

Tutorial lecture on Characterization and Macromodeling of 3D Interconnects

Original

Tutorial lecture on Characterization and Macromodeling of 3D Interconnects / GRIVET TALOCIA, Stefano. -
ELETTRONICO. - (2004). (8th IEEE Workshop on Signal Propagation on Interconnects (SPI) Heidelberg (Germany)
May 9-12, 2004).

Availability:

This version is available at: 11583/1412861 since: 2015-07-15T07:09:37Z

Publisher:

Published

DOI:

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

(Article begins on next page)



Characterization and Macromodeling of 3D Interconnects

S. Grivet-Talocia

Politecnico di Torino, Italy

grivet@polito.it

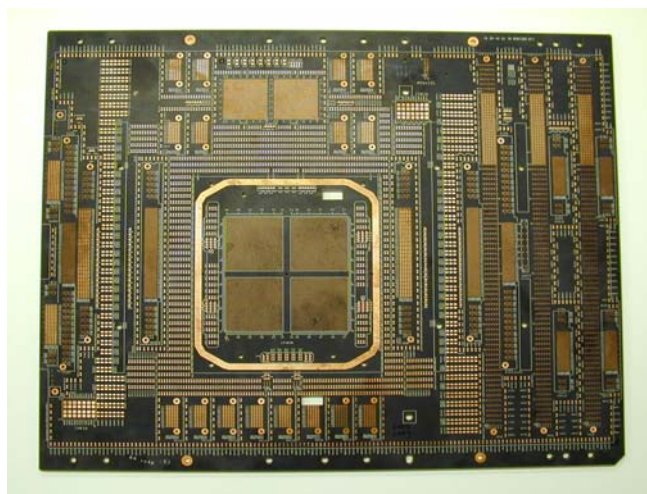
<http://www.eln.polito.it/research/emc>



S. Grivet-Talocia, SPI tutorial, 9 May 2004



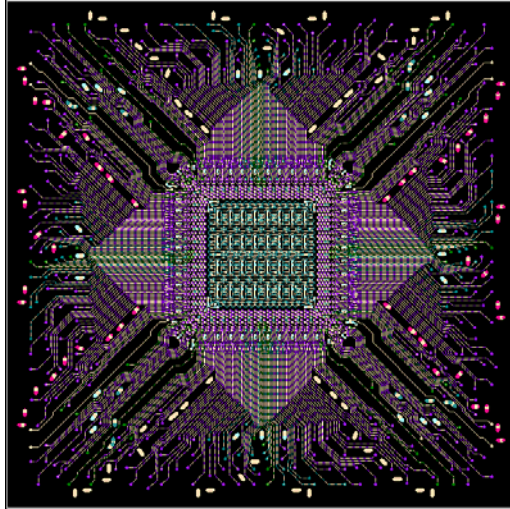
Introduction



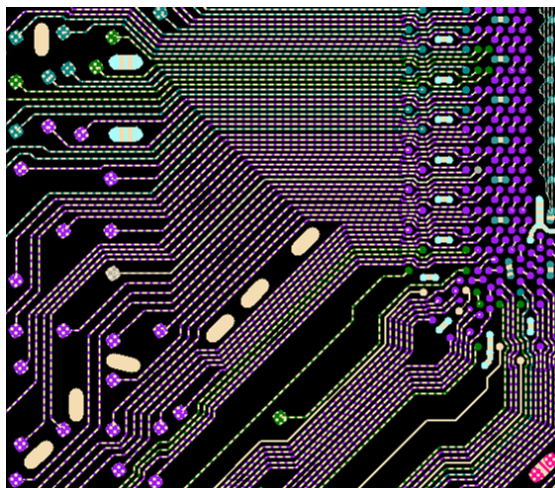
S. Grivet-Talocia, SPI tutorial, 9 May 2004



Introduction

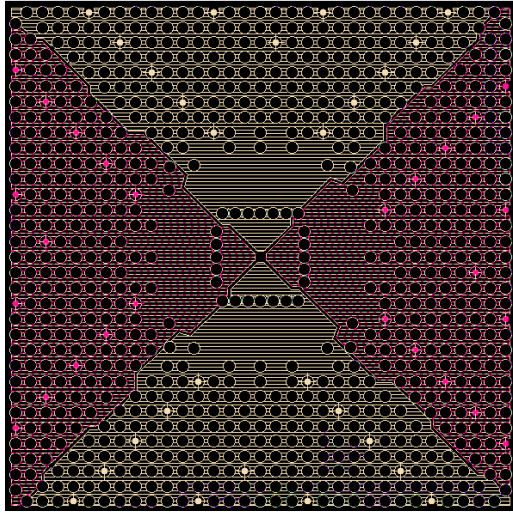


Introduction



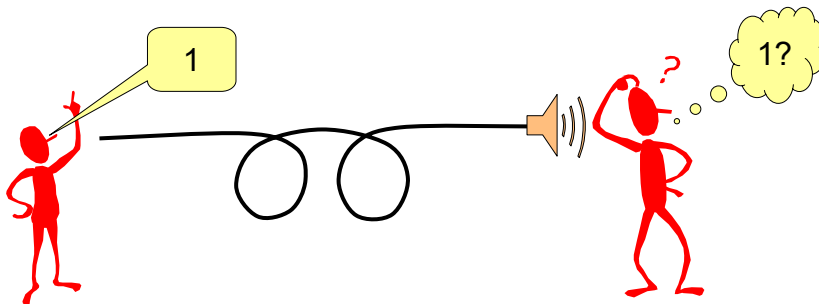


Introduction



Introduction

High-speed Data transmission requires
integrity of the signals
thru lines, bends, vias, connectors, ...

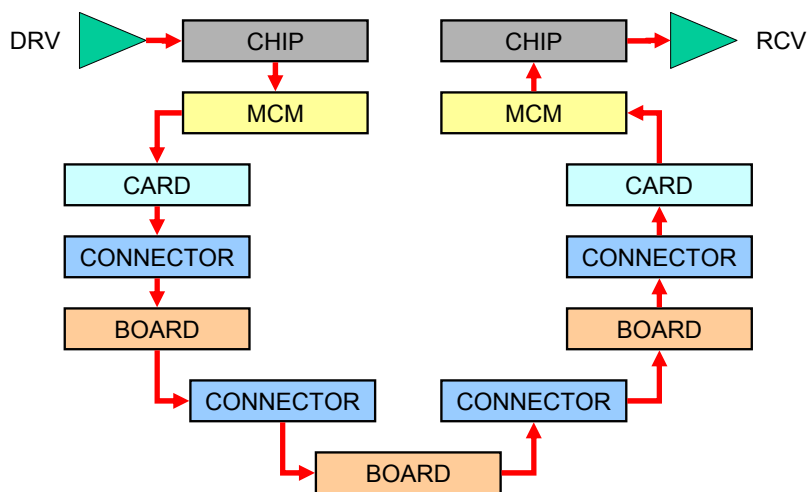




An example

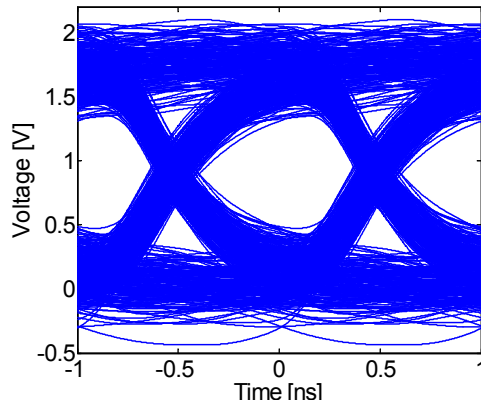


An example





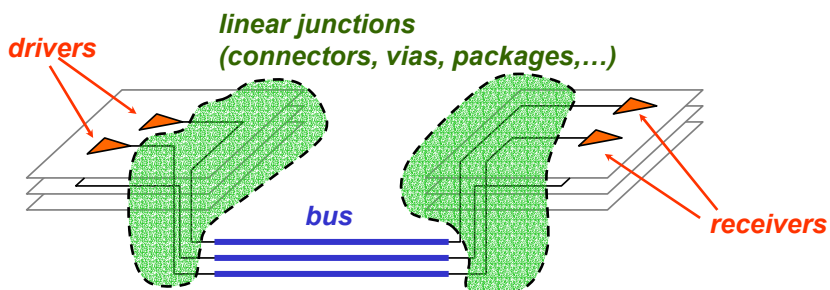
An example

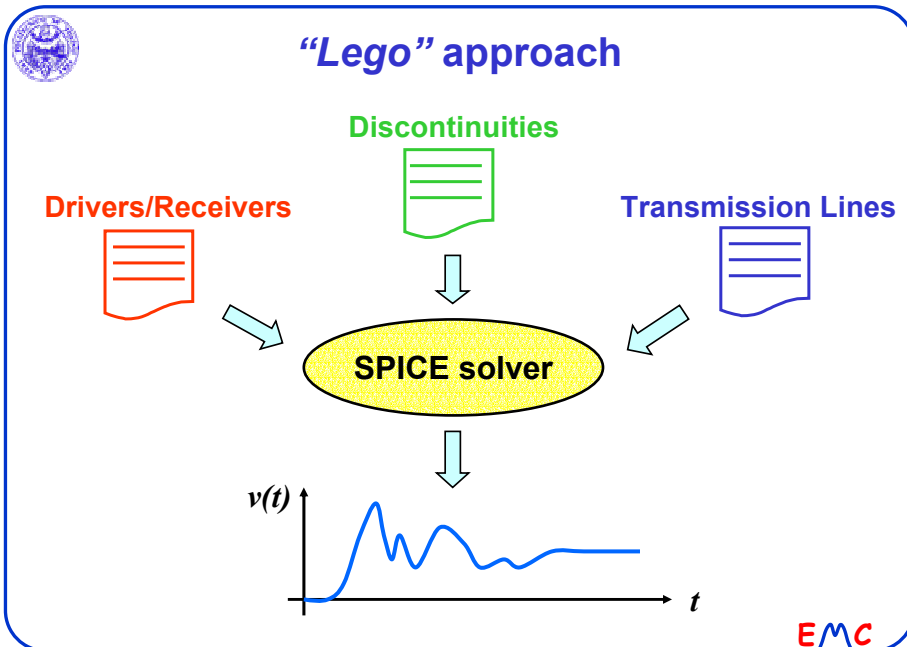
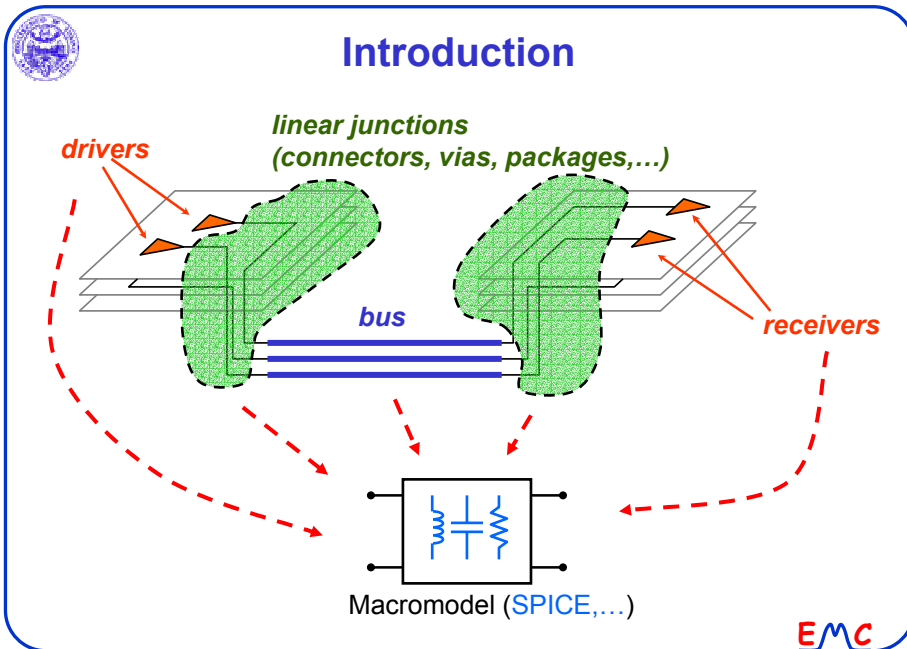


Introduction

Signal Integrity issues in high-speed digital systems

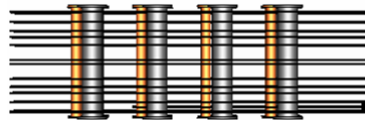
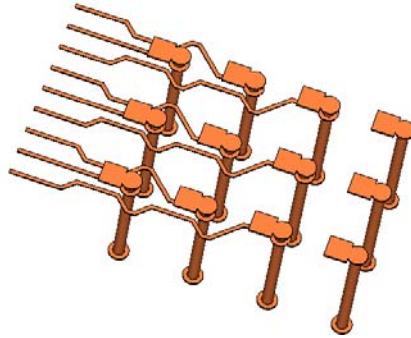
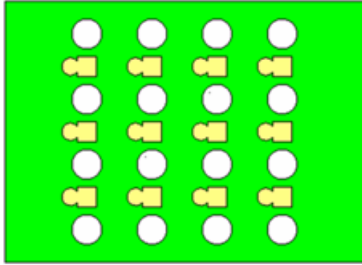
Crosstalk, couplings, reflections, losses, dispersion, attenuation, resonances, ground noise, nonlinear effects, radiation, EMI, ...



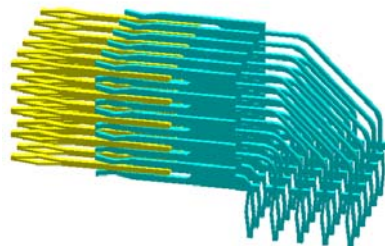
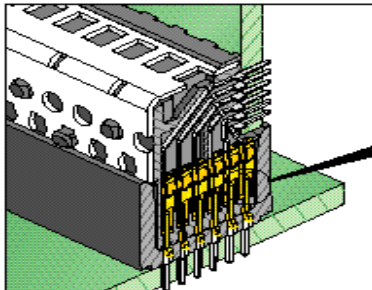




3D Interconnects

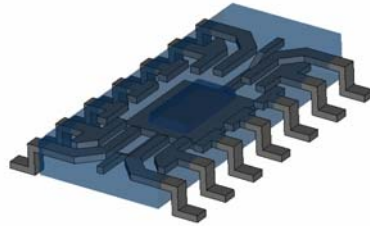
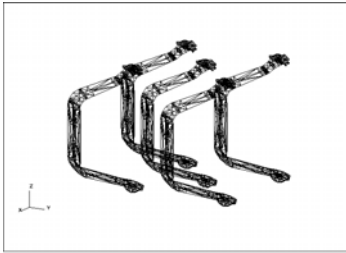
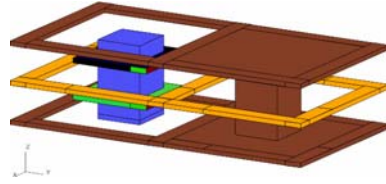
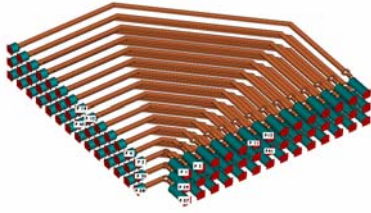


3D Interconnects





3D Interconnects



Outline

- Introduction
- **Macromodeling approaches for 3D Interconnects**
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Macromodeling approaches

Macromodeling of 3D interconnects for Signal Integrity

1. Capture physical effects leading to signal degradation
 - Must take into account **3D electromagnetic fields**
 - **Simulation or measurement**
 - Many different characterizations are possible!
2. Use this information to build a macromodel
 - **Many macromodeling approaches available!**



Macromodeling approaches

Characterization via equations

Discretization of Maxwell full-wave equations

Model Order Reduction methods: build a simplified model from an existing (large) one

Characterization via port responses (Black Box)

Time or frequency domain

Simulated or measured

Reduced-Order Model Identification methods: build a model from samples of the port responses



Macromodeling approaches

Main goal of all (lumped) macromodeling methods:

produce a rational approximation



$$\mathbf{H}_q(s) = \mathbf{H}_\infty + \sum_n \frac{\mathbf{R}_n}{s - p_n}$$

Lumped circuits

- **have rational transfer functions**
- **are governed by Ordinary Differential Equations**

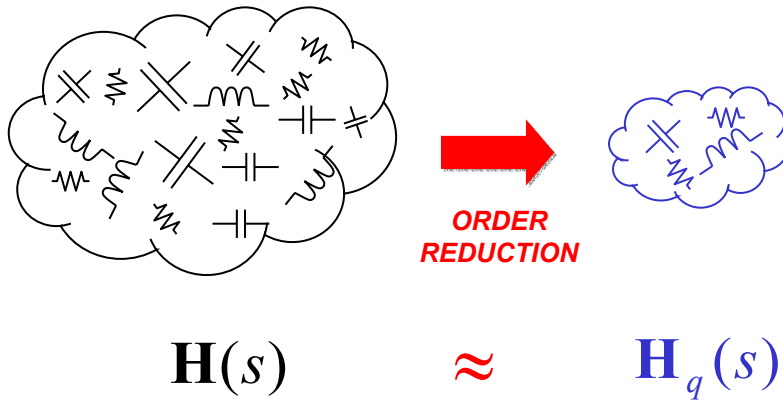


Outline

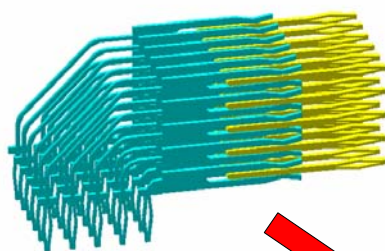
- Introduction
- Macromodeling approaches for 3D Interconnects
- **Model Order Reduction methods**
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Moder Order Reduction

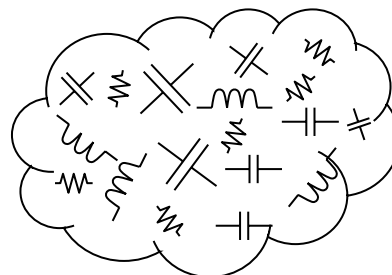


Possible scenarios



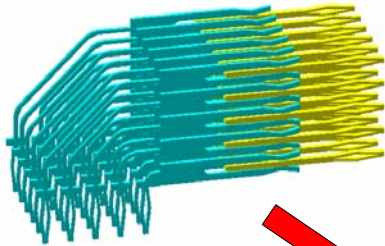
Large circuit

PEEC (Partial Element
Equivalent Circuit)
discretization



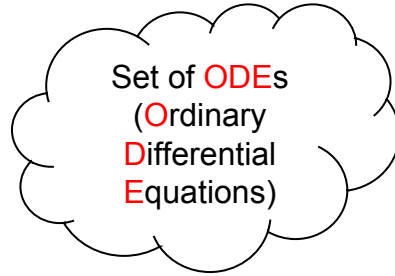


Possible scenarios

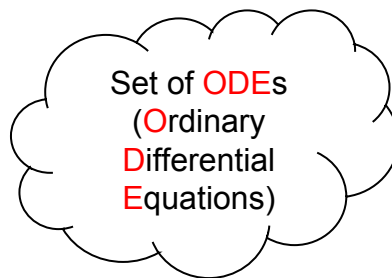
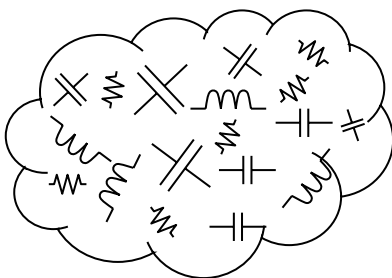


Large system

Spatial discretization of
Maxwell equations
(FDTD, FEM, MoM, ...)



