



Westfälische
Wilhelms-Universität
Münster

A Modularized Modeling, Discretization and Model Order Reduction Workflow

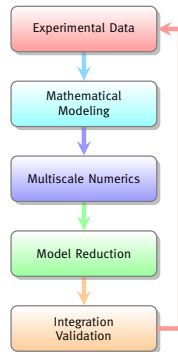
for the Simulation of Li-ion Batteries



Outline

- ▶ The MULTIBAT Project
- ▶ Reduction of Microscale Battery Models
- ▶ Software Implementation

The MULTIBAT Project



- ▶ Understand degradation processes in rechargeable Li-Ion Batteries through mathematical modeling and simulation.
- ▶ Focus: Li-Plating.

Problem Setting

- ▶ Li-plating initiated at interface between active particles and electrolyte.
- ▶ Need microscale models which resolve active particle geometry.
- ▶ Huge nonlinear discrete models.
 - ▶ Cannot be solved at cell scale on current hardware.
 - ▶ **Parameter studies extremely expensive, even on small domains.**

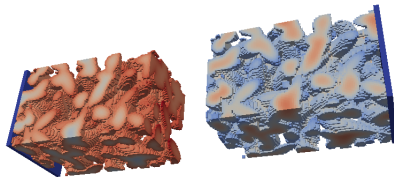
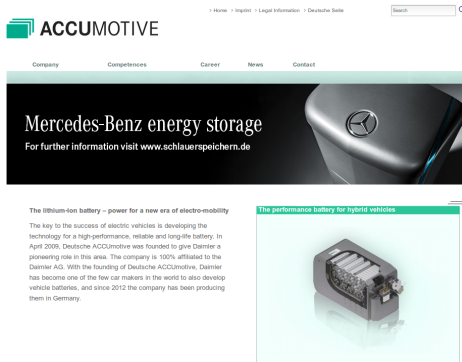


Figure : Simulation of microscale battery model on $246\mu\text{m} \times 60\mu\text{m} \times 60\mu\text{m}$ domain with random electrode geometry.

Our Industry Partner



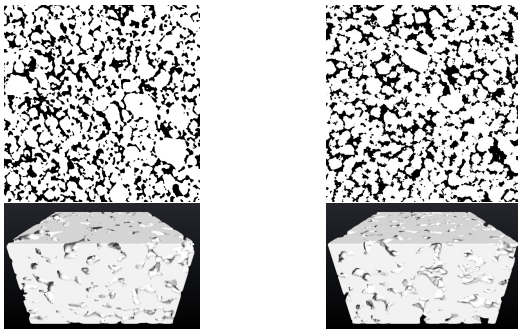
The screenshot shows the ACCUMOTIVE website. At the top, there is a navigation bar with links for Home, Impact, Legal Information, and Deutsche Seite, along with a search box. Below the navigation bar, there are tabs for Company, Competences, Career, News, and Contact. The main content area features a large image of a Mercedes-Benz battery pack with the text "Mercedes-Benz energy storage" and "For further information visit www.schlauerspeichern.de". Below this, there are two text blocks: "The lithium-ion battery – power for a new era of electro-mobility" and "The performance battery for hybrid vehicles". The second text block is accompanied by an image of a battery pack.

Provides:

- ▶ synchrotron imaging data of battery electrodes
- ▶ industrial know-how

Imaging and Stochastic Structure Modeling

Voker Schmidt, Julian Feinauer (Ulm, Accumotive)

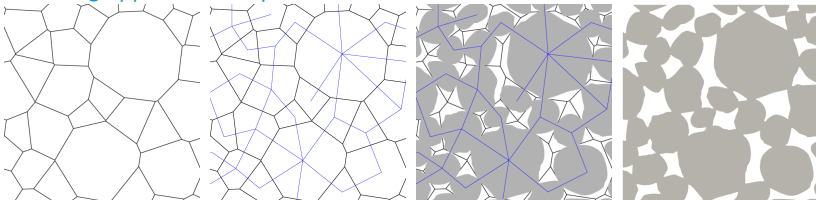


- ▶ Visual comparison of 2D and 3D cut-outs of experimental data (left) and simulated (right) shows good agreement.

