

# Proper Orthogonal Decomposition for PDE Constrained Optimization

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AICES, 3 November 2011

## General outline of the lecture

### 1.) The Proper Orthogonal Decomposition (POD) method:

- What is a **POD basis**?
- How can we **compute** the basis **numerically**?
- Which **theory** is behind?

### 2.) Reduced-order modelling (ROM) with POD:

- What is a **POD reduced-order model**?
- How can we derive **a-priori error** estimates?
- Can we determine an improved ROM in an **adaptive** way?

### 3.) POD suboptimal control:

- How do we apply the POD in **PDE constrained optimization**?
- Can we **control the error**?
- What can be done for **feedback control**?

## Part 3:

# POD Suboptimal Control

- How do we apply the POD in **PDE constrained optimization**?
- Can we **control the error**?
- What can be done for **feedback control**?

# Outline of the third part: POD Suboptimal Control

- Nonlinear heat control
- A-posteriori error analysis
- Optimality-System POD (OS-POD)
- Multilevel SQP
- Static output feedback (SOF)
- References

# Nonlinear heat control [Diwoky/V.'01]

- **Model problem:**

$$\min J(y, u) = \frac{1}{2} \int_{\Omega} |y(T, x) - z(x)|^2 dx + \frac{\beta}{2} \int_0^T \int_{\Gamma} |u(t, s)|^2 ds dt$$

subject to

$$\begin{aligned} y_t(t, x) &= k \Delta y(t, x) && \text{for } (t, x) \in Q = (0, T) \times \Omega \\ \frac{\partial y}{\partial n}(t, s) &= b(y(t, s)) + u(t, s) && \text{for } (t, s) \in \Sigma = (0, T) \times \Gamma \\ y(0, x) &= y_0(x) && \text{for } x \in \Omega \subset \mathbb{R}^2 \end{aligned}$$

- **Assumptions:**  $T, \beta, k > 0$ ,  $z, y_0 \in C(\bar{\Omega})$ ,  $b \in C^{2,1}(\mathbb{R})$  with  $b' \leq 0$

## Infinite-dimensional problem

- **Optimization variables:**  $z = (y, u) \in Z$ ,  $Z$  function space
- **Equality constraints:**  $e = (e_1, e_2)$

$$\begin{aligned} \langle e_1(z), \varphi \rangle &= \int_0^T \int_{\Omega} y_t(t, x) \varphi(t, x) + k \nabla y(t, x) \cdot \nabla \varphi(t, x) \, dx dt \\ &\quad - \int_0^T \int_{\Gamma} (b(y(t, s)) + u(t, s)) \varphi(t, s) \, ds dt \\ e_2(z) &= y(0, \cdot) - y_0 \end{aligned}$$

- **Infinite-dimensional optimization in function spaces:**

$$\min J(z) \quad \text{subject to} \quad e(z) = 0$$

- **Lagrange function:**  $L(z, p) = J(z) + \langle e(z), p \rangle$
- **Optimality conditions:**  $\nabla L(z, p) \stackrel{!}{=} 0$  (Fréchet-derivatives)

## First-order optimality conditions

- $\nabla_y L(y, u, p) \stackrel{!}{=} 0$ : adjoint equation

$$-p_t(t, x) = k\Delta p(t, x) \quad \text{for } (t, x) \in Q = (0, T) \times \Omega$$

$$\frac{\partial p}{\partial n}(t, s) = b'(y(t, s))p(t, s) \quad \text{for } (t, s) \in \Sigma = (0, T) \times \Gamma$$

$$p(T, x) = -(y(T, x) - z(x)) \quad \text{for } x \in \Omega$$

- $\nabla_u L(z, p) \stackrel{!}{=} 0$ : optimality condition  $\beta u = kp$  on  $\Sigma$

- $\nabla_p L(z, p) \stackrel{!}{=} 0$ : state equation

$$y_t(t, x) = k\Delta y(t, x) \quad \text{for } (t, x) \in Q$$

$$\frac{\partial y}{\partial n}(t, s) = b(y(t, s)) + u(t, s) \quad \text{for } (t, s) \in \Sigma$$

$$y(0, x) = y_0(x) \quad \text{for } x \in \Omega$$

## SQP methods

- **SQP**: **S**equential **Q**uadratic **P**rogramming
- **Quadratic programming problem**:  $L(z, p) = J(z) + \langle e(z), p \rangle$

$$\begin{aligned} \min_{z_\delta} L(z^n, p^n) + L_z(z^n, p^n)z_\delta + \frac{1}{2} L_{zz}(z^n, p^n)(z_\delta, z_\delta) \\ \text{subject to } e(z^n) + e'(z^n)z_\delta = 0 \end{aligned} \quad (\text{QP}^n)$$

- **First-order optimality conditions for (QP<sup>n</sup>)**: KKT system

$$\begin{pmatrix} L_{zz}(z^n, p^n) & e'(z^n)^* \\ e'(z^n) & 0 \end{pmatrix} \begin{pmatrix} z_\delta \\ p_\delta \end{pmatrix} = - \begin{pmatrix} L_z(z^n, p^n) \\ e(z^n) \end{pmatrix}$$

- **Convergence**: locally quadratic rate in  $(z^n, p^n)$  (infinite-dimensional)
- **Globalization**: modification of the Hessian and line-search methods
- **Alternative**: trust-region methods



## POD model reduction

- **Goal:** POD Galerkin ansatz using  $\ell$  POD basis functions
- **Snapshot POD:** solve of heat equation for  $0 \leq t_1 < \dots < t_n \leq T$
- **Problems:**
  - unknown optimal control  $\Rightarrow$  good snapshot set?
  - $u = \frac{k}{\beta} p$  depends on  $p \Rightarrow$  POD approximation for  $p$ ?
- **Strategy:** iterate basis computation and include adjoint information in the snapshot ensemble

