



Model Order Reduction for Boundary Condition Estimation in Casting Machinery

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Reduced Order Modelling, Simulation and
Optimization of Coupled Systems
(ROMSOC)

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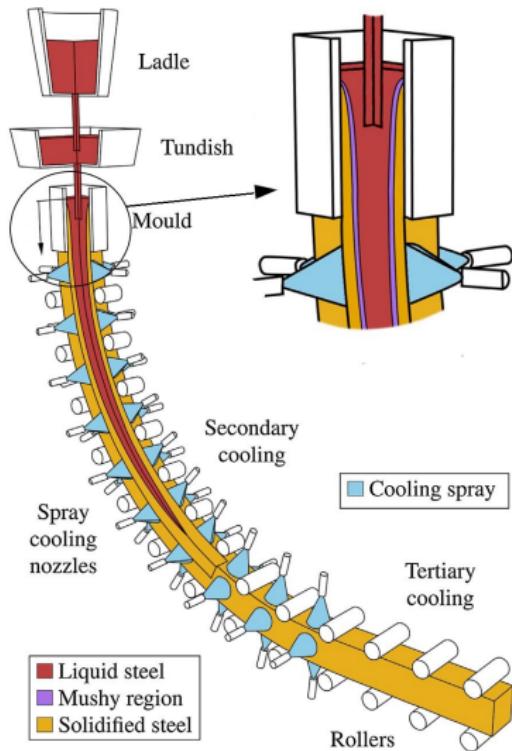
1 Introduction

2 Full Order Direct Problem

3 Full Order Inverse Problem

4 Reduced Order Inverse Problem

Motivation

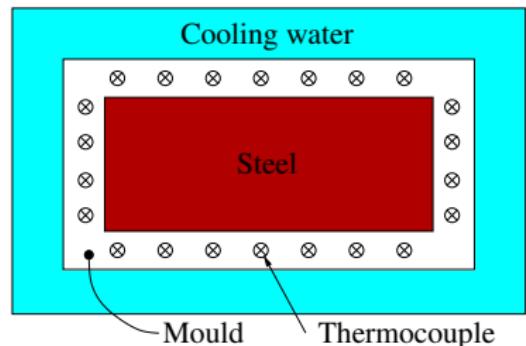


Credits: [4]

- Control mould behaviour
- Improve production quality
- Predict and avoid catastrophic events
- Increase machinery operative life

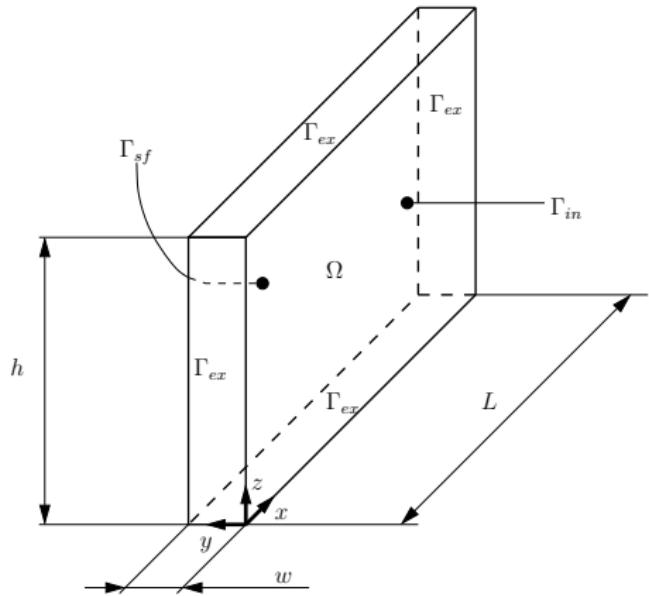


Real time boundary heat flux computation



- 1 Introduction
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- Steady-state thermal model
- Homogeneous and isotropic material
- Solid domain, Ω



