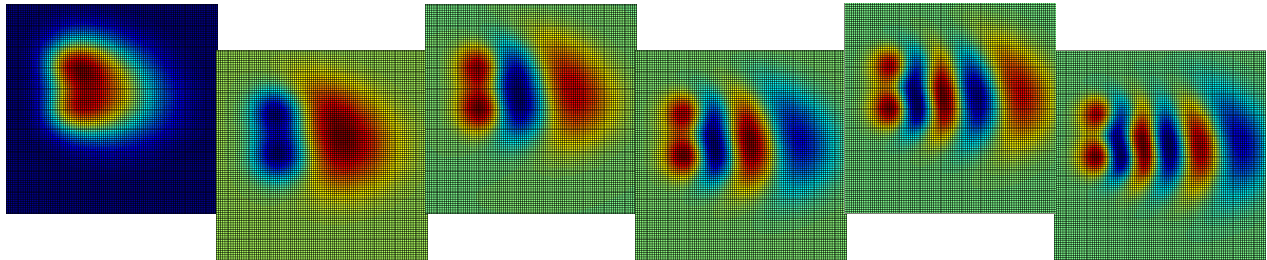
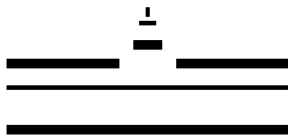


Adaptive Basis Enrichment for the Reduced Basis Method applied to Finite Volume Schemes



Bernard Haasdonk and Mario Ohlberger

FVCA5, Aussois, June 08-13, 2008



Outline

- Reduced Basis Method
- Adaptive Basis Enrichment
- Numerical Experiments
- Outlook

Reduced Basis Method for Parametrized Evolution Equations

[Haasdonk, Ohlberger '08], [Haasdonk, Ohlberger '08]

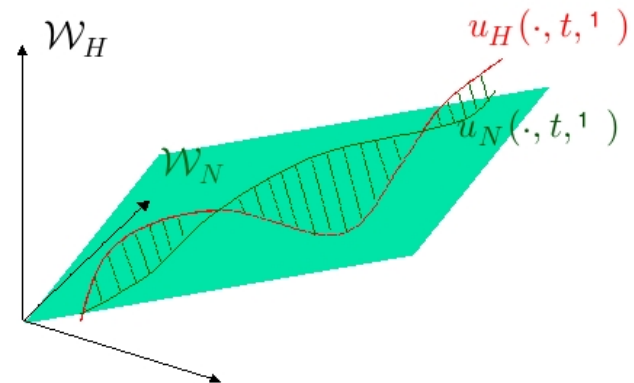
[Haasdonk, Ohlberger, Rozza '07]

Goal: Fast “Online”-Simulation of Complex Evolution Systems for

- Parameter Optimization
- Desig Optimization
- Optimal Control
- Integration into System Simulation

Ansatz:

- Reduced Basis Method (RB)
 $\dim(W_N) \ll \dim(W_H) !$



Example: Convection-Diffusion Problem

$$\partial_t c(\mu) + \nabla \cdot (\mathbf{v}(\mu)c(\mu) - d(\mu)\nabla u(\mu)) = 0 \quad \text{in } \Omega \times [0, T_{\max}],$$

$$c(\cdot, 0; \mu) = u_0(\mu) \quad \text{in } \Omega,$$

$$c(\mu) = b_{\text{dir}}(\mu) \quad \text{in } \Gamma_{\text{dir}} \times [0, T_{\max}],$$

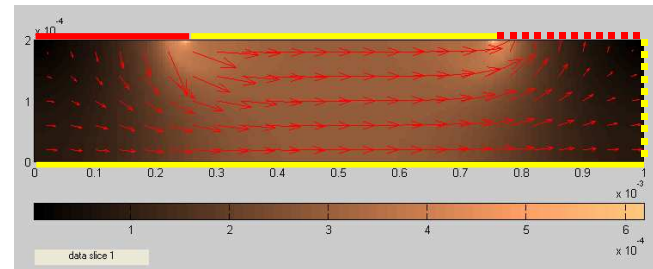
$$(\mathbf{v}(\mu)c(\mu) - d(\mu)\nabla c(\mu)) \cdot \mathbf{n} = b_{\text{neu}}(u; \mu) \quad \text{in } \Gamma_{\text{neu}} \times [0, T_{\max}].$$