Possible scenarios



MNA
$$\begin{cases} \mathbf{G}\mathbf{x} + \mathbf{C}\dot{\mathbf{x}} = \mathbf{B}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T\mathbf{x} \end{cases}$$

$$\mathbf{H}(s) = \mathbf{L}^T(\mathbf{G} + s\mathbf{C})^{-1}\mathbf{B}$$



Approximation via moment matching

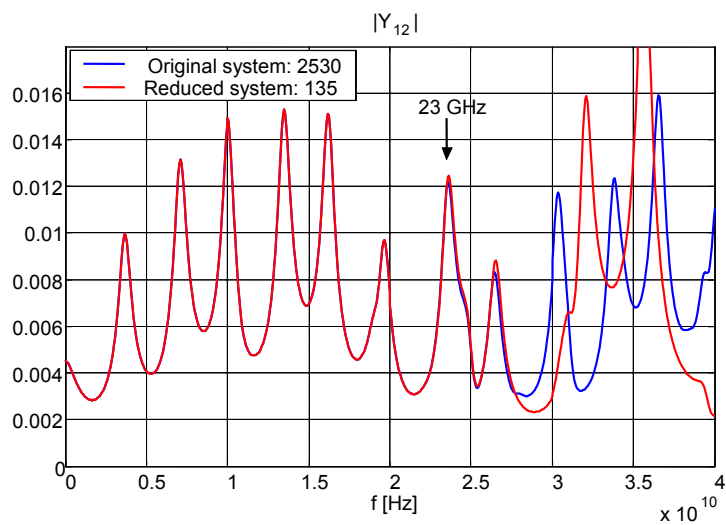


$$\mathbf{H}(s) = \mathbf{M}_0 + \mathbf{M}_1 s + \mathbf{M}_2 s^2 + \dots + \mathbf{M}_N s^N + \dots$$

$$\mathbf{H}_q(s) = \mathbf{M}_0 + \mathbf{M}_1 s + \mathbf{M}_2 s^2 + \dots + \mathbf{M}_q s^q + \dots$$



Moment matching: an example





Moments

$$\begin{cases} \mathbf{G}\mathbf{x} + \mathbf{C}\dot{\mathbf{x}} = \mathbf{B}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T\mathbf{x} \end{cases} \quad \begin{cases} \mathbf{x} = \mathbf{A}\dot{\mathbf{x}} + \mathbf{R}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T\mathbf{x} \end{cases} \quad \begin{cases} \mathbf{A} = -\mathbf{G}^{-1}\mathbf{C} \\ \mathbf{R} = \mathbf{G}^{-1}\mathbf{B} \end{cases}$$

$$\mathbf{H}(s) = \mathbf{L}^T(\mathbf{I} - s\mathbf{A})^{-1}\mathbf{B}\mathbf{u}$$

$$\mathbf{H}(s) = \mathbf{M}_0 + \mathbf{M}_1s + \mathbf{M}_2s^2 + \dots$$
$$\text{Moments} \quad \mathbf{L}^T\mathbf{R} \quad \mathbf{L}^T\mathbf{A}\mathbf{R} \quad \mathbf{L}^T\mathbf{A}^2\mathbf{R}$$



Moment matching techniques

Explicit $\mathbf{M}_i = \mathbf{L}^T\mathbf{A}^i\mathbf{R} \rightarrow \mathbf{H}_q(s)$

Asymptotic Waveform Evaluation (AWE)

Pade` Approximations

Complex Frequency Hopping (CFH)

- Good theoretical properties, convergence
- Bad numerical properties, intrinsic ill-conditioning due to
 - Moment generation
 - Moment matching



Moment matching techniques



Implicit

Krylov subspace projection methods

- Same information stored in moments
- Much better numerical performance, robustness
- Several versions
 - Arnoldi, PRIMA, Lanczos, ...
- Possibility of preserving stability and passivity by construction!



Krylov subspaces

$$\mathbf{H}(s) = \mathbf{M}_0 + \mathbf{M}_1 s + \mathbf{M}_2 s^2 + \dots$$

$$\begin{array}{ccc} \downarrow & \downarrow & \downarrow \\ \text{Moments} & \mathbf{L}^T \mathbf{R} & \mathbf{L}^T \mathbf{A} \mathbf{R} & \mathbf{L}^T \mathbf{A}^2 \mathbf{R} \end{array}$$

$$Kr(\mathbf{A}, \mathbf{R}, q) = \text{span}\{\mathbf{R}, \mathbf{A}\mathbf{R}, \mathbf{A}^2\mathbf{R}, \dots, \mathbf{A}^{q-1}\mathbf{R}\}$$

$$\mathbf{V}_q = \text{basis of } Kr(\mathbf{A}, \mathbf{R}, q)$$

Constructed via iterative (stable) algorithms



Arnoldi (basic) algorithm

$$\begin{cases} \mathbf{x} = \mathbf{A}\dot{\mathbf{x}} + \mathbf{R}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T \mathbf{x} \end{cases}$$

$$\mathbf{V}_q^T \mathbf{A} \mathbf{V}_q = \mathbf{A}_q$$

$$\mathbf{x} \approx \mathbf{V}_q \mathbf{x}_q$$

$$\begin{cases} \mathbf{x}_q = \mathbf{A}_q \dot{\mathbf{x}}_q + \mathbf{R}_q \mathbf{u} \\ \mathbf{y} = \mathbf{L}_q^T \mathbf{x}_q \end{cases}$$



PRIMA algorithm

$$\begin{cases} \mathbf{G}\mathbf{x} + \mathbf{C}\dot{\mathbf{x}} = \mathbf{B}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T \mathbf{x} \end{cases}$$

$$\mathbf{V}_q^T \mathbf{C} \mathbf{V}_q = \mathbf{C}_q$$

$$\mathbf{V}_q^T \mathbf{G} \mathbf{V}_q = \mathbf{G}_q$$

$$\mathbf{x} \approx \mathbf{V}_q \mathbf{x}_q$$

$$\begin{cases} \mathbf{G}_q \mathbf{x}_q + \mathbf{C}_q \dot{\mathbf{x}}_q = \mathbf{B}_q \mathbf{u} \\ \mathbf{y} = \mathbf{L}_q^T \mathbf{x}_q \end{cases}$$



Passivity conditions (PRIMA)

$$\begin{cases} \mathbf{G}\mathbf{x} + \mathbf{C}\dot{\mathbf{x}} = \mathbf{B}\mathbf{u} \\ \mathbf{y} = \mathbf{L}^T\mathbf{x} \end{cases}$$

Can often be enforced
by construction building
the original system



$$\begin{cases} \mathbf{G}_q\mathbf{x}_q + \mathbf{C}_q\dot{\mathbf{x}}_q = \mathbf{B}_q\mathbf{u} \\ \mathbf{y} = \mathbf{L}_q^T\mathbf{x}_q \end{cases}$$

$$\mathbf{G} \geq 0 \quad \mathbf{C} \geq 0$$

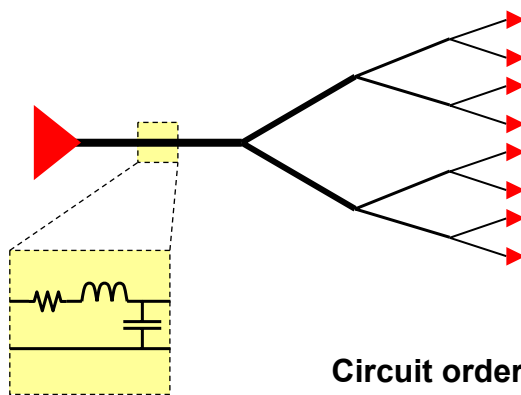
\mathbf{C} symmetric

$$\mathbf{L} = \pm \mathbf{B}$$

\mathbf{V}_q must be full rank



An example: RLC tree circuit

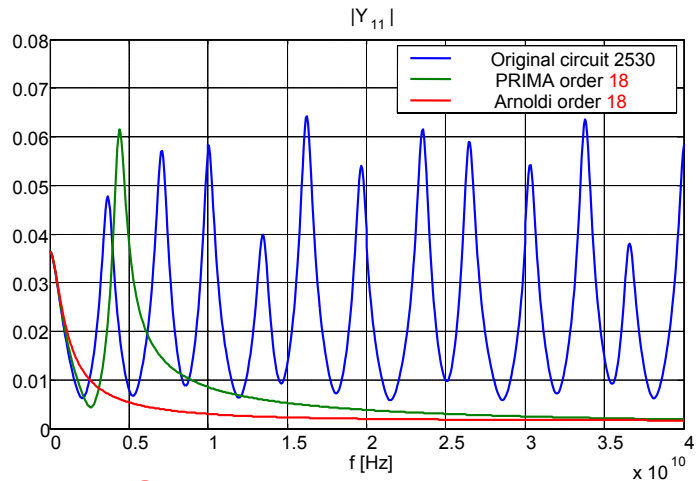


Circuit order: 2530

Ports: 9



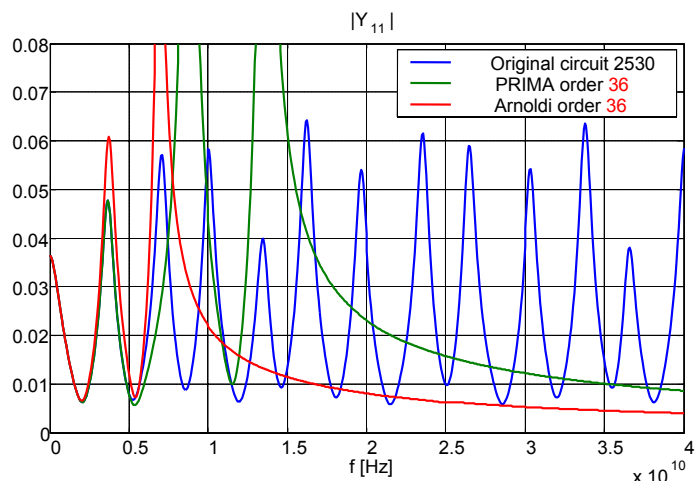
RLC tree circuit: order reduction



■ 1 GHz



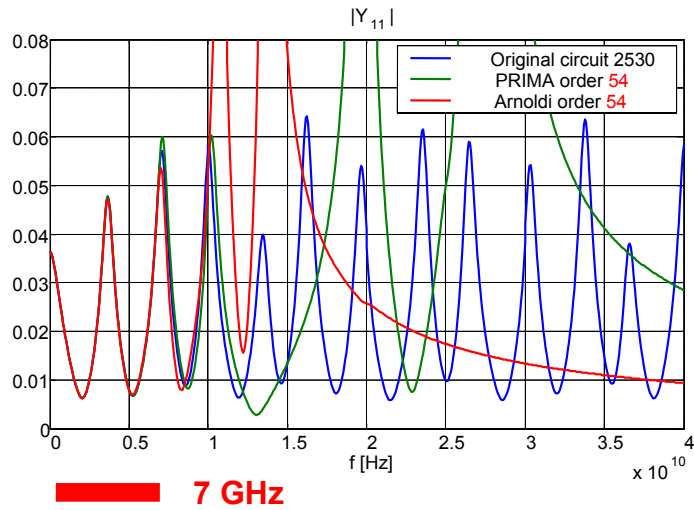
RLC tree circuit: order reduction



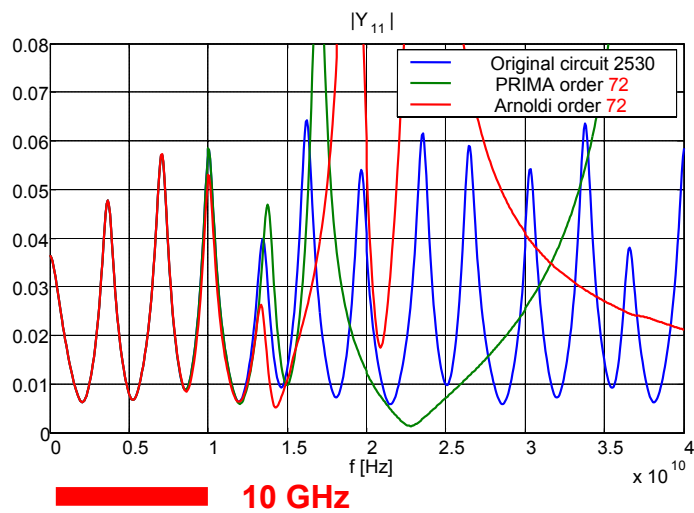
■ 2 GHz



RLC tree circuit: order reduction

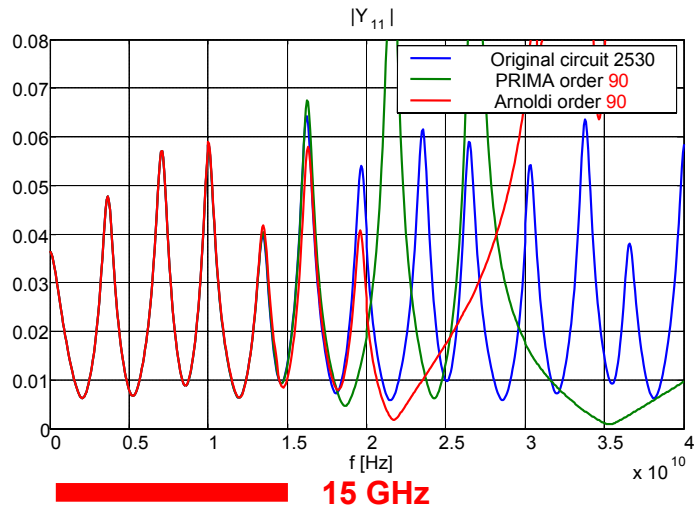


RLC tree circuit: order reduction

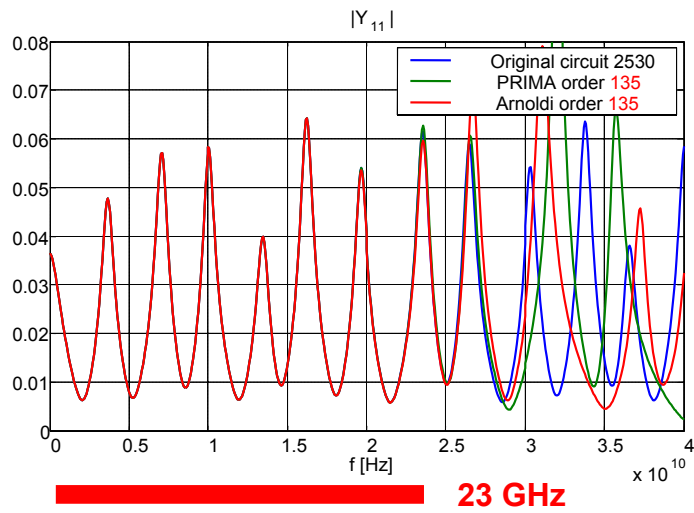




RLC tree circuit: order reduction

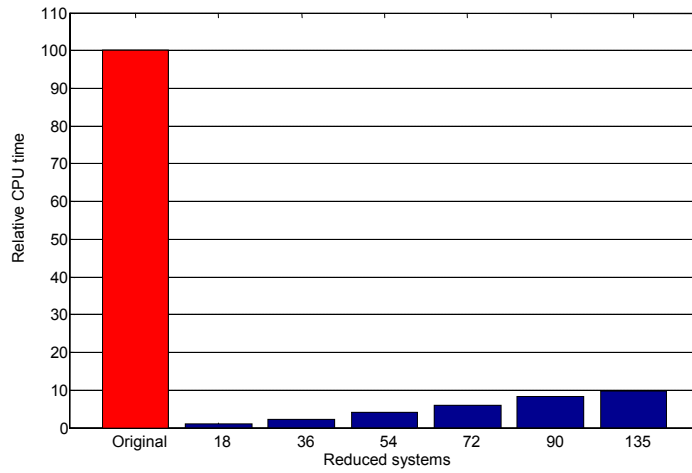


RLC tree circuit: order reduction

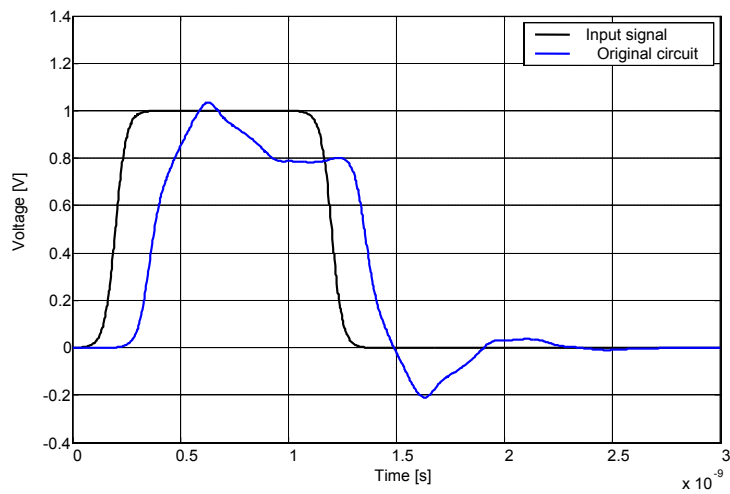




RLC tree circuit: efficiency

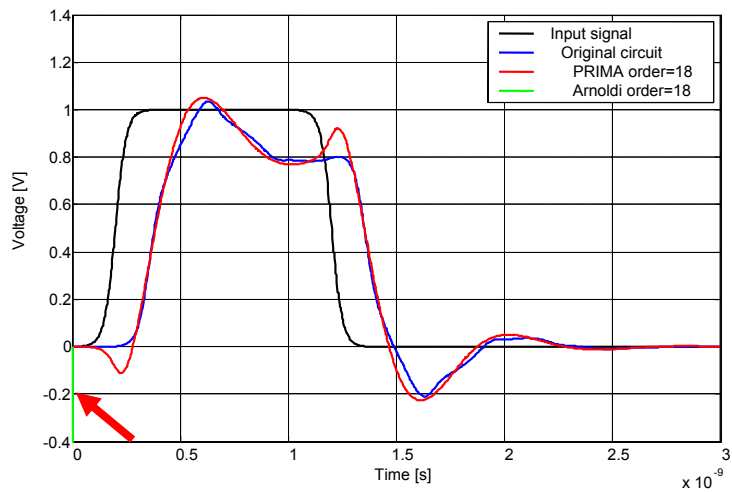


RLC tree circuit: transient analysis

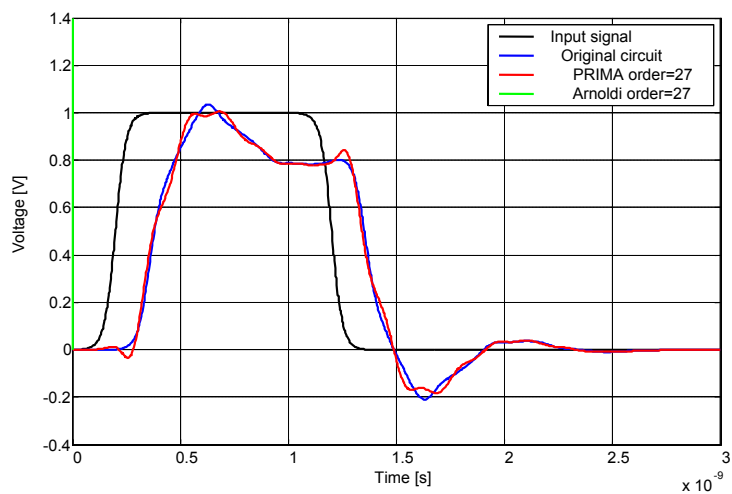




RLC tree circuit: transient analysis

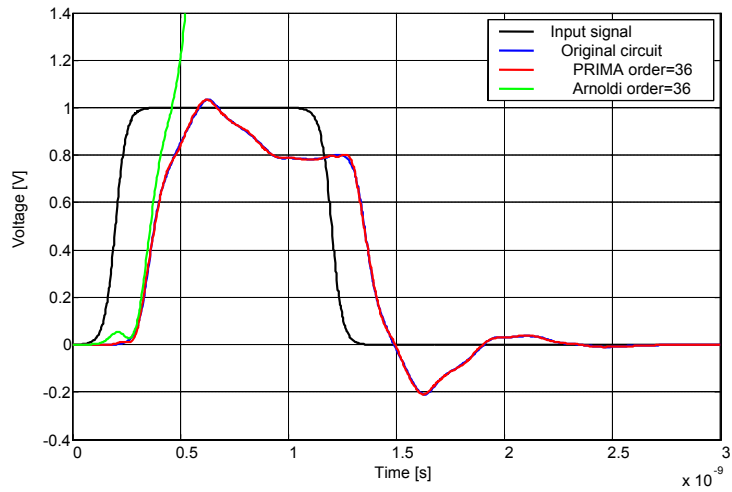


RLC tree circuit: transient analysis

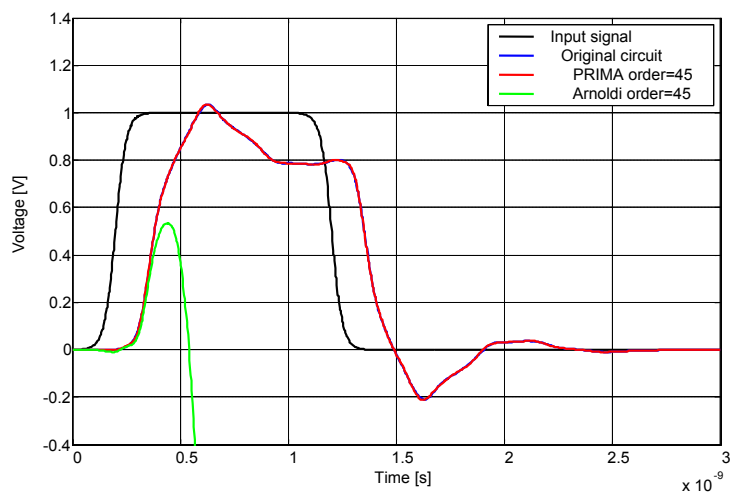




RLC tree circuit: transient analysis



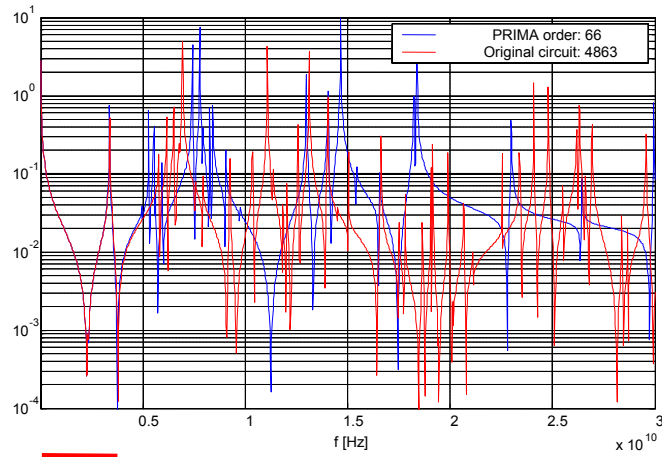
RLC tree circuit: transient analysis





Example: MNA, 22 ports, order 4863

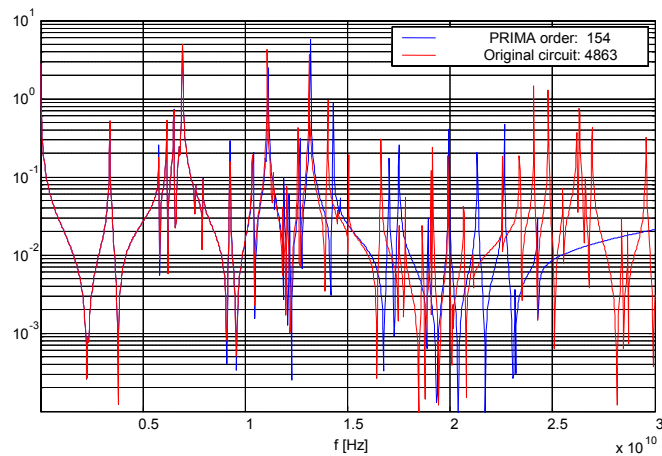
(www.win.tue.nl/niconet/NIC2/benchmodred.html)