Direct problem

Given $k \in \mathbb{R}^+$, $h \in \mathbb{R}^+$, $\textcolor{brown}{g} \in L^2(\Gamma_{in})$ and $T_f \in L^2(\Gamma_{in})$. Find T such that

$$-k\Delta T(\mathbf{x}) = 0, \quad \forall \mathbf{x} \in \Omega,$$

$$\begin{cases} -k\nabla T(\mathbf{x}) \cdot \mathbf{n} = \textcolor{brown}{g}(\mathbf{x}) & \forall \mathbf{x} \in \Gamma_{in}, \\ -k\nabla T(\mathbf{x}) \cdot \mathbf{n} = 0 & \forall \mathbf{x} \in \Gamma_{ex}, \\ -k\nabla T(\mathbf{x}) \cdot \mathbf{n} = h(T(\mathbf{x}) - T_f(\mathbf{x})) & \forall \mathbf{x} \in \Gamma_{sf}, \end{cases}$$

Discretization by Finite Volumes Method

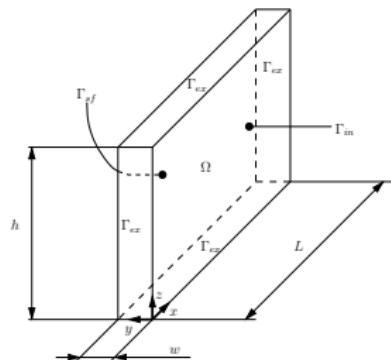
For any cell, C , of the mesh, \mathcal{T}

$$-k \sum_{\sigma \in \mathcal{E}_C \setminus \Gamma} F_{C,\sigma} + \sum_{\sigma \in \mathcal{E}_C \cap \Gamma_{sf}} R_\sigma T_C = \sum_{\sigma \in \mathcal{E}_C \cap \Gamma_{sf}} R_\sigma T_{f_\sigma} - \sum_{\sigma \in \mathcal{E}_C \cap \Gamma_{in}} m(\sigma) \mathbf{g}_\sigma,$$

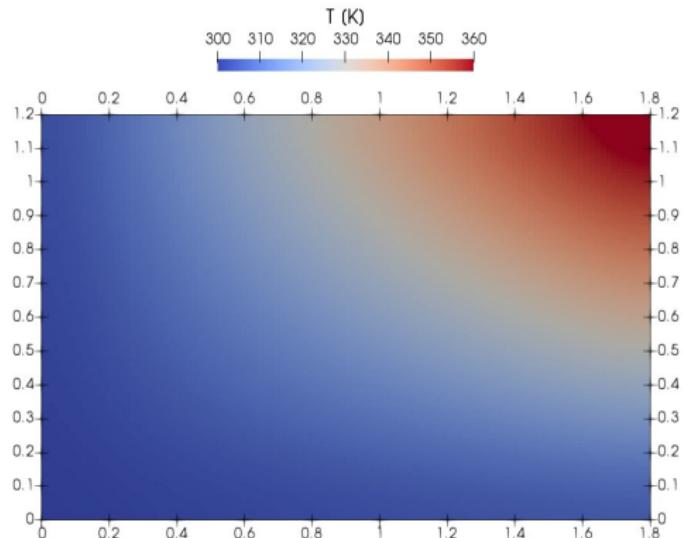
where

- ▶ \mathcal{E}_C is the set of faces of the cell C , σ is the single face
- ▶ $F_{C,\sigma} := m(\sigma) \frac{T_L - T_C}{d_{C,L}}$
- ▶ $R_\sigma := \frac{hk}{hd_{C,\sigma} + k}$

Results



Parameter	Value
k	$300 \frac{\text{W}}{\text{m K}}$
g	$-x \cdot y \cdot 10^5 \frac{\text{W}}{\text{m}^2}$
h	$6 \cdot 10^3 \frac{\text{W}}{\text{m}^2\text{K}}$
T_f	300K
Grid type	Hexahedral, orthogonal
Grid size	$3 \cdot 10^5$



Numerical solution at $y = 0.5$ m.