Discretization by Finite Volumes $\implies \mathbf{c}_H(\mu) \in \mathbf{W}_H.$

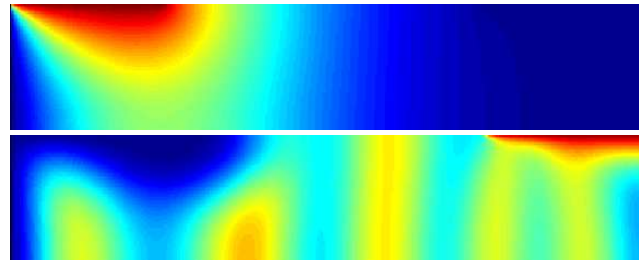
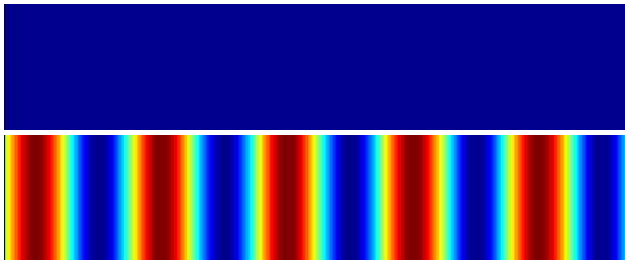
Example: Convection-Diffusion Problem

Parameter:

- Initial Data
- Boundary Values
- Diffusion Parameter



Possible Variations of the Solution:



Model Reduction: Reduced Basis Method

Goal: Find $c(\cdot, t; \mu) \in L^2(\Omega)$ for $t \in [0, T]$, $\mu \in P \subset \mathbb{R}^p$ with

$$\partial_t c(\mu) + L_\mu(c(\mu)) = 0 \quad \text{in } \Omega \times [0, T],$$

plus suitable Initial and Boundary Conditions.

Assumption: FV/DG Approximation $c_H(\mu) \in W_H$ for given Parameter μ

Ansatz (RB): Define low dimensional Subspace $W_N \subset W_H$
and project FV/DG Scheme onto the Subspace
 $\implies$ **RB Approximation** $c_N(\mu) \in W_N$.

Requirement:

- Efficient **Choice of** W_N (Exponential Convergence in N)
- **Offline–Online Decomposition** for fast Calculation of $c_N(\mu)$
- **Error Control** for $\|c_H(\mu) - c_N(\mu)\|$

Model Reduction: Reduced Basis Method

Assumption: FV/DG Scheme for Evolution Equations of the Form

$$c_H^0 = P[c_0(\mu)], \quad L_I^k(\mu)[c_H^{k+1}(\mu)] = L_E^k(\mu)[c_H^k(\mu)] + b^k(\mu).$$

with timestep counter k and $c_H^k(\mu) \in W_H$.

RB Method: Let $W_N \subset W_H$ be given, $\{\varphi_1, \dots, \varphi_N\}$ a ONB of W_N .
Sought: $c_N^k(\mu) = \sum_{n=1}^N a_n^k(\mu) \varphi_n$ with

$$\mathbf{L}_I^k(\mu) \mathbf{a}^{k+1} = \mathbf{L}_E^k(\mu) \mathbf{a}^k + \mathbf{b}^k(\mu).$$

We then have

$$\begin{aligned} (\mathbf{L}_I^k(\mu))_{nm} &:= \int_{\Omega} \varphi_n L_I^k(\mu)[\varphi_m], & (\mathbf{L}_E^k(\mu))_{nm} &:= \int_{\Omega} \varphi_n L_E^k(\mu)[\varphi_m], \\ (\mathbf{a}^0(\mu))_n &= \int_{\Omega} P[c_0(\mu)] \varphi_n, & (\mathbf{b}^k(\mu))_n &:= \int_{\Omega} \varphi_n b^k(\mu). \end{aligned}$$

A Posteriori Error Estimate

Definition: Residuum of the FV/DG Method at Time t^k

$$R^{k+1}(\mu)[c_N] := \frac{1}{\Delta t} \left(L_I^k(\mu)[c_N^{k+1}(\mu)] - L_E^k(\mu)[c_N^k(\mu)] - b^k(\mu) \right)$$

Theorem: A Posteriori Error Estimate

$$\|c_N^k(\mu) - c_H^k(\mu)\|_{L^2(\Omega)} \leq \sum_{l=0}^{k-1} \Delta t (C_E)^{k-1-l} \|R^{l+1}(\mu)[c_N(\mu)]\|_{L^2(\Omega)}$$

Offline–Online Decomposition

Goal: All Steps for the Calculation of $c_N(\mu)$ and for the Calculation of the Error Estimator are split into Two Parts:

- **Offline**–Step: Complexity **depending** on $\dim(W_H)$
- **Online**–Step: Complexity **independent** of $\dim(W_H)$