Imaging and Stochastic Structure Modeling

Voker Schmidt, Julian Feinauer (Ulm, Accumotive)

Modeling Approach: Complete Simulation Model



- ▶ Create realization φ of the random Laguerre tessellation.
- ▶ Construct the connectivity graph.
- ▶ For each Laguerre cell $C \in \varphi$:
 - ▶ Define constraints $A \cdot c = b$ for particle placed in centroid x of C .
 - ▶ Sample coefficients c that fulfill $A \cdot c = b$ from $\mathcal{N}(\mu, \Sigma)$.
 - ▶ Reconstruct particle from coefficients c .
- ▶ Smooth structure with morphological closing.

Basic Microscale Model

Variables:

c : Li^+ concentration

ϕ : electrical potential

Electrolyte:

$$\frac{\partial c}{\partial t} - \nabla \cdot (D_e \nabla c) = 0$$

$$-\nabla \cdot \left(\kappa \frac{1-t_+}{F} RT \frac{1}{c} \nabla c - \kappa \nabla \phi \right) = 0$$

Electrodes:

$$\frac{\partial c}{\partial t} - \nabla \cdot (D_s \nabla c) = 0$$

$$-\nabla \cdot (\sigma \nabla \phi) = 0$$

Coupling: Normal fluxes at interfaces given by Butler-Volmer kinetics

$$j_{se} = 2k \sqrt{c_e c_s (c_{max} - c_s)} \sinh \left(\frac{\eta}{2RT} \cdot F \right) \quad \eta = \phi_s - \phi_e - U_0 \left(\frac{c_s}{c_{max}} \right)$$

$$N_{se} = \frac{1}{F} \cdot j_{se}$$

Modeling of Lithium Plating

Arnulf Latz, Simon Hein (DLR at Helmholtz Institute Ulm)

Two possible reaction at negative electrode (Graphite):

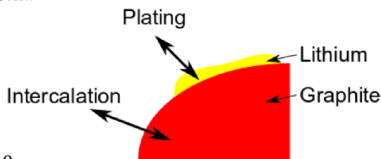
- Intercalation $\text{Li}_{\text{Electrolyte}}^+ + e_{\text{Solid}}^- \rightleftharpoons \text{LiC}_{6,\text{Solid}}$
- Lithium plating $\text{Li}_{\text{Electrolyte}}^+ + e_{\text{Solid}}^- \rightleftharpoons \text{Li}_{\text{Solid}}^{\ominus}$

Overpotential with lithium reference:

- $\eta_i = \Phi_{\text{Solid}} - \varphi_{\text{Electrolyte}}^{\text{Li}^+} - U_0(c_{\text{Solid}})$
- $\eta_p = \Phi_{\text{Solid}} - \varphi_{\text{Electrolyte}}^{\text{Li}^+}$

Lithium plating if $\eta_p \leq 0$

$$\eta_i + U_0(c_{\text{So}}) \leq 0$$



Active material and Electrolyte

$$i_{\text{Inter}} = i_{\text{Li},0} \left(\exp \left[\frac{F}{2RT} \eta_i \right] - \exp \left[-\frac{F}{2RT} \eta_i \right] \right)$$

$$i_{\text{Li},0} = i_{\text{Li},00} \cdot \sqrt{c_E \cdot c_S \cdot (c_S^{\text{max}} - c_S)}$$

Plated Lithium and Electrolyte

$$i_{\text{Li}} = i_{\text{Li},0} \left(\exp \left[\frac{F}{2RT} \eta_{\text{Li}} \right] - \exp \left[-\frac{F}{2RT} \eta_{\text{Li}} \right] \right)$$


$$i_{\text{Li},0} = i_{\text{Li},00} \cdot \sqrt{c_E}$$

Discretization

Oleg Iliev, Sebastian Schmidt, Jochen Zausch (Fraunhofer ITWM)

