Machine Learning for Efficient Process Optimization in Textile Draping for Composite Production

ITA Reinforced! Innovation Day

26 September 2023 | Aachen, Germany

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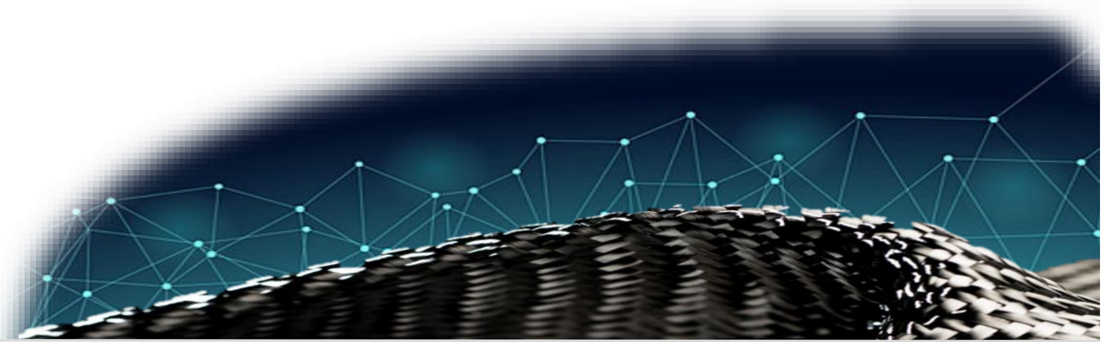


Motivation

Overview

Lightweight Engineering

- Lightweight potential ↔ Engineering efforts

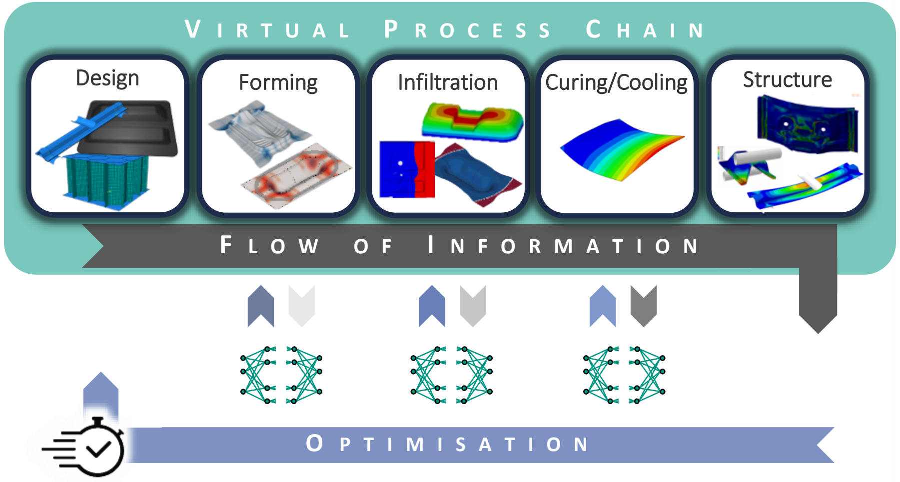
Process simulation for engineering design

- Early assessment of manufacturability
- Reduction of expensive prototype trials
- Numerical expertise and computation efforts (iterative optimisation!)

Goal: Accelerate process optimisation

- Integration of knowledge from similar components via Machine Learning (ML)
- Joint project *OptiFeed* (ITA and FAST) on fabric forming

adapted from [Kärger et al. 2015]



Example virtual process chain for continuous-fibre reinforced plastics (Resin-Transfer-Moulding, RTM)

