



### A Globally Mass Conservative Nonlinear Reduced Basis Method for Parabolic Free Boundary Problems

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### Outline

- 1. Reduced Basis Methods for Advection Dominated Problems.
- A Globally Mass Conservative Nonlinear Reduced Basis Method for Parabolic Free Boundary Problems.



# Reduced Basis Methods for Advection Dominated Problems



### Parametric Model Order Reduction

Consider time-dependent parametric problems

$$\Phi: \mathcal{P} \to X([0,T]; V_h), \qquad s: X([0,T]; V_h) \to \mathbb{R}^S$$

where

- $ightharpoonup \mathcal{P} \subset \mathbb{R}^P$  parameter domain.
- ▶  $V_h$  "truth" solution state space, dim  $V_h \gg 0$ .
- Φ maps parameters to solutions (hard to compute).
- s maps state vectors to quantities of interest.

#### Objective

Compute

$$s \circ \Phi : \mathbb{R}^P \to X([0, T]; V_h) \to \mathbb{R}^S$$

for many  $\mu \in \mathcal{P}$  or quickly for unknown single  $\mu \in \mathcal{P}$ .



### Reduced Basis Methods: Three Basic Ideas

#### Objective

Compute

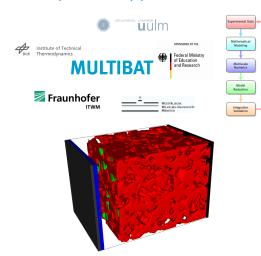
$$s \circ \Phi : \mathbb{R}^P \to X([0, T]; V_h) \to \mathbb{R}^S$$

When  $\Phi$ , s sufficiently smooth, quickly computable low-dimensional approximation of  $s \circ \Phi$  should exist.

- ▶ **Idea 1:** State space projection:
  - ▶ Define approximation  $\Phi_N : \mathcal{P} \to X([0, T]; V_N), N := \dim V_N \ll \dim V_h$ , via (Petrov-)Galerkin projection.
  - ▶ Approximate  $s \circ \Phi \approx s \circ \Phi_N$ .
- ▶ **Idea 2:** Construct  $V_N$  from PODs of solution snapshots  $\Phi(\mu_1), \ldots, \Phi(\mu_k)$ .
- ▶ **Idea 3:** Select  $\mu_1, \ldots, \mu_k$  iteratively via greedy search over  $\mathcal{P}$  using quickly computable surrogate  $\eta(\Phi_N(\mu), \mu) \geq \|\Phi(\mu) \Phi_N(\mu)\|$  (POD-GREEDY).
- + Hyper-reduction technique (EIM, DEIM, GEIM, Gappy POD, ...)



### Example: RB Approximation of Li-Ion Battery Models



MULTIBAT: Gain understanding of degradation processes in rechargeable Li-Ion Batteries through mathematical modeling and simulation at the pore scale.

#### Full order model:

- 2.920.000 DOFs
- ► Simulation time:  $\approx$  13h

#### Reduced order model:

- Snapshots: 3
- dim  $V_N = 145$
- ▶ Rel. err.:  $< 1.5 \cdot 10^{-3}$
- Reduction time:  $\approx$  9h
- ► Simulation time:  $\approx$  5m
- Speedup: 154

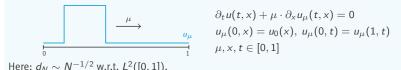


### Trouble with Advection Dominated Problems

Typically slow decay of Kolmogorov N-widths  $d_N$  of the solution manifold, but RB will only work well for rapid decay!

$$d_N := \inf_{\substack{V_N \subseteq V_h \\ \dim V_N \le N}} \sup_{\substack{u \in \Phi(\mathcal{P}) \\ t \in [0, T]}} \|u(t) - \frac{P_{V_N}(u(t))\|.$$

#### Basic example



However: We can describe solution easily as

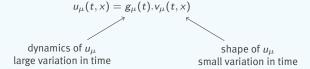
$$u_{\mu}(t,x) = u_0(x - \mu \cdot t \mod 1).$$



### Nonlinear Approximation

#### General Idea

Write  $u_{\mu}(t,x)$  as



where  $\mathcal{V}$  function space,  $v_{\mu}(t) \in \mathcal{V}$  and  $g_{\mu}(t)$  is element of Lie group G acting on  $\mathcal{V}$ .

- $\triangleright$   $v_{\mu}(t,x)$  should be easier to approximate by a linear space than  $u_{\mu}(t,x)$ !
- Related/other approaches: [Rowley, Marsden, 2000] [Gerbeau, Lombardi, 2014] [Iollo, Lombardi, 2014] [Carlberg, 2015] [Taddei, Perotto, Quarteroni, 2015] [Reiss, Schulze, Sesterhenn, Mehrmann, 2015] [Cagniart, Maday, Stamm, 2016] [Nair, Balajewicz, 2017] [Welper, 2017] [Rim, Moe, LeVeque, 2018] . . .