- ▶ Cell centered finite volume on voxel grid + implicit Euler:

$$\begin{bmatrix} \frac{1}{\Delta t} (c_{\mu}^{(t+1)} - c_{\mu}^{(t)}) \\ 0 \end{bmatrix} + A_{\mu} \left(\begin{bmatrix} c_{\mu}^{(t+1)} \\ \phi_{\mu}^{(t+1)} \end{bmatrix} \right) = 0, \quad c_{\mu}^{(t)}, \phi_{\mu}^{(t)} \in V_h$$

- ▶ Numerical fluxes on interfaces = Butler-Volmer fluxes.
- ▶ Newton scheme with algebraic multigrid solver.
- ▶ Implemented by Fraunhofer ITWM in  **BEST**.
- ▶ $\mu \in \mathcal{P}$ indicates dependence on model parameters (e.g. temperature T , charge rate).



Reduction of Microscale Battery Models

Model Reduction

- ▶ **Reduced Model:** Find $[\tilde{c}_\mu^{(t)}, \tilde{\phi}_\mu^{(t)}] \in \tilde{V}_c \oplus \tilde{V}_\phi = \tilde{V}$ solving projected equation

$$\begin{bmatrix} \frac{1}{\Delta t} (\tilde{c}_\mu^{(t+1)} - \tilde{c}_\mu^{(t)}) \\ 0 \end{bmatrix} + \{P_{\tilde{V}} \circ A_\mu\} \left(\begin{bmatrix} \tilde{c}_\mu^{(t+1)} \\ \tilde{\phi}_\mu^{(t+1)} \end{bmatrix} \right) = 0.$$

- ▶ **Basis generation:** POD of a priori selected solution trajectories, separately for c and ϕ (different scales).
- ▶ **Next steps:**
 - ▶ better a priori choices for snapshot set (instead of equidistant μ)
 - ▶ efficient a posteriori error bound \rightarrow POD-GREEDY
 - ▶ localized MOR (\rightarrow LRBMS)

Empirical Operator Interpolation

Problem: Still expensive to evaluate

$$P_{\tilde{V}} \circ A_{\mu} : \tilde{V}_c \oplus \tilde{V}_{\phi} \longrightarrow V_h \oplus V_h \longrightarrow \tilde{V}_c \oplus \tilde{V}_{\phi}.$$

Solution:

- ▶ Use locality of finite volume operators:
to evaluate M DOFs of $A_{\mu}(c, \phi)$ need only $M' \leq C \cdot M$ DOFs of (c, ϕ) .
- ▶ Approximate

$$P_{\tilde{V}} \circ A_{\mu} \approx P_{\tilde{V}} \circ (I_M \circ \tilde{A}_{M,\mu} \circ R_{M'}) =: P_{\tilde{V}} \circ \mathcal{I}_M[A_{\mu}]$$

where

$R_{M'}$: Restriction to M' DOFs needed for evaluation
 $\tilde{A}_{M,\mu}$: A_{μ} restricted to M interpolation DOFs
 I_M : Interpolation operator

Empirical Operator Interpolation (2)

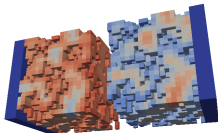
$$P_{\tilde{V}} \circ A_{\mu} \approx P_{\tilde{V}} \circ (I_M \circ \tilde{A}_{M,\mu} \circ R_{M'}) =: P_{\tilde{V}} \circ \mathcal{I}_M[A_{\mu}]$$


Basis Generation:

- ▶ Compute operator evaluations on solution snapshots (including Newton stages).
- ▶ Iteratively extend interpolation basis with worst-approximated evaluation. Choose new interpolation DOF where new vector is maximal (EI-GREEDY).
- ▶ Interpolate Butler-Volmer part of A_{μ} and $1/c \cdot \nabla c$ separately (ϕ -part of A_{μ} vanishes for solutions).
- ▶ Future: Build RB and interpolation basis simultaneously using error estimator to select snapshots (POD-EI-GREEDY).

