



MAX PLANCK INSTITUTE
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TECHNICAL SYSTEMS
MAGDEBURG



COMPUTATIONAL METHODS IN
SYSTEMS AND CONTROL THEORY

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Model Order Reduction for Gas and Energy Networks

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- Modular,
- extensible,
- open
- test platform
- for: model order reduction
- of: multi-dimensional network dynamics,
- such as: **Gas**, Heat, Water;
- compatible with: MATLAB & OCTAVE;
- part of the **MathEnergy** software library.

0.9 Initial release (Paper submission: Q1/2020)

1.0 Stable release (After publication)

1.1 Update release (After extensions and testing)

Affine model (short “compressor pipe”):

$$\begin{aligned}\dot{p}(t) &= -p(t) + p_c(\theta) \\ \dot{q}(t) &= 0\end{aligned}$$

See also:

- Simple model¹
- Factor model²
- Affine model³

¹K. Ehrhardt and M.C. Steinbach. **Nonlinear optimization in gas networks**. In Modeling, Simulation and Optimization of Complex Processes: 139–148. Springer, 2005.

²K. Sundar and A. Zlotnik. **State and parameter estimation for natural gas pipeline networks using transient state data**. IEEE Transactions on Control Systems Technology, 27(5): 2110–2124, 2019.

³T.P. Azevedo-Perdicoulis and G. Jank. **Modelling aspects of describing gas networks through a DAE system**. IFAC Proceedings Volume (3rd IFAC Symposium on Structure and Control), 40(20): 40–45, 2007.

Data-Driven Model Reduction Algorithms:

- Proper Orthogonal Decomposition
- Empirical Balanced Truncation
- Empirical Cross Gramian
- Empirical Non-Symmetric Cross Gramian
- Empirical Dominant Subspaces*
- Dynamic Mode Decomposition*

Features:

- Based on system theory.
- Galerkin projection.
- Error indicator⁴.
- Surprisingly good for hyperbolic systems⁵.
- Works for nonlinear gas network models.

⁴P. Benner and C.H. **Cross-Gramian-Based Dominant Subspaces**. Advances in Computational Mathematics (Model Reduction of Parametrized Systems Topical Collection), 2019.

⁵S. Grundel, C.H. and J. Saak. **On Empirical System Gramians**. Proceedings in Applied Mathematics and Mechanics, 19: e201900006, 2019.

Features:

- Based on Koopman theory.
- Galerkin projection.
- Solve via generalized eigenvalue problem⁶.
- Use dynamic mode decomposition with control⁷.
- Robust for parametric gas network models.

⁶W. Zhang and M. Wei. **Solving generalized eigenvalue problem: an alternative approach for dynamic mode decomposition**. AIAA Scitech 2019 Forum: 1897, 2019.

⁷J.L. Proctor, S.L. Brunton, and J.N. Kutz. **Dynamic mode decomposition with control**. SIAM J. Applied Dynamical Systems, 15(1): 142–161, 2016.

Hyperbolic Problem:

$$\frac{\partial u_\mu}{\partial t} = - \frac{\partial f_\mu(u_\mu)}{\partial x}$$

- Slow decay of Kolmogorov N -width⁸.
- Poor approximability in a linear space (i.e. via POD).
- → Try non-linear approximation spaces!

⁸C. Greif and K. Urban. Decay of the Kolmogorov N -width for wave problems. Applied Mathematics Letters, 96: 216–222, 2019.

Nonlinear Approximation Spaces:

- Split into transport and shape change operators^{9 10}.
- Transport operator requires a non-linear approximation space.
- Shape change operator approximable by linear spaces.
- Not extendable to non-periodic boundaries!
- Residual minimization allows to drop periodicity assumption¹¹.
- WIP: hyper-reduction for residual minimization.
- Linearized Euler equation for pipelines already reducible.

⁹ C.W. Rowley and J.E. Marsden. **Reconstruction equations and the Karhunen–Loeve expansion for systems with symmetry**. *Physica D: Nonlinear Phenomena*, 142(1–2): 1–19, 2000.