### Method of Freezing [Beyn, Thümmler, 2004], [Rowley et. al., 2000, 2003]

#### Definition (Method of Freezing)

With initial conditions  $v_{\mu}(0) = u(0), g_{\mu}(0) = e$ , solve:

$$\partial_t v_\mu(t) + \mathcal{L}_\mu(v_\mu(t)) + \mathfrak{g}_\mu(t) \cdot v_\mu(t) = 0$$
  
 $\Phi(v_\mu(t), \mathfrak{g}_\mu(t)) = 0$ 

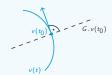
 $g_{\mu}(t) = g(t)_{\mu}^{-1} \partial_t g_{\mu}(t)$ 

frozen PDAE

reconstruction equation

### Orthogonality phase condition

$$\begin{split} \Phi(v,\mathfrak{g}) &= 0 \iff \partial_t v(t) \perp G.v(t) \\ &\iff (\mathcal{L}(v) + \mathfrak{g}.v, \, \mathfrak{h}.v) = 0 \quad \forall \mathfrak{h} \in G \end{split}$$





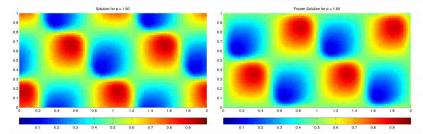
### **Test Problem**

#### 2D Burgers-type problem

Solve on  $\Omega = [0,2] \times [0,1]$  with periodic boundaries,  $t \in [0,0.3]$ ,  $\vec{v} \in \mathbb{R}^2$  and  $\mu \in [1,2]$ :

$$\begin{split} \partial_t u + \nabla \cdot (\vec{v} \cdot u^\mu) &= 0 \\ u(0, x_1, x_2) &= 1/2(1 + \sin(2\pi x_1)\sin(2\pi x_2)) \end{split}$$

Let  $G := \mathbb{R}^2$  act on u by periodic shifts.





### Combining RB with the Method of Freezing

#### FrozenRB-Scheme for 2D-shifts [Ohlberger, R, 2013]

Solve

$$\begin{split} \partial_t v_{\mu(t),N} + & \textbf{\textit{P}}_{\textbf{\textit{V}}_{\textbf{\textit{N}}}} \circ \textbf{\textit{I}}_{\textbf{\textit{M}}}[\mathcal{L}_{\mu}](v_{\mu,N}(t)) - \mathfrak{g}_{\mu(t),N} \cdot (\textbf{\textit{P}}_{\textbf{\textit{V}}_{\textbf{\textit{N}}}} \circ \nabla)(v_{\mu,N}(t)) = 0 \\ & \left[ (\partial_{x_i} v_{\mu,N}, \, \partial_{x_j} v_{\mu,N}) \right]_{i,j} \cdot \left[ \mathfrak{g}_{\mu,N} \right]_j = \left[ (\textbf{\textit{I}}_{\textbf{\textit{M}}}[\mathcal{L}_{\mu}](v_{\mu}), \, \partial_{x_i} v_{\mu,N}) \right]_i \end{split}$$

and

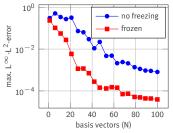
$$\partial_t g_\mu(t) = \mathfrak{g}_\mu(t)$$

with initial conditions  $v_{\mu}(0) = u(0)$ ,  $g_{\mu}(0) = (0,0)^{T}$ .

- ► EI-GREEDY, POD-GREEDY algorithms for basis generation.
- ► Full offline/online decomposition.
- ▶ No additional evaluations of nonlinearity.



### Results for the Burgers Problem

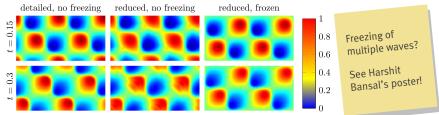


#### Left:

- ▶ 1.9 · *N* interpolation points.
- ▶ Test set: 100 random  $\mu$ .

#### Bottom:

- dim  $V_N = 20$ , 38 interpolation points.
- $\mu = 1.5.$





# A Globally Mass Conservative Nonlinear Reduced Basis Method for Parabolic Free Boundary Problems

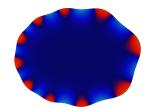


### A Free Boundary Problem

#### Osmotic cell swelling model [Lippoth, Prokert, 2012]

Given  $\Omega(0) \subset \mathbb{R}^d$ ,  $u(0) \in H^1(\Omega(0))$  and coefficients  $u_0, \alpha, \beta, \gamma \in \mathbb{R}$ , the **concentration** u(t) and **normal velocity**  $\mathcal{V}_n$  of  $\partial\Omega(t)$  is given by:

$$\begin{array}{ll} \partial_t u - \alpha \Delta u = 0 & \text{in } \Omega(t) \\ \mathcal{V}_n u + \alpha \partial_n u = 0 & \text{on } \partial \Omega(t) \\ -\beta H + \gamma (u - u_0) = \mathcal{V}_n & \text{on } \partial \Omega(t) \end{array}$$



