THREE-DIMENSIONAL PERMEABILITY MEASUREMENT USING ARTIFICIAL NEURAL NETWORKS

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1D-case:

Permeability of fiber structure

Pressure drop

Volume-averaged flow velocity

$$v = -\frac{K}{\eta} \cdot \frac{\Delta P}{\Delta L}$$

Viscosity

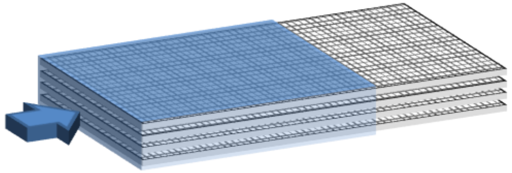
Flow length

3D-case: Permeability is described by a 2nd grade tensor

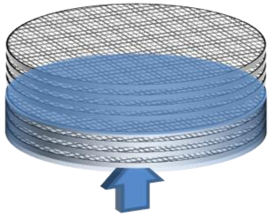
$$\begin{bmatrix} K_{xx} & K_{xy} & K_{xz} \\ K_{yx} & K_{yy} & K_{yz} \\ K_{zx} & K_{zy} & K_{zz} \end{bmatrix}$$

Measurement methods (unsaturated):

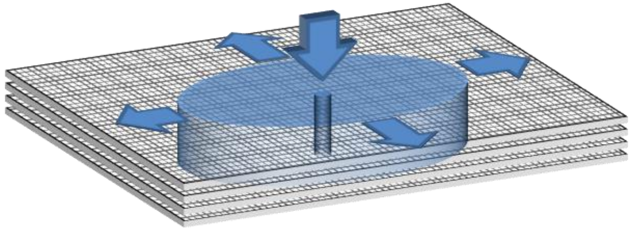
1D (in-plane)



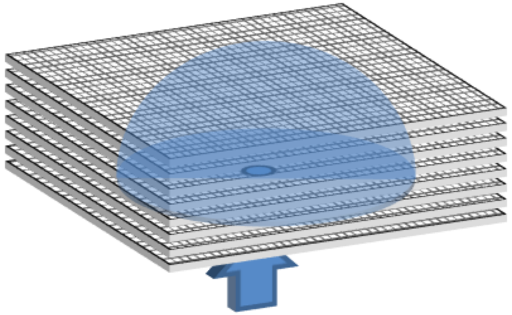
1D (out-of-plane)



2D



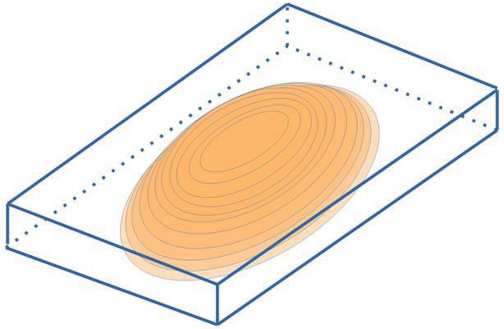
3D



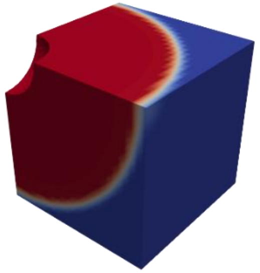
Introduction: 3D Permeability Measurements

- **Benefit:** “All-in-one”-approach for full tensor measurement
- **Challenges:**
  - Analytical solution only available for
    - point source assumption
    - isotropic in-plane permeability (so no “all-in-one”)
    - half-ellipsoidal shape (not top plate contact)
  - Reverse engineering by comparison with simulation data and optimization scheme possible, but quite time-consuming

Half-ellipsoidal flow front in 3D measurement



Point source assumption (quarter model)



