Space Mapping: A Sensible Concept For Engineering Optimization Exploiting Surrogates

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Outline

"Space Mapping" coined in 1993

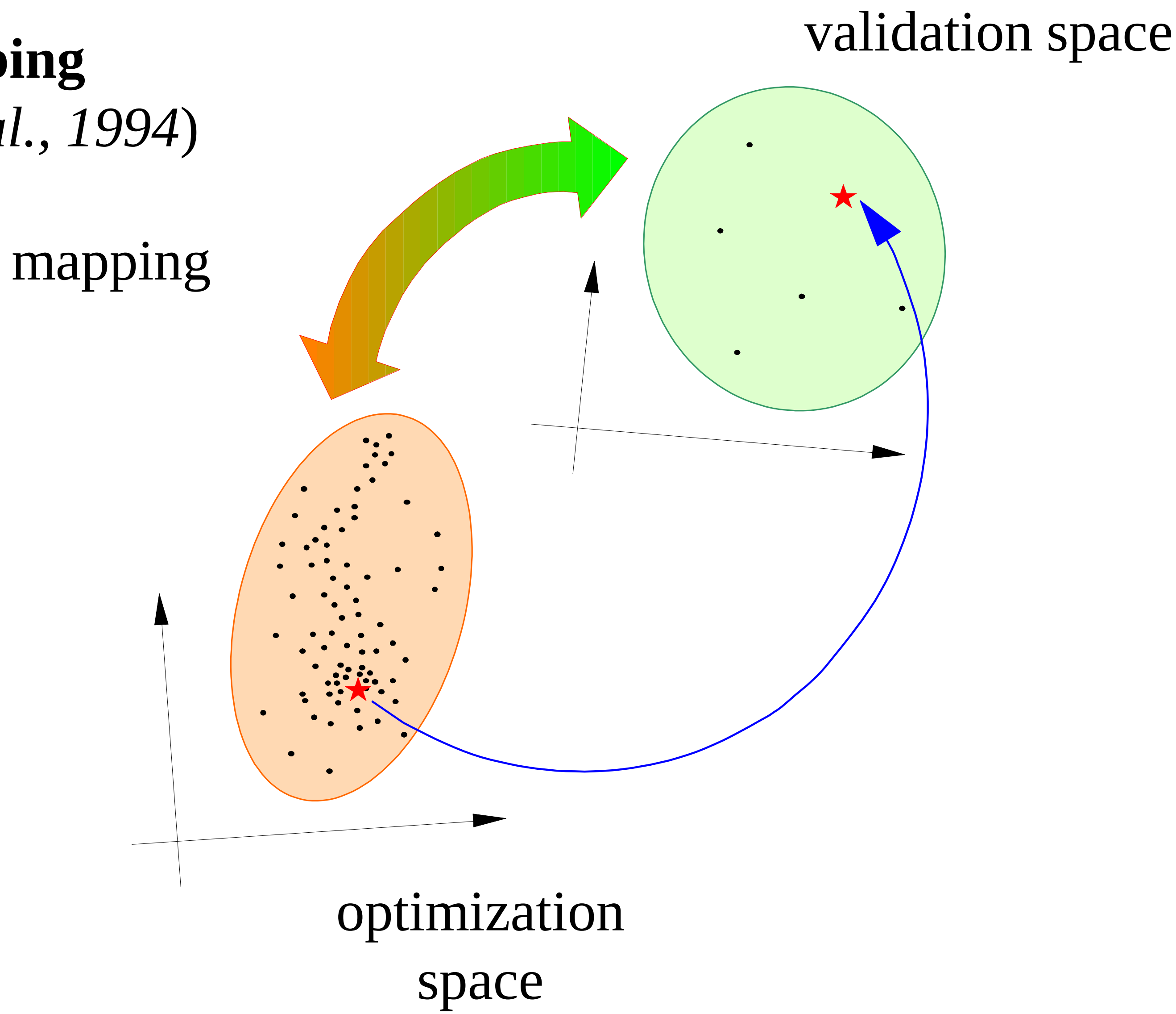
Space Mapping intelligently links companion "coarse" and "fine" models—full-wave electromagnetic (EM) simulations and empirical models

Space Mapping optimization follows traditional experience of designers

we discuss the 1993 concept and subsequent Aggressive Space Mapping

Space Mapping

(*Bandler et al., 1994*)

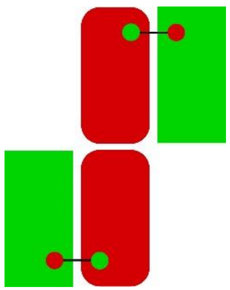


Space Mapping: a Glossary of Terms

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



mapped or enhanced coarse model

Surrogate Model — alternative expression for Surrogate

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

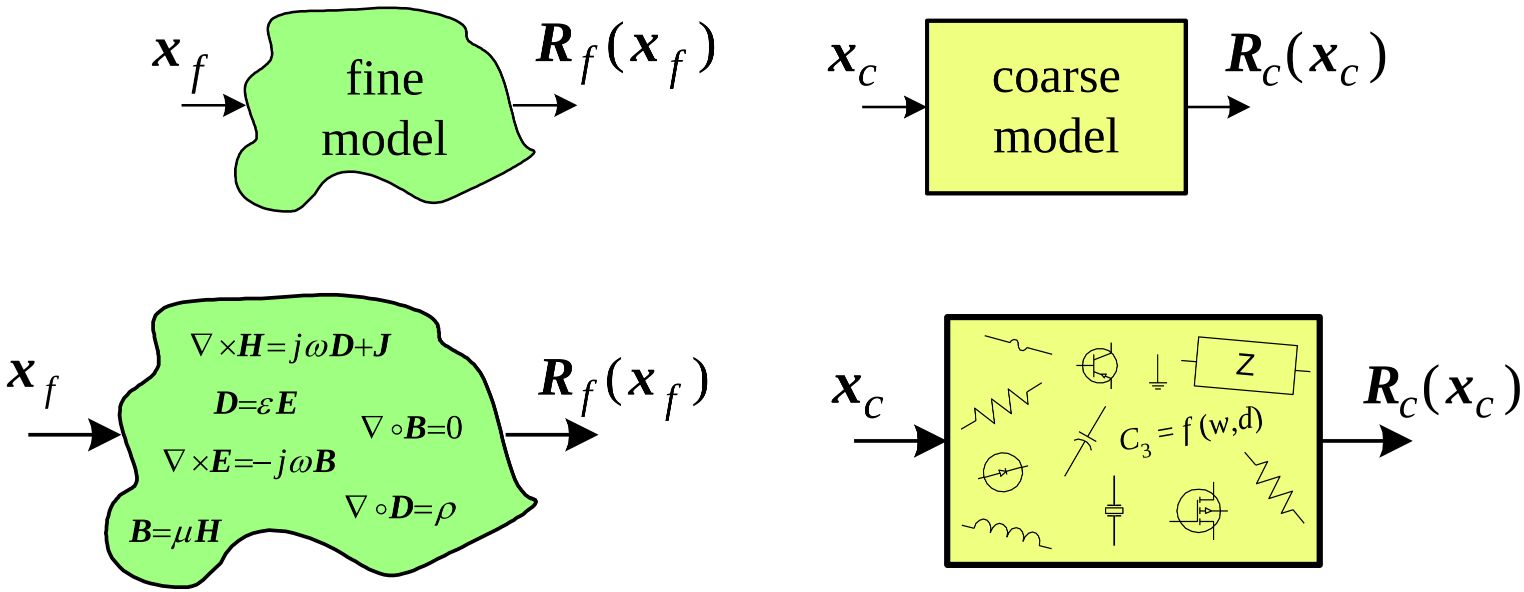
Companion	coarse
Low Fidelity/ Resolution	coarse
High Fidelity/ Resolution	fine
Empirical	coarse
Simplified Physics	coarse
Physics-based	coarse or fine
Device under Test	fine
Electromagnetic	fine or coarse
Simulation	fine or coarse
Computational	fine or coarse

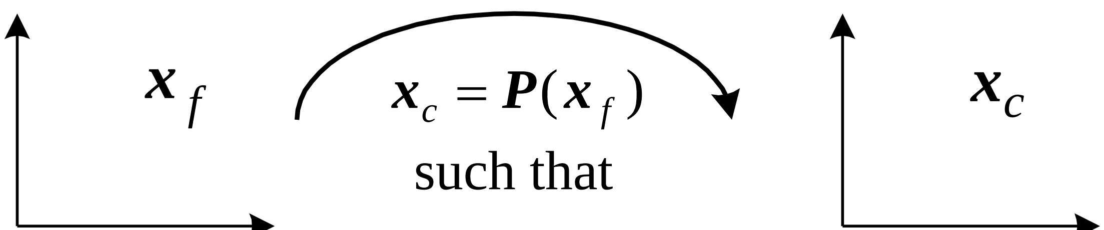
Space Mapping: a Glossary of Terms

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

The Space Mapping Concept

(Bandler et al., 1994-)





$$x_c = P(x_f)$$

such that

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

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 $\boldsymbol{J}_c$ and space mapping matrix $\boldsymbol{B}$ we estimate

$$\boldsymbol{J}_f(\boldsymbol{x}_f) \approx \boldsymbol{J}_c(\boldsymbol{x}_c)\boldsymbol{B}$$

given $\boldsymbol{J}_c$ and $\boldsymbol{J}_f$ we estimate (least squares)

$$\boldsymbol{B} \approx (\boldsymbol{J}_c^T \boldsymbol{J}_c)^{-1} \boldsymbol{J}_c^T \boldsymbol{J}_f$$

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Space Mapping Notation

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

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

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

Space Mapping Practice—Cheese Cutting Problem

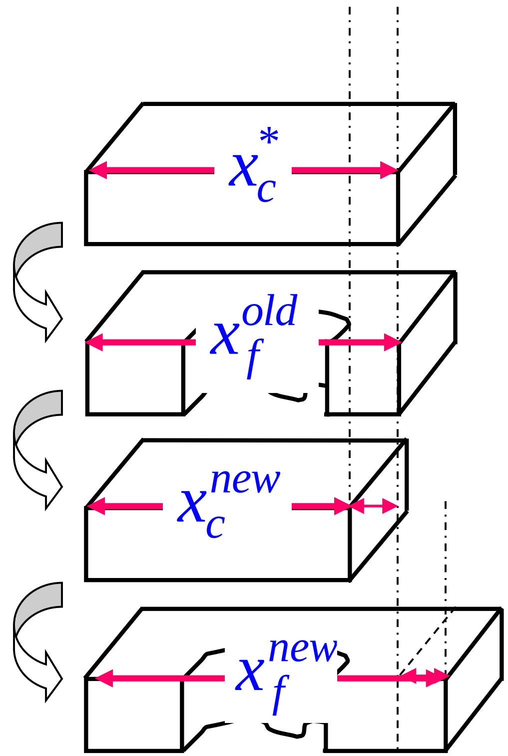
(*Bandler 2002*)

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 …

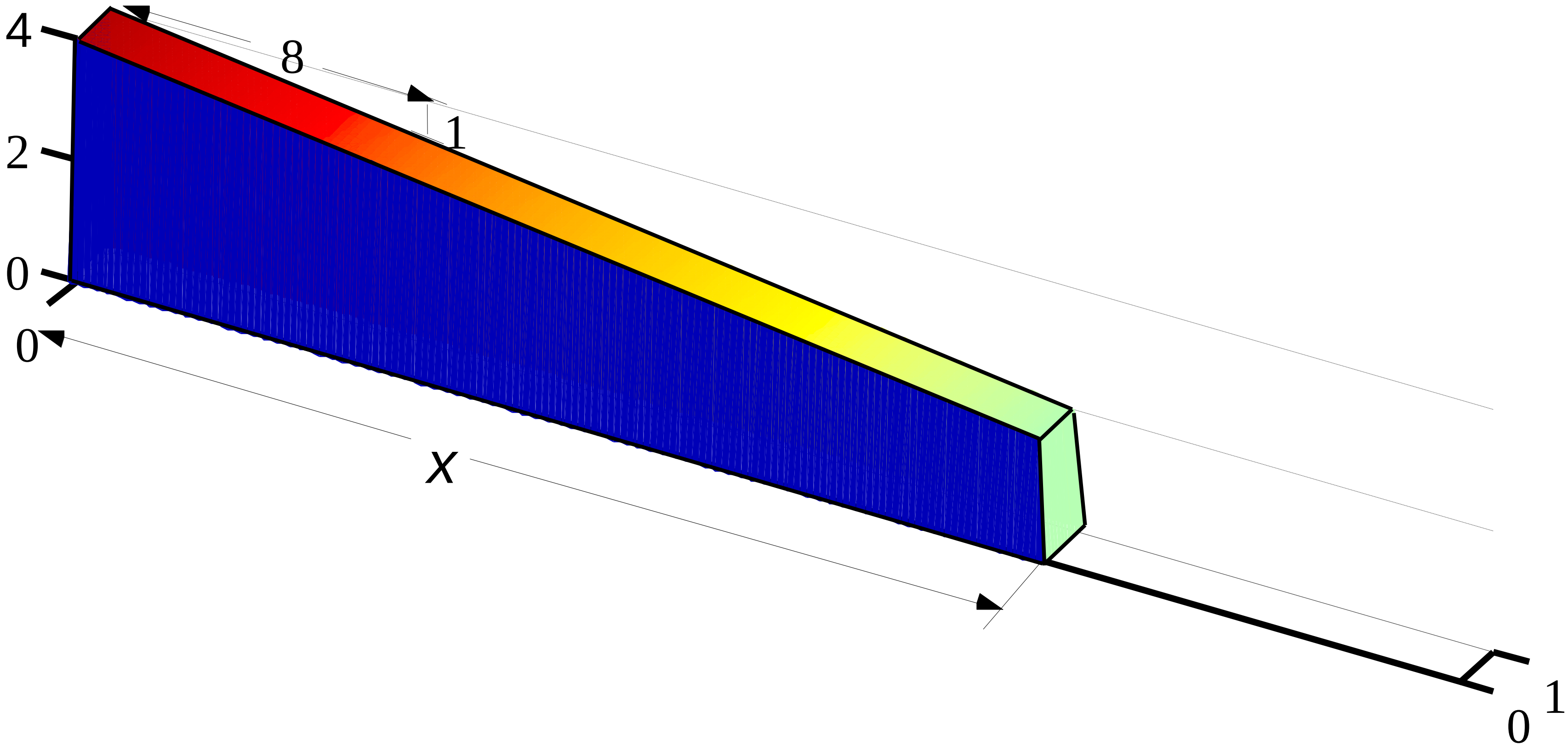
… as new information flows into it … the brain automatically
compares it with what it already knows.

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

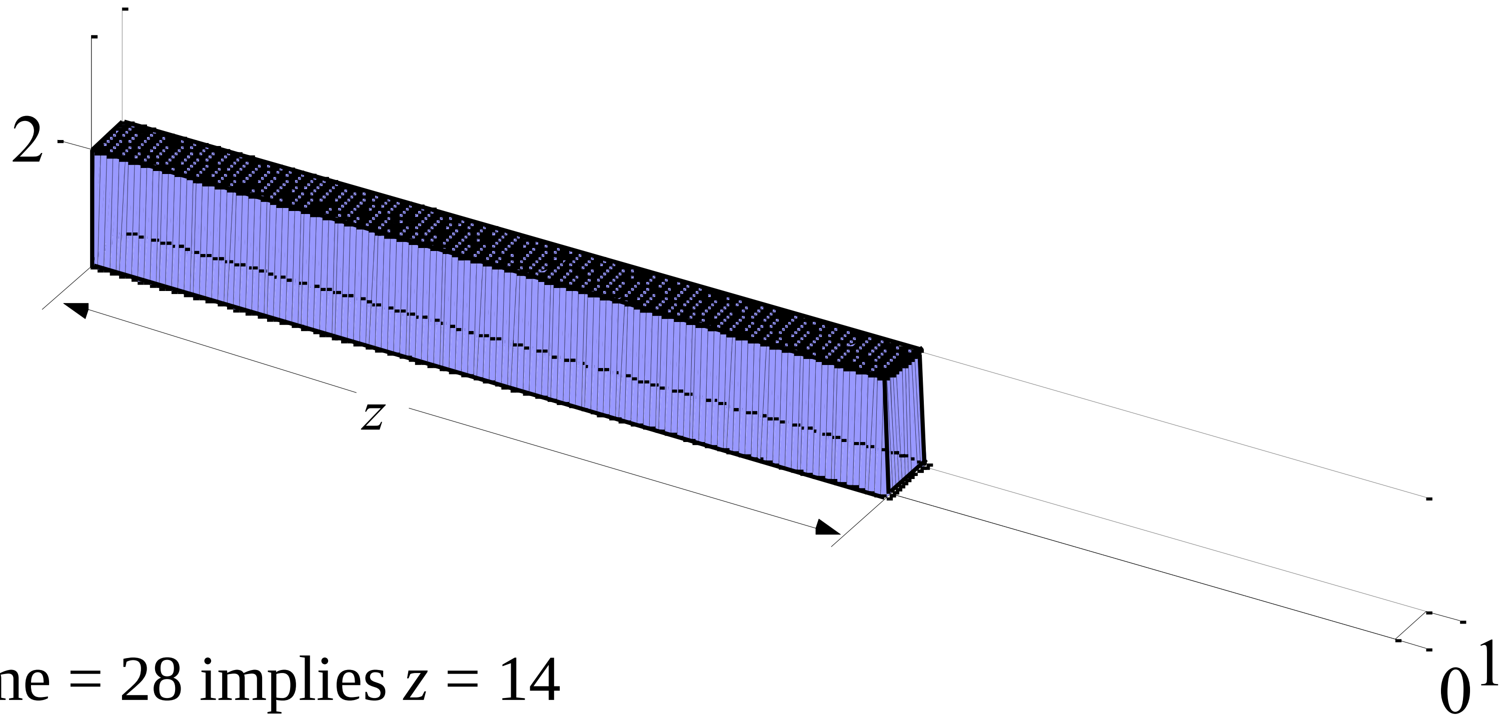
Drawing on past experience … a decision is made …

Wedge Cutting Problem (*Bandler, 2002*)

use space mapping to find the optimal position *x* of a cut such that the volume is equal to 28



Proposed Coarse Model



volume = 28 implies $z = 14$

ASM Algorithm (*Bandler et al., 1995*)

Step 1 initialize $\boldsymbol{x}^{(1)} = \boldsymbol{z}^*$, $\boldsymbol{B}^{(1)} = \boldsymbol{1}$, $i = 1$

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

Step 3 evaluate $\boldsymbol{f}^{(1)} = \boldsymbol{z}^{(1)} - \boldsymbol{z}^*$, if $\|\boldsymbol{f}^{(1)}\| \le \varepsilon$, stop

Step 4 solve $\boldsymbol{B}^{(i)}\boldsymbol{h}^{(i)} = -\boldsymbol{f}(\boldsymbol{x}^{(i)})$ for $\boldsymbol{h}^{(i)}$

Step 5 set $\boldsymbol{x}^{(i+1)} = \boldsymbol{x}^{(i)} + \boldsymbol{h}^{(i)}$

Step 6 evaluate $\boldsymbol{R}_f(\boldsymbol{x}^{(i+1)})$

ASM Algorithm (*Bandler et al., 1995*)

Step 7 extract $\boldsymbol{z}^{(i+1)}$ such that $\boldsymbol{R}_c(\boldsymbol{z}^{(i+1)}) \approx \boldsymbol{R}_f(\boldsymbol{x}^{(i+1)})$

Step 8 evaluate $\boldsymbol{f}^{(i+1)} = \boldsymbol{z}^{(i+1)} - \boldsymbol{z}^*$, if $\left\| \boldsymbol{f}^{(i+1)} \right\| \leq \varepsilon$, stop

Step 9 update $\boldsymbol{B}^{(i+1)} = \boldsymbol{B}^{(i)} + \dfrac{\boldsymbol{f}^{(i+1)} \boldsymbol{h}^{(i)^T}}{\boldsymbol{h}^{(i)^T} \boldsymbol{h}^{(i)}}$

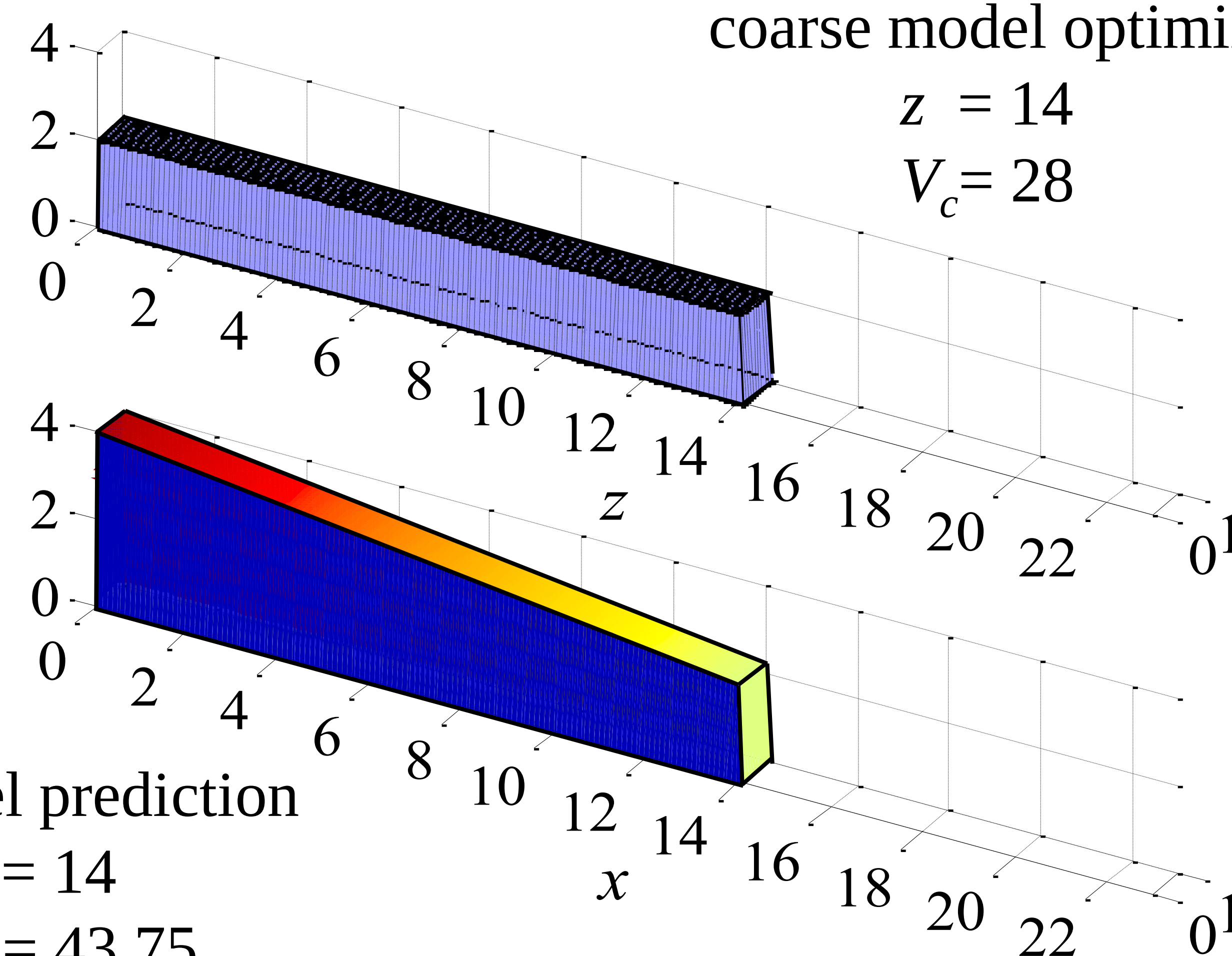
Step 10 set $i = i + 1$ and go to *Step* 4