## Dynamic POD strategy [Afanasyev/Hinze'01, Arian/Fahl/Sachs'00, Ravindran'00]

- 1) Choose estimate  $u^0$ ; compute snapshots by solving state equation with  $u = u^0$  and adjoint equation with  $y = y(u^0)$ ;  $i = 0$
- 2) Determine  $\ell$  POD basis functions and associated ROM of infinite-dimensional optimization problem
- 3) Compute solution  $u^{i+1}$  of optimization problem (e.g., by SQP)
- 4) If  $\Psi(i) = \frac{\|u^{i+1} - u^i\|}{\|u^{i+1}\|} \leq TOL$  then stop (stopping criterium)
- 5)  $i = i + 1$ ; compute snapshots by solving state equation with control  $u = u^i$  and adjoint equation with  $y = y(u^i)$ ; go back to 2)

**Alternative:** Optimality-System POD (OS-POD), i.e., change of basis within the optimization w.r.t. optimality conditions

## Numerical results

**Data:**  $y_0(x_1, x_2) = 10x_1x_2$ ,  $z(x_1, x_2) = 2 + 2|2x_1 - x_2|$ ,  $b(y) = \arctan(y)$ ,  $k = \beta = \frac{1}{10}$ ,  $T = 1$ , 185 FEs

**Recall:**  $\Psi(i) = \frac{\|u^{i+1} - u^i\|}{\|u^{i+1}\|}$  stopping criterium for dynamic POD strategy

i	relative $L^2$ error for y	relative $L^2$ error for u	$J(y, u)$	$\Psi(i)$
0	4.4	12.0	0.358	1.00
1	1.0	8.1	0.360	0.13
2	0.9	6.8	0.361	0.08
POD <sub>opt</sub>	0.5	5.7	0.358	
FE			0.358	

		POD	FE	
Compute snapshots	M-flops	18		
	CPU time in s	3.3		
Compute POD basis	M-flops	0.44		
	CPU time in s	0.01		
Solve with SQP	M-flops	84		
	CPU time in s	22		
total	M-flops	$1.0 \cdot 10^2$		$1.9 \cdot 10^5$
	CPU time in s	$2.5 \cdot 10^1$		$6.6 \cdot 10^3$

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# A-posteriori error analysis [Tröltzsch/V.'09, Kammann/Tröltzsch/V.'11]

- (Abstract) linear-quadratic problem:

$$\min_{(y,u)} \frac{1}{2} \|Cy - y_d\|^2 + \frac{\kappa}{2} \|u\|^2$$

$$\text{s.t. } \dot{y}(t) = \mathcal{A}(t)y(t) + \mathcal{B}(t)u(t) + f(t), \quad t \in (0, T], \quad y(0) = y_0$$

$$u_a(t) \leq u(t) \leq u_b(t), \quad t \in [0, T]$$

- State  $y(t) = y(t, \cdot) : \Omega \rightarrow \mathbb{R}$  or  $\mathbb{C}$
- Input  $u(t) = u(t, \cdot)$  (boundary or distributed control)
- $\mathcal{A}$  time-dependent, e.g.,  $\mathcal{A}(t) = \nabla \cdot (c(t, \cdot) \nabla \bullet) - a(t, \cdot)$
- Control input operator  $\mathcal{B}(t)$
- Balanced truncation or moment matching not directly applicable
- Applicable for elliptic problems, extension to nonlinear problems

## First-order necessary and sufficient optimality system

- Optimal state  $\bar{y}$  and control  $\bar{u} \in U_{ad} = \{u \mid u_a \leq u \leq u_b \text{ in } [0, T]\}$
- **State equation:**

$$\frac{d}{dt}\bar{y}(t) = \mathcal{A}(t)\bar{y}(t) + \mathcal{B}(t)\bar{u}(t) + f(t), \quad t \in (0, T], \quad \bar{y}(0) = y_0.$$

- **Adjoint equation:**

$$-\frac{d}{dt}\bar{p}(t) = \mathcal{A}(t)^*\bar{p}(t) + \mathcal{C}^*(y_d - \mathcal{C}\bar{y})(t), \quad t \in (0, T], \quad \bar{p}(T) = 0$$

with adjoints  $\mathcal{A}(t)^*$  and  $\mathcal{C}^*$

- **Variational inequality:**

$$\int_0^T \left( \kappa \bar{u}(t) - \mathcal{B}(t)^*\bar{p}(t) \right) (u(t) - \bar{u}(t)) dt \geq 0 \quad \forall u \in U_{ad}$$

with adjoint  $\mathcal{B}(t)^*$

## Perturbation analysis

- **Arbitrary control:**  $u^P \in U_{ad} \setminus \{\bar{u}\}$

$$\int_0^T \left( \kappa u^P(t) - \mathcal{B}(t)^* p^P(t) \right) (u(t) - u^P(t)) dt \not\geq 0 \quad \forall u \in U_{ad}$$

with

$$-\frac{d}{dt} p^P(t) = \mathcal{A}(t)^* p^P(t) + \mathcal{C}^*(y_d - \mathcal{C}y^P)(t), \quad t \in (0, T], \quad p^P(T) = 0$$

$$\frac{d}{dt} y^P(t) = \mathcal{A}(t)y^P(t) + \mathcal{B}(t)u^P(t) + f(t), \quad t \in (0, T], \quad y^P(0) = y_0$$