Approach: Overview

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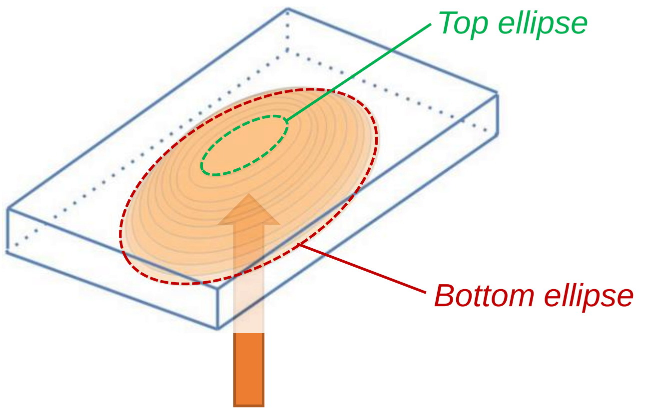
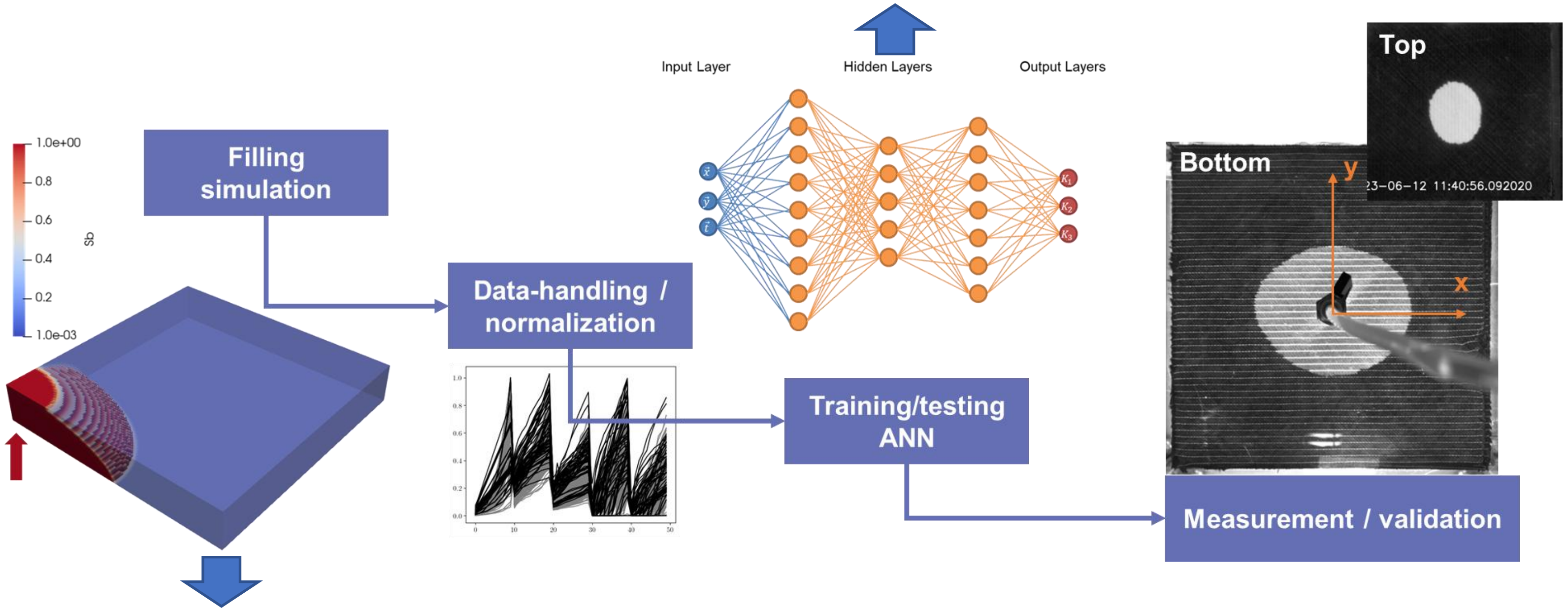
Basic approach:
Deliberate generation of
top and bottom flow ellipses



Central point-injection
(one-sided)

Approach for ANN training and application:

$$\left(\vec{x}_f(t), \mu, p\,(t), \eta\right) \rightarrow (\boldsymbol{K})$$

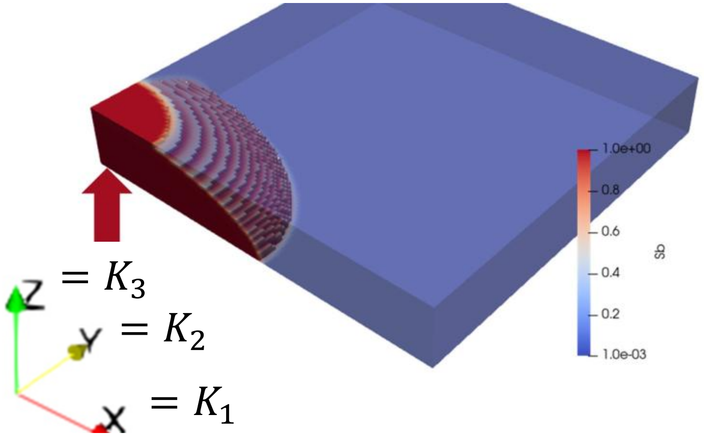


$$(\boldsymbol{K}(\vec{x}), \mu, p\,(t), \eta) \rightarrow \left(\vec{x}_f(t)\right)$$