Initialization

coarse model optimization

$z = 14$

$V_c = 28$

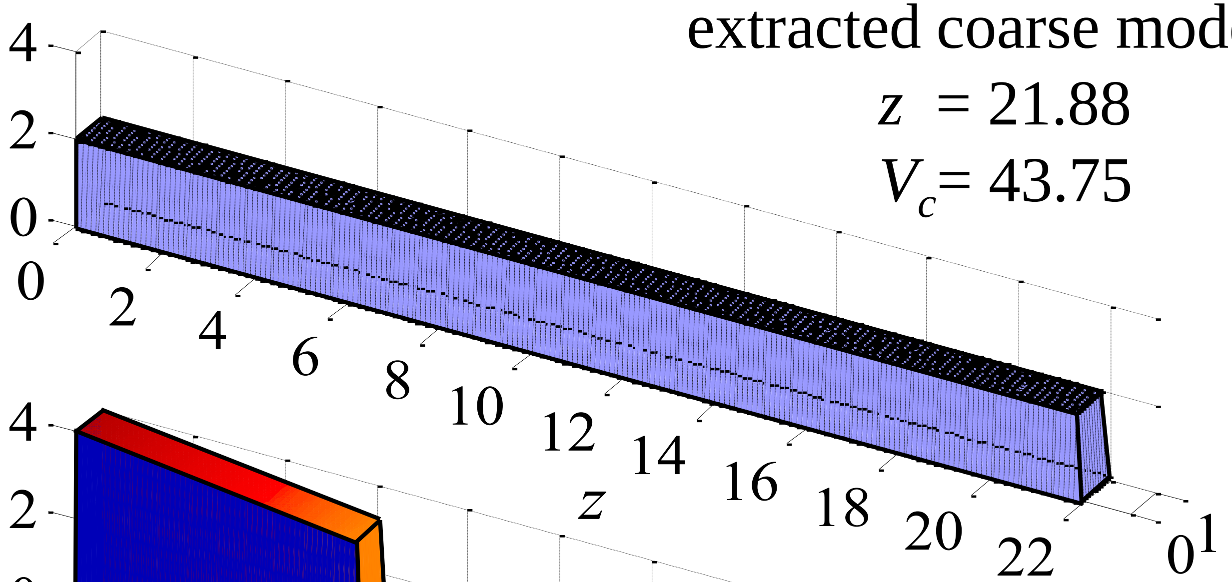


fine model prediction

$x = 14$

$V_f = 43.75$

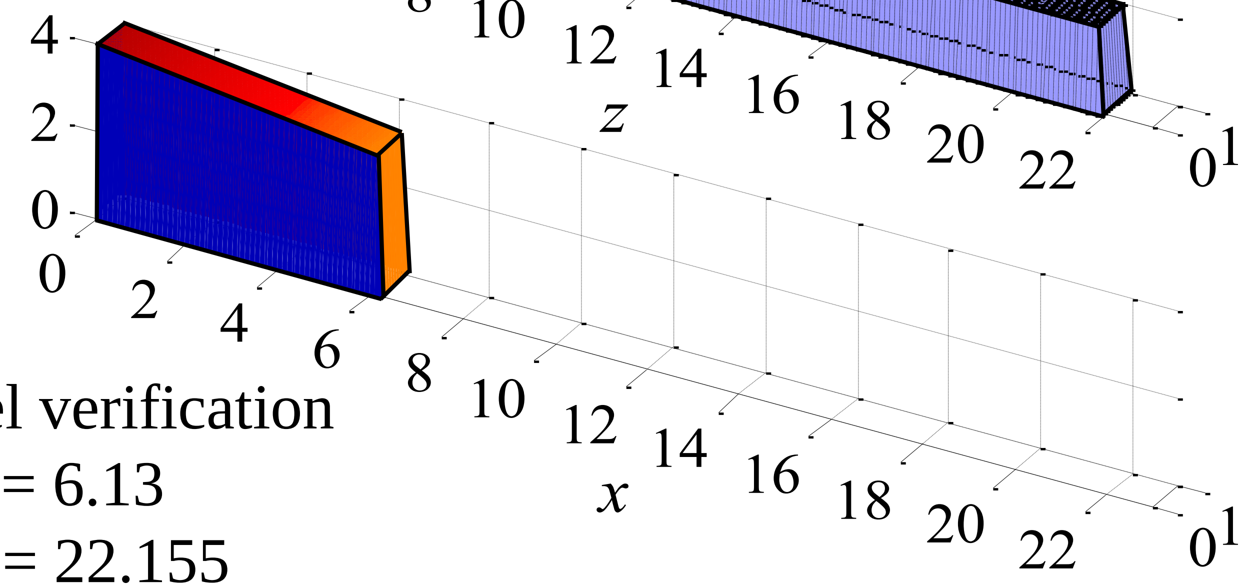
Iteration 1



extracted coarse model

$z = 21.88$

$V_c = 43.75$



fine model verification

$x = 6.13$

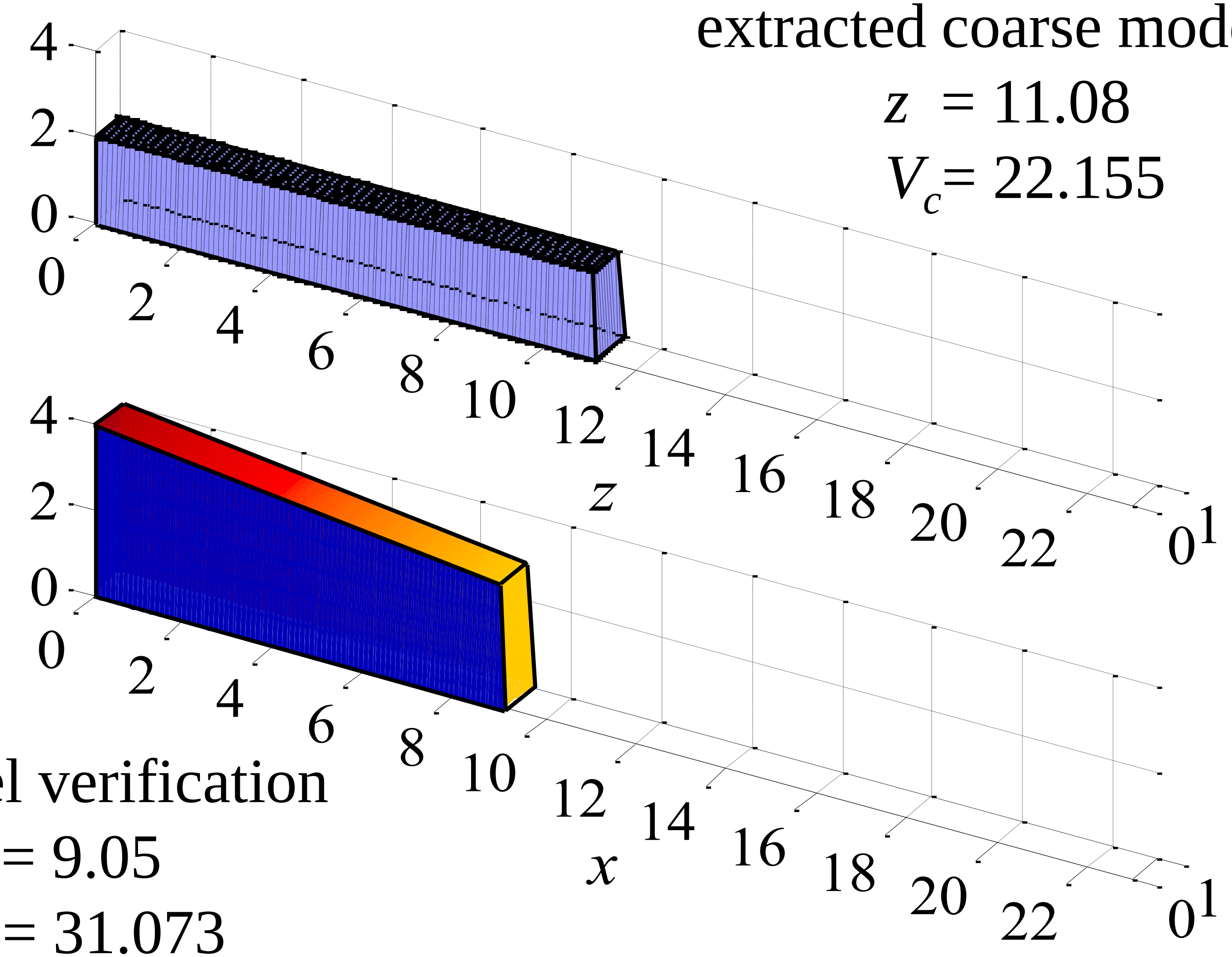
$V_f = 22.155$

Iteration 2

extracted coarse model

$z = 11.08$

$V_c = 22.155$



fine model verification

$x = 9.05$

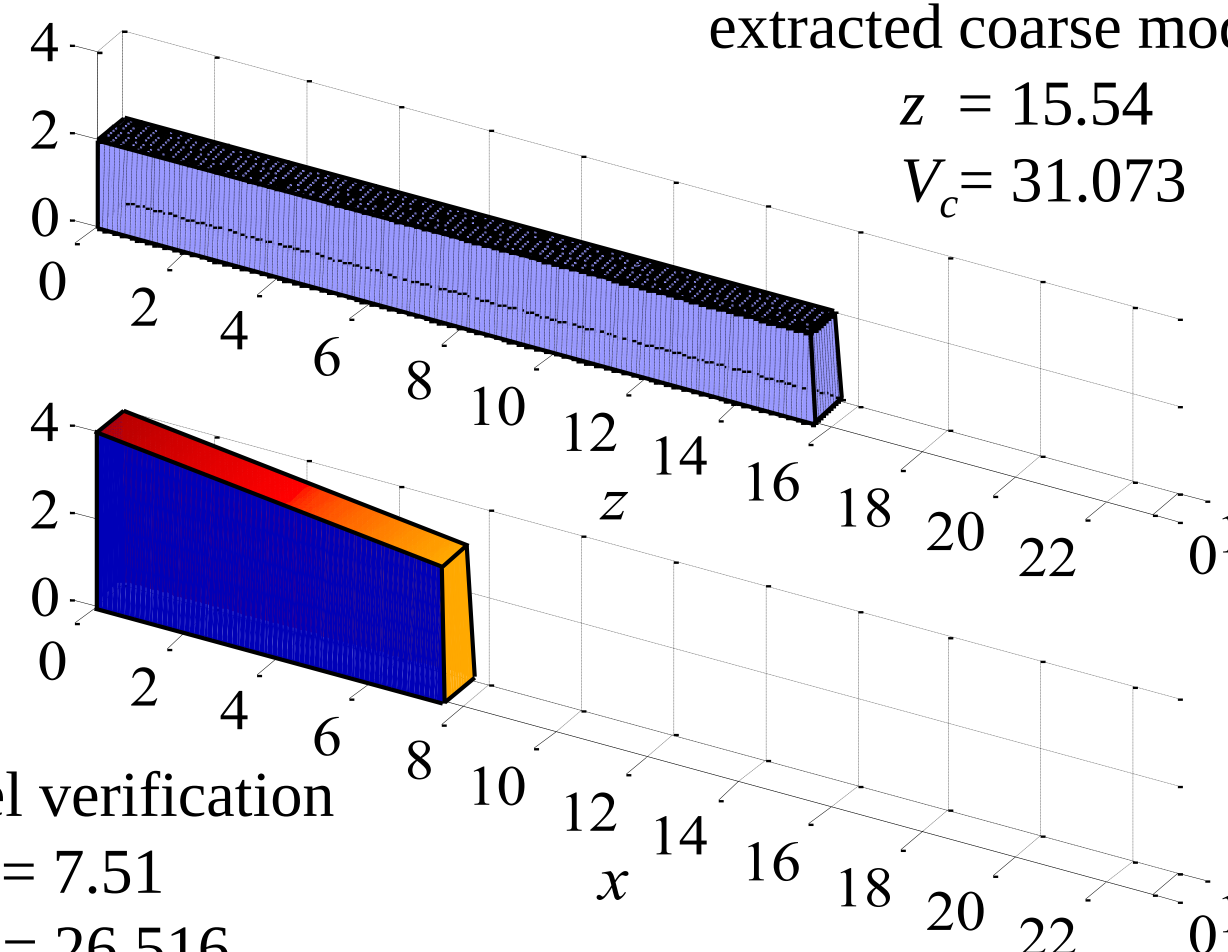
$V_f = 31.073$

Iteration 3

extracted coarse model

$z = 15.54$

$V_c = 31.073$



fine model verification

$x = 7.51$

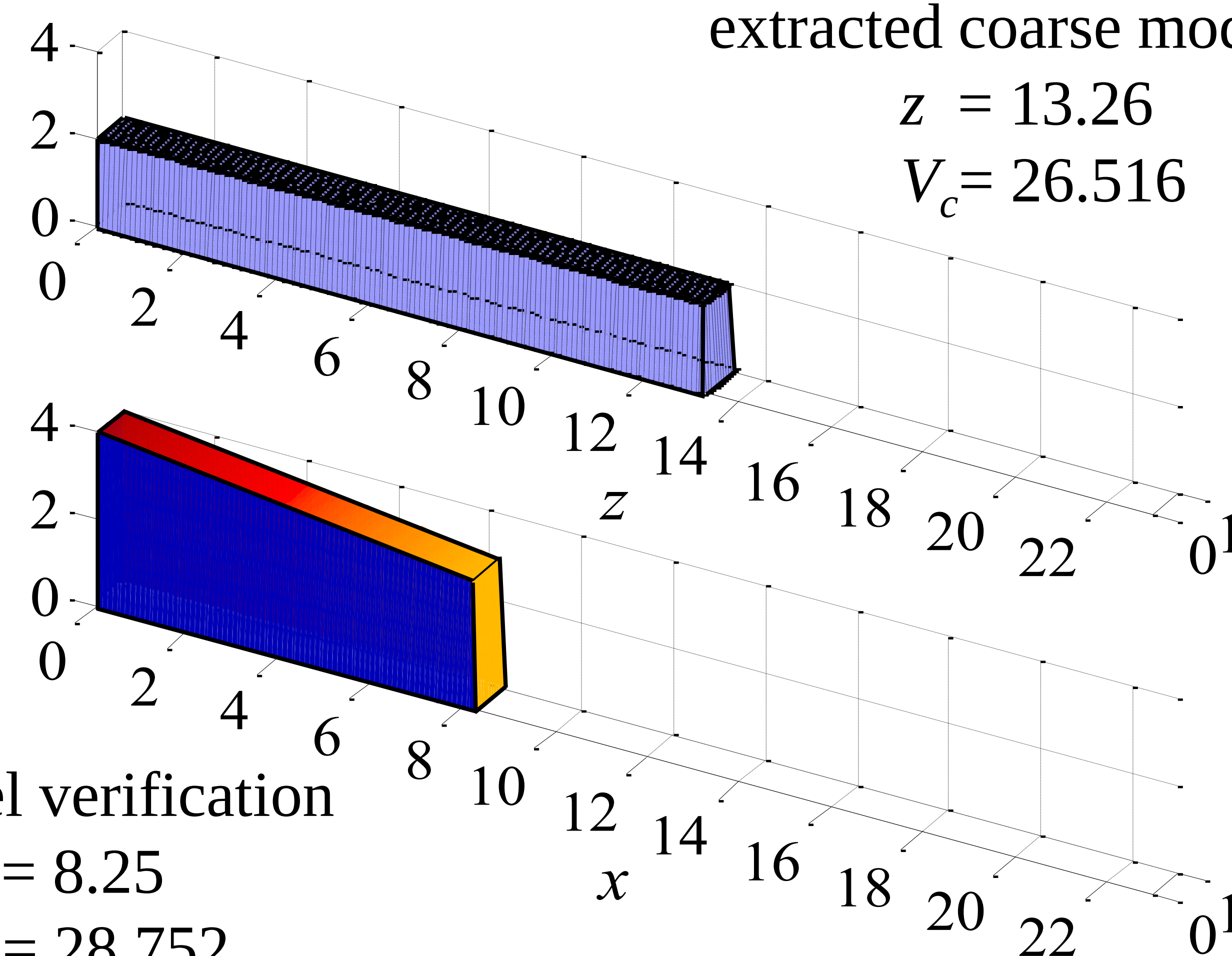
$V_f = 26.516$

Iteration 4

extracted coarse model

$z = 13.26$

$V_c = 26.516$



fine model verification

$x = 8.25$

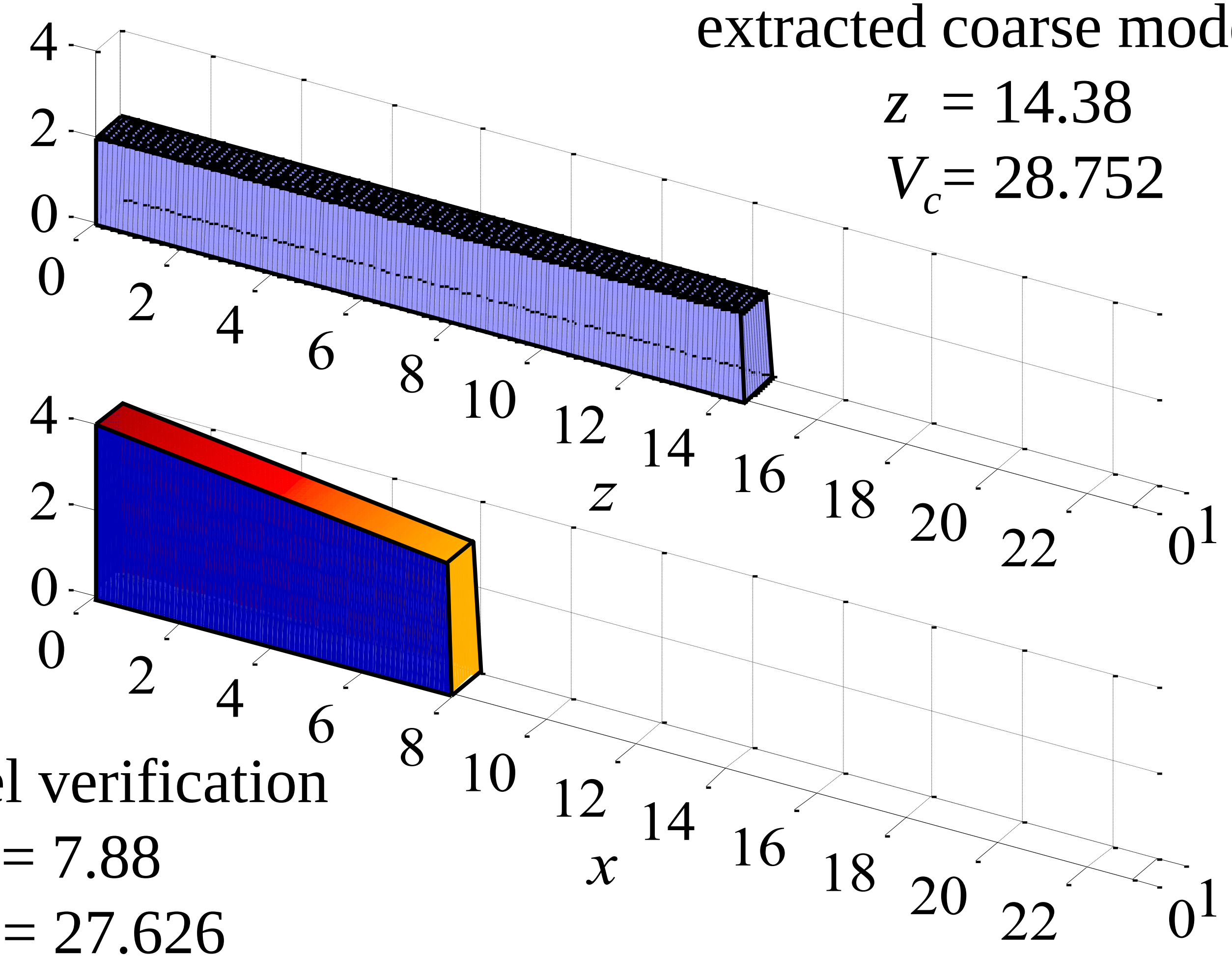
$V_f = 28.752$

Iteration 5

extracted coarse model

z = 14.38

V_c = 28.752



fine model verification

x = 7.88

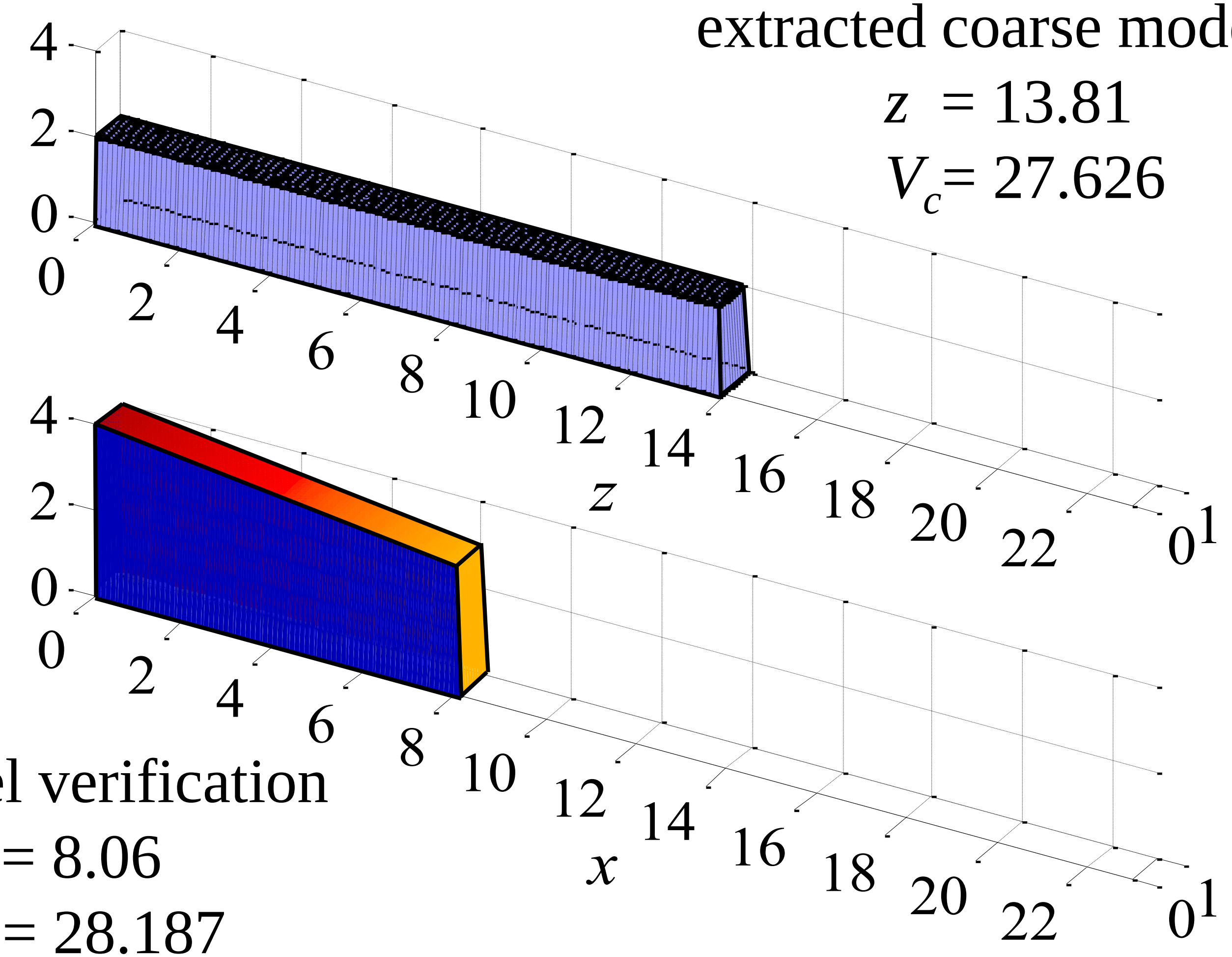
V_f = 27.626

Iteration 6

extracted coarse model

$z = 13.81$

$V_c = 27.626$



fine model verification

$x = 8.06$

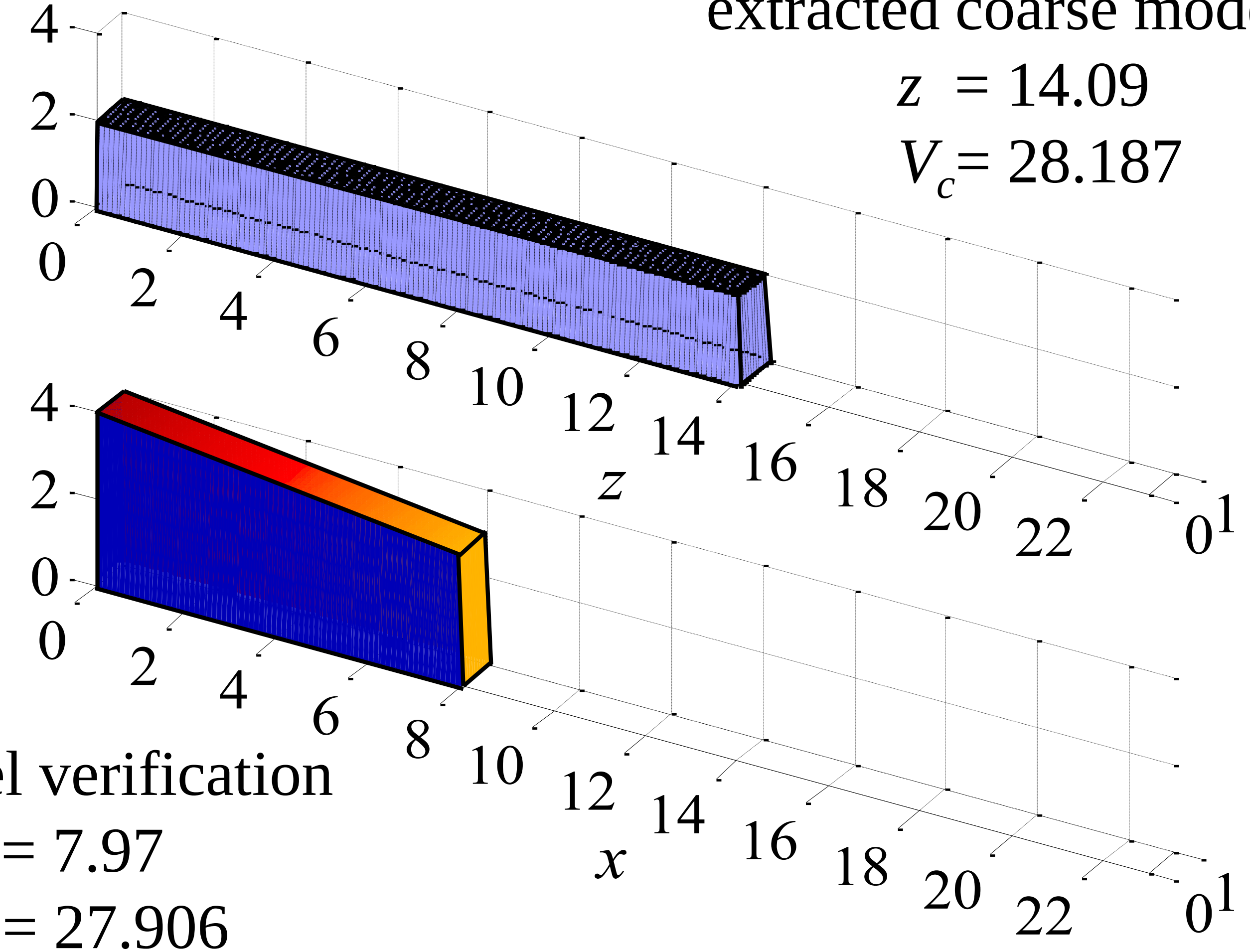
$V_f = 28.187$

Iteration 7

extracted coarse model

$z = 14.09$

$V_c = 28.187$



fine model verification

$x = 7.97$

$V_f = 27.906$

TRASM Algorithm (*Bakr et al., 2000*)