Constrained: Affine Parameter Dependency of the Evolution Scheme

$$L_I^k(\mu)[\cdot] = \sum_{q=1}^Q \underbrace{L_I^{k,q}[\cdot]}_{\text{depending on } x} \underbrace{\sigma_{L_I}^q(\mu)}_{\text{depending on } \mu}$$

$$\Rightarrow \text{Precompute offline: } (L_I^{k,q})_{nm} := \int_{\Omega} \varphi_n L_I^{k,q}[\varphi_m]$$

$$\Rightarrow \text{Assemble online: } (L_I^k(\mu))_{nm} := \sum_{q=1}^Q (L_I^{k,q})_{nm} \sigma_{L_I}^q(\mu)$$

Numerical Results

CPU-Time Comparison for the Convection-Diffusion Problem:

Diskretization: 40×200 Elements, $K = 200$ time steps

	timedependent data			constant data		
	Reference	RB online	RB offline	Reference	RB online	RB offline
implicit Factor	155.94s	16.67s 9.44	447.16s	45.67s	1.02s 44.77	2.41s
explizit Factor	105.97s	16.53s 6.41	437.20s	1.51s	0.79s 1.91	2.31s

Discretization: 80×400 Elements, $K = 1000$ time steps

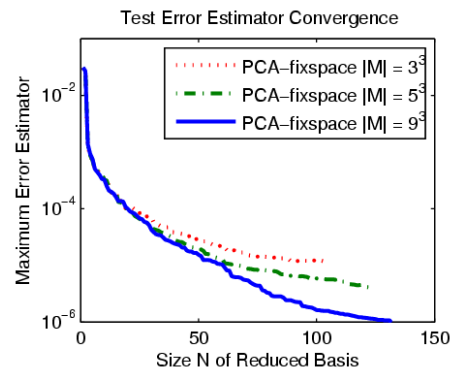
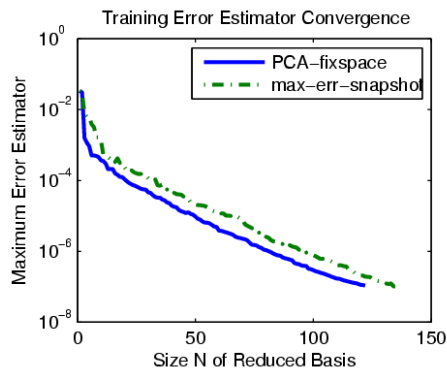
	time dependent data			constant data		
	Reference	RB online	RB offline	Reference	RB online	RB offline
implicit Factor	4043.18s	143.57s 28.27	8693.90s	924.91s	6.18s 149.66	9.22s
explizit Factor	2758.20s	134.00s 20.58	8506.60s	17.41s	3.64s 4.78	8.83s

Efficient Choice of W_N

- Idea:**
- Construct $\tilde{W}_N$ as the span of Snapshots $c_H(\mu)$, $\mu \in D \subset P$.
 - Use Error Estimator for a efficient Choice of the Snapshots with **Guaranteed Error Control** on a Training Set.
 - Reduce $\tilde{W}_N$ zu W_N with **Principal Component Analysis (PCA)**.

Goal: Exponential Convergence in N !

Preliminary Result: Convergence in N for Training and Test Sets



Improvement through Adaptive Basis Enrichement

Algorithms for Basis Enrichment: Fixed / Adaptive Training Sets

ESGREEDY($\Phi_0, M_{train}, \varepsilon_{tol}, M_{val}, \rho_{tol}$)

```

1   $\Phi := \Phi_0$ 
2  repeat
3       $\mu^* := \arg \max_{\mu \in M_{train}} \Delta(\mu, \Phi)$ 
4      if  $\Delta(\mu^*) > \varepsilon_{tol}$ 
5          then
6               $\varphi := \text{ONBASISEXT}(u_H(\mu^*), \Phi)$ 
7               $\Phi := \Phi \cup \{\varphi\}$ 
8       $\varepsilon := \max_{\mu \in M_{train}} \Delta(\mu, \Phi)$ 
9       $\rho := \max_{\mu \in M_{val}} \Delta(\mu, \Phi) / \varepsilon$ 
10 until  $\varepsilon \leq \varepsilon_{tol}$  or  $\rho \geq \rho_{tol}$ 
11 return  $\Phi, \varepsilon$ 
```

RBADAPTIVE($\Phi_0, \mathcal{M}_0, \varepsilon_{tol}, M_{val}, \rho_{tol}$)