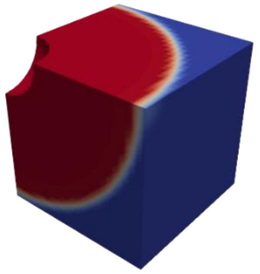
Approach: Simulation Model

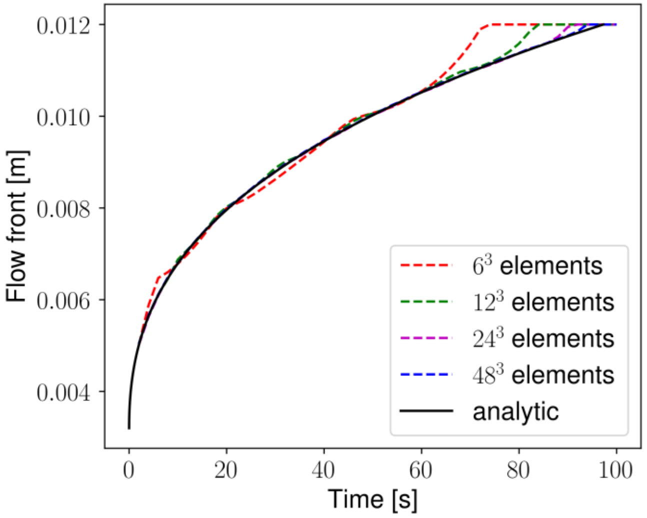
- Implemented with OpenFOAM v9, anIsoImpesFOAM (two-phase flow solver)
- Quarter model is used (assuming symmetry of permeability tensor)
- Size: 100 mm x 100 mm x 8 mm
- Boundary conditions according to experimental test set-up:
  - Inlet: 0.1 MPa
  - Outlet: 1700 Pa
  - Viscosity: 0.2 Pa·s
- Validation via analytical solution for 3D flow with point source
  - Element size of 1 and 0,25 mm for in- and out-of-plane
  - About 76 min computation time on standard PC

Test set-up and simulation[1]



Validation via analytical solution





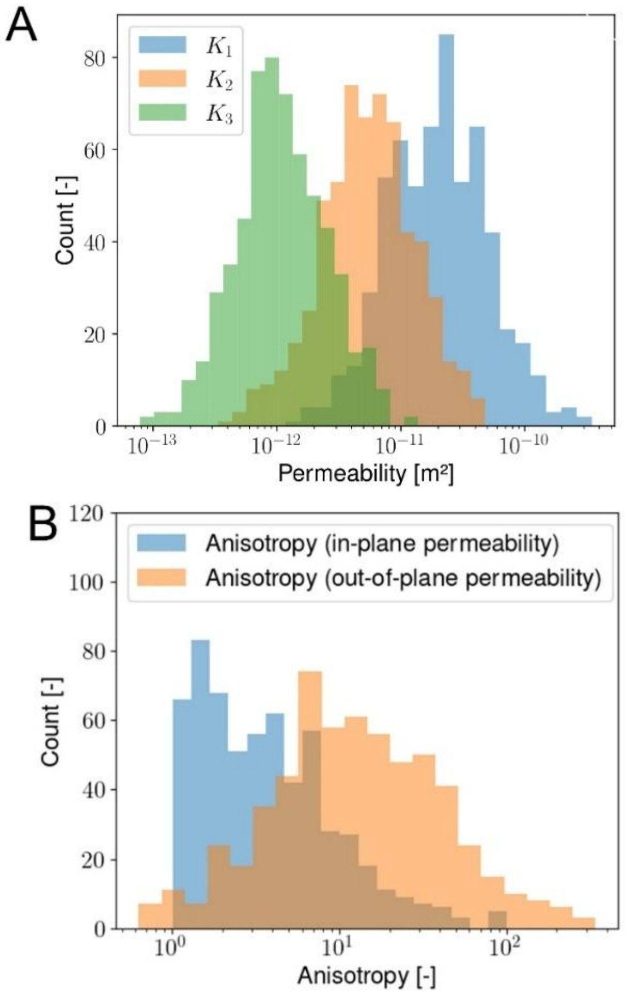
Approach: Simulation Data

- **575 simulation cases**
  - Variation of permeability values (around mean values)
  - Mean values: $K_1 = 3.08 \cdot 10^{-11}$ m²
    $K_2 = 7.76 \cdot 10^{-12}$ m²
    $K_3 = 1.55 \cdot 10^{-12}$ m²
  - K_1 has always the highest values

- **No variation of viscosity and FVC - can be rescaled:**

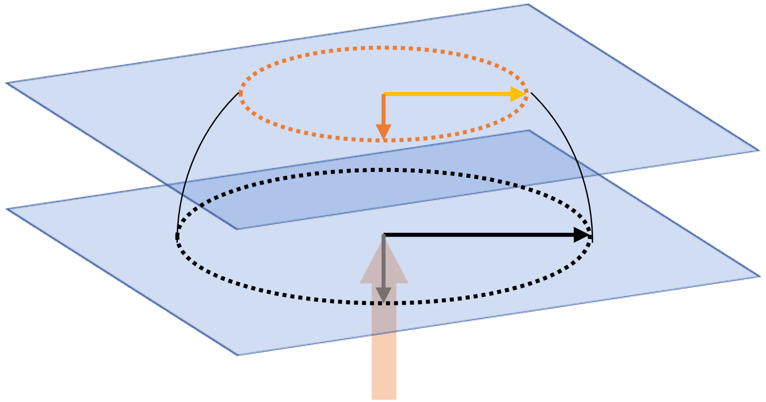
$$K_{i,Exp} = K_{i,Predict} \cdot \frac{\mu_{Exp} \cdot (1 - \nu_{f,Exp})}{\mu_{Sim} \cdot (1 - \nu_{f,Sim})}$$