- **Perturbation:** there exists a computable  $\zeta^P = \zeta(u^P)$  [Malanowski, Maurer,...]

$$\int_0^T \left( \kappa u^P(t) - \mathcal{B}(t)^* p^P(t) + \zeta^P(t) \right) (u(t) - u^P(t)) dt \geq 0 \quad \forall u \in U_{ad}$$

satisfying

$$\|\bar{u} - u^P\| \leq \frac{1}{\kappa} \|\zeta^P\|$$

## Application for Galerkin-based approximation schemes

Recall:  $\|\bar{u} - u^p\| \leq \frac{1}{\kappa} \|\zeta(u^p)\|$

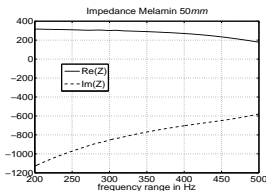
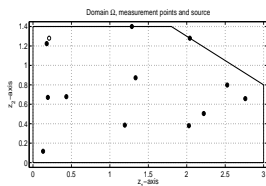
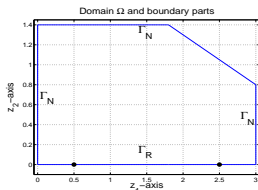
- 1: Choose basis  $\{\psi_i\}_{i=1}^{\ell}$  for Galerkin projection of the control problem;
- 2: Perform the reduced-order model;
- 3: Compute suboptimal control  $u^p = \bar{u}^{\ell}$  and perturbation  $\bar{\zeta}^{\ell} = \zeta^{\ell}(\bar{u}^{\ell})$ ;
- 4: **if**  $\|\bar{\zeta}^{\ell}\|/\kappa > \text{TOL}$  **then**
- 5:     **Enlarge**  $\ell$  and go back to step 2;
- 6: **else**
- 7:     **Stop**;
- 8: **end if**

Remarks:

- Applicable for **POD** and **reduced-basis** [Tonn/Urban/V.'11]
- $\|\bar{\zeta}^{\ell}\| \xrightarrow{\ell \rightarrow \infty} 0$  for **POD** [Hinze/V.'08, Tröltzsch/V.'09]
- analogously for **elliptic problems** [Kahlbacher/V.'07, Kahlbacher/V.'11]
- recent extension to **nonlinear problems** [Kammann/Tröltzsch/V.'11]



## Acoustic example [Tonn/Urban/V.'11]



- **Linear-quadratic problem** for any frequency  $f \in [f_a, f_b]$ :

$$\min J_f(y_f, u_f) := \frac{1}{20} \sum_{i=1}^{12} |y_f(z_i) - y_f^i|^2 + \frac{1}{2} |u_f - u_f^0|^2$$

$$\text{s.t. } -\Delta y_f - k_f^2 y_f = u_f b \text{ in } \Omega, \quad \frac{\partial y_f}{\partial n} = \begin{cases} y_f / Z_f & \text{on } \Gamma_R \\ 0 & \text{on } \Gamma_N \end{cases}$$

- **State**  $y_f : \Omega \rightarrow \mathbb{C}$  (sound pressure) and **control**  $u_f \in \mathbb{C}$  (intensity)
- $\omega_f = 2\pi f$  and  $k_f = \omega_f / c$
- **Source term**:  $b(\mathbf{z}) = e^{-50 \|\mathbf{z} - \mathbf{z}_q\|_2^2}$  for  $\mathbf{z} = (z_1, z_2) \in \Omega$

## Computation of the POD basis

- **Frequency grid:**  $f_a \leq f_1 < \dots < f_n \leq f_b$
- **Snapshots:**  $p_j = p_{f_j} : \Omega \rightarrow \mathbb{C}$  solution for “some  $u$ ”,  $j = 1, \dots, n$
- **Minimization problem:**

$$\min_{\psi_i: \Omega \rightarrow \mathbb{C}} \sum_{j=1}^n \left\| p_j - \sum_{i=1}^{\ell} \langle p_j, \psi_i \rangle \psi_i \right\|^2 \quad \text{s.t.} \quad \langle \psi_i, \psi_j \rangle = \delta_{ij}$$

- **Optimality condition:**

$$\mathcal{R}\psi_i = \lambda_i \psi_i, \quad i = 1, \dots, \ell$$

$$\text{with } \mathcal{R}\psi = \sum_{j=1}^n \langle p_j, \psi \rangle p_j : \Omega \rightarrow \mathbb{C}$$

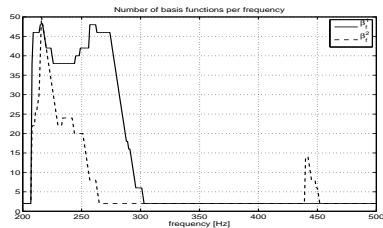
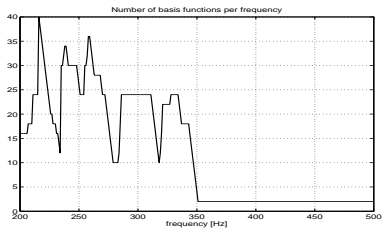
- **Reduced-order model (ROM):**

$$\underbrace{\langle -\Delta p_f^\ell - k_f^2 p_f^\ell, \psi_i \rangle}_{\langle \nabla p_f^\ell, \nabla \psi_i \rangle - \langle k_f^2 p_f^\ell, \psi_i \rangle + \text{b.c.}} = \langle ub, \psi_i \rangle \quad \text{with } p_f^\ell = \sum_{j=1}^{\ell} p_f^j \psi_j$$

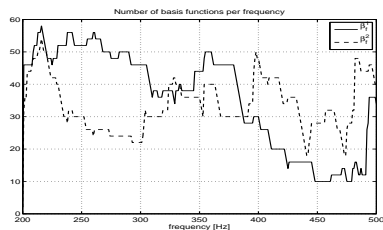
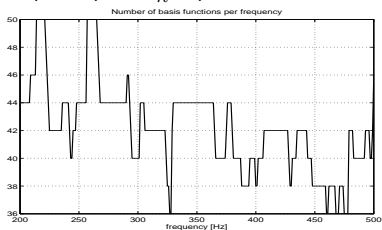
# Computation of the reduced-basis [Grepł, Haasdonk, Maday, Ohlberger, Patera, Rozza, Urban, Veroy-Grepł, ...]

