

MAX PLANCK INSTITUTE FOR DYNAMICS OF COMPLEX TECHNICAL SYSTEMS MAGDEBURG



COMPUTATIONAL METHODS IN SYSTEMS AND CONTROL THEORY 20 YEARS

Model Reduction Based on the Mapping from Boundary Values to Quantities of Interest P. Benner, S. Grundel, C. Himpe

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6th European Conference on Computational Mechanics (ECCM) 2018–06–13

Supported by:

Federal Ministry for Economic Aff and Energy



The Gas Network Situation:

- Volatile renewable energies.
- Fluctuating supply and demand.
- Fast response of gas-fired plants.
- Day-ahead forecasts.
- Many simulations before dispatch.
- MathEnergy project.









- Multi-Scale
- Large-Scale
- Nonlinear
- Hyperbolic
- Parametric

\rightarrow Structured (Data-Driven) Model Reduction



Multi-Scale Properties:

- Coupling of quantites,
- evolving on different scales.
- Practical issues:
- Numerical annihilation,
- Operator condition.

We Assume:

- Spatially discrete (PDAE \rightarrow DAE),
- Index reduced (DAE \rightarrow ODE),
- Sufficiently regular boundary values (i.e.: *L*₂).



Gas Flow in a Pipe:



- Modeled by Euler equations,
- coupling mass-flow and pressure.
- For example:
 - Boundary values: p_s , q_d ,
 - Quantites of Interest: p_d , q_s .



Coupled Input-Output System:

$$\dot{p}(t) = f_p(p(t), q(t), u(t), \theta)$$
$$\dot{q}(t) = f_q(p(t), q(t), u(t), \theta)$$
$$y(t) = g(p(t), q(t), u(t), \theta)$$

Large State: p: ℝ → ℝ^{N_p} (Large Degrees of Freedom)
Small State: q: ℝ → ℝ^{N_q} (Small Degrees of Freedom)
Input: u: ℝ → ℝ^M (Boundary Values)
Output: y: ℝ → ℝ^Q (Quantites of Interest)
Parameter: θ ∈ ℝ^P
Large Vector Field: f_p: ℝ^{N_p} × ℝ^{N_q} × ℝ^M × ℝ^P → ℝ^{N_p}
Small Vector Field: f_q: ℝ^{N_p} × ℝ^{N_q} × ℝ^M × ℝ^P → ℝ^{N_q}
Output Functional: q: ℝ^{N_p} × ℝ^{N_q} × ℝ^M × ℝ^P → ℝ^Q



Input-Output Map:

- from Boundary Values *u*,
- via Degrees of Freedom (p,q),
- to Quantites of Interest *y*.

$$u \ \mapsto \ (p,q) \ \mapsto \ y$$

$$N_p = \dim(p(t))$$

$$N_q = \dim(q(t))$$

$$N_p + N_q \gg 1$$

$$M = \dim(u(t)) \ll N_p + N_q$$

$$Q = \dim(y(t)) \ll N_p + N_q$$



Reduced Order System:

$$\dot{p}_r(t) = f_{p,r}(p_r(t), q_r(t), u(t), \theta)$$
$$\dot{q}_r(t) = f_{q,r}(p_r(t), q_r(t), u(t), \theta)$$
$$\tilde{y}(t) = g_r(p_r(t), q_r(t), u(t), \theta)$$

- **Reduced Large State**: $p_r : \mathbb{R} \to \mathbb{R}^{n_p}$, $n_p \ll N_p$
- Reduced Small State: $q_r : \mathbb{R} \to \mathbb{R}^{n_q}$, $n_q \ll N_q$
- Approximate Output: $\tilde{y} : \mathbb{R} \to \mathbb{R}^Q$
- Reduced Large Vector Field: $f_{p,r} : \mathbb{R}^{n_p} \times \mathbb{R}^n \times \mathbb{R}^M \times \mathbb{R}^P \to \mathbb{R}^{n_p}$
- Reduced Small Vector Field: $f_{q,r} : \mathbb{R}^{n_p} \times \mathbb{R}^{n_q} \times \mathbb{R}^M \times \mathbb{R}^P \to \mathbb{R}^{n_q}$
- Reduced Output Functional: $g_r : \mathbb{R}^{n_p} \times \mathbb{R}^{n_q} \times \mathbb{R}^M \times \mathbb{R}^P \to \mathbb{R}^Q$
- **Reduction Error**: $||y(\theta) \tilde{y}(\theta)|| \ll 1$



Structured System:

$$\begin{split} \dot{p}(t) &= f_p(p(t), q(t), u(t), \theta) \\ \dot{q}(t) &= f_q(p(t), q(t), u(t), \theta) \\ y(t) &= g(p(t), q(t), u(t), \theta) \end{split}$$

Structured (Truncated) Projections:

$$V_p^{\mathsf{T}}(p) = p_r, \quad U_p(p_r) \approx p, \quad V_q^{\mathsf{T}}(q) = q_r, \quad U_q(q_r) \approx q$$

Compute separate transformations for large and small equations.