Distribution of permeability values

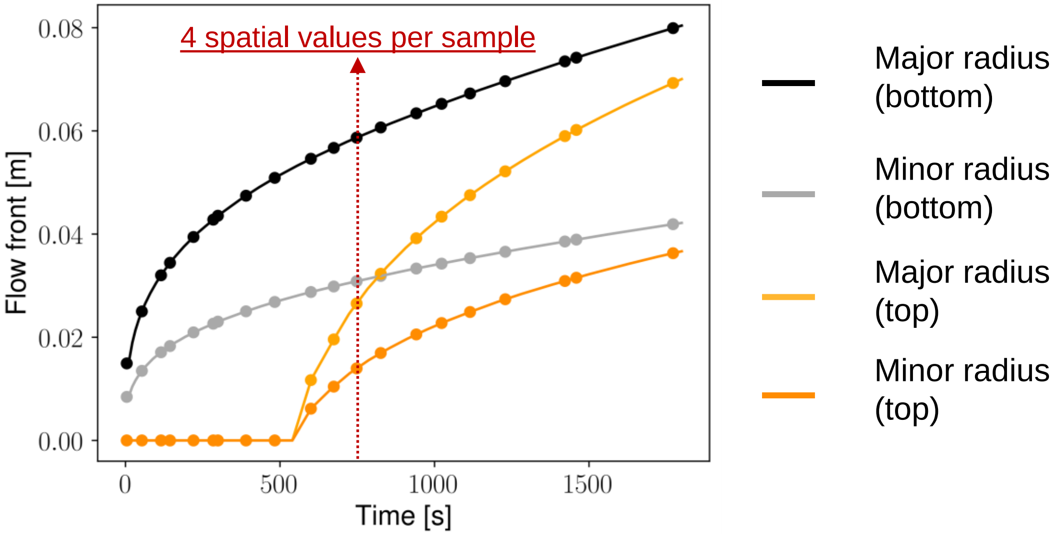


Approach: Data Sampling

- Focus on top and bottom flow ellipses
- Semi-randomized selection of n_{st} time steps
- n_{st} varied: 1, 2, 5, 10, 15, 20
- Multiple sampling gives more data
- Data normalization
  - Input data: min-max-scaling
  - Output data: normalization with 10^{-11} (in-plane) and 10^{-12} (out-of-plane)
- Data split:
  - 60 % for training
  - 20 % for testing (overfitting detection)
  - 20 % for validation

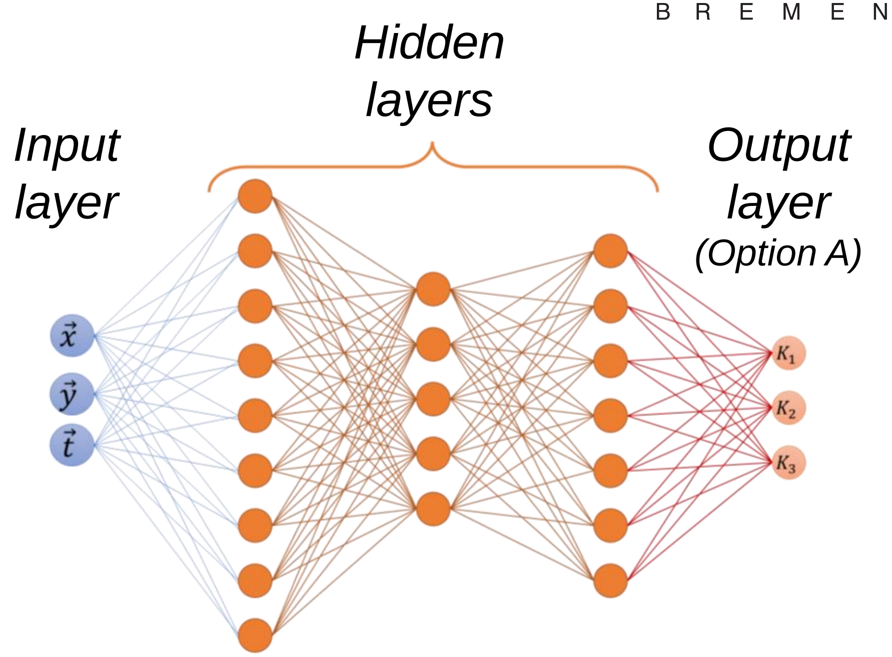


Example for data sampled for a each simulation



Approach: Artificial Neural Network

- Input Layer – observed flow front data:
  - Major x_i and minor y_i radii of top and bottom ellipse for each time step
  - Number of time steps, n_{ts}: 10
  - Number of nodes is $n_{Input} = 5 \cdot n_{ts}$
- Output Layer – computed permeability values:
  - Option A: K_1, K_2, K_3 computed at once (3 nodes)
  - Option B: Only one K_i iscomputed (1 node)
  - (Orientation is easily derived from visual data)
- Hidden Layer(s) – permeability computation:
  - Hyperparameter optimization with KerasTuner for 3 node variant with $n_{ts} = 10$
  - 3-nodes and 1-node output variants use the same structure



Parameter	Optimized Value
Number hidden layers	2
Number nodes hidden layers	192 , 96
Activation functions	ReLU, Linear (Output)
Optimizer	Nadam
Loss function	MAPE
Learning rate	0.01

