

8. Advanced Methods

Model Reduction of Linear Time Invariant Systems

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Error Estimate for Moment Matching
Parametric Model Reduction
Iterative Grammian-based methods

- Global Error Estimate

$$\|G - G_{red}\|_{\infty} < 2(\sigma_{r+1} + \dots + \sigma_N)$$

- Local Error Estimate

$$|G(s) - G_{red}(s)| \approx |G_{red,i}(s) - G_{red,i-1}(s)|$$

- Difference between i and $i-1$ reduced model is about the difference between i -th and the full model.

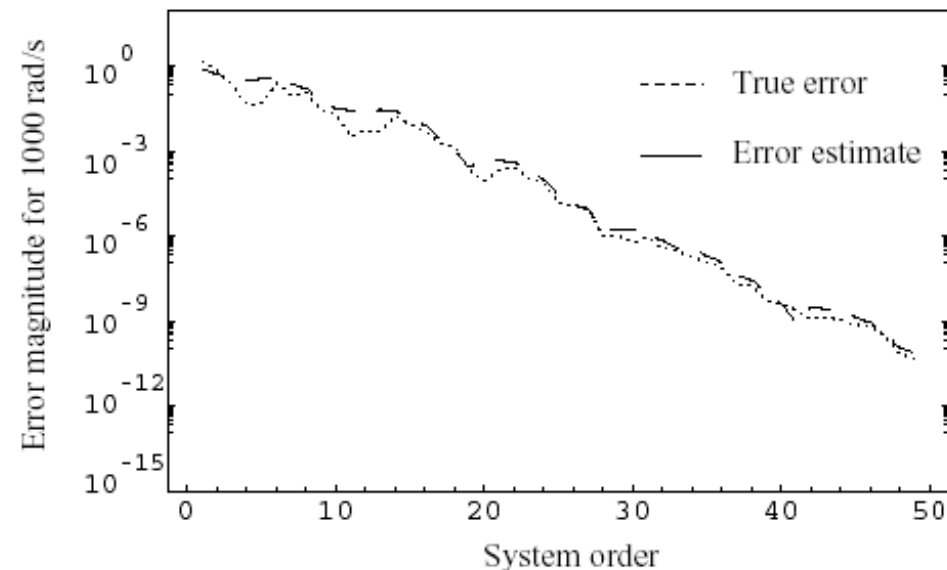
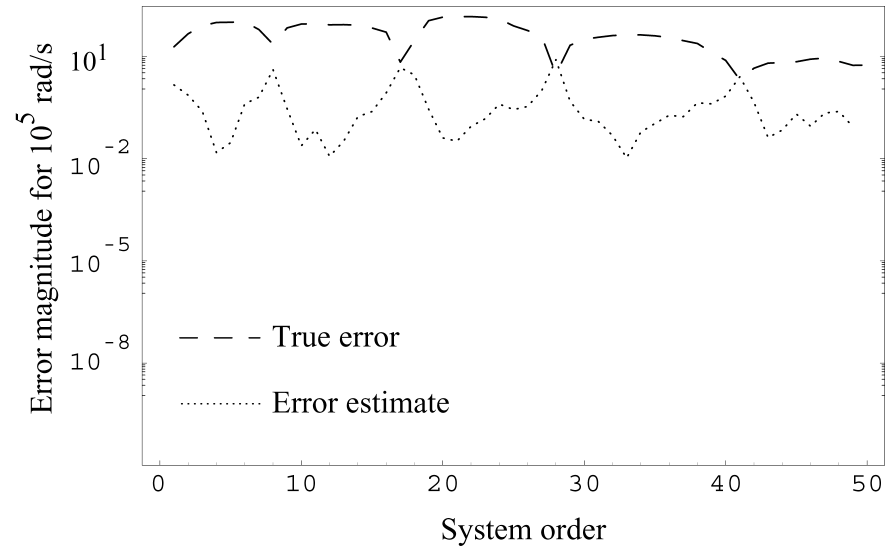
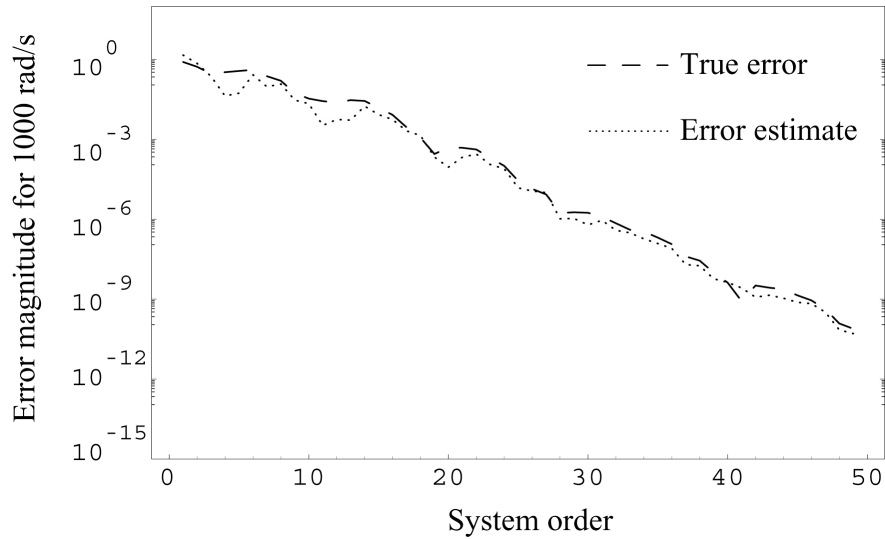
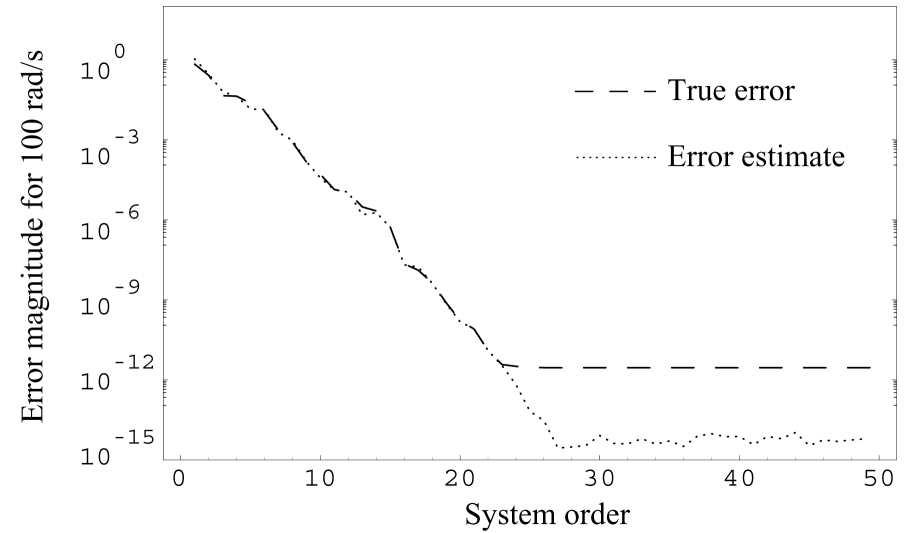
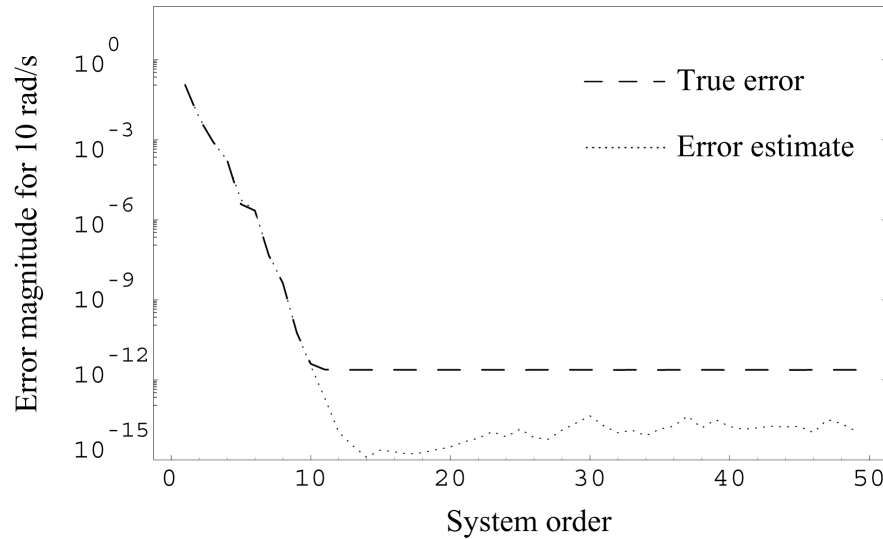
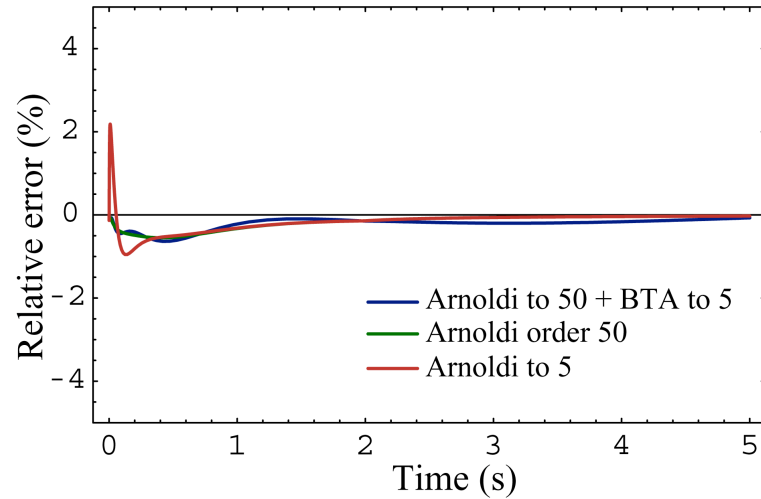