- **Frequency grid:**  $F^\ell = \{f_1, \dots, f_\ell\} \subset [f_a, f_b]$
- **Snapshots:**  $p_f : \Omega \rightarrow \mathbb{C}$ ,  $f \in F^\ell$ , solution for “some  $u$ ”
- **Choice of the basis:** ONB for  $X^\ell = \text{Span}\{p_f : f \in F^\ell\}$
- **Relative error estimator:**  $\Delta_f^\ell \geq \max_{p_f^\ell \in X^\ell} \|p_f - p_f^\ell\| / \|p_f\|$
- **Greedy algorithm:**
  - 1: Choose  $f_1 \in [f_a, f_b]$  and set  $F^1 = \{f_1\}$ ,  $X^1 = \text{Span}\{p_{f_1}\}$ ,  $\ell = 1$ ;
  - 2: **while**  $\max_{f \in [f_a, f_b]} \Delta_f^\ell > \varepsilon$  **do**
  - 3:   Compute  $f^{\ell+1} := \operatorname{argmax}_{f \in [f_a, f_b]} \Delta_f^\ell$  and set  $\ell = \ell + 1$ ;
  - 4:   Define  $F^\ell = F^{\ell-1} \cup \{f^\ell\}$  and  $X^\ell = \text{Span}\{p_f : f \in F^\ell\}$ ;
  - 5:   Compute ONB  $\{\psi_i\}_{i=1}^\ell$  for  $X^\ell$  (Gram-Schmidt);
  - 6: **end while**
- **Reduced-order modell (ROM):** analogous to POD

# Numerical results for the number $\ell = \ell(f)$ of basis functions



$\|u_f^* - u_f^\ell\| \leq \frac{1}{\kappa} \|\zeta_f^\ell\| \leq 10^{-4}$ :  $\ell(f)$  for POD (left) & reduced bases (right)



$\|u_f^* - u_f^\ell\| \leq \frac{1}{\kappa} \|\zeta_f^\ell\| \leq 10^{-6}$ :  $\ell(f)$  for POD (left) & reduced bases (right)

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# Motivation

- **Problem:**
  - convergence without any rate in  $\ell$
  - possibly inappropriate basis for control
- **Basis change** [Afanasiev/Hinze'01, Arian/Fahl/Sachs'00, Ravindran'00, Willcox et al.'07]:
  - **Optimality-System POD (OS-POD)** [Kunisch/V.'08]
  - with respect to **minimization of the cost**
  - combination with a-posteriori analysis [V.'11]

## Optimality System POD (OS-POD) [Kunisch/V.'08, Müller'11]

- **Original problem:**

$$\min J(y, u) \text{ s.t. } \begin{cases} \dot{y}(t) = F(t, y(t), u(t)), & t \in (0, T] \\ y(0) = y_0 \end{cases}$$

- **Approximate problem:**

$$\min J(y^\ell, u) \text{ s.t. } \begin{cases} \dot{y}^\ell(t) = F^\ell(t, y^\ell(t), u(t)), & t \in (0, T] \\ y^\ell(0) = y_0^\ell \end{cases}$$

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- **Approximate problem:**

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- **Reduced cost:**  $\hat{J}_{ospod}(u) = J(y^\ell(u), u, \psi(u), \lambda(u), y(u))$



## Combination with a-posteriori analysis [V.11]

**Algorithmus:**

- 1: Choose  $u^0$ , compute  $y^0 = y^0(u^0)$  and set  $j = 0$ ;
- 2: Determine **POD basis**  $\{\psi_i\}_{i=1}^\ell$  using  $y^0$ ;
- 3: Compute  $m$  **gradient steps** for  $\hat{J}_{ospod}$  and determine  $u^m$ ;
- 4: **if**  $\|\zeta^\ell\|/\kappa > \text{TOL}$  **then**
- 5:   Apply **a-posteriori algorithm**;
- 6: **else**
- 7:   **Stop**;
- 8: **end if**

**Remarks:**

- Other strategies for the combination possible
- Combine **adaptivity** (w.r.t.  $\ell$ ) and **basis changes** ( $\psi_i = \psi_i(u)$ )

## Numerical example

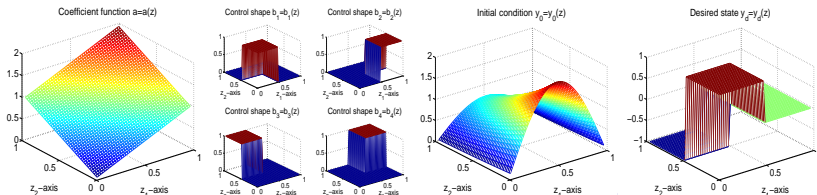
- Linear-quadratic optimal control problem:

$$\min_{(y,u)} \frac{1}{2} \|y - y_d\|_{L^2(Q)}^2 + \frac{1}{40} \sum_{i=1}^4 |u_i|^2$$

$$\text{s.t. } y_t - \Delta y + ay = \sum_{i=1}^4 u_i b_i + \sin(\pi t) \text{ in } Q = (0, T) \times \Omega,$$