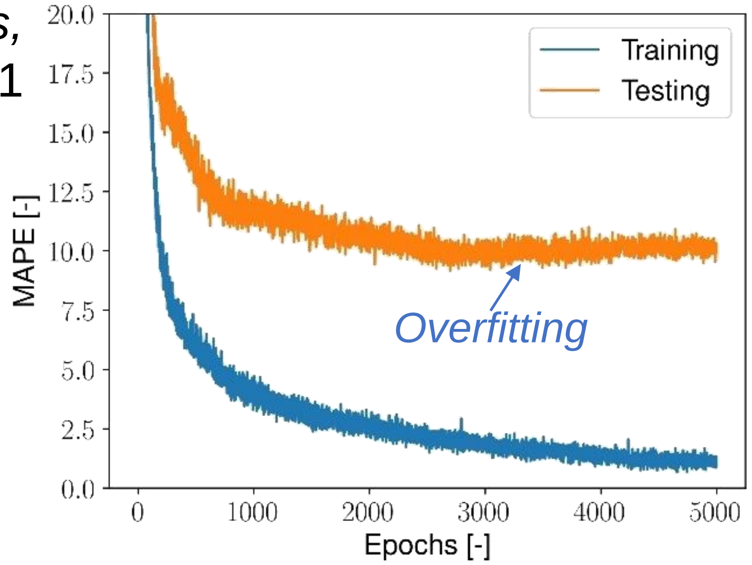
AI-Implementation: Training/Testing

- **Loss function**: Mean Average Percentage Error (MAPE)

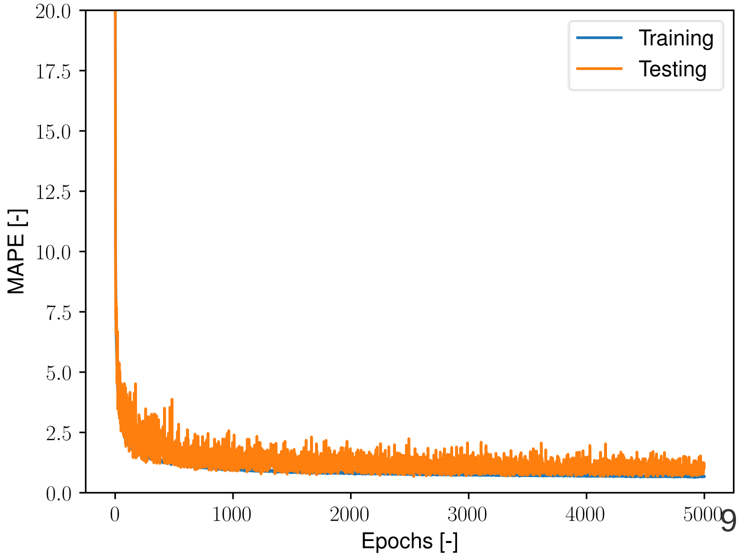
$$Loss_{MAPE} = 100 \cdot \left| \frac{y_{true} - y_{predict}}{y_{true}} \right|$$

- **Training**: MAPE < 1 % after 5000 epochs for all variants
- **Testing** (3-node ANN):
  - **60** simulations, n_{st} = 10*1: MAPE = 10 %
  - **345** simulations, n_{st} = 10*1: MAPE = 2.6 %
  - 345 simulations, $\boldsymbol{n_{st}}$ **= 10*10**: MAPE = 1.09 %
- **1-node** approach with 3 ANNs slightly improves prediction (~0.9 %)
- Introducing **random variation** for every spatial value (range ± 10 %) increases MAPE to 5.7 %

60 simulations,
n_{st} = 10*1



345 simulations,
n_{st} = 10*10



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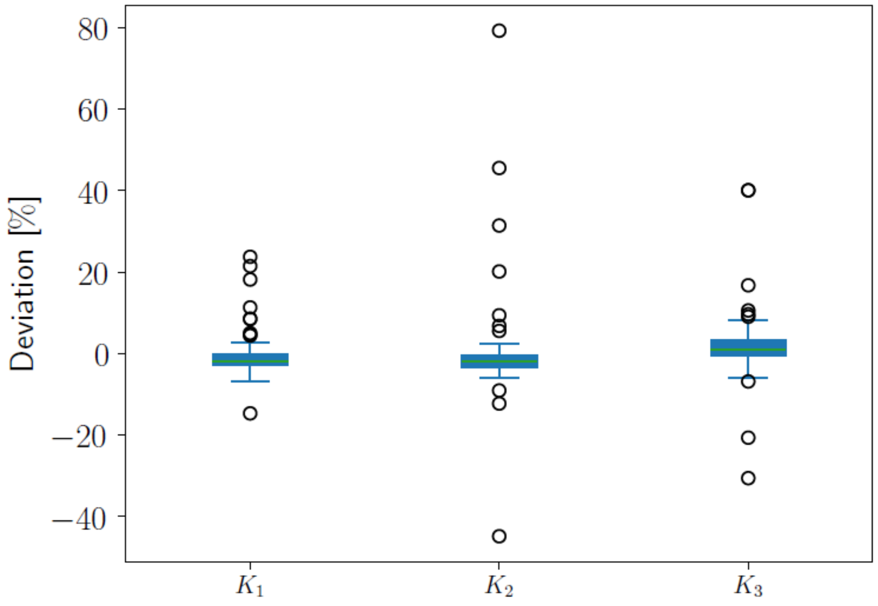
Results: Validation with Unseen Data