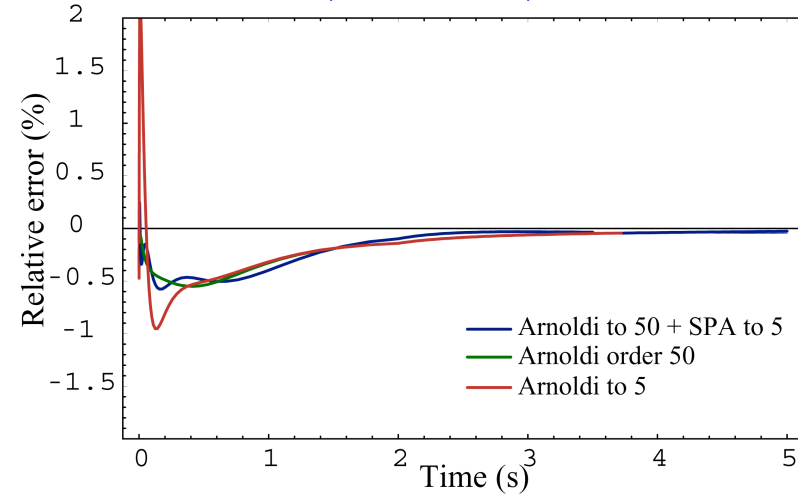
Fig. 5 Error estimate for $\omega = 10^3 \text{ rad/s}$.



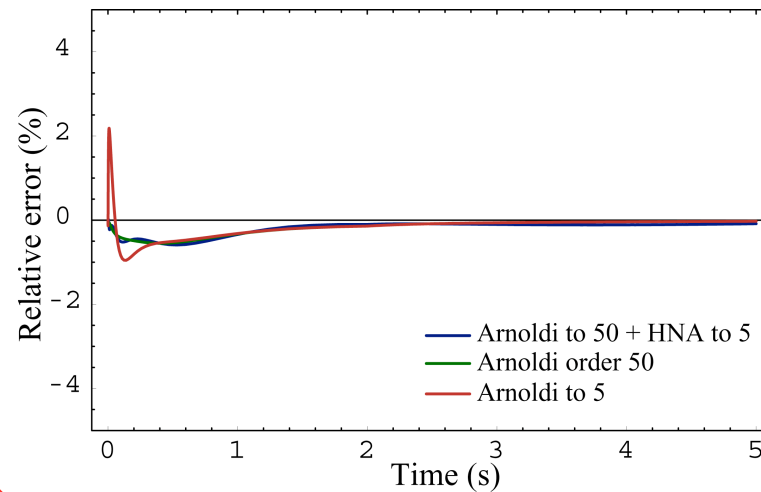
BTA, $r_1 = 50, r_2 = 5$



SPA, $r_1 = 50, r_2 = 5$



HNA, $r_1 = 50, r_2 = 5$



- It would be good to preserve some properties as parameters.
- Natural for mixed boundary conditions and material properties.
- Can include geometry but it is much more work.
- Projection formalism is working for linear systems.

$$E\dot{x} = Ax + Bu$$

$$y = Cx$$

$$A = A_0 + \sum_i k_i A_i$$

$$V^T AV = V^T A_0 V + \sum_i k_i V^T A_i V$$

- s does not have to be frequency.
- Can be a design parameter.
- Model reduction for stationary problem.
- Make multivariate Taylor expansion and match multivariate moments.