Step 1 initialize $\boldsymbol{x}^{(1)} = \boldsymbol{z}^{*}, \ \boldsymbol{B}^{(1)} = \boldsymbol{1}, \ i = 1, \ \delta^{(1)} = \delta_0$

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

Step 3 evaluate $\boldsymbol{f}^{(1)} = \boldsymbol{z}^{(1)} - \boldsymbol{z}^{*}$, if $\left\| \boldsymbol{f}^{(1)} \right\| \le \varepsilon$, stop

Step 4 find the minimizer $\boldsymbol{h}^{(i)}$ of $\left\| \boldsymbol{f}^{(i)} + \boldsymbol{B}^{(i)} \boldsymbol{h}^{(i)} \right\|$

subject to $\left\| \boldsymbol{h}^{(i)} \right\| \le \delta^{(i)}$

Step 5 set $\boldsymbol{x}^{(i+1)} = \boldsymbol{x}^{(i)} + \boldsymbol{h}^{(i)}$

TRASM Algorithm (*Bakr et al., 2000*)

Step 6 evaluate $\boldsymbol{R}_f(\boldsymbol{x}^{(i+1)})$

Step 7 extract $\boldsymbol{z}^{(i+1)}$ such that $\boldsymbol{R}_c(\boldsymbol{z}^{(i+1)}) \approx \boldsymbol{R}_f(\boldsymbol{x}^{(i+1)})$

Step 8 evaluate $\boldsymbol{f}^{(i+1)} = \boldsymbol{z}^{(i+1)} - \boldsymbol{z}^{*}$, if $\left\| \boldsymbol{f}^{(i+1)} \right\| \leq \varepsilon$ stop

Step 9 find $\rho^{(i)} = \dfrac{\left\| \boldsymbol{f}^{(i)} \right\| - \left\| \boldsymbol{f}^{(i+1)} \right\|}{\left\| \boldsymbol{f}^{(i)} \right\| - \left\| \boldsymbol{f}^{(i)} + \boldsymbol{B}^{(i)} \boldsymbol{h}^{(i)} \right\|}$

Step 10 adjust the trust region size

if $\rho^{(i)} < \eta_1$ reject $\boldsymbol{x}^{(i+1)}$, take $\delta^{(i+1)} \in [\alpha_1 \delta^{(i)}, \alpha_2 \delta^{(i)}]$

TRASM Algorithm (*Bakr et al., 2000*)

else if $\eta_1 \le \rho^{(i)} < \eta_2$, accept $\boldsymbol{x}^{(i+1)}$, $\delta^{(i+1)} \in [\alpha_2 \delta^{(i)}, \delta^{(i)}]$

else accept $\boldsymbol{x}^{(i+1)}$, take $\delta^{(i+1)} \ge \delta^{(i)}$

Comment $0 < \alpha_1 \le \alpha_2 < 1$, $0 < \eta_1 \le \eta_2 < 1$

(for example, $\eta_1 = 0.1$, $\eta_2 = 0.9$ and $\alpha_1 = \alpha_2 = 0.5$)

Step 11 update $\boldsymbol{B}^{(i+1)} = (\boldsymbol{J}_c^T \boldsymbol{J}_c)^{-1} \boldsymbol{J}_c^T \boldsymbol{J}_f$

Comment $\boldsymbol{J}_f$, $\boldsymbol{J}_c$ are evaluated at $\boldsymbol{x}^{(i+1)}$, $\boldsymbol{z}^{(i+1)}$

Step 12 set $i = i + 1$ and go to *Step* 4

Wedge Cutting Problem (*Bandler et al., 2002*)

Step 1 $x^{(1)} = z^{*} = 14,\ B^{(1)} = 1,\ \delta^{(1)} = 2$

Step 2 $V_f(x^{(1)}) = 4x^{(1)} - \dfrac{(x^{(1)})^2}{16} = 43.75 \xrightarrow{\text{PE}} z^{(1)} = 21.875$

Step 3 $f^{(1)} = 21.875 - 14 = 7.875$

Step 4 $h^{(1)} = \arg\min_{h} \|7.875 + 1.h\| \text{ subject to } \|h\| < 2$

$h^{(1)} = -2$

Step 5 $x^{(2)} = 14 + (-2) = 12$

Wedge Cutting Problem (*Bandler et al., 2002*)

Step 6 $V_f(x^{(2)}) = 39$

Step 7 PE $z^{(2)} = 19.5$

Step 8 $f^{(2)} = 19.5 - 14 = 5.5$

Step 9 $\rho^{(1)} = \dfrac{7.875 - 5.5}{7.875 - (7.875 + 1(-2))} = 1.18$

Step 10 adjust trust region size $\delta^{(2)} = 2\delta^{(1)} = 4$

Step 11 $J_f = 4 - x^{(2)}/8, \; J_c = 2 \longrightarrow B^{(2)} = \dfrac{J_f}{J_c} = 1.25$

Wedge Cutting Problem (*Bandler et al., 2002*)

Step 4b $h^{(2)} = \arg\min_{h} \|5.5 + 1.25h\|$ subject to $\|h\| < 4$

$h^{(2)} = -4$

Step 5b set $x^{(3)} = 12 + (-4) = 8$

Step 6b $V_f(x^{(3)}) = 28$

Step 7b PE $z^{(3)} = 14$

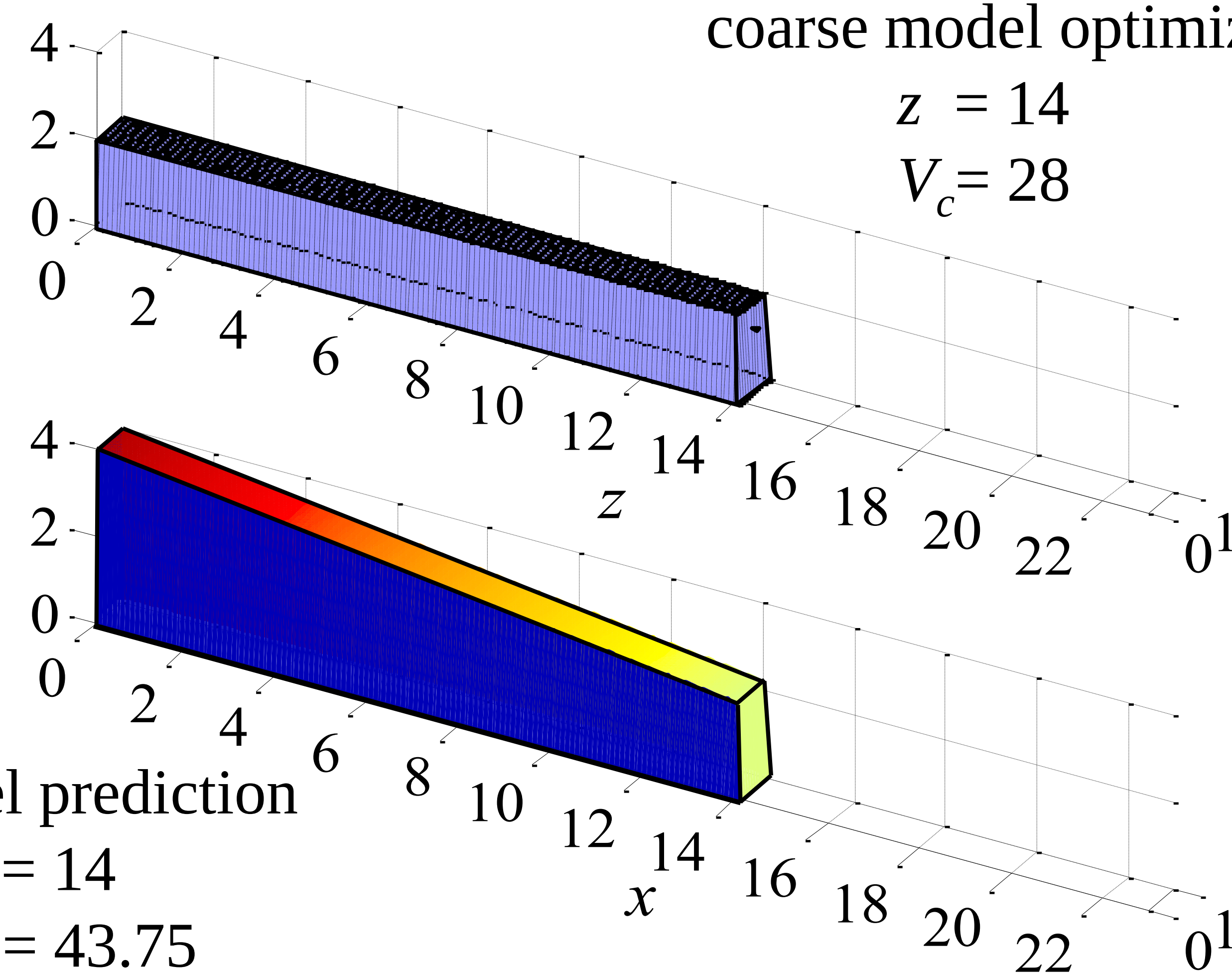
Step 8b $f^{(3)} = 14 - 14 = 0$ stop the algorithm

Initial Step

coarse model optimization

$z = 14$

$V_c = 28$



fine model prediction

$x = 14$

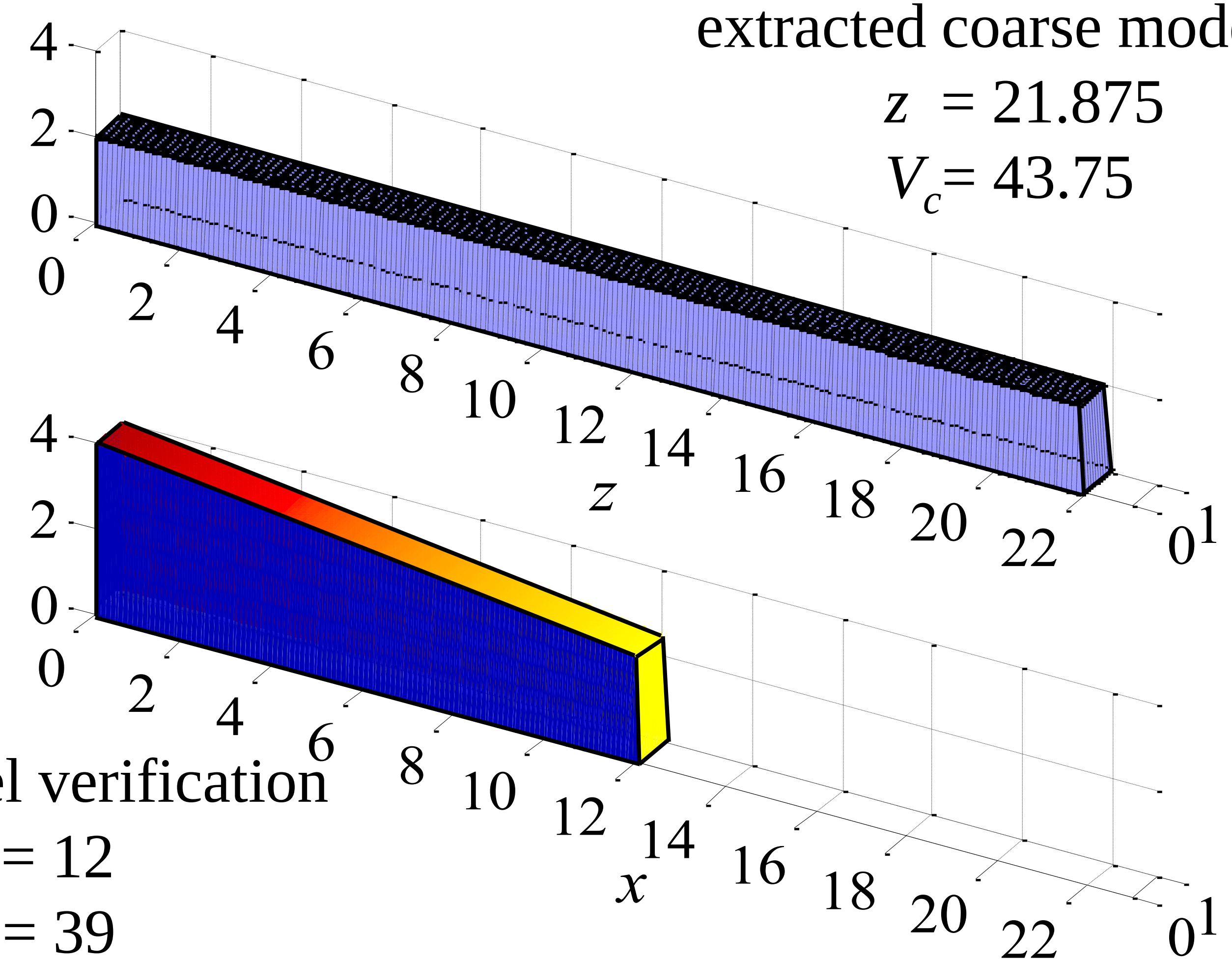
$V_f = 43.75$

Iteration 1

extracted coarse model

$z = 21.875$

$V_c = 43.75$



fine model verification

$x = 12$

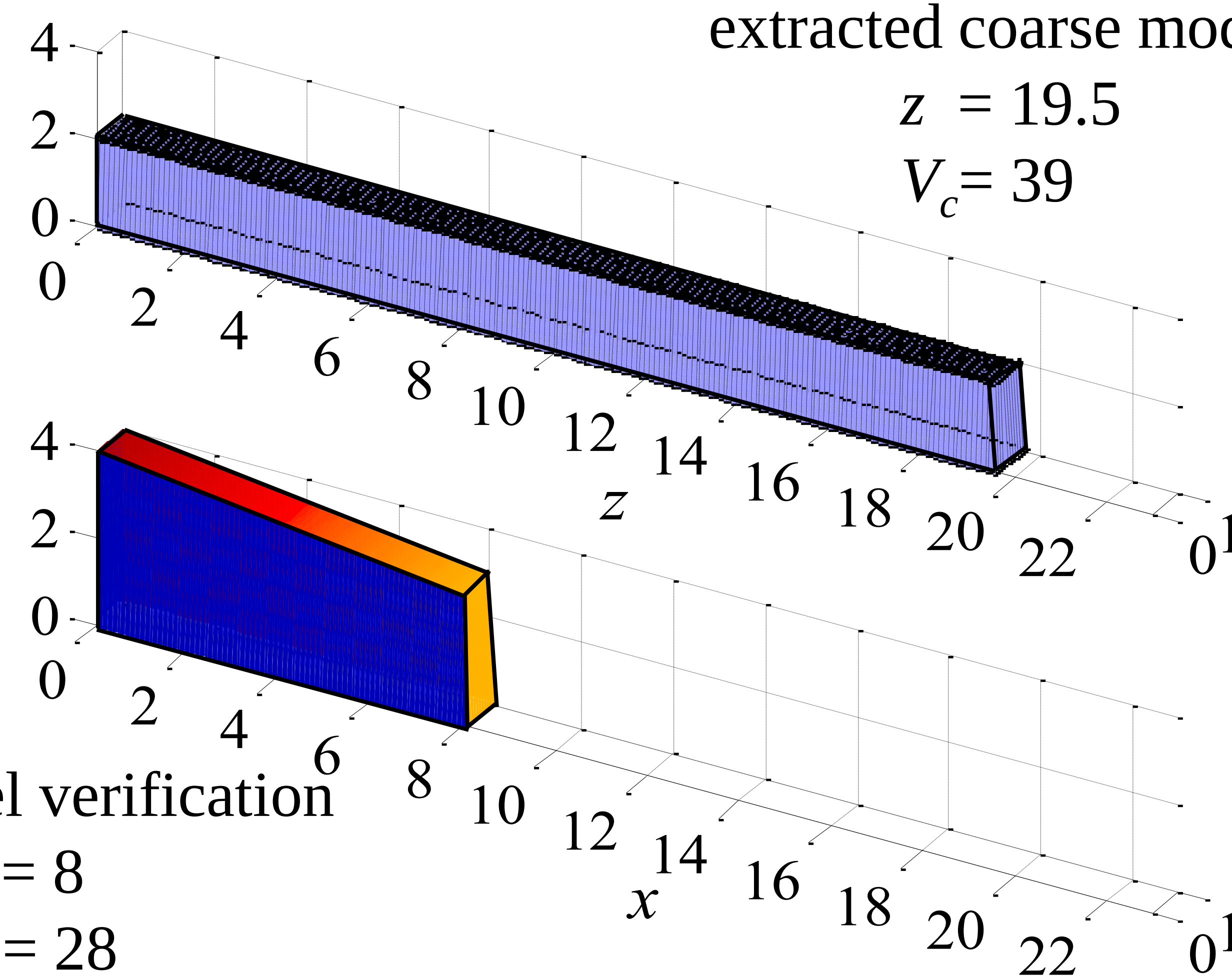
$V_f = 39$

Iteration 2

extracted coarse model

$z = 19.5$

$V_c = 39$



fine model verification

$x = 8$

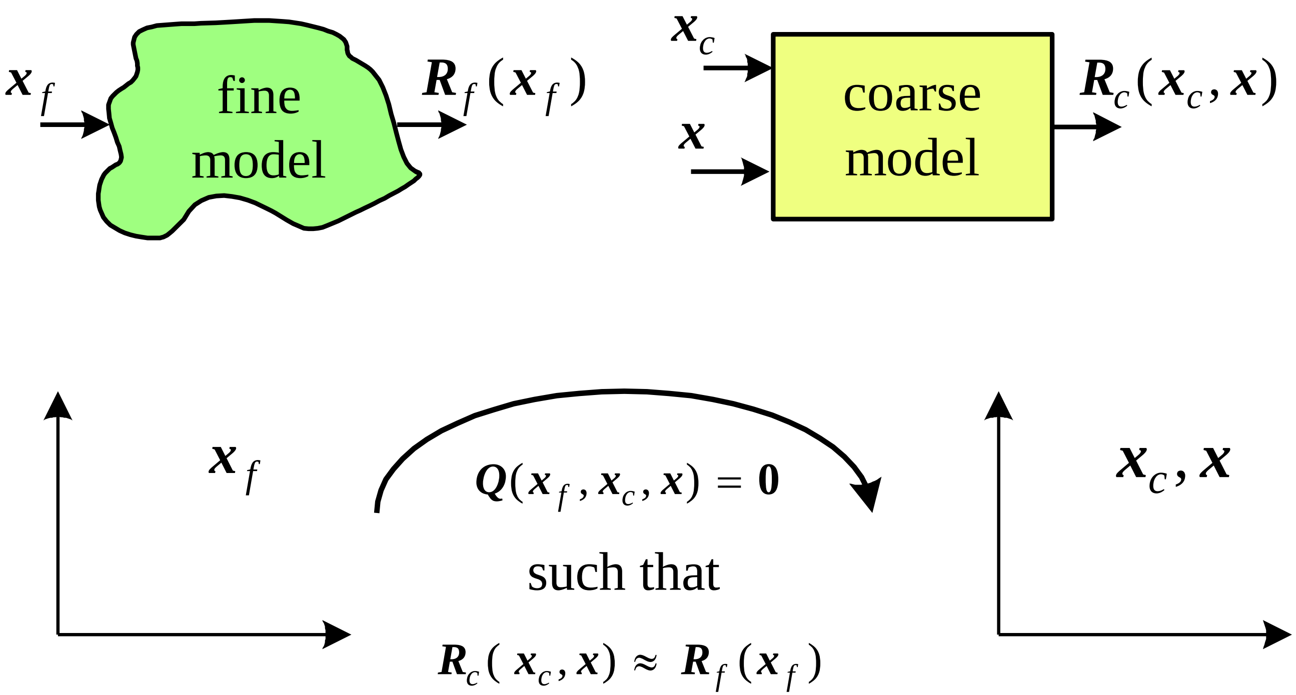
$V_f = 28$

Change of Initial Trust Region Size

$\delta^{(1)}$	x^*	V_f	number of iterations
1	7.99905	27.99715	4
2	8	28	2
3	7.99905	27.99715	3
4	7.99983	27.99948	3

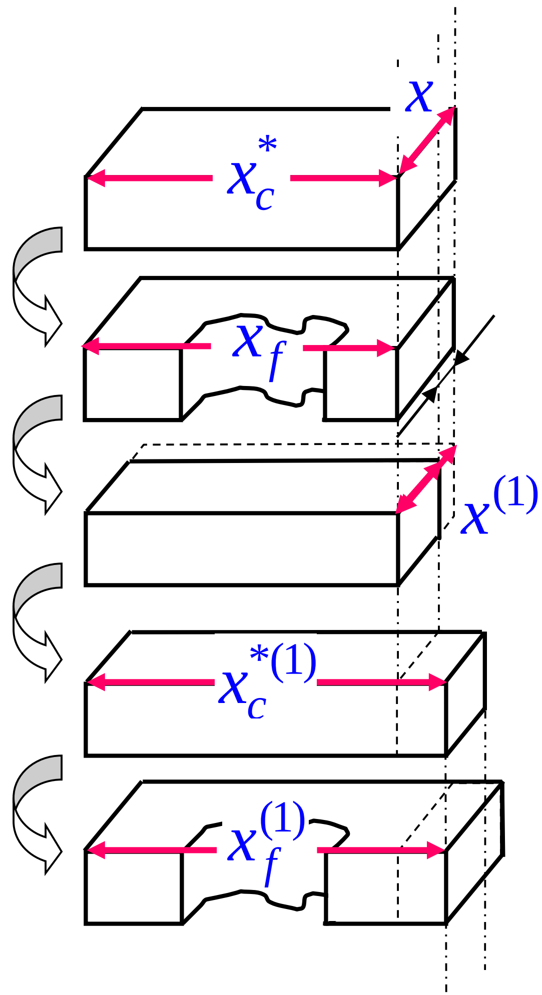
Implicit Space Mapping Theory

(*Bandler et al., 2002*)



Implicit Space Mapping Practice—Cheese Cutting Problem

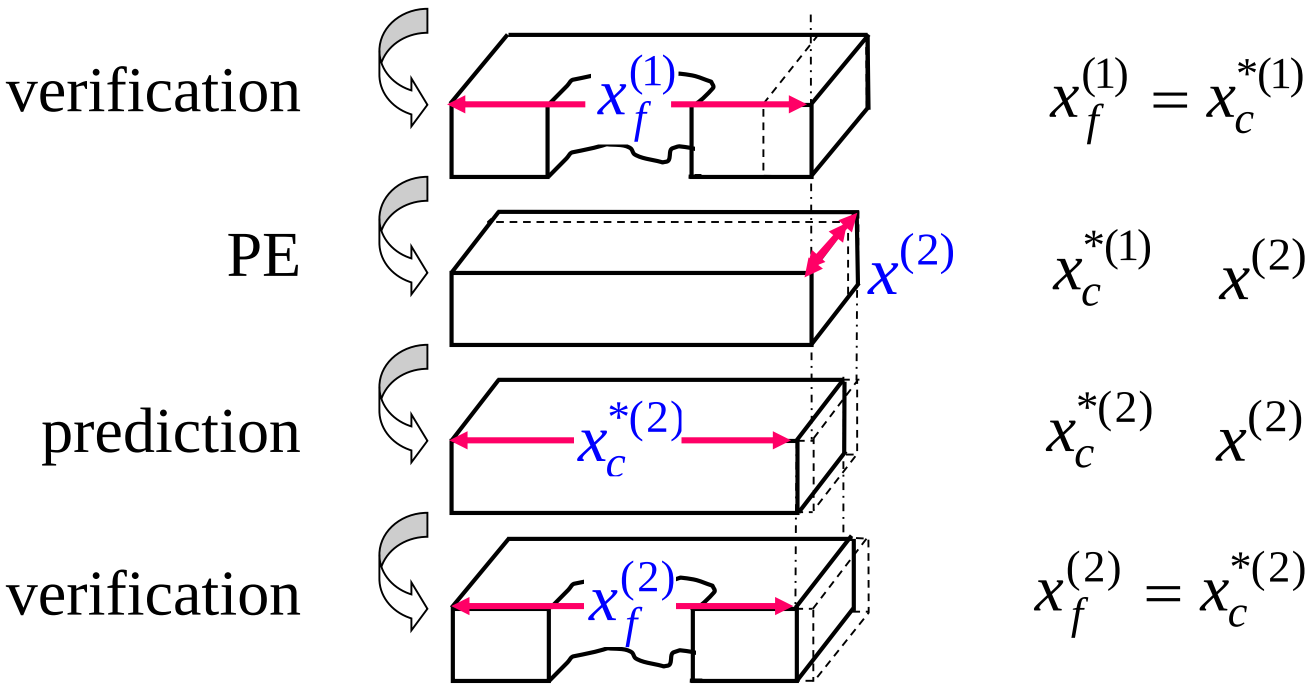
(*Bandler 2002*)



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

Implicit Space Mapping Practice—Cheese Cutting Problem

(*Bandler 2002*)



⋮

Cheese Cutting Problem—A Numerical Example

(*Bandler 2002*)