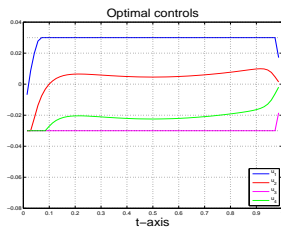
$$y(\cdot, 0) = 0 \text{ auf } \Sigma = (0, T) \times \partial\Omega, \quad y(0, \cdot) = y_0 \text{ in } \Omega = (0, 1)^2$$

$$-0.03 \leq u_i \leq 0.03 \text{ in } [0, T], \quad 1 \leq i \leq 4$$



## Numerical results

- Primal-dual active set strategy for control constraints
- Large-scale optimization: 546 seconds
- POD optimization ( $u^0 = 0$ ,  $m = 1$ ): 15 seconds ( $Y^T Y$ )
- Estimator:  $\|\zeta^\ell\|/\kappa < 6.38e-6$  for  $\ell = 26$
- Error:  $\|u^* - u^\ell\| \approx 6.37e-6 < \frac{1}{2} \max(h^2, \Delta t^2) \approx 2e-4 =: \text{TOL}$



- A-posteriori algorithm without OS-POD:

$$\|\zeta^\ell\|/\kappa \approx 1.23e-3 \not\leq \text{TOL} < 6.38e-6$$

for  $\ell = 50(!)$

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# Multilevel SQP [Kahlbacher/V.'10, Sachs/V.'10]

- **Infinite dimensional optimization:**

$$\min J(x) \quad \text{s.t.} \quad e(x) = 0 \quad (\mathbf{P})$$

- **Lagrange functional for (P):**  $\mathcal{L}(x, p) = J(x) + \langle e(x), p \rangle$
- **(Local) SQP method:** at  $z_k = (x_k, p_k)$  solve

$$\begin{cases} \min_{x_\delta} \mathcal{L}(x_k, p_k) + \mathcal{L}_x(z_k)x_\delta + \frac{1}{2}\mathcal{L}_{xx}(z_k)(x_\delta, x_\delta) \\ \text{subject to } e(x_k) + e'(x_k)x_\delta = 0 \end{cases} \quad (\mathbf{QP}^k)$$

- **KKT system:** solution  $\bar{x}_\delta$  to  $(\mathbf{QP}^k)$  is characterized by

$$\underbrace{\begin{pmatrix} \mathcal{L}_{xx}(z_k) & e'(x_k)^* \\ e'(x_k) & 0 \end{pmatrix}}_{A_k} \cdot \underbrace{\begin{pmatrix} \bar{x}_\delta \\ \bar{p}_\delta \end{pmatrix}}_{\bar{z}_\delta} = - \underbrace{\begin{pmatrix} \mathcal{L}_x(z_k) \\ e(x_k) \end{pmatrix}}_{b_k}$$

## Inexact SQP by using POD or RB

- **KKT system**: inexact solve of  $A_k \bar{z}_\delta = b_k$  by discretization
- **Discretization**: (POD or RB or BT or...) model reduction

$$A_k^\ell \bar{z}_\delta^\ell = b_k^\ell \in \mathbb{R}^n, \quad n = n(\ell)$$

- **Convergence of (local) SQP method**:  $\bar{z}_\delta^\ell$  reduced-order solution

$$\|A_k \mathcal{P} \bar{z}_\delta^\ell - b_k\| = \mathcal{O}(\|\mathcal{L}'(z_k)\|^q), \quad q \in [1, 2]$$

with prolongation  $\mathcal{P}$

- **Rate of convergence**: **superlinear** ( $1 < q < 2$ ), **quadratic** ( $q = 2$ )
- **Control of reduced-order approach**:

$$\|A_k \mathcal{P} \bar{z}_\delta^\ell - b_k\| \simeq \|\bar{z}_\delta - \mathcal{P} \bar{z}_\delta^\ell\| \simeq \|\mathcal{L}'(z_k)\|^q$$

## Local convergence result

- **Variables in optimal control:**  $x = (y, u)$ ,  $y = y(u)$
- **KKT system:**  $z_k = (x_k, p_k)$ ,  $x_k = (y_k, u_k)$

$$\left( \begin{array}{cc|c} \mathcal{L}_{yy}(z_k) & \mathcal{L}_{yu}(z_k) & e_y(x_k)^* \\ \mathcal{L}_{uy}(z_k) & \mathcal{L}_{uu}(z_k) & e_u(x_k)^* \\ \hline e_y(x_k) & e_u(x_k) & 0 \end{array} \right) \begin{pmatrix} y_\delta \\ u_\delta \\ p_\delta \end{pmatrix} = \begin{pmatrix} -\mathcal{L}_y(z_k) \\ -\mathcal{L}_u(z_k) \\ -e(x_k) \end{pmatrix}$$

- **Suboptimal solution to KKT system:**  $\bar{z}_\delta^\ell = (\bar{y}_\delta^\ell, \bar{u}_\delta^\ell, \bar{p}_\delta^\ell)$
- **Prolongation  $\mathcal{P}$ :**  $\bar{z}_\delta^\ell \mapsto \mathcal{P}\bar{z}_\delta^\ell = (\tilde{y}_\delta, \tilde{u}_\delta^\ell, \tilde{p}_\delta)$  with

$$\begin{aligned} e_y(x_k)\tilde{y}_\delta &= -e(x_k) - e_u(x_k)\tilde{u}_\delta^\ell \\ e_y(x_k)^*\tilde{p}_\delta &= -\mathcal{L}_y(z_k) - \mathcal{L}_{yy}(z_k)\tilde{y} - \mathcal{L}_{yu}(z_k)\tilde{u}_\delta^\ell \end{aligned}$$