- $u_0$ : constant concentration in  $\Omega(t)^c$
- ► H: mean curvature of  $\partial Ω(t)$
- $\triangleright \alpha$ : diffusivity of u
- ►  $-\beta H$ : surface tension
- $\gamma(u-u_0)$ : osmotic pressure

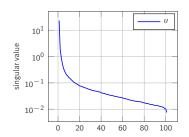


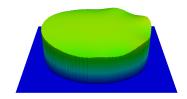
### **Eulerian Approximation**

- ► Consider  $u(t) \in L^2(\Omega(t)) \hookrightarrow L^2(\mathbb{R}^d)$  as joint approximation space.
- moving domain boundary

 $\Longrightarrow$  moving discontinuity in u(t)

 $\implies$  slow singular value decay





#### Idea

Use nonlinear transformation

$$\Psi(t).u(t)(x):=u(t)[\Psi(t)[x]]$$

to freeze boundary  $\Gamma(t)$  in space.

Fix reference domain

$$\hat{\Omega} := \Psi(t)^{-1}(\Omega(t)).$$



### **ALE Formulation**

Fix reference domain  $\widehat{\Omega}$  and introduce deformation field  $\Psi(t)$  s.t.  $\Psi(t)(\widehat{\Omega}) = \Omega(t)$ . Pulling back the equations to  $\widehat{\Omega}$  leads to the following time-discretization scheme:

1. Compute boundary velocity:

$$\begin{split} \int_{\hat{\Gamma}} J_{\Gamma} \hat{V}_{\Gamma}^{n-1} \cdot \hat{s} \, ds + \Delta t \int_{\hat{\Gamma}} J_{\Gamma} \beta \left( (F^{n-1})^{-T} \nabla_{\hat{\Gamma}} \hat{V}_{\Gamma}^{n-1} \right) : \left( (F^{n-1})^{-T} \nabla_{\hat{\Gamma}} \hat{s} \right) \, ds \\ = \int_{\hat{\Gamma}} \beta (P : (F^{n-1})^{-T} \nabla_{\hat{\Gamma}} \hat{s} + \gamma (\hat{u} - u_{\text{ext}}) \hat{s} \cdot ((F^{n-1})^{-T} \hat{v})) \, ds. \end{split}$$

2. Extend velocity to interior via harmonic extension:

$$\int_{\hat{\Gamma}} \frac{1}{h} (\nabla \hat{V}^{n-1} + (\nabla \hat{V}^{n-1})^T) : (\nabla \hat{s} + (\nabla \hat{s})^T) dx = 0, \qquad \hat{V}^{n-1} = \hat{V}_{\Gamma}^{n-1} \quad \text{on } \partial \hat{\Omega}.$$

3. Update deformation field:

$$\Psi^n = \Psi^{n-1} + \Delta t \hat{V}^{n-1}.$$

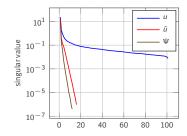
4. Update concentration field:

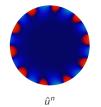
$$\begin{split} \int_{\hat{\Omega}} J^n \; \hat{u}^n \hat{v} \; dx + \Delta t \int_{\hat{\Omega}} J^n \; \hat{u}^n \; V_h^{n-1} \cdot ((F^n)^{-T} \nabla \hat{v}) dx \\ &+ \Delta t \int_{\hat{\Omega}} J^n \; \alpha \left( (F^n)^{-T} \nabla \hat{u}^n \right) \cdot ((F^n)^{-T} \nabla \hat{v}) \; dx = \int_{\hat{\Omega}} J^{n-1} \; \hat{u}^{n-1} \hat{v} \; dx. \end{split}$$



### **ALE Formulation**

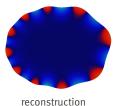
- Rapid singular value decay of both concentration and deformation fields.
- After space discretization this corresponds to moving-mesh approach (ALE), where  $\Psi^n(v)$  is the trajectory of the vertex v.
- In contrast to "parameterized domain problems", the domain deformation  $\Psi^n$  is part of the equation system.













### Nonlinear RBM for Free Boundary Problems

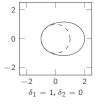
Use standard RB machinery to construct ROM:

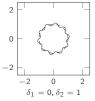
- Compute low-rank approximation spaces for  $\hat{u}^n$ ,  $\Psi^n$ ,  $\hat{V}^n_{\Gamma}$  via POD. (Could also use POD-GREEDY).
- Use EIM to approximate coefficient functions, vectors, tensors depending nonlinearly on  $\Psi^n$ .
- ► Similar to [Ballarin, Rozza, 2016] in context of FSI.