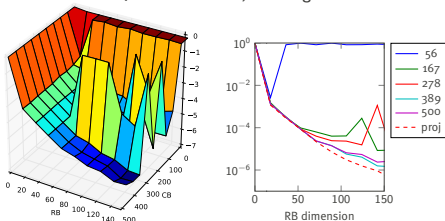
First Results

- ▶ Geometry (36,800 DOFs):

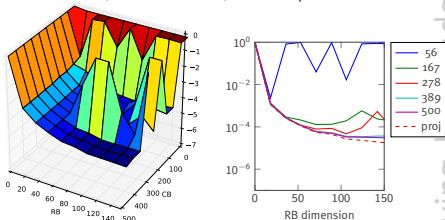


- ▶ -based solver.
- ▶ Charge rate $\in [0.1C, 1C]$, constant temperature.
- ▶ 10 snapshots for training.
- ▶ Time for solution $\approx 1000s$.
- ▶ Time for red. solution $\approx 40s$.
(dim $RB = 50$, dim $CB = 278$)
- ▶ Speedup: $\times 25$

$L^\infty - L^2$ err., concentration, training set

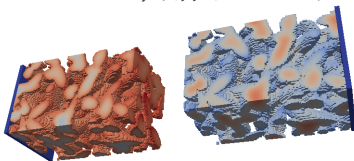



$L^\infty - L^2$ err., concentration, random params.



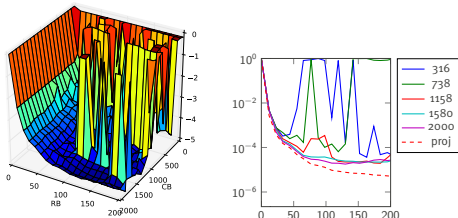
More Results

- ▶ Geometry (1,771,200 DOFs):

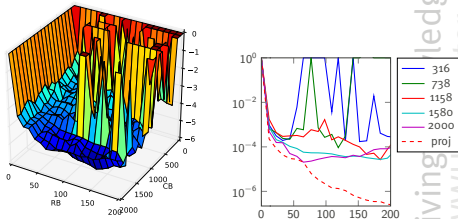


- ▶ -based solver.
- ▶ Charge rate $\in [0.1C, 1C]$, constant temperature.
- ▶ 17 snapshots for training.
- ▶ Time for solution $\approx 15h$.
- ▶ Time for red. solution $\approx 156s$ (dim $RB = 55$, dim $CB = 1580$).
- ▶ Speedup: $\times 340$

$L^\infty - L^2$ err., concentration, random params.



$L^\infty - L^2$ err., potential, random params.



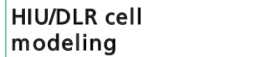
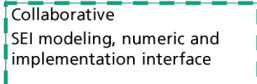
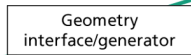
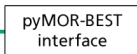


Software Implementation

Software Interfaces in MULTIBAT






WESTFÄLISCHE
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Software Interfaces in MULTIBAT

Interfaces allow us to:

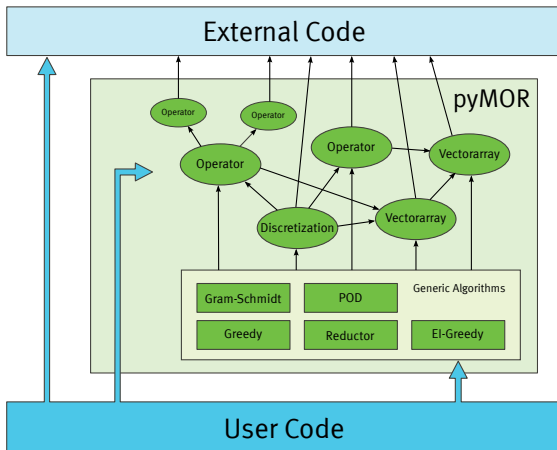
- ▶ easily exchange  solver with  BEST.
- ▶ independently develop MOR algorithms.
- ▶ easily apply MOR algorithms to updated models in  BEST.
- ▶ reuse MOR algorithms for other problems.