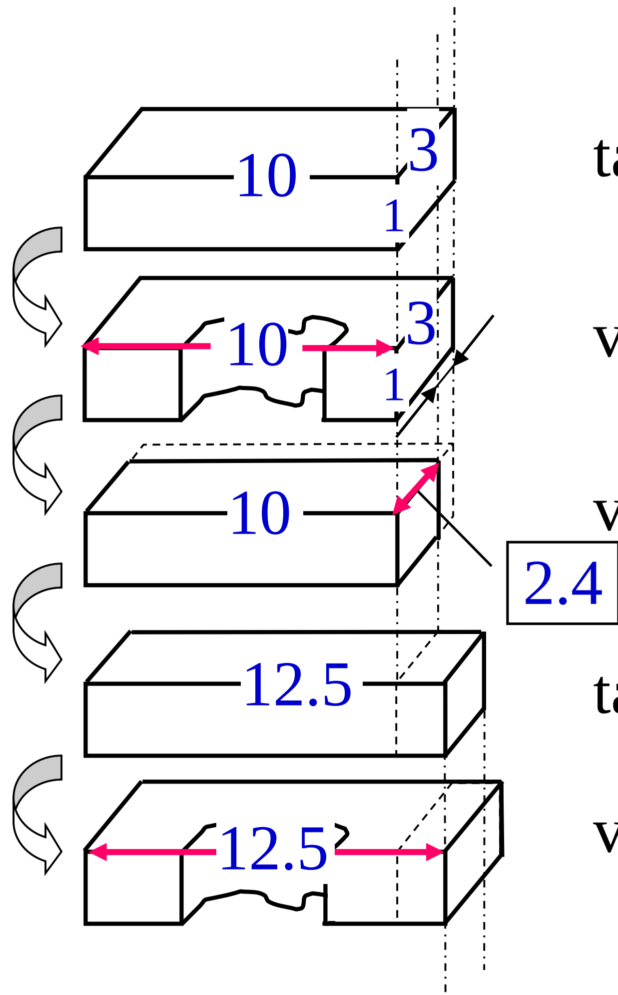
optimal coarse model — target volume =30

initial guess — volume =24

PE — volume =24

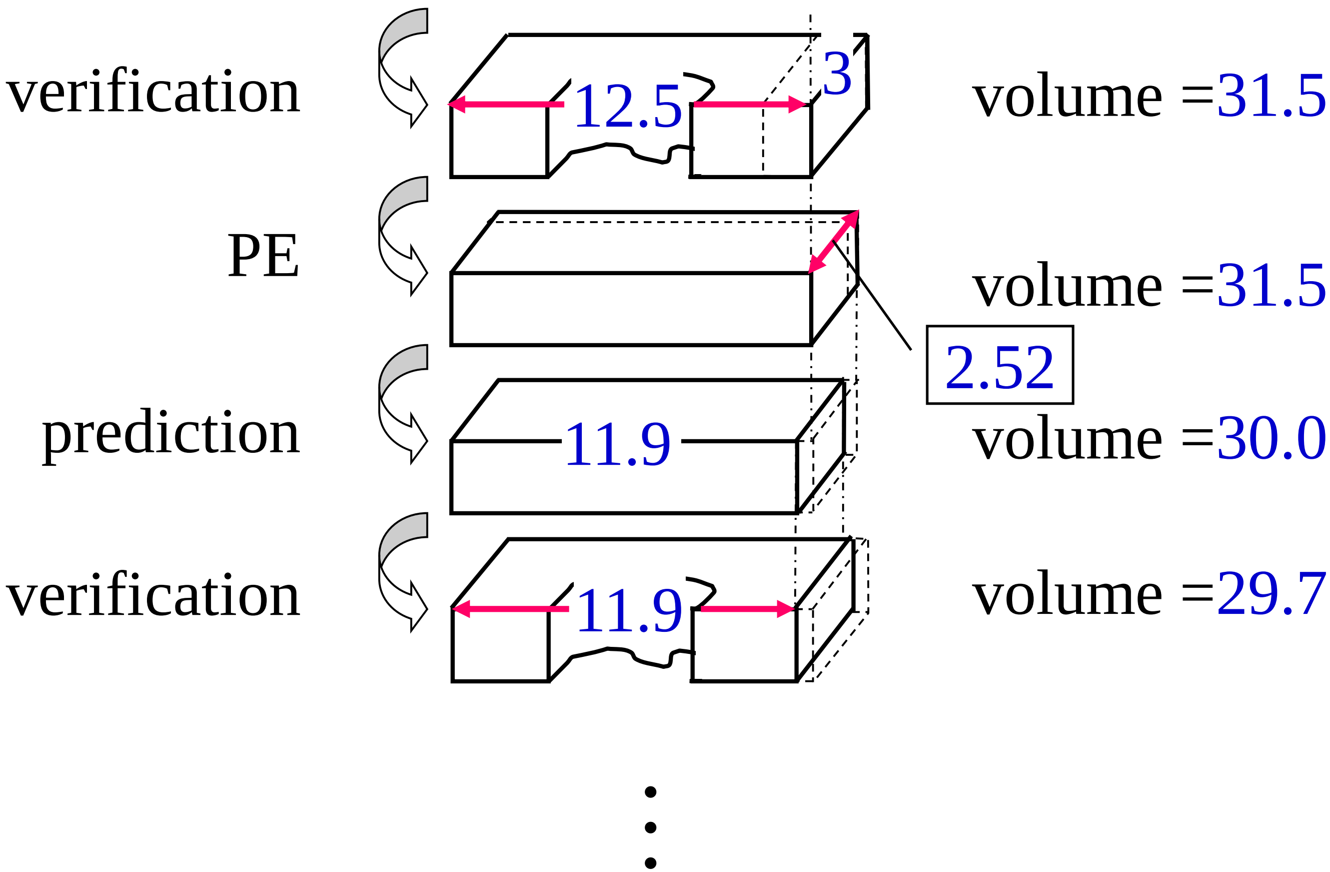
prediction — target volume =30

verification — volume =31.5



Cheese Cutting Problem—A Numerical Example

(*Bandler 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

An Implicit Space Mapping Algorithm—Preassigned Parameters

Step 1 select candidate preassigned parameters $\boldsymbol{x}$ as in ESMDF or by experience

Step 2 set $i = 0$ and initialize $\boldsymbol{x}^{(0)}$

Step 3 obtain optimal *coarse model*

$$\boldsymbol{x}_c^{*(i)} = \arg\min_{\boldsymbol{x}_c} U(\boldsymbol{R}_c(\boldsymbol{x}_c, \boldsymbol{x}^{(i)}))$$

Step 4 predict $\boldsymbol{x}_f^{(i)}$ from

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

An Implicit Space Mapping Algorithm—Preassigned Parameters (continued)

Step 5 simulate the fine model at $\boldsymbol{x}_f^{(i)}$

Step 6 terminate if a stopping criterion (e.g., response meets specifications) is satisfied

Step 7 calibrate the coarse model by extracting the preassigned parameters $\boldsymbol{x}$

$$\boldsymbol{x}^{(i+1)} = \arg\min_{\boldsymbol{x}} \left\| \boldsymbol{R}_f(\boldsymbol{x}_f^{(i)}) - \boldsymbol{R}_c(\boldsymbol{x}_f^{(i)}, \boldsymbol{x}) \right\|$$

where we set

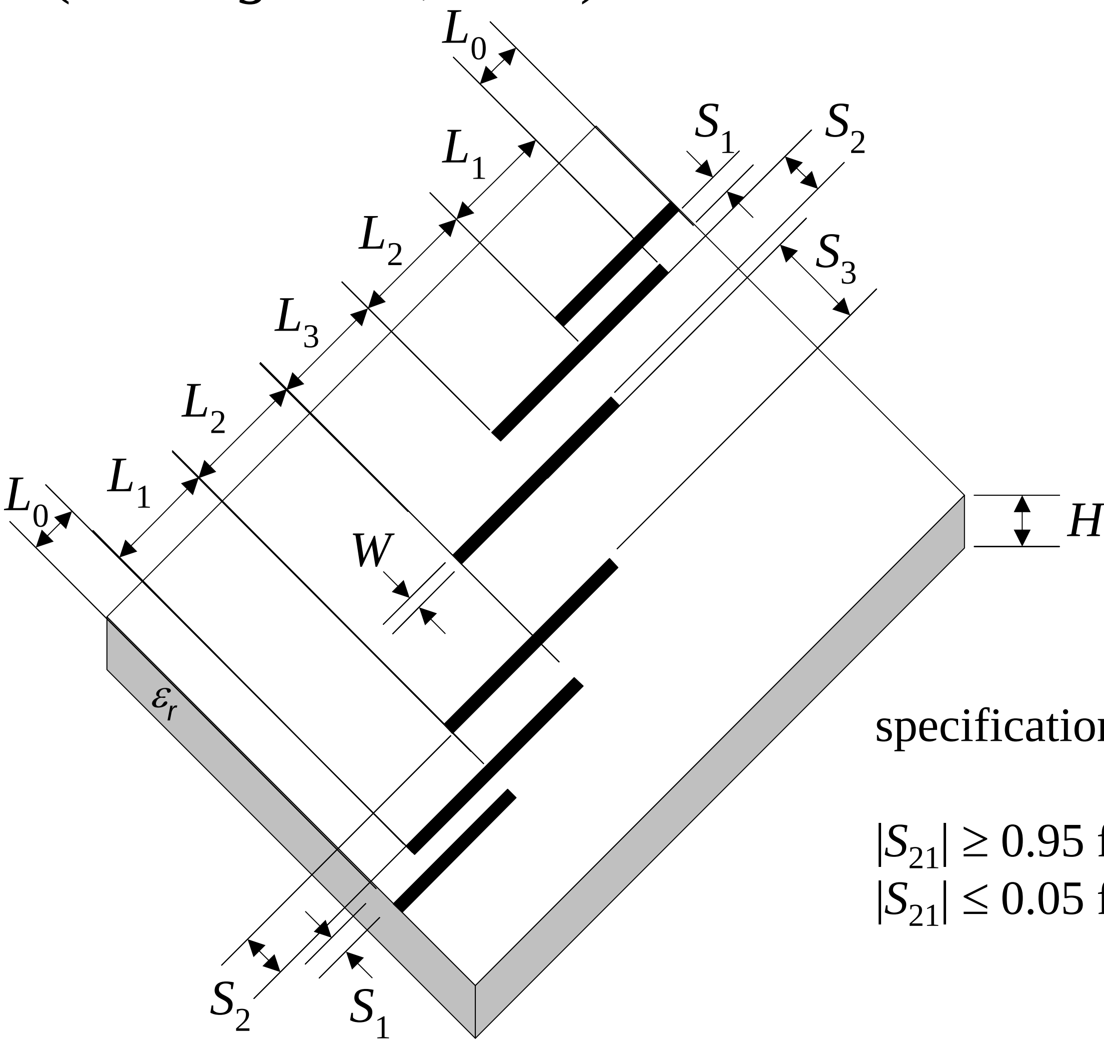
$$\boldsymbol{x}_c = \boldsymbol{x}_f^{(i)}$$

An Implicit Space Mapping Algorithm—Preassigned Parameters (continued)

Step 8 increment *i* and go to *Step* 3

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(*Westinghouse, 1993*)



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

the design parameters are

$\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$

specifications

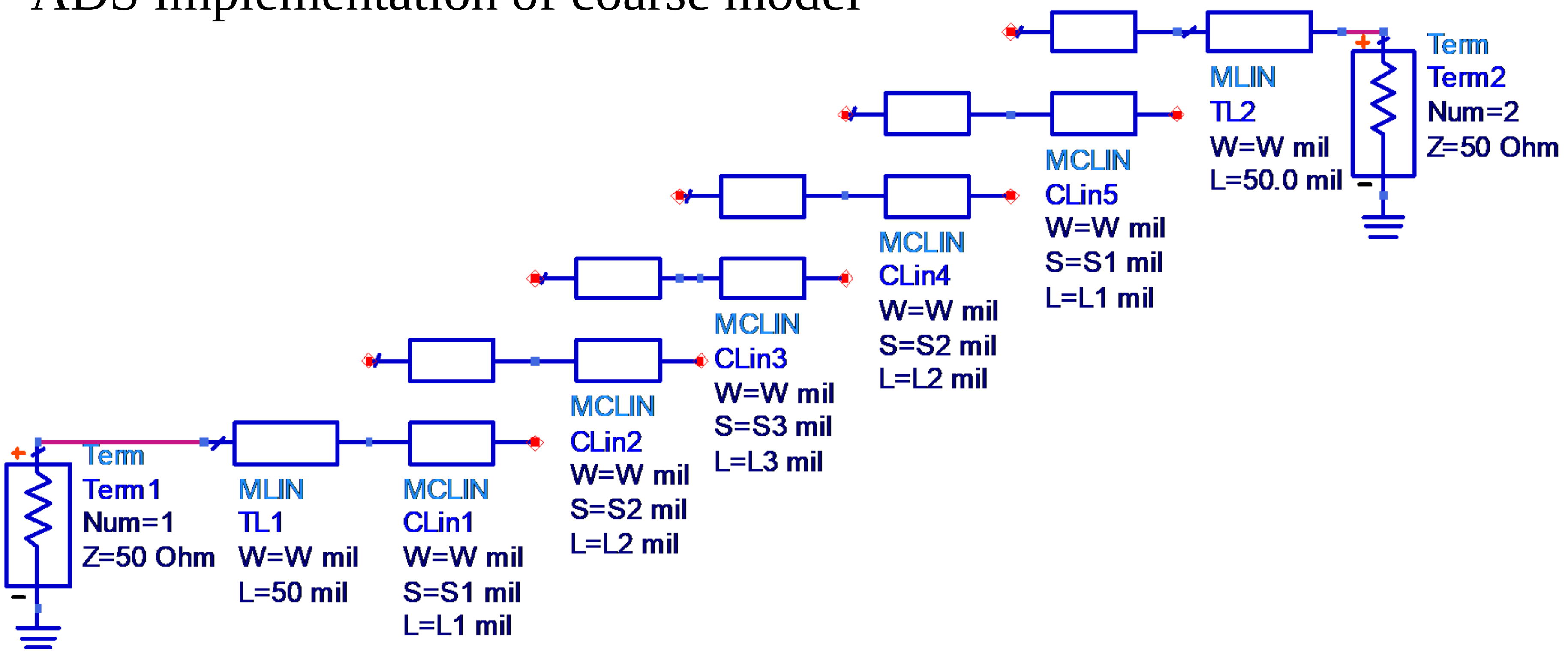
$|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq$ 4.058 GHz

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

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(*Westinghouse, 1993*)

ADS implementation of coarse model



HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(*Westinghouse, 1993*)

parameter	initial solution	solution reached by the algorithm
L_1	189.65	187.10
L_2	196.03	191.30
L_3	189.50	186.97
S_1	23.02	22.79
S_2	95.53	93.56
S_3	104.95	104.86
all values are in mils		

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

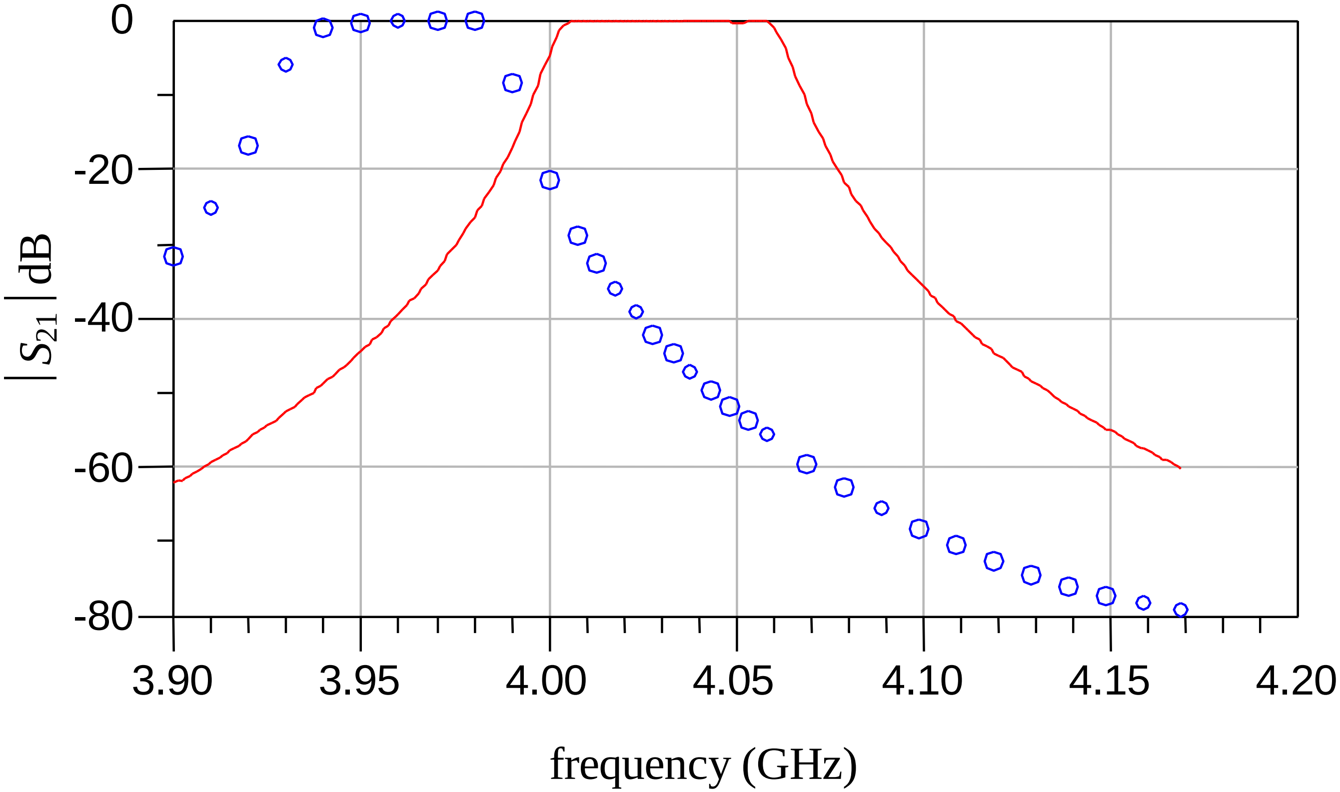
(*Westinghouse, 1993*)

preassigned parameters	original values	final iteration
H_1	20 mil	19.80 mil
H_2	20 mil	19.05 mil
H_3	20 mil	19.00 mil
ε_{r1}	23.425	24.404
ε_{r2}	23.425	24.245
ε_{r3}	23.425	24.334

HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(*Westinghouse, 1993*)

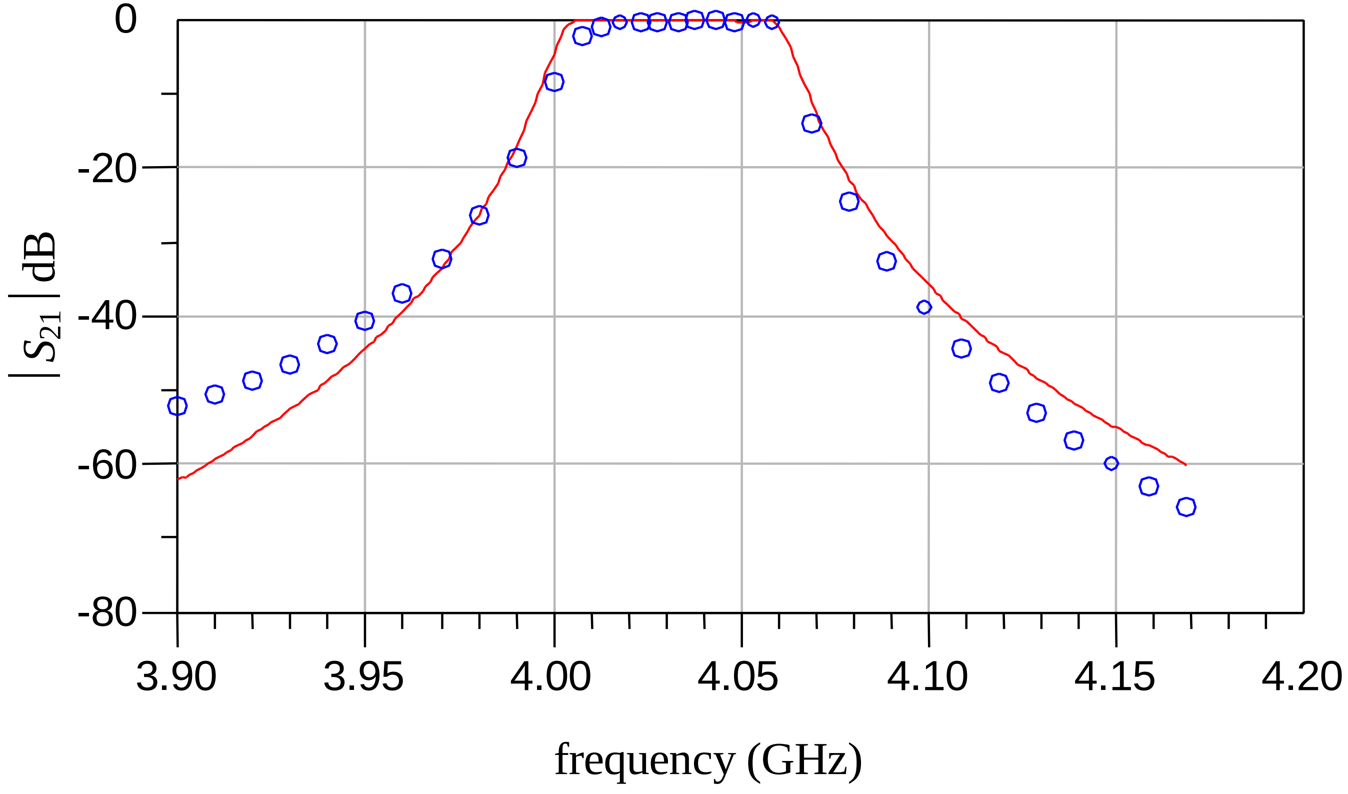
the fine (○) and optimal coarse model (——) responses at the initial solution



HTS Quarter-Wave Parallel Coupled-Line Microstrip Filter

(*Westinghouse, 1993*)

the fine (○) and optimal coarse model (——) responses at the final iteration



Bandler’s Conjecture No. 1

Space Mapping is a natural mechanism for the brain to relate objects or images with other objects, images, reality, or experience

Bandler’s Conjecture No. 2

brains of “clever”, experienced or intuitive individuals employ a Broyden-like update in the Space Mapping process

Bandler’s Conjecture No. 3

“experienced” engineering designers, knowingly or not, routinely employ Space Mapping to achieve complex designs

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-)

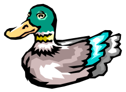
circuit calibration technique

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-)

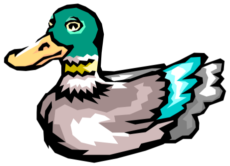
knowledge based neural networks, space mapping

Jan Snel (Philips Semiconductors, Netherlands, 2001)

RF component design, library model enhancement

Dan Swanson (Bartley RF Systems, 2001)

combline filter design

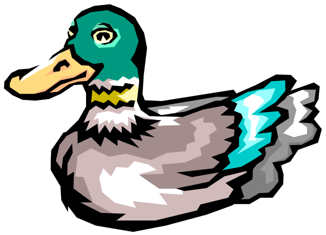


Selected Space Mapping Contributors

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

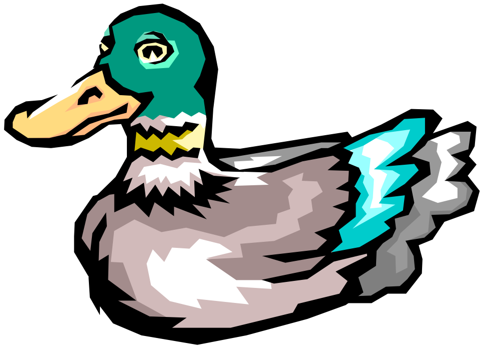
Selected Space Mapping Contributors

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

Conclusions

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

Space Mapping optimization follows traditional experience of designers

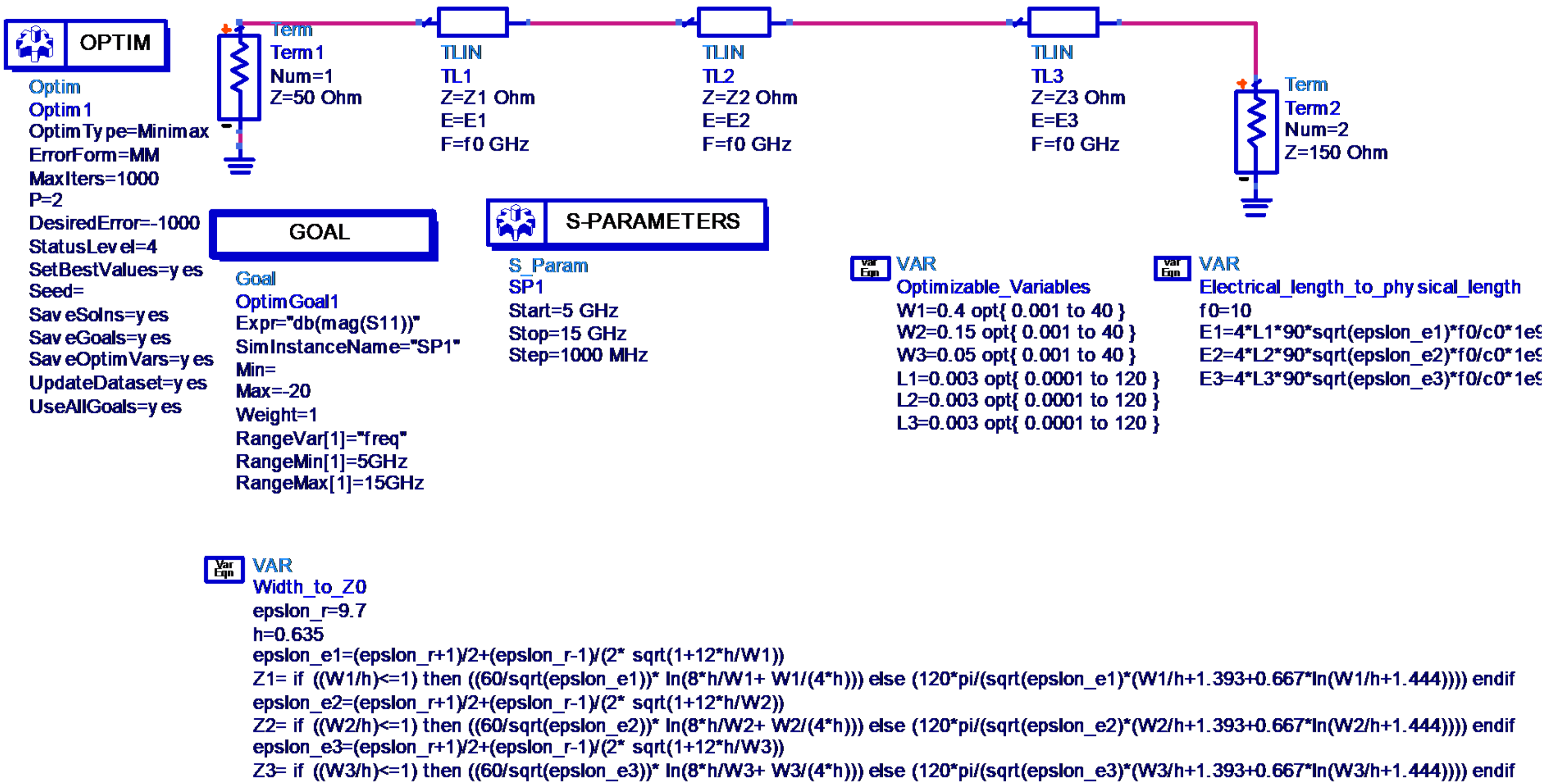
researchers and practitioners attracted to Aggressive Space Mapping

