UNIVERSITEIT GENT

University of L'Aquila UAq EMC Lab

FACULTY OF ENGINEERING

EMC'12 ROMA

Tutorial: Scalable Models for Efficient Design in EMC and SI Applications

Scalable Compact Models for Efficient Design in EMC and SI Applications

F. Ferranti*, T. Dhaene*, L. Knockaert*, G. Antonini**, A. Ciccomancini Scogna†

* Department of Information Technology (INTEC), Ghent University – IBBT

** Dipartimento di Ingegneria Elettrica e dell'Informazione, Università degli Studi dell'Aquila

† CST of America

Outline

Introduction

Scalable Macromodels

Numerical examples
- EMC example
- SI example

Conclusions

Outline

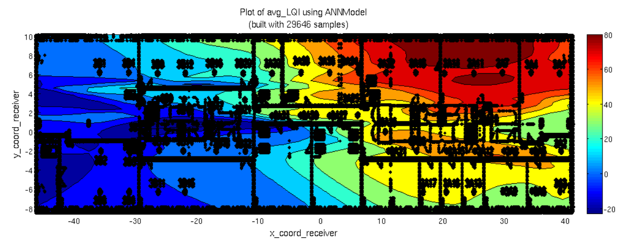
Introduction

Scalable Macromodels

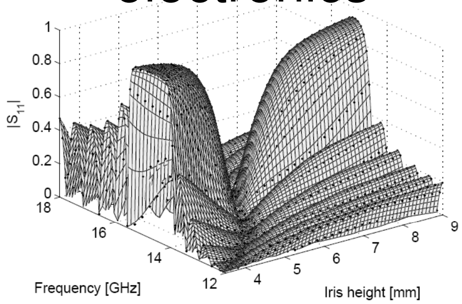
Numerical examples
- EMC example
- SI example

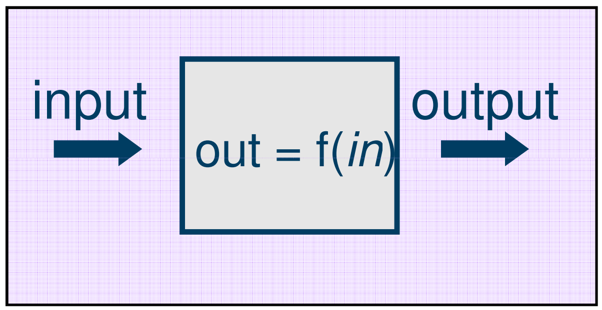
Conclusions

telecom

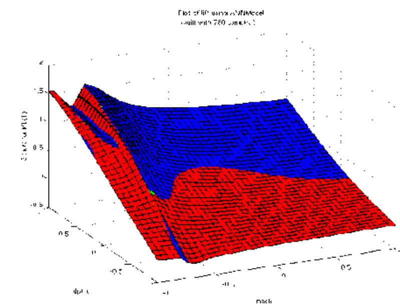


electronics

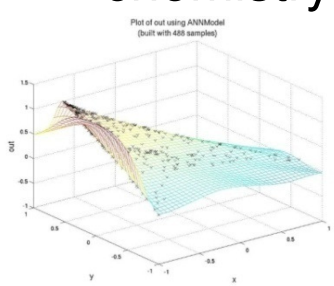




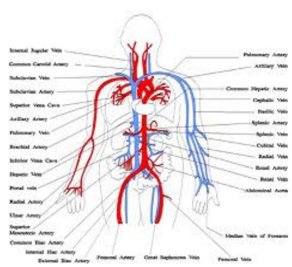
fluid dynamics



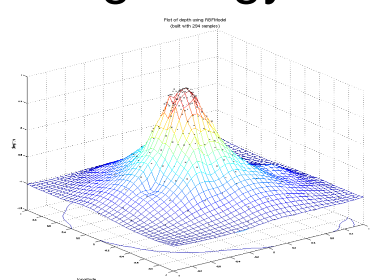
chemistry



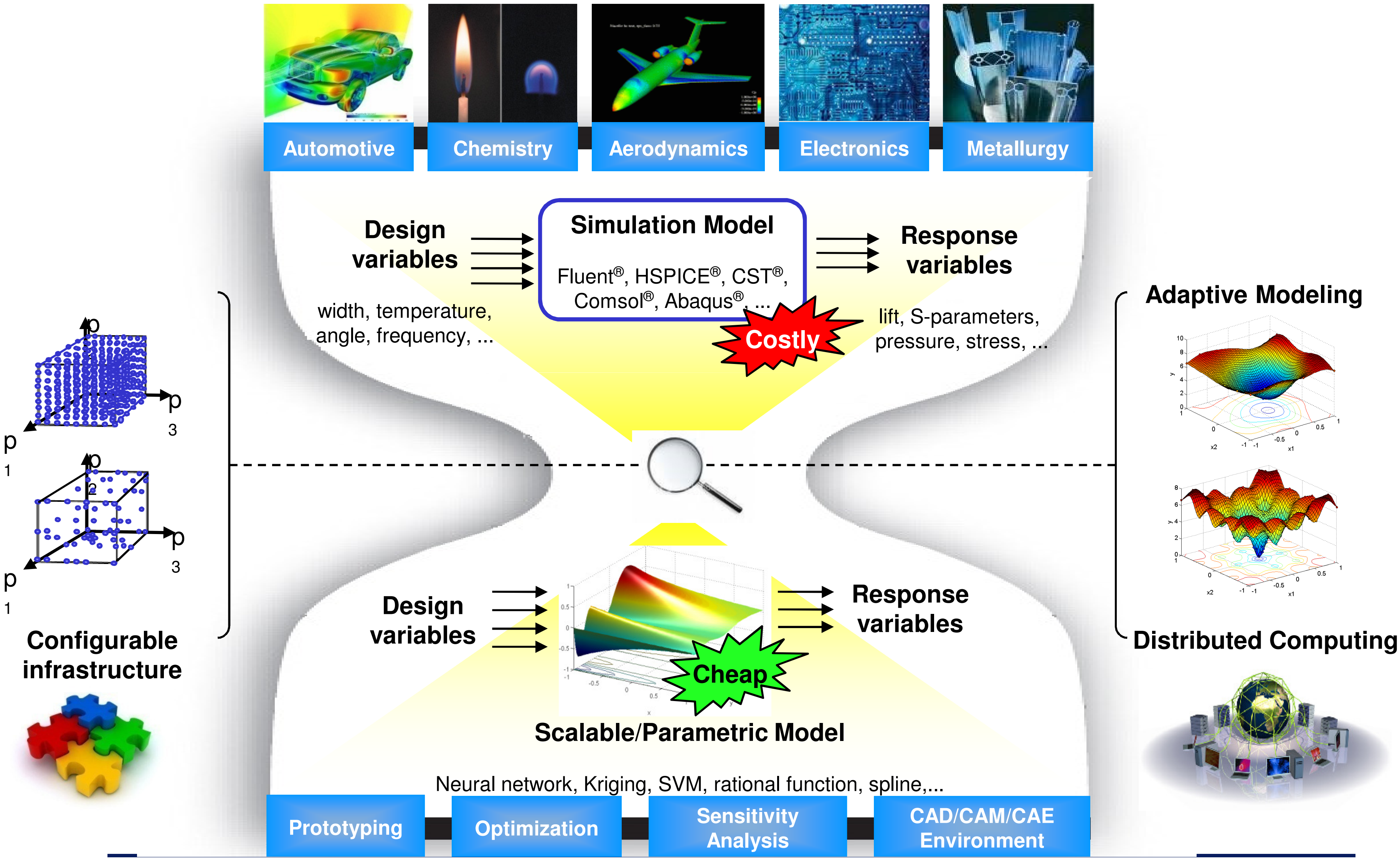
biomodeling

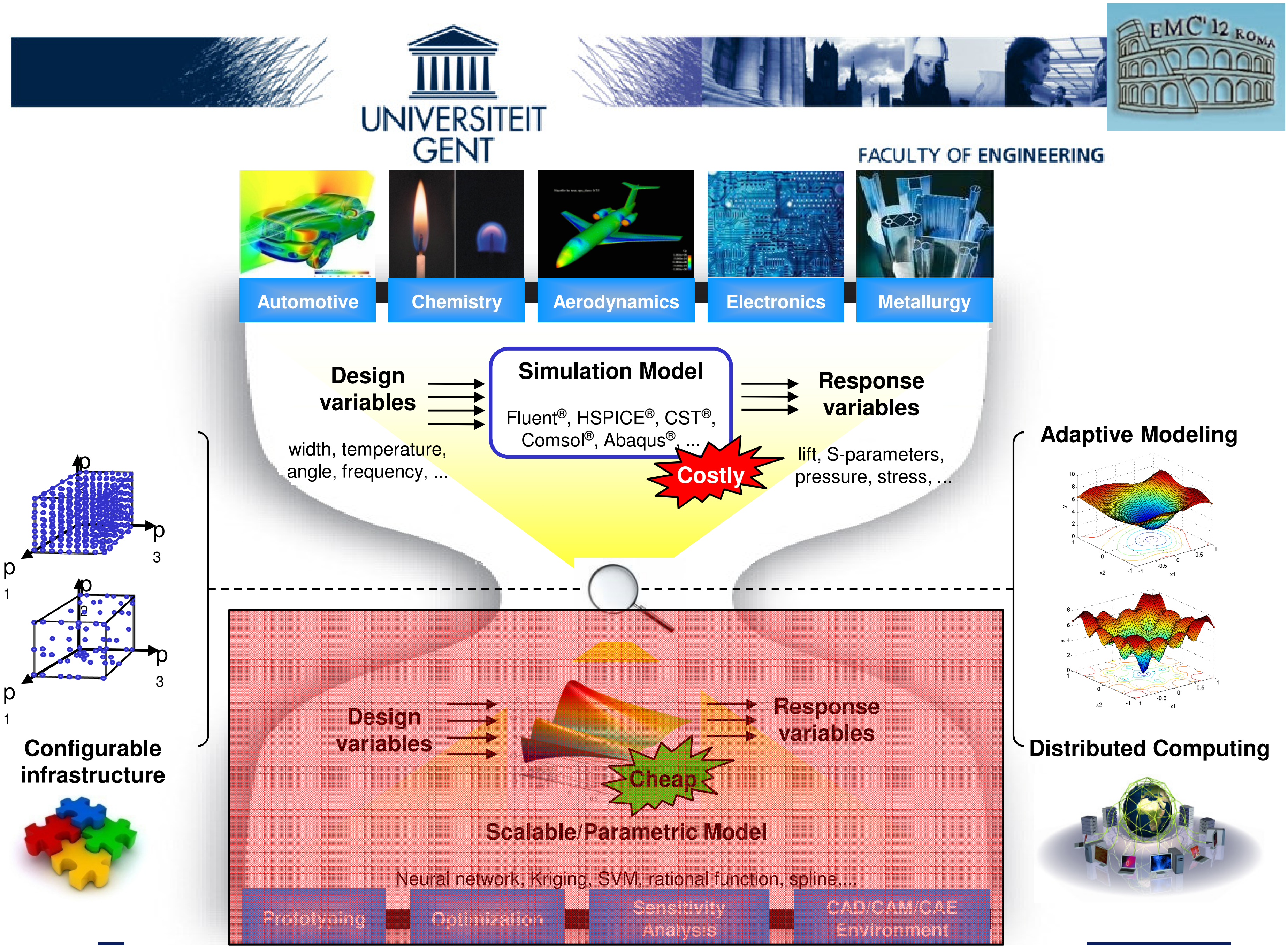


geology

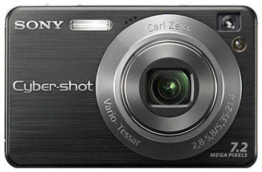


automotive

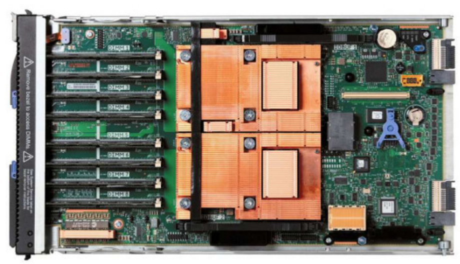

Automotive
Chemistry
Aerodynamics
Electronics
Metallurgy
Design variables
Simulation Model
Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...
Response variables
width, temperature, angle, frequency, ...
Costly
lift, S-parameters, pressure, stress, ...
Adaptive Modeling
Configurable infrastructure
Design variables
Response variables
Cheap
Scalable/Parametric Model
Distributed Computing
Neural network, Kriging, SVM, rational function, spline,...
Prototyping
Optimization
Sensitivity Analysis
CAD/CAM/CAE Environment

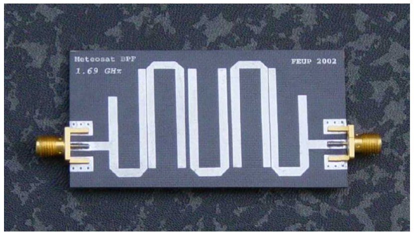


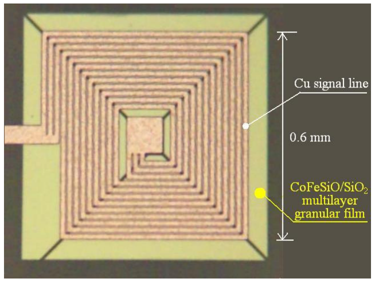
UNIVERSITEIT GENT
EMC'12 ROMA
FACULTY OF ENGINEERING
Automotive
Chemistry
Aerodynamics
Electronics
Metallurgy
Design variables
Simulation Model
Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...
Response variables
width, temperature, angle, frequency, ...
Costly
lift, S-parameters, pressure, stress, ...
Adaptive Modeling
Configurable infrastructure
Design variables
Response variables
Cheap
Scalable/Parametric Model
Neural network, Kriging, SVM, rational function, spline,...
Prototyping
Optimization
Sensitivity Analysis
CAD/CAM/CAE Environment
Distributed Computing


SONY
Cyber-shot
7.2


DELL




FEUP 2002


Cu signal line
0.6 mm
$CoFeSiO/SiO_2$ multilayer granular film

Design process

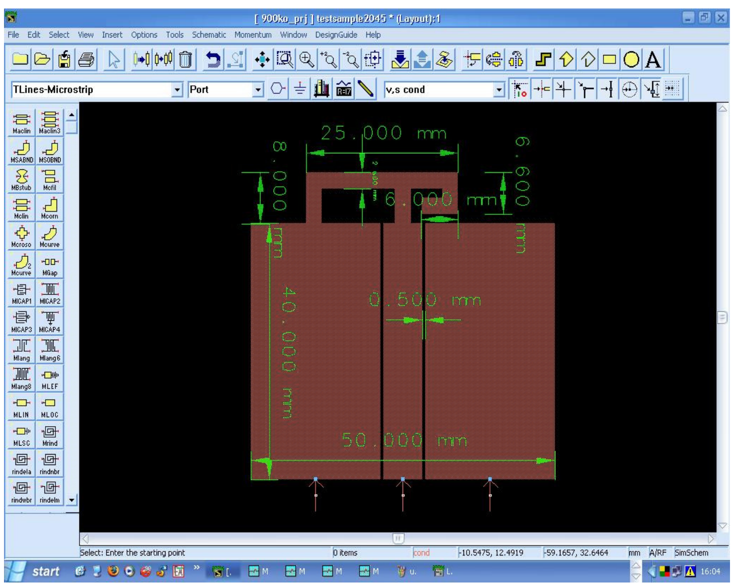
- several decisions
  - materials
  - geometrical dimensions
  - shape
  - constraints
    - space
    - cost
    - performance

