

Proper Orthogonal Decomposition for PDE Constrained Optimization

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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 2:

Reduced-Order Modelling (ROM)

- 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?

Outline of the second part: ROM

- ROM and error estimation
- Applications (λ - ω systems, laser surface hardening, battery)
- Optimal snapshot locations
- References

ROM and error estimation [V.09]

- Initial value problem in \mathbb{R}^m :

$$\dot{y}(t) = Ay(t) + f(t, y(t)) \text{ for } t \in (0, T] \text{ and } y(0) = y_0$$

with given $y_0 \in \mathbb{R}^m$ and $f : [0, T] \times \mathbb{R}^m \rightarrow \mathbb{R}^m$

- Snapshots:** $y(t) \in \mathbb{R}^m$ for all $t \in [0, T]$
- POD basis of rank $\ell \leq m$:** $\psi_1, \dots, \psi_\ell \in \mathbb{R}^m$
- Galerkin ansatz:** $y^\ell(t) = \sum_{j=1}^{\ell} (\psi_j^T y^\ell(t)) \psi_j = \sum_{j=1}^{\ell} y_j^\ell(t) \psi_j$
- Galerkin projection of the ODE:**

$$\begin{aligned} \psi_i^T \dot{y}^\ell(t) &= \psi_i^T Ay^\ell(t) + \psi_i^T f(t, y^\ell(t)), & t \in (0, T], \quad i = 1, \dots, \ell \\ \psi_i^T y^\ell(0) &= \psi_i^T y_0, & i = 1, \dots, \ell \end{aligned}$$

POD Galerkin projection of the ODE

- **Galerkin projection of the ODE:** $f \equiv 0$ (for simplicity)

$$\psi_i^T \dot{y}^\ell(t) = \psi_i^T A y^\ell(t), \quad t \in (0, T], \quad i = 1, \dots, \ell$$

$$\psi_i^T y^\ell(0) = \psi_i^T y_0 \quad i = 1, \dots, \ell$$

- **Inserting Galerkin ansatz:**

$$\psi_i^T \dot{y}^\ell(t) = \sum_{j=1}^{\ell} \dot{y}_j^\ell(t) \psi_i^T \psi_j = \dot{y}_i^\ell(t)$$

$$\psi_i^T A y^\ell(t) = \psi_i^T \left(\sum_{j=1}^{\ell} y_j^\ell(t) A \psi_j \right) = \sum_{j=1}^{\ell} y_j^\ell(t) \psi_i^T A \psi_j$$

- **ROM** in \mathbb{R}^ℓ : $y^\ell = (y_i^\ell)$, $A^\ell = ((\psi_i^T A \psi_j))$, $y_0^\ell = (\psi_i^T y_0)$

$$\dot{y}^\ell(t) = A^\ell y(t) \quad \text{for } t \in (0, T]$$

$$y^\ell(0) = y_0^\ell$$

Error analysis — Part 1

- **Goal:** estimate $\int_0^T \|y(t) - y^\ell(t)\|_{\mathbb{R}^m}^2 dt$

- **Orthogonal projector onto $V^\ell = \text{span}\{\psi_i\}_{i=1}^\ell$:**

$$\mathcal{P}^\ell \psi = \sum_{j=1}^{\ell} (\psi^T \psi_j) \psi_j \quad \text{for } \psi \in \mathbb{R}^m$$

$$\Rightarrow y^\ell(0) = \mathcal{P}^\ell y_0 = \mathcal{P}^\ell y(0)$$

- **POD basis:**

$$\int_0^T \left\| y(t) - \sum_{i=1}^{\ell} (y(t)^T \psi_i) \psi_i \right\|^2 dt = \int_0^T \left\| y(t) - \mathcal{P}^\ell y(t) \right\|^2 dt$$

- **Decomposition:**

$$y(t) - y^\ell(t) = \underbrace{y(t) - \mathcal{P}^\ell y(t)}_{\in (V^\ell)^\perp} + \underbrace{\mathcal{P}^\ell y(t) - y^\ell(t)}_{\in V^\ell} = \varrho^\ell(t) + \vartheta^\ell(t)$$