3 GHz



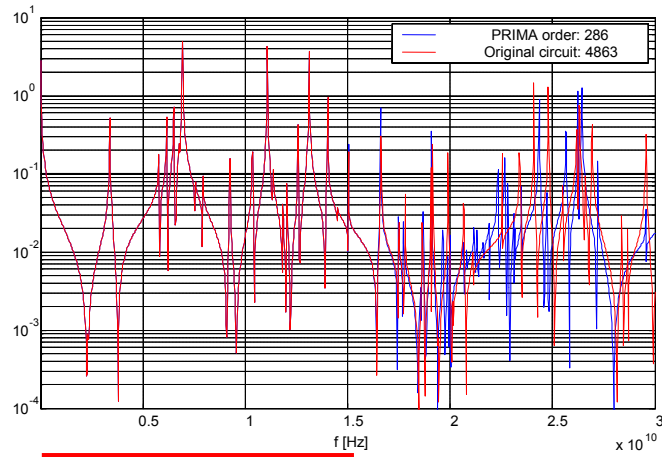
Example: MNA, 22 ports, order 4863



6 GHz



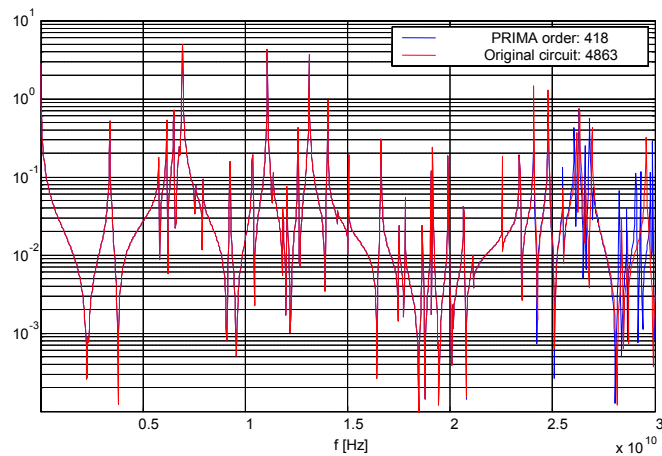
Example: MNA, 22 ports, order 4863



15 GHz



Example: MNA, 22 ports, order 4863



24 GHz



Key references

M.Celik, L.Pileggi, A.Odabasioglu, IC Interconnects Analysis, Kluwer, 2002

...and references therein

R.Achar, M.S.Nakhla, Proceedings of the IEEE, Vol.89, 2001, 693-728

... and references therein

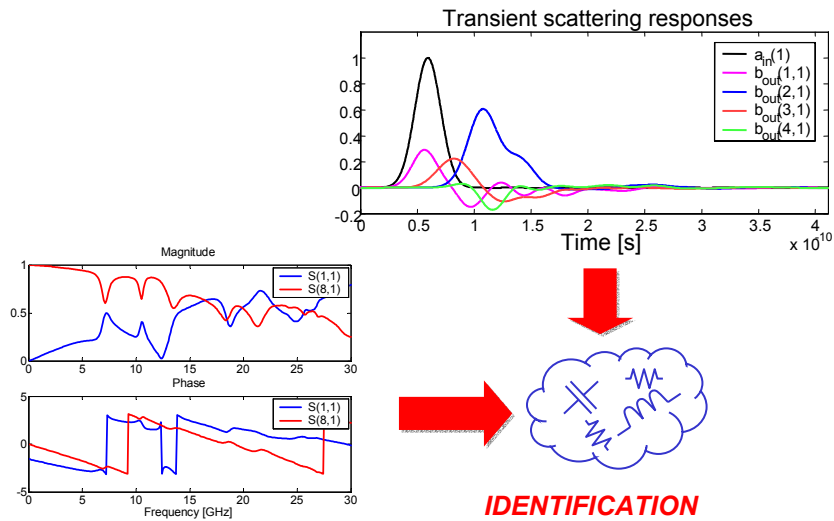


Outline

- Introduction
- Macromodeling approaches for 3D Interconnects
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Model Identification



Model identification

From samples to model: **identification** process

Reduced-order identification: **approximation** process

Several identification methods exist

Characterized by use of different:

- Input data
- Modeling criteria
- Model parameter estimation



Identification methods

Block Complex Frequency Hopping (BCFH)

[R.Achar, M.S.Nakhla, *IEEE Proceedings*, Vol.89, 2001]

Rational **Padé** approximation of network functions

Convergence property in a neighborhood of the expansion point

Hopping along frequency axis to cover the modeling bandwidth

May lead to **ill-conditioned** numerical systems when used for identification from sampled responses



Identification methods

Global Rational Approximation

[M.Elzinga, K.L.Virga, J.L.Prince, *IEEE Trans. MTT*, 9/2000]

[W.Beyene, J.Schutt-Aine, *IEEE Trans. CPMT*, Vol.21, 3/1998]

[K.L.Choi, M.Swaminathan, *IEEE Trans. CAS II*, vol.47, 4/2000]

[J.Morsey, A.C.Cangellaris, *Proc. EPEP*, 2001]

[... many, many, many others...]

A matrix of rational functions is **fitted** to the samples of a network function matrix (e.g. the Y matrix)



Identification methods

Pencil of Functions

[Y.Hua, T.Sarkar, *IEEE Trans. AP*, vol.37, 2/1989]

Time-domain data

Estimates model poles by **fitting** a sum of exponential functions to the samples of transient port responses

Poles obtained as eigenvalues of a generalized eigenvalue problem

Automatic order estimation



Identification methods

Subspace-based State-Space System Identification methods (4SID)

[M. Viberg, *Automatica*, 12/1995]

[T.McKelvey, H.Akcaay, L.Ljung, *IEEE Trans. AC*, vol.41, 7/1996]

Based on **projections** of data onto orthogonal subspaces, leading to direct state-space estimation

Built-in **automatic order estimation** (based on SVD)

Available in both **time and frequency** domain

Equivalent to Pencil of Functions methods



Identification methods

Nevanlinna-Pick Interpolation

[C.P.Coelho, J.R.Phillips, L.M.Silveira, Proc. DATE 2002]

Interpolation of samples of the scattering matrix with a (unitary bounded) matrix rational function

Nice theoretical properties

Very complex

Leads to models with large dynamical order



Identification methods

Vector Fitting

[B.Gustavsen, A. Semlyen, IEEE Trans. PD, vol.14, 7/1999]

Performs data fitting with rational functions avoiding nonlinear optimization

Iterative process converging to the dominant poles

Available for both time and frequency domain



Identification methods

Identification methods are not expected to work for every possible problem

Any method performs well for a certain class of identification problems

Vector Fitting is selected here as one of the most promising methods for a wide range of applications



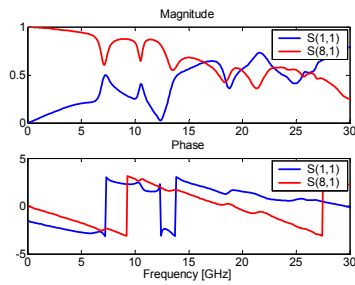
Outline

- Introduction
- Macromodeling approaches for 3D Interconnects
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - **Frequency-Domain Vector Fitting**
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Frequency-domain macromodeling

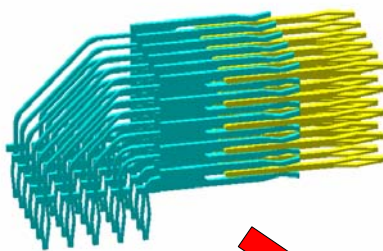
Model identification from frequency-domain responses



IDENTIFICATION



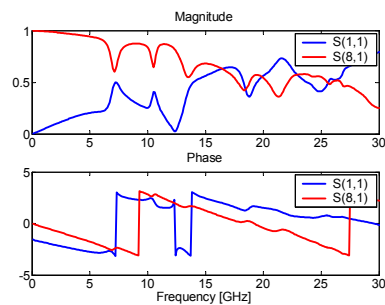
Possible scenarios



**Frequency-Domain
full-wave simulation
(MoM, FEM, ...)**

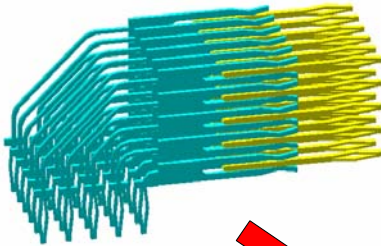


Frequency tables
of transfer matrix
(S, Y, Z, ...)





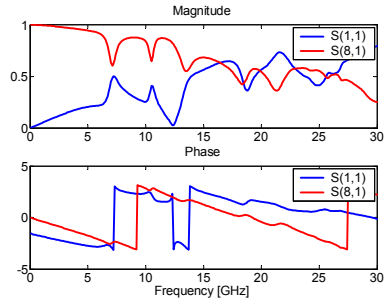
Possible scenarios



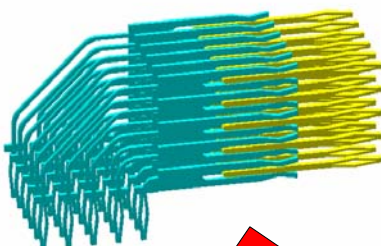
Time-Domain full-wave simulation (FIT, FDTD)

FFT postprocessing

Frequency tables of transfer matrix (S, Y, Z, ...)

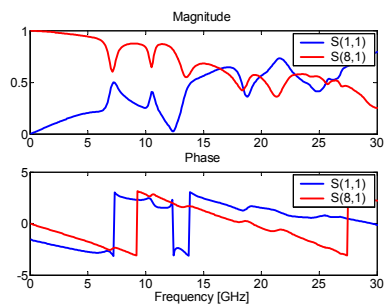


Possible scenarios



Direct VNA measurement

Frequency tables of transfer matrix (S)





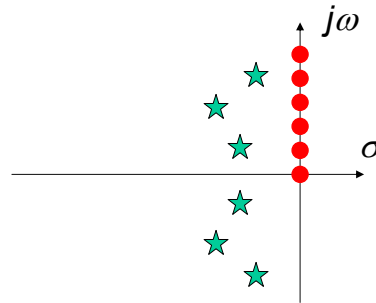
Frequency-Domain Macromodeling

Input data
 $\{ \hat{H}(j\omega_k), k = 1, \dots, K \}$

Approximation

$$H(s) = \sum_{n=1}^N \frac{R_n}{s - p_n} + H_\infty$$

Fitting condition
 $H(j\omega_k) \approx \hat{H}(j\omega_k), \forall k$



Unknowns:

- Poles p_n
- Residues R_n
- Constant H_∞



Frequency-Domain Macromodeling

Direct fitting condition: nonlinear!

$$\sum_{n=1}^N \frac{R_n}{j\omega_k - p_n} + H_\infty \approx \hat{H}(j\omega_k), \quad \forall k$$

- Nonlinear dependence on poles
- Requires nonlinear optimization (e.g. nonlinear least squares)
- Convergence problems (local minima, etc...)





Frequency-Domain Macromodeling

Direct fitting condition: nonlinear!

$$\sum_{n=1}^N \frac{R_n}{j\omega_k - p_n} + H_\infty \approx \hat{H}(j\omega_k), \quad \forall k$$

**Vector Fitting
avoids nonlinear optimization**

B. Gustavsen, A. Semlyen, "Rational approximation of frequency responses by **vector fitting**", *IEEE Trans. Power Delivery*, Vol.14, July 1999, pp.1052-1061



Frequency-Domain Vector Fitting

Input data

$$\left\{ \hat{H}(j\omega_k), \quad k = 1, \dots, K \right\}$$

Approximation

$$H(s) = \sum_{n=1}^N \frac{R_n}{s - p_n} + H_\infty$$

Weight function

$$w(s) = \sum_{n=1}^N \frac{c_n}{s - q_n} + 1$$

- $w(s)$ is unitary for $s \rightarrow \infty$
- poles q_n are fixed a priori
- residues c_n are unknown

Vector Fitting condition

$$w(s) H(s) \cong \sum_{n=1}^N \frac{\tilde{c}_n}{s - q_n} + \tilde{H}_\infty$$

The poles of

$w(s) H(s)$
are $\{q_n\}$ only!



Frequency-Domain Vector Fitting

Input data

$$\left\{ \hat{H}(j\omega_k), \quad k = 1, \dots, K \right\}$$

Approximation

$$H(s) = \sum_{n=1}^N \frac{R_n}{s - p_n} + H_\infty$$

Weight function

$$w(s) = \sum_{n=1}^N \frac{c_n}{s - q_n} + 1$$

$$= \prod_{n=1}^N \frac{(s - z_n)}{(s - q_n)}$$

There are N zeros $\{z_n\}$

Vector Fitting condition

$$w(s) H(s) \cong \sum_{n=1}^N \frac{\tilde{c}_n}{s - q_n} + \tilde{H}_\infty$$

$$\{p_n\} \cong \{z_n\}$$



Frequency-Domain Vector Fitting

Input data

$$\left\{ \hat{H}(j\omega_k), \quad k = 1, \dots, K \right\}$$

Weight function

$$w(s) = \sum_{n=1}^N \frac{c_n}{s - q_n} + 1$$

$$\left\{ \sum_{n=1}^N \frac{c_n}{j\omega_k - q_n} + 1 \right\} \hat{H}(j\omega_k) \cong \sum_{n=1}^N \frac{\tilde{c}_n}{j\omega_k - q_n} + \tilde{H}_\infty$$

Vector Fitting condition

$$w(s) H(s) \cong \sum_{n=1}^N \frac{\tilde{c}_n}{s - q_n} + \tilde{H}_\infty$$



Frequency-Domain Vector Fitting

Unknowns

$$\{c_n, \tilde{c}_n, \tilde{H}_\infty\}$$

$$\left\{ \sum_{n=1}^N \frac{c_n}{j\omega_k - q_n} + 1 \right\} \hat{H}(j\omega_k) \cong \sum_{n=1}^N \frac{\tilde{c}_n}{j\omega_k - q_n} + \tilde{H}_\infty$$

Linear least squares problem: easy to solve!

$$w(s) = \sum_{n=1}^N \frac{c_n}{s - q_n} + 1 = \prod_{n=1}^N \frac{(s - z_n)}{(s - q_n)}$$

Poles of $H(s)$

EMC
GROUP



Frequency-Domain Vector Fitting

$$w(s) = \sum_{n=1}^N \frac{c_n}{s - q_n} + 1 = \prod_{n=1}^N \frac{(s - z_n)}{(s - q_n)}$$

Poles of $H(s)$

Theorem: the zeros $\{z_n\}$ are the eigenvalues of

$$\mathbf{Q} = \mathbf{A} - \mathbf{b} \mathbf{c}^T$$

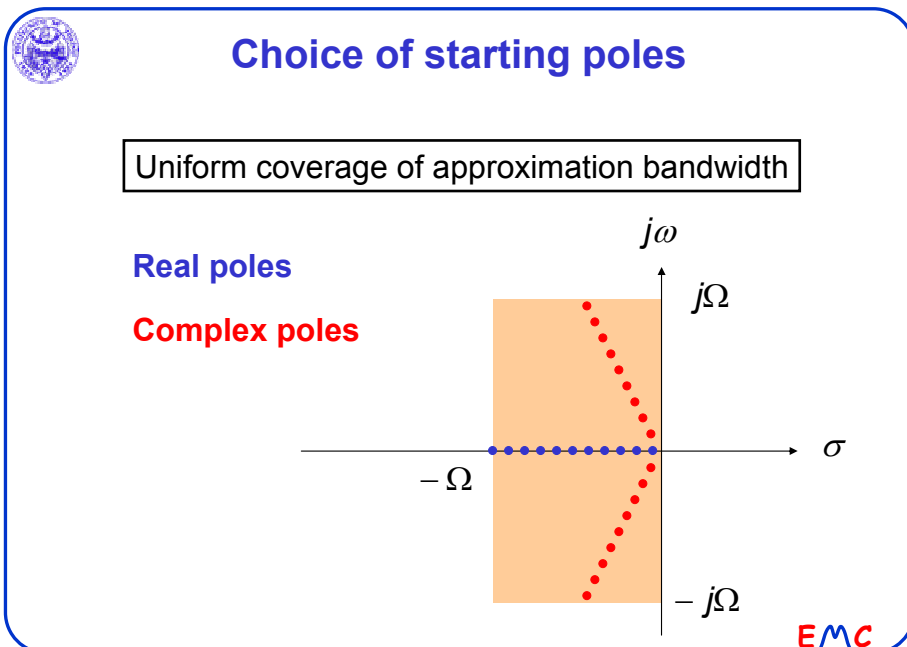
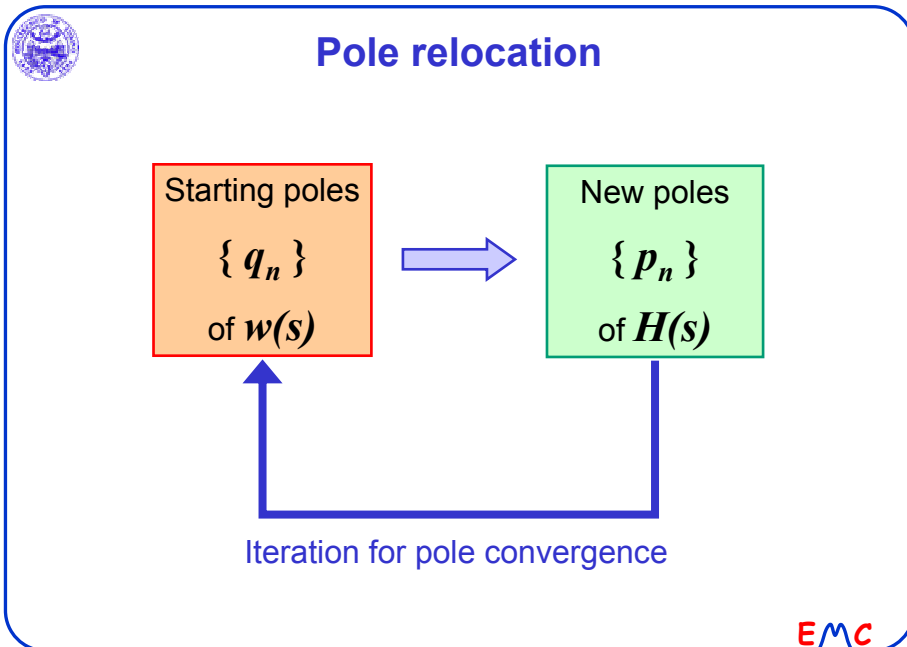
where

$$\mathbf{A} = \text{diag} \{q_n\}$$

$$\mathbf{b} = (1 \quad 1 \quad \dots \quad 1)^T$$

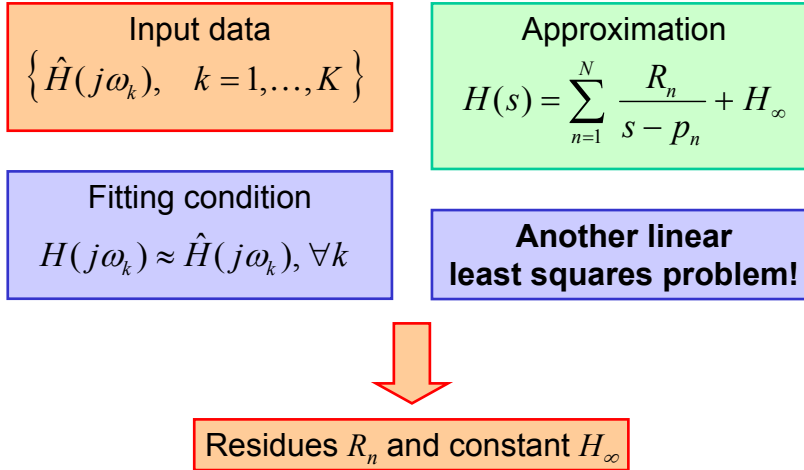
$$\mathbf{c} = (c_1 \quad c_2 \quad \dots \quad c_N)^T$$