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

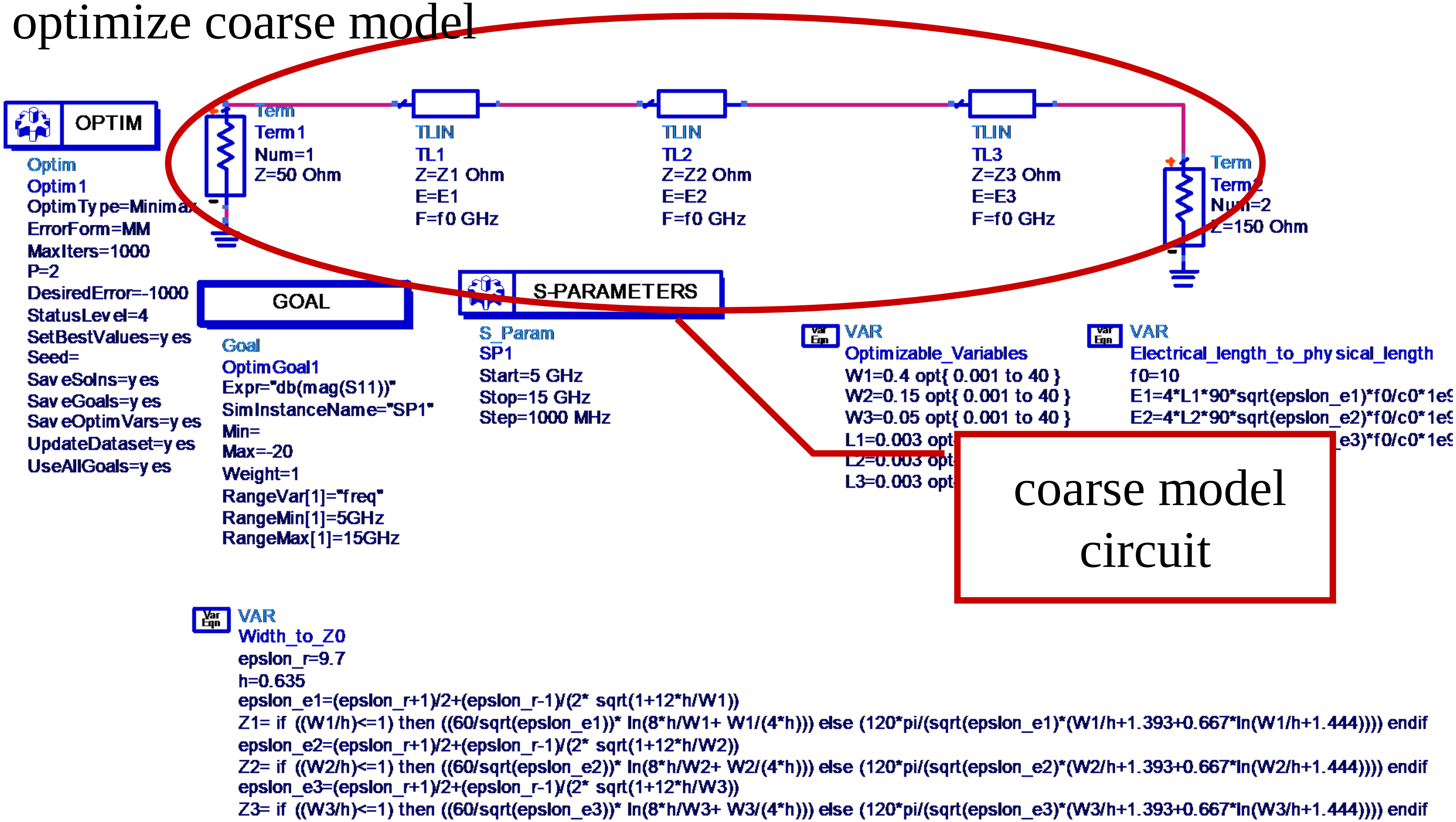
Implicit Space Mapping: Steps 1-3

optimize coarse model



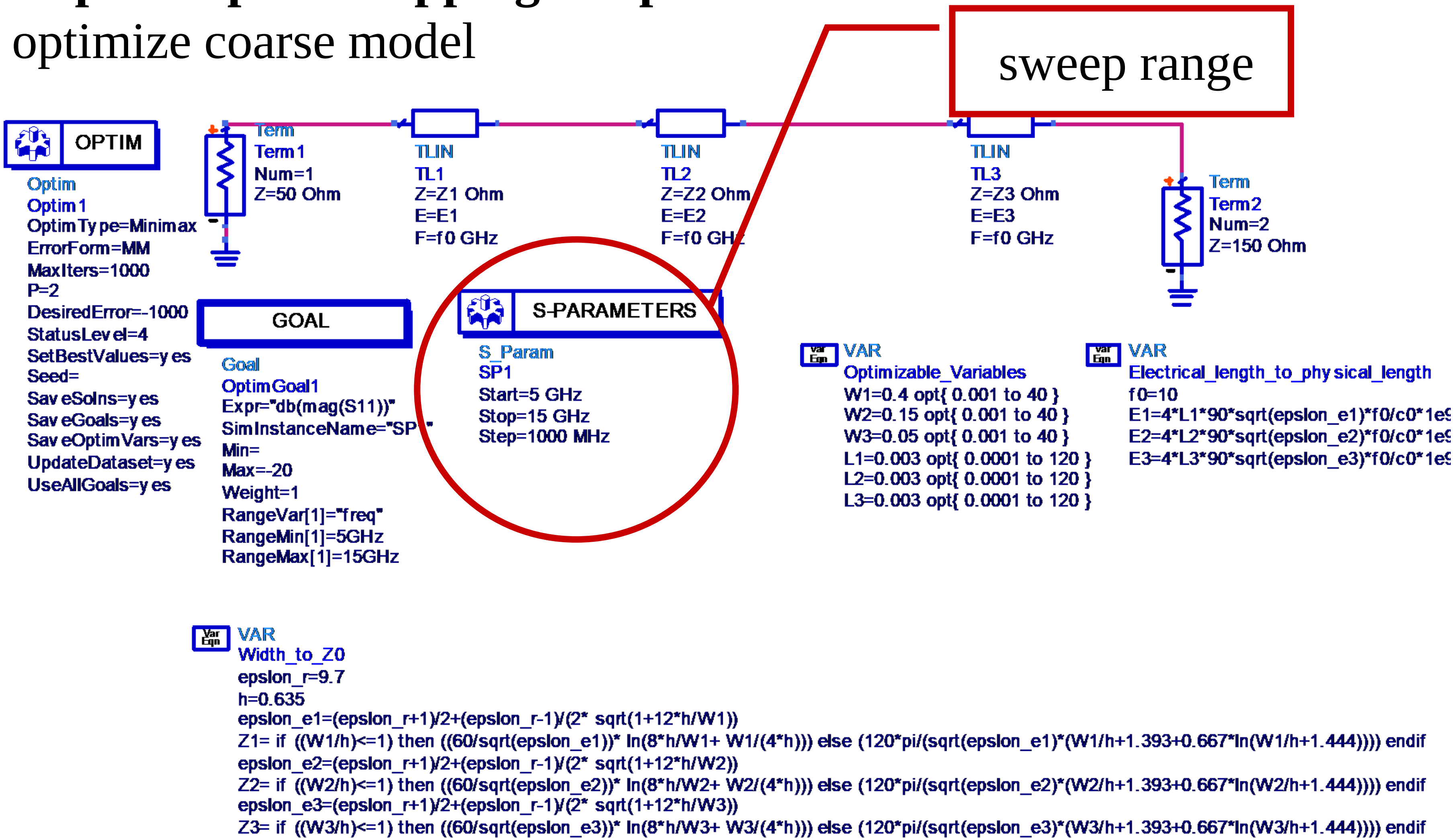
Implicit Space Mapping: Steps 1-3

optimize coarse model



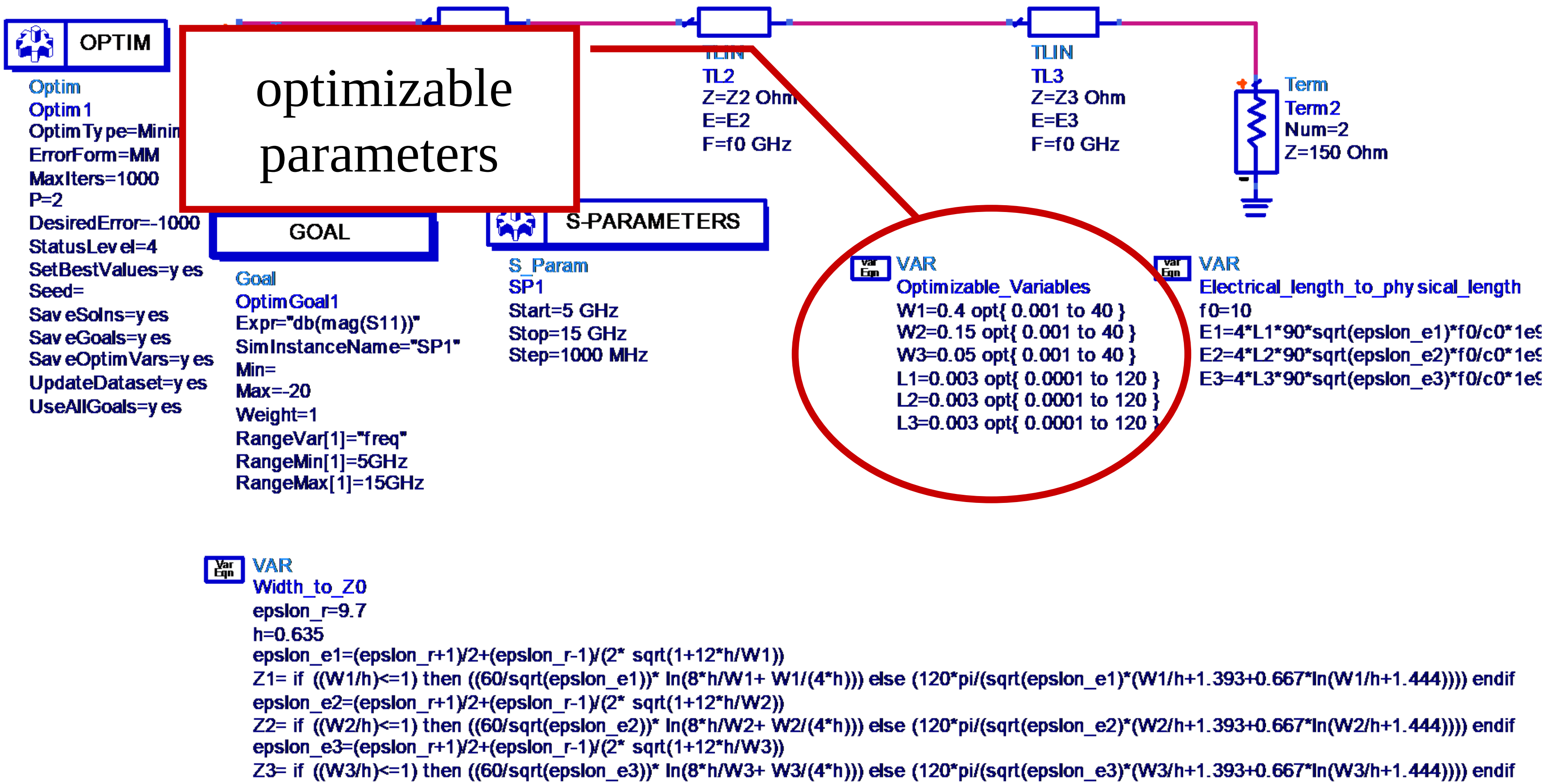
Implicit Space Mapping: Steps 1-3

optimize coarse model



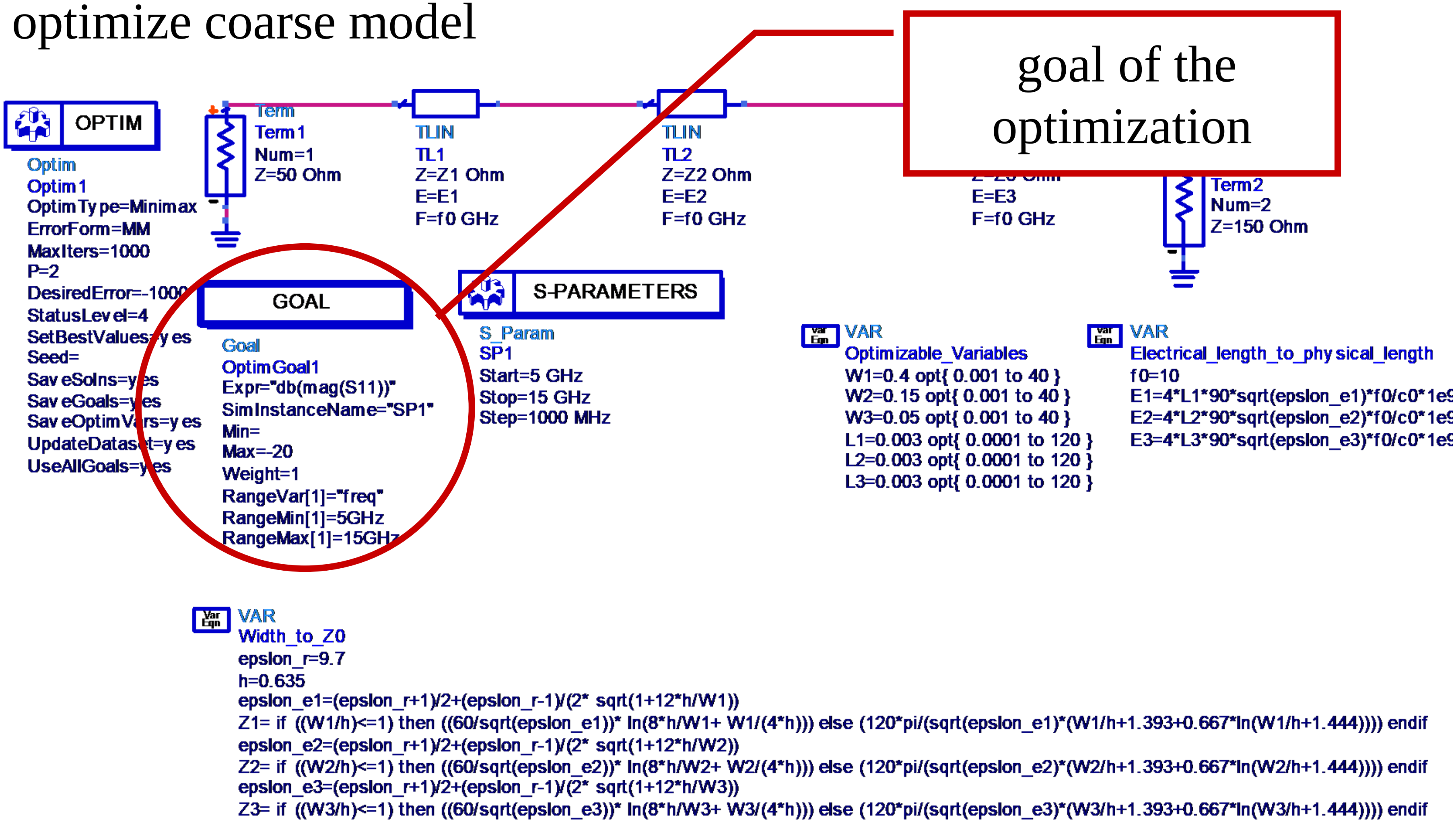
Implicit Space Mapping: Steps 1-3

optimize coarse model



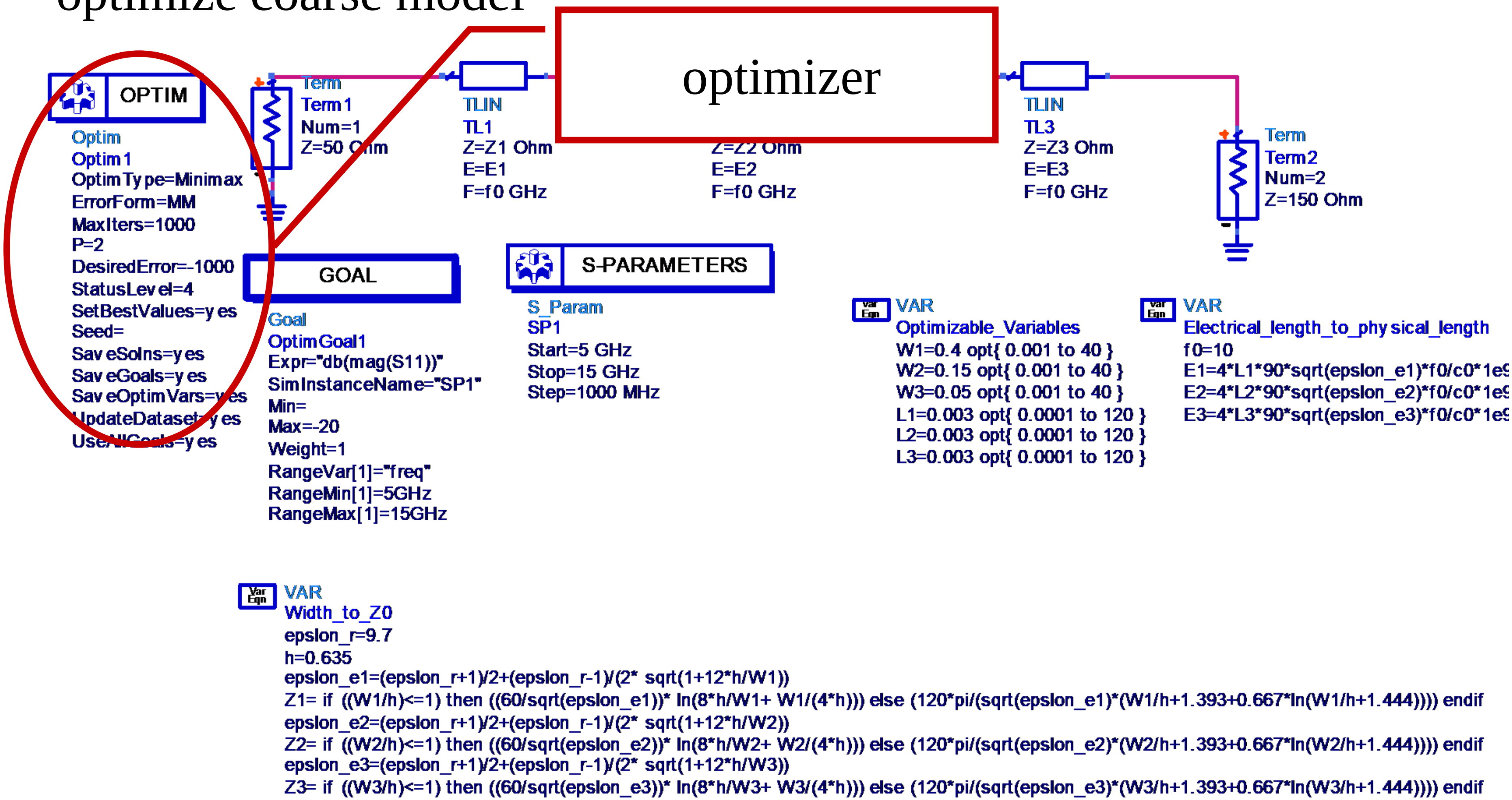
Implicit Space Mapping: Steps 1-3

optimize coarse model



Implicit Space Mapping: Steps 1-3

optimize coarse model

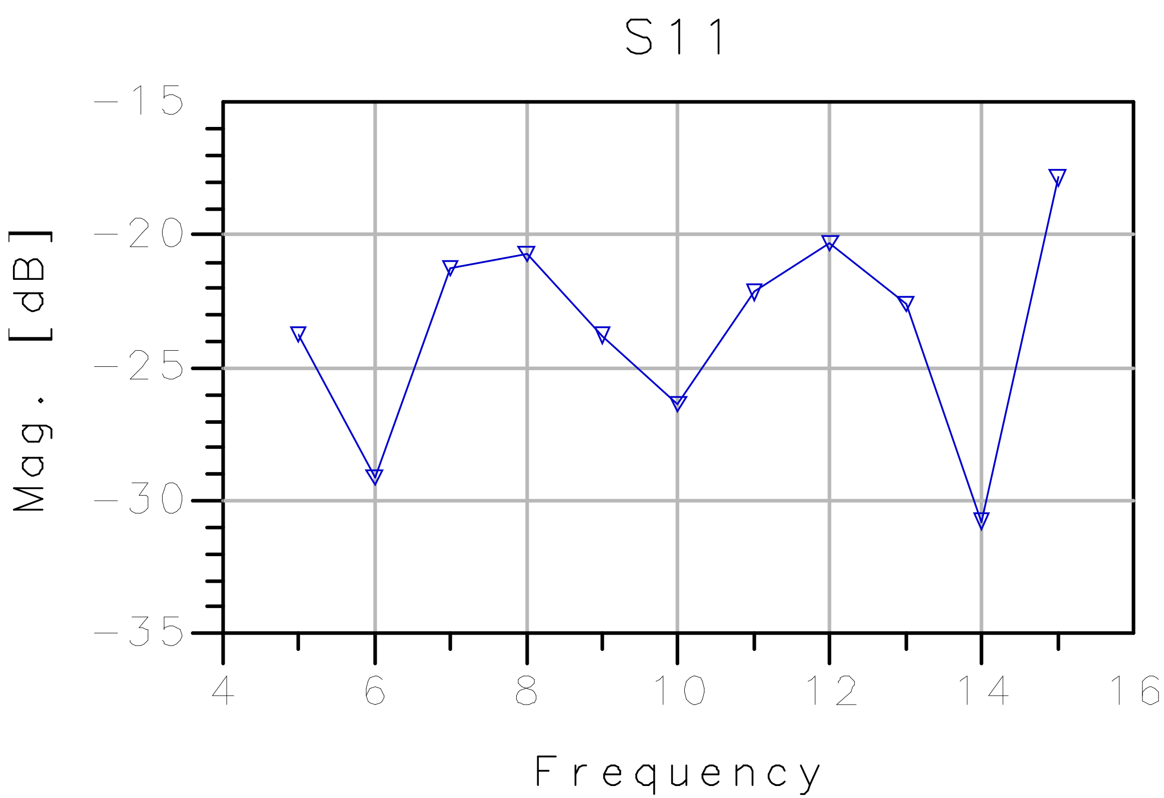


Implicit Space Mapping: Steps 4-5

simulate fine model using Momentum

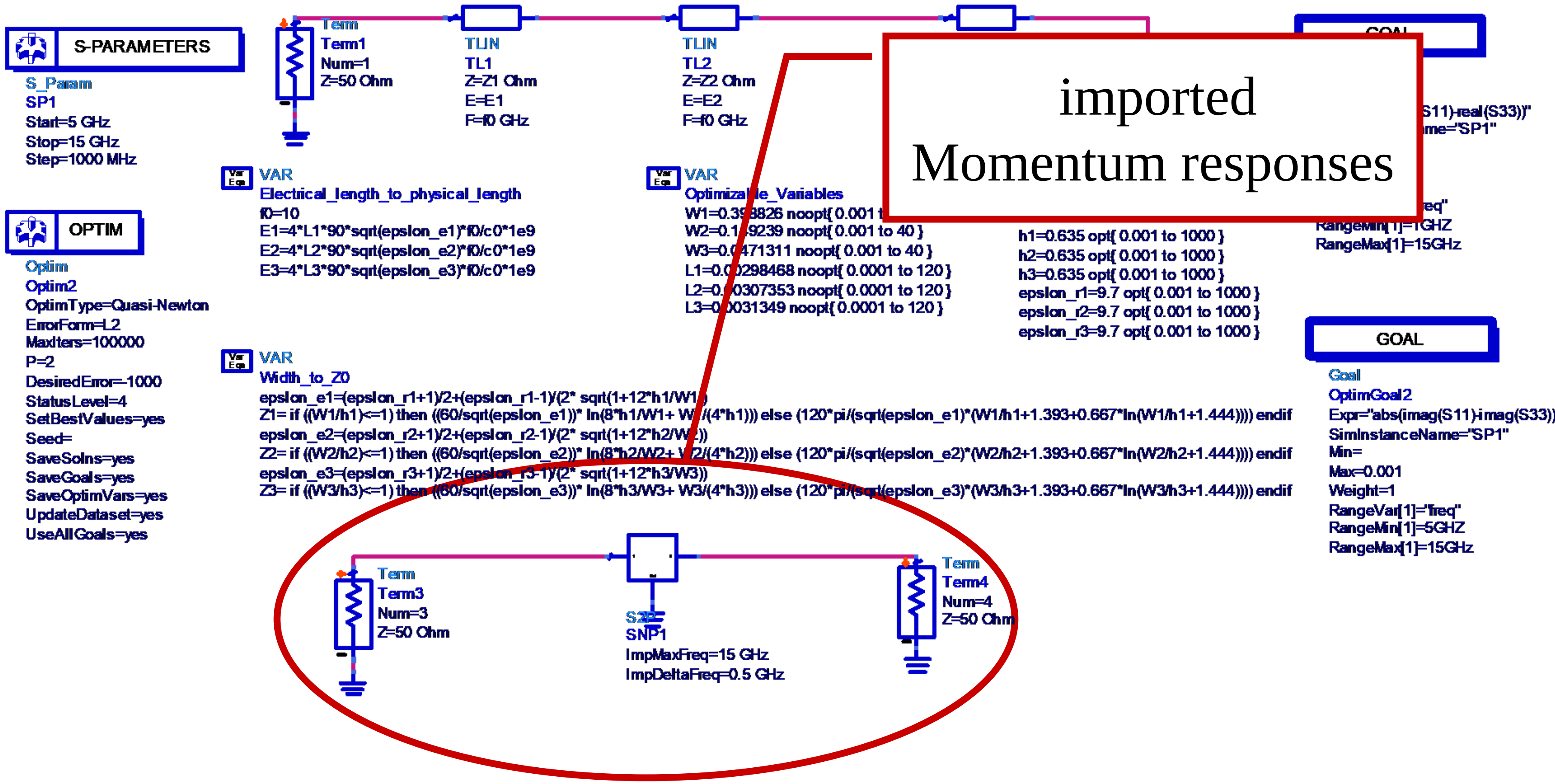
Implicit Space Mapping: Steps 5-6

obtain the fine model result and check stopping criteria



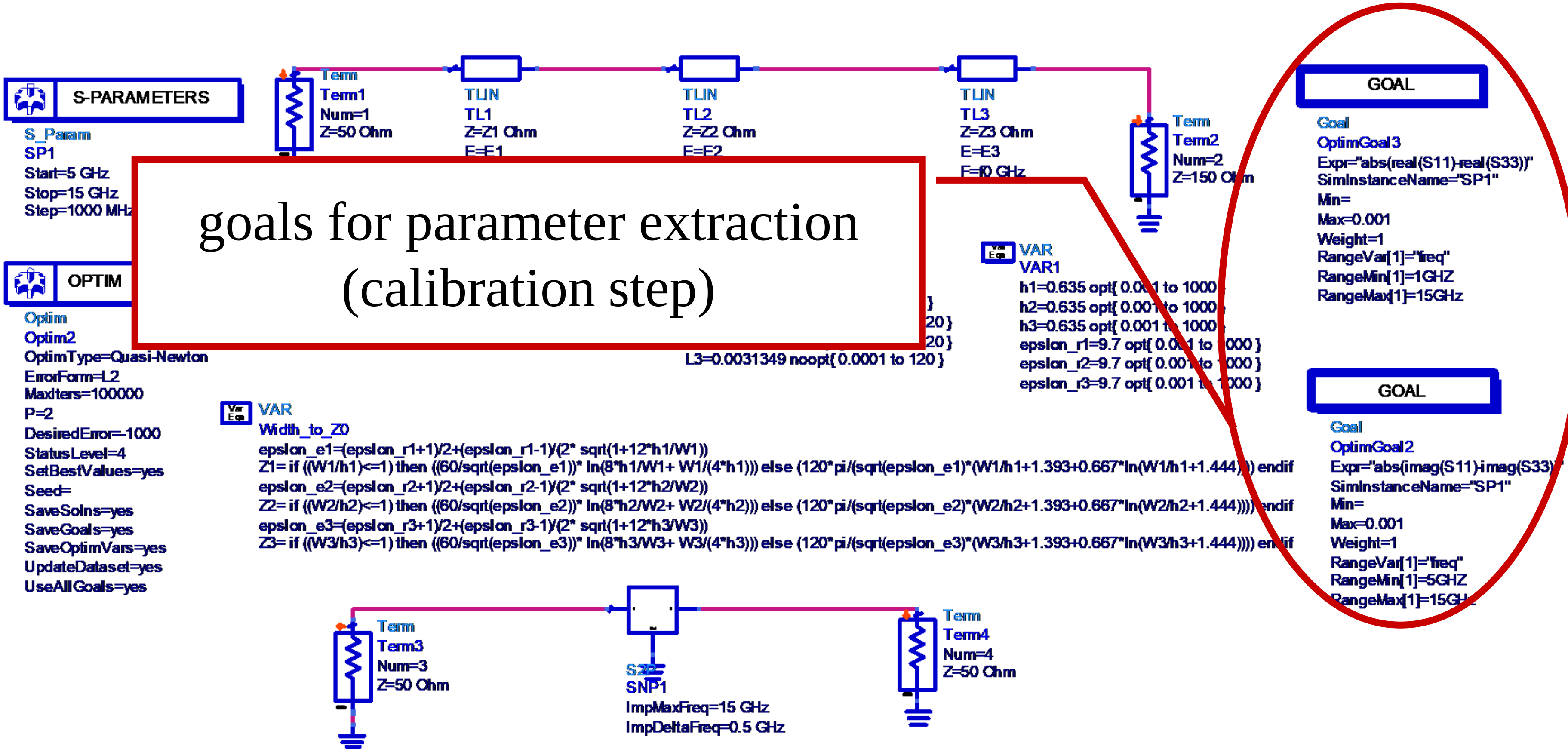
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters ***x***



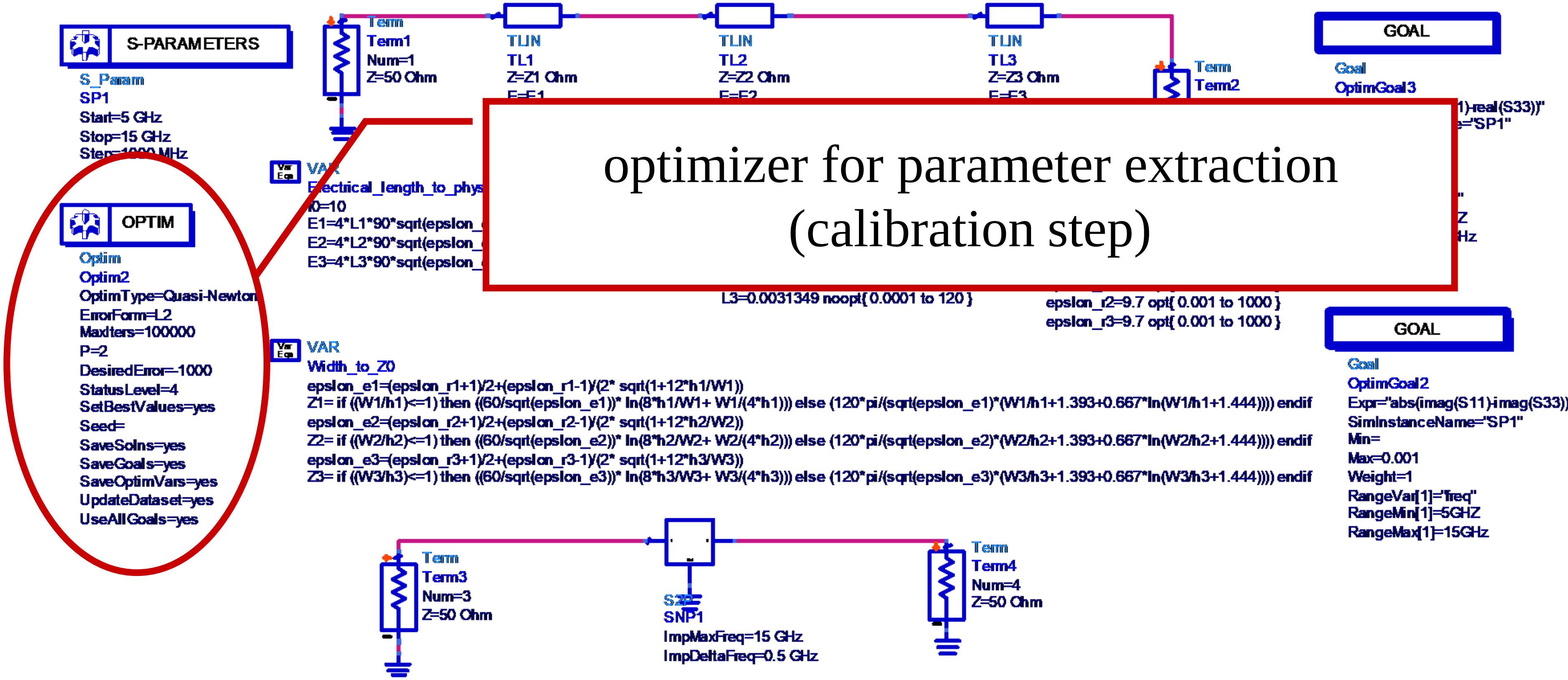
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters ***x***



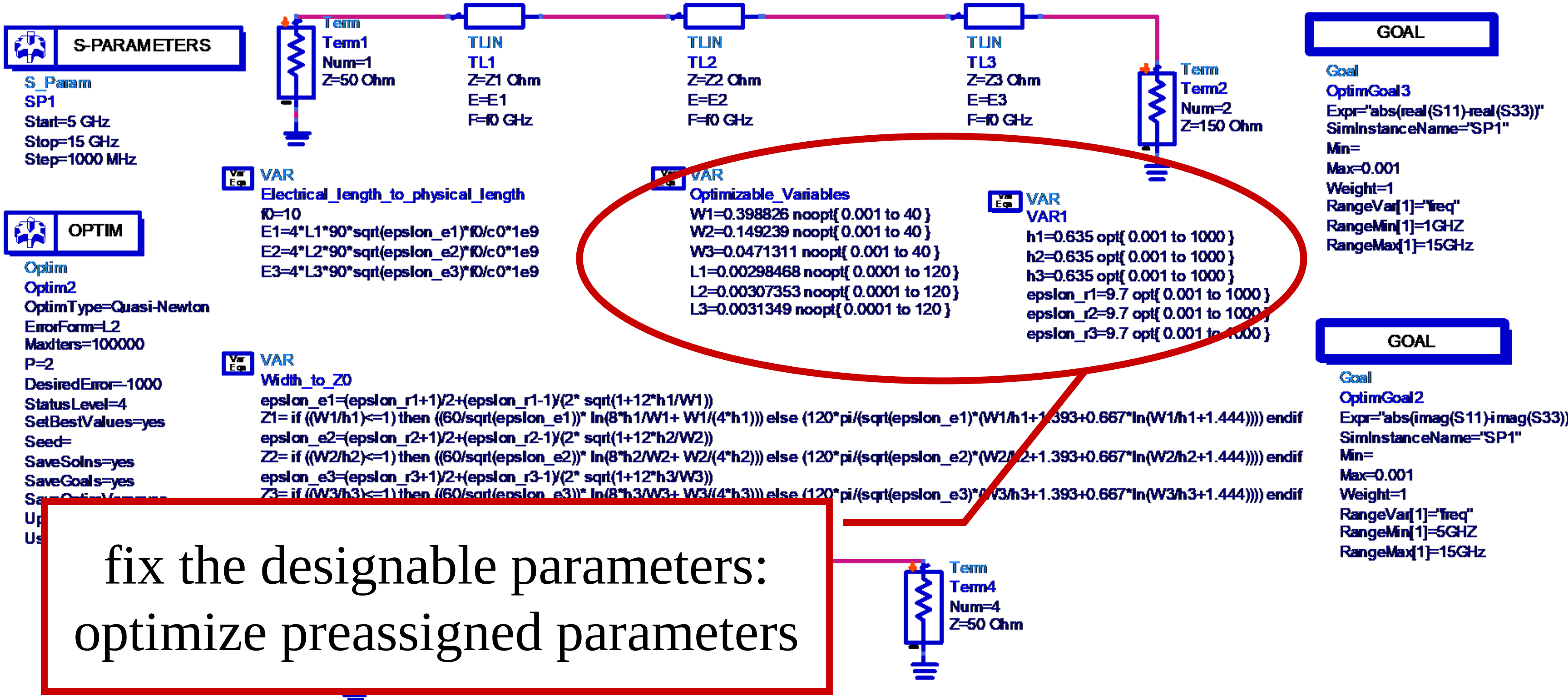
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters ***x***



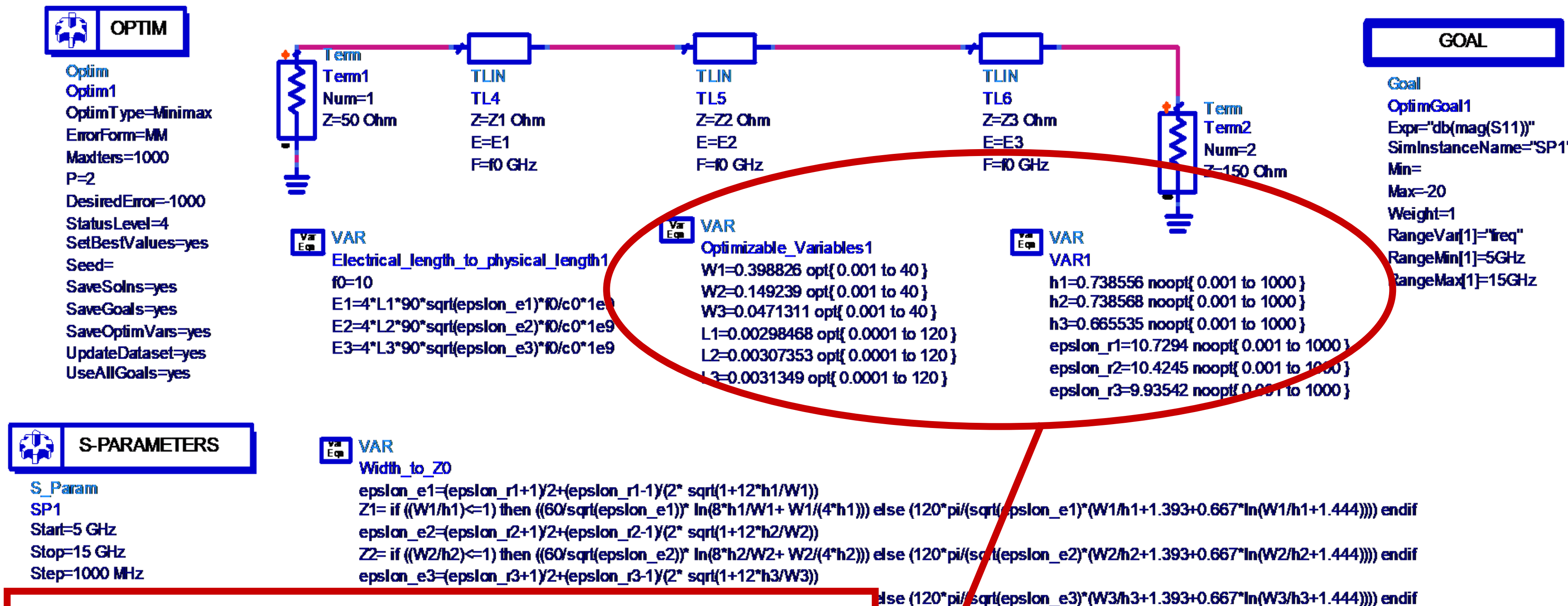
Implicit Space Mapping: Step 7

calibrate coarse model: extract preassigned parameters ***x***



Implicit Space Mapping: Steps 8-3

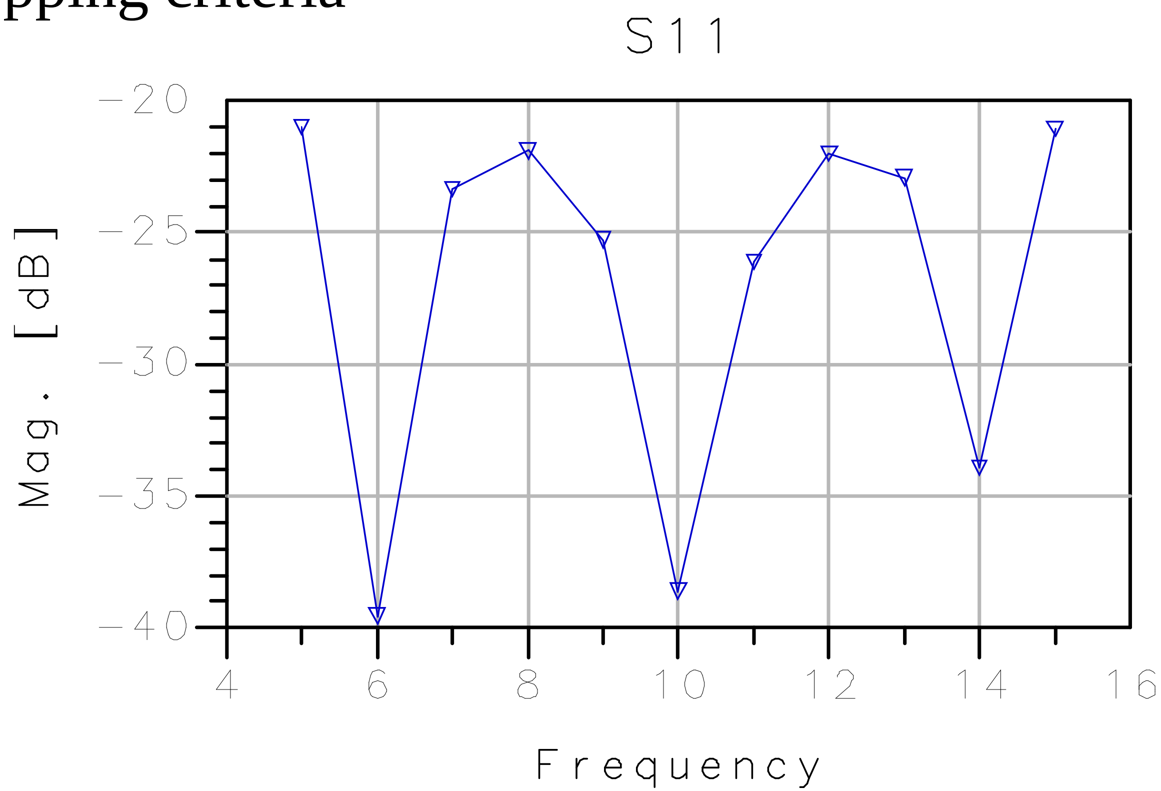
fix preassigned parameters: reoptimize calibrated coarse model



fix preassigned parameters:
reoptimize calibrated coarse model

Implicit Space Mapping: Steps 4-6

simulate fine model using Momentum,
satisfy stopping criteria

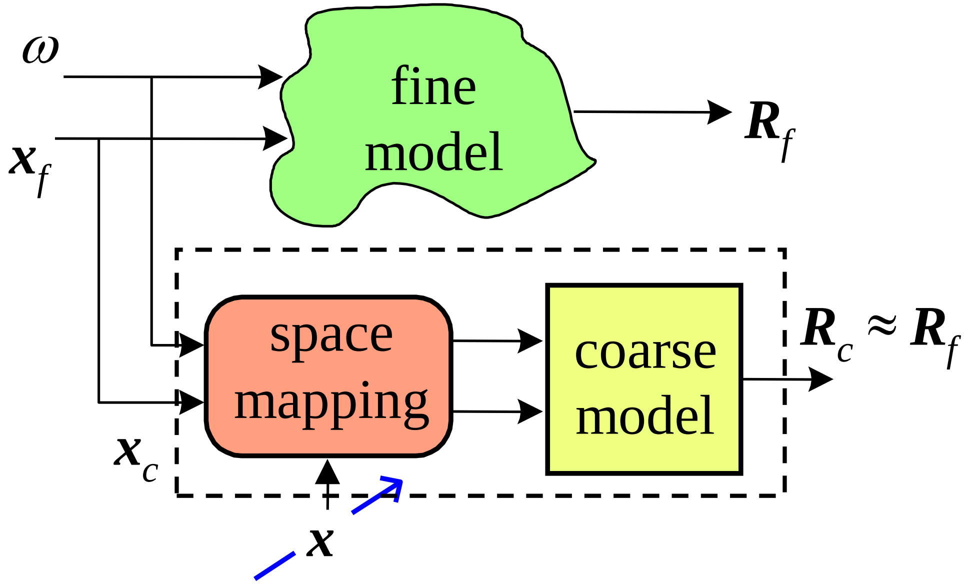


Space Mapping: a Glossary of Terms

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	?

General Space Mapping Technology (*Bandler et al., 1994-2002*)

linearized: original and Aggressive Space Mapping
nonlinear: Neural Space Mapping, etc.
implicit: preassigned parameters (ISM)



parameters x: coarse space parameters, neuron weights mapping tableau, KPP (ISM)

Space Mapping Milestones

Space Mapping - conceived as abstract concept by Bandler (1993), in collaboration with Biernacki, Chen and Madsen

Space Mapping - a fundamental new theory for design with CPU intensive simulators (1994)

EM design of high-temperature superconducting (HTS) microwave filters (1994)

Aggressive Space Mapping for EM design (1995)

Space Mapping Milestones

Aggressive Space Mapping for EM design (1995)