$$G(s) = C(sE - A)^{-1}B$$

$$P(s)x = b$$

$$G(s, k_i) = C \left(sE - A_0 + \sum_i k_i A_i \right)^{-1} B$$

- Ms Feng has developed two methods how to find a good V .
- There is a paper from Nakhla's group.
- There is a paper from White's group.
- Many questions to research.
- **Exciting opportunities:**
 - Boundary Condition Independent Model Reduction
 - Preserving material properties: Inverse problem
 - One can insert nonlinearity after model reduction

$$V^T AV = V^T A_0 V + \sum_i k_i V^T A_i V$$

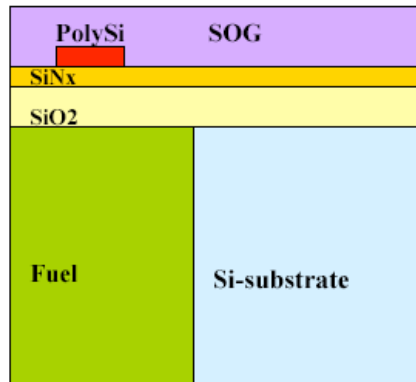


Fig. 1. A 2D-axisymmetrical model of the microthruster unit (not scaled). The axis of the symmetry on the left side. A heater is shown by a red spot.

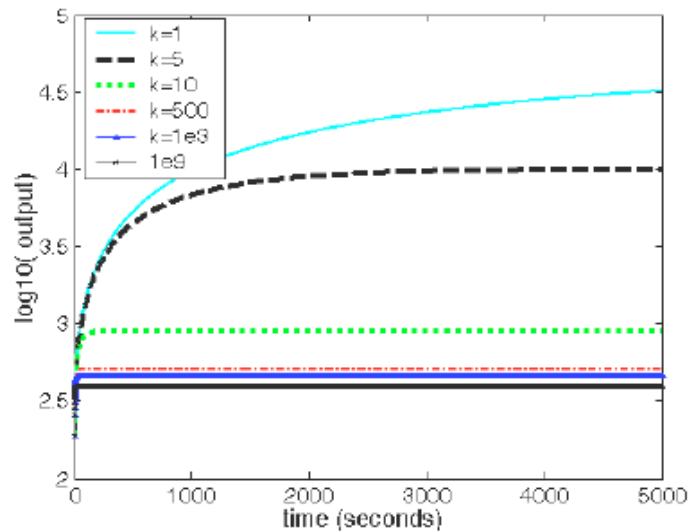
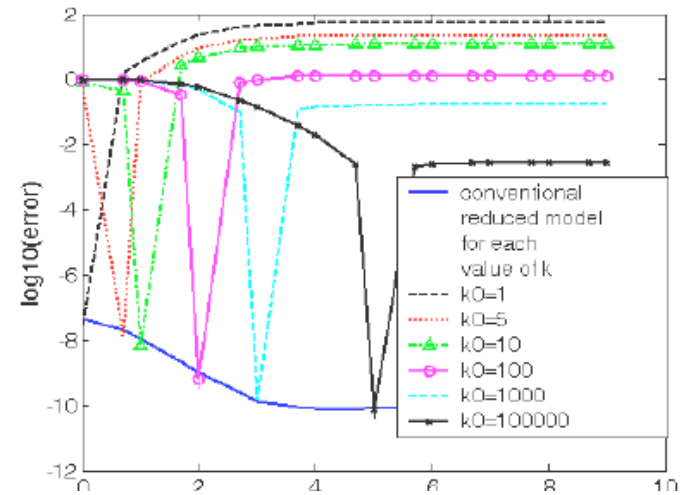
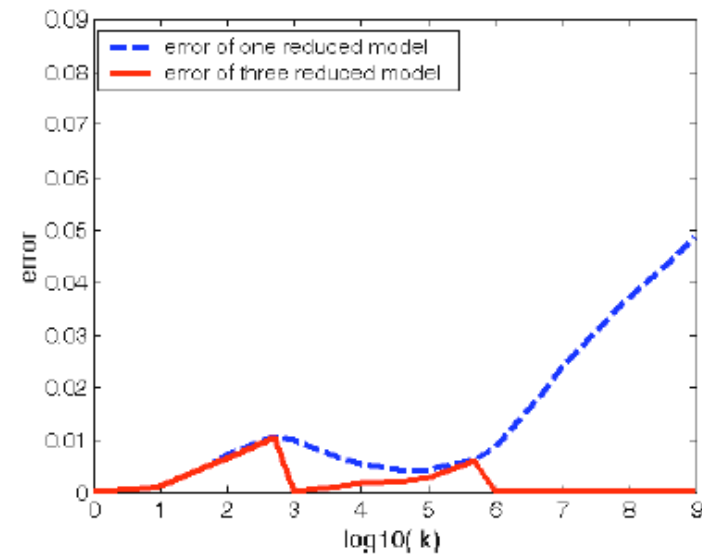