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Inverse problem

Given the temperature measurements $\tilde{T}(\mathbf{x}_i) \in \mathbb{R}^+, i = 1, 2, \dots, M$, find $\mathbf{g}(\mathbf{x}) \in L^2(\Gamma_{in})$ which minimizes the functional

$$J[\mathbf{g}] = \frac{1}{2} \sum_{i=1}^M [T[\mathbf{g}](\mathbf{x}_i) - \tilde{T}(\mathbf{x}_i)]^2,$$

where $T[\mathbf{g}](\mathbf{x})$ is solution of the direct problem.

- Thermocouples measurements within the domain
- Deterministic least-square approach
- Ill-posed problem
- Alifanov's regularization

- 1 Set $\mathbf{g}^0(\mathbf{x})$;
 - 2 **while** $n \leq nMax$ **do**
 - 3 Solve direct problem;
 - 4 Compute J ;
 - 5 **if** $J \leq Jtol$ **then**
 - 6 Stop;
 - 7 Solve adjoint problem;
 - 8
$$\gamma^n = \frac{\int_{\Gamma_{s_{in}}} [J'_{g^n}(\mathbf{x})]^2 d\mathbf{x}}{\int_{\Gamma_{s_{in}}} [J'_{g^{n-1}}(\mathbf{x})]^2 d\mathbf{x}}$$
;
 - 9 Search direction, $P^n(\mathbf{x}) = J'_{g^n}(\mathbf{x}) + \gamma^n P^{n-1}(\mathbf{x})$;
 - 10 Solve sensitivity problem;
 - 11
$$\beta^n = \arg \min_{\beta} J[\mathbf{g}^n - \beta P^n] = \frac{\sum_{i=1}^M \{ T[\mathbf{g}^n](\mathbf{x}_i) - \hat{T}(\mathbf{x}_i) \} \delta T[P^n](\mathbf{x}_i)}{\sum_{i=1}^M (\delta T[P^n](\mathbf{x}_i))^2}$$
;
 - 12 $\mathbf{g}^{n+1} = \mathbf{g}^n - \beta^n P^n$;
 - 13 $n = n + 1$;
-

It is a conjugate gradient method applied to the adjoint problem.

The solution of the adjoint problem is the gradient of J evaluated at g , so it gives us the search direction

Adjoint problem

$$\frac{1}{k} \Delta \lambda(\mathbf{x}) + \sum_{i=1}^M (T[g](\mathbf{x}_i) - \tilde{T}(\mathbf{x}_i)) \delta(\mathbf{x} - \mathbf{x}_i) = 0, \quad \forall \mathbf{x} \in \Omega,$$

$$\begin{cases} \frac{1}{k} \nabla \lambda(\mathbf{x}) \cdot \mathbf{n} = 0 & \forall \mathbf{x} \in \Gamma_{in} \cup \Gamma_{ex}, \\ \frac{1}{k} \nabla \lambda(\mathbf{x}) \cdot \mathbf{n} + \frac{1}{k^2} h \lambda(\mathbf{x}) = 0 & \forall \mathbf{x} \in \Gamma_{sf}. \end{cases}$$

It is a conjugate gradient method applied to the adjoint problem.

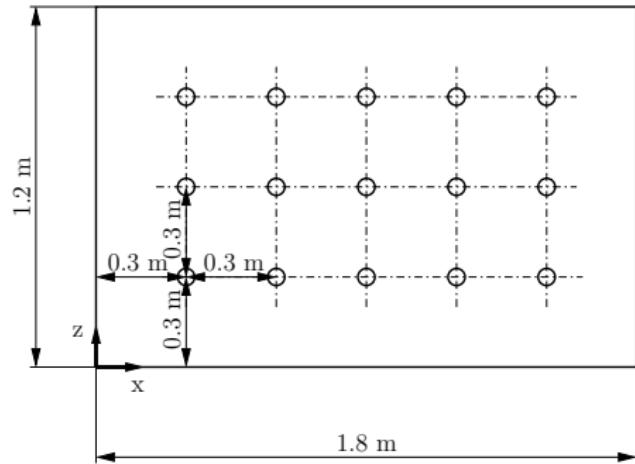
The step size along the search direction is given by the solution of the sensitivity problem