- Per component computation.
- Per component approximation.
- Error estimator for linear systems¹.

 $^{^{1}}$ H. Sandberg and R.M. Murray. Model reduction of interconnected linear systems. Optimal Control Applications and Methods, 30(3): 225–245, 2009.

Sc Projection-Based Model Reduction

Projected System:

$$\dot{p}_r(t) = V_p^{\mathsf{T}} f_p(U_p p_r(t), U_q q_r(t), u(t), \theta)$$
$$\dot{q}_r(t) = V_q^{\mathsf{T}} f_q(U_p p_r(t), U_q q_r(t), u(t), \theta)$$
$$\tilde{y}(t) = g(U_p p_r(t), U_q q_r(t), u(t), \theta)$$

- Reducing Large Projection: $V_p \in \mathbb{R}^{N_p \times n_p}$
- Reducing Small Projection: $V_q \in \mathbb{R}^{N_q \times n_q}$
- Reconstructing Large Truncated Projection: $U_p \in \mathbb{R}^{N_p imes n_p}$
- Reconstructing Small Truncated Projection: $U_q \in \mathbb{R}^{N_q imes n_q}$
- Bi-Orthogonality: $V_p^{\mathsf{T}}U_p = \mathbb{1}_{n_p}$, $V_q^{\mathsf{T}}U_q = \mathbb{1}_{n_q}$

$$ightarrow$$
 Task: Compute V_p , U_p , V_q , U_q



Linear Time-Invariant System:

 $\dot{x}(t) = Ax(t) + Bu(t)$ y(t) = Cx(t)

Controllability Operator:

Observability Operator:

$$\mathcal{C}(u)(t) := \int_{-\infty}^{0} e^{At} Bu(-t) dt$$

$$\mathcal{O}(x_0)(t) := C \operatorname{e}^{At} x_0$$

Controllability Gramian:

Observability Gramian:

$$W_C = \int_0^\infty e^{At} B B^{\mathsf{T}} e^{A^{\mathsf{T}}t} dt \qquad \qquad W_O = \int_0^\infty e^{A^{\mathsf{T}}t} C^{\mathsf{T}}C e^{At} dt$$

Balancing (and Truncation):

$$U, V: V^{\mathsf{T}} W_C U = U^{-1} W_O V^{-\mathsf{T}} = \operatorname{diag}(\sigma_1, \dots, \sigma_N)$$



Conjoining Controllability and Observability:

$$W_X := \int_0^\infty \mathrm{e}^{At} \, BC \, \mathrm{e}^{At} \, \mathrm{d}t$$

Approximate Balancing:

$$W_X \stackrel{\mathsf{SVD}}{=} UDV$$

- Combines controllability with observability operator.
- Basic variant only for square systems.
- Non-square extensions exist²
- Classic or approximate balancing.

 $^{^{2}}$ C.H. and M. Ohlberger. A note on the cross Gramian for non-symmetric systems. System Science and Control Engineering 4(1): 199–208, 2016.

Sc CSC From Linear To Nonlinear Systems

Data-Driven Computation (linear):

$$W_X := \int_0^\infty (\mathrm{e}^{At} B) (\mathrm{e}^{A^{\mathsf{T}}t} C)^{\mathsf{T}} \, \mathrm{d}t$$

Cross-covariance of primal and adjoint impulse response,for linear systems only.

Data-Driven Computation (nonlinear):

$$\widehat{W}_X := \sum_{i=m}^M \int_0^\infty \Psi^m(t) \,\mathrm{d}t$$
$$\Psi^m_{ij} = (x^m_i(t) - \bar{x}_i)(y^j_m(t) - \bar{y}_m)$$

- cross-covariance of state and output trajectories,
- for linear systems equivalent to above³.

³C.H. and M. Ohlberger. Cross-Gramian-Based Combined State and Parameter Reduction for Large-Scale Control Systems. Mathematical Problems in Engineering, 2014: 1–13, 2014.

Sc Empirical Structured Cross Gramian

Large Empirical Cross Gramian:

$$\begin{split} \widehat{W}_{X,p} &:= \sum_{i=m}^{M} \int_{0}^{\infty} \Psi_{p}^{m}(t) \, \mathrm{d}t \\ \Psi_{p,ij}^{m} &= (p_{i}^{m}(t) - \bar{p}_{i})(y_{m}^{j}(t) - \bar{y}_{m}) \\ \widehat{W}_{X,p} \stackrel{\mathsf{SVD}}{=} U_{p} D_{p} V_{p}^{\mathsf{T}} \end{split}$$

Small Empirical Cross Gramian:

$$\widehat{W}_{X,q} := \sum_{i=m}^{M} \int_{0}^{\infty} \Psi_{q}^{m}(t) \,\mathrm{d}t$$
$$\Psi_{q,ij}^{m} = (q_{i}^{m}(t) - \bar{q}_{i})(y_{m}^{j}(t) - \bar{y}_{m})$$
$$\widehat{W}_{X,q} \stackrel{\mathsf{SVD}}{=} U_{q} D_{q} V_{q}^{\mathsf{T}}$$

Note: Output scaling important!



