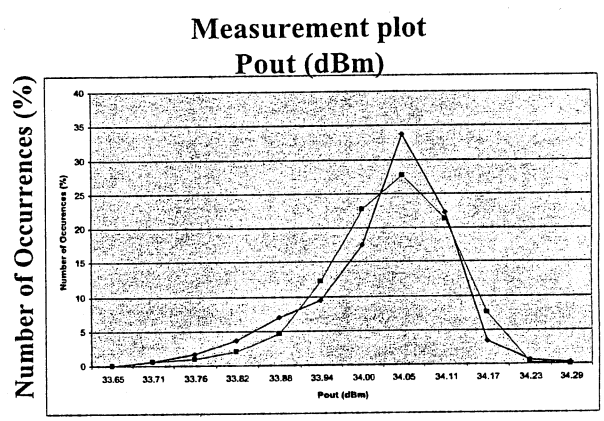
Constant = deviation of measurements in jig compared to the simulation (demoboard)

7. Comparison between Simulated and Measured @ 1710 MHz



	Mean	Stdev	Cpk
Simulated	41.0 %	0.63	2.43
Measured	43.3 %	0.63	2.43

deviation efficiency = 2.3%



	Mean	Stdev	Cpk
Simulated	34.0 dBm	0.087	5.75
Measured	34.0 dBm	0.090	5.56

No deviation Pout

— Simulated — Measured

Conclusions

- In this presentation statistical design and analysis tools were used for making a manufacturable design. Hereto we used,
  - Nominal optimization
  - Yield optimization
  - Measurement histograms
  - Sensitivity analysis

  Space Mapping as enabler
- Using these analysis and design tools an output matching circuit was designed with minimum sensitivity wrt component and technology tolerances.
  - Good agreement between simulated and measured
  - Design centering was used for minimum sensitivity
- We made a link from output match tolerances to module tolerances.
  - Good agreement between simulated and measured for efficiency and output power.
  - The module spread in efficiency and output power is dominated by the spread in the output match.

Knowledge Based Neural Network Approaches for Microwave Modeling and Design

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Abstract:

The effectiveness of CAD for RF and microwave design depends on the accuracy and efficiency of component models. Among various modeling approaches, 3 types of approaches best represent the diverse modeling philosophy. At one extreme is the approach based on first-principle theory, such as 3D EM modeling approach. It is accurate but slow. The second is based on human experimental and analytical skill, e.g., empirical/semi-analytical/equivalent models. Such models are fast but often constrained under assumptions and limitations. The third is based on learning/generalization from data, e.g., neural networks. Such models are fast and could be accurate if training is well done. However the need for much training data for each type of models could be a challenge.

In this talk, a concept called knowledge based neural networks will be described. It combines the advantages from all 3 extreme types of modeling approaches. The overall model includes empirical/equivalent models which embeds prior knowledge of the problem, and neural networks which will adapt the model to makeup for the missing information in the model. Accurate 3D EM information will be used to refine the accuracy of the overall model. Various modeling structures for such knowledge based neural networks will be presented. State of the art techniques for automatic generation of knowledge based models will be described. Examples of models with 3D EM effects for passive structures, physics effects for active devices, and their applications in circuit simulation, optimization and statistical design will be presented.

Knowledge Based Neural Network Approaches for Microwave Modeling and Design

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Ottawa, Canada

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Outline

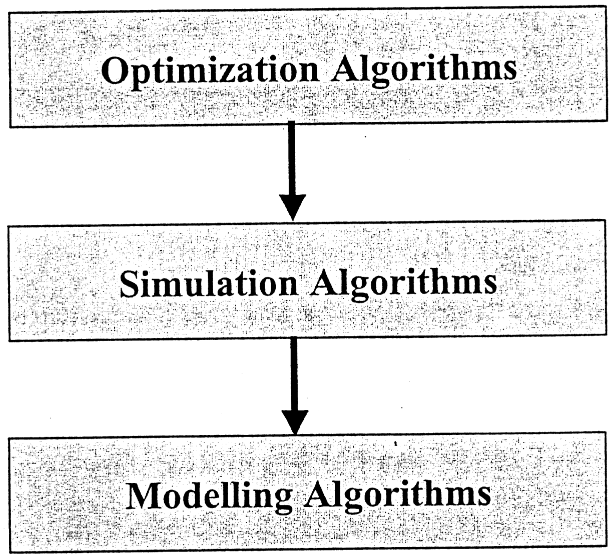
Knowledge based neural networks approaches