- **Theorem:** second-order sufficient optimality implies

$$\lim_{k \rightarrow \infty} z_k + \mathcal{P}\bar{z}_\delta^\ell = \bar{z} \quad \text{if} \quad \|A_k \mathcal{P}\bar{z}_\delta^\ell - b_k\| \simeq \|\tilde{u}_\delta - \tilde{u}_\delta^\ell\| < \text{TOL}$$

## Multilevel approach with reduced-order models

- **Convergence criterium:**  $\|A_k \mathcal{P} \bar{z}_\delta^\ell - b_k\| \simeq \|\bar{u}_\delta - \bar{u}_\delta^\ell\| < \text{TOL}$
- **A-posteriori error** [Tröltzsch/V.'09]:

$$\|\bar{u}_\delta - \bar{u}_\delta^\ell\| \simeq \underbrace{\|\mathcal{L}_{uy}(z_k) \tilde{y}_\delta + \mathcal{L}_{uu}(z_k) \bar{u}_\delta^\ell + e_u(x_k)^* \tilde{p}_\delta + \mathcal{L}_u(z_k)\|}_{:= -\bar{\zeta}^\ell}$$

with  $\|\bar{\zeta}^\ell\| \rightarrow 0$  for  $\ell \rightarrow \infty$

- **Convergence of  $\|\bar{\zeta}^\ell\|$ :** no rate, basis dependent [Hinze/V.'08]
- **POD basis:** combination with **Optimality-System POD** [V.'11]
- **Alternatives via nonlinear optimization:** **Trust-Region POD**  
[Arian/Fahl/Sachs'00, Schu/Sachs'07]
- **Combination with adaptive schemes** [Clever/Lang/Ulbrich/Ziems]



## Numerical experiments

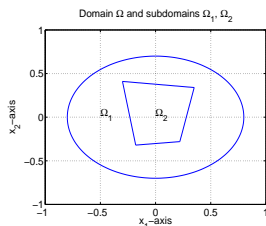
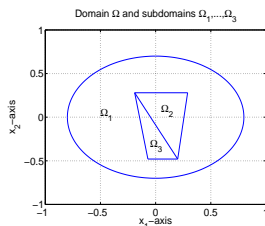
- **Optimal control problem:**

$$\min \frac{1}{2} \int_{\Omega_m} |y - y^d|^2 dx + \frac{\kappa}{2} \sum_{i=1}^{n_\Omega} |\Omega_i| |u_i - u_i^\circ|^2$$

$$\text{s.t. } u_i \geq 0, \quad -\Delta y + y \sum_{i=1}^{n_\Omega} u_i \chi_{\Omega_i} = 0 \text{ in } \Omega, \quad \frac{\partial y}{\partial n} + f = g \text{ on } \Gamma$$

- **Given data:**  $y^d$ ,  $u_i^\circ$ ,  $\kappa > 0$ ,  $f$ ,  $g$
- **Globalization of SQP:**
  - modification of the hessian
  - Armijo linesearch with  $\ell_1$  merit function
- **Equality constraint case:**  $x^* = (y^*, u^*)$  with inactive  $u^* > 0$

## Numerical examples

Reference control:  $u^\circ$ Desired state:  $y(u^\circ) + \text{noise}$ Measurement domain:  $\Omega_m \subsetneq \Omega$ 

SQP it.	$\ \mathcal{L}'(z_{k-1})\ $	a-post	$\ell$
$k = 1$	1.38e-0	1.16e-3	6
$k = 2$	8.53e-1	8.36e-2	12
$k = 3$	2.57e-1	7.87e-5	12
$k = 4$	4.65e-3	5.67e-6	12
$k = 4$	3.05e-5	1.90e-6	12
$k = 6$	4.66e-9	—	—

SQP it.	$\ \mathcal{L}'(z_k)\ $	a-post	$\ell$
$k = 1$	3.01e-2	1.58e-3	10
$k = 2$	4.48e-1	7.44e-4	10
$k = 3$	3.63e-1	3.46e-4	10
$k = 4$	5.16e-2	4.04e-5	10
$k = 5$	1.48e-2	4.98e-4	10
$k = 6$	1.62e-3	6.56e-4	10
$k = 7$	7.51e-7	—	—

# Outline of the third part: POD suboptimal control

- Nonlinear heat control
- A-posteriori error analysis
- Acoustic example
- Multilevel SQP
- **Static output feedback (SOF)**
- References

## Linear-quadratic-regulator (LQR) design

- **Linear dynamical system** in  $\mathbb{R}^\ell$ :

$$\dot{x}(t) = Ax(t) + Bu(t) \text{ for } t > 0, \quad x(0) = x_0$$

with **state**  $x(t) \in \mathbb{R}^\ell$ , **control**  $u(t) \in \mathbb{R}^{n_u}$  and  $A \in \mathbb{R}^{\ell \times \ell}$ ,  $B \in \mathbb{R}^{\ell \times n_u}$

- **Quadratic cost**:  $J(x, u) = \int_0^\infty x(t)^T Qx(t) + u(t)^T Ru(t) dt$

with  $Q \in \mathbb{R}^{\ell \times \ell}$ ,  $Q \succeq 0$  and  $R \in \mathbb{R}^{n_u \times n_u}$ ,  $R \succ 0$