Isothermal Euler Equations⁴:

Mass-Flux: q(x,t)

Pressure: p(x,t)

Elevation: h(x)

$$\begin{split} &\frac{\partial}{\partial t}\rho = -\frac{1}{S}\frac{\partial}{\partial x}q\\ &\frac{\partial}{\partial t}q = -S\frac{\partial}{\partial x}p - Sg\rho\frac{\partial}{\partial x}h - \frac{\lambda}{2DS}\frac{q|q|}{\rho}\\ &p = R_ST_0z\rho \end{split}$$

- **Density:** $\rho(x,t)$ **Constants:** S, g, D
 - Parameters: T_0 , R_S
 - Friction Factor: $\lambda(q)$
 - Compressibility Factor: z(p,T)

⁴ P. Benner, S. Grundel, C.H., C. Huck, T. Streubel, C. Tischendorf. Gas Network Benchmark Models. In: Differential Algebraic Equation Forum (Accepted), 2018.



Network as a Graph $(\mathcal{N}, \mathcal{E})$:

- Node set \mathcal{N} (Junctions)
- Edge set *E* (Pipes)

Node Types:

- Internal nodes \mathcal{N}_0
- $\blacksquare Supply nodes \mathcal{N}_s$
- Demand nodes \mathcal{N}_d

Kirchhoff Rules⁵:

1. $p_i = p_s, \quad p_i \in \mathcal{N}_s$

2.
$$\sum_{j \in \mathcal{E}_{-}} q_j - \sum_{k \in \mathcal{E}_{+}} q_k = q_d, \quad q_d \in \mathcal{N}_d$$

\rightarrow Partial Differential Algebraic Equation (PDAE)

⁵T.P. Azevedo-Perdicoúlis and G. Jank. Modelling Aspects of Describing a Gas Network Through a DAE System. 3rd IFAC Symposium on System Structure and Control 40(20): 40–45, 2007.



Semi-Discrete Gas Network Model:

$$\begin{pmatrix} \dot{p} \\ \dot{q} \end{pmatrix} = \begin{pmatrix} 0 & A_{pq} \\ A_{qp} & 0 \end{pmatrix} \begin{pmatrix} p \\ q \end{pmatrix} + \begin{pmatrix} 0 & B_d \\ B_s & 0 \end{pmatrix} \begin{pmatrix} p_s \\ q_d \end{pmatrix} + \begin{pmatrix} 0 \\ f_q(p, q, p_s, q_d, \theta) \end{pmatrix}$$
$$\begin{pmatrix} p_d \\ q_s \end{pmatrix} = \begin{pmatrix} C_d & 0 \\ 0 & C_s \end{pmatrix} \begin{pmatrix} p \\ q \end{pmatrix}$$

- Multi-Scale ($\sim 10^5$) \rightarrow Structured Reduction
- Always square \rightarrow Cross Gramian
- Nonlinear (Friction & Compressibility) → Empirical Gramian
- Stiff "linear" part \rightarrow IMEX⁶ Solver
- 2-dim parameter-space (Temperature & Specific Gas Constant)

⁶S. Grundel, L. Jansen. Efficient Simulation of Transient Gas Networks Using IMEX Integration Schemes and MOR Methods. IEEE 54th Annual Conference on Decision and Control: 4579–4584, 2015.

Solution Workflow

Offline:

- 1. Design input perturbation
- 2. Design parameter samples
- 3. Compute structured empirical Gramians
- 4. for short time horizons ($< 1 \, \mathrm{h}$)
- 5. Decompose empirical Gramians

Online:

- 1. Design scenarios
- 2. Simulate scenarios
- 3. for long time horizons $(24 \, h)$

Test Network and Scenario CSC



- 24 h time horizon
- $1 \min time resolution$

Single supply, multiple demands





(Unstructured or Structured) POD, (Unstructured Empircal BT & WX), DMD-Galerkin, (Unstructured or Structured) Linearized BT & WX did not work!



- System-theoretic interpretation
- Boundary-Value to Quantity-of-Interest mapping
- Structured empirical cross Gramian
- Output scaling necessary
- Gas network application

http://himpe.science

Acknowledgment:

Supported by the German Federal Ministry for Economic Affairs and Energy, in the joint project: "**MathEnergy** – Mathematical Key Technologies for Evolving Energy Grids", sub-project: Model Order Reduction (Grant number: 0324019**B**).