Error analysis — Part 2

- **Decomposition:**

$$y(t) - y^\ell(t) = y(t) - \mathcal{P}^\ell y(t) + \mathcal{P}^\ell y(t) - y^\ell(t) = \varrho^\ell(t) + \vartheta^\ell(t)$$

- **Projector onto $V^\ell = \text{span} \{\psi_i\}_{i=1}^\ell$:** $\mathcal{P}^\ell \psi = \sum_{j=1}^\ell (\psi^T \psi_j) \psi_j$

- **Estimate for ϱ^ℓ :**

$$\int_0^T \|\varrho^\ell(t)\|^2 dt = \int_0^T \|y(t) - \mathcal{P}^\ell y(t)\|^2 dt = \sum_{i=\ell+1}^m \lambda_i$$

- **Differential equation for ϑ^ℓ :** for $i \in \{1, \dots, \ell\}$

$$\begin{aligned} \psi_i^T \dot{\vartheta}^\ell(t) &= \psi_i^T (\mathcal{P}^\ell \dot{y}(t) - \dot{y}^\ell(t)) = \psi_i^T (\dot{y}(t) - \dot{y}^\ell(t) + \mathcal{P}^\ell \dot{y}(t) - \dot{y}(t)) \\ &= \psi_i^T (Ay(t) - Ay^\ell(t) + \mathcal{P}^\ell \dot{y}(t) - \dot{y}(t)) \\ &= \psi_i^T (A(\varrho^\ell(t) + \vartheta^\ell(t)) + \mathcal{P}^\ell \dot{y}(t) - \dot{y}(t)) \end{aligned}$$

Error analysis — Part 3

- **Differential equation for ϑ^ℓ** : for $i \in \{1, \dots, \ell\}$

$$\psi_i^T \dot{\vartheta}^\ell(t) = \psi_i^T (A(\varrho^\ell(t) + \vartheta^\ell(t)) + \mathcal{P}^\ell \dot{y}(t) - \dot{y}(t))$$

- **Summation**: $\vartheta^\ell(t) = \sum_{i=1}^{\ell} c_i(t) \psi_i$

$$\vartheta^\ell(t)^T \dot{\vartheta}^\ell(t) = \vartheta^\ell(t)^T (A(\varrho^\ell(t) + \vartheta^\ell(t)) + \mathcal{P}^\ell \dot{y}(t) - \dot{y}(t))$$

- **Estimation**:

$$\frac{1}{2} \frac{d}{dt} \|\vartheta^\ell(t)\|^2 \leq C \left(\|\vartheta^\ell(t)\|^2 + \|\varrho^\ell(t)\|^2 + \|\dot{y}(t) - \mathcal{P}^\ell \dot{y}(t)\|^2 \right)$$

- **Gronwall's lemma**: $\vartheta^\ell(0) = \mathcal{P}^\ell y_0 - y^\ell(0) = 0$

$$\begin{aligned} \|\vartheta^\ell(t)\|^2 &\leq C \left(\|\varrho^\ell(t)\|^2 + \|\dot{y}(t) - \mathcal{P}^\ell \dot{y}(t)\|^2 \right) \\ &= C \left(\sum_{i=\ell+1}^m \lambda_i + \|\dot{y}(t) - \mathcal{P}^\ell \dot{y}(t)\|^2 \right) \end{aligned}$$

Error estimate for continuous POD

- **Error estimate (continuous POD method):**

$$\begin{aligned} \int_0^T \|y(t) - y^\ell(t)\|^2 dt &\leq 2 \int_0^T \|\varrho^\ell(t)\|^2 + \|\vartheta^\ell(t)\|^2 dt \\ &\leq C \left(\sum_{i=\ell+1}^m \lambda_i + \int_0^T \|\dot{y}(t) - \mathcal{P}^\ell \dot{y}(t)\|^2 dt \right) \end{aligned}$$

- **Remarks:**

- dependence on the **decay of the eigenvalues** λ_i
- dependence on the **approximation quality for** $\dot{y}(t)$