IMS workshop on Automated Circuit Design Using Electromagnetic Simulators (Arndt, Bandler, Chen, Hoefer, Jain, Jansen, Pavio, Pucel, Sorrentino, Swanson, 1995)

fully-automated Space Mapping optimization of 3D structures (1996)

Space Mapping Milestones

OSA's Empipe connection of OSA90/hope with Sonnet Software's ***em*** field simulator (1992)

SONNET®

OSA's Empipe3D connection of OSA90/hope with

Hewlett-Packard's HFSS 3D EM simulator (1996)

Ansoft's Maxwell Eminence 3D EM simulator (1996)

Space Mapping Milestones

Space Mapping optimization with finite element (FEM) and mode matching (MM) EM simulators (1997)

further developments in Aggressive Space Mapping (1998-)

Generalized Space Mapping (GSM) tableau approach to device modeling (1999)

Neuro Space Mapping (NSM) device modeling (1999)

Space Mapping Milestones

research begins on surrogate model/space mapping optimization algorithms (1999)

the SMX engineering optimization system (2000)

First International Workshop on Surrogate Modelling and Space Mapping for Engineering Optimization (2000)

Neural Inverse Space Mapping (NISM) optimization (2001)

Expanded Space Mapping Design Framework (ESMDF) (2001)

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)

Original Rosenbrock Function (Coarse Model)

(*Bandler et al., 1999*)

$$R_c(\boldsymbol{x}_c) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2$$

where $\boldsymbol{x}_c = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $\boldsymbol{x}_c^* = \begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$

Shifted Rosenbrock Function (Fine Model)

(*Bandler et al., 1999*)

$$R_f(\boldsymbol{x}_f) = 100\left((x_2 + \alpha_2) - (x_1 + \alpha_1)^2\right)^2 + \left(1 - (x_1 + \alpha_1)\right)^2$$

where $\boldsymbol{x}_f = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$, $\begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} -0.2 \\ 0.2 \end{bmatrix}$ hence $\boldsymbol{x}_f^* = \begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$

Gradient Parameter Extraction (GPE)

(*Bandler et al., 2002*)

at the *j*th iteration

$$\boldsymbol{x}_c^{(j)} = \arg\min_{\boldsymbol{x}_c} \left\| [\boldsymbol{e}_0^T \quad \lambda \boldsymbol{e}_1^T \quad \cdots \quad \lambda \boldsymbol{e}_n^T]^T \right\|_2^2, \ \lambda \geq 0$$

where λ is a weighting factor and $\boldsymbol{E} = [\boldsymbol{e}_1 \ \boldsymbol{e}_2 \ \ldots \ \boldsymbol{e}_n]$

$$\boldsymbol{e}_0 = \boldsymbol{R}_f(\boldsymbol{x}_f^{(j)}) - \boldsymbol{R}_c(\boldsymbol{x}_c)$$

$$\boldsymbol{E} = \boldsymbol{J}_f(\boldsymbol{x}_f^{(j)}) - \boldsymbol{J}_c(\boldsymbol{x}_c)\boldsymbol{B}$$