Sensitivity problem

$$-k\Delta\delta T(\mathbf{x}) = 0, \quad \forall \mathbf{x} \in \Omega,$$

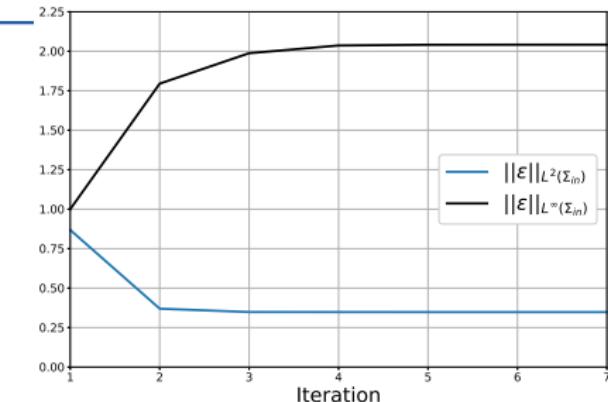
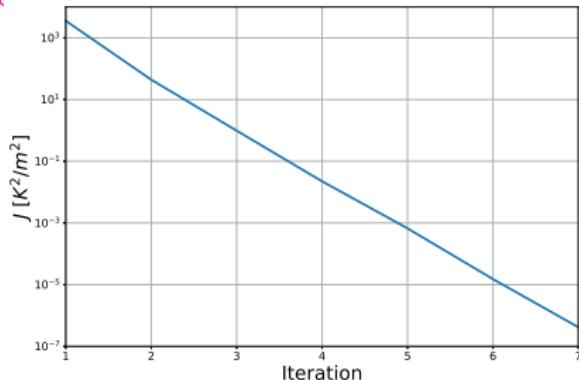
$$\begin{cases} -k\nabla\delta T(\mathbf{x}) \cdot \mathbf{n} = P^n(\mathbf{x}) & \forall \mathbf{x} \in \Gamma_{in}, \\ -k\nabla\delta T(\mathbf{x}) \cdot \mathbf{n} = 0 & \forall \mathbf{x} \in \Gamma_{ex}, \\ -k\nabla\delta T(\mathbf{x}) \cdot \mathbf{n} = h(\delta T(\mathbf{x})) & \forall \mathbf{x} \in \Gamma_{sf}. \end{cases}$$

- We want to estimate \mathbf{g} at Γ_{in}
- Finite Volume discretization for all problems
- Virtual thermocouples
- Measurements \tilde{T} taken from solution of the direct problem