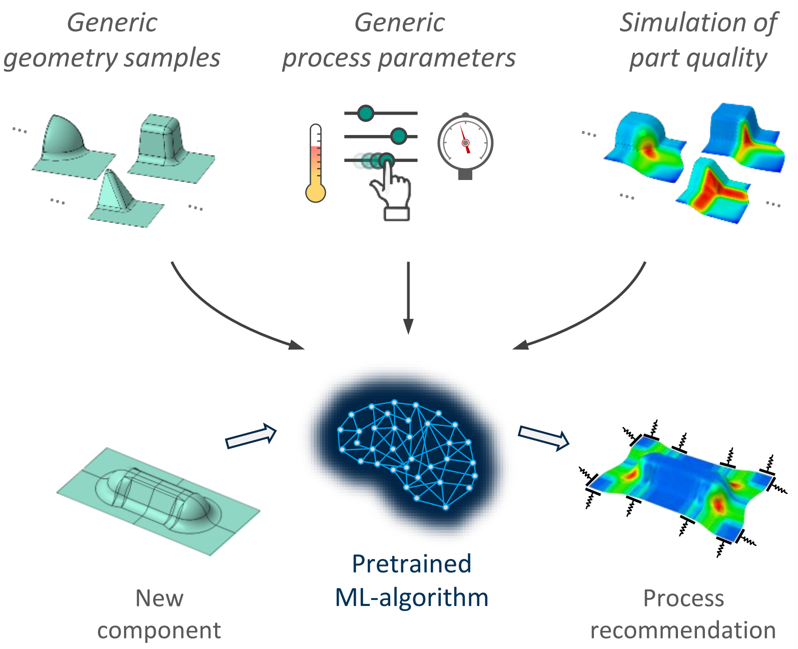
Vision

Combine simulation and ML-techniques

Virtual ‚process experience‘

- Use physics-based simulations as a ‚close-to-reality‘ proxy of experiments
  - → Generate extensive database with part-process-observations

- ML-algorithm extracts governing process dynamics (‚training‘)
  - → once trained, it can give recommendations for new geometries

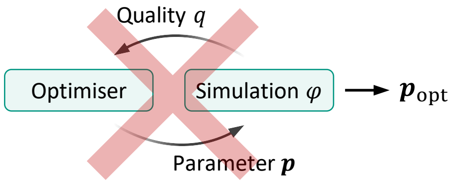


Process optimisation for variable geometries

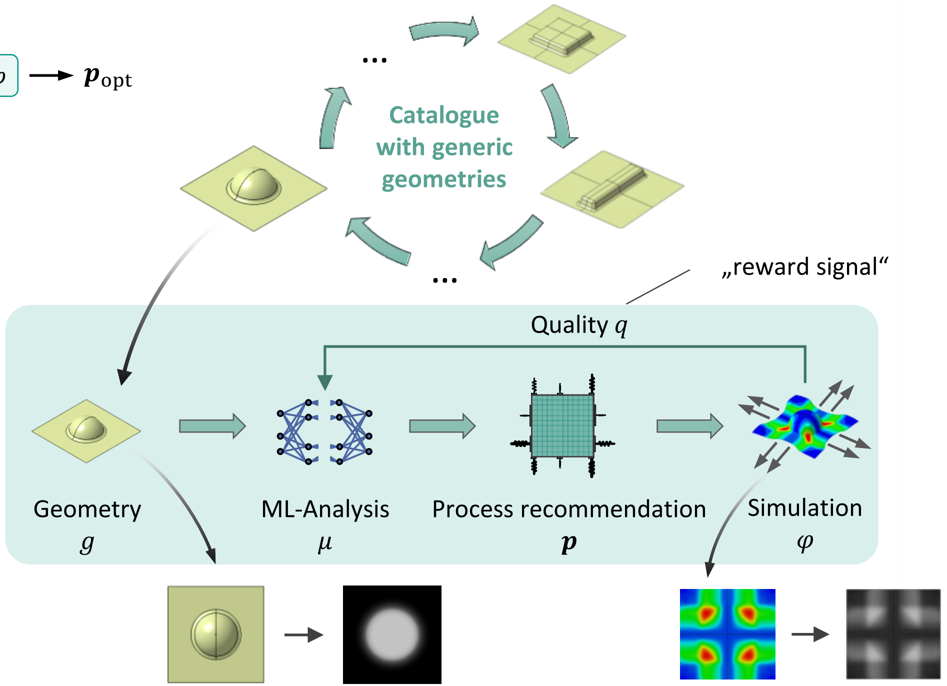
Concept

Idea

- Replace the ‚classical' iterative optimisation



  by a more general function $\mu : G \mapsto P^*$



Reinforcement Learning [Sutton and Barto, 2018]

- Trial-Error-Training in a simulation environment
- Algorithm is rewarded if part quality improves
- Information encoding in greyscale-images