- **Goal**: (full state) feedback law  $u(t) = Fx(t)$  with  $F \in \mathbb{R}^{n_u \times \ell}$
- **Solution**:  $F = -R^{-1}B^T P$  with  $P = P^T \in \mathbb{R}^{\ell \times \ell}$

$$A^T P + PA + Q - PBR^{-1}B^T P = 0 \quad (\text{Matrix Riccati})$$

- **Problem**: often only **partial state measurement** available

## $\mathcal{H}_2$ static output feedback (SOF) design

- **Linear dynamical system** in  $\mathbb{R}^\ell$ :

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + B_1 w(t) \text{ for } t > 0, & x(0) &= x_0 \\ y(t) &= Cx(t) \end{aligned}$$

with  $A \in \mathbb{R}^{\ell \times \ell}$ ,  $B \in \mathbb{R}^{\ell \times n_u}$ ,  $B_1 \in \mathbb{R}^{\ell \times n_w}$ ,  $C \in \mathbb{R}^{n_y \times \ell}$  and

$$x(t) \in \mathbb{R}^\ell, \quad u(t) \in \mathbb{R}^{n_u}, \quad y(t) \in \mathbb{R}^{n_y}, \quad w(t) \in \mathbb{R}^{n_w}$$

- **Feedback law:**  $u(t) = Fy(t)$  with  $F \in \mathbb{R}^{n_u \times n_y}$
- **Solution:**  $F$  given by nonconvex **semidefinite programming**

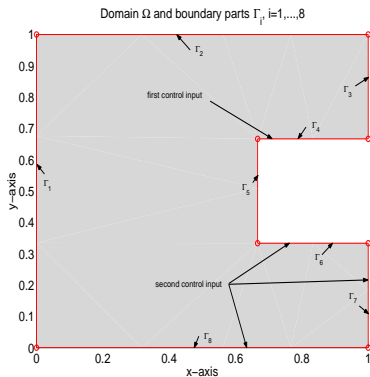
$$\min \text{trace}(LB_1 B_1^T) \quad \text{s.t.} \quad H(F, L, V) = 0 \ \& \ V \succ 0 \in \mathbb{R}^{\ell \times \ell} \quad (\text{SDP})$$

$$\text{with } H(F, L, V) = \begin{pmatrix} A(F)^T L + LA(F) + C(F)^T C(F) \\ A(F)^T V + VA(F) + I \end{pmatrix} \in \mathbb{R}^{2\ell \times \ell}$$

## SOF controller design [Leibfritz/V.'06]

$$\begin{aligned}
 v_t &= \kappa \Delta v + av \\
 -\lambda \frac{\partial v}{\partial n} &= 0 \\
 -\lambda \frac{\partial v}{\partial n} &= \alpha_4 (v - c_4 + u_4(t)) + \varepsilon_4 \sigma(v^4 - c_4^4) \\
 -\lambda \frac{\partial v}{\partial n} &= \hat{\alpha} (v - \hat{c} + \hat{u}(t)) \\
 v(0) &= v_o
 \end{aligned}$$

in  $\Omega \times (0, T)$   
 on  $\Gamma_j \times (0, T)$ ,  $j=1,2,3,5$   
 on  $\Gamma_4 \times (0, T)$   
 on  $\Gamma_j \times (0, T)$ ,  $j=6,7,8$   
 in  $\Omega$



**Control:**  $u(t) \in \mathbb{R}^2$ ,  $n_u = 2$

**Measurement:**  $y(t) \in \mathbb{R}^3$ ,  $n_y = 3$

$$y_1(t) = v(0, 1; t)$$

$$y_2(t) = v(0, 0; t)$$

$$y_3(t) = v(2/3, 1/2; t)$$

**Goal:**  $u(t) = Fy(t)$ ,  $F \in \mathbb{R}^{2 \times 3}$

## Variational form for nonlinear heat equation

- **Nonlinear heat equation:**

$$\begin{aligned}
 v_t &= \kappa \Delta v + av && \text{in } \Omega \times (0, T) \\
 -\lambda \frac{\partial v}{\partial n} &= 0 && \text{on } \Gamma_j \times (0, T), \quad j = 1, 2, 3, 5 \\
 -\lambda \frac{\partial v}{\partial n} &= \alpha_4 (v - c_4 + u_4(t)) + \varepsilon_4 \sigma (v^4 - c_4^4) && \text{on } \Gamma_4 \times (0, T) \\
 -\lambda \frac{\partial v}{\partial n} &= \hat{\alpha} (v - \hat{c} + \hat{u}(t)) && \text{on } \Gamma_j \times (0, T), \quad j = 6, 7, 8
 \end{aligned}$$

- **Variational form:** for all  $\varphi \in H^1(\Omega)$

$$\begin{aligned}
 \int_{\Omega} v_t(t) \varphi + \kappa \nabla v(t) \cdot \nabla \varphi - av(t) \varphi \, dx &= \kappa \int_{\Gamma} \frac{\partial v(t)}{\partial n} \varphi \, ds = \frac{\kappa}{\lambda} \int_{\Gamma} \lambda \frac{\partial v(t)}{\partial n} \varphi \, ds \\
 &= \frac{\kappa}{\lambda} \int_{\Gamma_4} (\alpha_4 c_4 + \varepsilon_4 \sigma c_4^4) \varphi - (\alpha_4 v(t) + \varepsilon_4 \sigma v^4(t)) \varphi - \alpha_4 u_4(t) \varphi \, ds \\
 &\quad + \frac{\kappa}{\lambda} \int_{\Gamma_6 \cup \Gamma_7 \cup \Gamma_8} \hat{\alpha} \hat{c} \varphi - \hat{\alpha} v(t) \varphi - \hat{\alpha} \hat{u}(t) \varphi \, ds
 \end{aligned}$$