EMC
GROUP

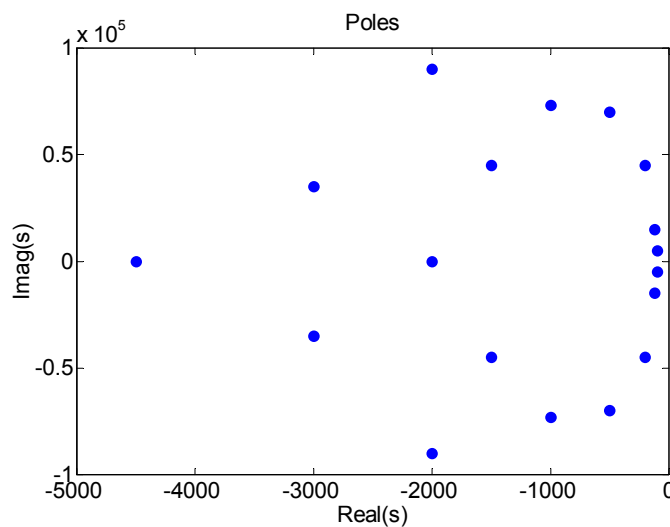




Vector Fitting: residues

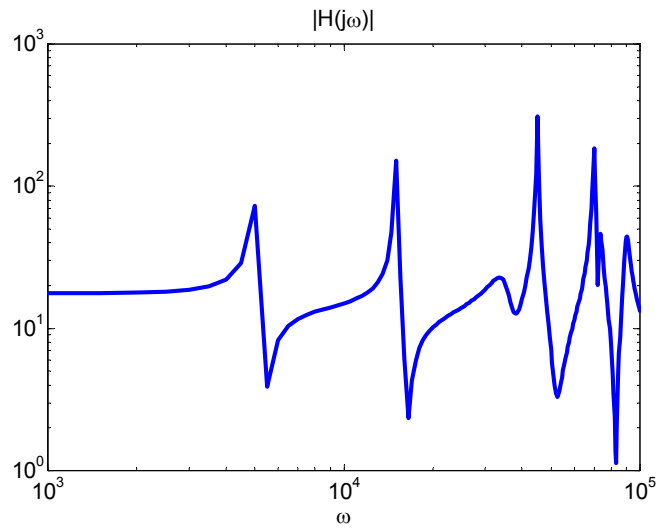


Example 1: 18 random poles/residues

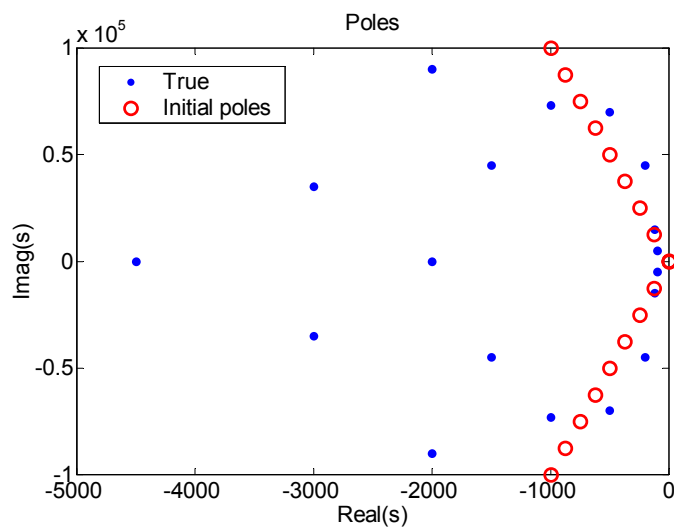




Example 1

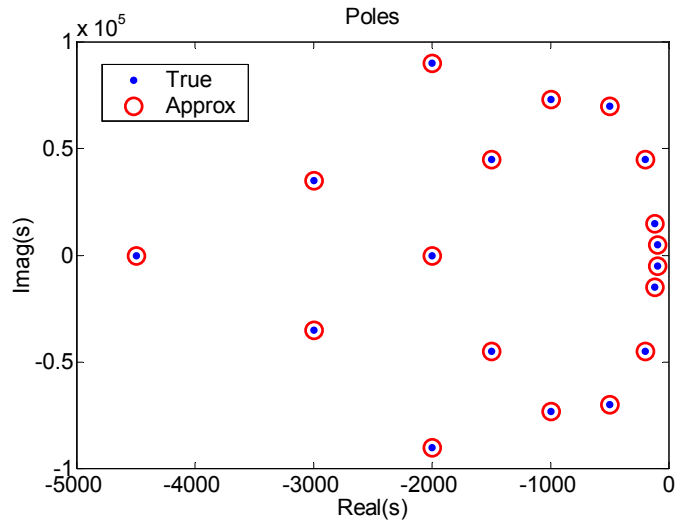


Example 1

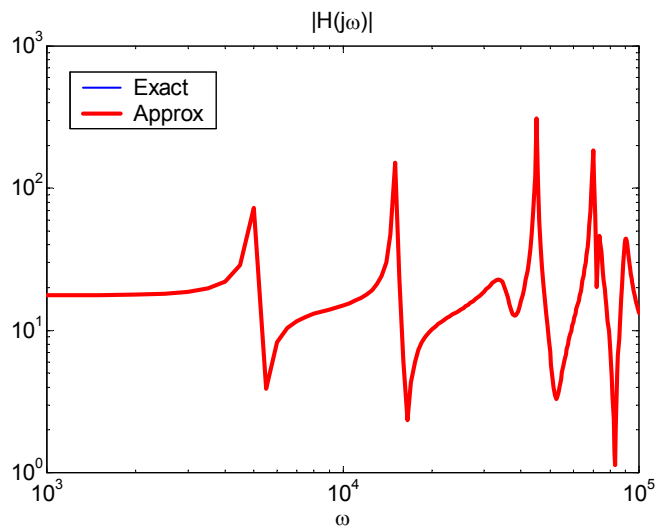




Example 1

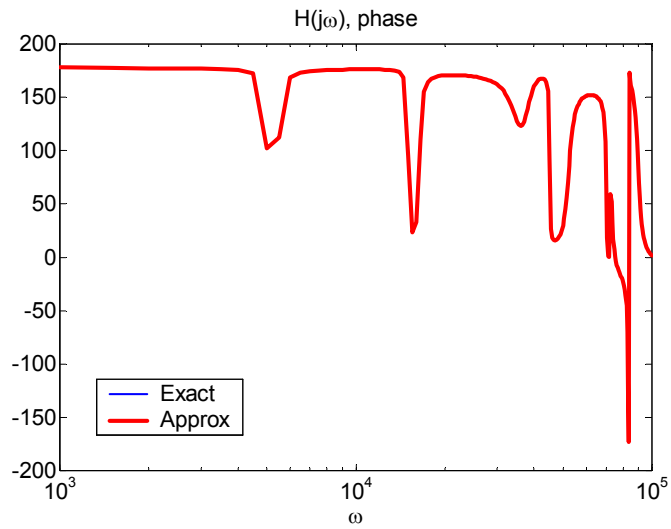


Example 1





Example 1



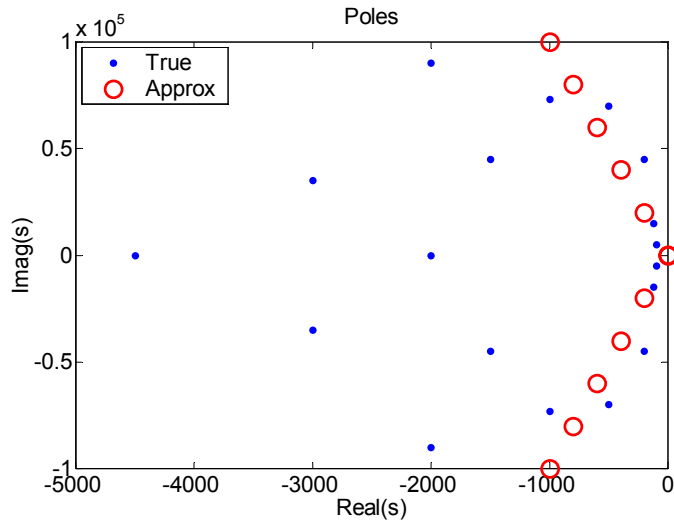
Example 2

Same 18-pole rational function

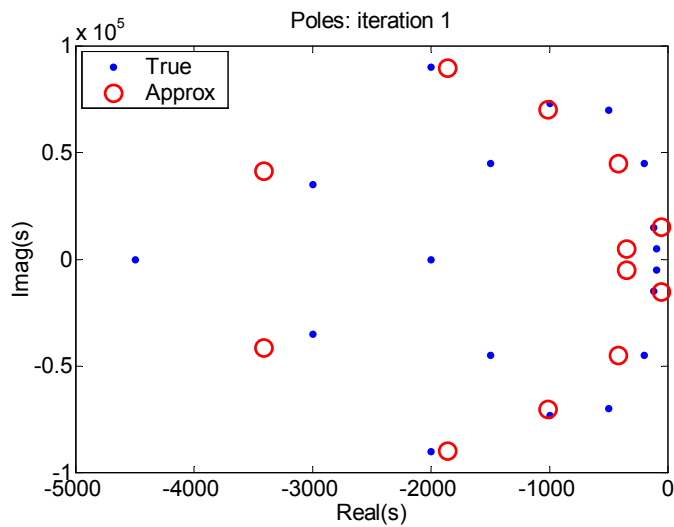
Reduced-order fitting (12th order)



Example 2

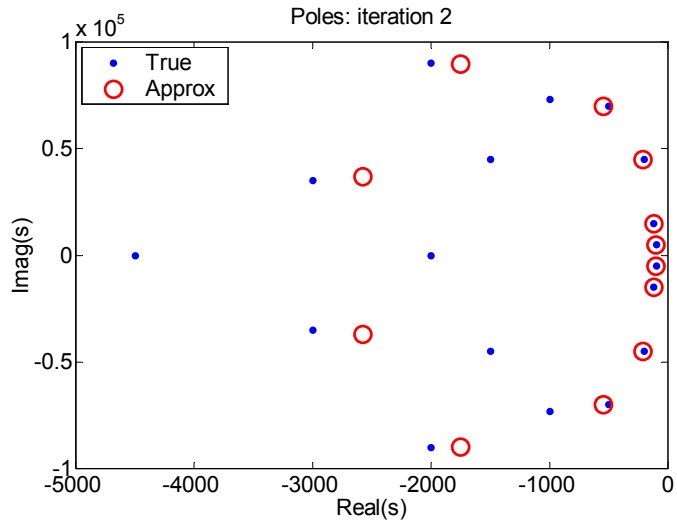


Example 2

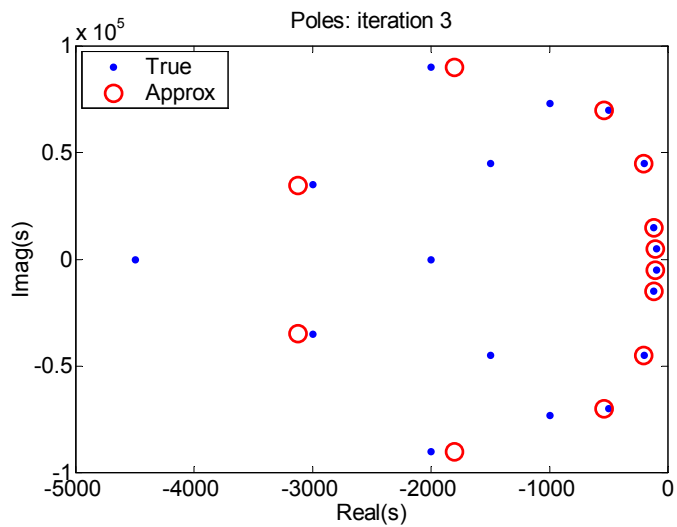




Example 2

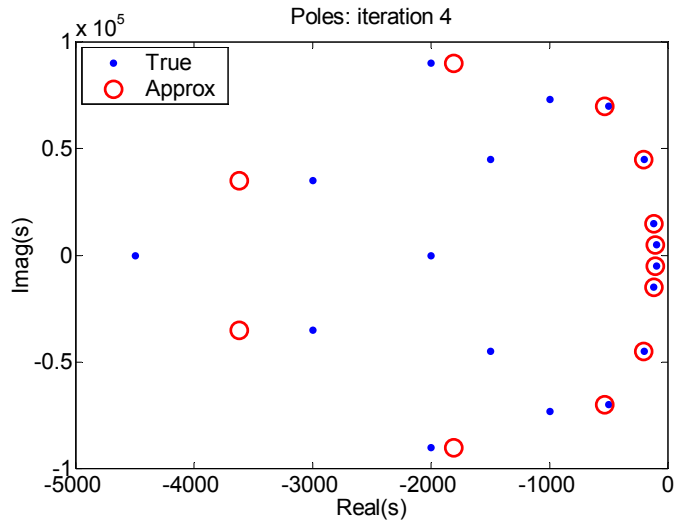


Example 2

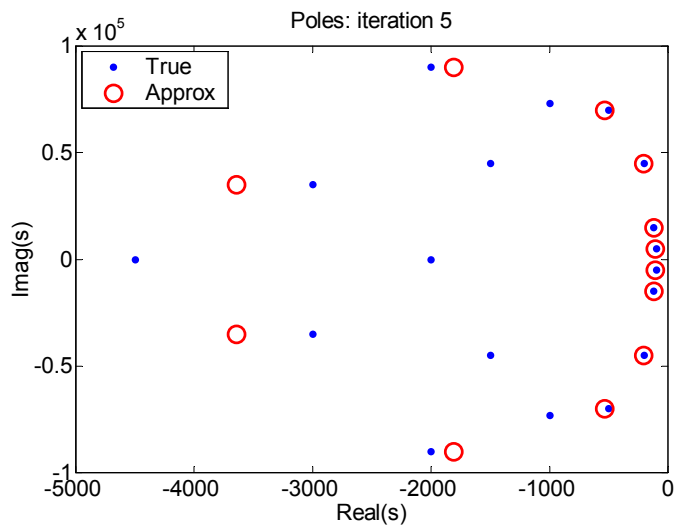




Example 2

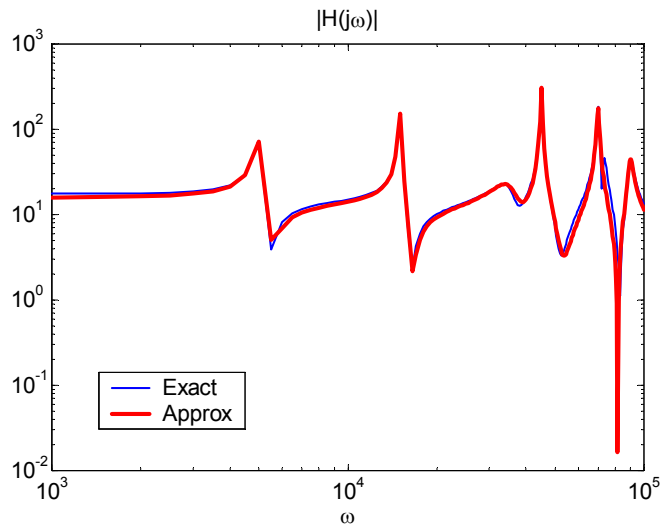


Example 2





Example 2



Example 3

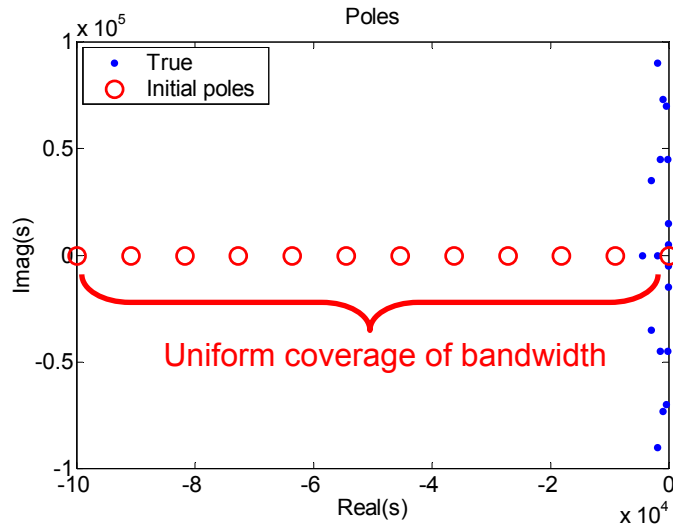
Same 18-pole rational function

Reduced-order fitting (12th order)

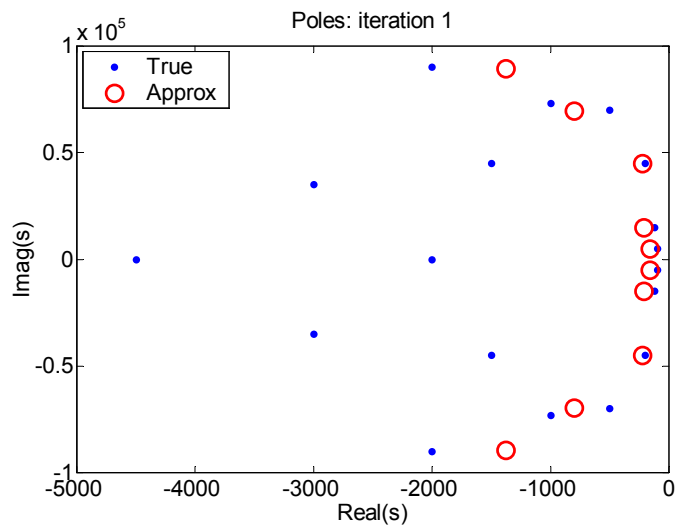
Different starting poles (real poles)