Process optimisation for variable geometries

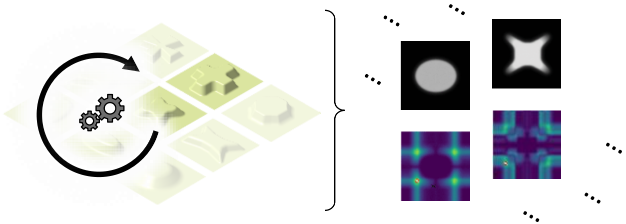
Visualisation example

Training

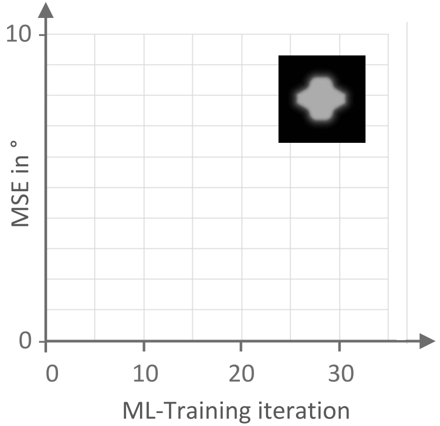
- Database with forming simulation samples
- Training: Iterative adaption of network parameters to minimise MSE

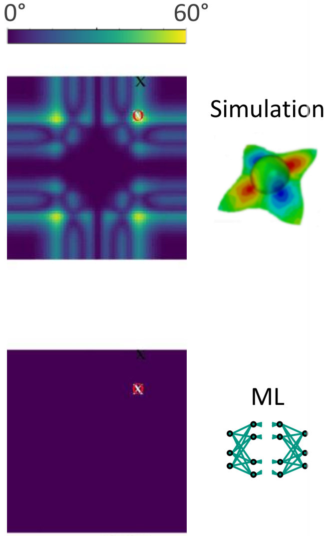
→ Images well suited to describe arbitrary forming geometries

$$\mathrm{MSE} = \frac{1}{n_s}\sum_{j=1}^{n_s}\left(\hat{\gamma}_j - \gamma_j\right)^2$$



Database with draping samples





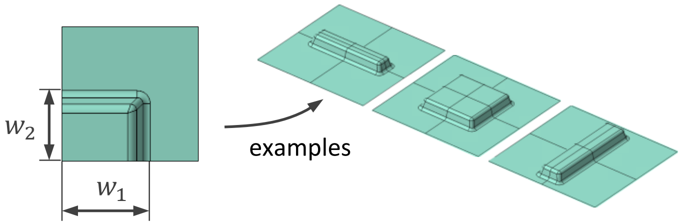
Images from [Trippe, 2019]

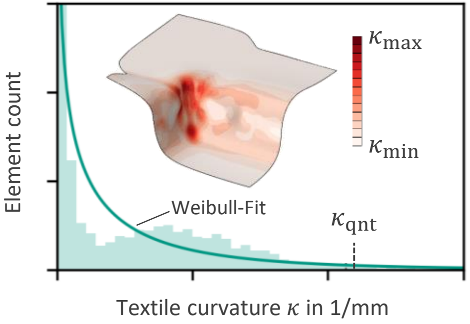
Optimisation of variable geometries

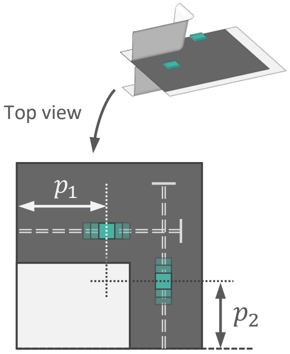
Application example

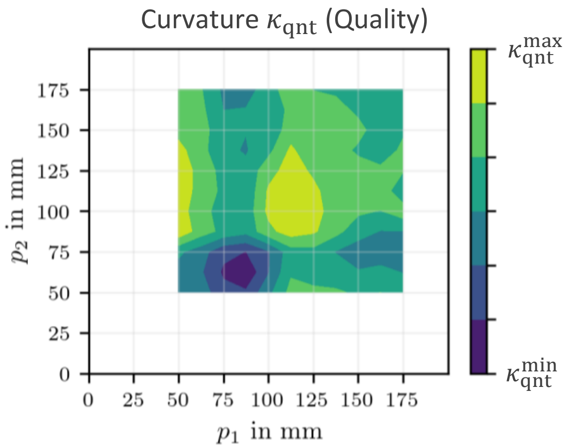
Pressure-pad assisted fabric forming [Zimmerling et al. 2020, 2022b]

- FE fabric model [Poppe et al. 2018, 2019]
  on geometry catalogue of cuboids
- Process manipulation by pressure pads
- Goal: Smoothest possible draw-in
  → textile curvature measures quality