- embedding empirical/equivalent models in neural networks
- trained by detailed/accurate data, e.g., 3D EM

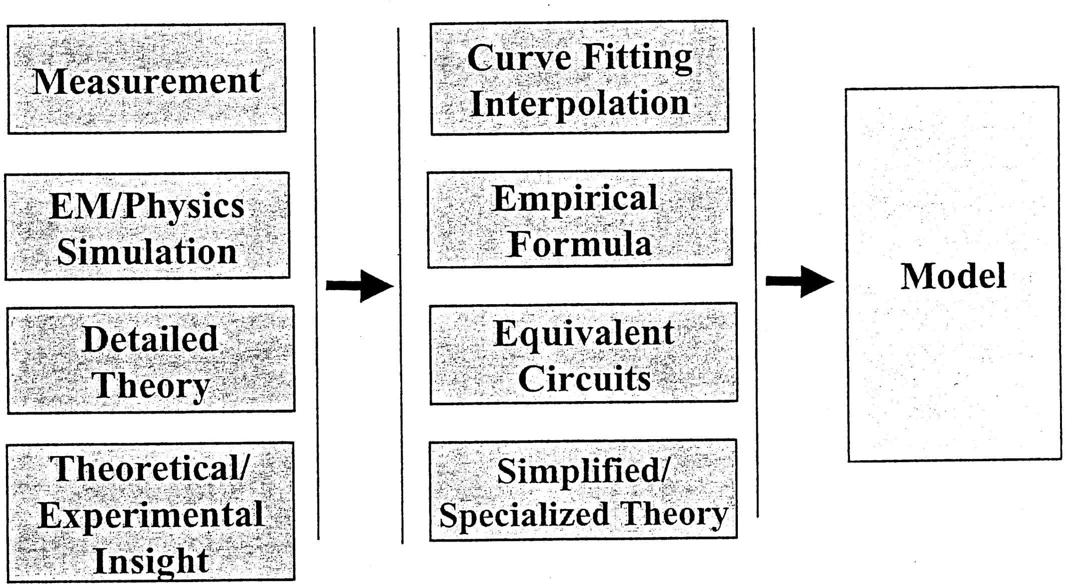
Knowledge based Automatic Model Generation

- using 2 types of training data:
  - fine data
  - coarse data

Levels of CAD Methodologies



Typical Model Development Process



Neural Network Modeling

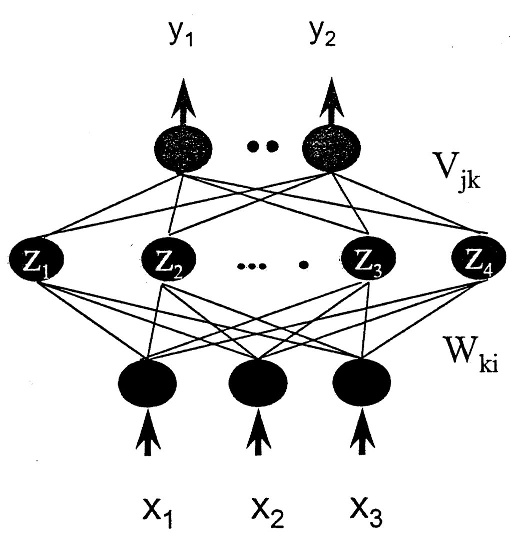
computerized learning of EM behavior

theoretically models any degree of nonlinearity

the speed of empirical models

the accuracy of detailed simulation

Input-output Computation of Multilayer Perceptrons (MLP)



