

Order Reduction of (Truly) Large-Scale Linear Dynamical Systems

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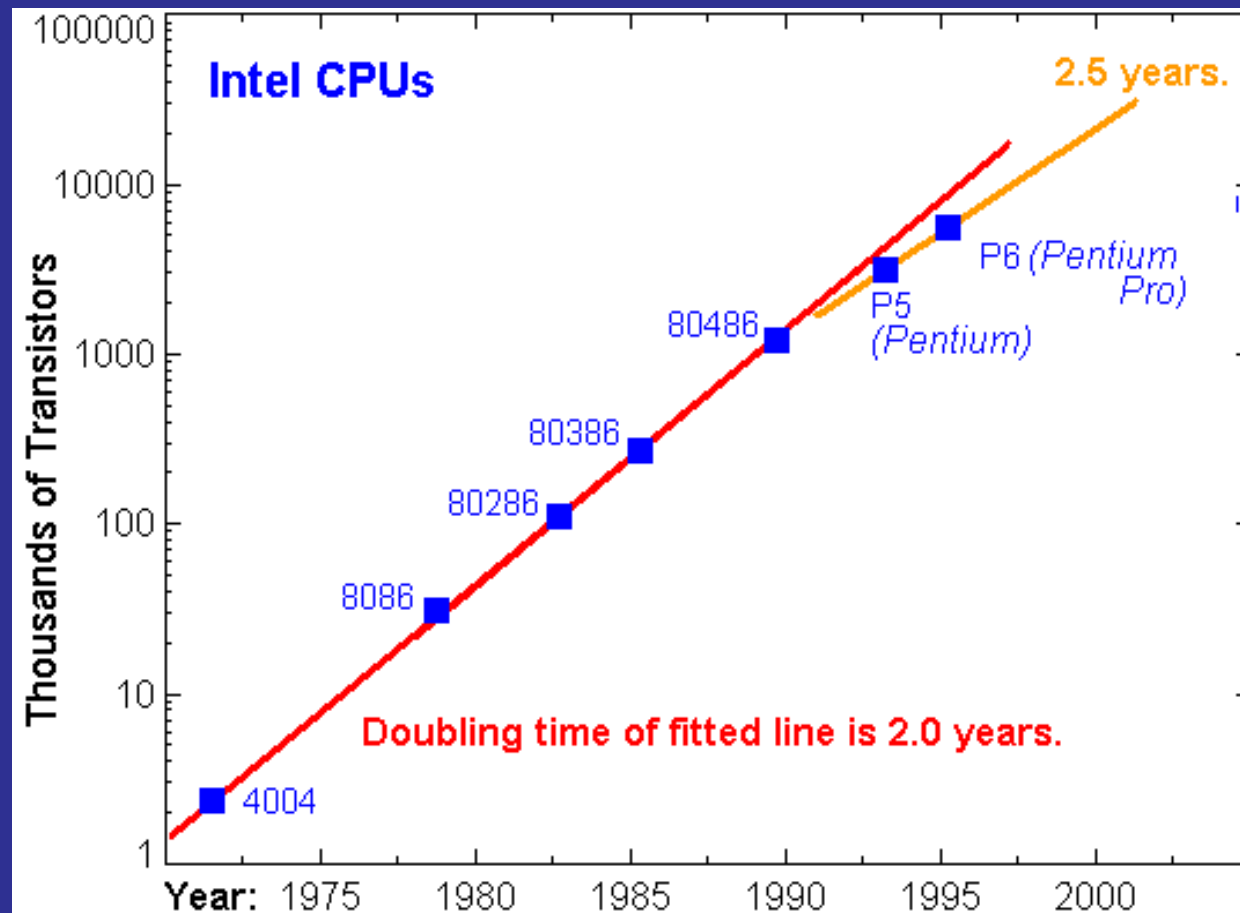
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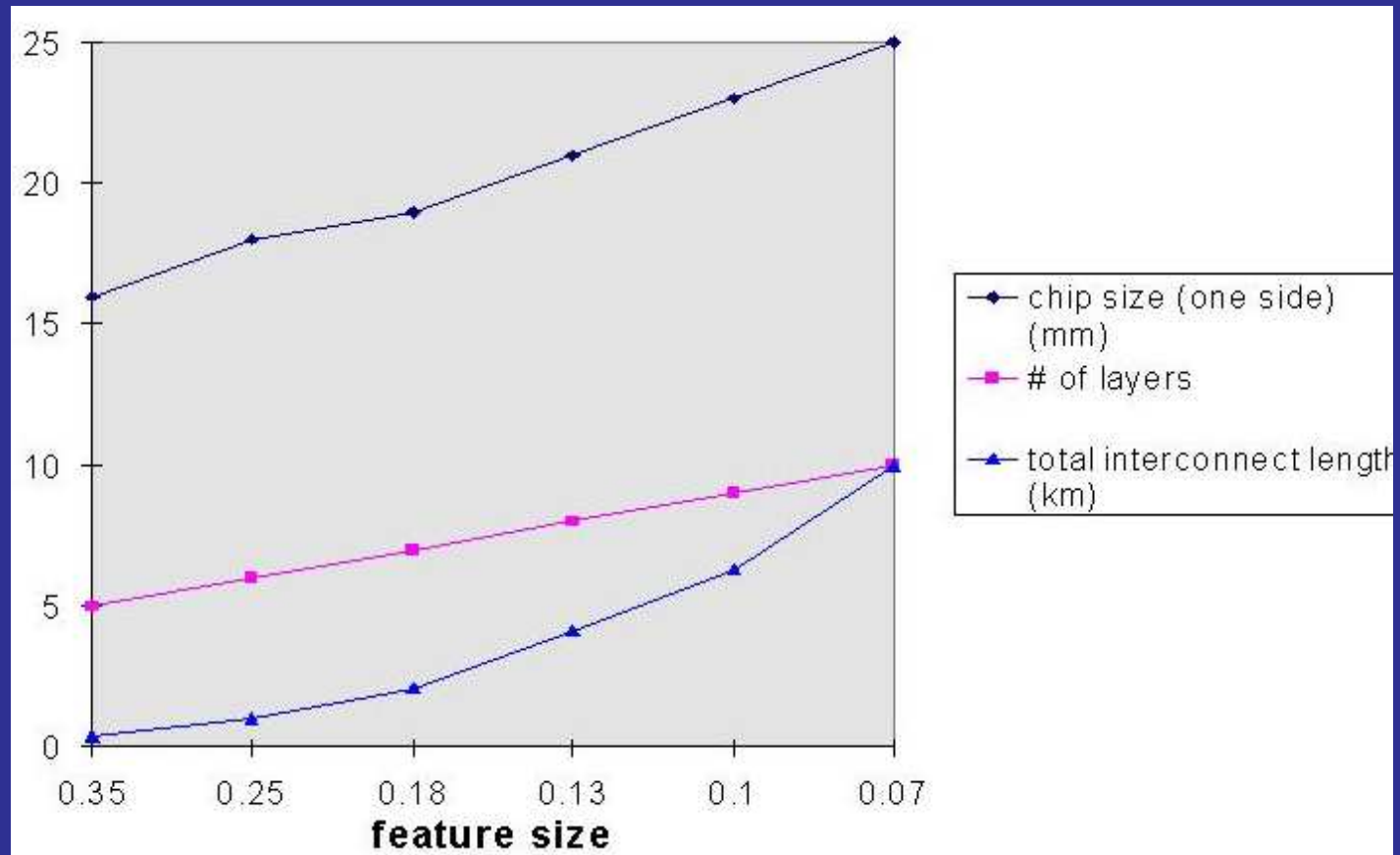
Motivation