Example 3

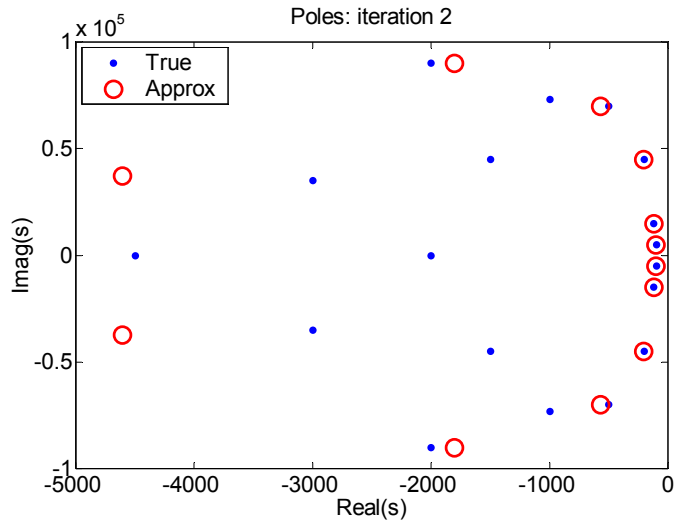


Example 3

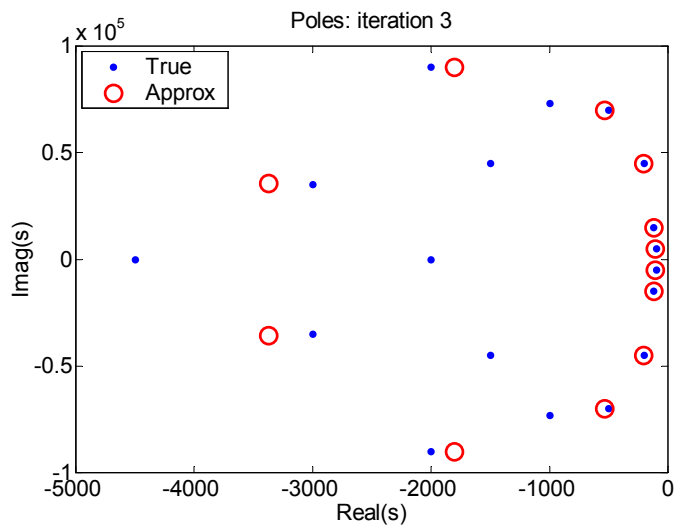




Example 3

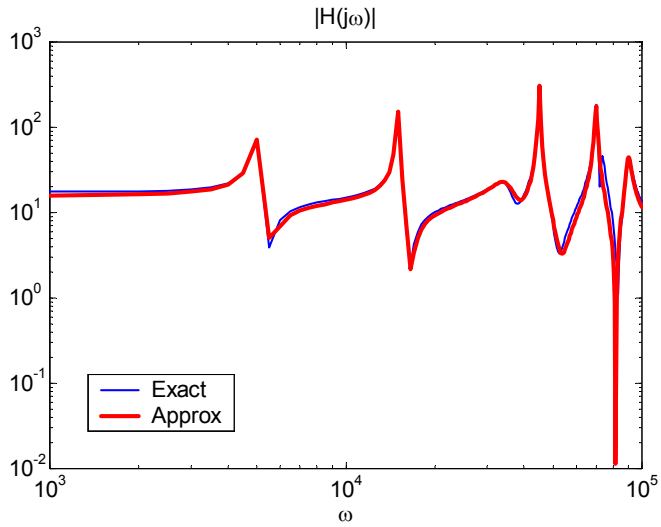


Example 3

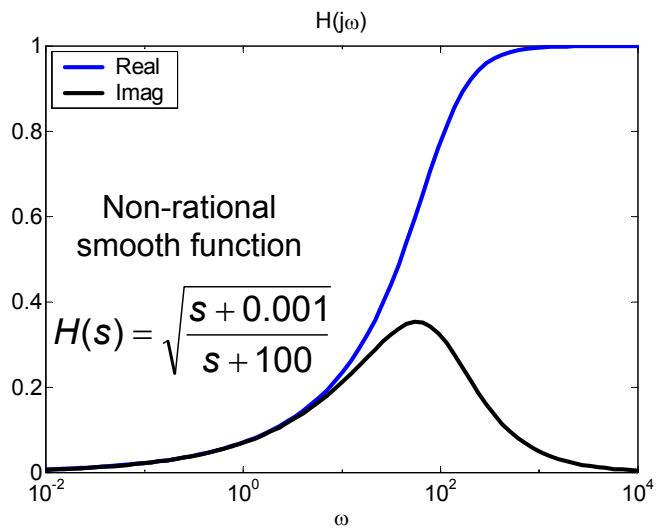


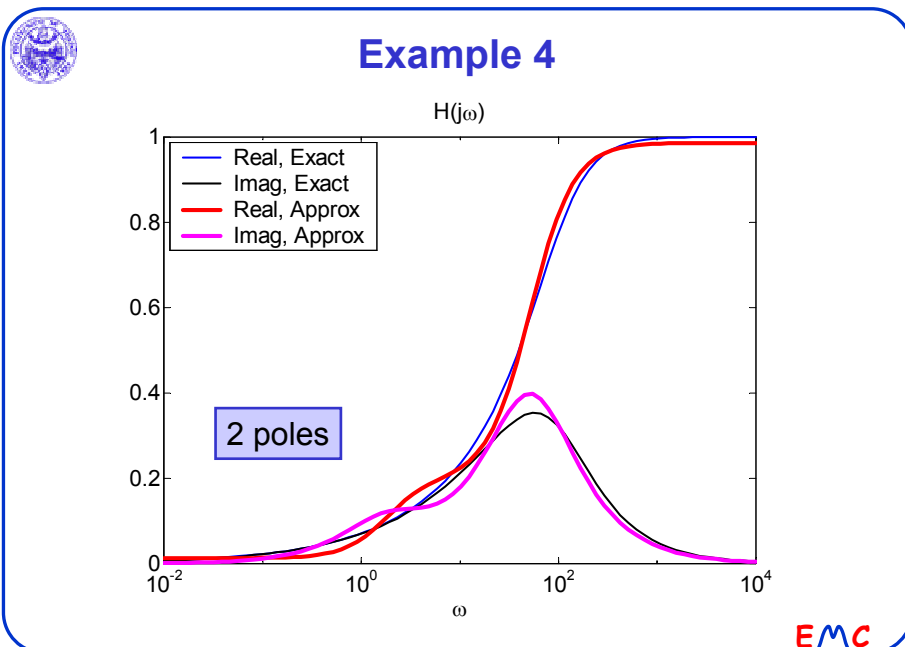
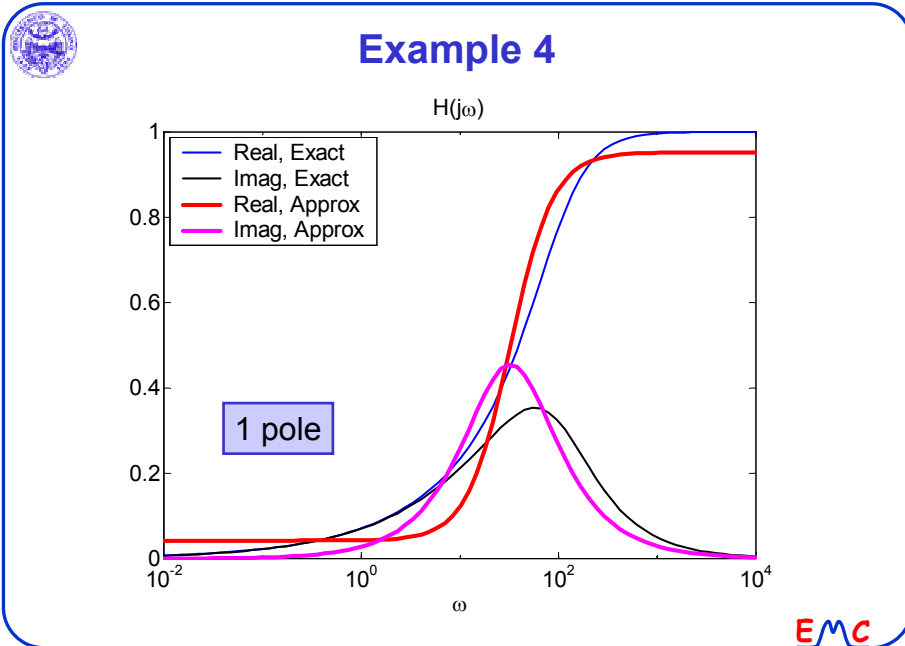


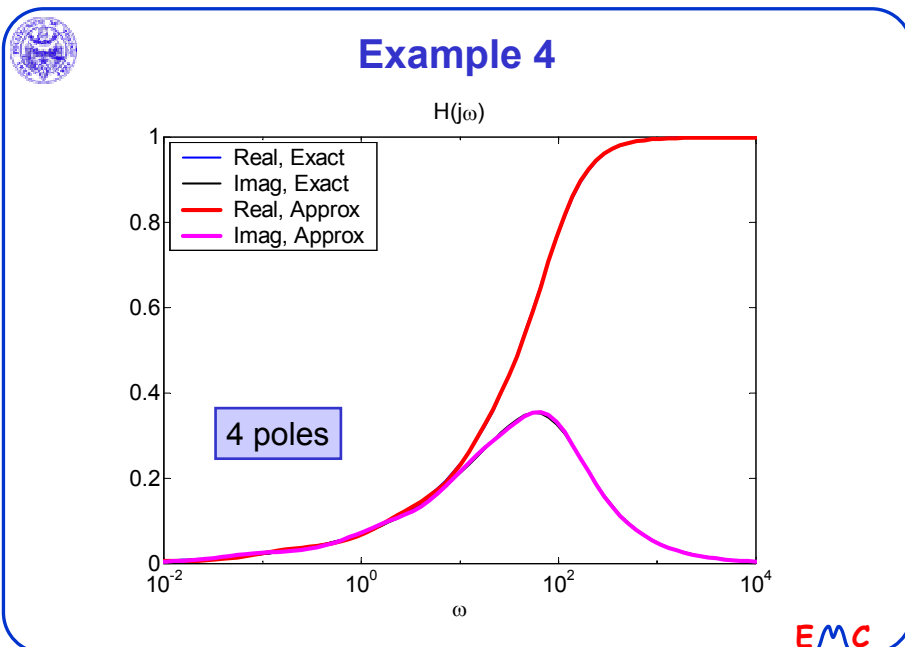
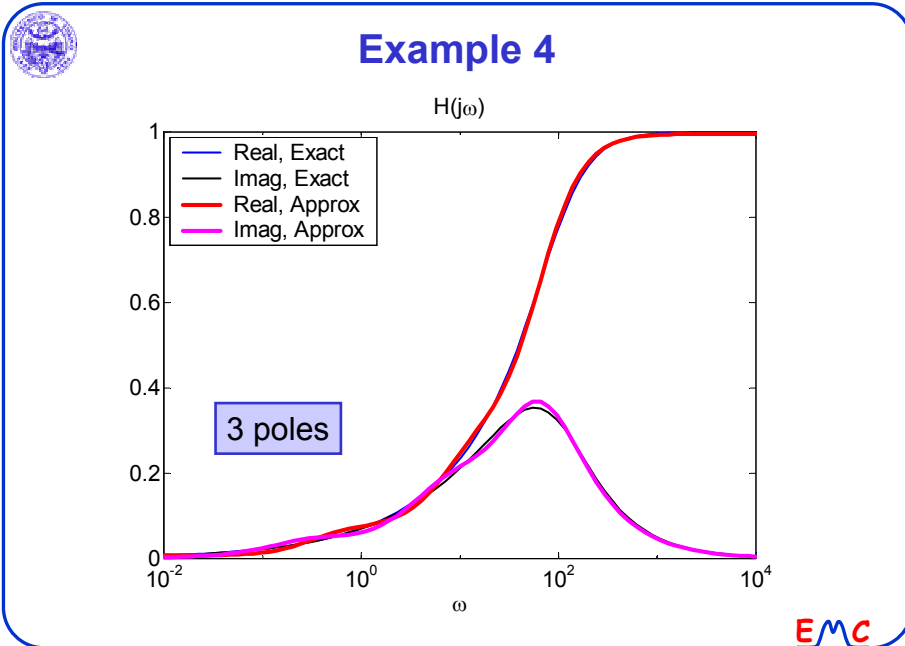
Example 3



Example 4

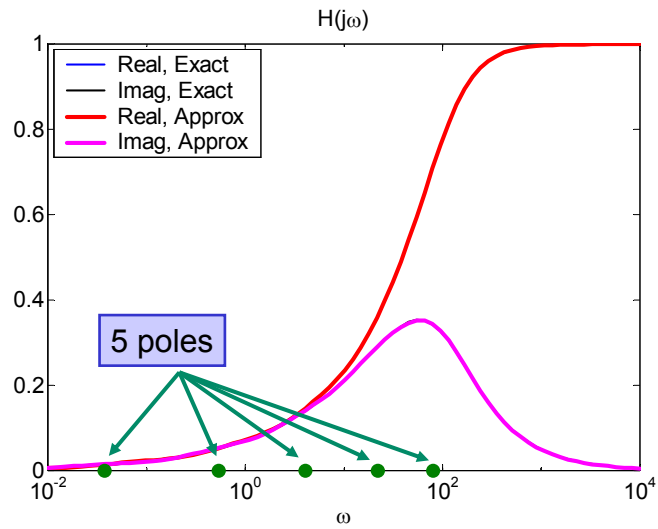




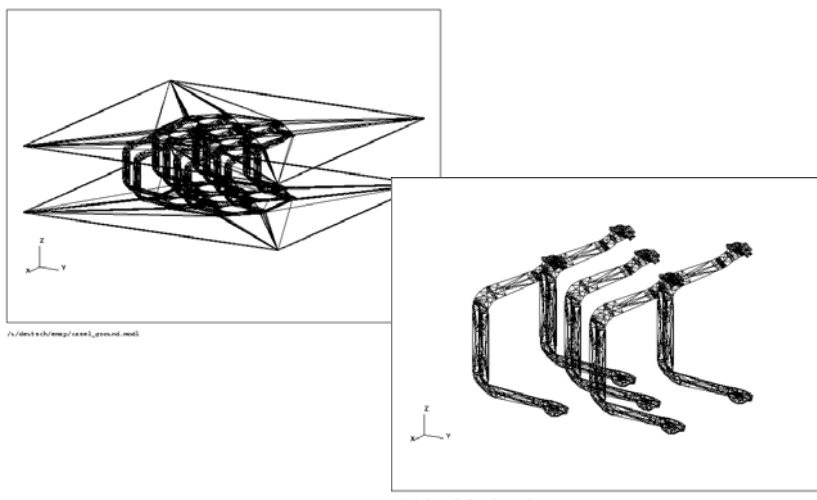




Example 4



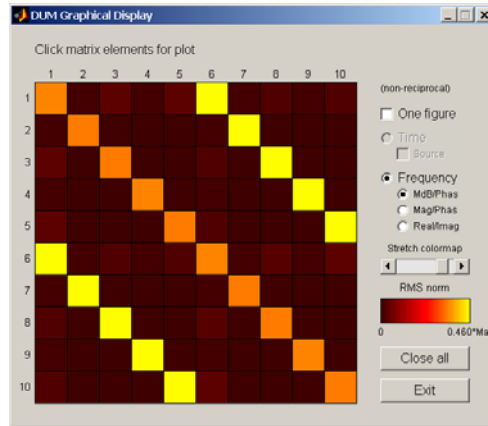
Example 5: MCM-board connector



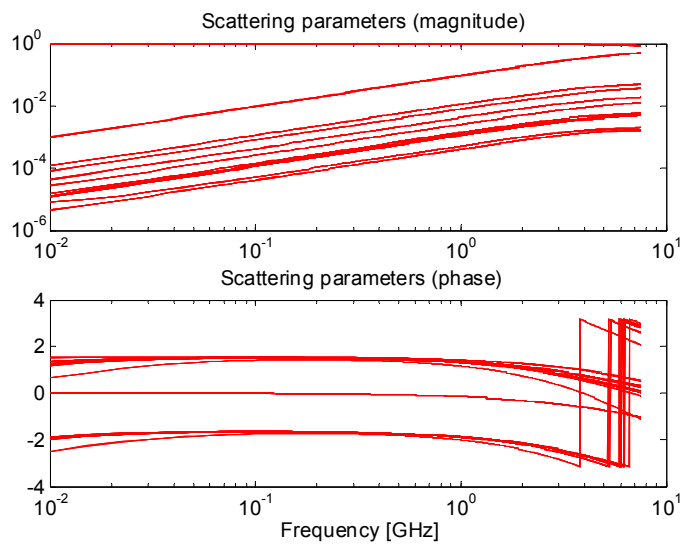


Example 5: MCM-board connector

Data: 10-port structure, frequency-domain S-matrix



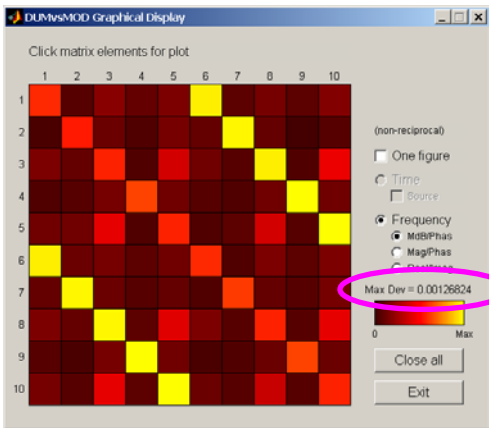
Example 5: MCM-board connector





Example 5: MCM-board connector

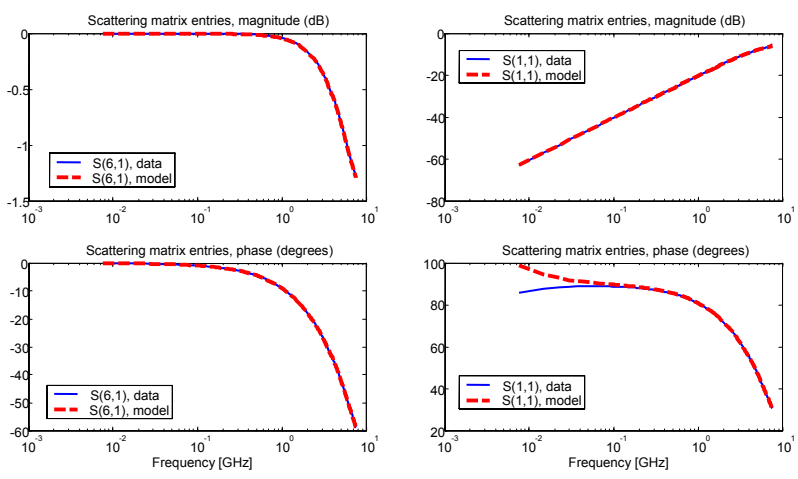
Macromodel: 4-poles



**Error:
0.1%**



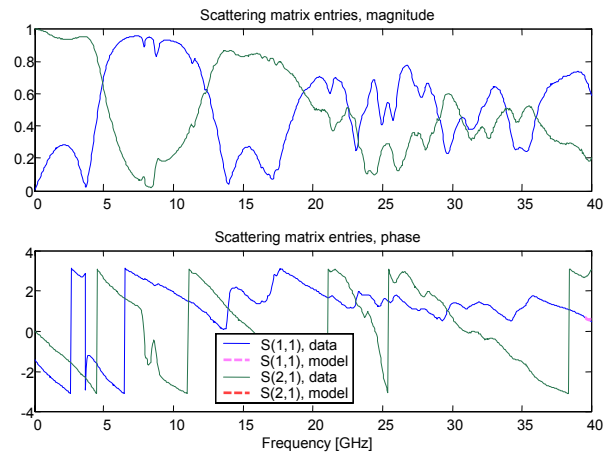
Example 5: MCM-board connector





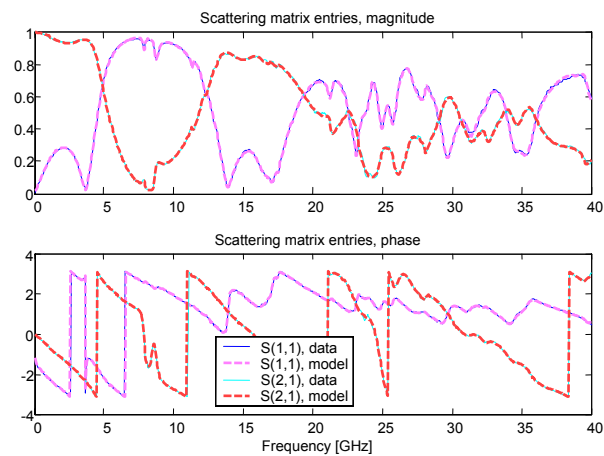
Example 6: stripline+lauches

Data: measured S-parameters



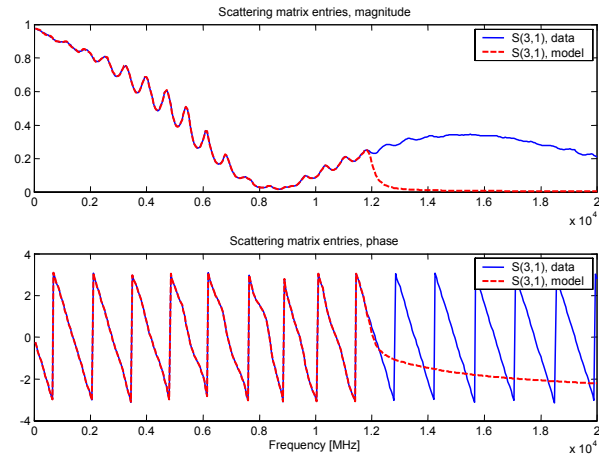
Example 6: stripline+lauches

Macromodel: 60 poles

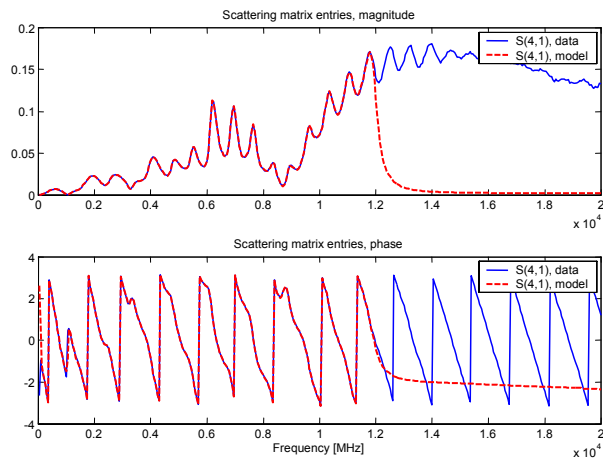




Example 7: PCB path, measured VF with frequency-selective weighting

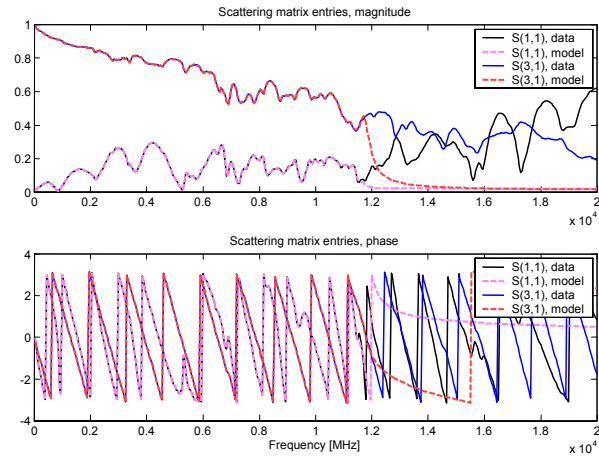


Example 7: PCB path, measured VF with frequency-selective weighting





Example 8: Connector, measured VF with frequency-selective weighting



Vector Fitting: summary

- Tool for frequency-domain rational approximation
 - rational transfer functions (system identification)
 - rational transfer functions (reduced-order modeling)
 - non-rational transfer functions
- Data from full-wave simulations
- Direct frequency-domain measurements



Vector Fitting: summary

www.energy.sintef.no/produkt/VECTFIT/home.asp

- Very accurate and robust
- Only linear least squares + eigenvalues required
- Stability is not guaranteed
 - can be fixed by flipping real part during relocation
- Passivity is not guaranteed
 - can be fixed a posteriori (see later)