Outputs

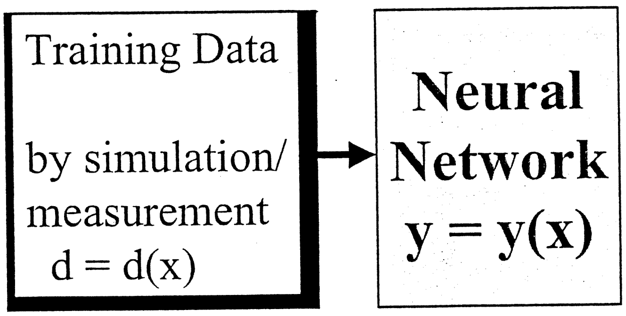
$$y_j = \sum_k V_{jk} \mathbf{Z_k}$$

Hidden

$$\mathbf{Z_k} = \tanh(\Sigma\, W_{ki} x_i)$$

Inputs

Neural Net Training



Objective:

to adjust W,V such that

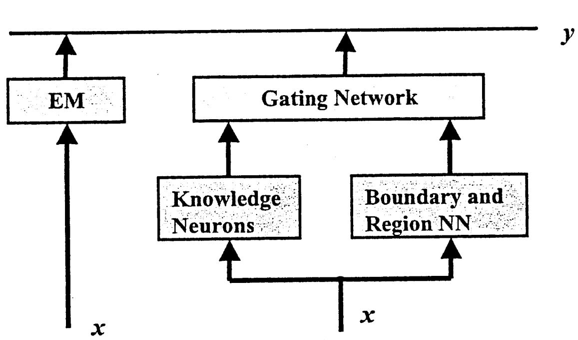
$$\min_{W,V} \sum_{x} (y - d)^2$$

Knowledge Based Neural Network (KBNN)

Microwave knowledge in the form of empirical functions or analytical approximations embedded into neural network

overall model is to be trained with accurate input-output data

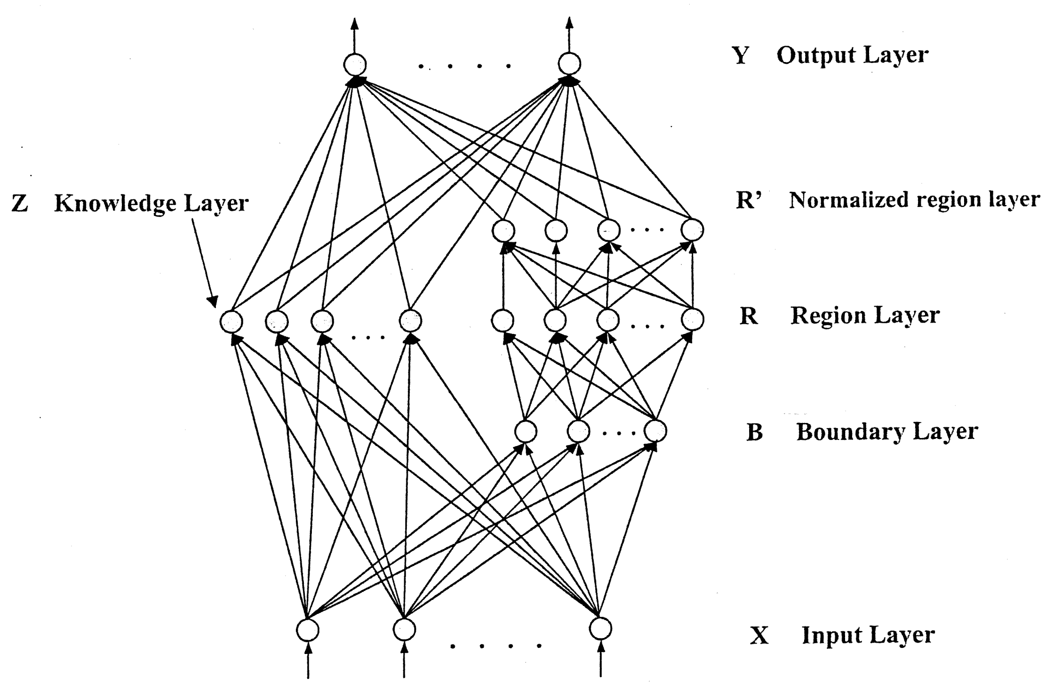
neural network regulate between knowledge space and overall problem space