- Need for order reduction in VLSI circuit simulation
- Corollary to Moore's Law
- **RCL networks:**
Electric networks consisting of only resistors (**R**'s), capacitors (**C**'s), and inductors (**L**'s)
- These networks are (truly) large

Moore's law

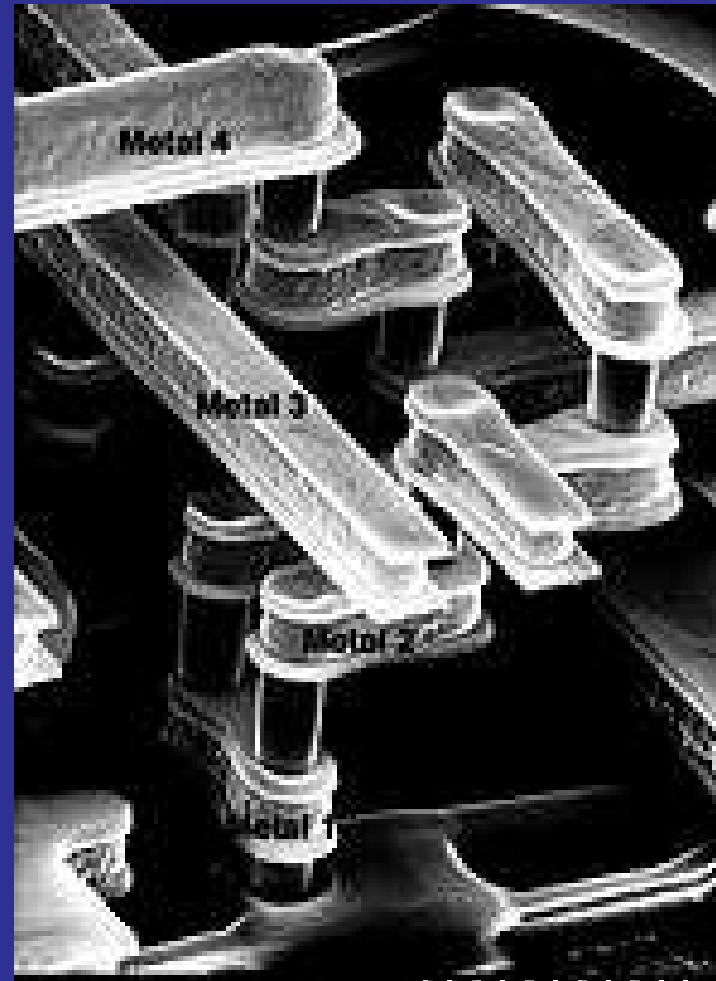


VLSI chip scaling

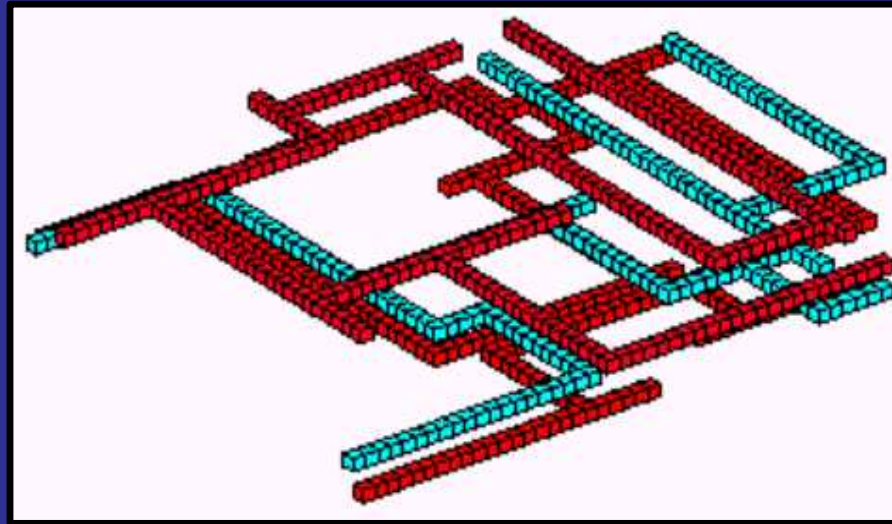


VLSI interconnect

- Wires are not ideal:
 - Resistance
 - Capacitance
 - Inductance
- Consequences:
 - Timing behavior
 - Noise
 - Energy consumption
 - Power distribution

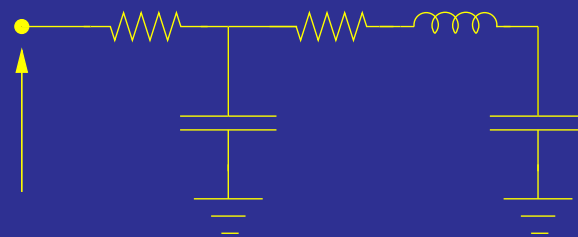
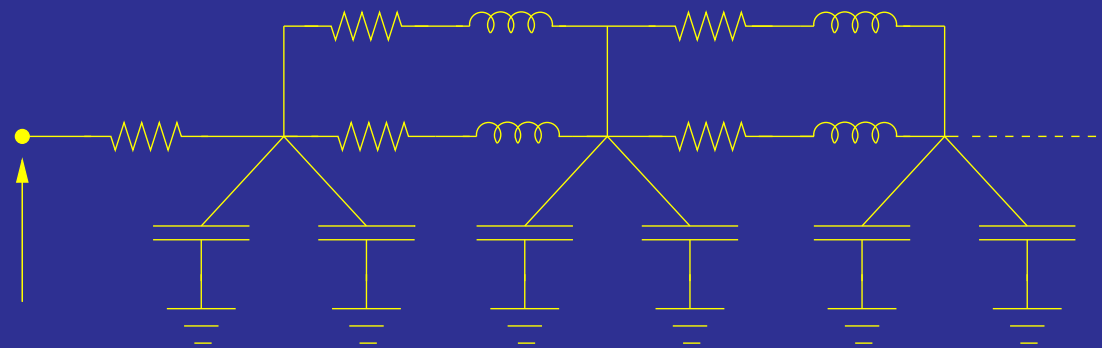