- **Multiple sampling** (n_{st} = 10*i):
  - Minimum MAPE at i=4 (~3 %)
  - Outlier range increases w/ increasing i
  - Accuracy losses esp. at edges of training range
  - Data set probably too small/narrow to impede overfit

- **1-node** ANN
  - MAPE consistently smaller (about 1 % less)
  - Outlier range is smaller
  - BUT: 3 ANNs need to be trained

Base line:
*Deviation between estimated and correct permeability of 115 simulations (3-node ANN, n_{st} = 10*1)*

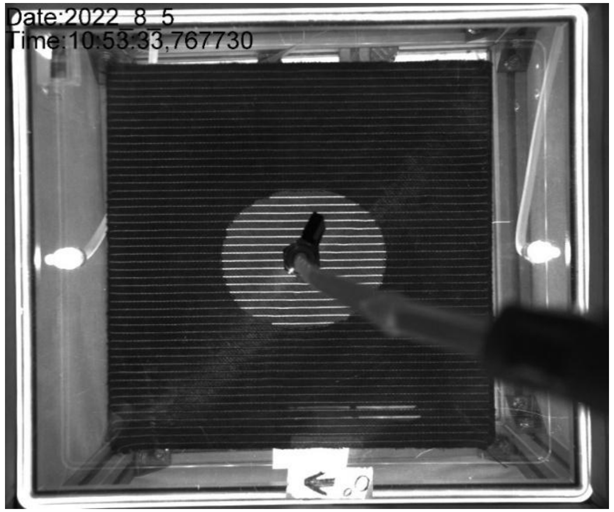


→ MAPE = 3.7 %, Outliers ± 40 %

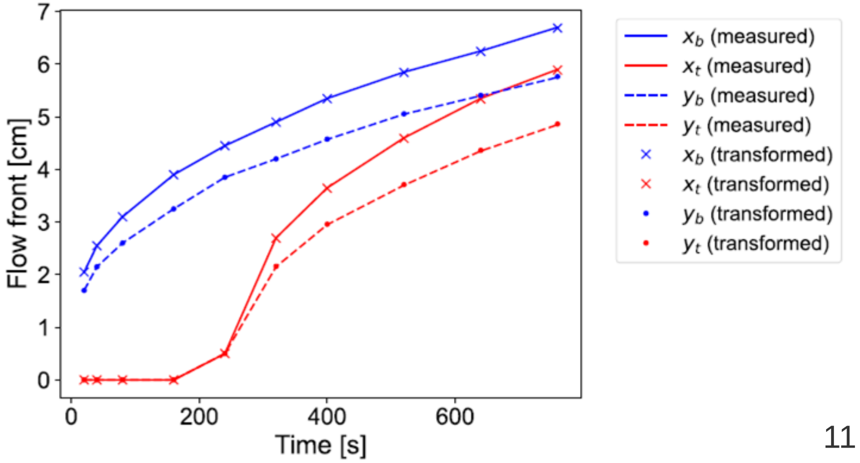
Results: Validation with Experimental Data

- **Validation approach**
  1. Perform experiment and approximation of ellipses
  2. Apply ANN (1 & 3-node, n_{st} = 10*1) to experimental data to get K_1, K_2, K_3
  3. Perform Simulation with calculated K_1, K_2, K_3
  4. Compare flow front in exp. and simulation for 10 time steps (→ MAPE)
- **Set-up**
  - Cavity of 350 mm x 350 mm x 8.2 mm
  - Vacuum infusion of silicon oil with 0.2 Pa·s
- **Experiments**
  - 16 different UD and bi-axial NCFs, GF and CF
  - FVC between 50 % and 58 %
  - Silicon oil with 0.2 Pa·s
  - 64 variants with 3-4 repetitions
  - c_v varies between 2.9 % and 71.6 % (Median is 19.9 %)