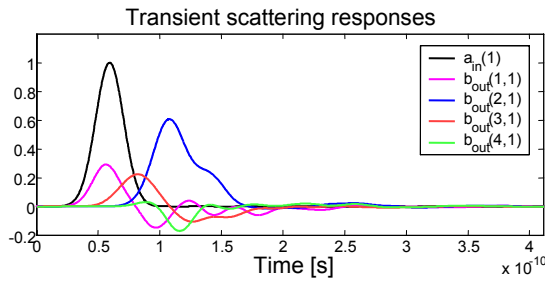
Outline

- Introduction
- Macromodeling approaches for 3D Interconnects
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Time-domain macromodeling

Model identification from time-domain responses



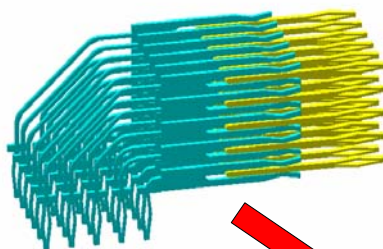
IDENTIFICATION



EMC
GROUP

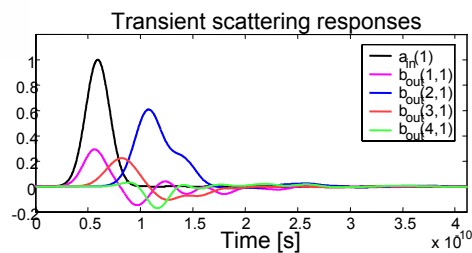


Possible scenarios



Time-Domain full-wave
simulation (FIT, FDTD)

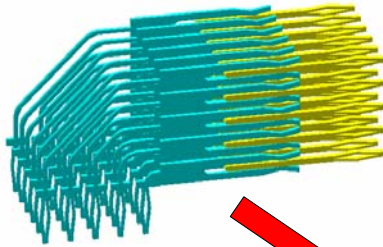
Port responses to
transient excitations
(usually gaussian)



EMC
GROUP



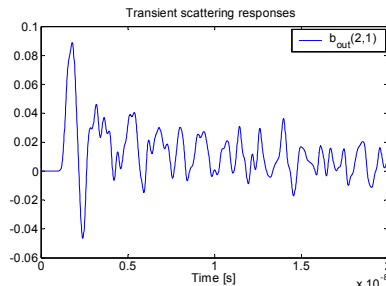
Possible scenarios



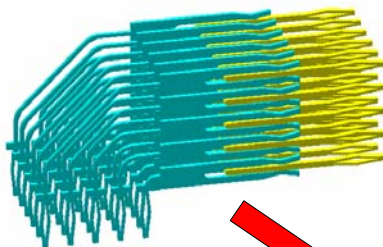
Port responses to transient excitations (usually gaussian)

Time-Domain full-wave simulation (FIT, FDTD)

Truncated waveforms from short FDTD runs

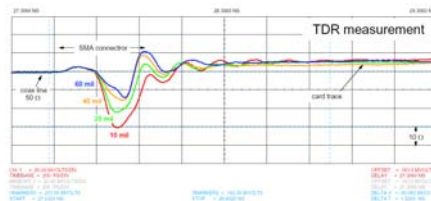


Possible scenarios



Port responses to transient excitations (usually gaussian)

Time-domain measurements (work in progress)





Time-Domain Macromodeling

Input pulse

$x(t)$ t – domain

Output responses

$y(t)$ t – domain

Transfer function

$$Y(s) = H(s)X(s)$$

Rational approximation

$$H(s) \approx H_\infty + \sum_n \frac{R_n}{s - p_n}$$

Unknowns:

- Poles p_n
- Residues R_n
- Constant H_∞



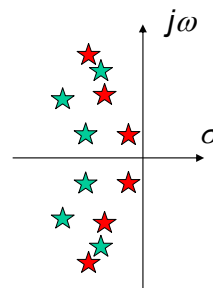
Time-Domain Vector Fitting

Step 1. Find the dominant poles via “relocation”

Guess poles
 $\{q_n\}$



New poles
 $\{p_n\}$



How to do it using time-domain data?

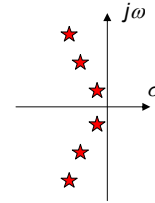
How to insure convergence to the right poles?



Time-Domain Vector Fitting

1a. Start with initial poles: $\{q_n\}$

1b. Define weight function: unknown $\{k_n\}$



$$w(s) = 1 + \sum_n \frac{k_n}{s - q_n}$$

Starting poles

1c. Assume the following condition

$$w(s)\mathbf{H}(s) = a + \sum_n \frac{b_n}{s - q_n}$$

Poles of $\mathbf{H}(s)$ = Zeros of $w(s)$



Time-Domain Vector Fitting

$$w(s)\mathbf{H}(s) = a + \sum_n \frac{b_n}{s - q_n} \quad \text{Apply the input pulse } \mathbf{X}(s)$$

$$w(s)\mathbf{Y}(s) = \left(a + \sum_n \frac{b_n}{s - q_n} \right) \mathbf{X}(s) \quad \text{Compute inverse Laplace transform}$$

$$\mathbf{y}(t) + \sum_n k_n \mathbf{y}_n(t) = a \mathbf{x}(t) + \sum_n b_n \mathbf{x}_n(t)$$

$$\mathbf{x}_n(t) = \int_0^t e^{q_n(t-\tau)} \mathbf{x}(\tau) d\tau$$

$$\mathbf{y}_n(t) = \int_0^t e^{q_n(t-\tau)} \mathbf{y}(\tau) d\tau$$

Low-pass filtered input and output signals



Time-Domain Vector Fitting

1d. Solve a linear least squares system for k_n , a , b_n

$$\mathbf{y}(t) + \sum_n k_n \mathbf{y}_n(t) = a \mathbf{x}(t) + \sum_n b_n \mathbf{x}_n(t)$$

1e. Compute the zeros $\{p_n\}$ of the weight function

$$w(s) = 1 + \sum_n \frac{k_n}{s - q_n} = \frac{\prod_n (s - p_n)}{\prod_n (s - q_n)}$$

These are the dominant poles!



S. Grivet-Talocia, "Package Macromodeling via Time-Domain Vector Fitting", *IEEE Microwave Wireless Comp. Lett.*, Nov. 2003



Time-Domain Vector Fitting

Step 2. Compute the residues

2a. Low-pass filter input signals with new poles

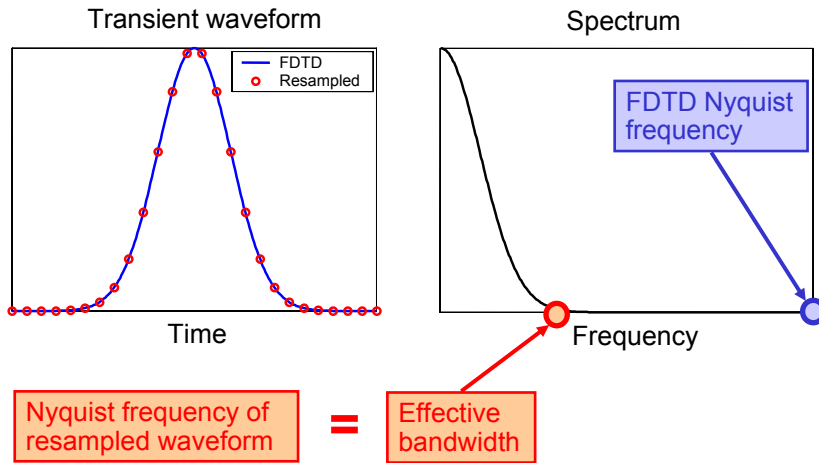
$$\tilde{\mathbf{x}}_n(t) = \int_0^t e^{p_n(t-\tau)} \mathbf{x}(\tau) d\tau$$

2b. Solve a linear least squares system for \mathbf{R}_n and \mathbf{H}_∞

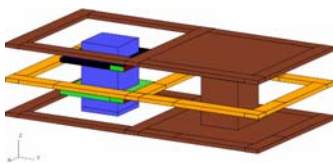
$$\mathbf{y}(t) = \mathbf{H}_\infty \mathbf{x}(t) + \sum_n \mathbf{R}_n \tilde{\mathbf{x}}_n(t)$$



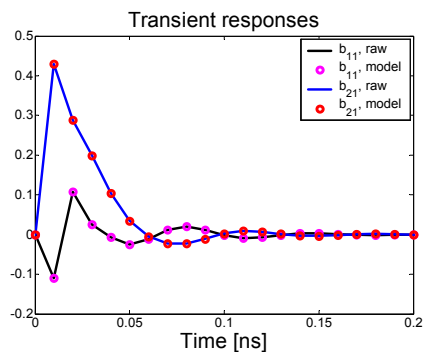
Subsampling



Example 1: single via

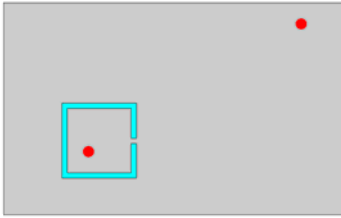


Raw data:
Triangle Impulse Responses
obtained by a transient PEEC
solver (by Dr. Ruehli, IBM)

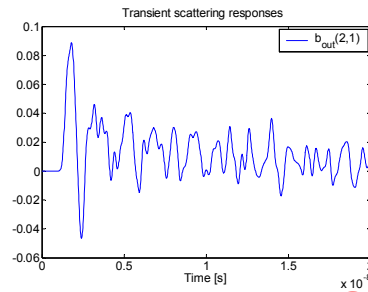
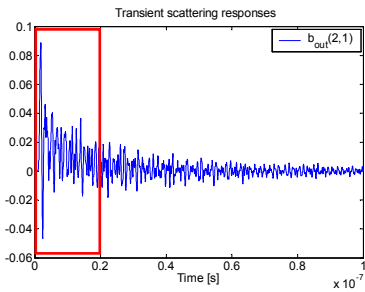




Example 2: segmented power bus



- 2-port structure
- Time-Domain solution
- CST Microwave Studio
- Bandwidth: 3 GHz
- 50Ω port terminations

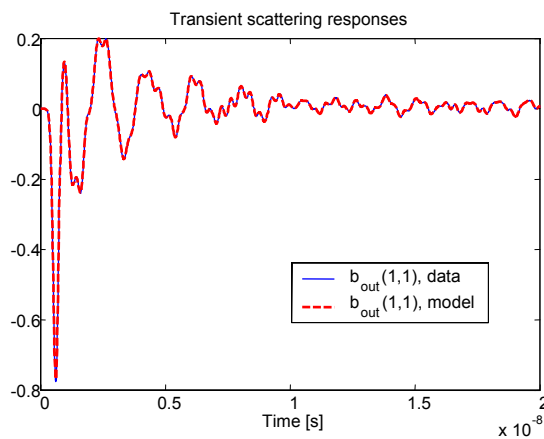


EMC
GROUP



Example 2: segmented power bus

80-poles model (Time-Domain Vector Fitting)

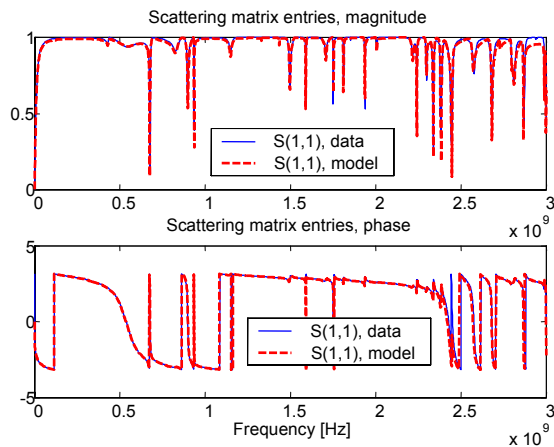


EMC
GROUP



Example 2: segmented power bus

Comparison vs. frequency-domain scattering data



Example 2: segmented power bus

Full-wave simulation time (CST) to compute...

... **frequency scattering data**: **60 hours**

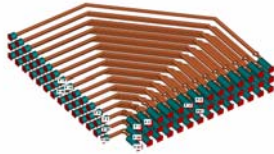
(wait until transients are finished for reliable FFT)

... **macromodel**: **6 hours**

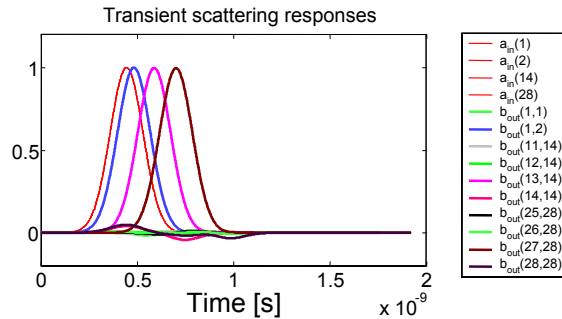
(can use truncated waveforms for TD-VF)



Example 3: 42-pin connector



3x14 pins, 84 ports
Characterized via FIT
(CST Microwave Studio 4)
(Courtesy: Erni - AdMOS)



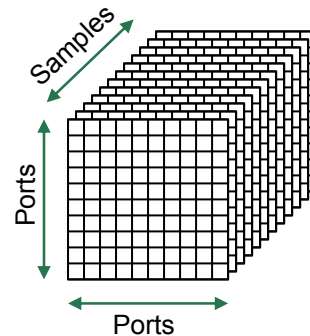
Handling many ports

Frequency-Domain Vector Fitting

$$\left(1 + \sum_n \frac{k_n}{s - q_n}\right) \mathbf{H}(s) = \mathbf{a} + \sum_n \frac{b_n}{s - q_n}$$

Time-Domain Vector Fitting

$$\mathbf{y}(t) + \sum_n k_n \mathbf{y}_n(t) = \mathbf{a} \mathbf{x}(t) + \sum_n b_n \mathbf{x}_n(t)$$



Processing **all** responses may lead to a **large** system!

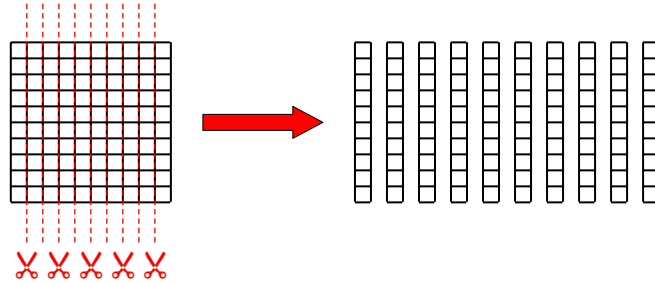


Handling many ports

1. Split port responses into subsets

Transfer matrix $\mathbf{H}(s)$

Subsets $\{\mathbf{h}_k(s)\}$



Handling many ports

2. Macromodel each subset via FD-VF or TD-VF



$$\mathbf{h}_k(s) \approx \mathbf{h}_{k,\infty} + \sum_n \frac{\mathbf{r}_{k,n}}{s - p_{k,n}}$$



Partial state-space representation

$$\begin{cases} \dot{\mathbf{w}}_k = \mathbf{A}_k \mathbf{w}_k + \mathbf{B}_k \mathbf{x}_k \\ \mathbf{y}_k = \mathbf{C}_k \mathbf{w}_k + \mathbf{D}_k \mathbf{x}_k \end{cases}$$

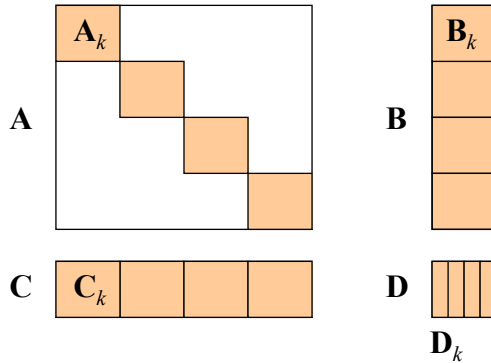


Handling many ports

4. Assemble all partial models into a global model

$$\begin{cases} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{B} \mathbf{x} \\ \mathbf{y} = \mathbf{C} \mathbf{w} + \mathbf{D} \mathbf{x} \end{cases}$$

All matrices can be constructed as sparse!

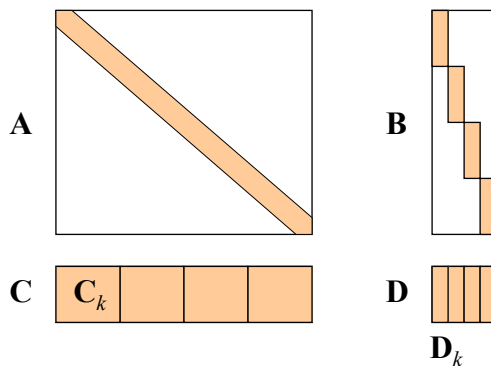


Handling many ports

4. Assemble all partial models into a global model

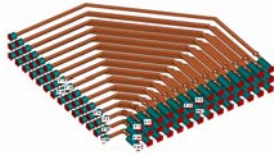
$$\begin{cases} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{B} \mathbf{x} \\ \mathbf{y} = \mathbf{C} \mathbf{w} + \mathbf{D} \mathbf{x} \end{cases}$$

All matrices can be constructed as sparse!

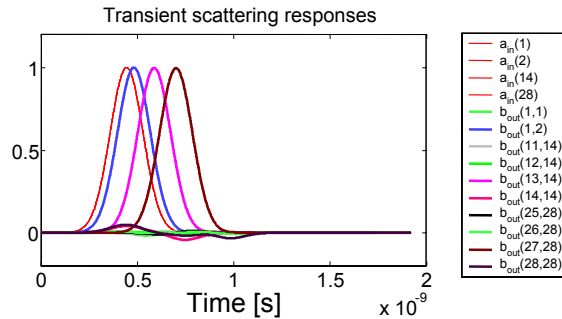




Example 3: 42-pin connector

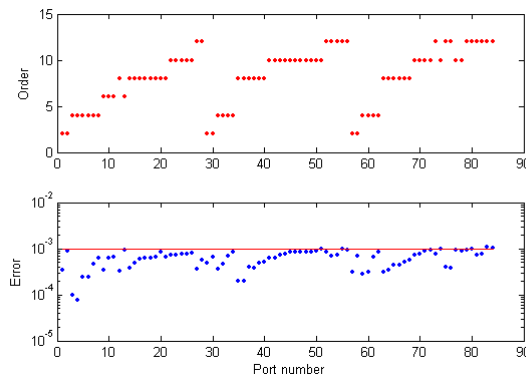


3x14 pins, 84 ports
Characterized via FIT
(CST Microwave Studio 4)
(Courtesy: Erni - AdMOS)



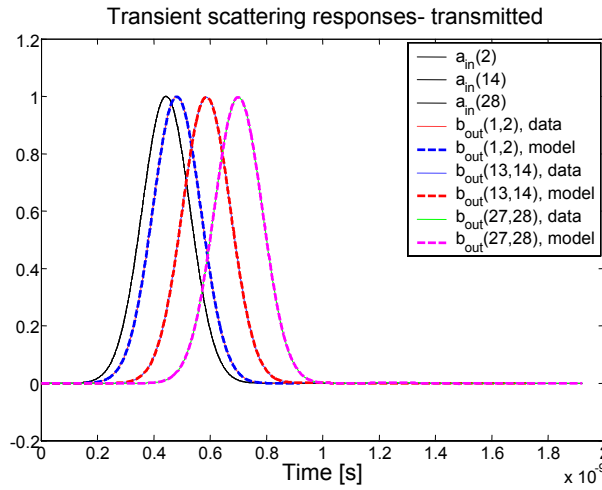
Example 3: model order selection

Automatic (iterative) order selection on each of the 84 subsets of port responses (reduced model complexity)

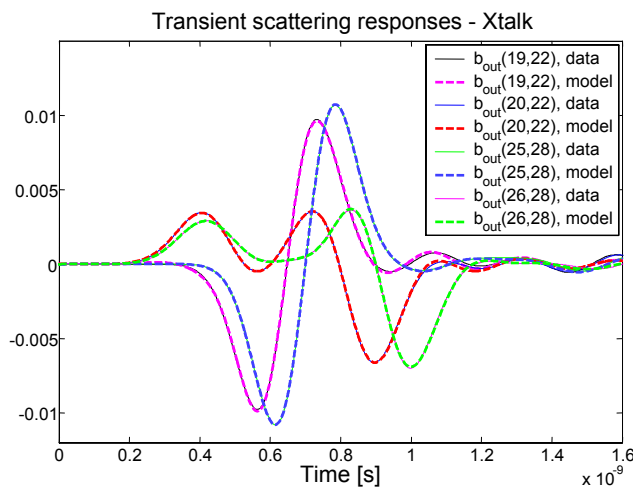




Example 3: macromodel accuracy

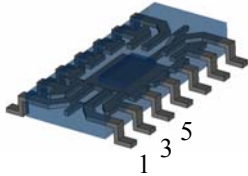


Example 3: macromodel accuracy

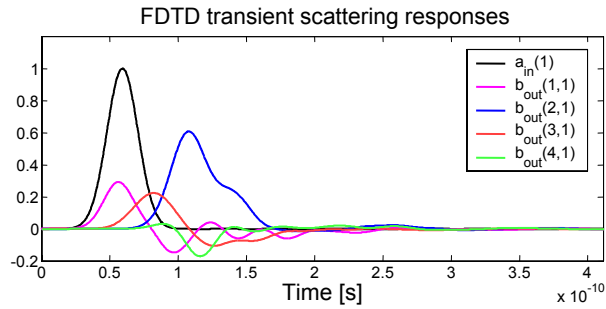




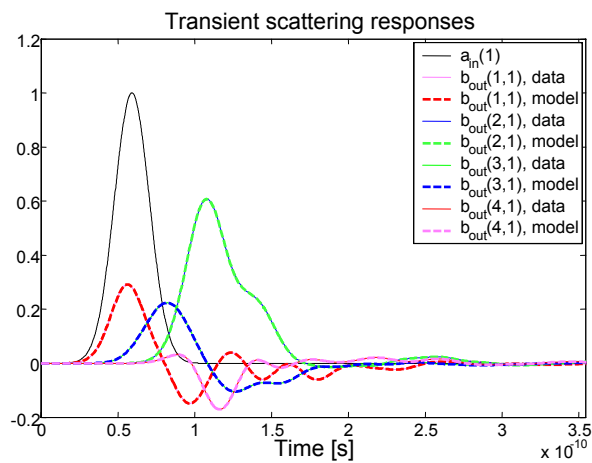
Example 4: 14-pin package



14-pin SOIC package
Simplified CAD for FDTD
Bandwidth: 40 GHz
50 Ω port terminations