Shifted Rosenbrock Function Results

useful notation

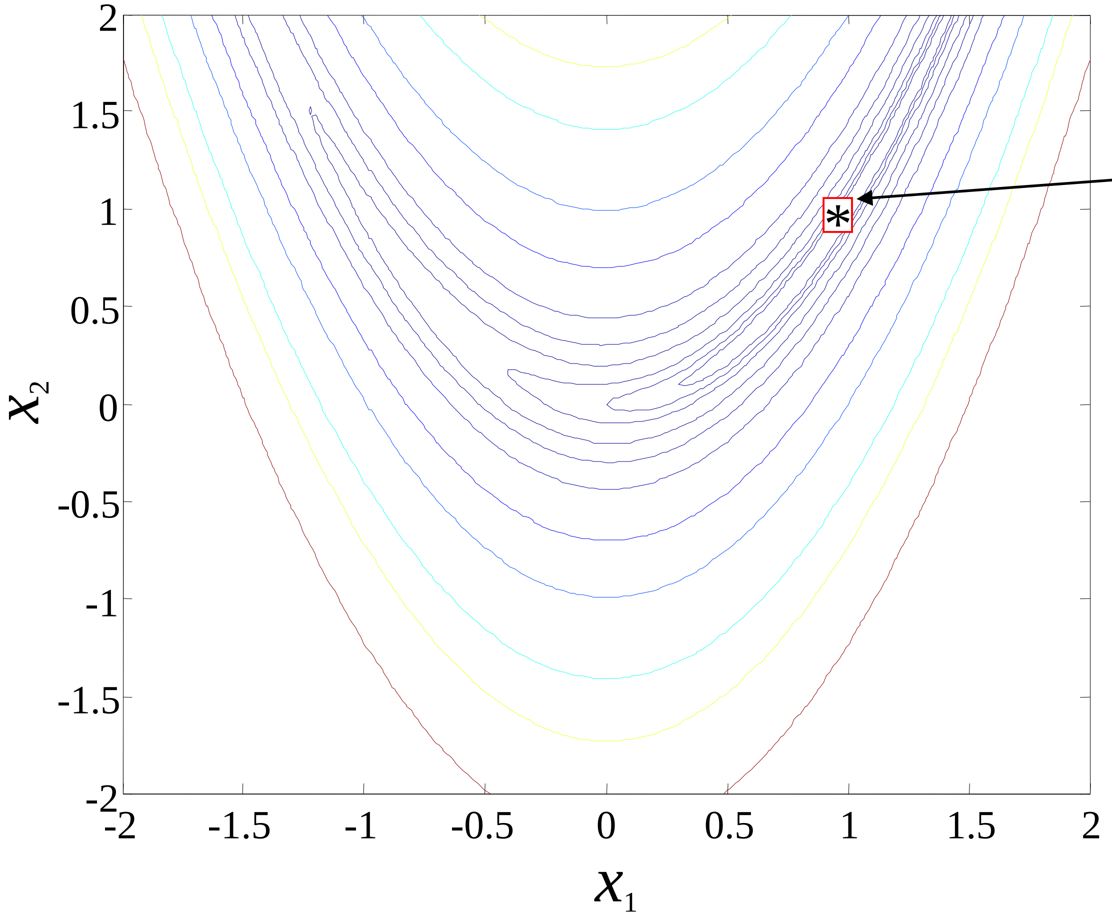
$$\boldsymbol{f}^{(j)} = \boldsymbol{x}_c^{(j)} - \boldsymbol{x}_c^{*} \, ,$$

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

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

Original Rosenbrock Function (Coarse Model Contour Plot)

(*Bandler et al., 1999*)

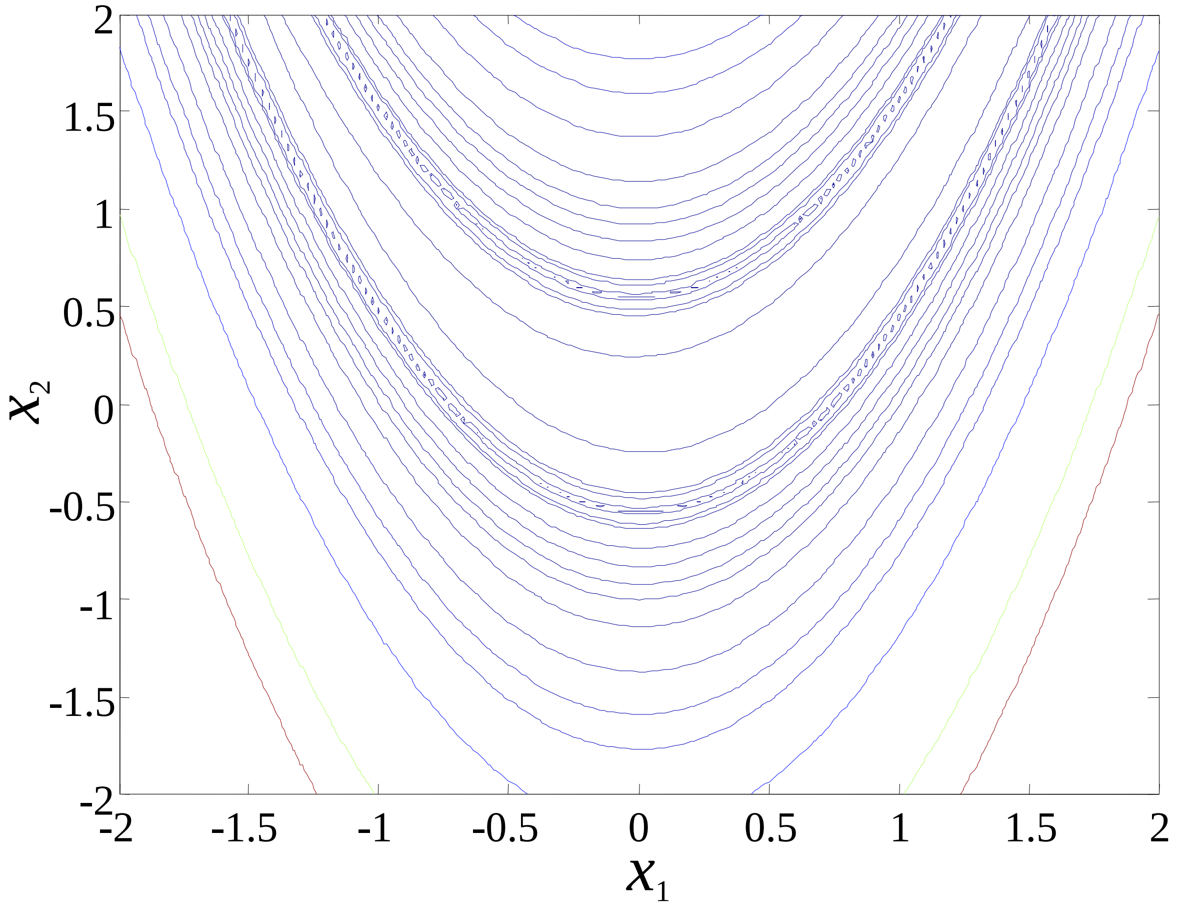


$$\boldsymbol{x}_c^* = \begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$$

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

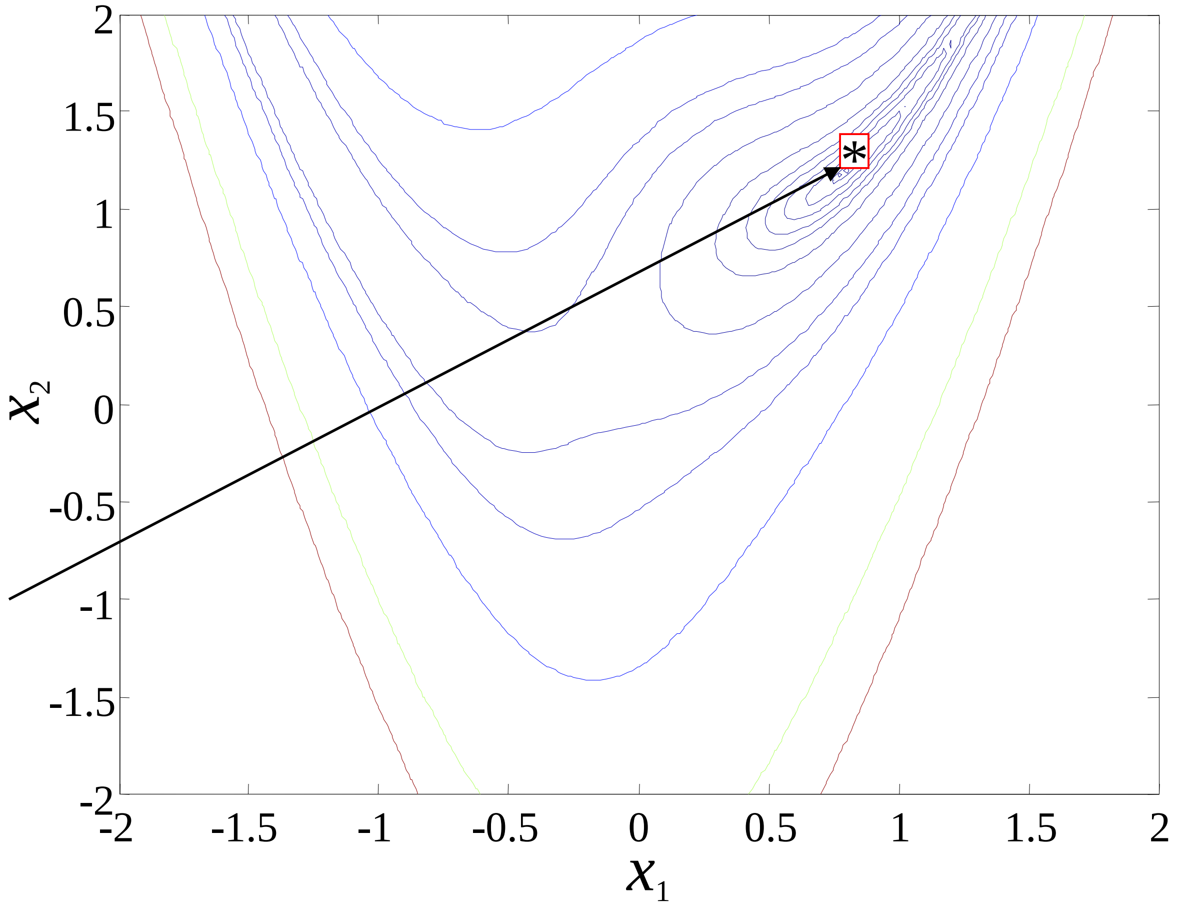
Shifted Rosenbrock Function (*Bandler et al., 2002*)

Single point PE (SPE): nonuniqueness exists



Shifted Rosenbrock Function (*Bandler et al., 2002*)

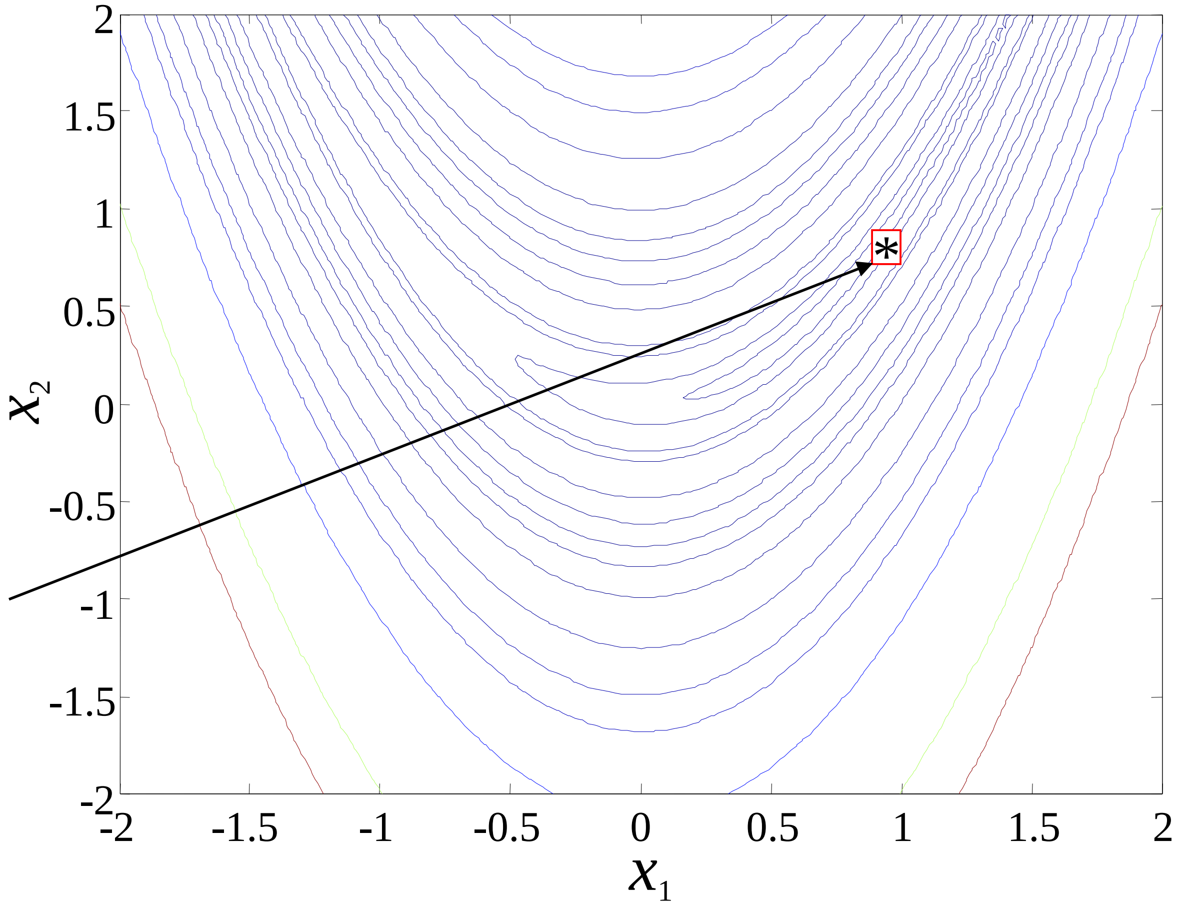
Gradient PE (1st iteration)



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

Shifted Rosenbrock Function (*Bandler et al., 2002*)

Gradient PE (2nd iteration)



$$\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$$

Shifted Rosenbrock Function Results

(*Bandler et al., 2002*)

iteration	$\boldsymbol{x}_c^{(j)}$	$\boldsymbol{f}^{(j)}$	$\boldsymbol{B}^{(j)}$	$\boldsymbol{h}^{(j)}$	$\boldsymbol{x}_f^{(j)}$	R_f
0	$\begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$	---	---	---	$\begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$	31.4
1	$\begin{bmatrix} 0.8 \\ 1.2 \end{bmatrix}$	$\begin{bmatrix} -0.2 \\ 0.2 \end{bmatrix}$	$\begin{bmatrix} 1.0 & 0.0 \\ 0.0 & 1.0 \end{bmatrix}$	$\begin{bmatrix} 0.2 \\ -0.2 \end{bmatrix}$	$\begin{bmatrix} 1.2 \\ 0.8 \end{bmatrix}$	0
	$\begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$	$\begin{bmatrix} 0 \\ 0 \end{bmatrix}$				

Transformed Rosenbrock Function (Fine Model)

(*Bandler et al., 2002*)

linear transformation of the original Rosenbrock function

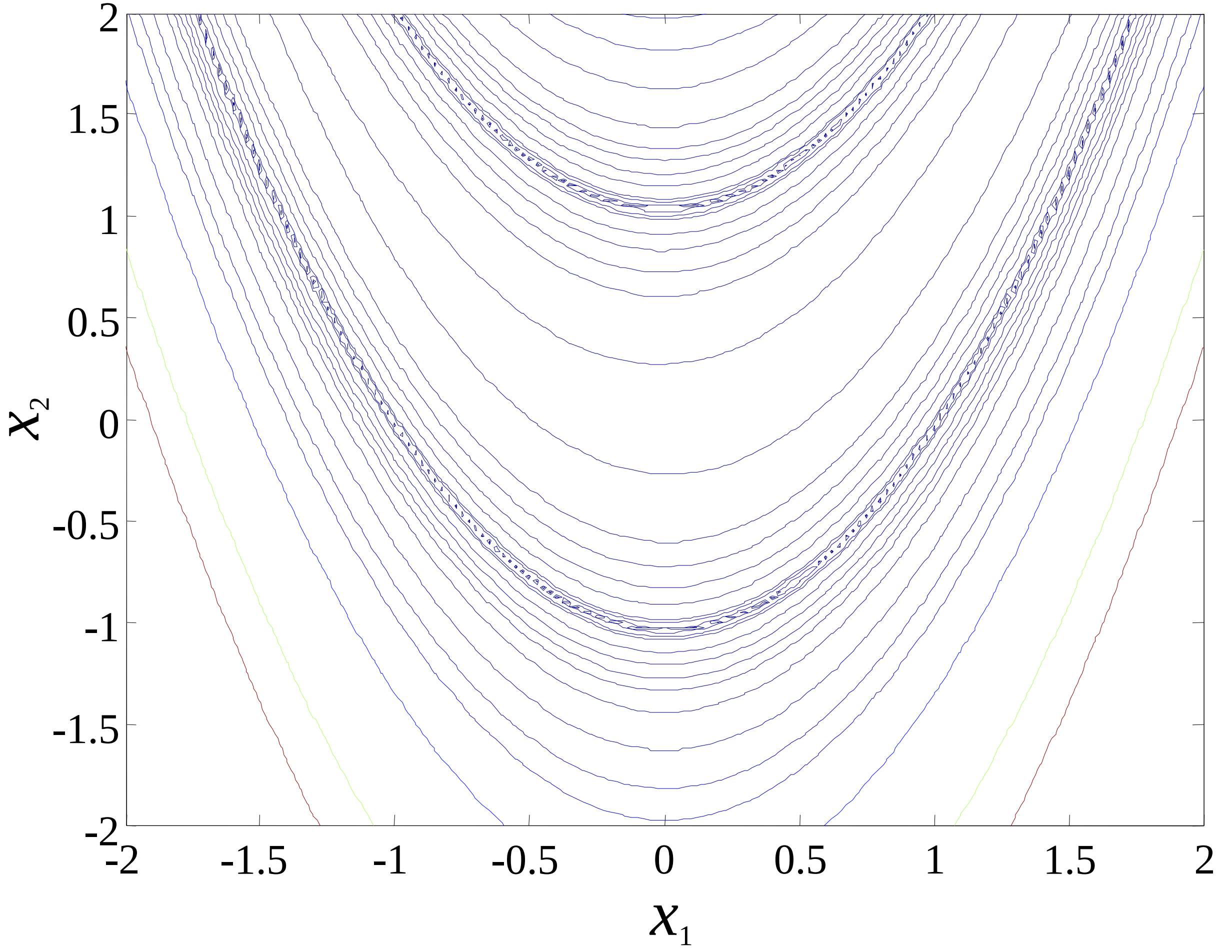
$$R_f(\boldsymbol{x}_f) = 100(u_2 - u_1^2)^2 + (1 - u_1)^2$$

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

$$\boldsymbol{x}_f^* = \begin{bmatrix} 1.2718447 \\ 0.4951456 \end{bmatrix}$$

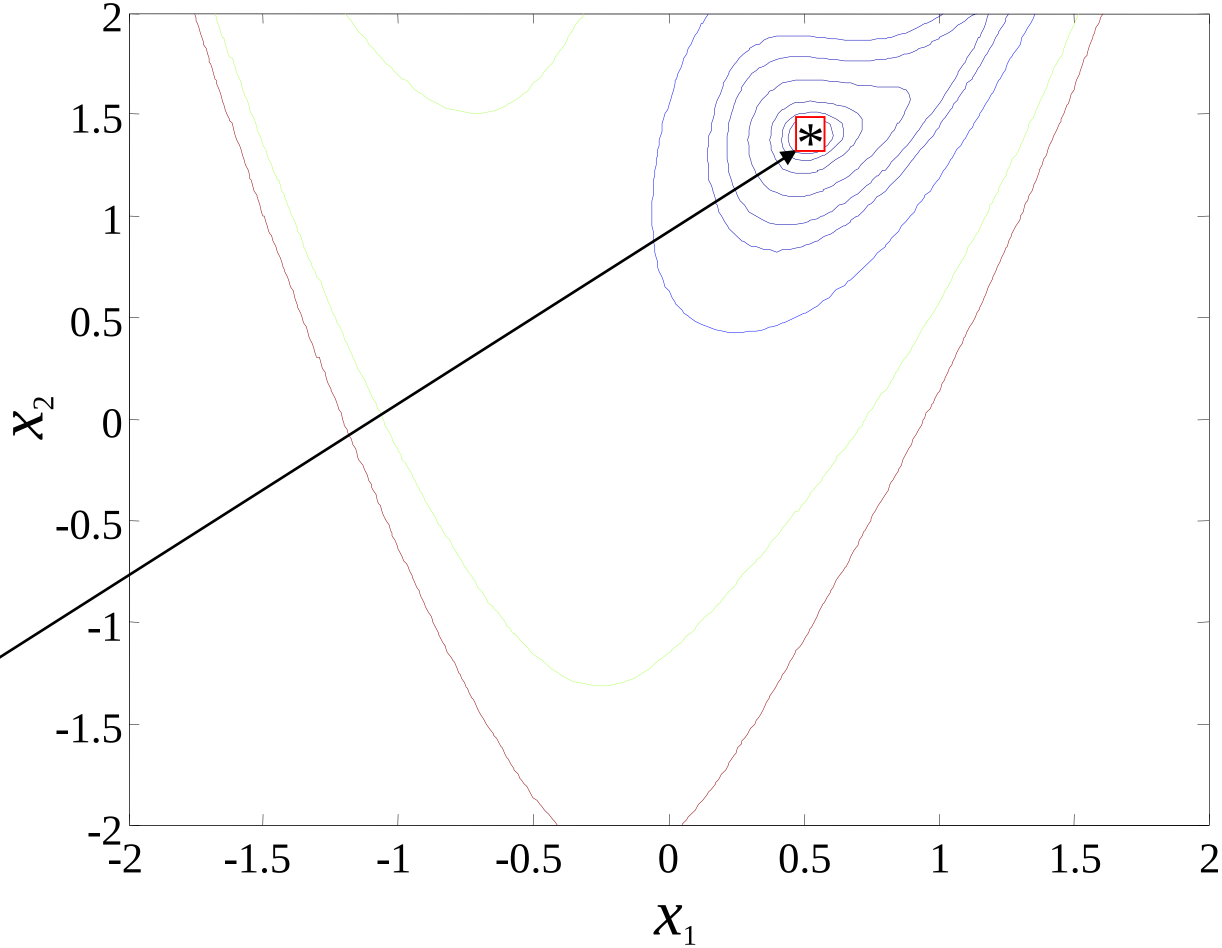
Transformed Rosenbrock Function (*Bandler et al., 2002*)

Single point PE (SPE): nonuniqueness exists



Transformed Rosenbrock Function (*Bandler et al., 2002*)

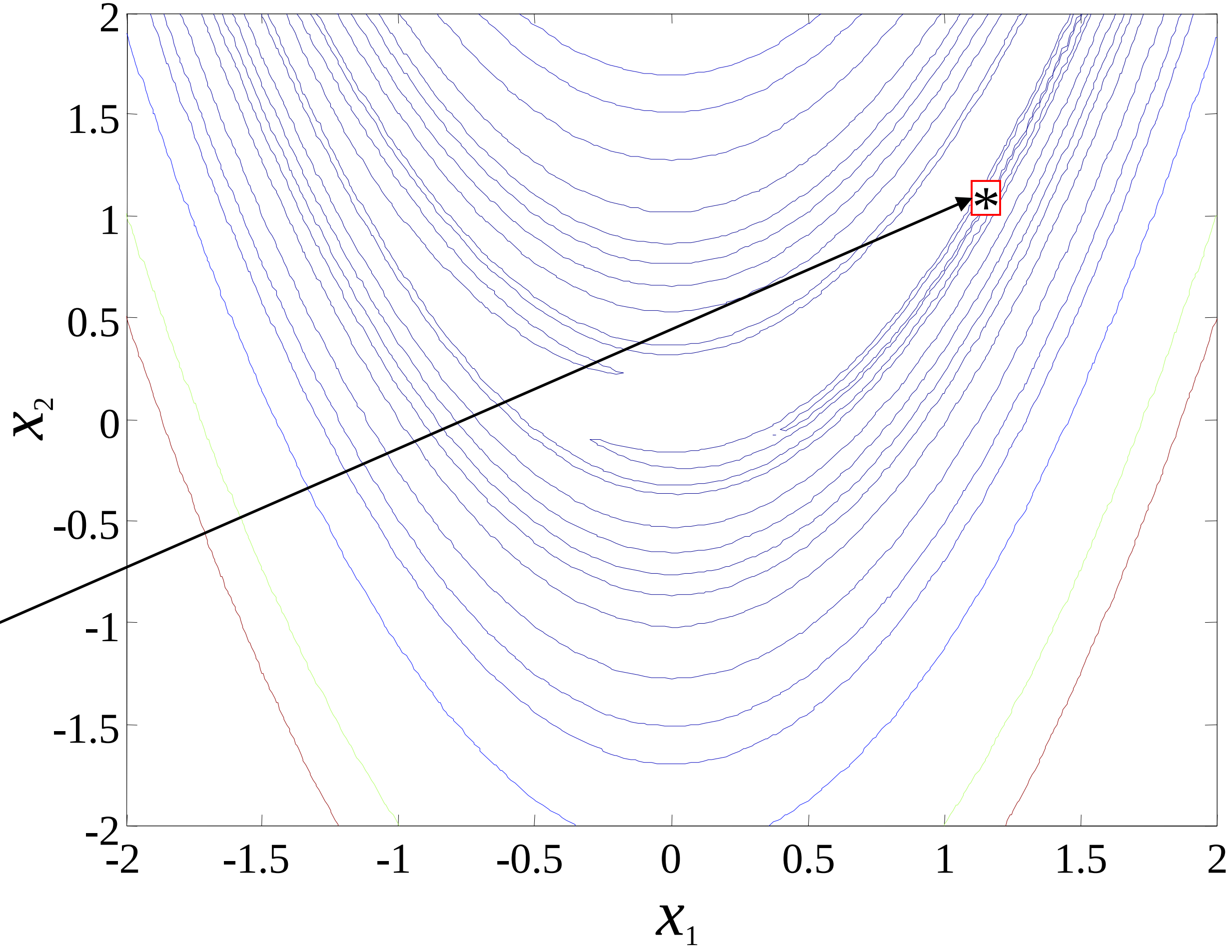
GPE (1st PE iteration)



$$\boldsymbol{x}_c^{(1)} = \begin{bmatrix} 0.53 \\ 1.38 \end{bmatrix}$$

Transformed Rosenbrock Function (*Bandler et al., 2002*)