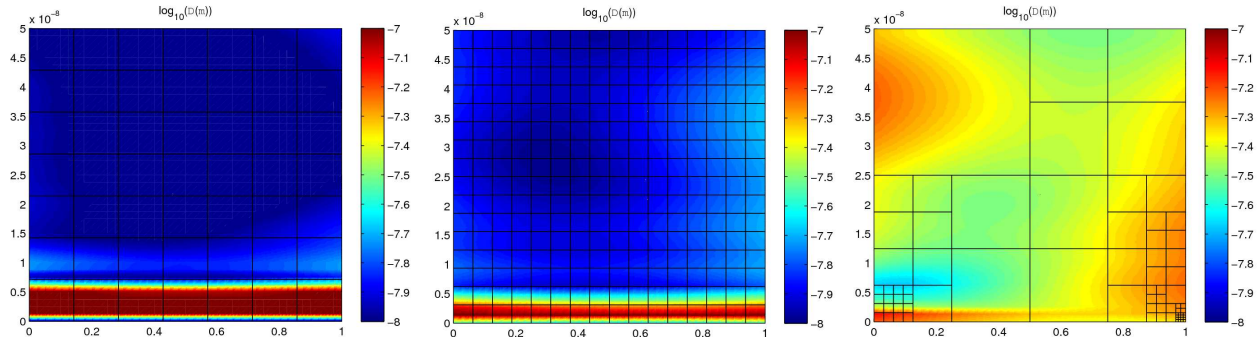
```

1   $\Phi := \Phi_0, \mathcal{M} := \mathcal{M}_0$ 
2  repeat
3       $M_{train} := V(\mathcal{M})$ 
4       $[\Phi, \varepsilon] := \text{ESGREEDY}(\Phi, M_{train}, \varepsilon_{tol},$ 
5                                $M_{val}, \rho_{tol})$ 
6      if  $\varepsilon > \varepsilon_{tol}$ 
7          then
8               $\eta = \text{ELEMENTINDICATORS}(\mathcal{M}, \Phi, \varepsilon)$ 
9               $\mathcal{M} := \text{MARK}(\mathcal{M}, \eta)$ 
10              $\mathcal{M} := \text{REFINE}(\mathcal{M})$ 
11 until  $\varepsilon \leq \varepsilon_{tol}$ 
12 return  $\Phi$ 
```

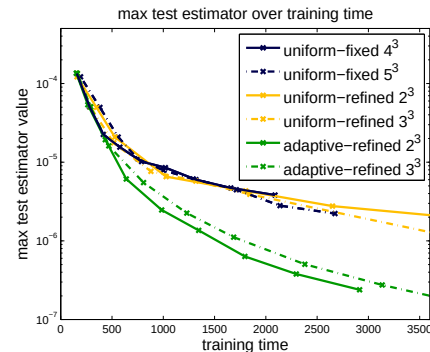
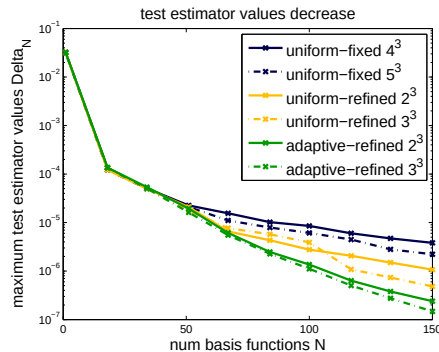
Here, $\mathcal{M}$ denotes a Partition of the Parameter Space,
and $V(\mathcal{M})$ are the Vertices of $\mathcal{M}$.

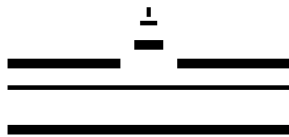
Improvement through Adaptive Basis Enrichment

Error Distribution for Uniform / Adaptive Training Sets



Exponential Convergence and CPU-Efficiency





Outlook

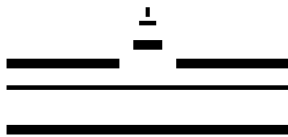
- Generalize to Non-Affine Parameter Dependency
- Generalize to Non-Linear Evolution Equations
- Error Estimates for more Complex Systems

First Results based on Empirical Interpolation:

B. Haasdonk, M. Ohlberger, G. Rozza.

A reduced basis method for evolution schemes with parameter-dependent explicit operators.

Preprint 09/07-N, FB 10, Universität Münster (2007). Accepted for publication in ETNA.



Thank you for your attention!

www.uni-muenster.de/math/u/ohlberger

Software: DUNE ALUGrid GRAPE

`www.uni-muenster.de/math/num/Arbeitsgruppen/ag\_ohlberger/software`