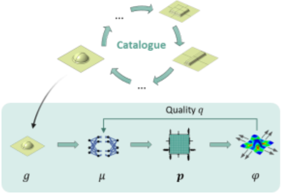






Optimisation of variable geometries

Application example | Training results



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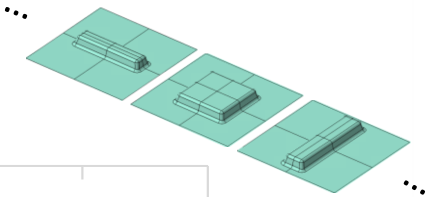
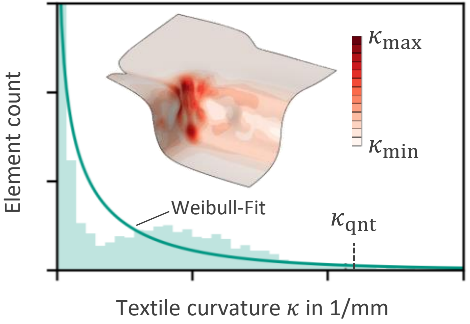
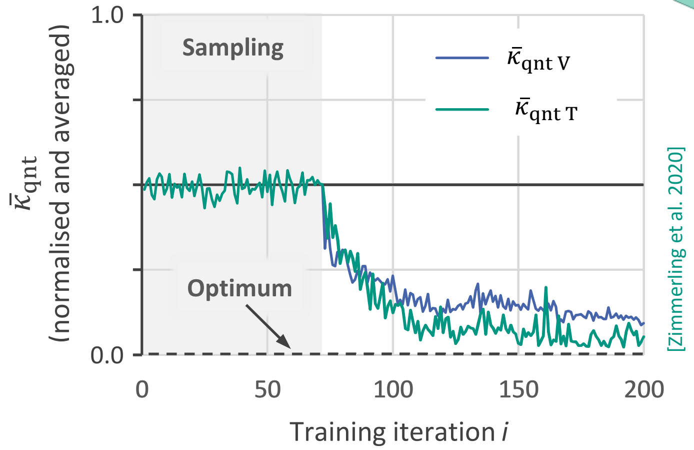
Training progress with Reinforcement Learning [Zimmerling et al. 2020, 2022b]

- Sampling phase to gather observations
- Successful minimisation of curvature across…
  - 14 training geometries
  - 5 validation geometries (hidden)