- **Modified POD method:**

$$\min \int_0^T \|y(t) - \mathcal{P}^\ell y(t)\|^2 + \|\dot{y}(t) - \mathcal{P}^\ell \dot{y}(t)\|^2 dt \quad \text{s.t.} \quad \psi_i^T \psi_j = \delta_{ij}$$

- **Error estimate:** $\int_0^T \|y(t) - y^\ell(t)\|^2 dt \leq C \sum_{i=\ell+1}^m \tilde{\lambda}_i$

Extensions [Hömburg/V.'03, Kahlbacher/V.'07, Kunisch/V.'01, Kunisch/V.'02, V.'09]

- **Full discrete method:** $t_j = j\Delta t$, $Y_j^\ell \approx y(t_j)$

$$\begin{aligned}\psi_i^T \left(\frac{Y_j^\ell - Y_{j-1}^\ell}{\Delta t} \right) &= \psi_i^T A Y_j^\ell + \psi_i^T f(t, Y_j^\ell), & j = 1, \dots, m, \quad i = 1, \dots, \ell \\ \psi_i^T Y_0^\ell &= \psi_i^T y_0, & i = 1, \dots, \ell\end{aligned}$$

- **Discrete POD:** $\lambda_i = \lambda_i^n$, $\psi_i = \psi_i^n$
- **Error estimate:**

$$\begin{aligned}\sum_{j=1}^n \alpha_j \|y(t_j) - Y_j^\ell\|_{\mathbb{R}^m}^2 &\leq C \left((\Delta t)^2 + \sum_{i=\ell+1}^m \lambda_i^n + \sum_{j=1}^n \alpha_j |\dot{y}(t_j)^T \psi_i^n|^2 \right) \\ &= O \left((\Delta t)^2 + \sum_{i=\ell+1}^m \left(\lambda_i + \int_0^T |\dot{y}(t)^T \psi_i|^2 dt \right) \right)\end{aligned}$$

- **nonlinear parabolic PDEs and parameter-dependent elliptic systems**

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- **Applications (λ - ω systems, laser surface hardening, battery)**
- Optimal snapshot locations
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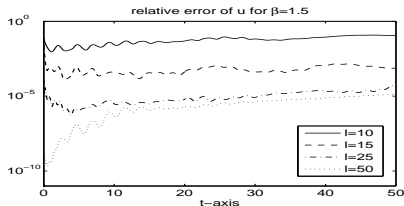
Application 1: λ - ω systems [Müller/V.'06]

- **Inner product:** $\langle u, v \rangle = \int_{\Omega} uv \, dx$
- **POD Galerkin ansatz:**

$$u_{\ell}(t, x) = \bar{u}(x) + \sum_{j=1}^{\ell} u_{\ell}^j(t) \psi_j(x), \quad v_{\ell}(t, x) = \bar{v}(x) + \sum_{j=1}^{\ell} v_{\ell}^j(t) \phi_j(x)$$

- **Reduced-order model (ROM):**
 - insert ansatz into PDEs
 - multiply by POD basis functions ψ_i respectively ϕ_i
 - integrate over Ω
- **Numerical results:**

$$t \mapsto \frac{\|u_{\ell}(t) - u(t)\|^2}{\|u(t)\|^2}$$



Application 1: relative POD errors for λ - ω systems

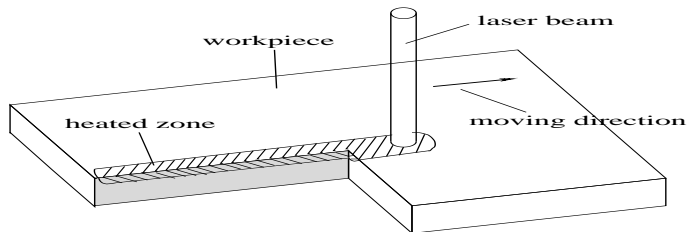
- **Offsets:** $u_m(x) = \sum_{j=1}^n \alpha_j u(t_j, x)$
- **Relative POD errors:**

| | $\bar{u} = 0$ | $\bar{u} = u_m$ | | $\bar{u} = 0$ | $\bar{u} = u_m$ |
|-------------|---------------|-----------------|-------------|---------------|-----------------|
| $\ell = 10$ | 0.005890 | 0.005945 | $\ell = 40$ | 0.577442 | 0.460188 |
| $\ell = 15$ | 0.000350 | 0.000335 | $\ell = 45$ | 0.898613 | 0.297619 |
| $\ell = 50$ | 0.000009 | 0.000009 | $\ell = 50$ | 0.071035 | 0.001774 |