Lumped-circuit paradigm



- Replace 'pieces' of the interconnect by RCL networks
- Up to $\mathcal{O}(10^6)$ circuit elements per network
- Up to $\mathcal{O}(10^6)$ networks

Need for order reduction



Outline

- The order reduction problem
- Projection + Krylov = Padé-type reduction
- SPRIM for general RCL networks
- SPRIM–SVD
- Padé-type approximation properties of SPRIM
- Concluding remarks

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RCL networks as descriptor systems

- System of linear time-invariant DAEs of the form

$$\mathbf{C} \frac{d}{dt} \mathbf{x}(t) + \mathbf{G} \mathbf{x}(t) = \mathbf{B} \mathbf{u}(t)$$
$$\mathbf{y}(t) = \mathbf{B}^T \mathbf{x}(t)$$

where $\mathbf{C}, \mathbf{G} \in \mathbb{R}^{N \times N}$ and $\mathbf{B} \in \mathbb{R}^{N \times m}$

- $\mathbf{x}(t) \in \mathbb{R}^N$ is the unknown vector of state variables
- m inputs, m outputs
- $s\mathbf{C} + \mathbf{G}$ is nonsingular except for finitely many values of $s \in \mathbb{C}$

Reduced-order models

- System of DAEs of the same form:

$$\mathbf{C}_n \frac{d}{dt} \mathbf{z}(t) + \mathbf{G}_n \mathbf{z}(t) = \mathbf{B}_n \mathbf{u}(t)$$
$$\tilde{\mathbf{y}}(t) = \mathbf{B}_n^T \mathbf{z}(t)$$

- But now:

$$\mathbf{C}_n, \mathbf{G}_n \in \mathbb{R}^{n \times n} \quad \text{and} \quad \mathbf{B}_n \in \mathbb{R}^{n \times m}$$

where $n \ll N$

Transfer functions

- Original descriptor system:

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

- Reduced-order model:

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

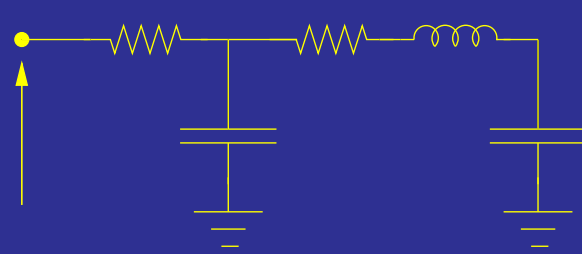
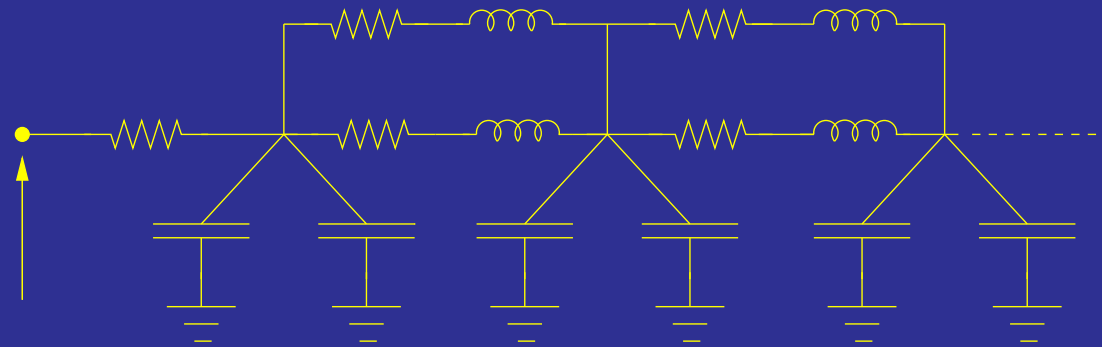
- 'Good' reduced-order model

$$\iff \text{'Good' approximation } \mathbf{H}_n \approx \mathbf{H}$$

Problem of structure preservation

- Any RCL network is stable, passive, . . .
- Reduced-order model should be stable, passive, . . .
- More difficult problem:
Reduced-order model of an RCL network should be synthesizable as an RCL network

Preservation of RCL structure



General RCL network equations

- System of linear time-invariant DAEs of the form

$$\mathbf{C} \frac{d}{dt} \mathbf{x}(t) + \mathbf{G} \mathbf{x}(t) = \mathbf{B} \mathbf{u}(t)$$
$$\mathbf{y}(t) = \mathbf{B}^T \mathbf{x}(t)$$

where

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_1 & \mathbf{G}_2 & \mathbf{G}_3 \\ -\mathbf{G}_2^T & \mathbf{0} & \mathbf{0} \\ -\mathbf{G}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 \end{bmatrix}$$

- Moreover:

$$\mathbf{C} \succeq \mathbf{0} \quad \text{and} \quad \mathbf{G} + \mathbf{G}^T \succeq \mathbf{0}$$

(This implies passivity!)

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Projection-based reduction

- Let $\mathbf{V}_n \in \mathbb{R}^{N \times n}$ be any matrix with full column rank n
- Use \mathbf{V}_n to explicitly project the data matrices of

$$\mathbf{C} \frac{d}{dt} \mathbf{x}(t) + \mathbf{G} \mathbf{x}(t) = \mathbf{B} \mathbf{u}(t)$$
$$\mathbf{y}(t) = \mathbf{B}^T \mathbf{x}(t)$$

onto the subspace spanned by the columns of \mathbf{V}_n

Projection-based reduction, continued

- Resulting reduced-order model

$$\mathbf{C}_n \frac{d}{dt} \mathbf{z}(t) + \mathbf{G}_n \mathbf{z}(t) = \mathbf{B}_n \mathbf{u}(t)$$

$$\tilde{\mathbf{y}}(t) = \mathbf{B}_n^T \mathbf{z}(t)$$

where

$$\mathbf{C}_n = \mathbf{V}_n^T \mathbf{C} \mathbf{V}_n, \quad \mathbf{G}_n = \mathbf{V}_n^T \mathbf{G} \mathbf{V}_n, \quad \mathbf{B}_n = \mathbf{V}_n^T \mathbf{B}$$

- Passivity is preserved:

$$\mathbf{C} \succeq \mathbf{0}, \quad \mathbf{G} + \mathbf{G}^T \preceq \mathbf{0} \quad \Rightarrow \quad \mathbf{C}_n \succeq \mathbf{0}, \quad \mathbf{G}_n + \mathbf{G}_n^T \preceq \mathbf{0}$$