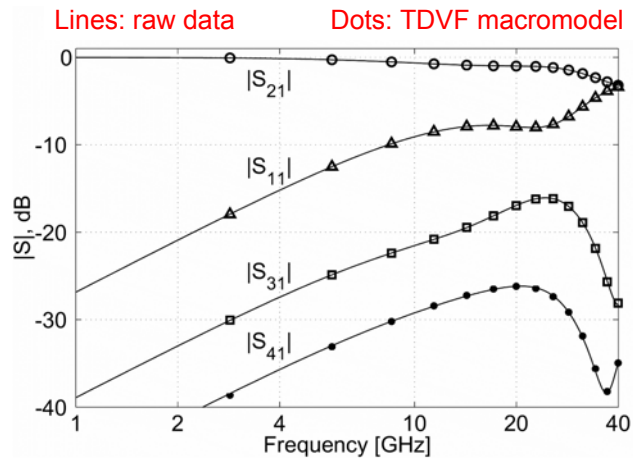
Example 4: macromodel responses



No visible difference between data and model



Example 4: macromodel responses



No visible difference between data and model



Example 4: macromodel accuracy

Maximum deviation between model and data for all 28x28 responses



Largest:
0.00074

TD-VF produces highly accurate macromodels



Macromodel properties

😊 Accuracy

Good initial data \Rightarrow small approximation errors

😊 Stability

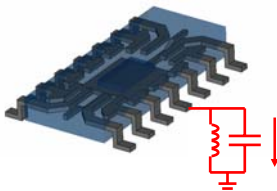
All poles with negative real part

☹ Passivity

The macromodel may not be passive



Example 4: change terminations

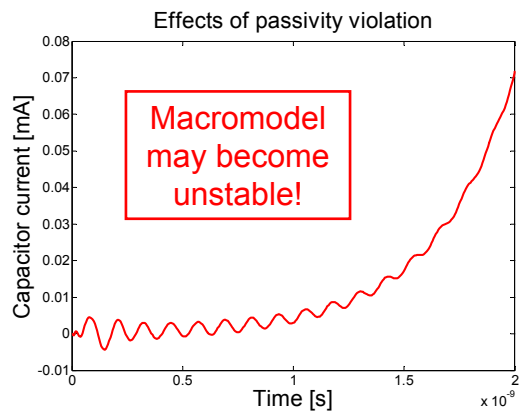


Port terminations:

$$R = 50 \text{ m}\Omega \div 50 \text{ }\Omega$$

$$L = 1 \text{ nH}$$

$$C = 1 \text{ pF}$$



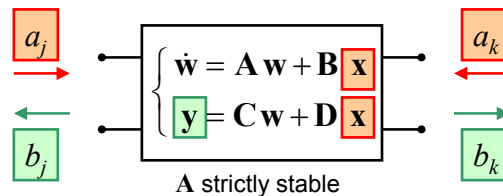


Outline

- Introduction
- Macromodeling approaches for 3D Interconnects
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - **Passivity characterization and enforcement**
- SPICE synthesis



Passivity conditions Scattering representation



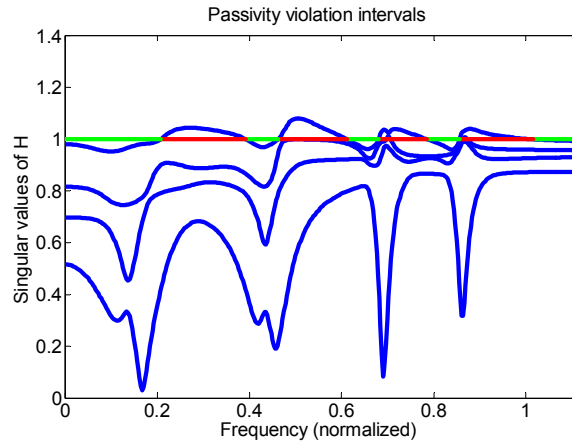
Scattering matrix: must be bounded real

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

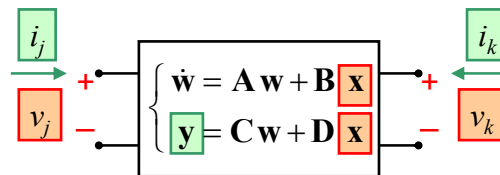
$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq \mathbf{1}, \quad \forall \omega$$



Passivity conditions Scattering representation



Passivity conditions Admittance representation



A strictly stable

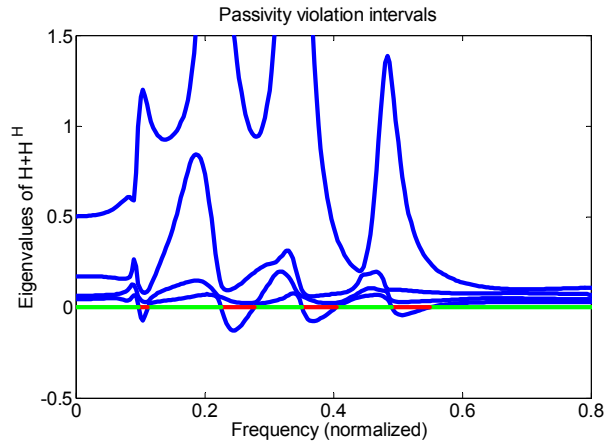
Admittance matrix: must be positive real

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

$$\left\{ \text{eigenvalues of } \left(\mathbf{H}(j\omega) + \mathbf{H}^H(j\omega) \right) \right\} \geq 0, \quad \forall \omega$$



Passivity conditions Admittance representation



Checking passivity Scattering representation

$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq 1, \quad \forall \omega$$

Several techniques can be used

Frequency sweep test: most straightforward

- Choose a set of frequency samples
- Compute \mathbf{H} and its singular values, and check
- **Time-consuming** for large models
- **May give wrong answers** due to poor sampling



Checking passivity Scattering representation

$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq 1, \quad \forall \omega$$

Equivalent purely algebraic conditions:

- Linear Matrix Inequalities (**LMI**)
- Algebraic Riccati Equations (**ARE**)
- Eigenvalues of **Hamiltonian matrices**

S. Boyd, L. El Ghaoui, E. Feron, V. Balakrishnan, "Linear Matrix Inequalities in System and Control Theory, SIAM, Philadelphia, 1994



Checking passivity Scattering representation

$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq 1, \quad \forall \omega$$

Linear Matrix Inequality (LMI)

$$\begin{pmatrix} \mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A} + \mathbf{C}^T \mathbf{C} & \mathbf{P} \mathbf{B} + \mathbf{C}^T \mathbf{D} \\ \mathbf{B}^T \mathbf{P} + \mathbf{D}^T \mathbf{C} & \mathbf{D}^T \mathbf{D} - \mathbf{I} \end{pmatrix} \leq 0 \quad \mathbf{P} = \mathbf{P}^T, \mathbf{P} > 0$$

Real matrix \mathbf{P} is the variable



Checking passivity Scattering representation

$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq 1, \quad \forall \omega$$

Algebraic Riccati Equation (ARE)

$$\mathbf{A}^T \mathbf{P} + \mathbf{P} \mathbf{A} + \mathbf{C}^T \mathbf{C} + (\mathbf{P} \mathbf{B} + \mathbf{C}^T \mathbf{D})(\mathbf{I} - \mathbf{D}^T \mathbf{D})^{-1} (\mathbf{P} \mathbf{B} + \mathbf{C}^T \mathbf{D})^T = \mathbf{0}$$

$$\mathbf{P} = \mathbf{P}^T$$

Real matrix \mathbf{P} is the variable



Checking passivity Scattering representation

$$\{\text{singular values of } \mathbf{H}(j\omega)\} \leq 1, \quad \forall \omega$$

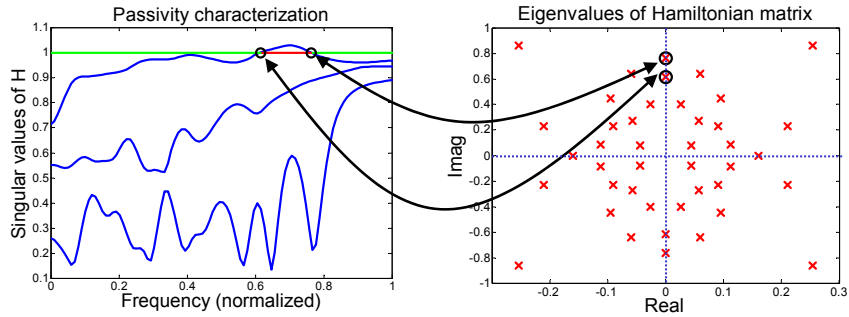
Eigenvalues of Hamiltonian matrix

$$\mathbf{M} = \begin{pmatrix} \mathbf{A} - \mathbf{B}(\mathbf{D}^T \mathbf{D} - \mathbf{I})^{-1} \mathbf{D}^T \mathbf{C} & -\mathbf{B}(\mathbf{D}^T \mathbf{D} - \mathbf{I})^{-1} \mathbf{B}^T \\ \mathbf{C}^T (\mathbf{D} \mathbf{D}^T - \mathbf{I})^{-1} \mathbf{C} & -\mathbf{A}^T + \mathbf{C}^T \mathbf{D} (\mathbf{D}^T \mathbf{D} - \mathbf{I})^{-1} \mathbf{B}^T \end{pmatrix}$$

Real matrix \mathbf{M} must have no imaginary eigenvalues



Checking passivity Scattering representation

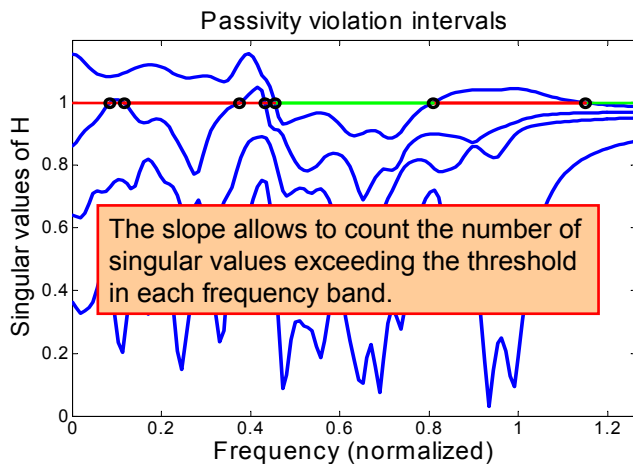


Theorem [Boyd, Balakrishnan, Kabamba, 1989]

$j\omega_0$ is an eigenvalue of $\mathbf{M} \Leftrightarrow \sigma = 1$ is a singular value of $\mathbf{H}(j\omega_0)$



Checking passivity Scattering representation

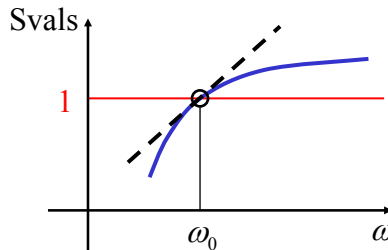




Checking passivity Scattering representation

First-order perturbation of Hamiltonian eigenvalues

$$\text{Slope} = \text{Im} \left\{ \frac{\mathbf{w}^T \mathbf{v}}{\mathbf{w}^T \mathbf{M}' \mathbf{v}} \right\}$$

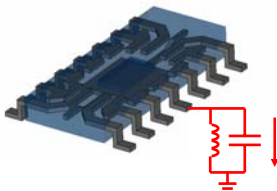


\mathbf{w}, \mathbf{v} : Left and right eigenvectors of \mathbf{M} associated to ω_0

\mathbf{M}' : Another Hamiltonian matrix (computed via $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$)



Example 4: change terminations

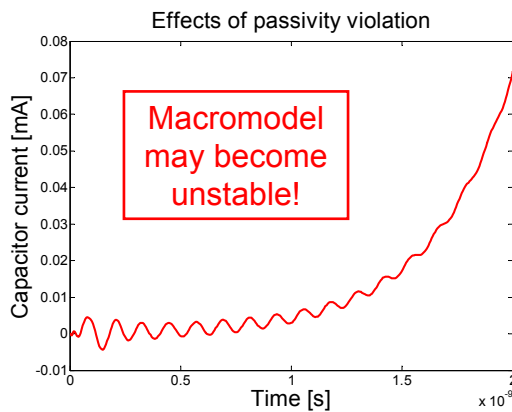


Port terminations:

$$R = 50 \text{ m}\Omega \div 50 \text{ }\Omega$$

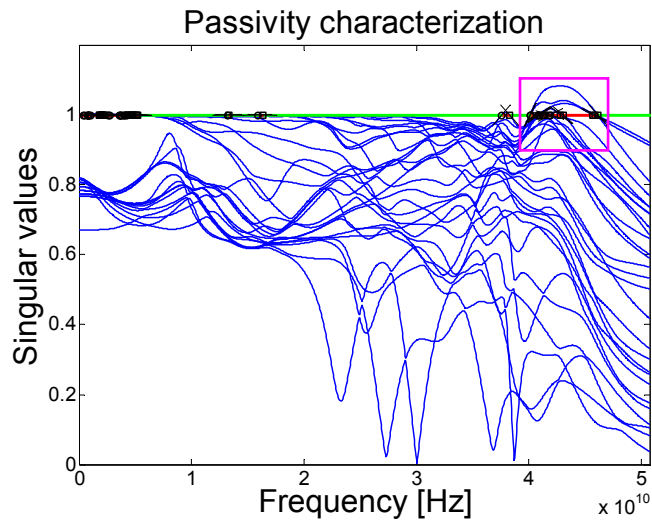
$$L = 1 \text{ nH}$$

$$C = 1 \text{ pF}$$

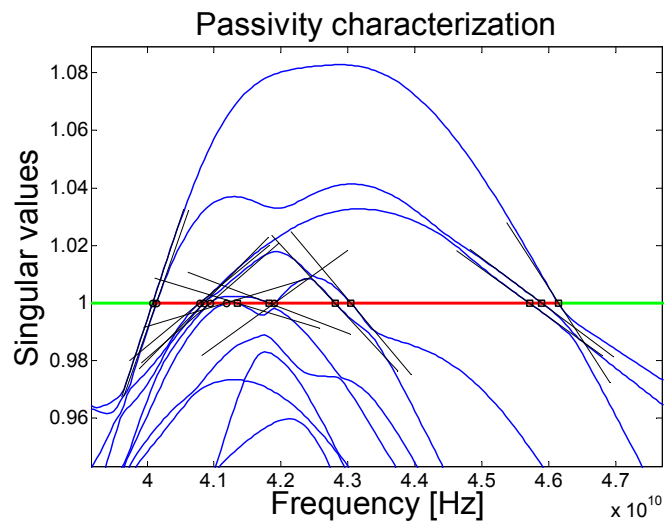




Example 4: passivity characterization

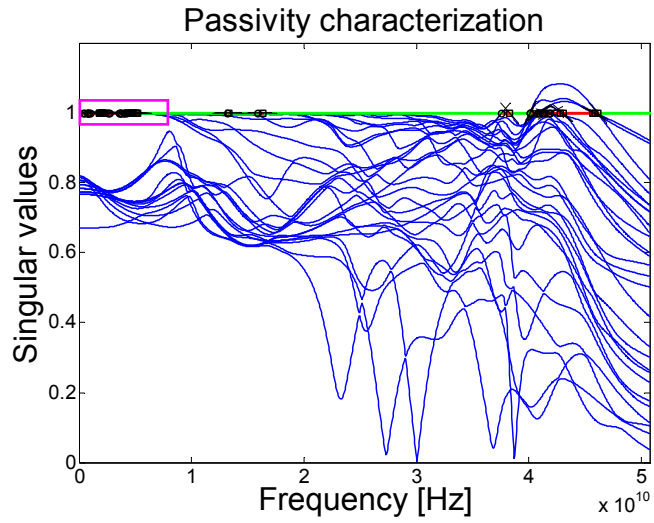


Example 4: passivity characterization

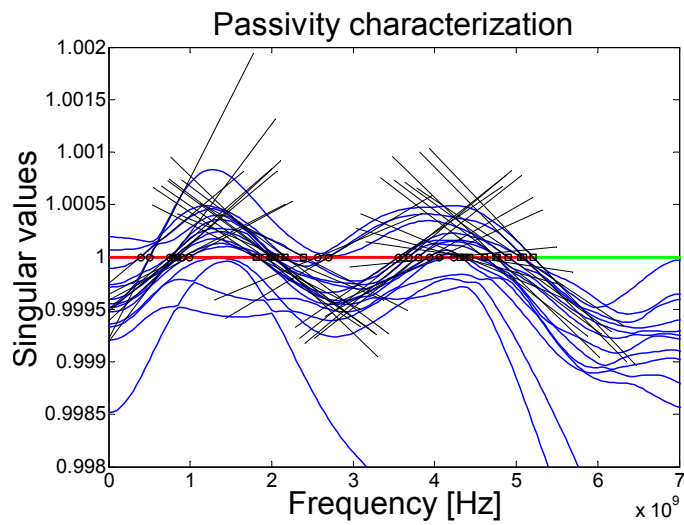




Example 4: passivity characterization



Example 4: passivity characterization





Passivity enforcement

- Generate a **new passive macromodel**
- Apply **small correction** to **preserve accuracy**
 - original dataset should be passive
 - original macromodel should be accurate
 - (usually) preserve poles

$$\begin{cases} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{B} \mathbf{x} \\ \mathbf{y} = \mathbf{C} \mathbf{w} + \mathbf{D} \mathbf{x} \end{cases} \longrightarrow \begin{cases} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{B} \mathbf{x} \\ \mathbf{y} = (\mathbf{C} + \mathbf{dC}) \mathbf{w} + \mathbf{D} \mathbf{x} \end{cases}$$



Passivity enforcement

Several different approaches are possible. Examples are

Quadratic/convex optimization

[B.Gustavsen, A.Semlyen: IEEE Trans. Power Systems, vol.16, 2001]

[C.P.Coelho, J.Phillips, L.M.Silveira, IEEE Trans. CADICAS, vol.23, 2004]

Trace parameterization/Semi-Definite Programming

[H.Chen, J.Fang: Proc. EPEP, 2003]

Perturbation of residues

[D.Saraswat, R.Achar, M.Nakhla: Proc. EPEP, 2003]

Perturbation of Hamiltonian eigenvalues

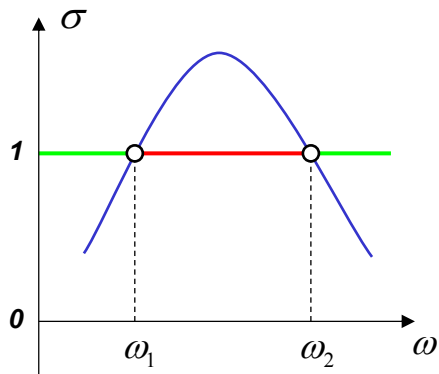
[S.Grivet-Talocia: Proc. SPI, 2003 and IEEE Trans. CAS (in press)]

Many others... Hot research topic!