¹⁰ S. Rave and M. Ohlberger. **Nonlinear reduced basis approximation of parameterized evolution equations via the method of freezing** *Comptes Rendus Mathematique*, 351(23–34): 901–906, 2013.

¹¹ K. Carlberg, D. Amsallem, P. Avery, M. Zahr and C. Farhat. **The GNAT nonlinear model reduction method and its application to fluid dynamics problems**. 6th AIAA Theoretical Fluid Mechanics Conference, 2011.

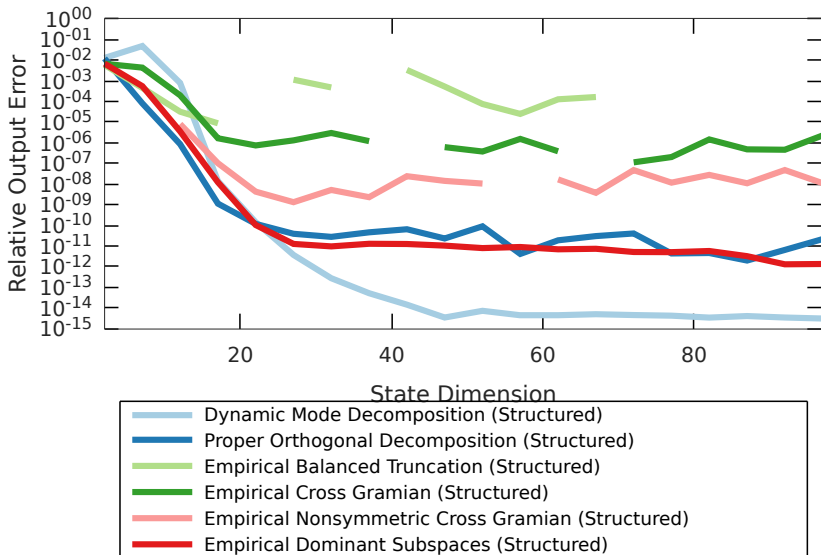
Training Input?

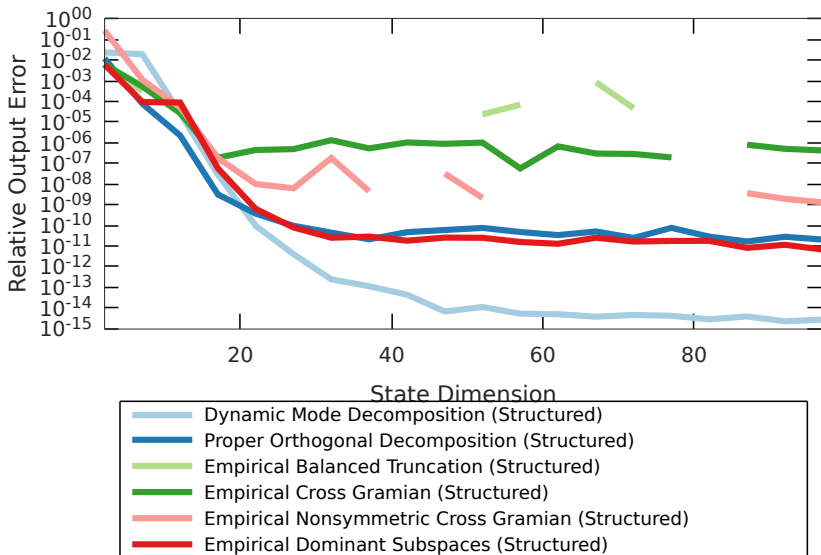
- Data-driven model reduction needs inputs.
- These training inputs cannot be scenario-specific,
- but need to excite the system sufficiently.
- System identification investigates excitation¹².