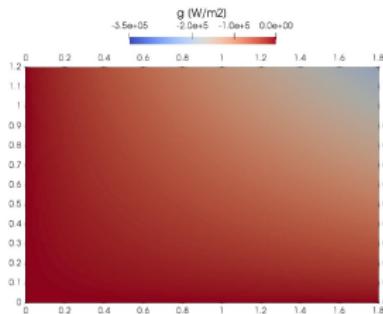


Thermocouples locations at the middleplane
of the plate

Results

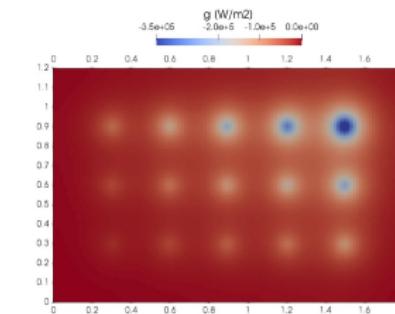


Convergence of the cost function J

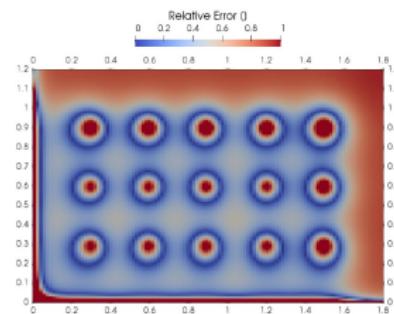


$$g(x) = -x \cdot y \cdot 10^5$$

L^2 and L^∞ norm of the relative error, ϵ



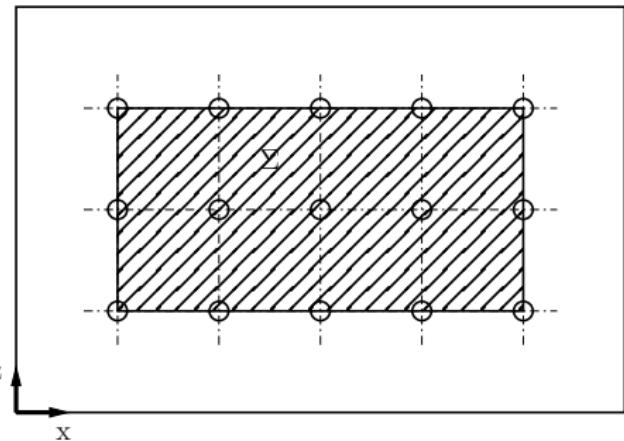
Reconstructed BC



Relative error, ϵ

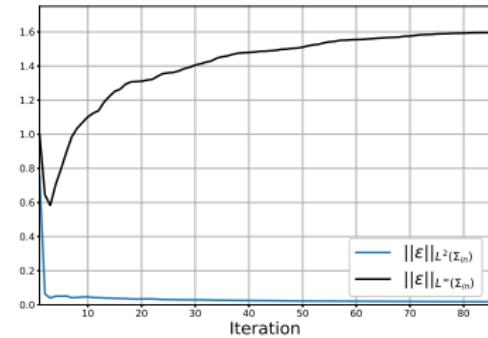
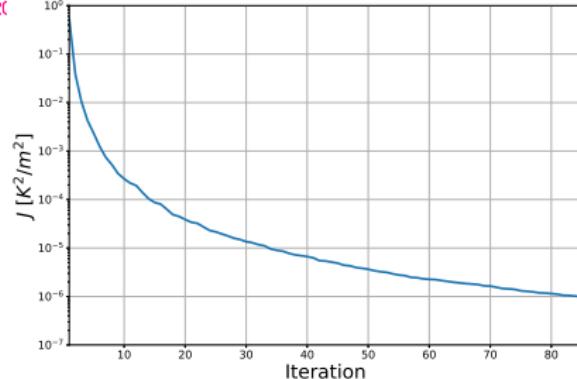
- Radial Basis Function interpolation

$$\begin{aligned}\tilde{T}(\mathbf{x}_i), i = 1, 2, \dots, M \\ \Downarrow \\ \tilde{T}(\mathbf{x}) \forall \mathbf{x} \in \Sigma\end{aligned}$$

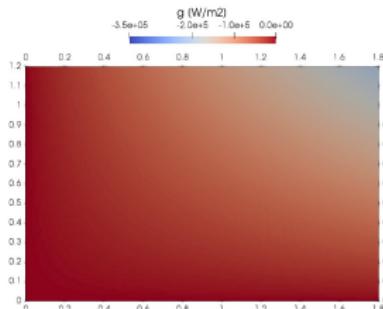


Measurements		Cost functional
$\tilde{T}(\mathbf{x}_i), i = 1, 2, \dots, M$	\Downarrow	$J[g] = \frac{1}{2} \sum_{i=1}^M [\mathcal{T}[g](\mathbf{x}_i) - \tilde{T}(\mathbf{x}_i)]^2$
$\tilde{T}_{int}(\mathbf{x}) \forall \mathbf{x} \in \Sigma$	\Downarrow	$J[g] = \frac{1}{2} \int_{\Sigma} (\mathcal{T}[g](\mathbf{x}) - \tilde{T}_{int}(\mathbf{x}))^2 d\gamma$