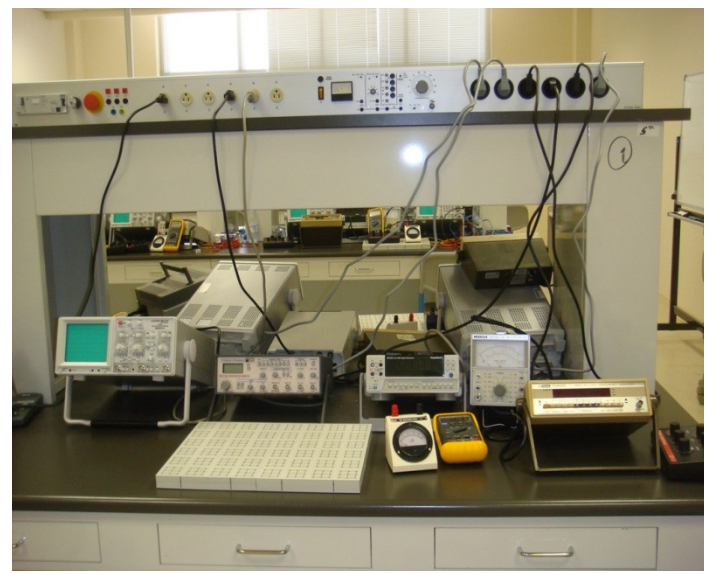
Simulators

- implementation of models
- describe systems behavior
- help designers

Measurements

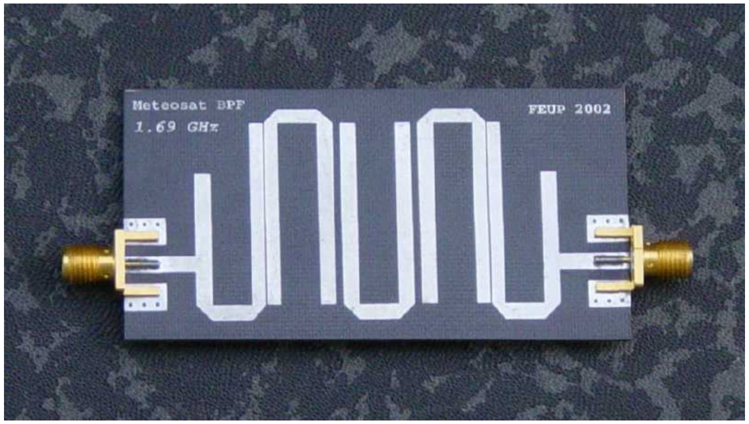
- post tuning
- verification
- help designers





A typical design process requires

- design space optimization
- design space exploration
- sensitivity analysis
  - multiple simulations (measurements)
  - different design parameters values (e.g. layout features)



A typical design process requires

- **Multiple simulations (measurements)**
  - **computationally expensive (time and memory)**

- **Can we do better?**

- **Yes**
  - **By scalable macromodels**

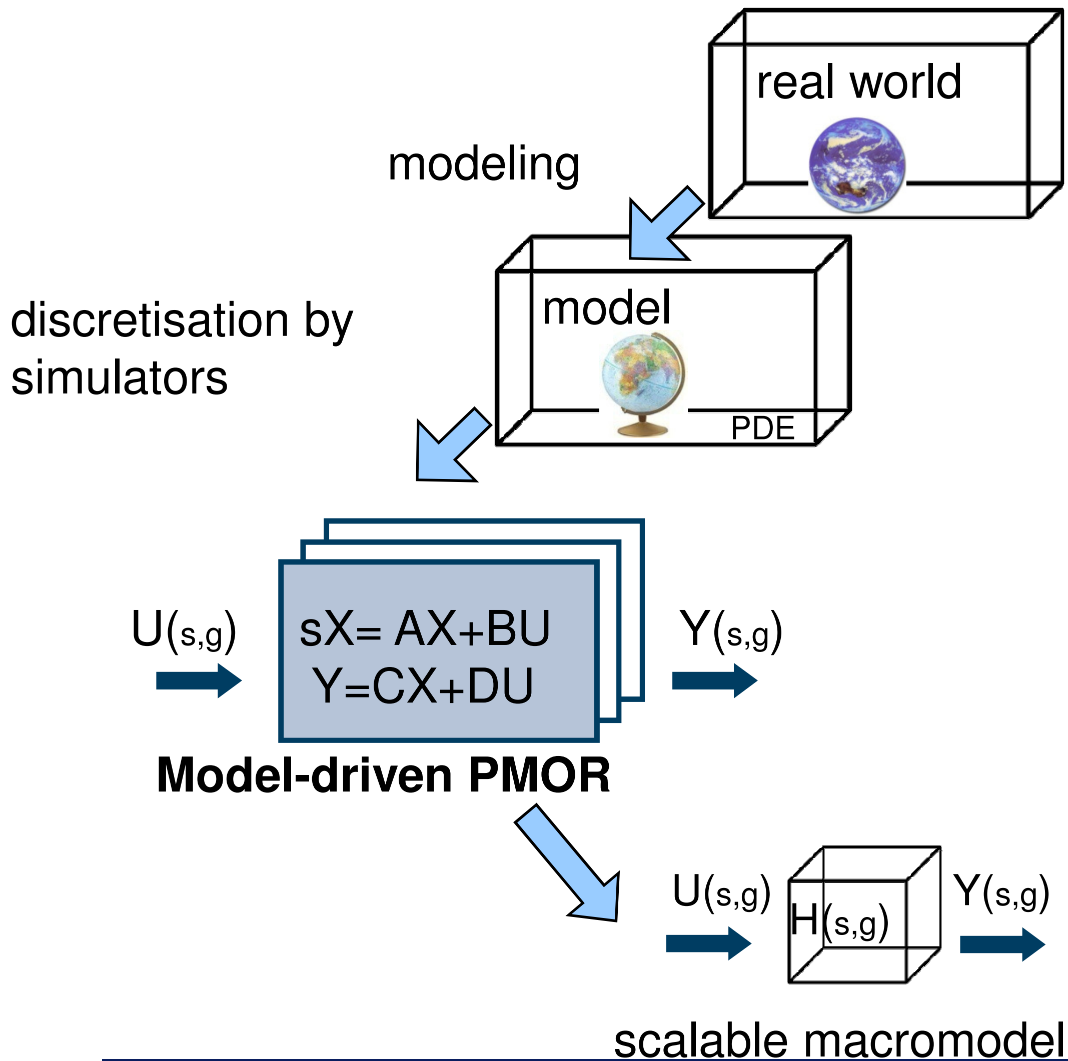
Outline

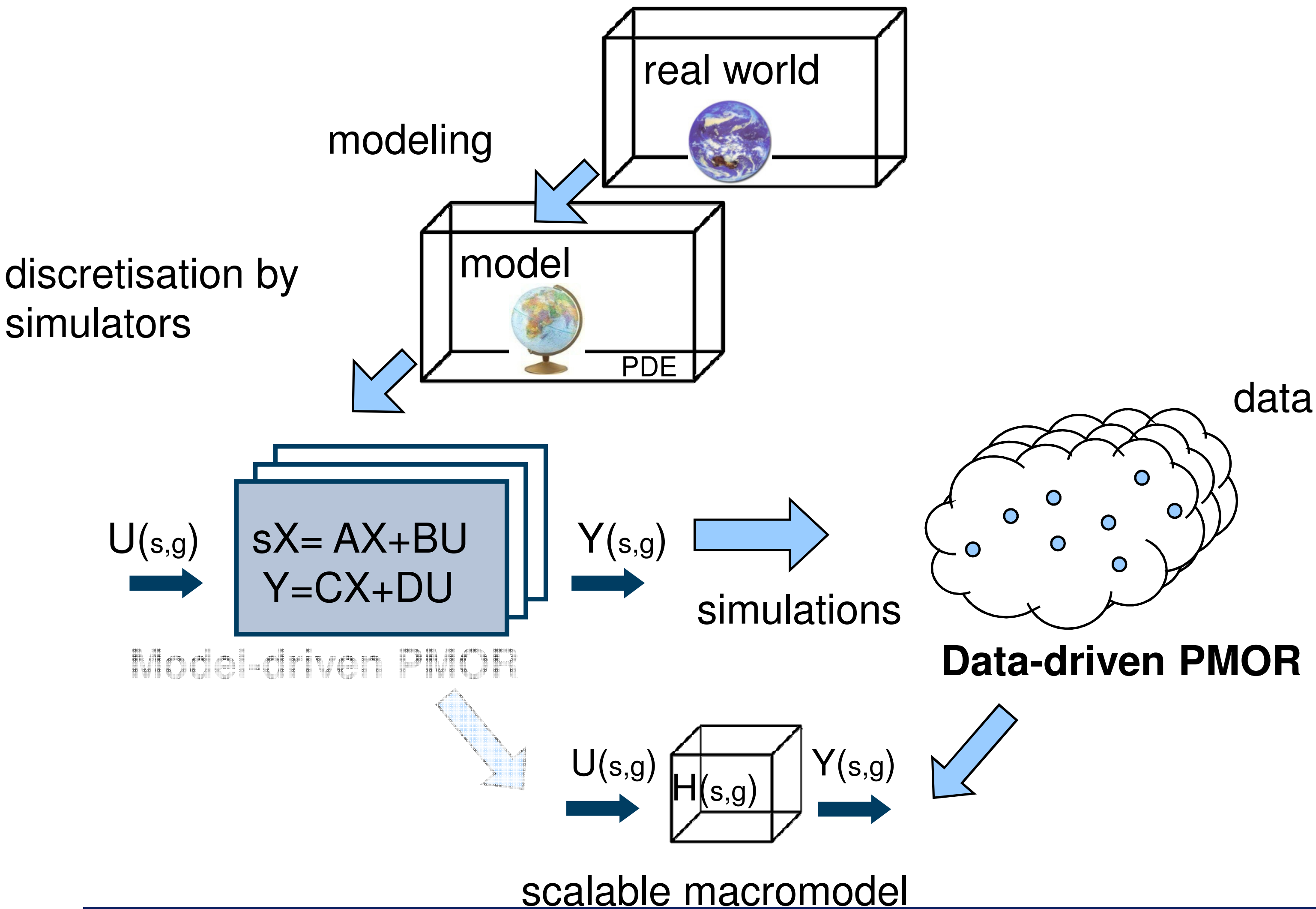
Introduction

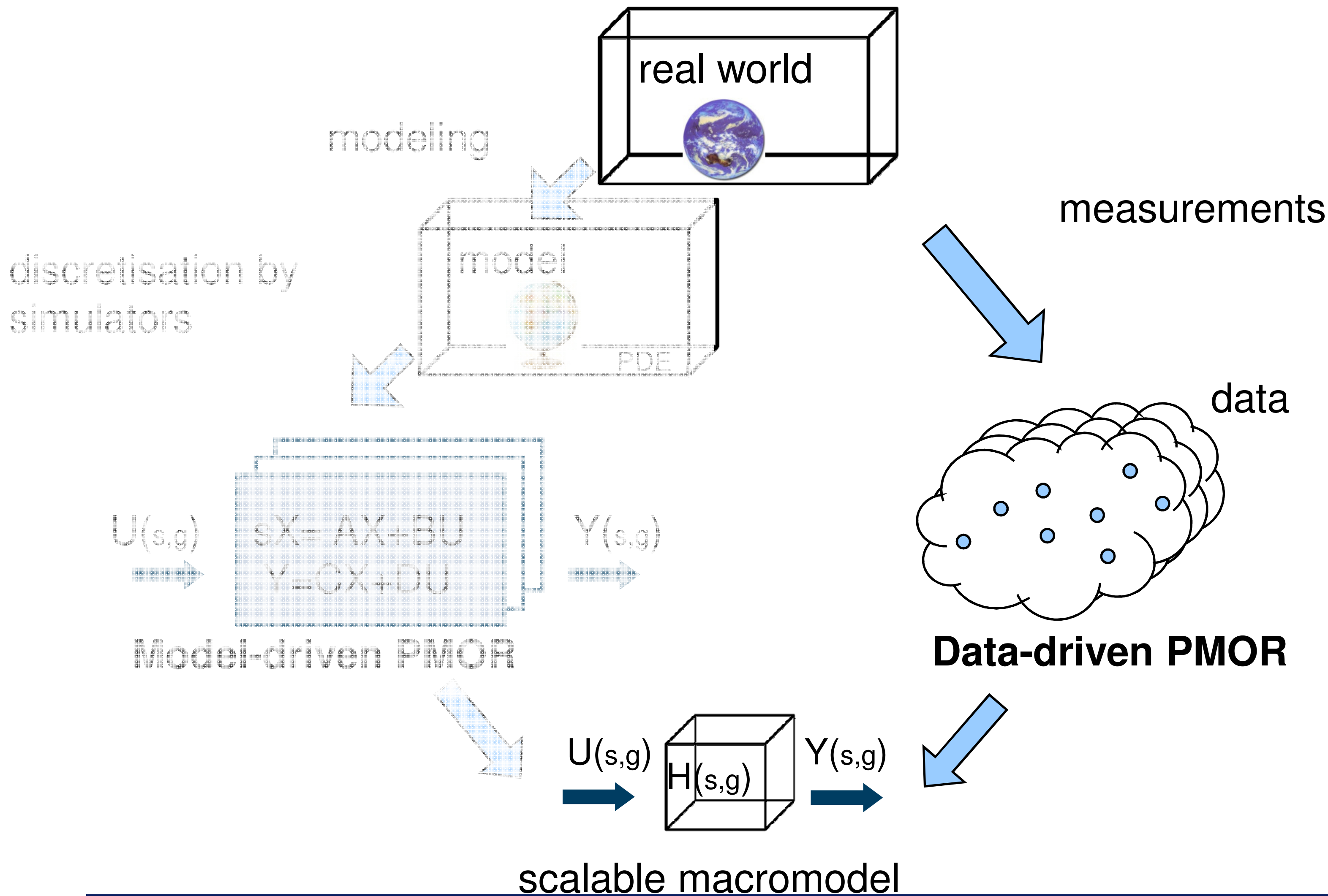
Scalable Macromodels

Numerical examples
- EMC example
- SI example

Conclusions


real world
modeling
model
PDE
discretisation by simulators
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
Model-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
scalable macromodel