Fig.2.a Output at node 1 with different values of k



- How to estimate the small HSV?
- Worst-case scenario does not work.
- Penzl's estimate is based on maximum and minimum eigenvalues of the system matrix.
- Antoulas' estimate is based on the whole spectrum.

$$\|G - G_{red}\|_{\infty} < 2(\sigma_{r+1} + \dots + \sigma_N)$$

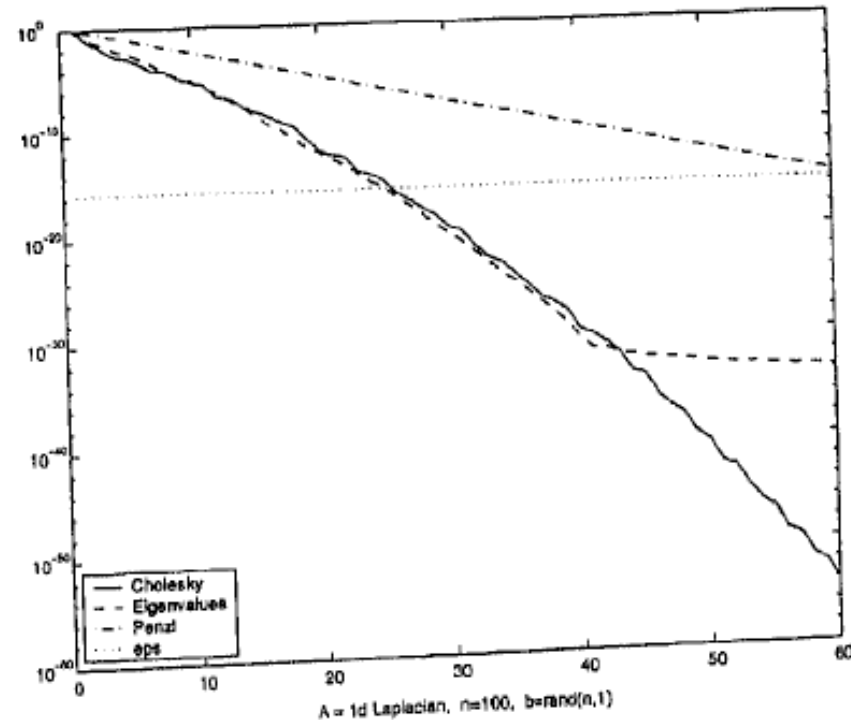


Fig. 2. Comparison of estimates: discrete Laplacian.

from Antoulas



- Lyapunov equations can be expressed as a normal linear system of order N^2 .
- One can apply iterative methods by making use of a special form for such a system.
- See chapter in Datta's book.

$$AX + XB = C$$

$$Gx = c$$

$$G = A \otimes I + I \otimes B^T$$

- Penzl; Lee and White; Gugercin, Sorensen and Antoulas.
- Express Grammian as $P = XX^T$
- Substitute into the Lyapunov equations and find an iterative method.
- Software LYAPACK, www.netlib.org/lyapack
- Problems:
 - there are two Lyapunov equations to solve
 - model reduction theory for symmetric systems
 - may not preserve stability

$$AP + PA^T = -BB^T$$

$$A^T Q + QA = -C^T C$$

- Theorem from Jing-Rebecca Li for symmetric systems.
- Low-rank Grammian approximation is equivalent to multi-point expansion.
- Gives us some approximate theory how to choose expansion points.
- Input: maximum and minimum eigenvalues of the system matrix and tolerance.
- Computing elliptic integrals.
- Output: number and values of expansion points.

- Sorenson and Antoulas: model reduction based on the Sylvester equation.
- Valid for symmetric transfer function matrices.
- SISO is always appropriate.
- Can always be done for an arbitrary MIMO system.

$$AP + PA^T = -BB^T$$

$$A^T Q + QA = -C^T C$$

$$AR + RA = -BC$$

cross-grammian