Training:

- Use original data as training data
- Extended BP for gradient information
- Both knowledge neurons and boundary & region neurons are trainable

Finished Model for User:



MESFET Neural Model

input parameters:

channel length, channel width,
channel thickness, doping density,
gate-source voltage
drain-source voltage

output parameter:

drain current

Model Accuracy Comparison

Training sample size	neural net type	model size	no. of weights	average test error	largest test error	correlation coefficient
100	Standard (MLP)	6-18-1	145	3.06%	40.16%	0.9417
	Standard (MLP)	6-25-1	201	3.69%	38.55%	0.9626
	Knowledge based (KBNN)	b5z3	147	1.17%	9.11%	0.9972
	Knowledge based (KBNN)	b6z4	207	1.00%	10.21%	0.9979

Transmission Line Neural Model

input parameters:

conductor width, conductor thickness,
separation between two conductors,
height of substrate, frequency,
relative dielectric constant

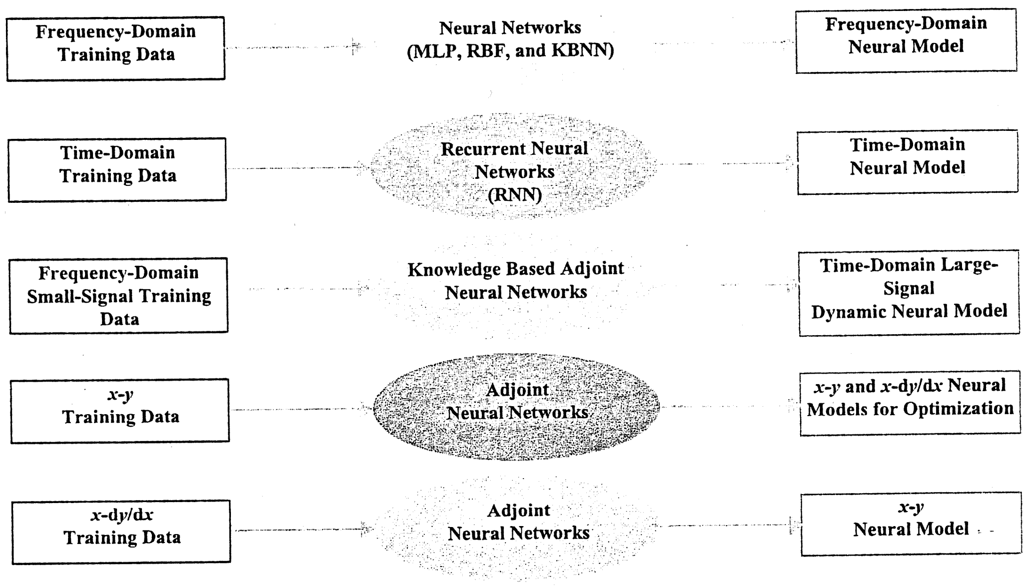
output parameter:

mutual inductance per unit length

Model Extrapolation Accuracy Comparison

Training sample size	neural net type	model size	no. of weights	average test error	largest test error	correlation coefficient
100	Standard (MLP)	6-7-1	57	2.30%	11.35%	0.9981
	Standard (MLP)	6-15-1	121	2.78%	12.42%	0.9962
	Standard (MLP)	6-20-1	161	3.44%	18.17%	0.9919
	Knowledge based (KBNN)	b2z3	51	1.16%	6.06%	0.9993
	Knowledge based (KBNN)	b4z6	128	1.12%	6.72%	0.9993

Neural Models for Different Domains



Adjoint Neural Networks

analytical connection between derivative space and original problem space for arbitrary nonlinear relationships

Allow training of neural models to learn device input/output behavior and/or their derivatives as well

second order sensitivity is used to train the neural network to learn first order sensitivity data

FET Modeling Example with Adjoint Neural Networks

DC and small signal S-parameter data are used to train neural networks

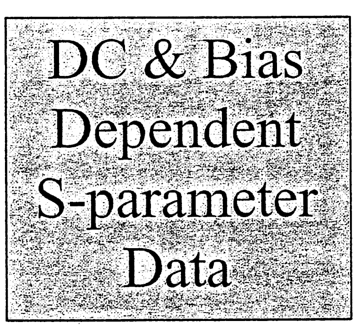
Adjoint neural networks are used to learn the small signal S-parameter data.