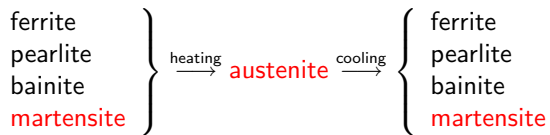
$$E_{\text{rel}}(u) = \frac{\sum_{j=1}^n \alpha_j \|u_\ell(t_j) - u_h(t_j)\|^2}{\sum_{j=1}^n \alpha_j \|u_h(t_j)\|^2} \quad \text{for } \beta = 1.5 \text{ (left) and } \beta = 2 \text{ (right)}$$

Application 2: laser surface hardening [Hömberg/V.'03]

- **Motivation:**



- **Phase transition of steel:**



Application 2: Model equations for laser surface hardening

- **Energy balance and Fourier's law:**

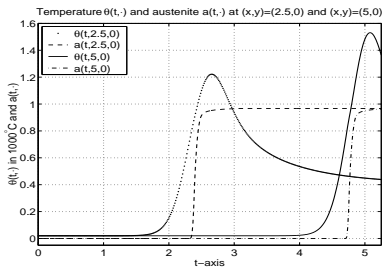
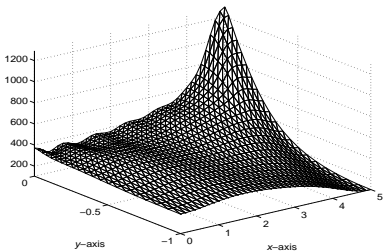
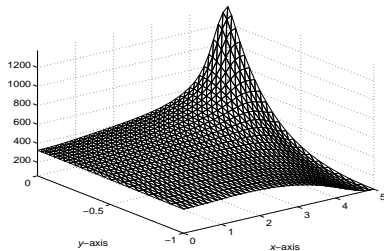
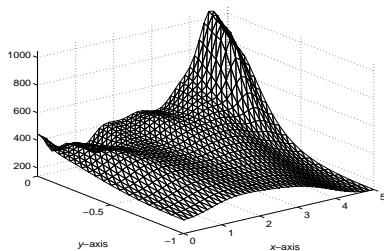
$$\left\{ \begin{array}{ll} \rho c_p \theta_t - k \Delta \theta = \alpha u - \rho L a_t & \text{in } Q = (0, T) \times \Omega \\ \frac{\partial \theta}{\partial n} = 0 & \text{auf } \Sigma = (0, T) \times \partial \Omega \\ \theta(0, \cdot) = \theta_0 & \text{in } \Omega \subset \mathbb{R}^d \end{array} \right.$$

- **Phase transition of austenite:**

$$\left\{ \begin{array}{ll} a_t = f(\theta, a) & \text{in } Q \\ a(0, \cdot) = 0 & \text{in } \Omega \end{array} \right.$$

- **Intensity of the laser:** $u = u(t) \in L^2(0, T)$
- **Nonlinearity:** $f_+(\theta, a) = \max \{ a_{eq}(\theta) - a, 0 \} / \tau(\theta)$, $\tau(\theta) > 0$

Application 2: FE and POD temperatures at $t = T$

POD 1 solution θ at time $t=T$ FE solution θ at time $t=T$ POD 2 solution θ at time $t=T$ 