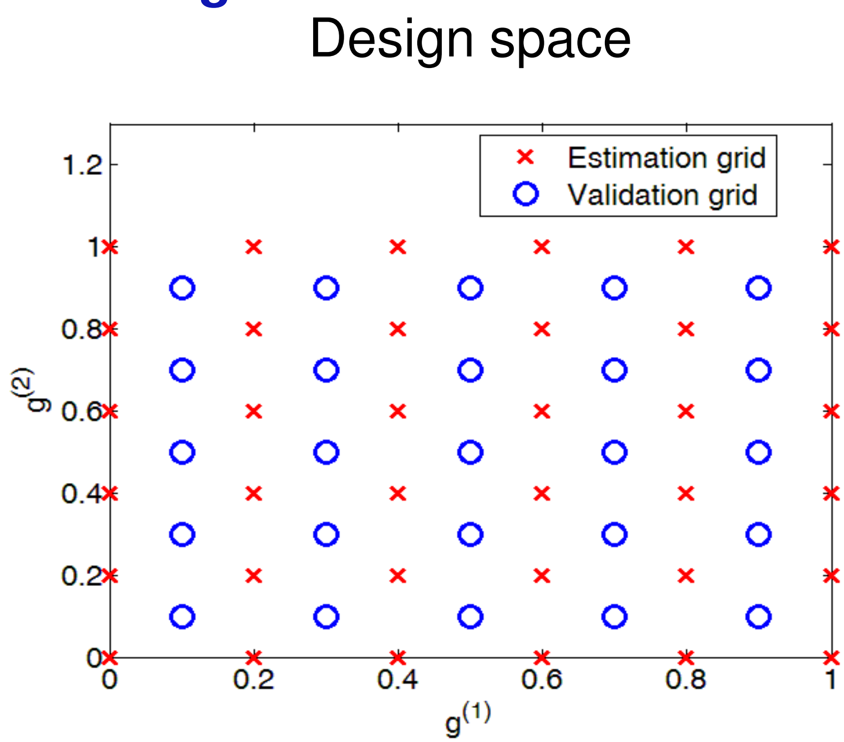

real world
modeling
model
PDE
discretisation by simulators
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
Model-driven PMOR
simulations
data
Data-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
scalable macromodel


real world
modeling
measurements
discretisation by simulators
model
PDE
data
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
Model-driven PMOR
Data-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
scalable macromodel

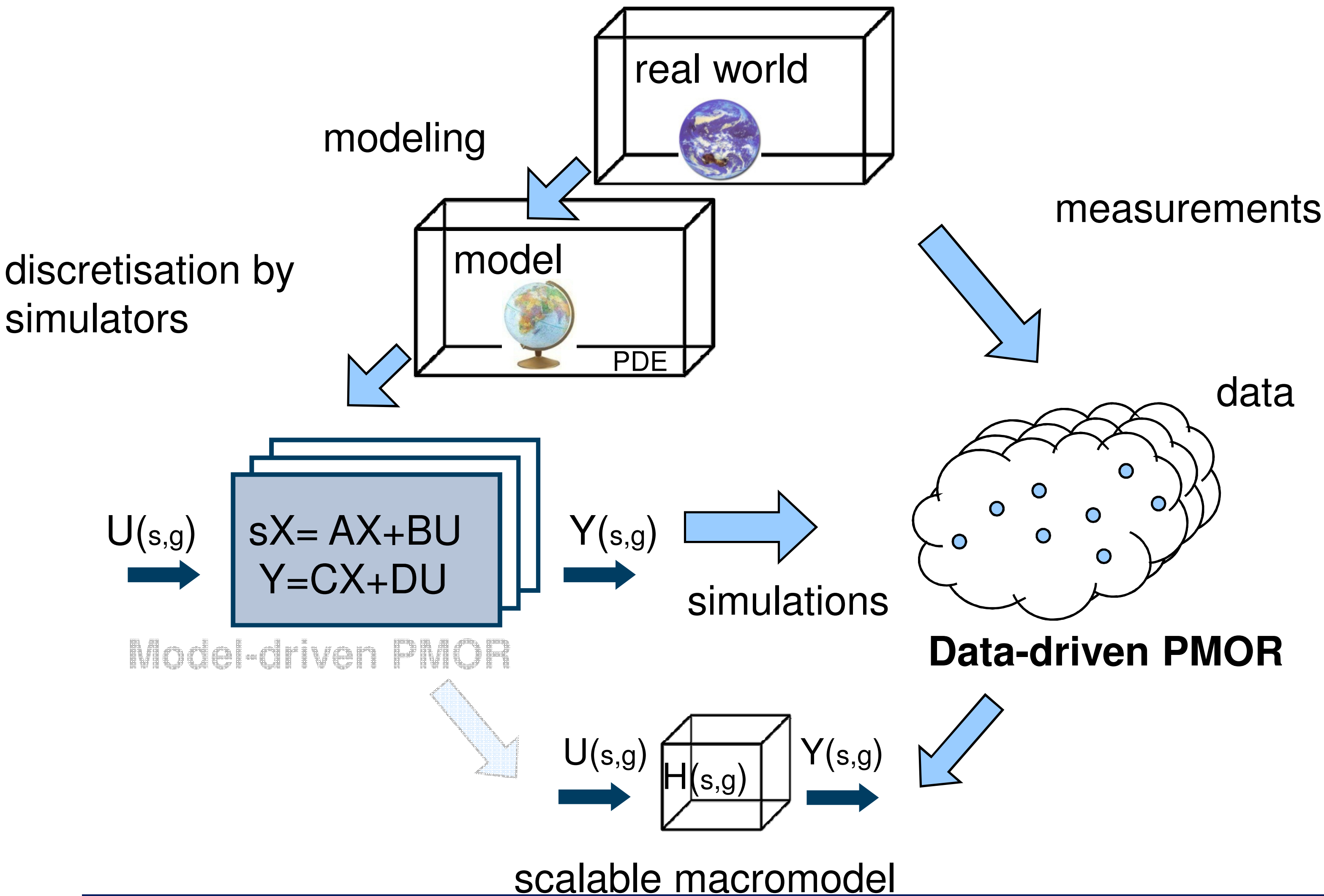
PMOR concepts

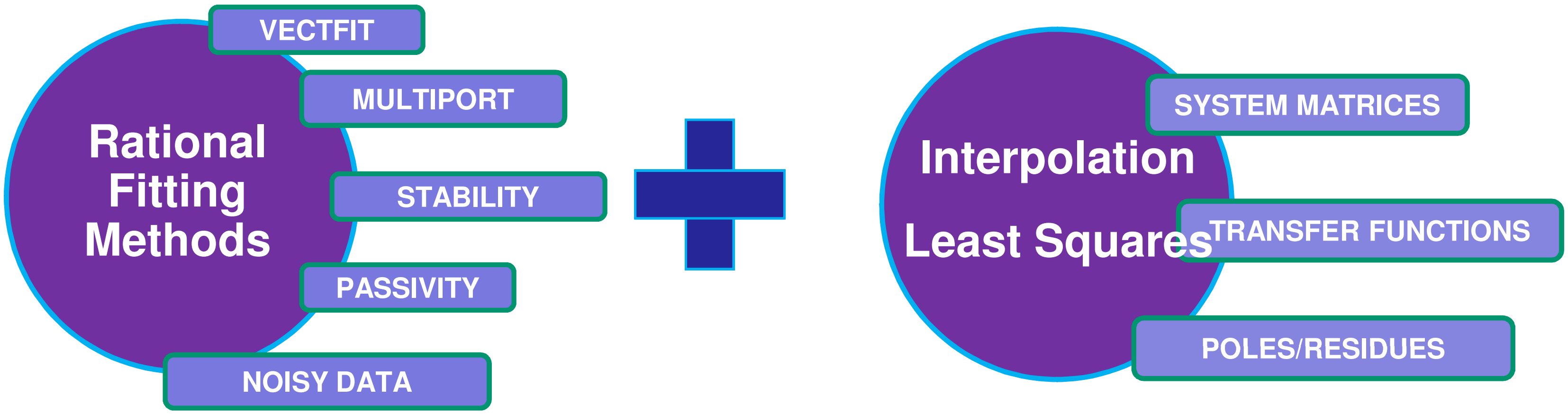
Two design space grids are used in the modeling process

- estimation grid
- validation grid

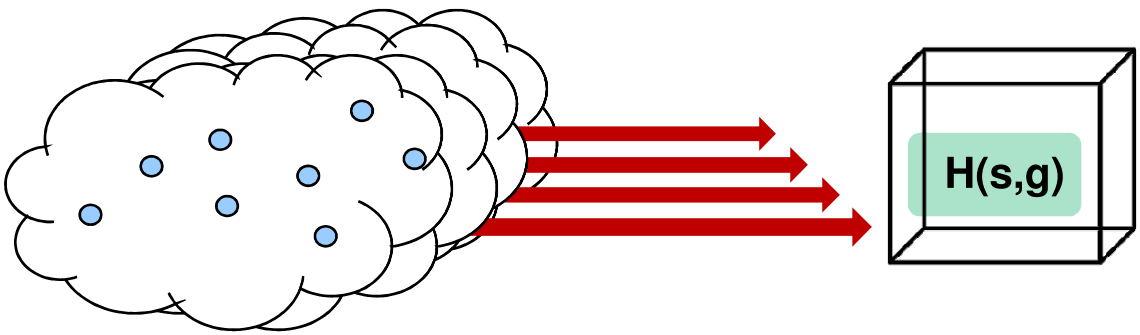


$$g = (g^{(n)})_{n=1}^{N}$$


real world
modeling
measurements
model
PDE
discretisation by simulators
data
U(s,g)
sX= AX+BU
Y=CX+DU
Y(s,g)
simulations
Model-driven PMOR
Data-driven PMOR
U(s,g)
H(s,g)
Y(s,g)
scalable macromodel



data-driven PMOR



- accuracy
- efficiency
- stability guaranteed
- passivity guaranteed

scattered data

Rational Fitting Methods

- VECTFIT
- MULTIPORT
- STABILITY
- PASSIVITY
- NOISY DATA

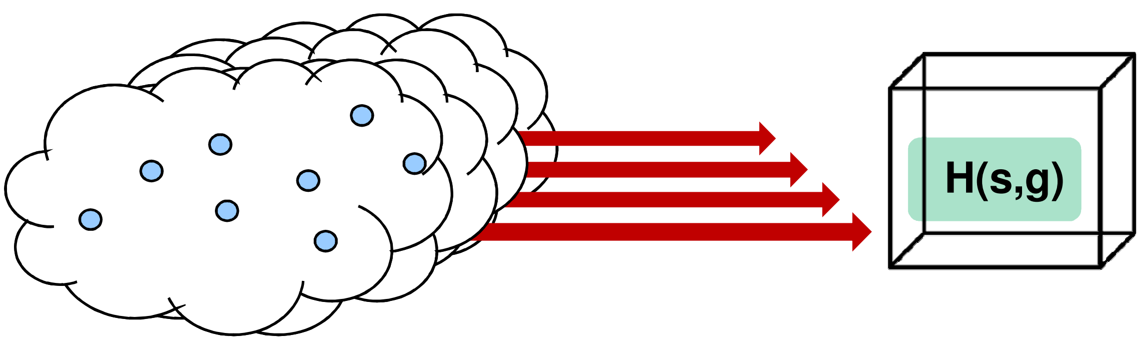
+

Interpolation

Least Squares

- SYSTEM MATRICES
- TRANSFER FUNCTIONS
- POLES/RESIDUES

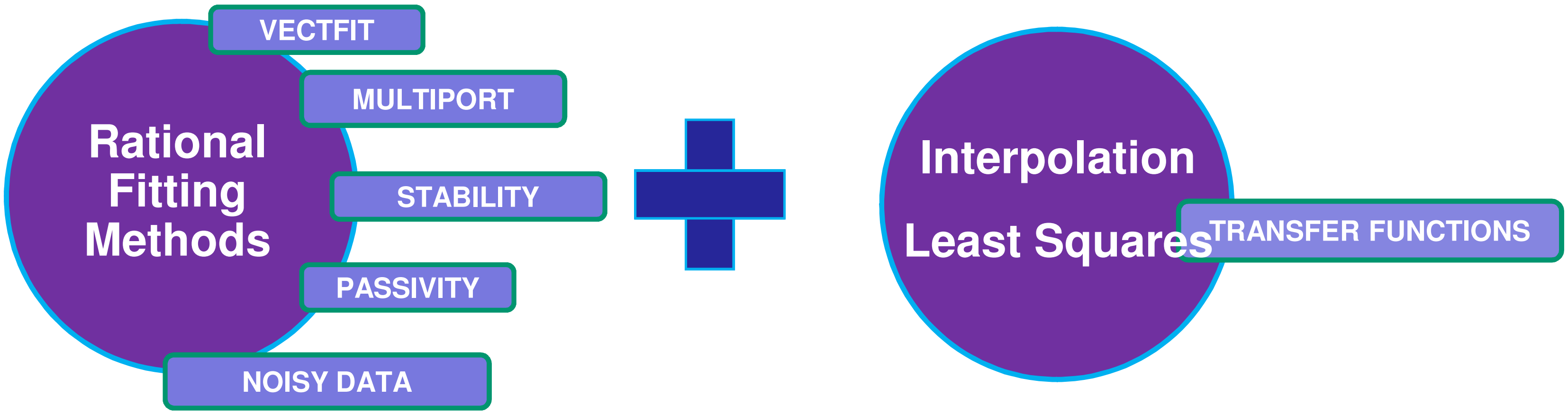
data-driven PMOR



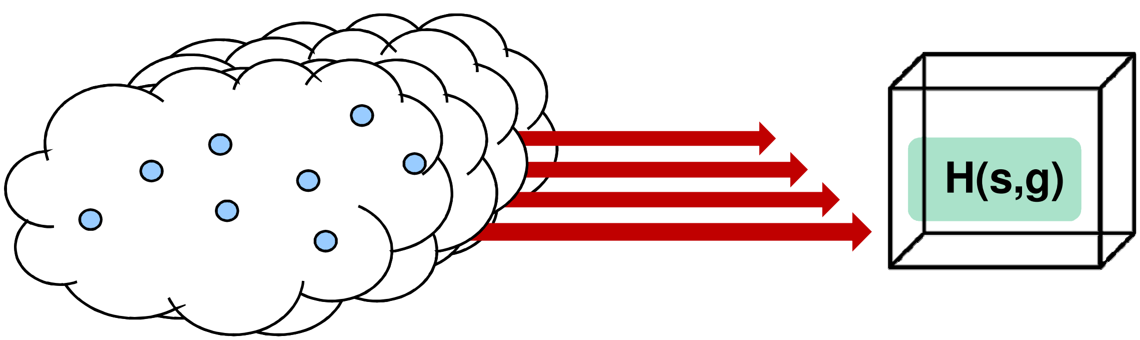
scattered data

$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$



data-driven PMOR

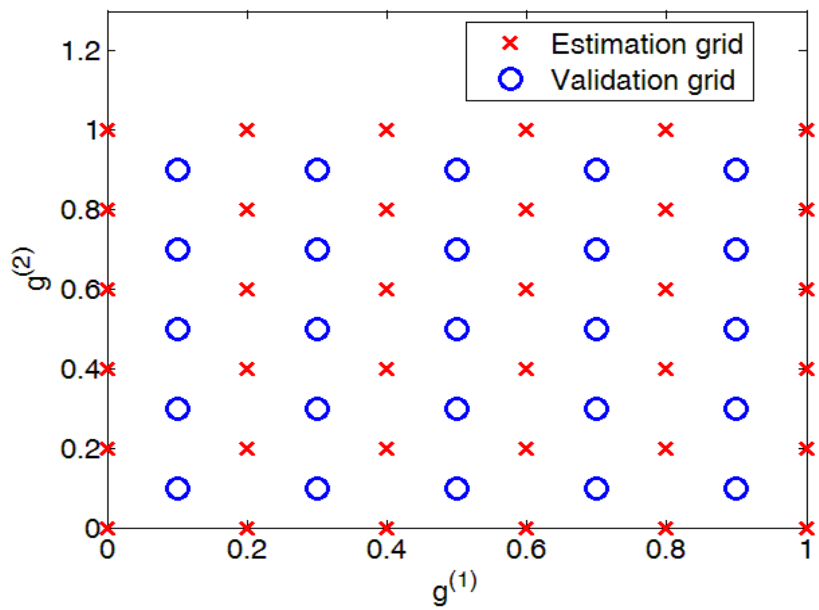


$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

scattered data

Design space $g = (g^{(n)})_{n=1}^{N}$



Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$ in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients $\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$ in the estimation design space grid