Results

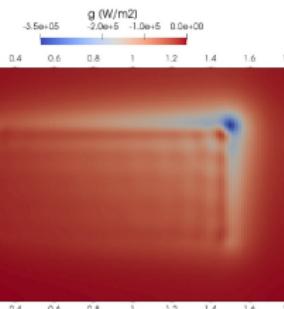


Convergence of the cost function J

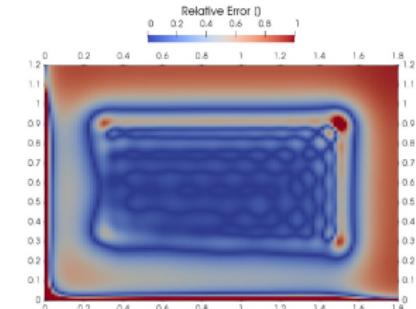


$$g(x) = -x \cdot y \cdot 10^5$$

L^2 and L^∞ norm of the relative error, ϵ



Reconstructed BC



Relative error, ϵ

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- Parameters are the temperature measurements $\tilde{\mathbf{T}} \in \mathbb{R}^M$
- Solve the inverse problem for different values of the parameters
- At each iteration obtain a solution (snapshot) for \mathbf{T} , λ and $\delta\mathbf{T}$

$$\mathbb{V}_T = \text{span}(\mathbf{T}_1, \mathbf{T}_2, \dots, \mathbf{T}_S), \quad \mathbb{V}_\lambda = \text{span}(\lambda_1, \lambda_2, \dots, \lambda_S),$$

$$\mathbb{V}_{\delta T} = \text{span}(\delta\mathbf{T}_1, \delta\mathbf{T}_2, \dots, \delta\mathbf{T}_S)$$

- POD on solution spaces to obtain orthonormal basis ϕ, φ, ψ

$$\mathbb{V}_T = \text{span}(\phi_1, \phi_2, \dots, \phi_S), \quad \mathbb{V}_\lambda = \text{span}(\varphi_1, \varphi_2, \dots, \varphi_S),$$

$$\mathbb{V}_{\delta T} = \text{span}(\psi_1, \psi_2, \dots, \psi_S)$$

- Select the first few modes for each problem to have a reduced basis spaces $\mathbb{V}_{T_{RB}}$, $\mathbb{V}_{\lambda_{RB}}$, $\mathbb{V}_{\delta T_{RB}}$

$$\mathbb{V}_{T_{RB}} = \text{span}(\phi_1, \phi_2, \dots, \phi_{N_T}) \quad \mathbb{V}_{\lambda_{RB}} = \text{span}(\varphi_1, \varphi_2, \dots, \varphi_{N_\lambda})$$

$$\mathbb{V}_{\delta T_{RB}} = \text{span}(\psi_1, \psi_2, \dots, \psi_{N_{\delta T}})$$

- Approximation of full order fields by linear combinations of the modes

$$T \approx \sum_{i=1}^{N_T} d_i \phi_i \quad \lambda \approx \sum_{j=1}^{N_\lambda} a_j \varphi_j \quad \delta T \approx \sum_{k=1}^{N_{\delta T}} s_k \psi_k$$

- Galerkin projection of the full order models on these basis to obtain reduced models

$$L_T := \begin{bmatrix} | & & | \\ \boldsymbol{\phi}_1 & \dots & \boldsymbol{\phi}_{N_T} \\ | & & | \end{bmatrix} \in \mathbb{R}^{N_h \times N_T}, L_\lambda := \begin{bmatrix} | & & | \\ \boldsymbol{\varphi}_1 & \dots & \boldsymbol{\varphi}_{N_\lambda} \\ | & & | \end{bmatrix} \in \mathbb{R}^{N_h \times N_\lambda}$$

$$L_{\delta T} := \begin{bmatrix} | & & | \\ \boldsymbol{\psi}_1 & \dots & \boldsymbol{\psi}_{N_{\delta T}} \\ | & & | \end{bmatrix} \in \mathbb{R}^{N_h \times N_{\delta T}}$$

Full order

$$\begin{array}{lll} A_T \mathbf{T} = \mathbf{b}_T & L_T^T A_T L_T \mathbf{d} = L_T^T \mathbf{b}_T & A_{T_r} \mathbf{d} = \mathbf{b}_{T_r} \\ A_\lambda \boldsymbol{\lambda} = \mathbf{b}_\lambda & L_\lambda^T A_\lambda L_\lambda \mathbf{a} = L_\lambda^T \mathbf{b}_\lambda & A_{\lambda_r} \mathbf{a} = \mathbf{b}_{\lambda_r} \\ A_{\delta T} \delta \mathbf{T}_r = \mathbf{b}_{\delta T} & L_{\delta T}^T A_{\delta T} L_{\delta T} \delta \mathbf{T}_r = L_{\delta T}^T \mathbf{b}_{\delta T_g} & A_{\delta T_r} \mathbf{s} = \mathbf{b}_{\delta T_r} \end{array}$$