Bottom view on experimental set-up



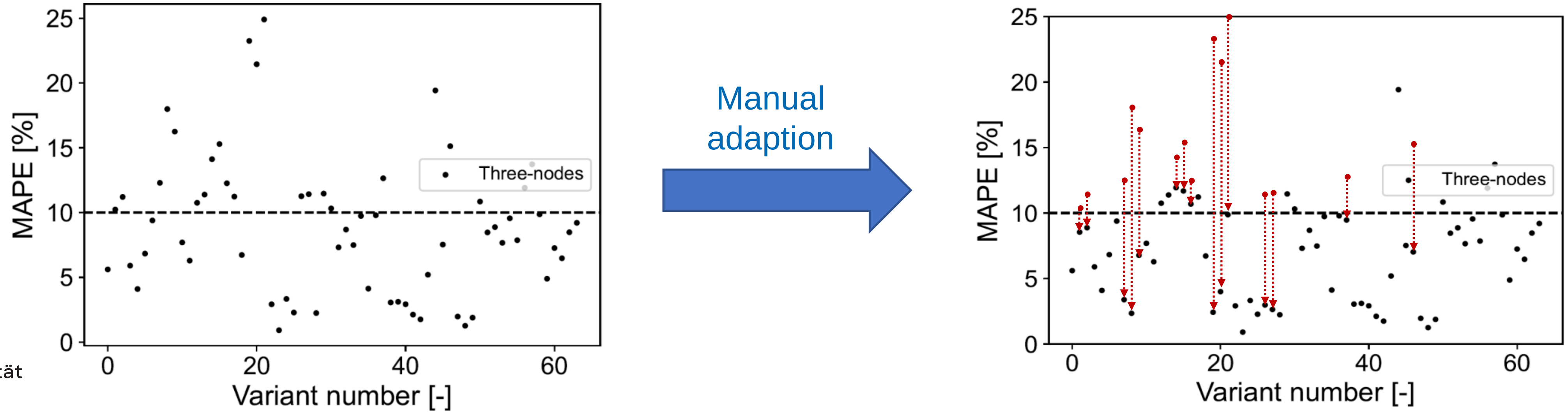
Example for extracted data



Results: Validation with Experimental Data

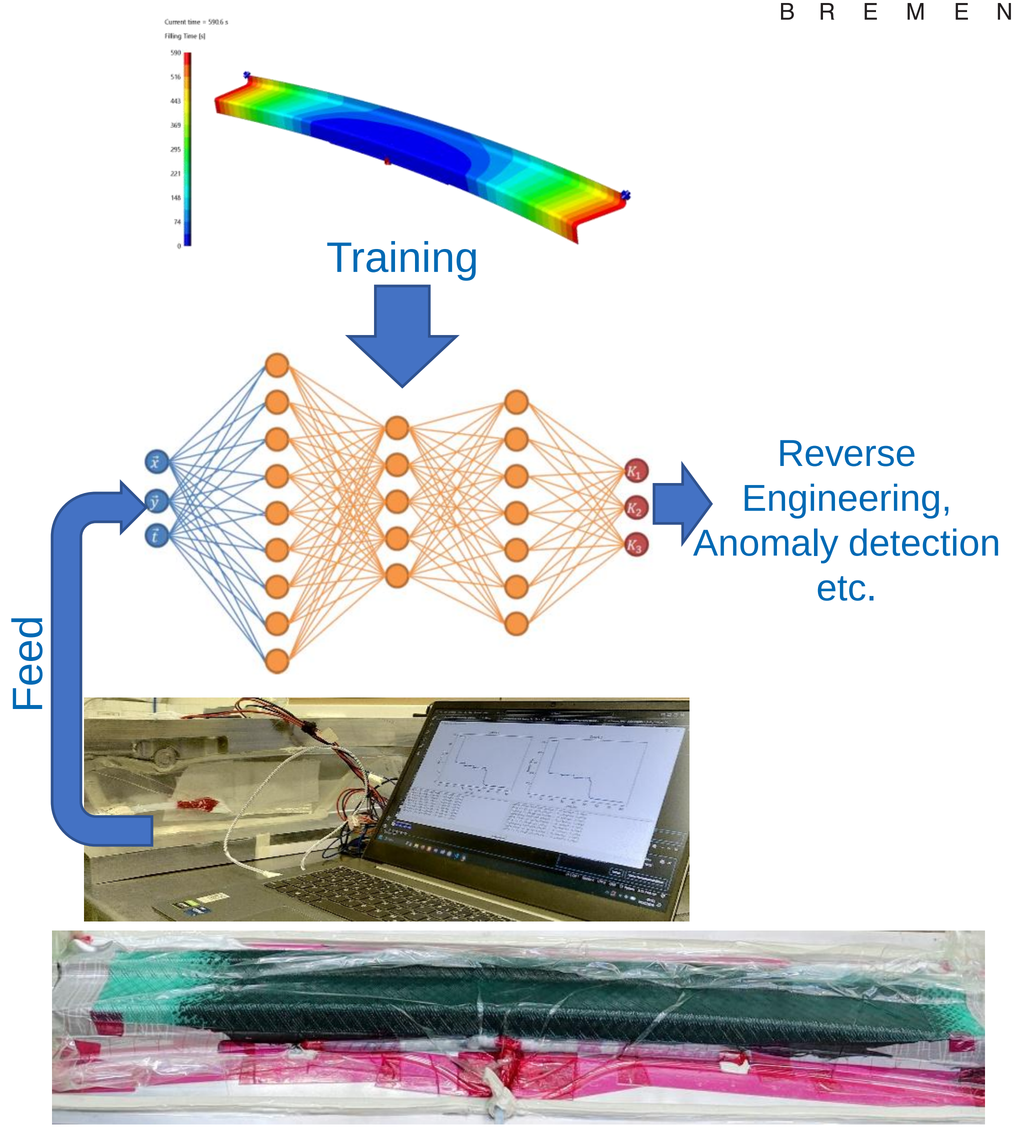
- **General observations**
  - Tendency of higher MAPE at/beyond training range edges
  - 1-node generally gives higher accuracy but is less resilient to data outside training range than 3-node
  - No general tendency for influence of anisotropy and UD vs. biax
- **Improvement potential?**
  - Variants with MAPE > 10 % (17) were manually adapted to check improvement potential
  - Local inhomogeneities, deviations from elliptical shape and material-inherent variations limit adaption