↓

Multivariate interpolation of scaling and frequency shifting coefficients $\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

Multivariate interpolation of scaled and shifted root macromodels $\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

Features

- **each design space cell has its own model**
- **local approach**
- **independent from a specific state-space realization**
- **stability and passivity guaranteed over the design space**
- **suitable to robust adaptive sampling**
- **different flavours**

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

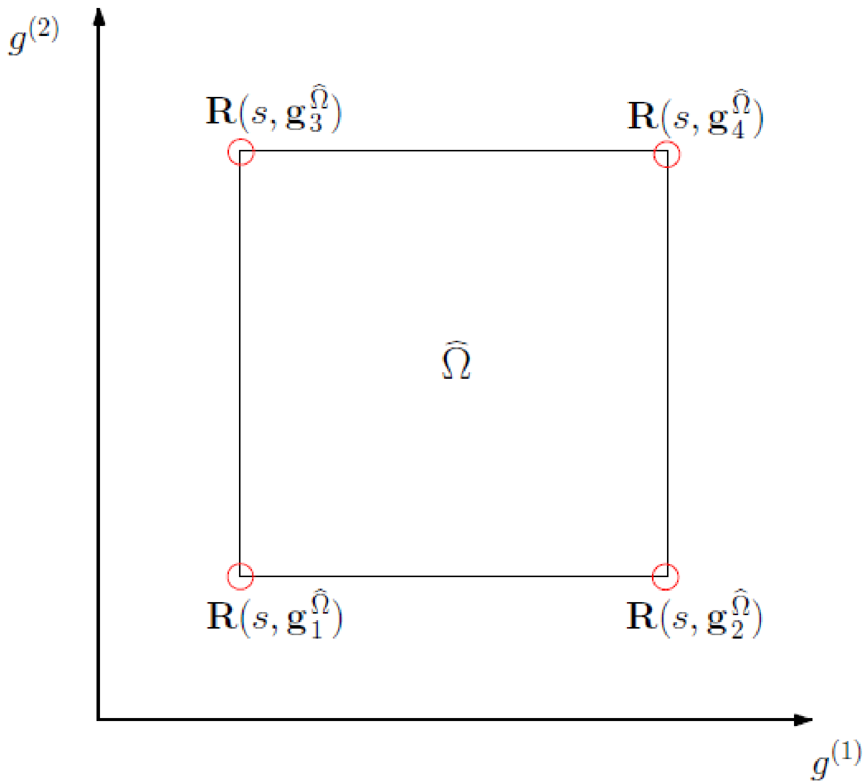
Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\mathbf{R}(s, \mathbf{g}_j^{\widehat{\Omega}}) = \mathbf{C}_0(\mathbf{g}_j^{\widehat{\Omega}}) + \sum_{n=1}^{N(\widehat{\Omega})} \frac{\mathbf{C}_n(\mathbf{g}_j^{\widehat{\Omega}})}{s - \mathbf{p}_n(\mathbf{g}_j^{\widehat{\Omega}})}$$

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

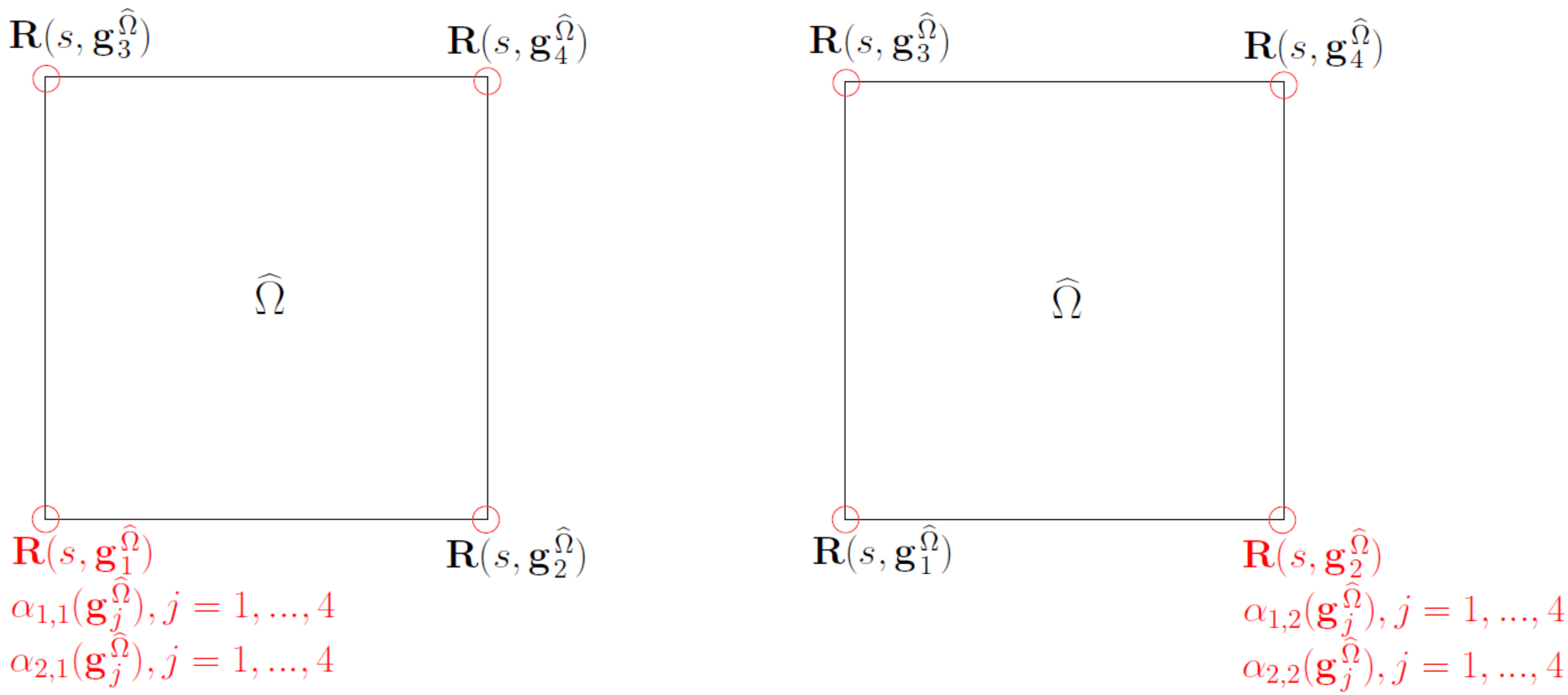
↓

Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$

$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

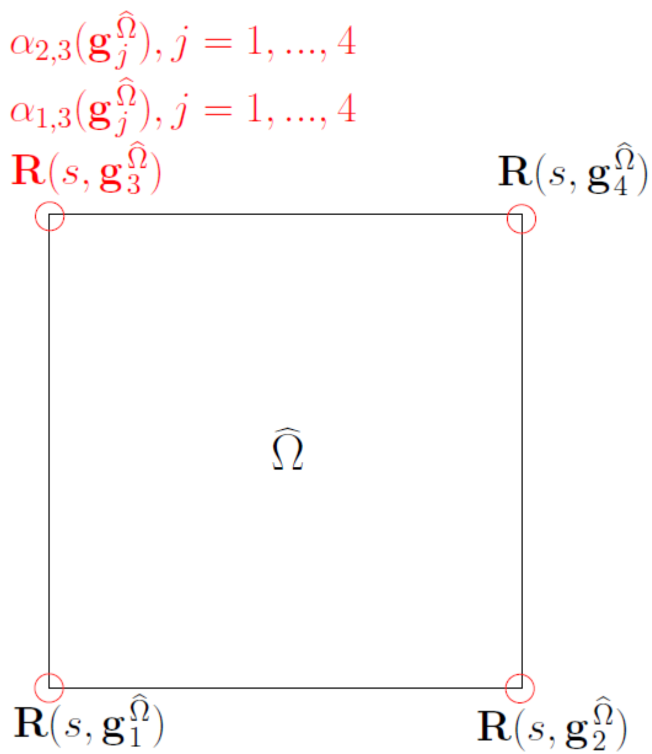
$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ \ j = k$$

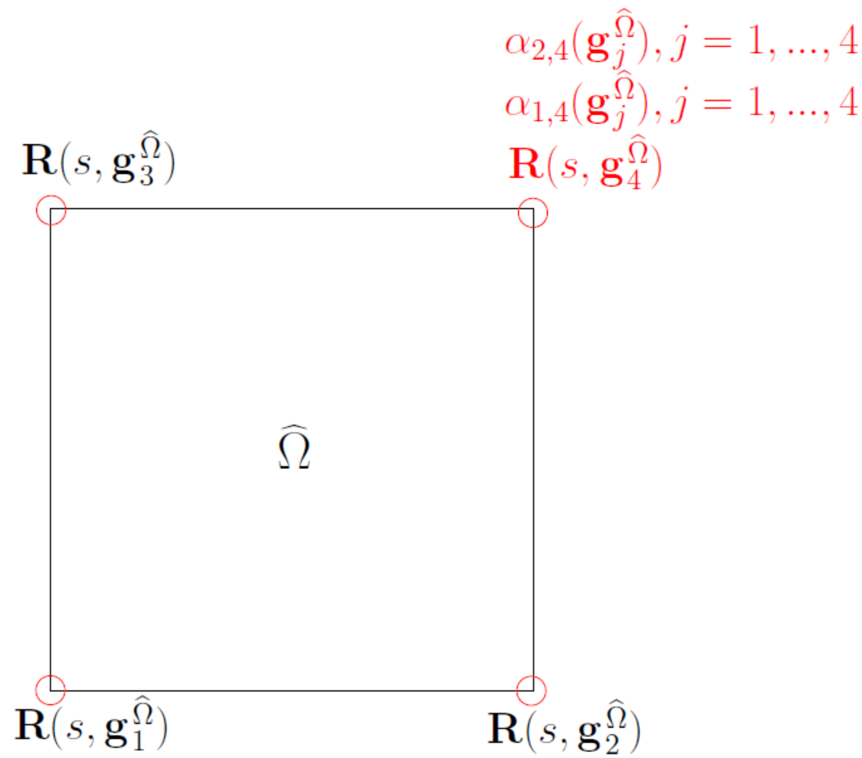


$$\min_{\alpha_{1,k}(\mathbf{g}_j^{\widehat{\Omega}}),\alpha_{2,k}(\mathbf{g}_j^{\widehat{\Omega}})} Err(\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}),\mathbf{R}(s,\boldsymbol{g}_j^{\widehat{\Omega}}))$$

$$\widetilde{\mathbf{R}}(s,\boldsymbol{g}_k^{\widehat{\Omega}}) = \alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}})\mathbf{R}(s\alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}),\boldsymbol{g}_k^{\widehat{\Omega}})$$

$$\alpha_{1,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = \alpha_{2,k}(\boldsymbol{g}_j^{\widehat{\Omega}}) = 1,\ \ j = k$$





Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$

in the estimation design space grid

↓

Compute scaling and frequency shifting coefficients

$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$

in the estimation design space grid

↓

Multivariate interpolation of

scaling and frequency shifting coefficients

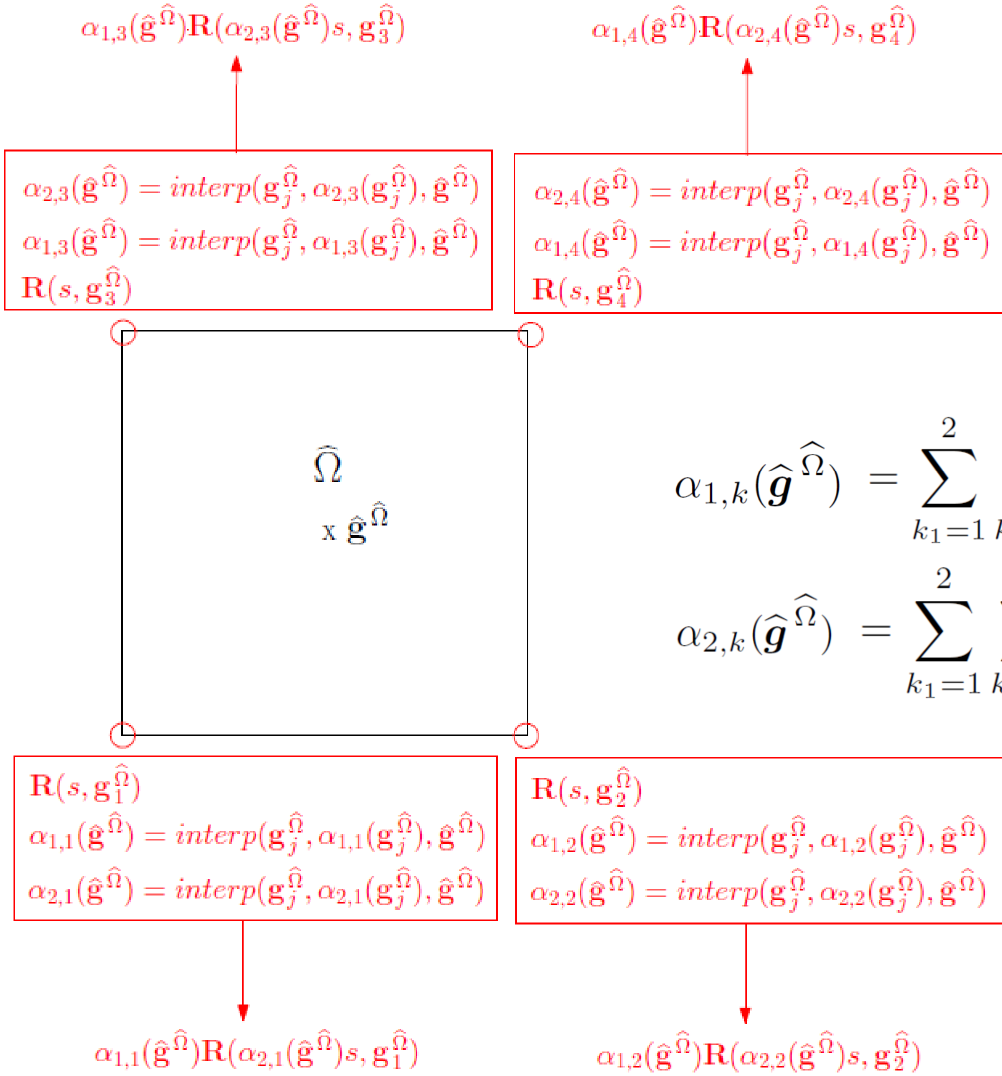
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