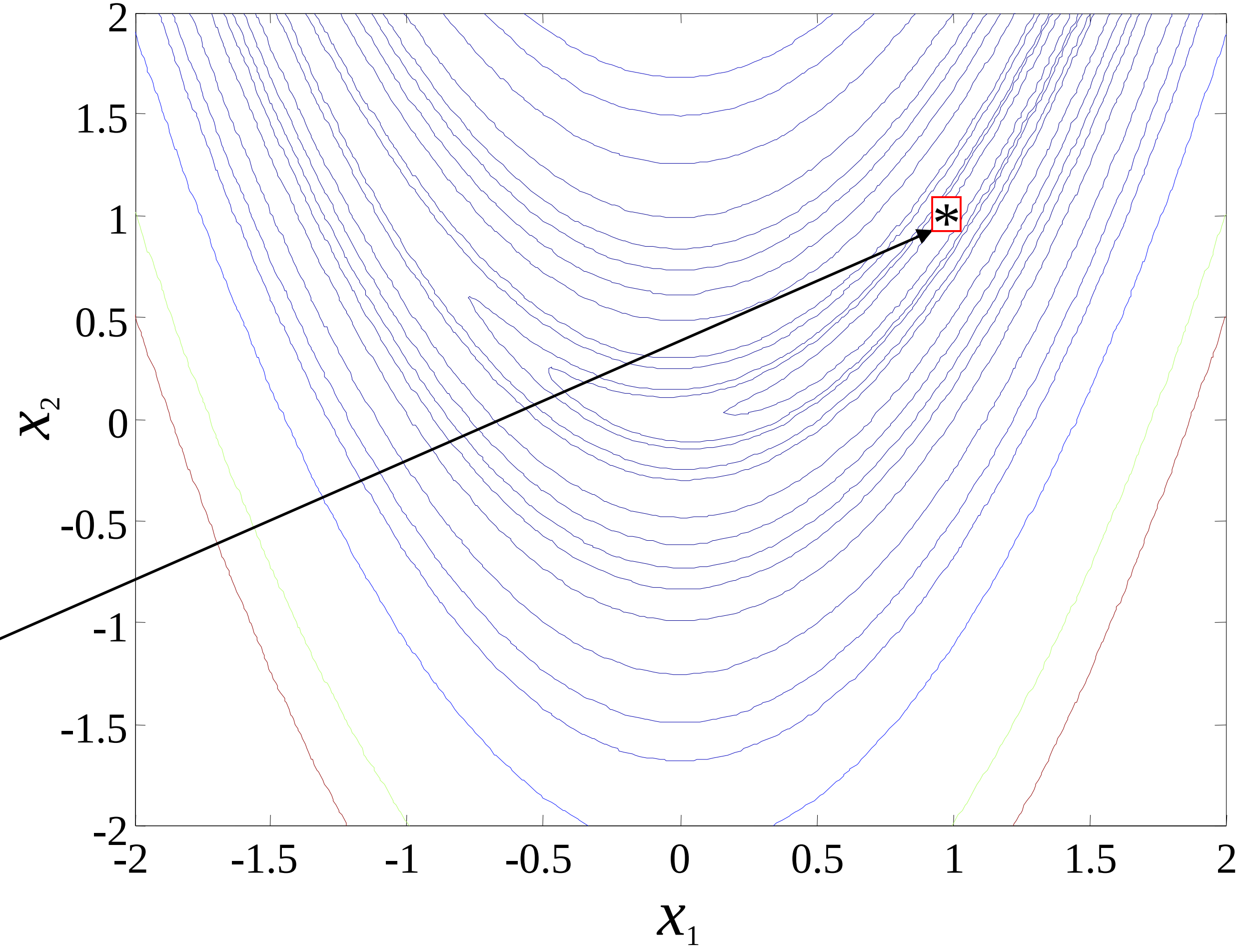
GPE (2nd PE iteration)



$$\boldsymbol{x}_c^{(2)} = \begin{bmatrix} 1.18 \\ 1.18 \end{bmatrix}$$

Transformed Rosenbrock Function (*Bandler et al., 2002*)

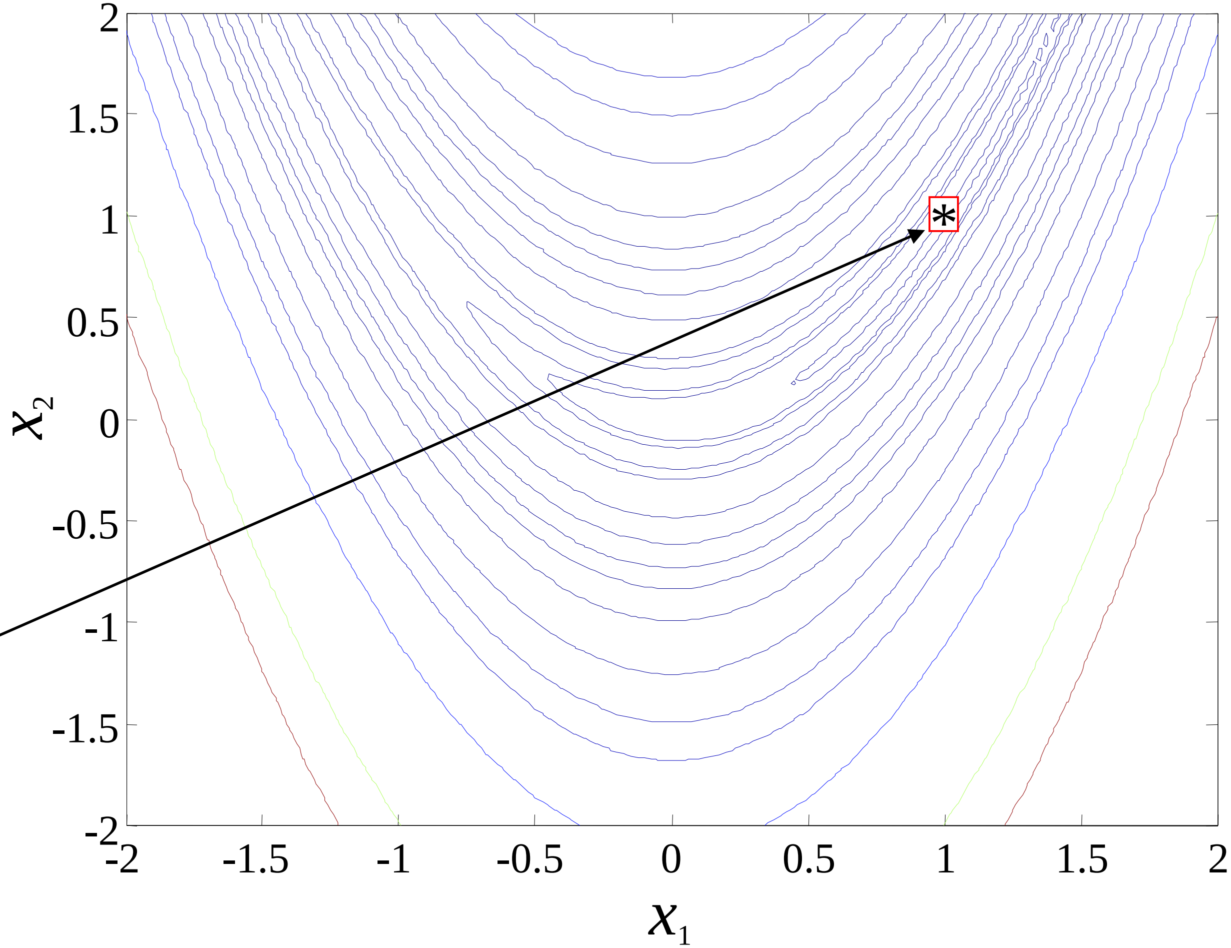
GPE (3rd PE iteration)



$$\boldsymbol{x}_c^{(3)} = \begin{bmatrix} 0.967 \\ 0.929 \end{bmatrix}$$

Transformed Rosenbrock Function (*Bandler et al., 2002*)

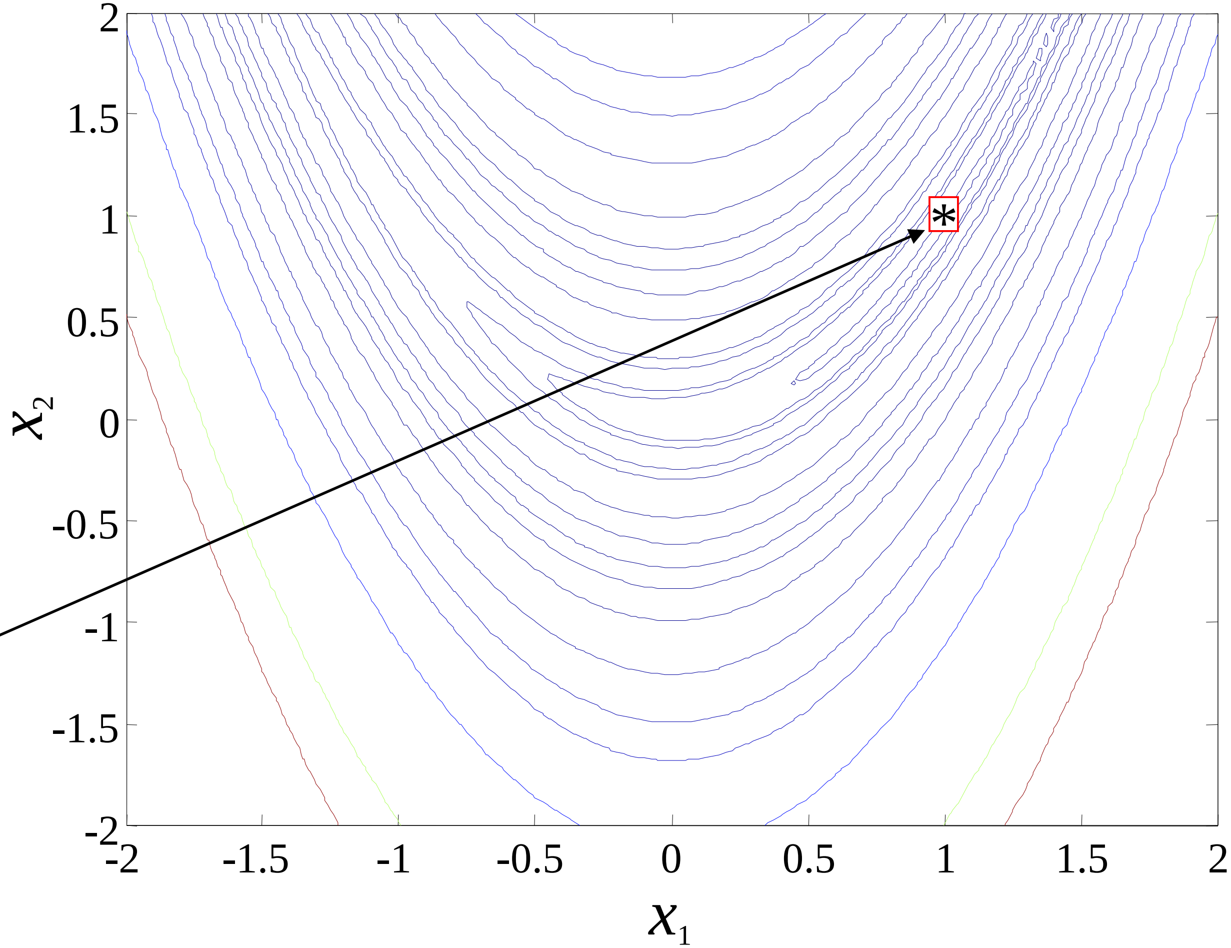
GPE (4th PE iteration)



$$\boldsymbol{x}_c^{(4)} = \begin{bmatrix} 1.0009 \\ 1.0018 \end{bmatrix}$$

Transformed Rosenbrock Function (*Bandler et al., 2002*)

GPE (5th and 6th PE iteration)



$$\boldsymbol{x}_c^{(5)} = \begin{bmatrix} 1.00002 \\ 1.00004 \end{bmatrix}$$

$$\boldsymbol{x}_c^{(6)} = \begin{bmatrix} 1.0 \\ 1.0 \end{bmatrix}$$

Transformed Rosenbrock Results (*Bandler et al., 2002*)

iteration	$\boldsymbol{x}_c^{(j)}$	$\boldsymbol{f}^{(j)}$	$\boldsymbol{B}^{(j)}$	$\boldsymbol{h}^{(j)}$	$\boldsymbol{x}_f^{(j)}$	R_f
0	$\begin{bmatrix}1.0\\1.0\end{bmatrix}$	---	---	---	$\begin{bmatrix}1.0\\1.0\end{bmatrix}$	108.3
1	$\begin{bmatrix}0.526\\1.384\end{bmatrix}$	$\begin{bmatrix}-0.474\\0.384\end{bmatrix}$	$\begin{bmatrix}1.01 & -0.05\\0.01 & 1.01\end{bmatrix}$	$\begin{bmatrix}0.447\\-0.385\end{bmatrix}$	$\begin{bmatrix}1.447\\0.615\end{bmatrix}$	5.119
2	$\begin{bmatrix}1.185\\1.178\end{bmatrix}$	$\begin{bmatrix}0.185\\0.178\end{bmatrix}$	$\begin{bmatrix}0.96 & -0.12\\-0.096 & 1.06\end{bmatrix}$	$\begin{bmatrix}-0.218\\-0.187\end{bmatrix}$	$\begin{bmatrix}1.23\\0.427\end{bmatrix}$	4.4E–3
3	$\begin{bmatrix}0.967\\0.929\end{bmatrix}$	$\begin{bmatrix}-0.033\\-0.071\end{bmatrix}$	$\begin{bmatrix}1.09 & -0.19\\0.168 & 0.92\end{bmatrix}$	$\begin{bmatrix}0.0429\\0.0697\end{bmatrix}$	$\begin{bmatrix}1.273\\0.4970\end{bmatrix}$	1.8E–6
4	$\begin{bmatrix}1.001\\1.001\end{bmatrix}$	$\begin{bmatrix}0.001\\0.001\end{bmatrix}$	$\begin{bmatrix}1.10001 & -0.1999\\0.1999 & 0.9001\end{bmatrix}$	$\begin{bmatrix}-0.001\\-0.002\end{bmatrix}$	$\begin{bmatrix}1.2719\\0.4952\end{bmatrix}$	5E–10

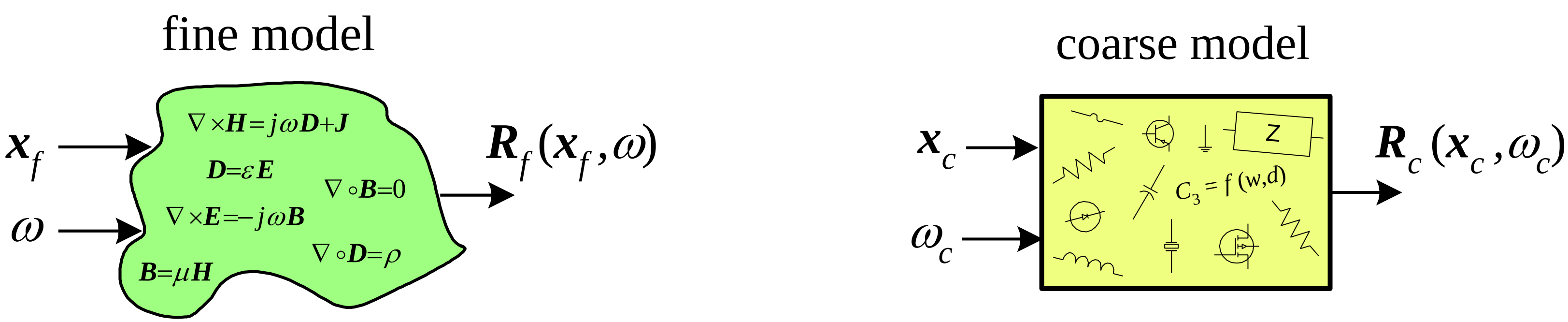
Transformed Rosenbrock Results (*Bandler et al., 2002*)

iteration	$\boldsymbol{x}_c^{(j)}$	$\boldsymbol{f}^{(j)}$	$\boldsymbol{B}^{(j)}$	$\boldsymbol{h}^{(j)}$	$\boldsymbol{x}_f^{(j)}$	R_f
5	$\begin{bmatrix}1.00002\\1.00004\end{bmatrix}$	$1E-4\times\begin{bmatrix}0.2\\0.4\end{bmatrix}$	$\begin{bmatrix}1.1 & -0.2\\0.2 & 0.9\end{bmatrix}$	$1E-4\times\begin{bmatrix}0.3\\0.5\end{bmatrix}$	$\begin{bmatrix}1.2718\\0.4951\end{bmatrix}$	3E–17
6	$\begin{bmatrix}1.0\\1.0\end{bmatrix}$	$1E-8\times\begin{bmatrix}0.1\\0.3\end{bmatrix}$	$\begin{bmatrix}1.1 & -0.2\\0.2 & 0.9\end{bmatrix}$	$1E-8\times\begin{bmatrix}0.2\\0.3\end{bmatrix}$	$\boldsymbol{x}_f^*$	9E–29

$$\boldsymbol{x}_f^* = \begin{bmatrix}1.27184466\\0.49514563\end{bmatrix}$$

Conventional Space Mapping for Microwave Circuits

(*Bandler et al., 1994*)



find

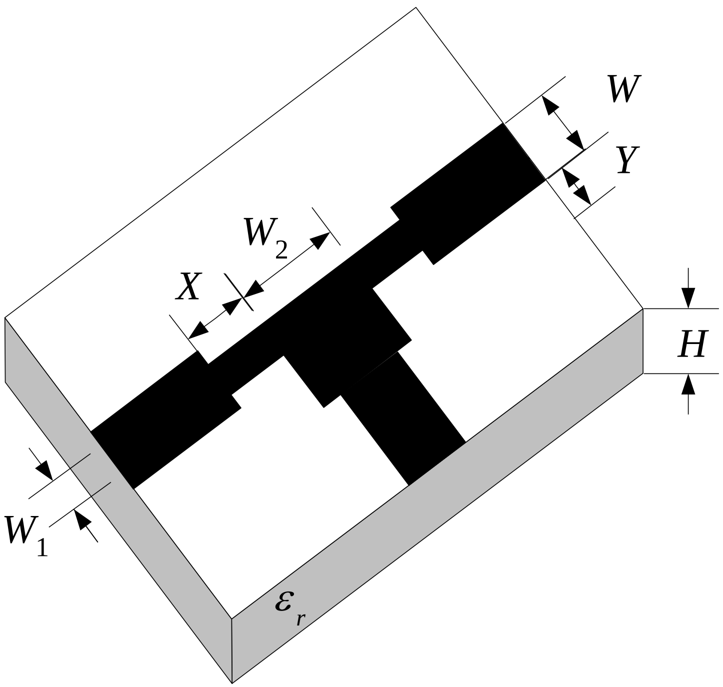
$$\begin{bmatrix} \boldsymbol{x}_c \\ \omega_c \end{bmatrix} = \boldsymbol{P}(\boldsymbol{x}_f, \omega)$$

such that

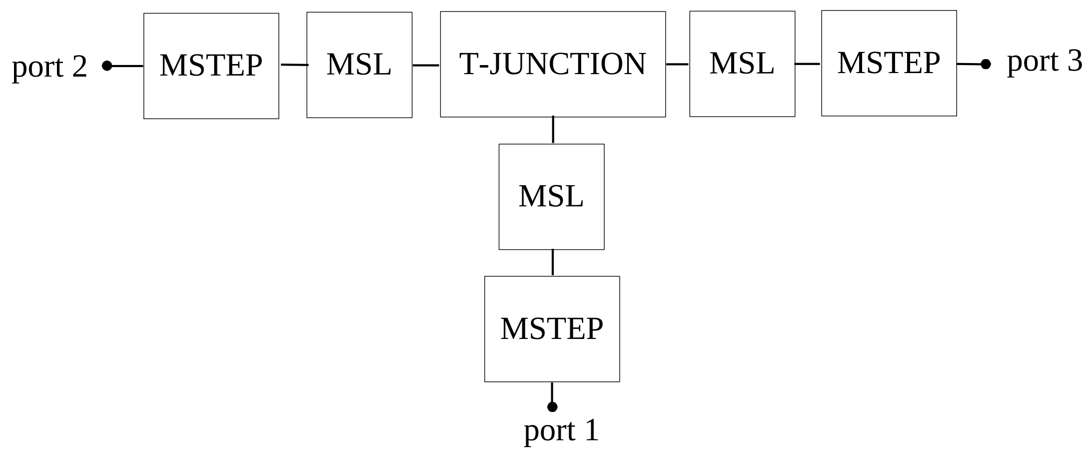
$$\boldsymbol{R}_c(\boldsymbol{x}_c, \omega_c) \approx \boldsymbol{R}_f(\boldsymbol{x}_f, \omega)$$

Microstrip Shaped T-Junction (*Bandler et al., 1999*)

fine model



coarse model



Microstrip Shaped T-Junction (*Bandler et al., 1999*)

the region of interest

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

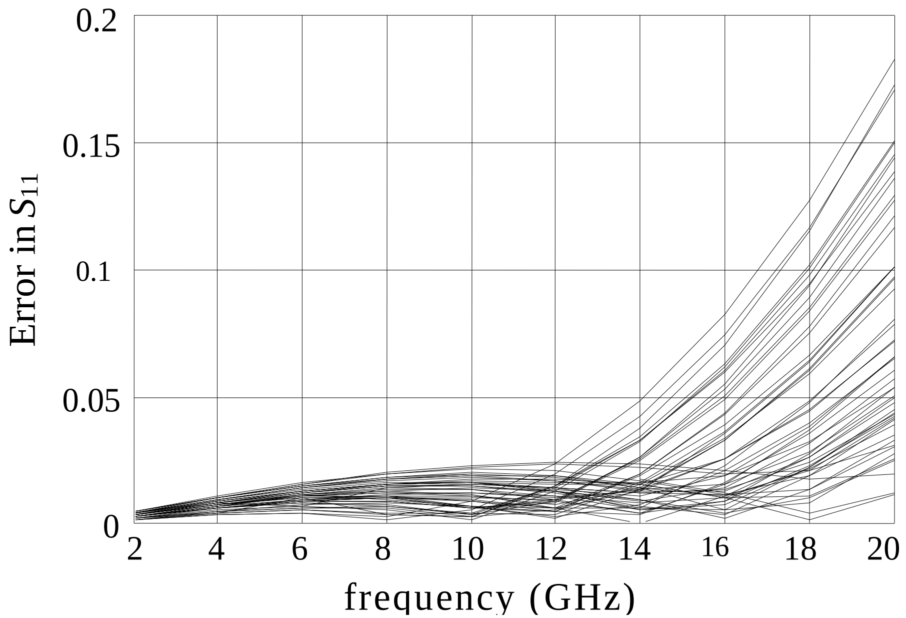
the frequency range is 2 GHz to 20 GHz with a step of 2 GHz
the number of base points is 9, the number of test points is 50

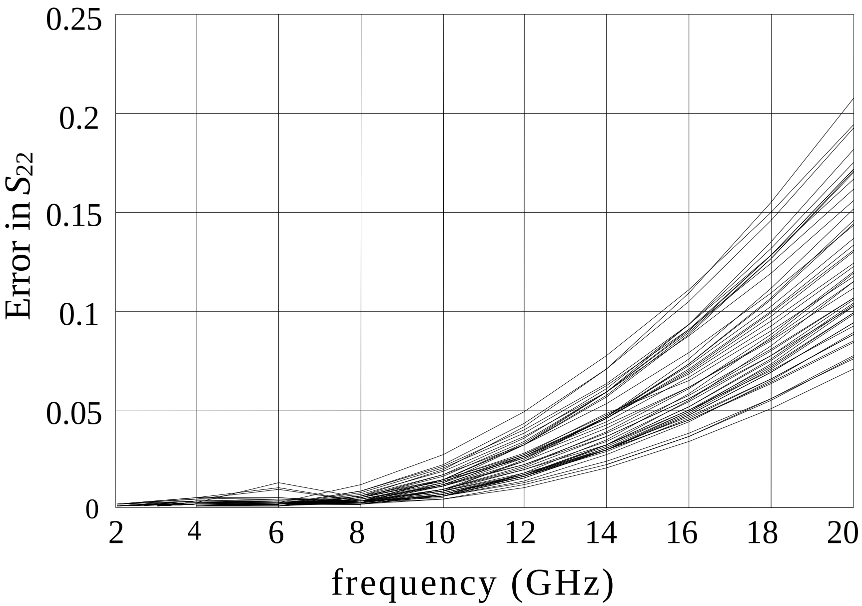
the widths W of the input lines track H so that their characteristic impedance is 50 ohm

$W_1 = W/3$, 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