Reduced order

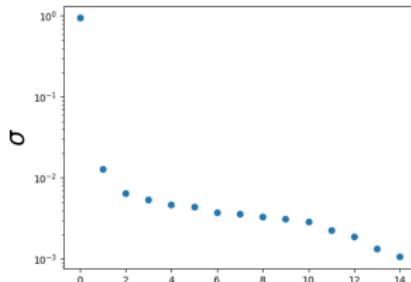
- ▶ Offline
 - Solve full problem, obtain snapshots
 - Perform POD on snapshots
 - Assemble linear systems
- ▶ Online
 - Solve reduced conjugate gradient



10 samples per 15 parameters $\rightarrow 10^{15}$ full order inverse problem solutions

Experimental temperature measurements available $\tilde{T}(\mathbf{x}_{TC}, t_i)$

$$Q := \begin{bmatrix} - & \tilde{T}_1 & - \\ - & \vdots & - \\ - & \tilde{T}_M & - \end{bmatrix}, \quad Q = U^T \Sigma V,$$

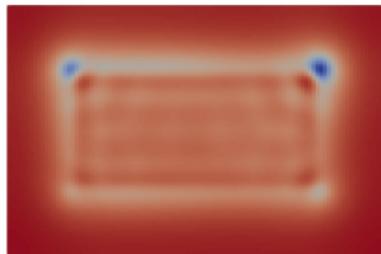


Singular values

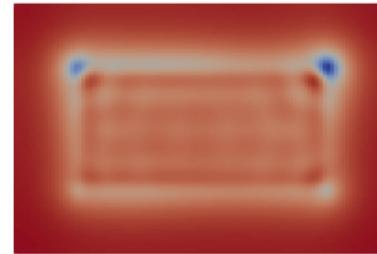
$$\tilde{T} = \sum_{i=1}^{N_{\tilde{T}}} c_i \theta_i,$$

where θ_i is the i -th column of U

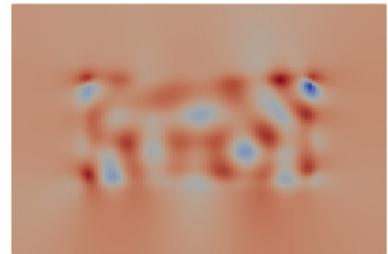
Results



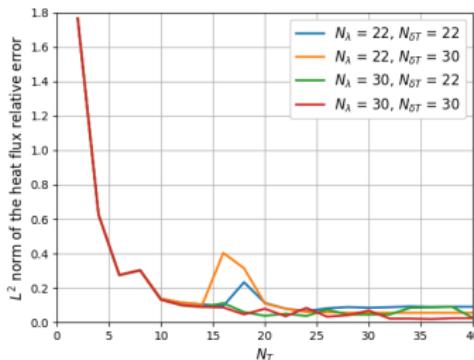
Full order



Reduced order



Relative error



Full	240s
Reduced	2s
Speedup	120

$N_T = 60, N_\lambda = 40, N_{\delta T} = 40$

Conclusions

- Implemented full order methodology
- Developed reduced method for inverse problem

Future Work

- Error estimate
- Study noise on input
- Bayesian approach

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-  Jan S Hesthaven, Gianluigi Rozza, Benjamin Stamm, et al. *Certified reduced basis methods for parametrized partial differential equations*. Springer, 2016.
-  Lubomír Klimeš and Josef Štětina. "A rapid GPU-based heat transfer and solidification model for dynamic computer simulations of continuous steel casting". In: *Journal of Materials Processing Technology* 226 (2015), pp. 1–14.



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Thank you