Multivariate interpolation of

scaled and shifted root macromodels

$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\alpha_{1,k}(\hat{\boldsymbol{g}}^{\hat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{1,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\hat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$

$$\alpha_{2,k}(\hat{\boldsymbol{g}}^{\hat{\Omega}}) = \sum_{k_1=1}^{2}\sum_{k_2=1}^{2} \alpha_{2,k}((g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\hat{\Omega}})\ell_{k_1}(g^{(1)})\ell_{k_2}(g^{(2)})$$

Compute root macromodels $\mathbf{R}(s, \mathbf{g}_k^{\Omega_i})$
in the estimation design space grid

↓

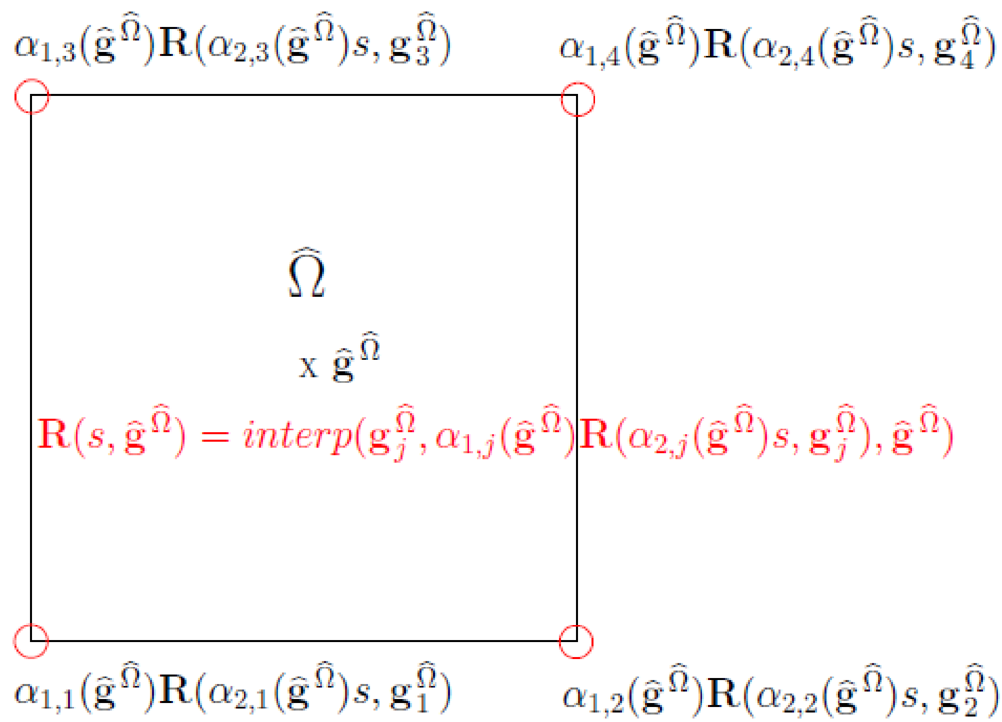
Compute scaling and frequency shifting coefficients
$\alpha_{1,k}(\mathbf{g}_j^{\Omega_i}), \alpha_{2,k}(\mathbf{g}_j^{\Omega_i})$
in the estimation design space grid

↓

Multivariate interpolation of
scaling and frequency shifting coefficients
$\alpha_1(\mathbf{g}), \alpha_2(\mathbf{g})$

↓

Multivariate interpolation of
scaled and shifted root macromodels
$\alpha_1(\mathbf{g})\mathbf{R}(s\alpha_2(\mathbf{g}), \mathbf{g})$



$$\mathrm{R}(s, \widehat{g}^{\widehat{\Omega}}) = \sum_{k_1=1}^{2} \sum_{k_2=1}^{2} \widetilde{\mathrm{R}}(s, (g_{k_1}^{(1)}, g_{k_2}^{(2)})^{\widehat{\Omega}}) \ell_{k_1}(g^{(1)}) \ell_{k_2}(g^{(2)})$$

Outline

Introduction

Scalable Macromodels

Numerical examples
- EMC example
- SI example

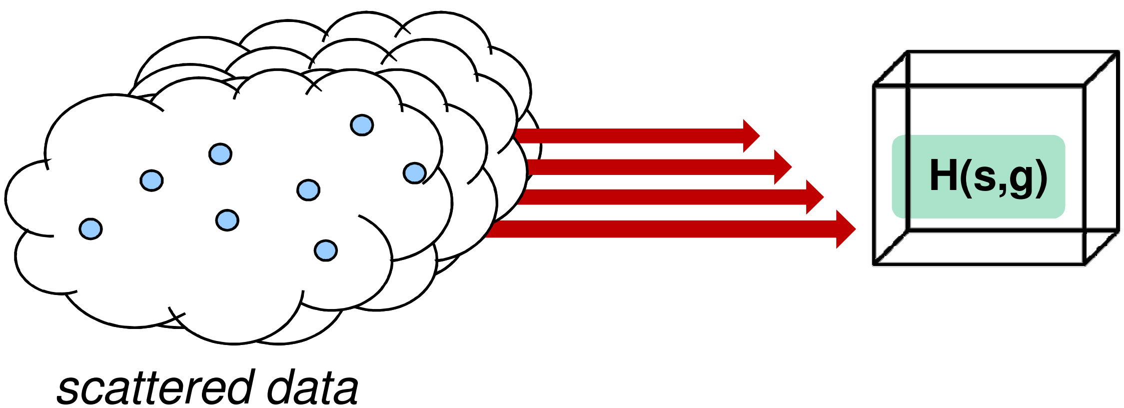
Conclusions

Rational Fitting Methods — VECTFIT, MULTIPORT

+

Interpolation / Least Squares — SYSTEM MATRICES

data-driven PMOR

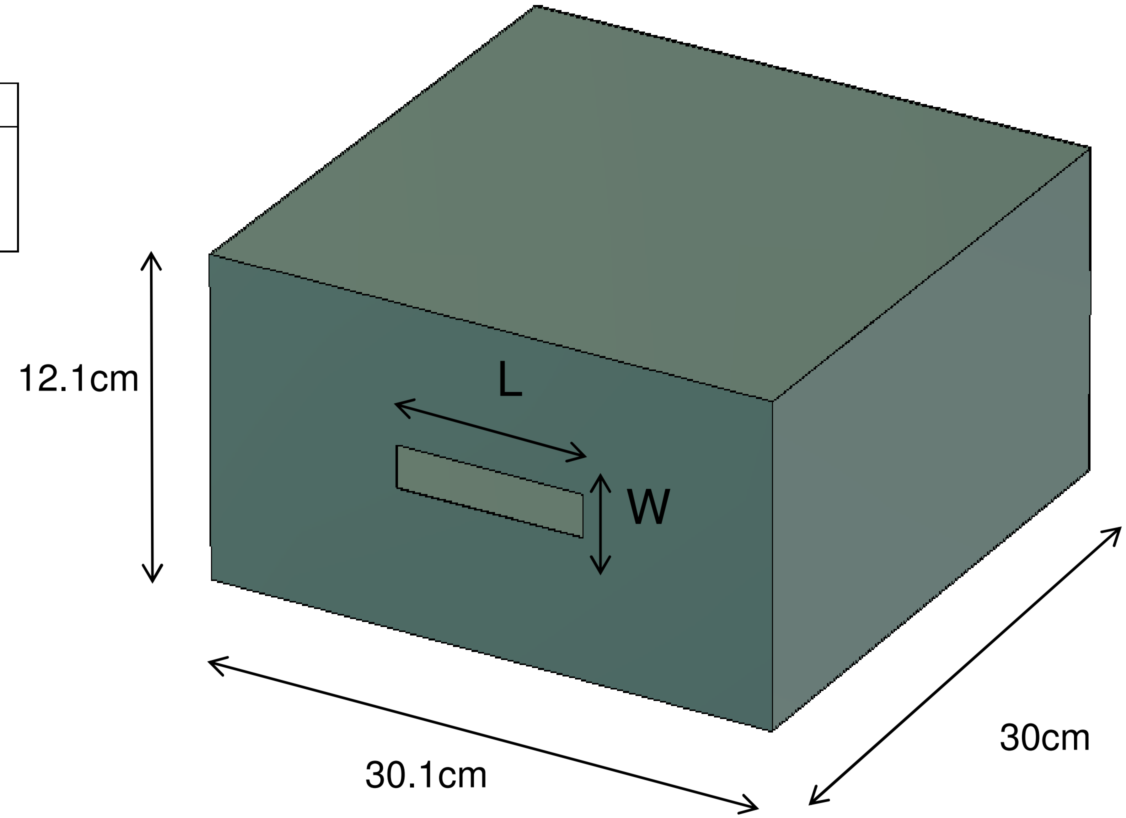


$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

3D example: Enclosure

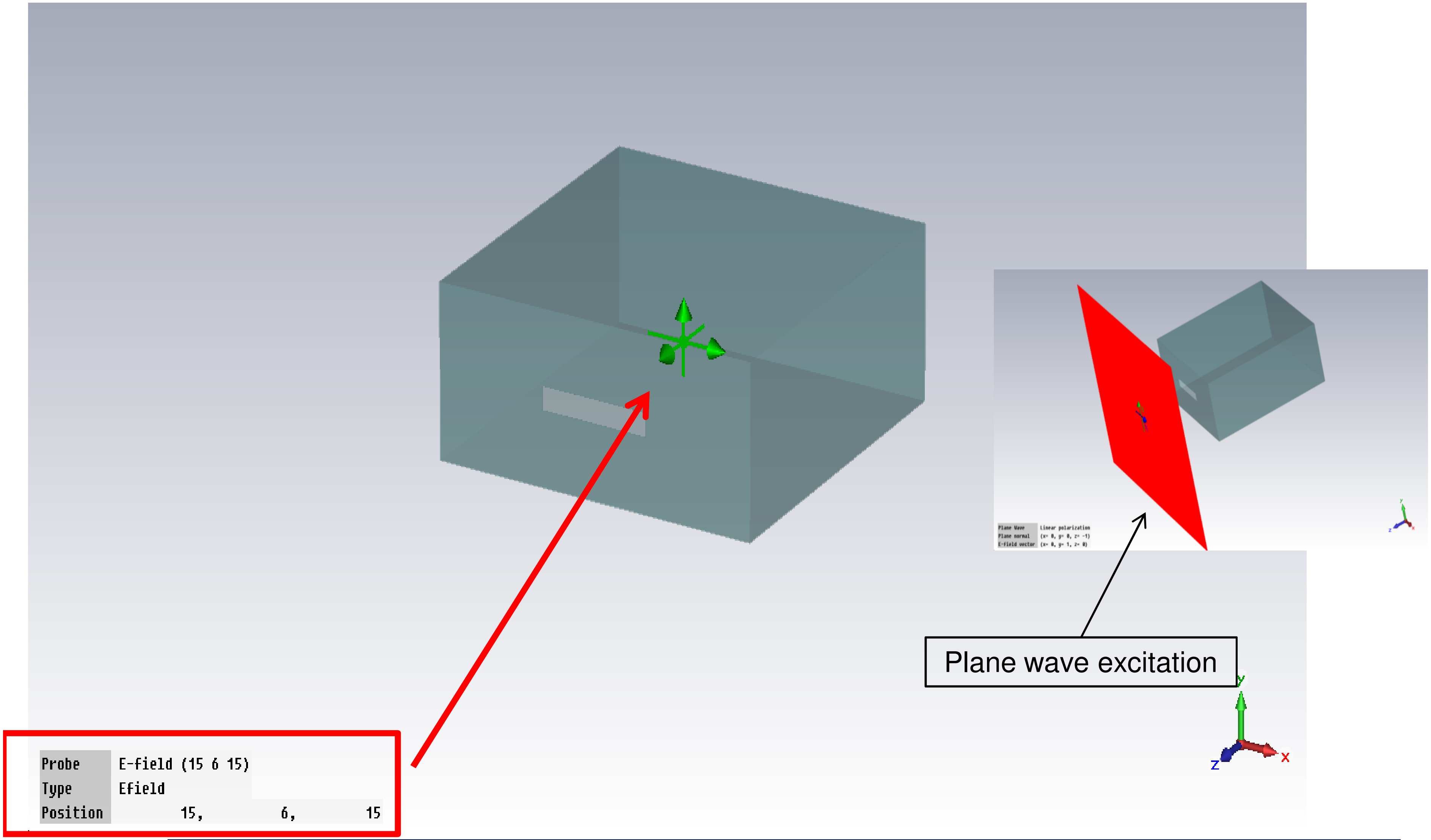
Parameter	Min	Max
Frequency (freq)	0 Hz	1 GHz
Length (L)	10 cm	20 cm
Width (W)	0.8 cm	2.8 cm

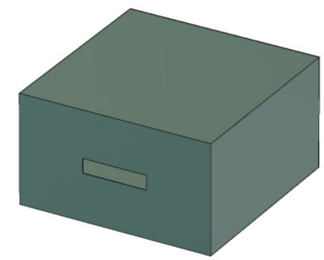


UNIVERSITEIT GENT

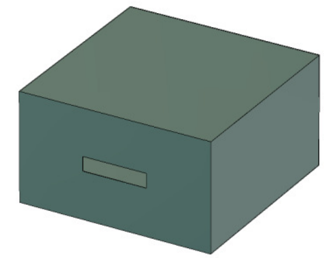
UAq EMC Lab

FACULTY OF ENGINEERING



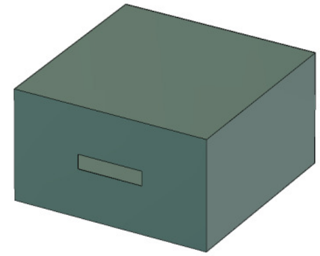


Step	CPU time
Estimation grid by solver (6×6) (L,W)	2 h 25 min 48 s
Validation grid by solver (5×5) (L,W)	1 h 41 min 15 s
Building model	3.08 s
Validating model	0.9 s
Evaluating solver (one frequency response)	4 min 3 s
Evaluating model (one frequency response)	7.2 ms