Original neural networks learn the DC data

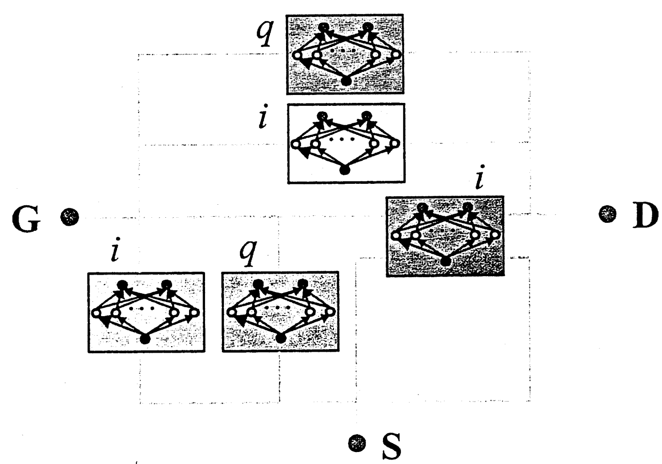
knowledge approach combining equivalent circuit with neural models for nonlinear gate charge and drain currents.

resulting model is a large signal FET model

FET Neural Model



Small-signal Training Data



Large-signal Nonlinear ***i*-*Q*** Model for Harmonic Balance

Automatic Model Generation (AMG)

Training and test data using adaptive data sampling and automated data generation

automatic adaptation of neural network size

automatic detection of underlearning and overlearning

trained model can be plugged in circuit simulators

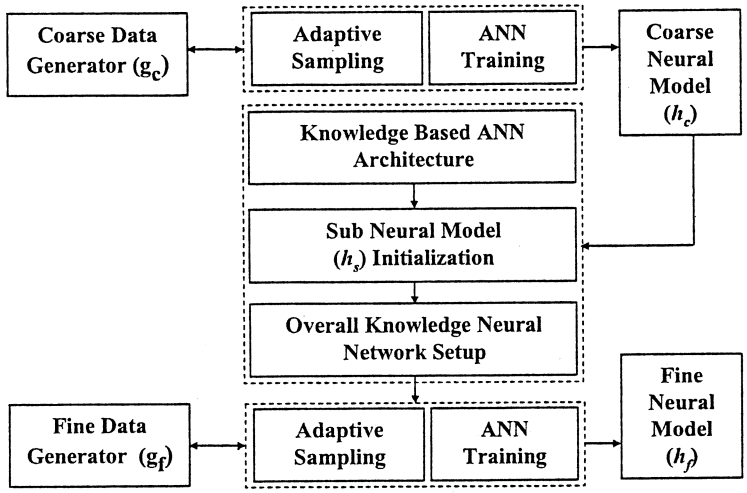
Knowledge-Based Automatic Model Generation (KAMG)

Use 2 types of data generators:
- Coarse data generator: e.g., 2D EM Simulator
- Fine data generator: e.g., 3D EM Simulator

KAMG:
- maximum use of coarse data generator
- minimum use of fine data generator
- overall model accuracy close to fine data

Knowledge based Neural Network
- to achieve reinforced learning between coarse and fine data

Knowledge-Based Automatic Model Generation



Initial Training Using Coarse Data

minimize the difference between coarse data generator outputs and coarse neural model outputs, i.e.,

$$\min_{w_c} \sum_{x \in L_c} \left\| g_c(x) - h_c(x, w_c) \right\|$$

where x represents model inputs, w_c represents weights in the coarse neural model, and L_c represents data set from coarse data generator