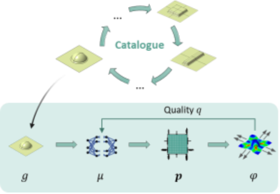






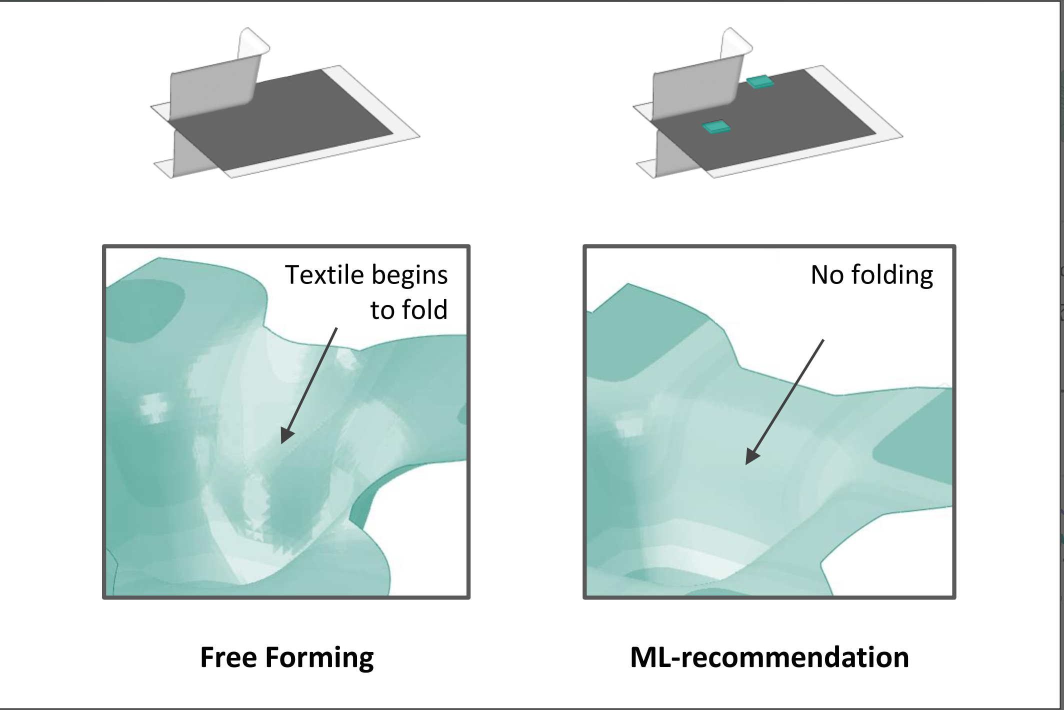
Optimisation of variable geometries

Application example | Training results



Training progress with R

- Sampling phase to ga
- Successful minimisat
  - 14 training geom
  - 5 validation geor



[Zimmerling et al. 2020]

Optimisation of variable geometries

Application example | Training results

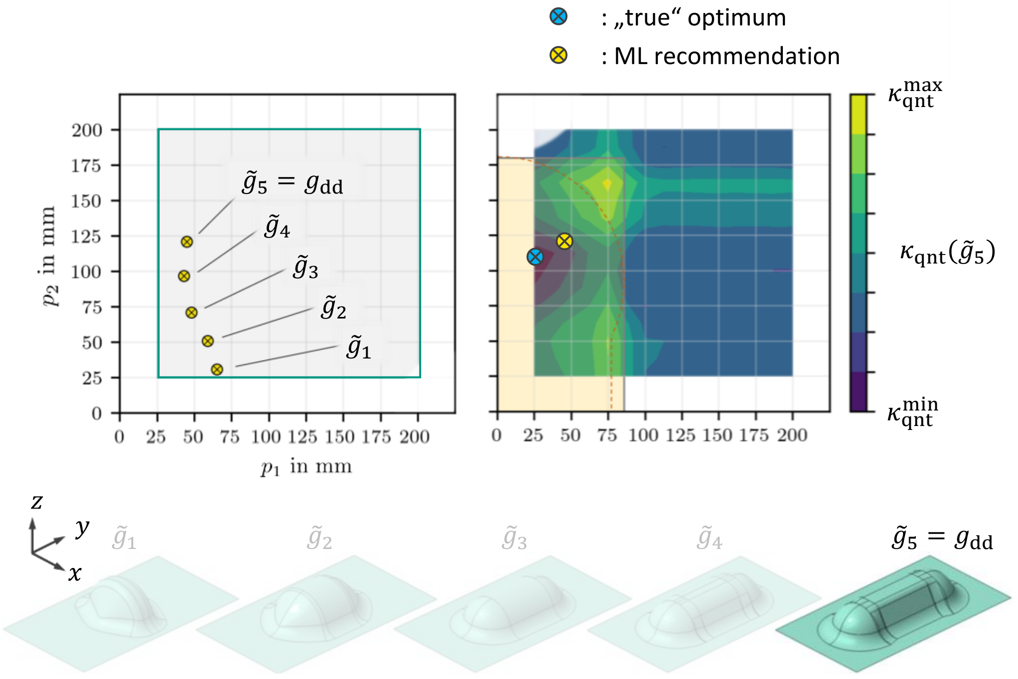
After training [Zimmerling et al. 2020, 2022b]

- Testing on new geometry variants
  - Doubly symmetric and mostly convex

Observation

- ML recommendations follow geometry variation
- Useful process recommendation
- Continued training refines recommendations

✓ Successful extraction of process experience and application to new geometries



[Zimmerling et al. 2022b]

Optimisation of variable geometries

Application example | Training results and Summary

Optimisation approach comparison

- *Conventional* *(genetic algorithm)*
- *ML-approach* *(geometry-informed)*

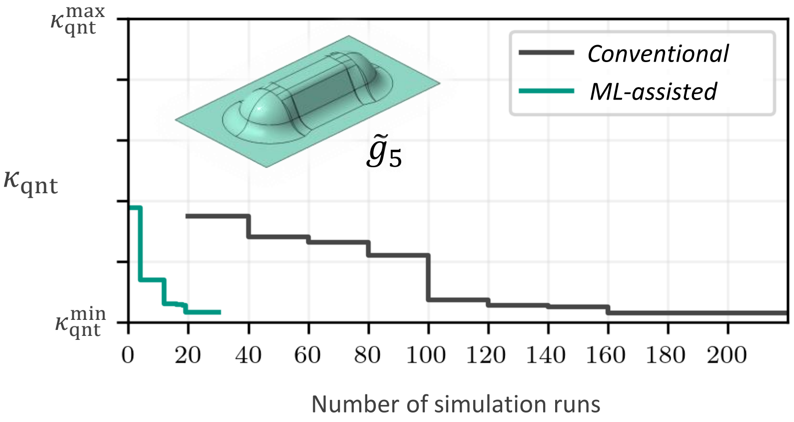
Observation

- *ML* more efficient than *conventional*
  → Utilise 'knowledge' from previous, generic samples