Application 2: POD error

- Measures for the error:

$$\psi^i = \frac{\max_{0 \leq j \leq N} \left(\sup_{x \in \Omega} |\theta_\ell^j(x) - \theta_{FE}^j(x)| \right)}{\max_{0 \leq j \leq N} \left(\sup_{x \in \Omega} |\theta_{FE}^j(x)| \right)} \quad \text{with} \quad \begin{cases} i = 1 & \text{POD with derivatives} \\ i = 2 & \text{POD without derivatives} \end{cases}$$

| | $X = L^2(\Omega)$ | | $X = H^1(\Omega)$ | |
|--------|-------------------|----------|-------------------|----------|
| ℓ | Ψ^1 | Ψ^2 | Ψ^1 | Ψ^2 |
| 10 | 24.1% | 40.6% | 21.0% | 40.1% |
| 25 | 1.6% | 26.9% | 4.0% | 24.6% |

- Heuristic: $\mathcal{E}(\ell) = \sum_{i=1}^{\ell} \lambda_i / \sum_{i=1}^d \lambda_i \cdot 100\% \geq 94\%$

| | $\ell = 10$ | $\ell = 15$ | $\ell = 20$ | $\ell = 25$ |
|--------------------------------------|-------------|-------------|-------------|-------------|
| $\mathcal{E}(\ell), X = L^2(\Omega)$ | 94.3 | 98.4 | 99.5 | 99.8 |
| $\mathcal{E}(\ell), X = H^1(\Omega)$ | 77.7 | 87.4 | 92.5 | 95.7 |

Application 3: Elliptic-parabolic systems [Lass/V.'11]

- **Elliptic-parabolic systems:** $T = 1$, $\Omega = (a, b)$

$$\begin{aligned}y_t - \nabla \cdot (c_1 \nabla y) - \mathcal{N}(y, p, q; \mu) &= 0 && \text{in } Q = (0, T) \times \Omega \\ -\nabla \cdot (c_2 \nabla p) - \mathcal{N}(y, p, q; \mu) &= 0 && \text{in } Q \\ -\nabla \cdot (c_3 \nabla q) + \mathcal{N}(y, p, q; \mu) &= 0 && \text{in } Q\end{aligned}$$

- **Parameter-dependent nonlinearity:** $\mu = (\mu_1, \mu_2) \geq 0$

$$\mathcal{N}(y, p, q; \mu) = \mu_2 \sqrt{y} \sinh(\mu_1 (q - p - \ln y))$$

- **Boundary conditions:** $y_x(t, a) = y_x(t, b) = p(t, a) = p_x(t, b) = 0$,
 $q_x(t, a) = q(t, b) = 0$

Application 3: ROM with different POD bases for y , p , and q

- **Fine model:**

$$\begin{aligned}
 y_t - \nabla \cdot (c_1 \nabla y) - \mathcal{N}(y, p, q; \mu) &= 0 & \text{in } Q \\
 -\nabla \cdot (c_2 \nabla p) - \mathcal{N}(y, p, q; \mu) &= 0 & \text{in } Q \\
 -\nabla \cdot (c_3 \nabla q) + \mathcal{N}(y, p, q; \mu) &= 0 & \text{in } Q
 \end{aligned} \tag{FM}$$

- **FE model for (FM):** $y^h(t) = \sum_{i=1}^{N_{FE}} \bar{y}_i(t) \varphi_i$ etc.

$$\begin{aligned}
 M \bar{y}_t(t) + S_{c_1} \bar{y}(t) - \bar{\mathcal{N}}(\bar{y}(t), \bar{p}(t), \bar{q}(t); \mu) &= 0 \\
 S_{c_2} \bar{p}(t) - \bar{\mathcal{N}}(\bar{y}(t), \bar{p}(t), \bar{q}(t); \mu) &= 0 \\
 S_{c_3} \bar{q}(t) + \bar{\mathcal{N}}(\bar{y}(t), \bar{p}(t), \bar{q}(t); \mu) &= 0
 \end{aligned}$$

- **ROM for (FM):** $y^\ell(t) = \sum_{i=1}^{\ell_y} \hat{y}_i(t) \psi_i^y$ etc. [Off-/Online]

$$\begin{aligned}
 \Psi_y^\top M \Psi_y \hat{y}_t(t) + \Psi_y^\top S_{c_1} \Psi_y \hat{y}(t) - \Psi_y^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) &= 0 \\
 \Psi_p^\top S_{c_2} \Psi_p \hat{p}(t) - \Psi_p^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) &= 0 \\
 \Psi_q^\top S_{c_3} \Psi_q \hat{q}(t) + \Psi_q^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) &= 0
 \end{aligned}$$