Overall Model Refinement Using Fine Data

minimize the difference between fine data generator outputs and overall neural model outputs, while keeping the coarse portion of model fixed, i.e.,

$$\min_{w_s} \sum_{x \in L_f} \left\| g_f(x) - h_f(x, w_c, w_s) \right\|$$

where w_s represents weights in the sub-neural model, and L_f represents data set from fine data generator

Embedded Capacitor Neural Model Development

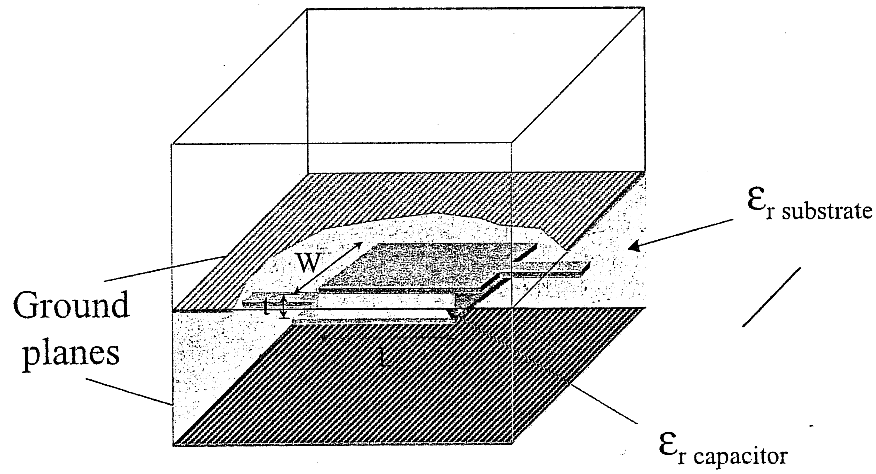
Modeling of embedded capacitor used in multi-layer PCB

Coarse Data Generator: Planar EM Simulator

Fine Data Generator: 3D-EM Simulator

Model input x: capacitor length and signal frequency.
Model outputs y: Real and imaginary parts of S-parameters

3D EM Based Capacitor Model



Comparison of Fine Data Needed by Various Neural Modeling Techniques to Achieve Capacitor Models with 1% Test Error

Neural Modeling Technique	No. of Fine Data	CPU for Data Generation
Conventional training	125	625 min
AMG (without knowledge)	96	480 min
Proposed KAMG-1	48	240 min
Proposed KAMG-2	14	70 min
Proposed KAMG-3	24	120 min
Proposed KAMG-4	23	115 min

MOSFET Neural Model Development

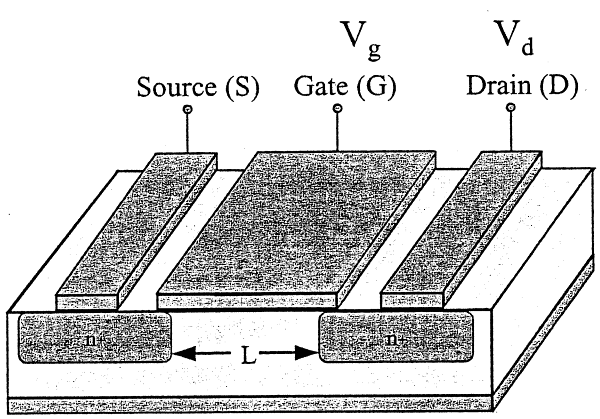
Modeling of MOSFET

Coarse Data Generator: HSPICE

Fine Data Generator: MINIMOS Physics based simulator

Model input *x*: gate and drain voltages
Model outputs *y*: drain current

Physics Based FET Modeling



Comparison of Fine Data Needed by Various Neural Modeling Techniques to Achieve MOSFET Models with 0.50% Test Error

Neural Modeling Technique	No. of Fine Data Used
Conventional training	66
AMG (without knowledge)	49
Proposed KAMG-1	32
Proposed KAMG-2	23
Proposed KAMG-3	25
Proposed KAMG-4	14

Conclusion

knowledge based neural networks combine empirical and simpler information of the original problem with neural networks

the overall model is trained using accurate data leading to model accuracy of fine level

the method achieves fine model accuracy and at the same time uses as few fine data as possible

improved model can be used to enhance microwave simulation and optimization.