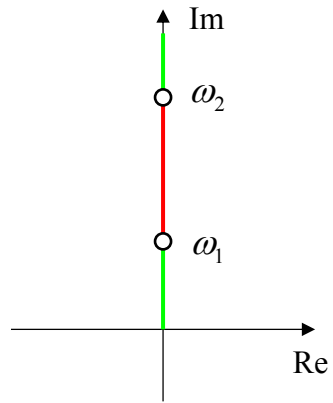


Perturbation of Hamiltonian Eigs

Singular values of H

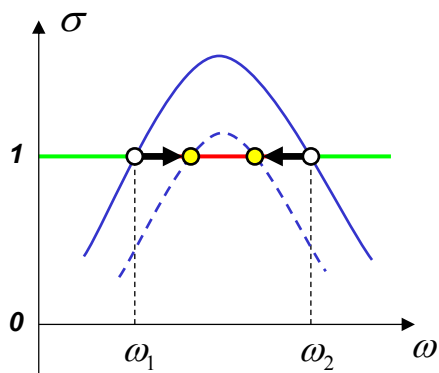


Eigenvalues of M

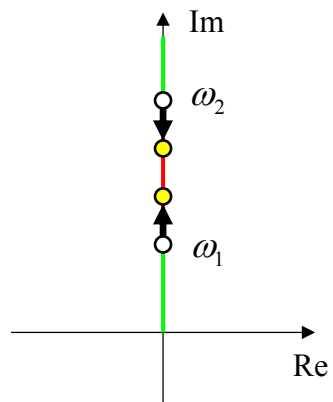


Perturbation of Hamiltonian Eigs

Singular values of H

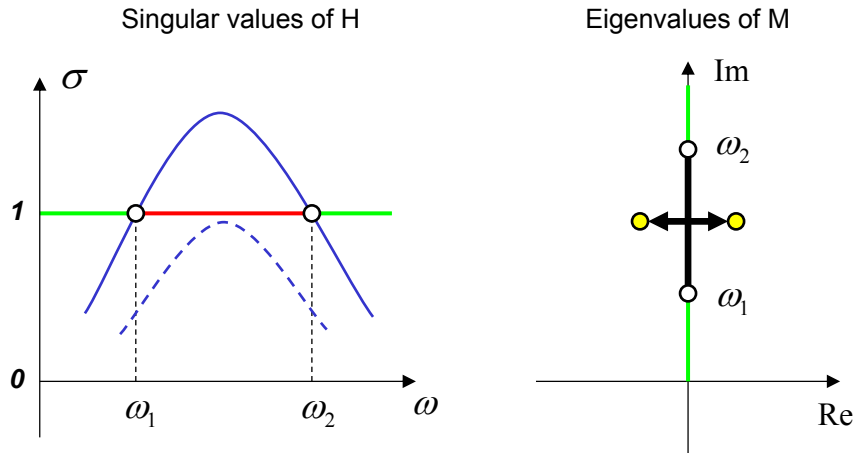


Eigenvalues of M





Perturbation of Hamiltonian Eigs



Perturbation of Hamiltonian Eigs

First-order perturbation of eigenvalues (again)

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{B} \mathbf{u} \\ \mathbf{y} = \mathbf{C} \mathbf{x} + \mathbf{D} \mathbf{u} \end{cases}$$

Perturb state matrix \mathbf{C}

$$\tilde{\mathbf{C}} = \mathbf{C} + \mathbf{dC}$$

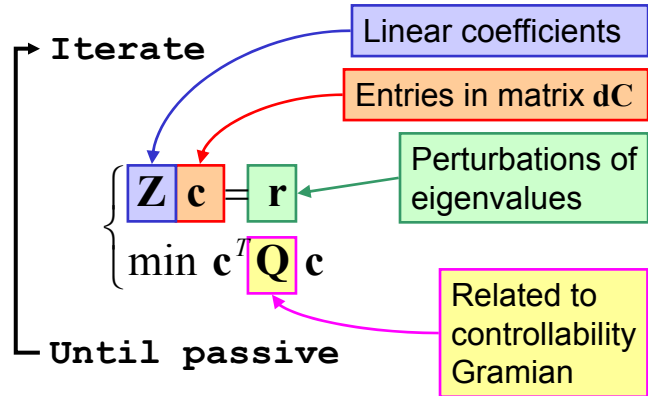
$$\tilde{\mathbf{M}} \approx \mathbf{M} + \mathbf{dM} \quad (\text{first-order: } \mathbf{dM} \text{ is linear in } \mathbf{dC})$$

$$\mathbf{w}_m^T \mathbf{dM} \mathbf{v}_m \approx j(\tilde{\omega}_m - \omega_m) \mathbf{w}_m^T \mathbf{v}_m$$

Linear constraint on the correction matrix \mathbf{dC}



Perturbation of Hamiltonian Eigs



Minimizes the perturbation on the original responses



Preserve accuracy of macromodel

Minimize this norm !

$$\sum_{i,j} \int_0^{\infty} (\tilde{h}_{i,j}(t) - h_{i,j}(t))^2 dt = \|\mathbf{dC} \mathbf{W} \mathbf{dC}^T\|_F^2$$

Induced perturbation in the impulse responses

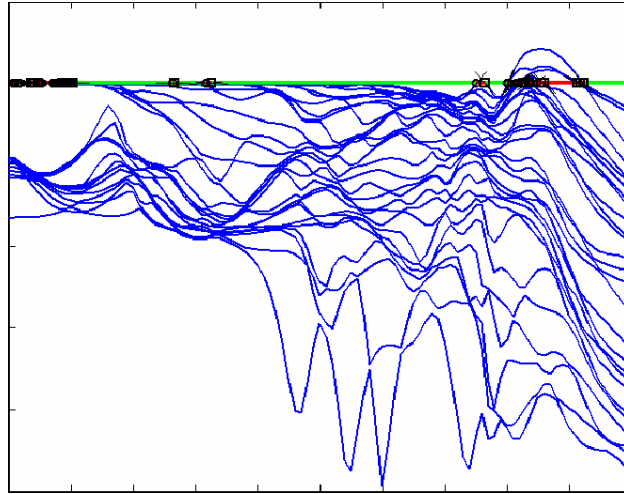
Weighted norm of state matrix perturbation

\mathbf{W} : controllability Gramian

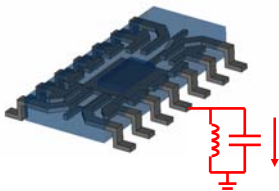
$$\mathbf{A}\mathbf{W} + \mathbf{W}\mathbf{A}^T = -\mathbf{B}\mathbf{B}^T$$



Example 4: passivity compensation



Example 4 : passivity compensation

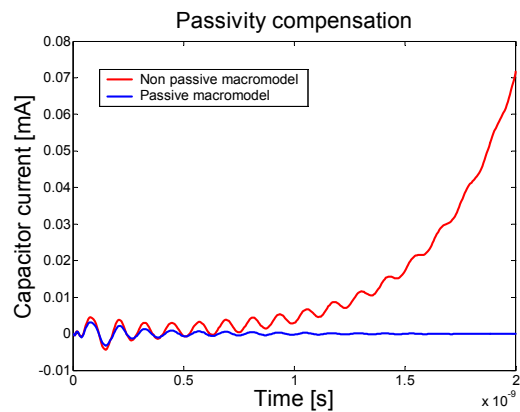


Port terminations:

$$R = 50 \text{ m}\Omega \div 50 \text{ }\Omega$$

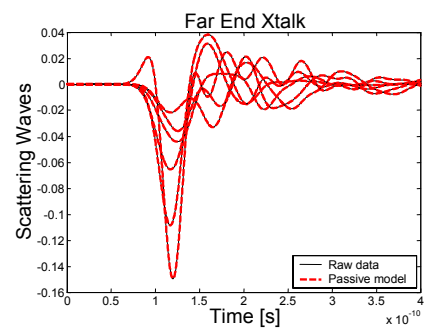
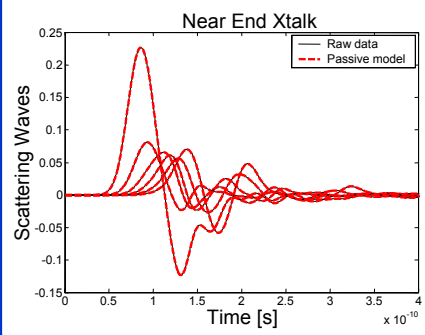
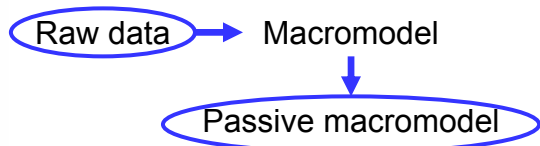
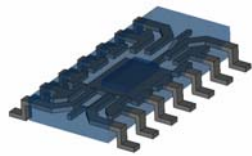
$$L = 1 \text{ nH}$$

$$C = 1 \text{ pF}$$

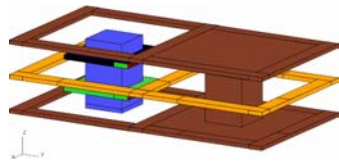




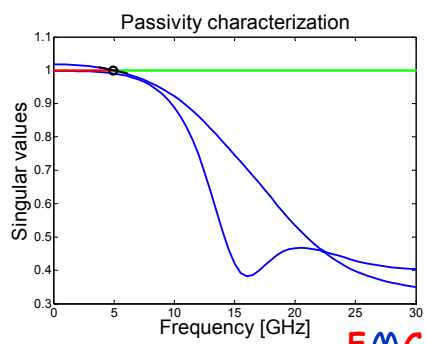
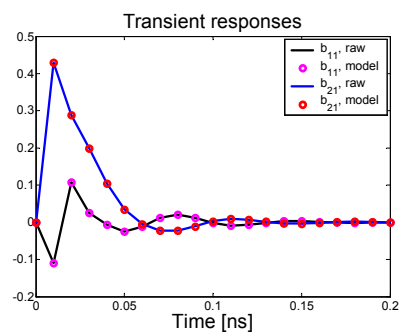
Example 4: passive macromodel



Example 1: single via, nonpassive

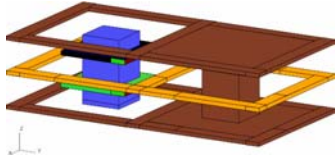


Raw data:
Triangle Impulse Responses
obtained by a transient PEEC
solver (by Dr. Ruehli, IBM)

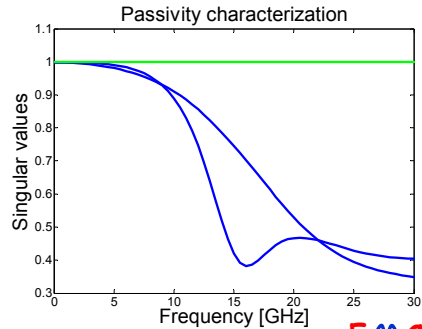
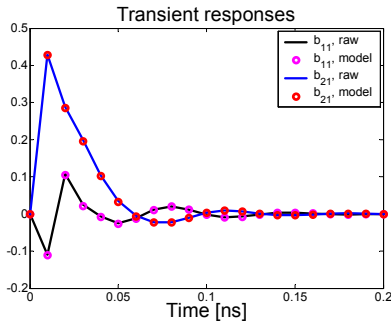




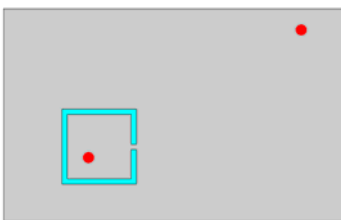
Example 1: single via, passive



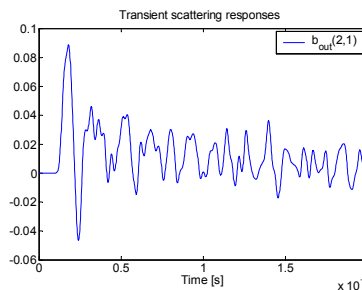
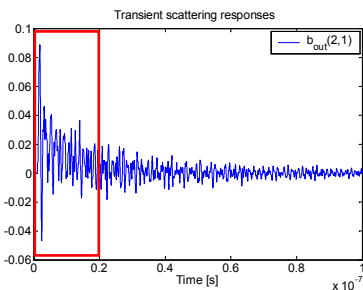
Raw data:
Triangle Impulse Responses
obtained by a transient PEEC
solver (by Dr. Ruehli, IBM)



Example 2: segmented power bus



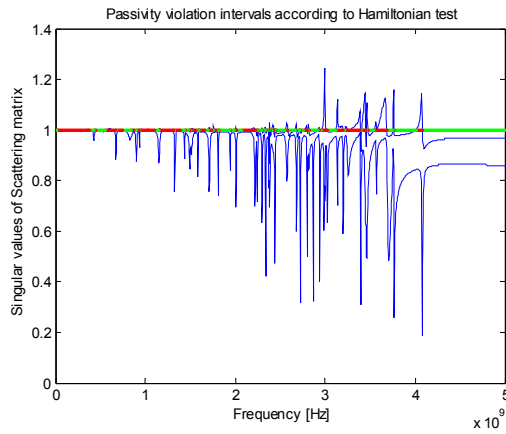
- 2-port structure
- Time-Domain solution
- CST Microwave Studio
- Bandwidth: 3 GHz
- 50 Ω port terminations





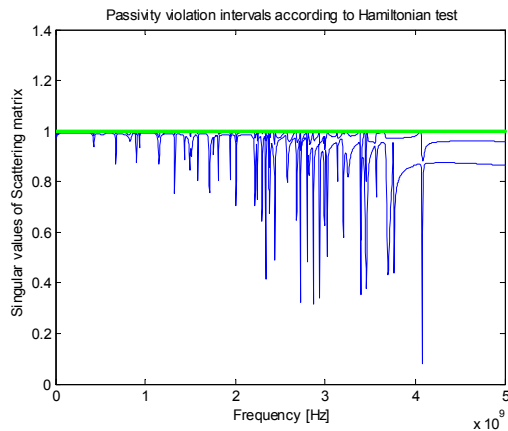
Example 2: segmented power bus

Passivity characterization



Example 2: segmented power bus

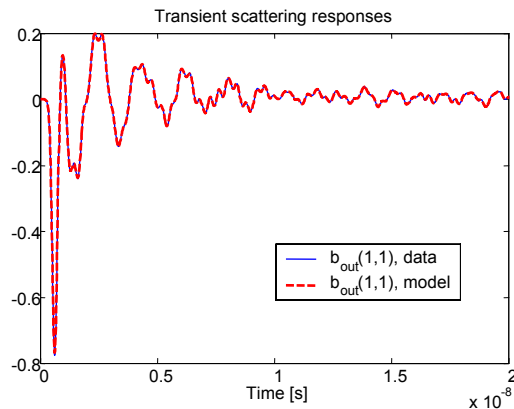
Passivity compensation





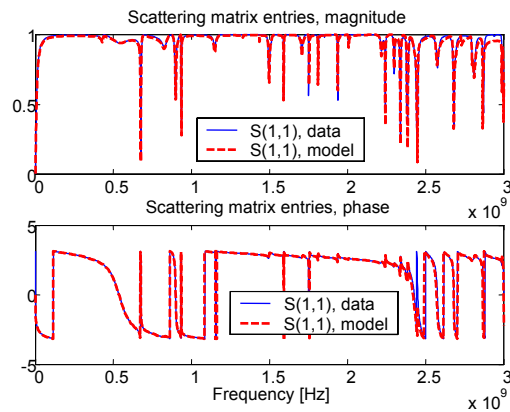
Example 2: segmented power bus

80-poles **passive** model



Example 2: segmented power bus

Comparison vs. frequency-domain scattering data





More examples...

41 poles, 2 ports

Compensation

Accuracy

110 poles, 5 ports

Compensation

Accuracy

308 poles, 11 ports

Compensation

Accuracy



Outline

- Introduction
- Macromodeling approaches for 3D Interconnects
- Model Order Reduction methods
 - PRIMA
- Model Identification methods
 - Frequency-Domain Vector Fitting
 - Time-Domain Vector Fitting
 - Passivity characterization and enforcement
- SPICE synthesis



Macromodel implementation

Main approaches

1. Synthesize an **equivalent circuit** in SPICE format
No access to SPICE kernel
Must use **standard circuit elements**
2. Direct SPICE implementation via **recursive convolution**
Laplace element, most efficient
3. Other languages for **mixed-signal** analyses
Verilog-AMS, VHDL-AMS, ...
Equation-based

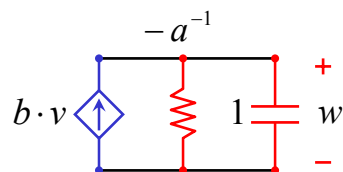
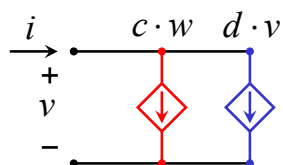


SPICE synthesis

Admittance representation

One-port, one-pole

$$\begin{cases} \dot{w} = a w + b v \\ i = c w + d v \end{cases}$$





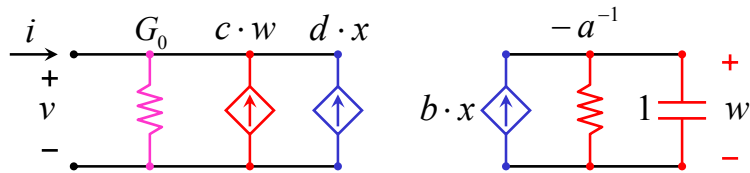
SPICE synthesis

Scattering representation

One-port, one-pole

$$x = G_0 v + i, \quad y = G_0 v - i$$

$$\begin{cases} \dot{w} = a w + b x \\ y = c w + d x \end{cases}$$



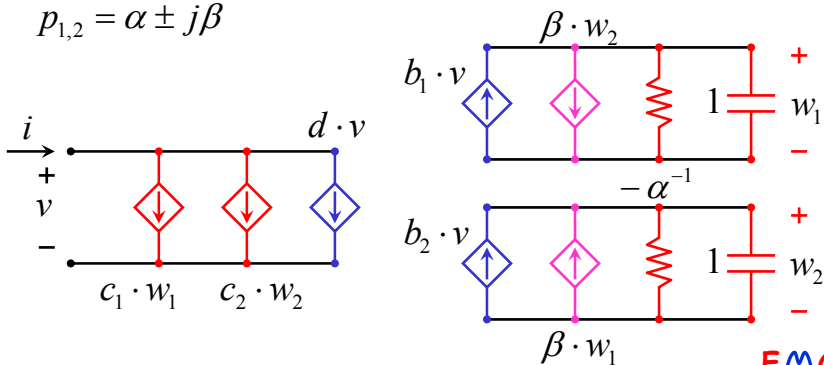
SPICE synthesis

Admittance representation

One-port, two-poles (complex)

$$p_{1,2} = \alpha \pm j\beta$$

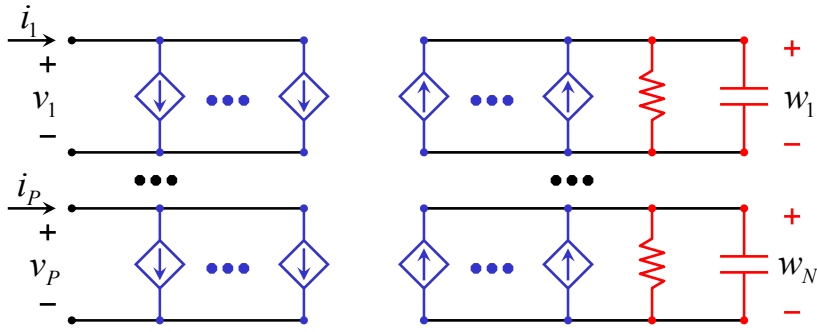
$$\begin{cases} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{b} v \\ i = \mathbf{c} \mathbf{w} + d v \end{cases}$$





SPICE synthesis

$$\begin{array}{l} \text{Admittance representation} \\ \text{General state-space synthesis} \end{array} \left\{ \begin{array}{l} \dot{\mathbf{w}} = \mathbf{A} \mathbf{w} + \mathbf{B} \mathbf{v} \\ \mathbf{i} = \mathbf{C} \mathbf{w} + \mathbf{D} \mathbf{v} \end{array} \right.$$



Recursive convolutions

$$\mathbf{H}(s) = \mathbf{D} + \mathbf{C}(s\mathbf{I} - \mathbf{A})^{-1} \mathbf{B} = \mathbf{D} + \sum_n \frac{\mathbf{R}_n}{s - p_n}$$

$$\mathbf{h}(t) = \mathbf{D}\delta(t) + \sum_n \mathbf{R}_n e^{p_n t} u(t)$$

$$\mathbf{y}(t) = \mathbf{D}\mathbf{x}(t) + \sum_n \mathbf{R}_n \int_0^t e^{p_n(t-\tau)} \mathbf{x}(\tau) d\tau$$



Recursive convolutions

$$\tilde{\mathbf{y}}(t_k) = \int_0^{t_k} e^{p(t_k-\tau)} \mathbf{x}(\tau) d\tau$$

Discrete time

$$t_k = t_{k-1} + \Delta t_k$$

$$= \int_0^{t_{k-1}} e^{p(t_k-\tau)} \mathbf{x}(\tau) d\tau + \int_{t_{k-1}}^{t_k} e^{p(t_k-\tau)} \mathbf{x}(\tau) d\tau$$

$$= e^{p\Delta t_k} \int_0^{t_{k-1}} e^{p(t_{k-1}-\tau)} \mathbf{x}(\tau) d\tau + \int_{t_{k-1}}^{t_k} e^{p(t_k-\tau)} \mathbf{x}(\tau) d\tau$$

$$\approx e^{p\Delta t_k} \tilde{\mathbf{y}}(t_{k-1}) + \frac{1 - e^{p\Delta t_k}}{p} \mathbf{x}(t_k)$$

Approximation!



The macromodeling dream...

Arbitrary characterization of the structure

- Equation-based or **Black-Box**
- Time or **frequency**, **simulation** or **measurement**

Generation of a broadband macromodel

- Any order, **any number of ports**
- Any prescribed accuracy
- **Stable** and **passive** by construction
- **Efficient** (reduced-order and low-complexity)
- Fully automatic