Projection-based order reduction

- **PRIMA**
Passive Reduced Interconnect Macromodeling Algorithm
(Odabasioglu, '96; Odabasioglu, Celik, and Pileggi, '97)
- Split-congruence transformations
(Kerns, Yang, '97)
- **SPRIM**
Structure-Preserving Reduced Interconnect Macromodeling
(F., '04 and '07)

PRIMA reduced-order models

- Let V_n be any matrix whose columns span the n -th **Krylov subspace** $\mathcal{K}_n(\mathbf{A}, \mathbf{R})$ where

$$\mathbf{A} := (s_0 \mathbf{C} + \mathbf{G})^{-1} \mathbf{C} \quad \text{and} \quad \mathbf{R} := (s_0 \mathbf{C} + \mathbf{G})^{-1} \mathbf{B}$$

and $s_0 \in \mathbb{R}$ is a suitably chosen expansion point

- Projection + Krylov subspace = **Padé-type approximant**:

$$\mathbf{H}_n(s) = \mathbf{H}(s) + \mathcal{O}((s - s_0)^q), \quad \text{where} \quad q \geq \lfloor n/m \rfloor$$

Structure is not preserved

- Structure of the data matrices:

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_1 & \mathbf{G}_2 & \mathbf{G}_3 \\ -\mathbf{G}_2^T & \mathbf{0} & \mathbf{0} \\ -\mathbf{G}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 \end{bmatrix}$$

- Structure of PRIMA reduced-order matrices:

$$\mathbf{C}_n = \boxed{\phantom{\mathbf{C}_n}}, \quad \mathbf{G}_n = \boxed{\phantom{\mathbf{G}_n}}, \quad \mathbf{B}_n = \boxed{\phantom{\mathbf{B}_n}}$$

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SPRIM

- As in PRIMA, let \mathbf{V}_n be any matrix such that

$$\mathcal{K}_n(\mathbf{A}, \mathbf{R}) = \text{colspan } \mathbf{V}_n$$

- Key insight that is exploited in SPRIM:
In order to have a Padé-type property as in PRIMA, we can project with any matrix $\tilde{\mathbf{V}}_n$ such that

$$\mathcal{K}_n(\mathbf{A}, \mathbf{R}) \subseteq \text{colspan } \tilde{\mathbf{V}}_n$$

- ... ; Odabasioglu, '96; Grimme, '97; Odabasioglu, Celik, and Pileggi, '97; ...

SPRIM, continued

- Recall:

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_1 & \mathbf{G}_2 & \mathbf{G}_3 \\ -\mathbf{G}_2^T & \mathbf{0} & \mathbf{0} \\ -\mathbf{G}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 \end{bmatrix}$$

- Partition \mathbf{V}_n accordingly:

$$\mathbf{V}_n = \begin{bmatrix} \mathbf{V}_n^{(1)} \\ \mathbf{V}_n^{(2)} \\ \mathbf{V}_n^{(3)} \end{bmatrix}$$

SPRIM, continued

- Set

$$\tilde{\mathbf{V}}_n = \begin{bmatrix} \mathbf{V}_n^{(1)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_n^{(2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{V}_n^{(3)} \end{bmatrix}$$

- Then: $\mathcal{K}_n(\mathbf{A}, \mathbf{R}) = \text{colspan } \mathbf{V}_n \subseteq \text{colspan } \tilde{\mathbf{V}}_n$
- This guarantees a Padé-type property!

SPRIM models

- Recall:

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_1 & \mathbf{G}_2 & \mathbf{G}_3 \\ -\mathbf{G}_2^T & \mathbf{0} & \mathbf{0} \\ -\mathbf{G}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 \end{bmatrix}$$

and

$$\tilde{\mathbf{V}}_n = \begin{bmatrix} \mathbf{V}_n^{(1)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_n^{(2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{V}_n^{(3)} \end{bmatrix}$$

SPRIM models, continued

- The projection now preserves this structure:

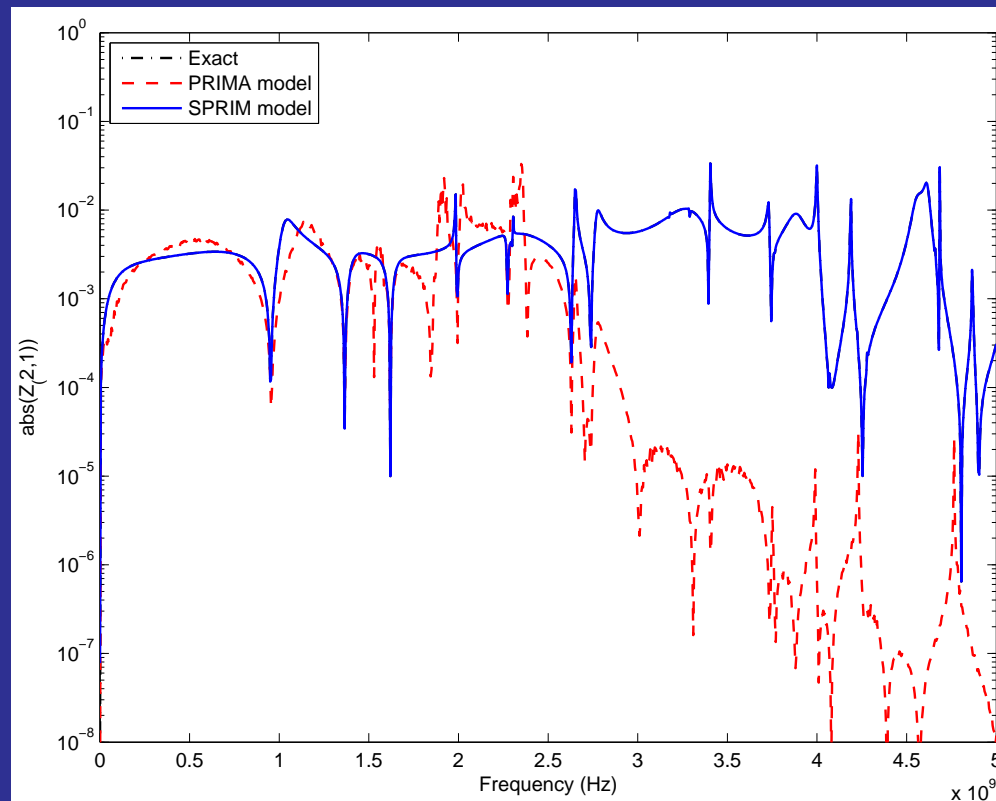
$$\mathbf{C}_n = \begin{bmatrix} \tilde{\mathbf{C}}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{C}}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \mathbf{G}_n = \begin{bmatrix} \tilde{\mathbf{G}}_1 & \tilde{\mathbf{G}}_2 & \tilde{\mathbf{G}}_3 \\ -\tilde{\mathbf{G}}_2^T & \mathbf{0} & \mathbf{0} \\ -\tilde{\mathbf{G}}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \mathbf{B}_n = \begin{bmatrix} \tilde{\mathbf{B}}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{B}}_2 \end{bmatrix}$$