Summary

- ML-based optimisation for variable geometries
- Process dynamics can be learned from generic samples
  - Useful process recommendations after training
  - Recommendations converge to optimum

  → **efficient optimisation of component variants possible!**



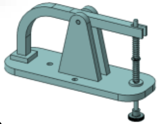
Once trained, the ML-model guides the optimiser and overall speeds up the optimisation

Outlook – Short term

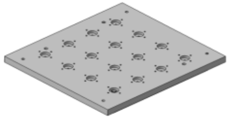
Experimental trials

Experimental trials

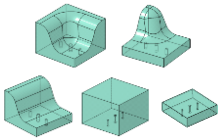
- Base plate to mount tool blocks
  → multiple geometries possible
- Frame-mounted clamps control draw-in
- Trials at ITA and *Schmidt & Heinzmann GmbH*
  → first results hint process improvement
  → ML-algorithm has learnt to give use process advise

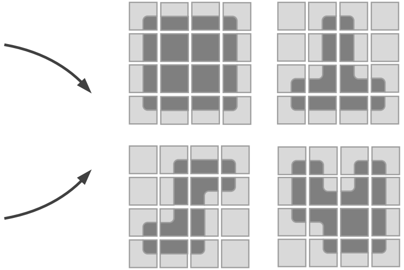


Base plate



Tool blocks

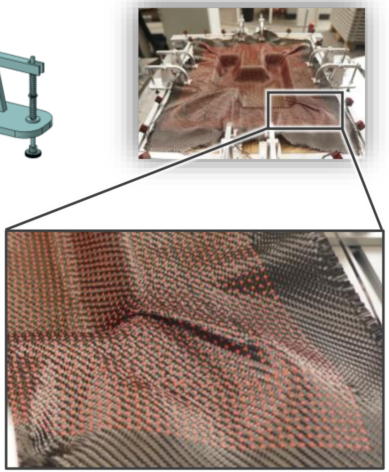




example tool configuration (view from top)

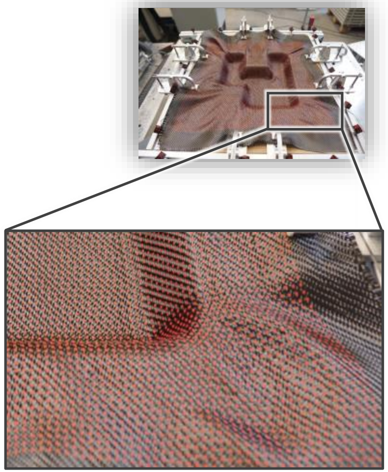
Thank you!

Reference clamping



↯ Severe folding ↯

ML-advised clamping



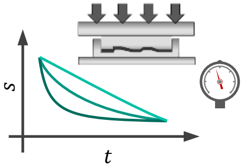
✓Folding mitigated ✓

Outlook – Long term

Efficient process optimisation

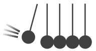
Use case

- Application to ‘real-world’ scenarios
  - Comlex geometry, more process parameters,…
  - Other manufacturing processes

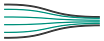


Integration of prior knowledge [Raissi et al. 2019]

- Integration of known physics into training (PINNs)
  → physically-consistent results [Würth 2022]



$$\sum_{l=1}^{3} \frac{\partial \sigma_{lk}}{\partial x_l} + f_k = \rho \frac{\partial^2 u_k}{\partial t^2}$$

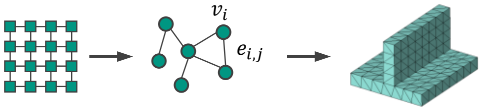


$$\frac{\partial \rho}{\partial t} + \nabla(\rho u) = 0$$

$$\frac{\partial T}{\partial t} - a\Delta T = h_{\mathrm{inh}}$$

More advanced ML-techniques

- Graph neural networks for further generalisability



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Thank you

for the great support.