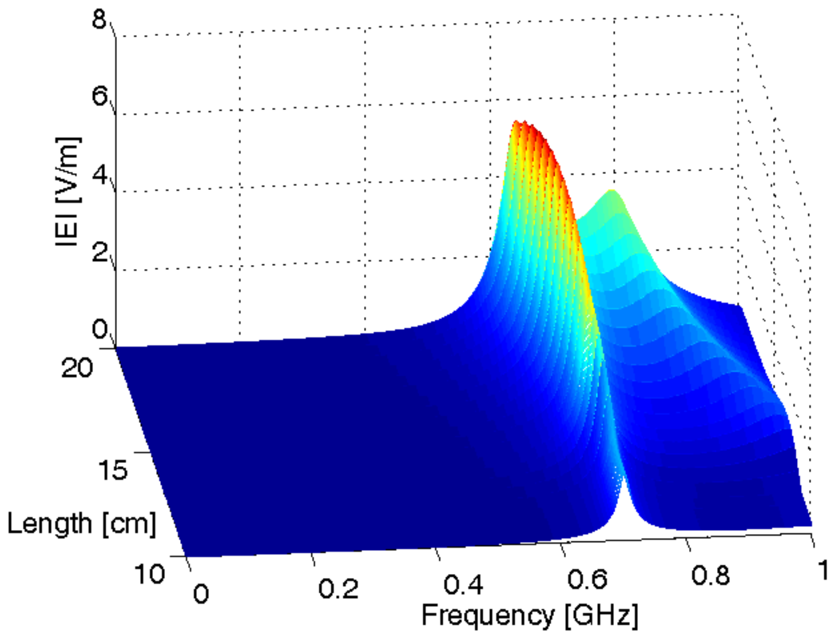


Step	CPU time
Estimation grid by solver (6 × 6) (L,W)	2 h 25 min 48 s
Validation grid by solver (5 × 5) (L,W)	1 h 41 min 15 s
Building model	3.08 s
Validating model	0.9 s
Evaluating solver (one frequency response)	4 min 3 s
Evaluating model (one frequency response)	7.2 ms

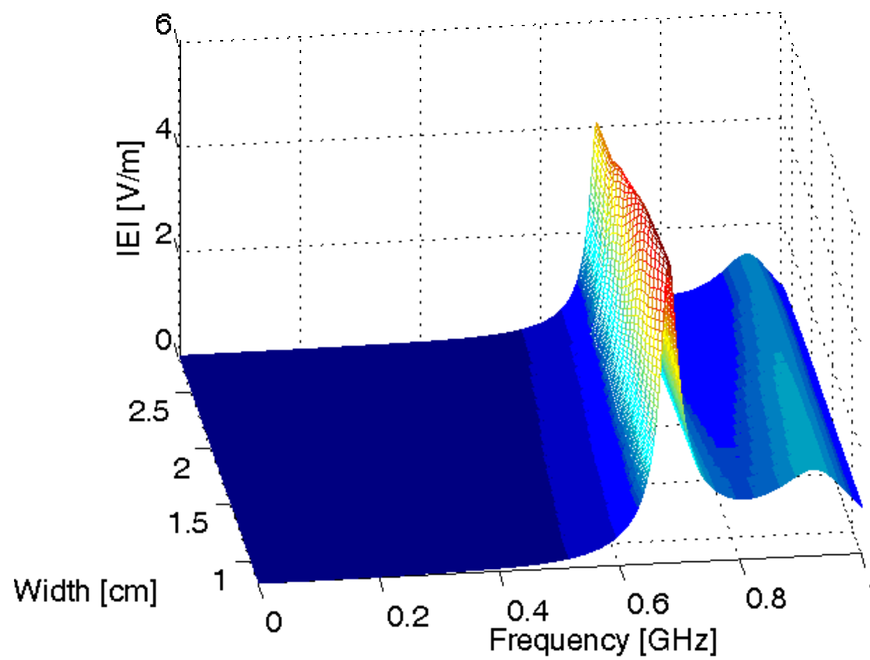
Speed-up 33750 x

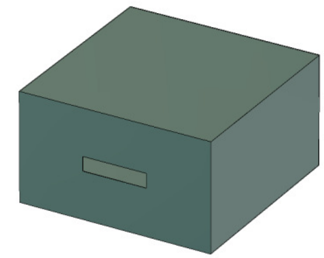


W=1.8 cm

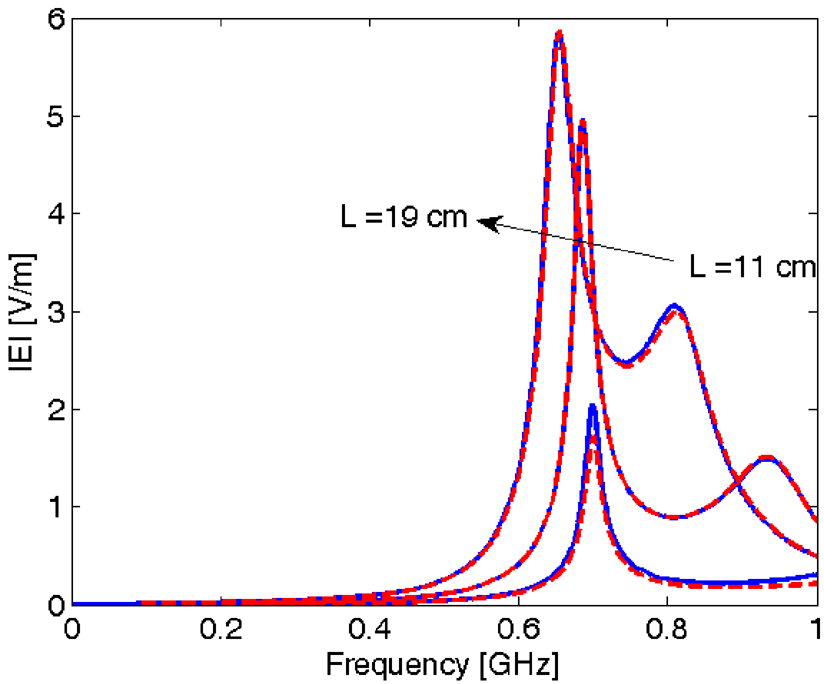

IEI [V/m]
Length [cm]
Frequency [GHz]
0
0.2
0.4
0.6
0.8
1
10
15
20
0
2
4
6
8

L=15 cm

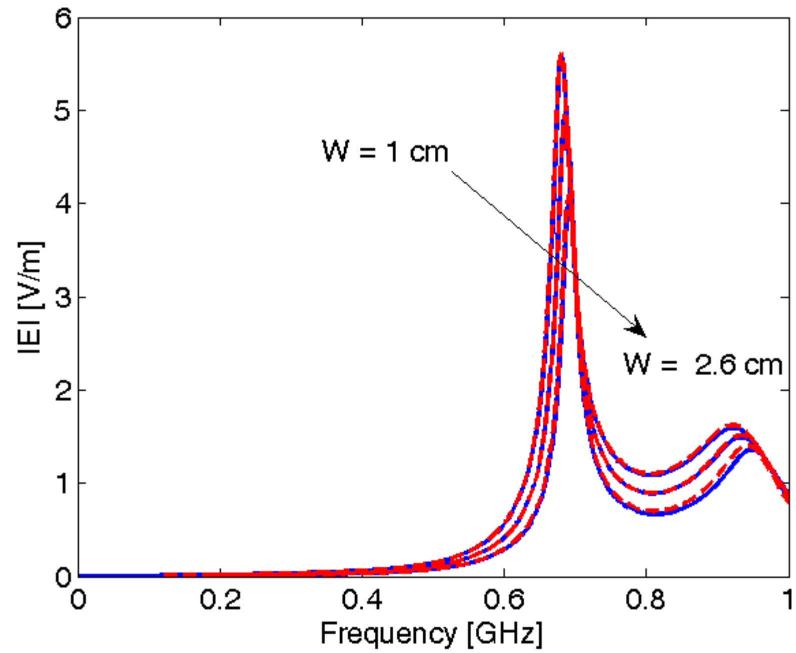

IEI [V/m]
Width [cm]
Frequency [GHz]
0
0.2
0.4
0.6
0.8
1
1
1.5
2
2.5
0
2
4
6



W=1.8 cm


6
5
4
3
2
1
0
IEI [V/m]
0
0.2
0.4
0.6
0.8
1
Frequency [GHz]
L =19 cm
L =11 cm

L=15 cm


6
5
4
3
2
1
0
IEI [V/m]
0
0.2
0.4
0.6
0.8
1
Frequency [GHz]
W = 1 cm
W = 2.6 cm

Outline

Introduction

Scalable Macromodels

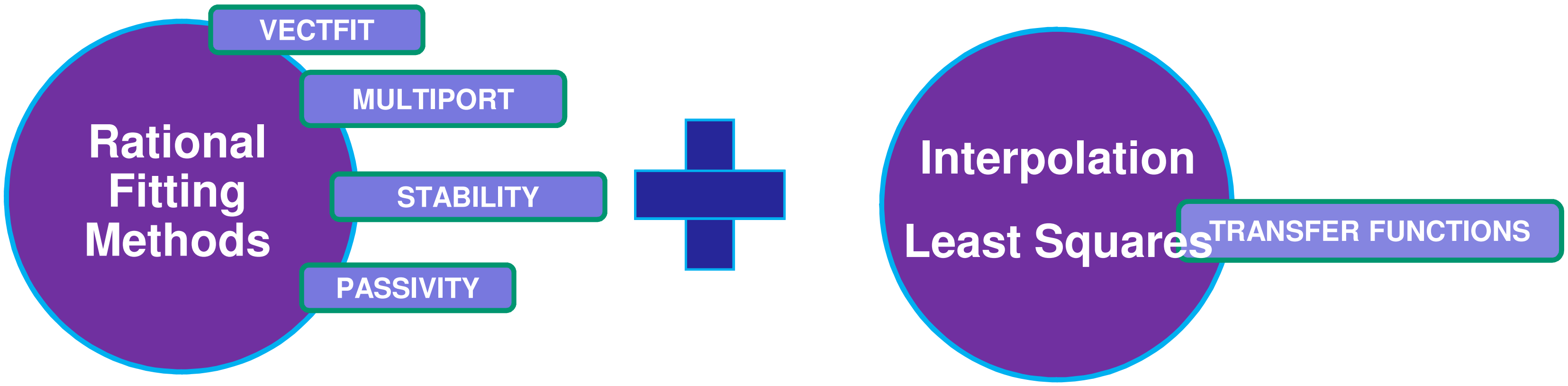
Numerical examples

- EMC example
- SI example

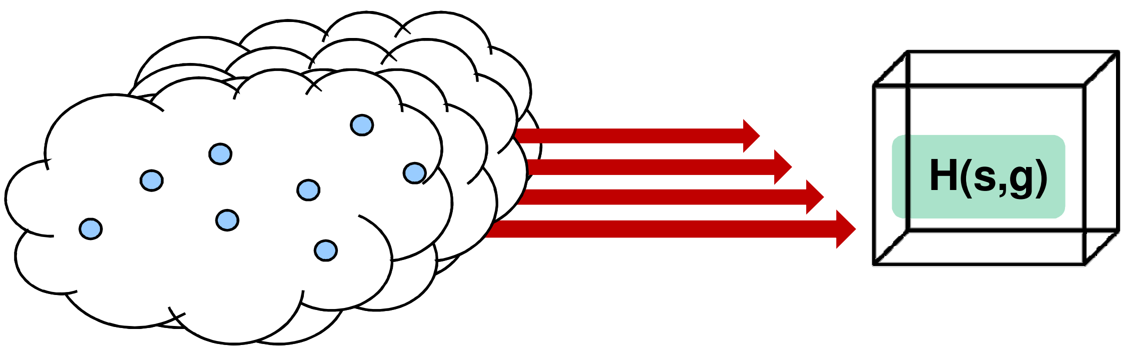
Conclusions

UNIVERSITEIT GENT

FACULTY OF ENGINEERING



data-driven PMOR



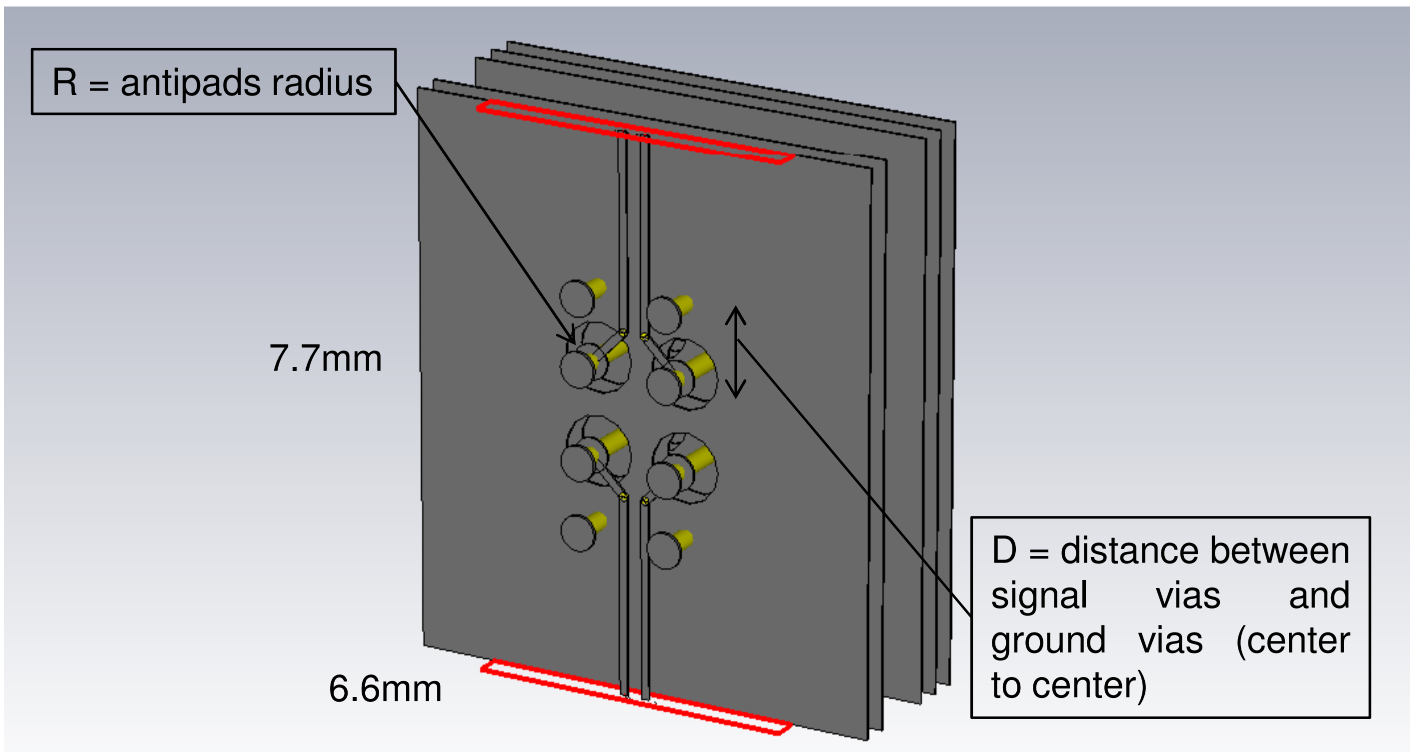
scattered data

$$\mathbf{H}(s,\mathbf{g}) = \sum_{p=1}^{P} \frac{\mathbf{Q}(\mathbf{g})}{s - a_p(\mathbf{g})}$$

$$\mathbf{H}(s,\mathbf{g}) = \mathbf{C}(\mathbf{g})(s\mathbf{I} - \mathbf{A}(\mathbf{g}))^{-1}\mathbf{B}(\mathbf{g}) + \mathbf{D}(\mathbf{g})$$