Application 3: Problems for the ROM

- **ROM for (FM):** $y^\ell(t) = \sum_{i=1}^{\ell_y} \hat{y}_i(t) \psi_i^y$ etc.

$$M^{\ell_y} \hat{y}_t(t) + S_{c_1}^{\ell_y} \hat{y}(t) - \Psi_y^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) = 0$$

$$S_{c_2}^{\ell_p} \Psi_p \hat{p}(t) - \Psi_p^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) = 0$$

$$S_{c_3}^{\ell_q} \hat{q}(t) + \Psi_q^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) = 0$$

- **Problem 1:** Imply the reconstruction error

$$\int_0^T \left\| y(t) - \sum_{i=1}^{\ell} \langle y(t), \psi_i \rangle \psi_i \right\|^2 dt = \sum_{i>\ell} \lambda_i$$

the error relation

$$\|y - y^\ell\|^2 + \|p - p^\ell\|^2 + \|q - q^\ell\|^2 = \mathcal{O}(\sum_{i>\ell} \lambda_i)$$

- **Problem 2:** evaluation of the nonlinear terms

$$\Psi_y^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) \text{ etc.}$$

is of complexity $N_{FE} \gg \ell$

Application 3: Problem 1 – A-priori error estimation

- **Problem 1:** Imply the reconstruction error

$$\int_0^T \left\| y(t) - \sum_{i=1}^{\ell} \langle y(t), \psi_i \rangle \psi_i \right\|^2 dt = \sum_{i>\ell} \lambda_i$$

the error relation

$$\|y - y^\ell\|^2 + \|p - p^\ell\|^2 + \|q - q^\ell\|^2 = \mathcal{O}(\sum_{i>\ell} \lambda_i)$$

- **Theorem:** There is a constant $C > 0$ such that

$$\begin{aligned} & \int_0^T \left(\|y(t) - y^\ell(t)\|^2 + \|p(t) - p^\ell(t)\|^2 + \|q(t) - q^\ell(t)\|^2 \right) dt \\ & \leq C \left(\|\mathcal{P}^{\ell_Y} y_0 - y^\ell(0)\|^2 + \|\mathcal{P}^{\ell_Y} y_t - y_t^\ell\|^2 \right) \\ & \quad + C \left(\sum_{i>\ell_Y} \lambda_i^Y + \sum_{i>\ell_P} \lambda_i^P + \sum_{i>\ell_Q} \lambda_i^Q \right) \end{aligned}$$

Application 3: Problem 2 – evaluation of $\Psi_y^\top \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu)$

- **Replace:** $F(t) = \bar{\mathcal{N}}(y^\ell(t), p^\ell(t), q^\ell(t); \mu) \approx \sum_{i=1}^m c_i(t) u_i \in \mathbb{R}^{N_{FE}}$.
- **Interpolation condition** for $1 \leq k \leq m \ll N_{FE}$:

$$(F(t))_{p_k} = \left(\sum_{i=1}^m c_i(t) u_i \right)_{p_k} = \sum_{i=1}^m c_i(t) (u_i)_{p_k}, \quad p_k \in \{1, \dots, N_{FE}\}$$

- **Computation of $c(t)$:** $\underbrace{(P^T U)}_{m \times m} c(t) = P^T F(t) \in \mathbb{R}^m$
- **Complexity reduction:** $P^T F(t) = \bar{\mathcal{N}}(P^T y^\ell(t), P^T p^\ell(t), P^T q^\ell(t); \mu)$
- **Choice for U** (DEIM): POD basis for $\text{span} \{F(t_j)\}_{j=0}^{N_t}$.
- **Theorem:** error estimate for POD-DEIM compare [Chaturantabut/Sorensen'10]
- **Alternative:** EIM compare [Grepl, Maday, Ohlberger, Patera, Tonn,...]