- Padé-type property:

$$\mathbf{H}_n(s) = \mathbf{H}(s) + \mathcal{O}((s - s_0)^q)$$

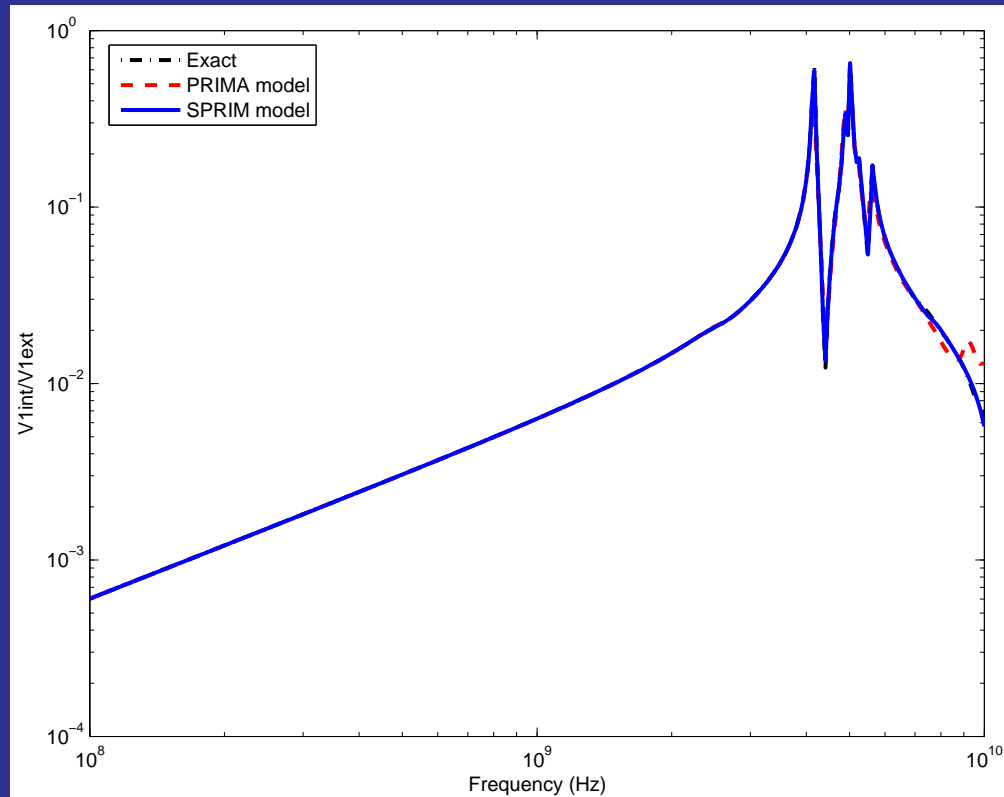
with $q \geq \lfloor n/m \rfloor$

An RCL circuit with mostly C's and L's



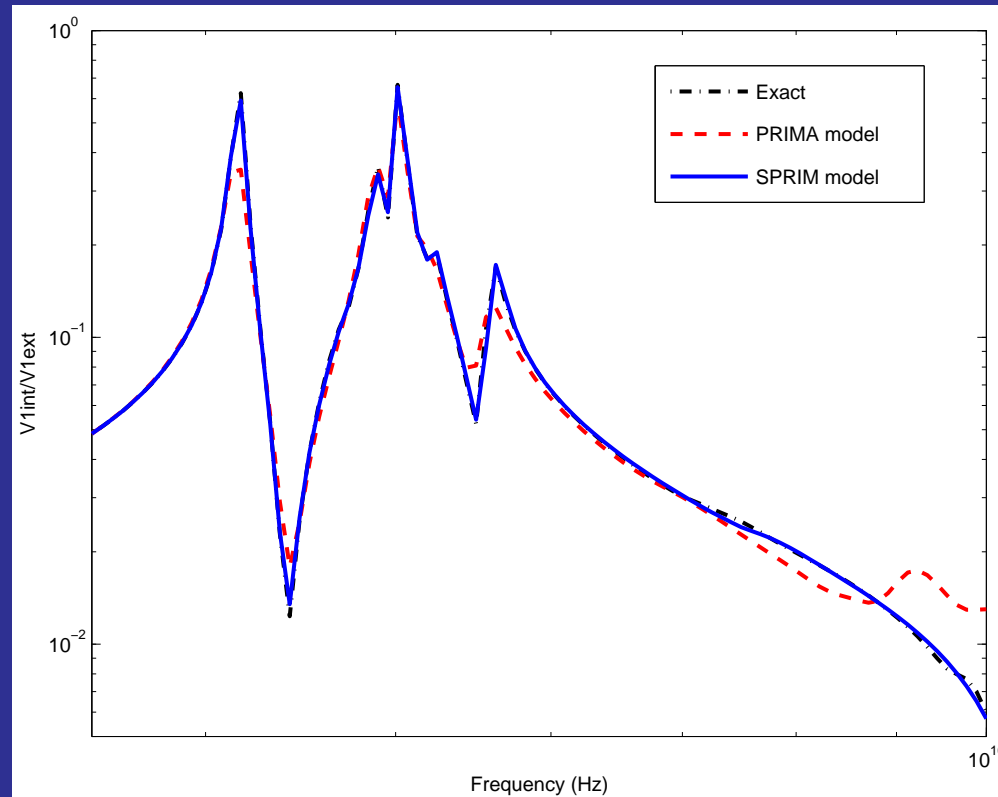
Exact and models corresponding to $n = 120$