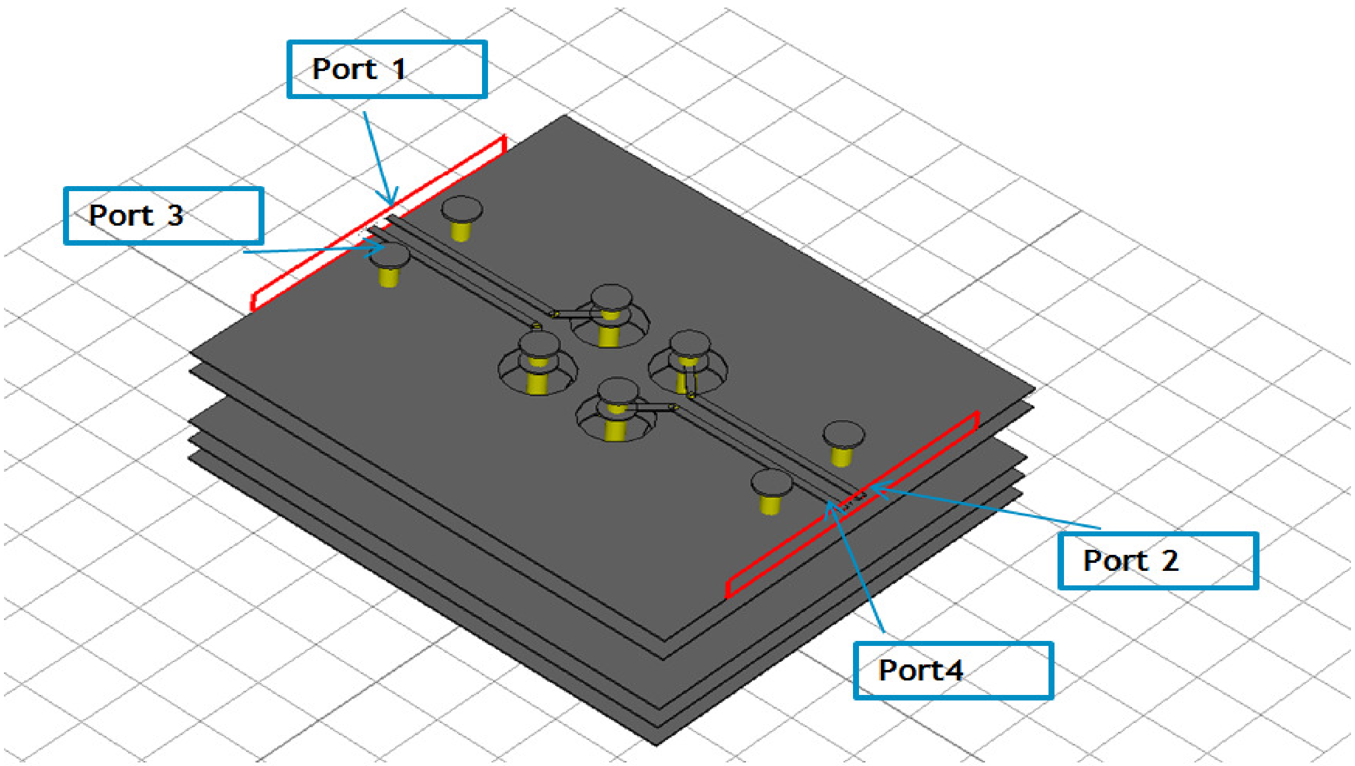
3D example: PCB

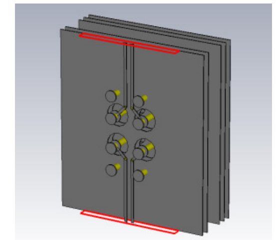
Parameter	Min	Max
Frequency (freq)	0 Hz	20 GHz
Antipads radius (R)	0.4826 mm	0.6026 mm
Distance (D)	1.2525 mm	2.4525 mm



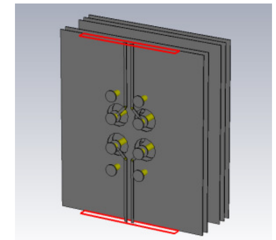
3D example: PCB

Parameter	Min	Max
Frequency (freq)	0 Hz	20 GHz
Antipads radius (R)	0.4826 mm	0.6026 mm
Distance (D)	1.2525 mm	2.4525 mm





Step	CPU time
Estimation grid by solver (4×6) (R,D)	3 h 6 min
Validation grid by solver (3×5) (R,D)	1 h 56 min 15 s
Building model	5 min 49 s
Validating model	11 s
Evaluating solver (one frequency response)	7 min 45 s
Evaluating model (one frequency response)	0.1 s



Step	CPU time
Estimation grid by solver (4×6) (R,D)	3 h 6 min
Validation grid by solver (3×5) (R,D)	1 h 56 min 15 s
Building model	5 min 49 s
Validating model	11 s
Evaluating solver (one frequency response)	7 min 45 s
Evaluating model (one frequency response)	0.1 s