Application 3: accuracy (a-priori analysis) for fixed parameter μ

- “Truth” solution: $N_x = 1000$, $N_t = 100$, 2^{nd} order elements
- POD and EIM: $\ell_y = 12$, $\ell_p = 10$, $\ell_q = 10$, $\ell_{DEIM} = \ell_{EIM} = 25$
- Average relative L^2 error (FEM and POD):

| | ROM | ROM-EIM | ROM-DEIM |
|-----|-------------------------|-------------------------|-------------------------|
| y | 1.6765×10^{-7} | 1.6763×10^{-7} | 1.6762×10^{-7} |
| p | 2.8723×10^{-7} | 2.7560×10^{-7} | 2.7467×10^{-7} |
| q | 9.7545×10^{-8} | 9.4332×10^{-8} | 9.1929×10^{-8} |

- CPU time:

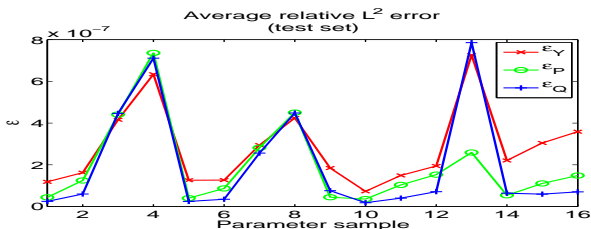
| FEM | POD | EIM | DEIM | ROM | ROM-EIM | ROM-DEIM |
|--------------|------|------|------|------|--------------------------------|-------------|
| 18.20 | 0.20 | 0.19 | 0.03 | 6.03 | 0.24 ($\approx 1/75$) | 0.48 |

Application 3: multiple parameters

- **Sample set:** $\mu_{\text{sample}} \in \{1, 2\} \times \{1, 2\}$
- **Test set:** $\mu_{\text{test}} \in \{0.5, 1.5, 2.5, 3\} \times \{0.5, 1.5, 2.5, 3\}$
- **POD and EIM:** $l_y = 20$, $l_p = 18$, $l_q = 18$, $l_{\text{EIM}} = l_{\text{DEIM}} = 40$
- **CPU time:**

| FEM | POD | EIM | DEIM | ROM | ROM-EIM | ROM-DEIM |
|-----------|------|------|------|-------------|-------------|-------------|
| ~ 18 | 0.54 | 0.74 | 0.09 | ~ 7.50 | ~ 0.30 | ~ 0.60 |

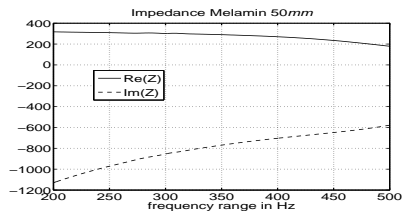
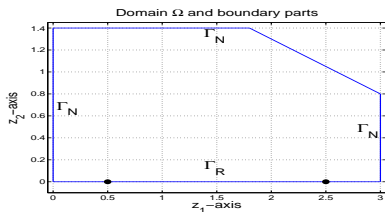
- **Average relative L^2 error:**



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- ROM and error estimation
- Applications (λ - ω systems, laser surface hardening, battery)
- **Optimal snapshot locations**
- References

Acoustic application [Lass/V.1?]



- **Helmholtz equation** for frequencies $f \in [f_a, f_b]$:

$$-\Delta p_f - k_f^2 p_f = q_f \text{ in } \Omega, \quad \frac{j}{\rho_0 \omega_f} \frac{\partial p_f}{\partial n} = \begin{cases} p_f / Z_f & \text{on } \Gamma_R \\ 0 & \text{on } \Gamma_N \end{cases}$$

- **Sound pressure** $p_f : \Omega \rightarrow \mathbb{C}$
- **Angular frequency** $\omega_f = 2\pi f$, **wave number** $k_f = \omega_f / c$
- **source term** $q_f(\mathbf{z}) = c(f)e^{-50 \|\mathbf{z} - \mathbf{z}_q\|_2^2}$ for $\mathbf{z} = (z_1, z_2) \in \Omega$

Computation of the POD basis (elliptic case)