- Using all APs
- Using all Interfaces

pyMOR

- ▶ Python-based MOR library (in particular reduced basis method).
- ▶ BSD license, <http://www.pymor.org/>.
- ▶ `VectorArray`, `Operator`, `Discretization` interfaces for tight integration of external solvers.
- ▶ Generic algorithms based on these interfaces:
 - ▶ RB-Projection, EI, error estimation
 - ▶ Greedy, EI-Greedy, POD, Gram-Schmidt
 - ▶ Timestepping, (iterative linear solvers)
- ▶ Small NumPy/SciPy-based discretization toolkit for easy prototyping.

Interfacing external PDE-solvers



New: Now with FEniCS Support

- ▶ Directly interfaces FEniCS LA backend, no copies needed.
- ▶ Use same MOR code with both backends!
- ▶ Only 150 SLOC for bindings.
- ▶ Thermal block demo:
30 SLOC FEniCS +
15 SLOC wrapping for pyMOR.
- ▶ Easily increase FEM order, etc.

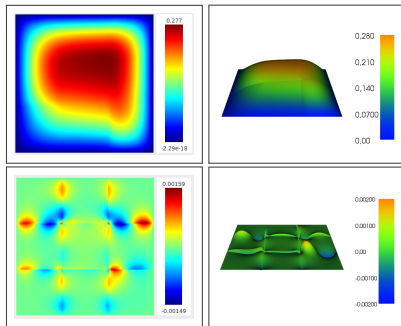


Figure : 3x3 thermal block problem
top: red. solution, bottom: red. error
left: pyMOR solver, right: FEniCS solver

New: Tools for interfacing MPI parallel solvers

- ▶ Automatically make sequential bindings MPI aware.
- ▶ Reduce HPC-Cluster models without thinking about MPI at all.
- ▶ Interactively debug MPI parallel solvers.

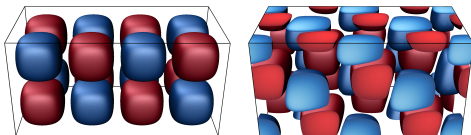



Figure : FV solution of 3D Burgers-type equation
($27.6 \cdot 10^6$ DOFs, 600 timesteps) using 

Table : Time (s) needed for solution using DUNE / DUNE with pyMOR timestepping.

MPI ranks	1	2	3	6	12	24	48	96	192
DUNE	17076	8519	5727	2969	1525	775	395	202	107
pyMOR	17742	8904	6014	3139	1606	816	418	213	120
overhead	3.9%	4.5%	5.0%	5.7%	5.3%	5.3%	6.0%	5.4%	11.8%

People Involved

with pyMOR



Mario Ohlberger



Rene Milk



Stephan Rave



Felix Schindler



Andreas Buhr



Michael Laier



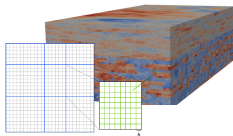
Falk Meyer



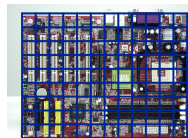
Michael Schaefer

Main Projects

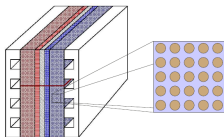
using pyMOR



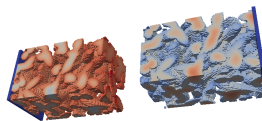
Localized Reduced Basis MultiScale method



Reduction of Maxwell's equations allowing
Arbitrary Local Modifications



Reduced basis approximation for multiscale
optimization problems



Reduction of microscale Li-ion battery models



Thank you for your attention!

AG Ohlberger

<http://wwwmath.uni-muenster.de/num/ohlberger/>

pyMOR – Model Order Reduction with Python

<http://www.pymor.org/>

arXiv:1506.07094

MULTIBAT

<http://j.mp/multibat>