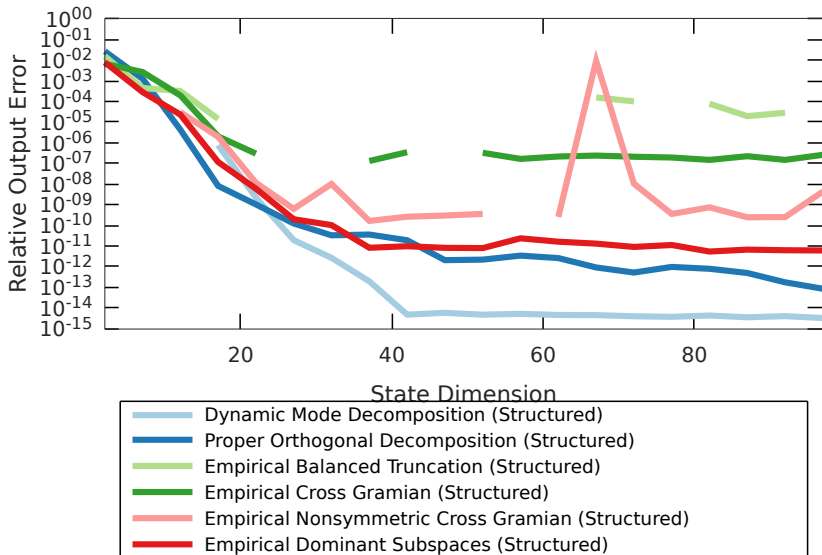
Excitation Comparison for a Pipeline:

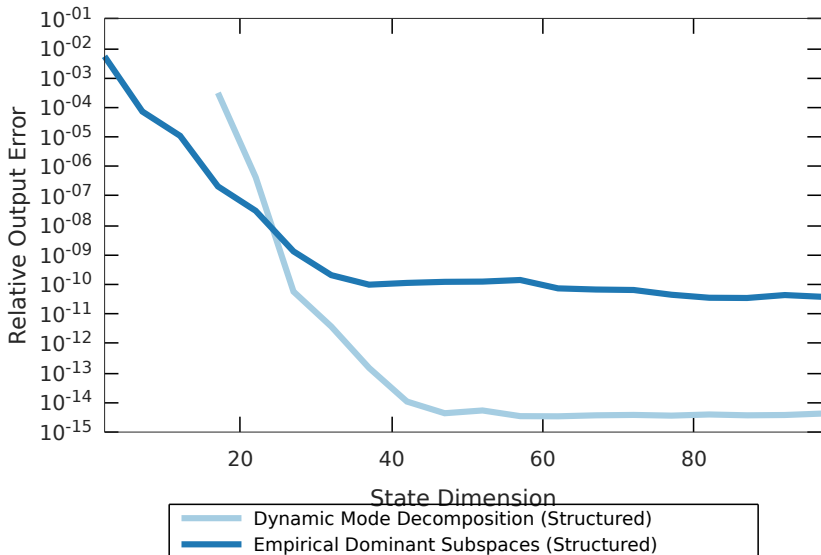
- Impulse
- Step
- Random Binary
- White Noise

¹²O. Nelles. **Nonlinear System Identification**. Springer, 2001.









Further Work:

- CFL-based automatic refinement¹³.
- IMEX solver evaluation.
- Sustainable scientific software¹⁴ (“sequel” to RRR¹⁵).

¹³ J.F. Helgaker, B. Müller and T. Ytrehus. **Transient Flow in Natural Gas Pipelines Using Implicit Finite Difference Schemes**. *Journal of Offshore Mechanics and Arctic Engineering*, 136(3): 031701, 2014.

¹⁴ J. Fehr, C. Himpe, S. Rave and J. Saak. **Sustainable Research Software Hand-Over**. arXiv (Submitted), cs.GL: 1909.09469, 2019.

¹⁵ J. Fehr, J. Heiland, C. Himpe and J. Saak. **Best Practices for Replicability, Reproducibility and Reusability of Computer-Based Experiments Exemplified by Model Reduction Software**. *AIMS Mathematics (AIMS Math)* 1(3): 261–281, 2016.

Next:

- Theory: Provably convergent hyper-reduction
- Networks: **SciGrid_Gas**
- Models: (nonlinear) Port-Hamiltonian
- Reductors: Empirical Balanced Gains
- Tests: Distributed integration testing
- Other: Visualization

<https://himpe.science>

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