- **Frequency grid:** $f_a \leq f_1 < \dots < f_n \leq f_b$
- **Snapshots:** $p_j = p_{f_j}$ for $f = f_j$
- **Minimization problem:**

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

- **First-order optimality conditions:**

$$\mathcal{R}\psi_i = \lambda_i \psi_i, \quad i = 1, \dots, \ell \quad (YY^T)$$

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

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

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

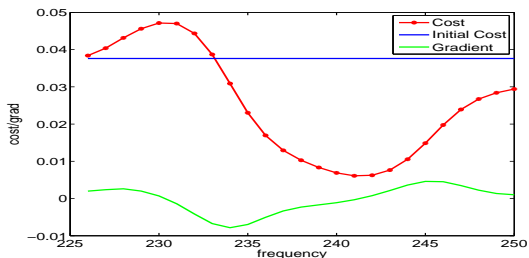
Optimal snapshot locations [Kunisch/V.'10, Lass/V.'1?]

- **Given snapshots:** p_{f_j} with $f_j = 199 + j$, $j = 1, \dots, 26$
- **Goal:** optimal choice of snapshot $p_{\bar{f}}$ with $\bar{f} \in [225, 250]$

$$\min_{\bar{f} \in [225, 250]} \frac{1}{2\beta} \int_{200}^{250} \|p_f - p_{\bar{f}}^\ell\|^2 df, \quad \beta = \int_{200}^{250} \|p_f\|^2 df$$

where p_f^ℓ is computed using the POD basis $\{\psi_i\}_{i=1}^\ell$ with

$$\sum_{j=1}^{26} \alpha_j \langle p_{f_j}, \psi_i \rangle p_{f_j} + \underbrace{\bar{\alpha} \langle p_{\bar{f}}, \psi_i \rangle p_{\bar{f}}}_{\text{add snapshot } p_{\bar{f}}} = \lambda_i \psi_i, \quad i = 1, \dots, \ell$$



Optimal frequency:

$$\bar{f} = 241.35$$

Adaptive POD basis computation

Add k frequencies per frequency interval:

- 1: Choose frequency grid $\mathcal{F}^0 = \{f_j\}_{j=1}^n$, number ℓ of POD functions and number m of frequency intervals;
- 2: **for** $i = 1, \dots, m$ **do**
- 3: Compute optimal frequencies $\{f_j^i\}_{j=1}^k$;
- 4: Set $\mathcal{F}^i = \mathcal{F}^{i-1} \cup \{f_j^i\}_{j=1}^k$;
- 5: Enlarge $\ell = \ell + 1$;
- 6: **end for**

Numerical results

- **Frequency grid:** $\mathcal{F}^0 = \{199 + j\}_{j=1}^{26} \subset [200, 225]$
- **Additional frequency intervals:** $m = 5$, more precisely $[225, 250]$, $[250, 275]$, $[275, 300]$, $[300, 325]$, $[325, 350]$
- **Comparison of different strategies:** $\beta = \int_{200}^{350} \|p_f\|^2 df$

| Snapshot strategy | $\frac{1}{2\beta} \int_{200}^{350} \ p_f - p_f^\ell\ ^2 df$ |
|-----------------------------------|---|
| Add $\{f_1^i\}$ | 0.0967 |
| Add $\{f_1^i, f_2^i\}$ | 0.0092 |
| Add $\{224 + j\}_{j=1}^{26}$ etc. | 0.0077 |
| Add the mean values | 0.1381 |
| No additional snapshots | 0.2804 |

References

- Hömberg/V.'03: Control of laser surface hardening by a reduced-order approach using POD
- Kahlbacher/V.'07: Galerkin POD methods for parameter dependent elliptic systems
- Kunisch/V.'01: Galerkin POD methods for parabolic problems
- Kunisch/V.'02: Galerkin POD methods for a general equation in fluid dynamics
- Kunisch/V.'10: Optimal snapshot location for computing POD basis functions
- Lass/V.'11: POD Galerkin schemes for nonlinear elliptic-parabolic systems
- Müller/V.'06: Model reduction by POD for λ - ω systems
- V.'09: Model Reduction using POD. Lecture notes