## $\mathcal{H}_2$ SOF design

- **Dynamical system** in  $\mathbb{R}^N$ : spatial discretization (e.g., FE or FD) and linearization

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + B_1 w(t) \text{ for } t > 0, & x(0) &= x_0 \\ y(t) &= Cx(t) \end{aligned}$$

- **Goal:** feedback law  $u(t) = Fy(t)$  with  $F \in \mathbb{R}^{2 \times 3}$
- **Solution:**  $F$  given by

$$\min \text{trace}(LB_1 B_1^T) \quad \text{s.t.} \quad H(F, L, V) = 0 \ \& \ V \succ 0 \quad (\text{SDP})$$

$$\text{with } H(F, L, V) = \begin{pmatrix} A(F)^T L + LA(F) + C(F)^T C(F) \\ A(F)^T V + VA(F) + I \end{pmatrix} \in \mathbb{R}^{2N \times N}$$

- $N = \#$  FE or FD unknowns (!)



## Reduced-order model (ROM)

- Compute solution  $y$  of nonlinear heat equation with FE or FD at time instances  $0 \leq t_1 < \dots < t_n \leq T$
- **Snapshots:**  $y_j = y(t_j)$  for  $i = 1, \dots, n$
- **POD:**  $\mathcal{R}^n \psi_i = \lambda_i \psi_i$  with  $\mathcal{R}^n \psi_i = \sum_{j=1}^n \alpha_j \int_{\Omega} \psi_i y_j dx$   $y_j$
- **ROM:** Galerkin ansatz for nonlinear heat equation with  $\psi_1, \dots, \psi_\ell$

$$\dot{x}(t) = A^\ell x(t) + G^\ell(x(t)) + B^\ell u(t) + B_1^\ell w(t), \quad x(0) = x_0^\ell$$

$$y(t) = C^\ell x(t)$$

$$u(t) = F^\ell y(t), \quad F^\ell \in \mathbb{R}^{2 \times 3}$$

## Feedback synthesis

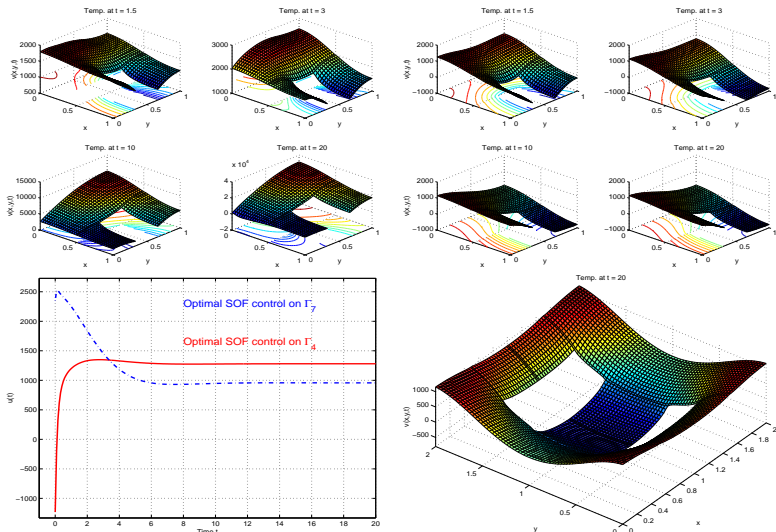
- Reduction in the variable  $x$ , not in  $y$  and  $u$
- Linearize and set up the SDP problem
  - $\Rightarrow \ell$  is the size of the SDP problem
  - $\Rightarrow 5 = \ell \ll 3796$  FD unknowns
- Solve SDP by **Interior-point trust-region method** [Leibfritz/Mostafa]
- Plug in the computed feedback law into the FD modell (**closed-loop**)

$$\dot{x}(t) = Ax(t) + G(x(t)) + B \underbrace{F^\ell Cx(t)}_{=F^\ell y(t)=u(t)} + B_1 w(t), \quad x(0) = x_0$$

$$y(t) = Cx(t)$$

$$u(t) = F^\ell y(t) = F^\ell Cx(t)$$

## Numerical example (Part 3)



# References

- Diwoky/V.'01: Nonlinear boundary control for the heat equation utilizing POD
- Hinze/V.'08: Error estimates for abstract linear-quadratic optimal control problems using POD
- Kunisch/V.'08: POD for optimality systems
- Leibfritz/V.'04: Reduced order output feedback control design for PDE systems using POD and nonlinear semidefinite programming
- Sachs/V.'10: POD-Galerkin approximations in PDE-constrained optimization
- Tonn/Urban/V.'11: Comparison of the reduced-basis and POD a-posteriori error estimators for an elliptic linear-quadratic optimal control problem
- Tröltzsch/V.'09: POD a-posteriori error estimates for linear- quadratic optimal control problems
- V.'11: POD a-posteriori error estimates for linear-quadratic optimal control problems
- Kammann/Tröltzsch/V.'11: A method of a-posteriori error estimation with application to POD

## Ongoing research

- A-posteriori analysis for **nonlinear problems** [Kammann/Tröltzsch/V., Trenz/V.]
- OS-POD for mixed **control-state constraints** [Gubisch/V.]
- POD for **battery equations** [Lass/V.]
- **Stable** KKT approximations [Gerner/Veroy-Grepl/V.]
- **Comparison** of various model-order strategies [Vossen/V.]
- A-posteriori error analysis for **reduced basis schemes** [Grepl/Kärcher/V.]