A package example



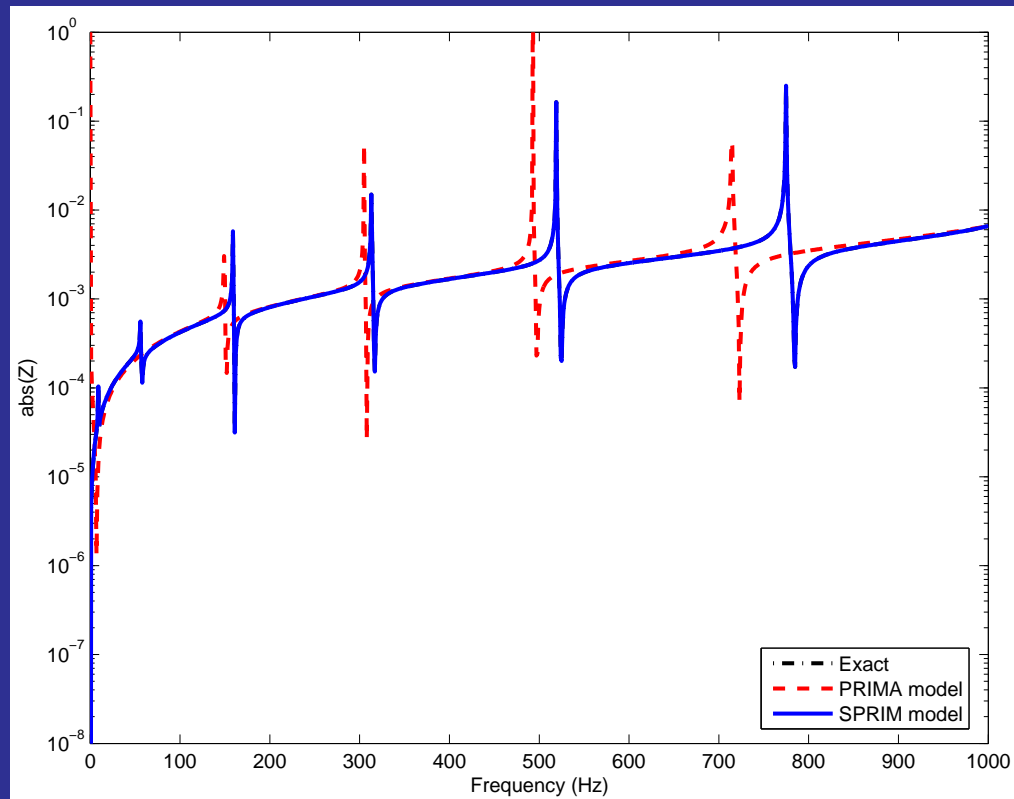
Exact and models corresponding to $n = 80$

Package example, high frequencies



Exact and models corresponding to size $n = 80$

A finite-element model of a shaft



Exact and models corresponding to $n = 15$

SPRIM vs. PRIMA

- Pros:
 - Same computational work
 - SPRIM preserves block structure and reciprocity
 - Higher accuracy
- Cons:
 - SPRIM models are two or three times as large as corresponding PRIMA models

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SPRIM-SVD

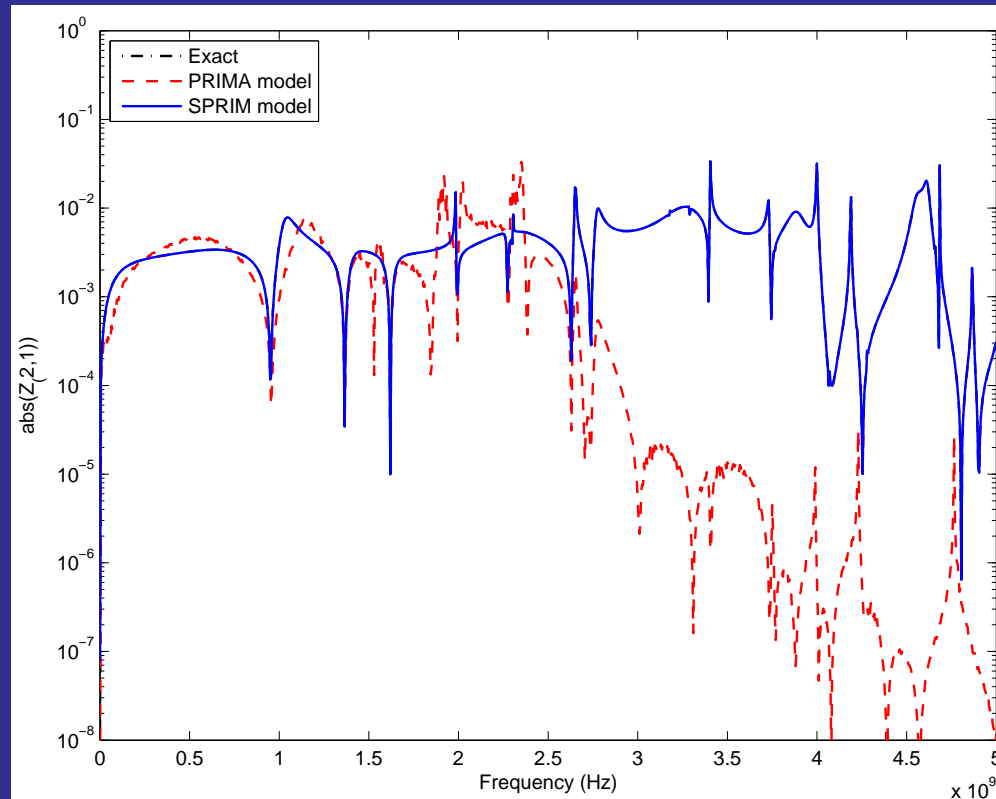
- Columns of \mathbf{V}_n span $\mathcal{K}_n(\mathbf{A}, \mathbf{R})$
- SPRIM projection:

$$\mathbf{V}_n = \begin{bmatrix} \mathbf{V}_n^{(1)} \\ \mathbf{V}_n^{(2)} \\ \mathbf{V}_n^{(3)} \end{bmatrix} \Rightarrow \tilde{\mathbf{V}}_n = \begin{bmatrix} \mathbf{V}_n^{(1)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_n^{(2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{V}_n^{(3)} \end{bmatrix}$$

- But:

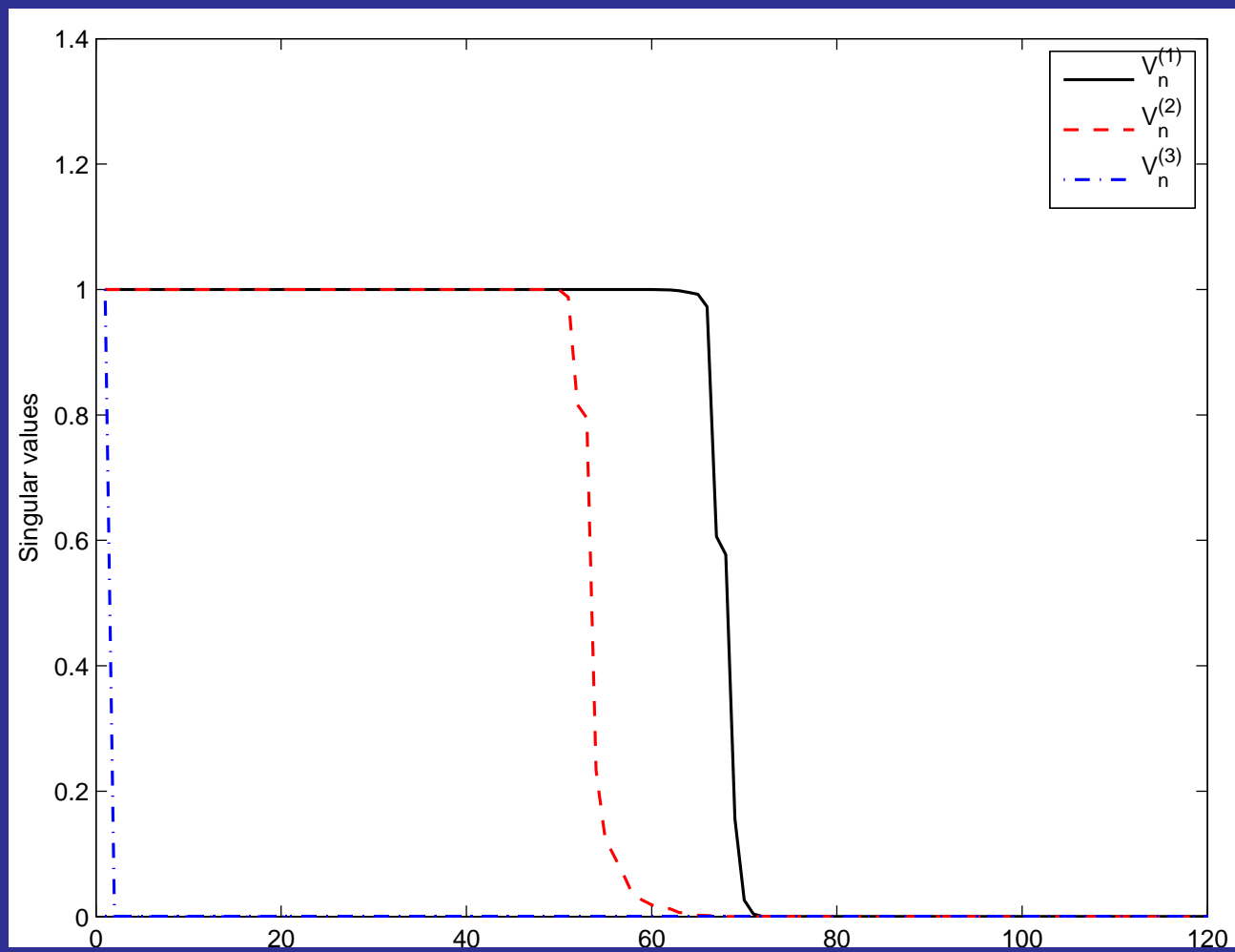
of rows of $\mathbf{V}_n^{(3)} \ll$ # of rows of $\mathbf{V}_n^{(1)}$ and $\mathbf{V}_n^{(2)}$

The RCL circuit with mostly C's and L's



Exact and models corresponding to $n = 120$

Singular values of projection subblocks



SPRIM–SVD, continued

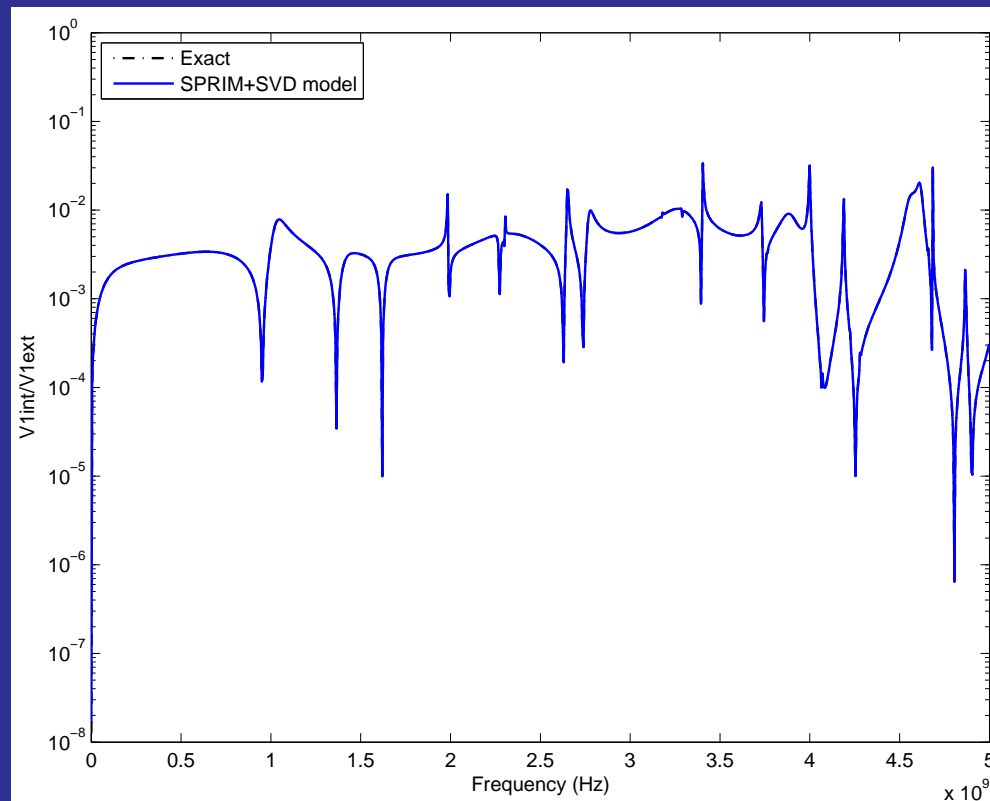
- For $l = 1, 2, 3$, replace $V_n^{(l)}$ by the matrix $U_n^{(l)}$ containing the left singular vectors corresponding to the 'non-zero' singular values
- SPRIM–SVD projection:

$$\tilde{V}_n = \begin{bmatrix} V_n^{(1)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & V_n^{(2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & V_n^{(3)} \end{bmatrix} \implies \hat{V}_n = \begin{bmatrix} U_n^{(1)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & U_n^{(2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & U_n^{(3)} \end{bmatrix}$$

- For the example:

$$3n = 360 \implies 74 + 72 + 1 = 147$$

The RCL circuit with mostly C's and L's



Exact and models corresponding to $n = 120$

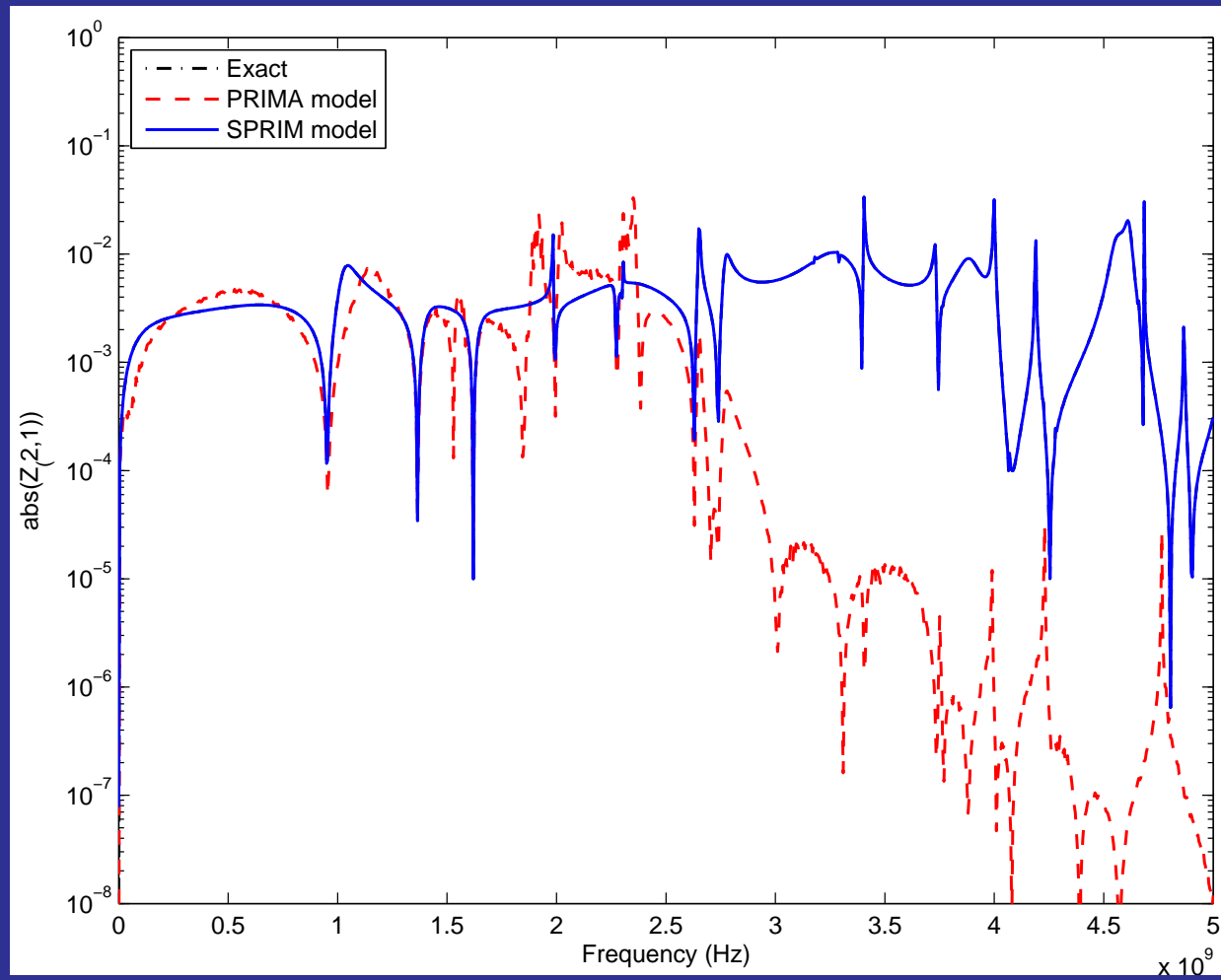
Theory of SPRIM–SVD?

- Number of small singular values of the subblocks $V_n^{(1)}$ and $V_n^{(2)}$?
- Structure is understood in the case of no voltage sources, i.e., no third subblock $V_n^{(3)}$ (F. '05)
- Key is the structure of the block Krylov subspaces $\mathcal{K}_n(\mathbf{A}, \mathbf{R})$; but what is it?

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SPRIM vs. PRIMA



Padé-type property

- So far, we only know that both PRIMA and SPRIM produce Padé-type reduced-order models with

$$\mathbf{H}_n(s) = \mathbf{H}(s) + \mathcal{O}((s - s_0)^q), \quad \text{where } q \geq \lfloor n/m \rfloor$$

- Can we say more in the case of SPRIM?
- Easy in the case of no third subblock $\mathbf{V}_n^{(3)}$
(F. '05)
- General case: **J**-symmetric linear dynamical systems
(F. '07)

J-symmetry

- Recall:

$$\mathbf{C} \frac{d}{dt} \mathbf{x}(t) + \mathbf{G} \mathbf{x}(t) = \mathbf{B} \mathbf{u}(t)$$
$$\mathbf{y}(t) = \mathbf{B}^T \mathbf{x}(t)$$

where

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}_2 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_1 & \mathbf{G}_2 & \mathbf{G}_3 \\ -\mathbf{G}_2^T & \mathbf{0} & \mathbf{0} \\ -\mathbf{G}_3^T & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 \end{bmatrix}$$

- \mathbf{C} and \mathbf{G} are \mathbf{J} -symmetric:

$$\mathbf{J} \mathbf{C} = \mathbf{C}^T \mathbf{J} \quad \text{and} \quad \mathbf{J} \mathbf{G} = \mathbf{G}^T \mathbf{J}, \quad \text{where} \quad \mathbf{J} := \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & -\mathbf{I} \end{bmatrix}$$

J-symmetry, continued

- The input-output matrix \mathbf{B} satisfies

$$\text{Range}(\mathbf{J}\mathbf{B}) = \text{Range}(\mathbf{B})$$

\mathbf{J}_n -symmetry of SPRIM models

- The SPRIM models

$$\mathbf{C}_n \frac{d}{dt} \mathbf{z}(t) + \mathbf{G}_n \mathbf{z}(t) = \mathbf{B}_n \mathbf{u}(t)$$

$$\mathbf{y}(t) = \mathbf{B}_n^T \mathbf{z}(t)$$

preserve the structure of $\mathbf{C}_n, \mathbf{G}_n, \mathbf{B}_n$

- Therefore, \mathbf{C}_n and \mathbf{G}_n are \mathbf{J}_n -symmetric with

$$\mathbf{J}_n := \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & -\mathbf{I} \end{bmatrix} \quad \text{and} \quad \text{Range}(\mathbf{J}_n \mathbf{B}_n) = \text{Range}(\mathbf{B}_n)$$

- Moreover, the projection matrix \mathbf{V}_n satisfies

$$\mathbf{J} \mathbf{V}_n = \mathbf{V}_n \mathbf{J}_n$$

Padé-type property

- **Theorem** (F., '05 and '07)

For \mathbf{J} -symmetric systems and real expansion points s_0 , the n -th SPRIM model is \mathbf{J}_n -symmetric and satisfies

$$\mathbf{H}_n(s) = \mathbf{H}(s) + \mathcal{O}\left((s - s_0)^{\tilde{q}}\right), \quad \text{where } \tilde{q} \geq 2 \lfloor n/m \rfloor$$

- Twice as accurate as PRIMA!

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Concluding remarks

- SPRIM and SPRIM–SVD for general RCL networks
- Key property for higher accuracy of SPRIM:
 \mathbf{J}_n -symmetry reduced-order models
- Theory of the zero singular values exploited in SPRIM–SVD?
- Projection-based reduction requires the storage of $\mathbf{V}_n \in \mathbb{R}^{N \times n}$ and is thus limited to moderately large N
- Structure-preserving reduction for truly large-scale RCL networks?