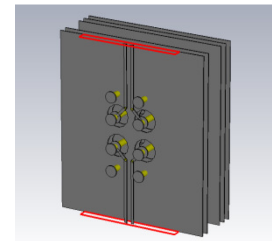
Speed-up 4650 x

UNIVERSITEIT GENT

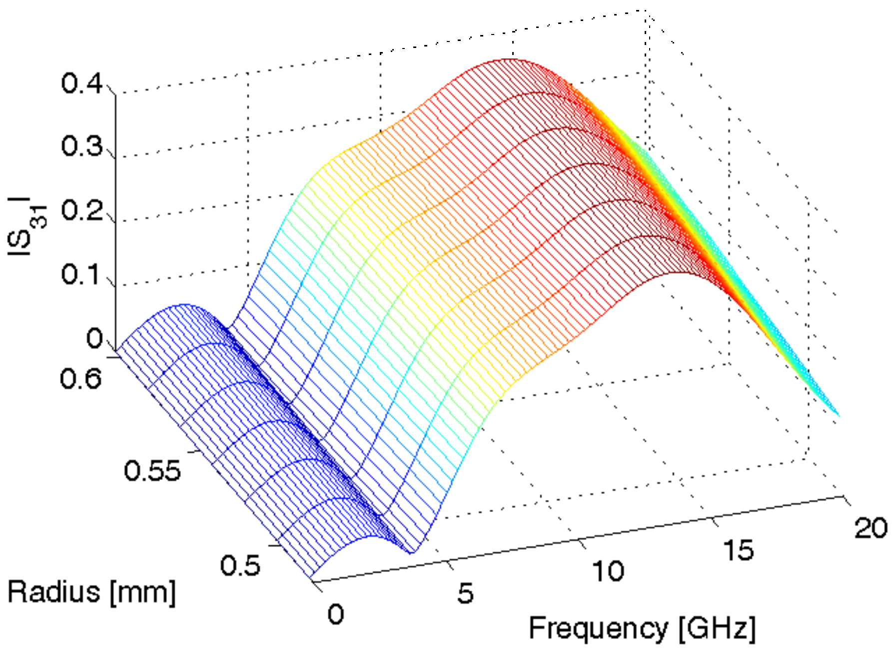
University of L'Aquila UAq EMC Lab

FACULTY OF ENGINEERING

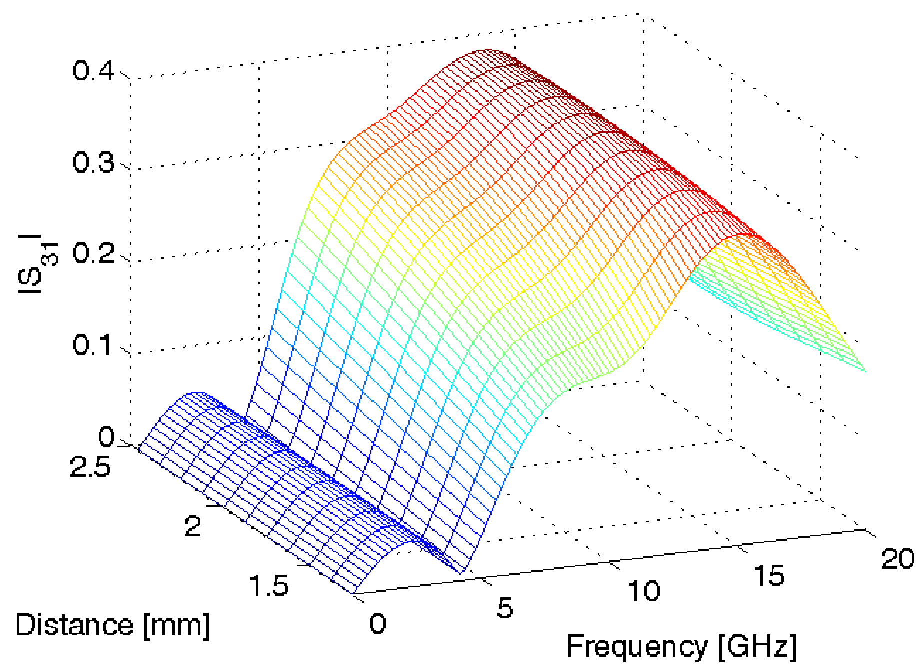
EMC'12 ROMA

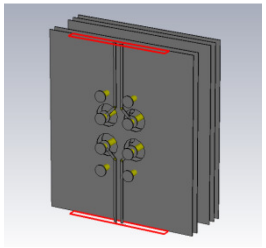


D=1.8525 mm

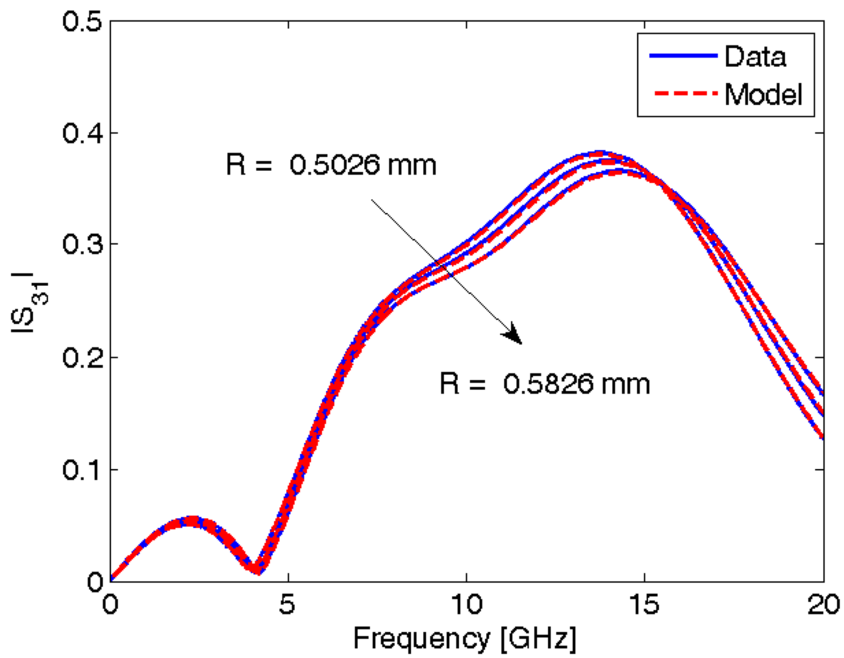


R=0.543 mm

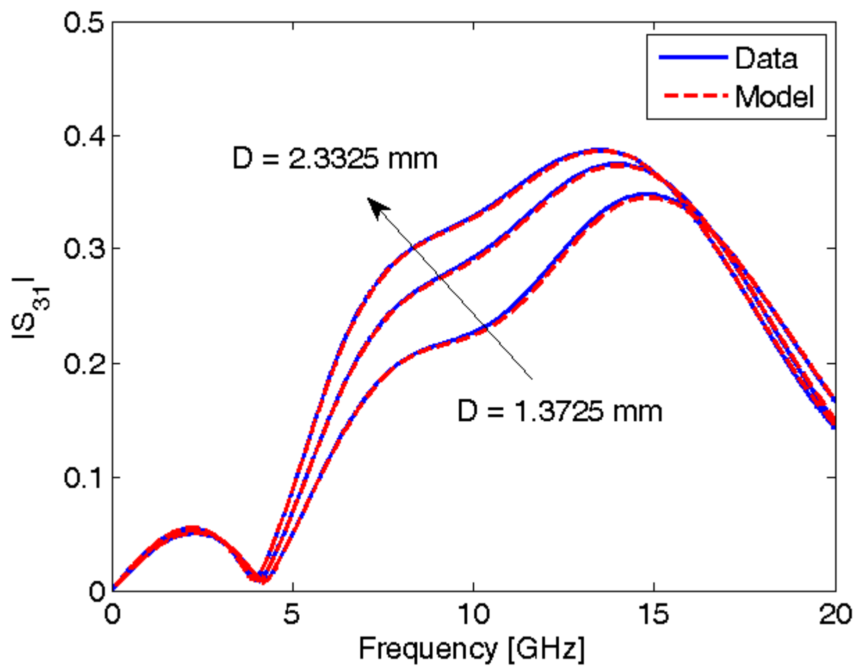


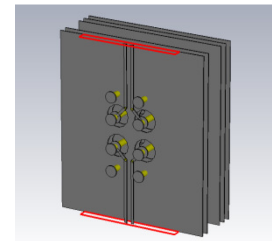


D=1.8525 mm

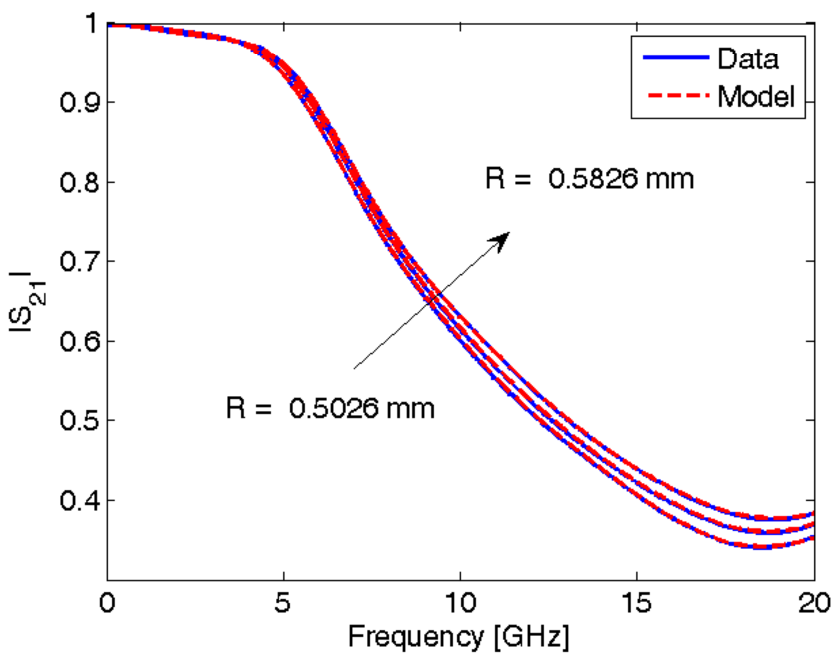


R=0.543 mm

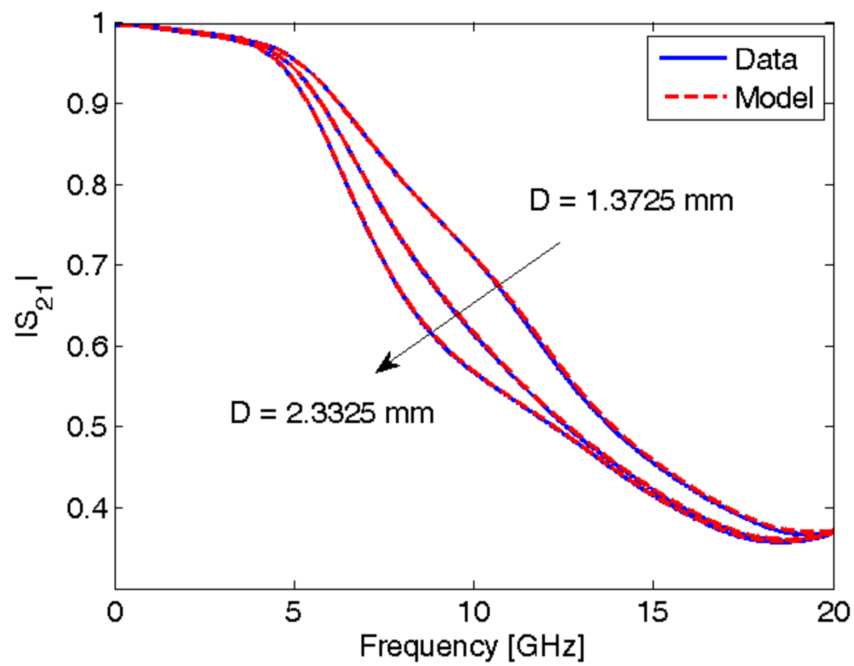




D=1.8525 mm



R=0.543 mm



Outline

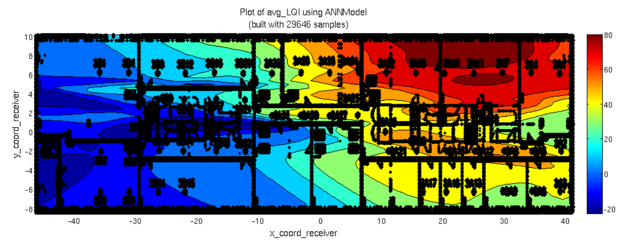
Introduction

Scalable Macromodels

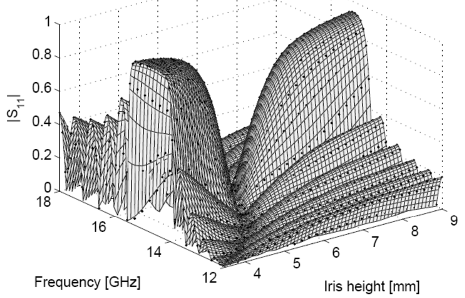
Numerical examples
- EMC example
- SI example

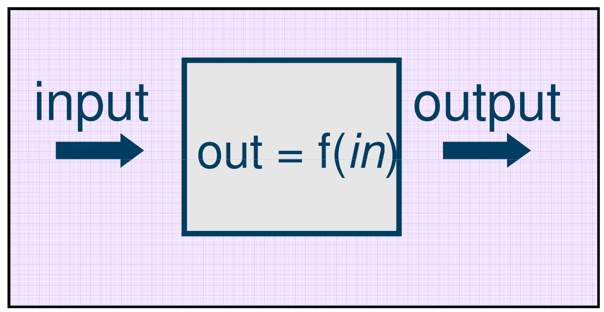
Conclusions

telecom

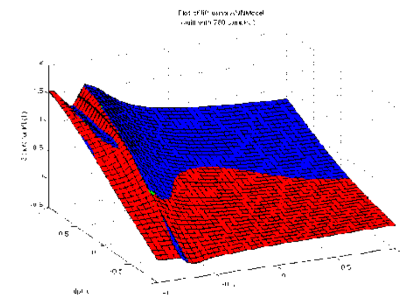


electronics



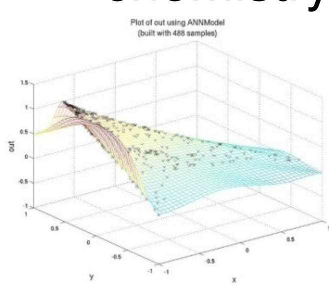


fluid dynamics

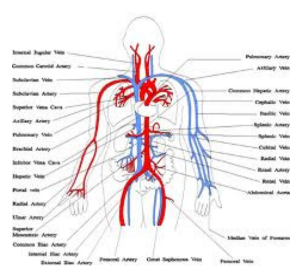


automotive

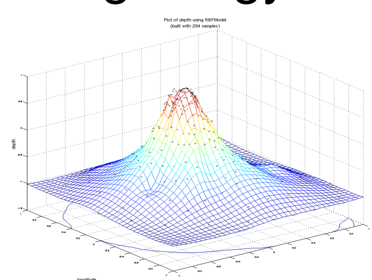
chemistry

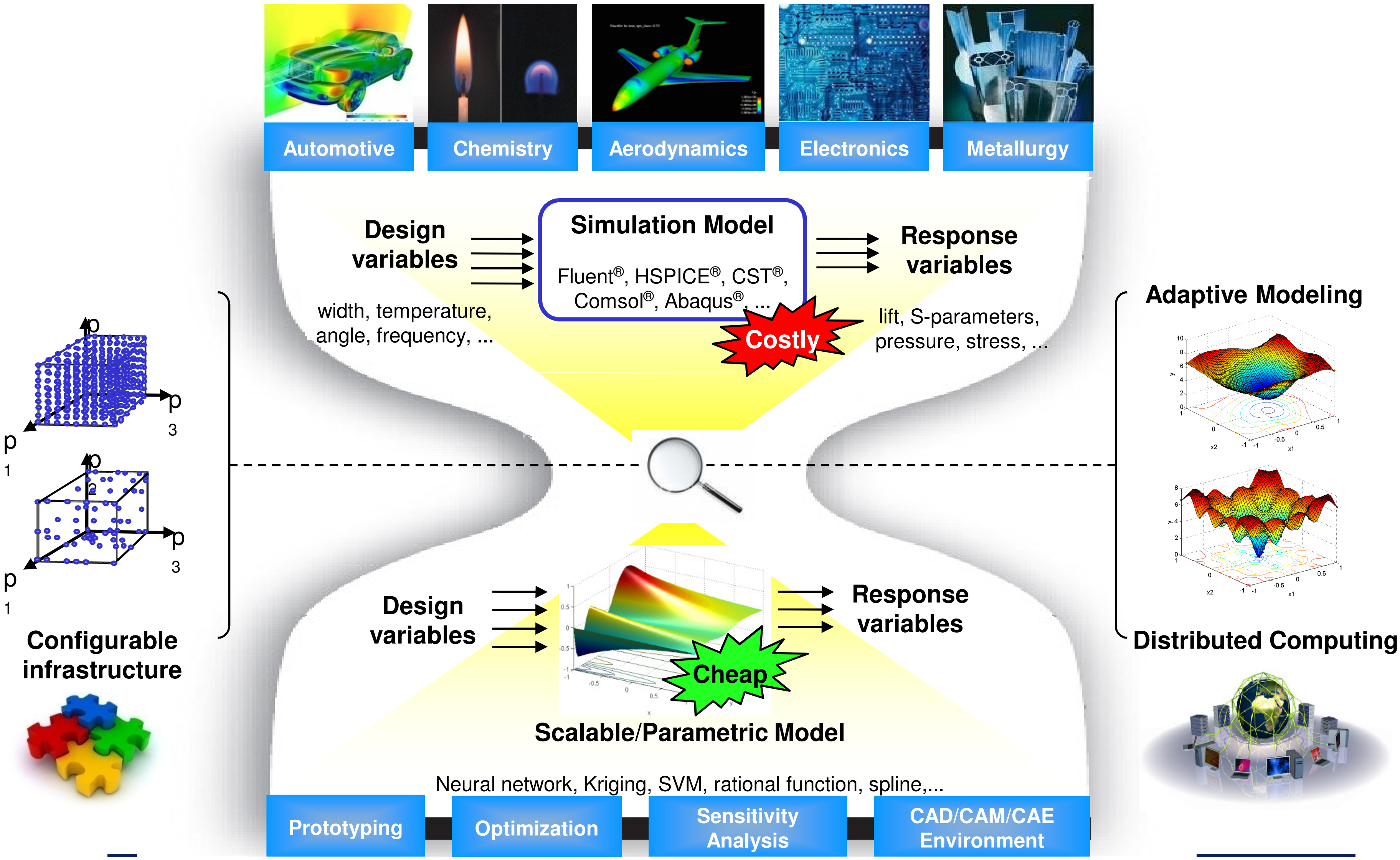


biomodeling



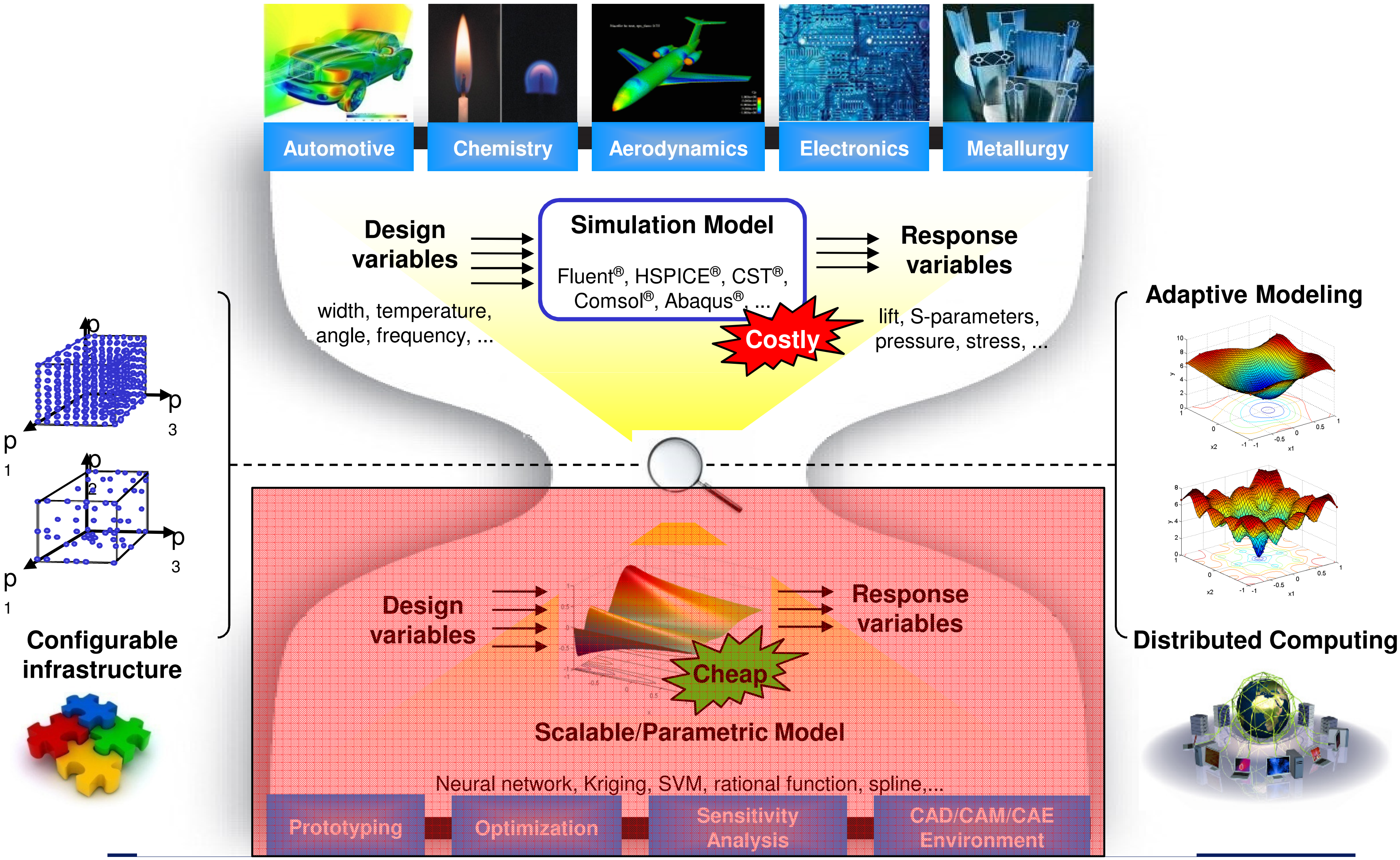
geology




Automotive
Chemistry
Aerodynamics
Electronics
Metallurgy
Design variables
Simulation Model
Fluent®, HSPICE®, CST®, Comsol®, Abaqus®, ...
Response variables
width, temperature, angle, frequency, ...
Costly
lift, S-parameters, pressure, stress, ...
Adaptive Modeling
Configurable infrastructure
Design variables
Cheap
Response variables
Distributed Computing
Scalable/Parametric Model
Neural network, Kriging, SVM, rational function, spline,...
Prototyping
Optimization
Sensitivity Analysis
CAD/CAM/CAE Environment

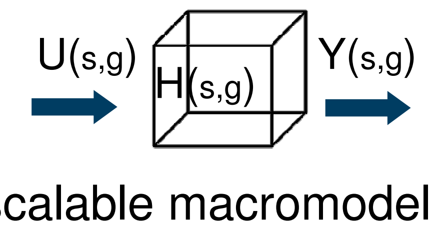
UNIVERSITEIT GENT

FACULTY OF ENGINEERING



ibbt

Scalable macromodels



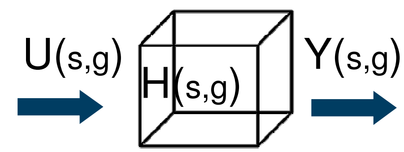
Multiple design variables

Compact models

Efficient design activities (excellent speed-ups)

- **Multiple simulations (measurements)**
  - **Design space optimization, exploration, sensitivity analysis**

Scalable macromodels



scalable macromodel

Time-domain simulations

- **Non-linear drivers and receivers**

Stochastic modeling

- **impact of manufacturing tolerances**

Models from measurements

- **noise to handle**

Applications in different domains


Thank you

Questions

Contact info: francesco.ferranti@ugent.be

Recent publications

F. Ferranti, L. Knockaert, T. Dhaene, "Passivity-Preserving Parametric Macromodeling by Means of Scaled and Shifted State-Space Systems", IEEE Trans. on Microwave Theory and Techniques, vol. 59, no. 10, pp.2394-2403, October 2011.

F. Ferranti, T. Dhaene, L. Knockaert, G. Antonini and A. Ciccomancini Scogna, "Scalable Compact Models for Fast Design Optimization of Complex Electromagnetic Systems", International Journal of RF and Microwave Computer-Aided Engineering, vol. 22, no. 1, pp. 20-29, January 2012.

F. Ferranti, M. Nakhla, G. Antonini, T. Dhaene, L. Knockaert, A. E. Ruehli, “Interpolation-based Parameterized Model Order Reduction of Delayed Systems”, IEEE Trans. on Microwave Theory and Techniques, vol. 60, no. 3, pp. 431-440, March 2012.

Contact info: francesco.ferranti@ugent.be