ANN-based (3-node) Simulation vs. Experiment (MAPE)



Conclusions & Outlook

- ML-based permeability calculation seems generally viable, with acceptable accuracy
- Further research required concerning:
  - Distorted flow fronts (non-elliptical)
  - Extension of simulation-base (full range coverage)
- Transfer of approach to real part manufacturing
  - Simulation of actual part filling
  - Reverse engineering of permeability, including local variations
  - Identify critical flow patterns (risk of incomplete impregnation, porosity)



[Droste, D., May, D. and Dimassi, A., “Estimation of the three-dimensional permeability tensor […] using artificial neural networks”, 2025, Journal of Comp. Mat.]

Acknowledgement

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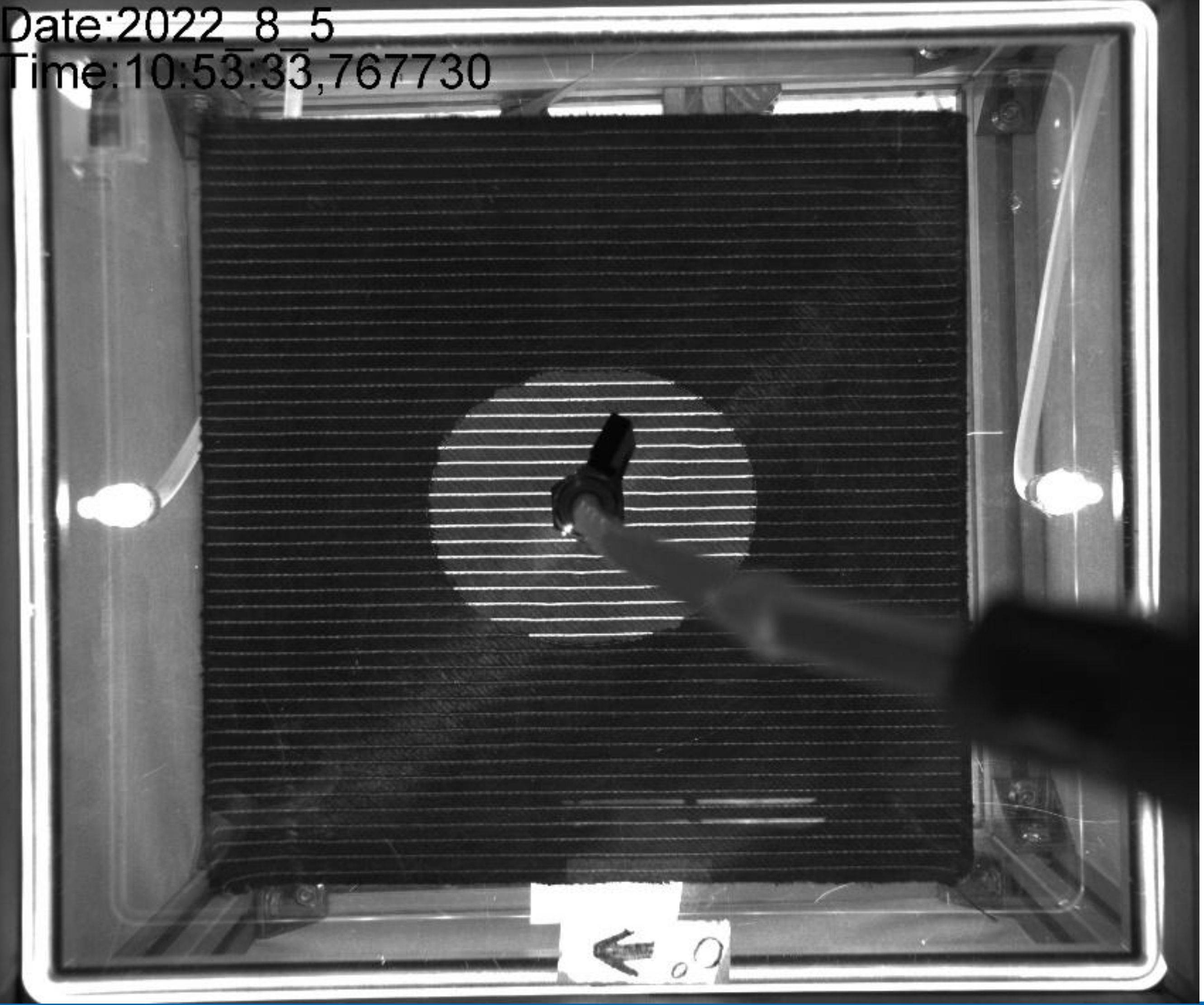

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Thank you!

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