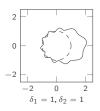


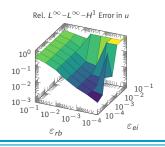
### **Numerical Experiment**

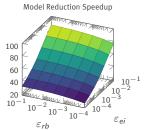
- Parameterization:
  - $\alpha \in [0.1, 1]$
  - $\beta \in [0.01, 0.1]$
  - $\qquad \qquad \bullet_1, \delta_2 \in [0,1]$
- ► Snapshots: 3<sup>4</sup>
- FOM: 3988 + 7976 DOFS

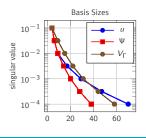














### **Global Mass Conservation**

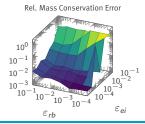
#### Concentration update

$$\begin{split} \int_{\hat{\Omega}} J^n \; \hat{u}^n \hat{v} \; dx + \Delta t \int_{\hat{\Omega}} J^n \; \hat{u}^n \; V_h^{n-1} \cdot \left( (F^n)^{-T} \nabla \hat{v} \right) dx \\ &+ \Delta t \int_{\hat{\Omega}} J^n \; \alpha \left( (F^n)^{-T} \nabla \hat{u}^n \right) \cdot \left( (F^n)^{-T} \nabla \hat{v} \right) \, dx = \int_{\hat{\Omega}} J^{n-1} \; \hat{u}^{n-1} \hat{v} \; dx. \end{split}$$

► Testing with  $\hat{v} \equiv 1$  yields:

$$\int_{\Omega^n} u^n \, dx = \int_{\hat{\Omega}} J^n \, \hat{u}^n \, dx + 0 + 0 = \int_{\hat{\Omega}} J^{n-1} \, \hat{u}^n = \int_{\Omega^{n-1}} u^{n-1} \, dx$$

- Mass conservation is preserved by RB projection by adding 1 to RB for u<sup>n</sup>.
- Inexact assembly of mass matrix due to El destroys mass conservation.





### Global Mass Conservation with El

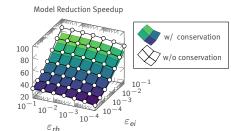
Note that in 2D:

$$\int_{\hat{\Omega}} J^n \, \hat{u}^n \hat{v} = m(\Psi^n, \Psi^n, \hat{u}^n, \hat{v}),$$

where

$$m(\Phi^n, \Psi^n, \hat{u}^n, \hat{v}) = \int_{\hat{O}} \partial_x \Phi_x^n \cdot \partial_y \Psi_y^n \cdot \hat{u}^n \cdot \hat{v} + \partial_x \Phi_y^n \cdot \partial_y \Psi_x^n \cdot \hat{u}^n \cdot \hat{v} \, dx.$$

- ► Could assemble mass matrix 4-tensor exactly.
- ► Relatively expensive. (dim RB = 30 ⇒ 6MB for reduced tensor)
- 5-tensor in 3D!
- Better approach:
  - 1. Assemble mass matrix using El.
  - 2. Assemble 3-tensor  $m(\Phi^n, \Psi^n, \hat{u}^n, 1)$  exactly and set corresponding row of mass matrix.





### Outlook: Remeshing

Strongly anisotropic mesh deformations in ALE schemes lead to:

- bad approximation spaces.
- ill-conditioned system matrices.

#### Possible MOR approach:

- In FOM: Locally adapt mesh  $\hat{T}_h$  on  $\hat{\Omega}$  s.t.  $\Psi^n(\hat{T}_h)$  has good shape regularity properties.
- Solve extension problem for  $\hat{V}_{\Gamma}^n$  on  $\Omega^n$  instead of  $\hat{\Omega}$ .
- Use "RB for AFEM" methods to construct ROM [Ullmann, Rotkvic, Lang, 2016]
   [Yano 2016] [Ali, Steih, Urban, 2017] [Hinze, Gräßle, 2017].
- Deformation-dependent norms?
- Dictionary-based approaches?



## Thank you for your attention!

Ohlberger, R, Nonlinear reduced basis approximation of parameterized evolution equations via the method of freezing, C. R. Math. Acad. Sci. Paris, 351 (2013).

Ohlberger, R, *Reduced Basis Methods: Success, Limitations and Future Challenges*, Proceedings of ALGORITMY 2016.

Milk, R, Schindler, pyMOR – Generic Algorithms and Interfaces for Model Order Reduction SIAM J. Sci. Comput., 38(5), 2016. http://www.pymor.org/

My homepage (with FrozenRB code) http://stephanrave.de/