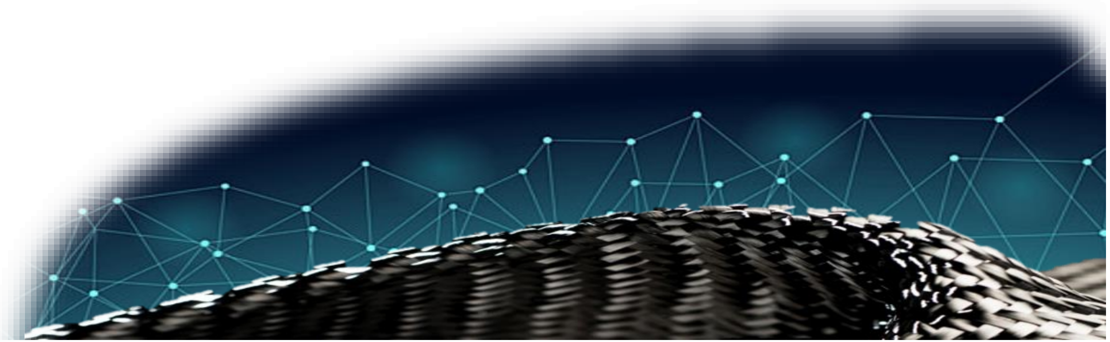
Machine learning algorithms for efficient process optimisation of variable geometries at the example of fabric forming

Lionel Fourment PhD-Prize for Industrial Research



20 April 2023

26th ESAFORM in Krakow, Poland

Clemens Zimmerling

Institute of Vehicle Systems Technology – Lightweight Design
Karlsruher Institute of Technology

Motivation

Overview

Lightweight Engineering

- Lightweight potential ↔ Engineering efforts

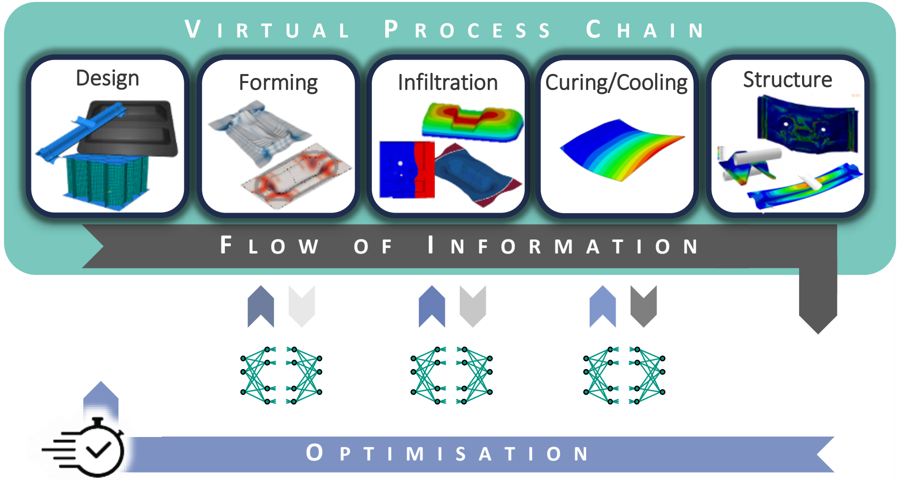
Process simulation for engineering design

- Early assessment of manufacturability
- Structural simulation with manufacturing effects
- ✓ Reduction of expensive prototype trials
- Computation efforts (iterative optimisation!)

Goal: Accelerate process optimisation

- Integration of prior knowledge from similar components via Machine Learning (ML)

adapted from [Kärger et al. 2015]



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

Motivation

Overview

Lightweight Engineering

- Lightweight potential ↔ Engineering efforts

Process simulation for engineering design

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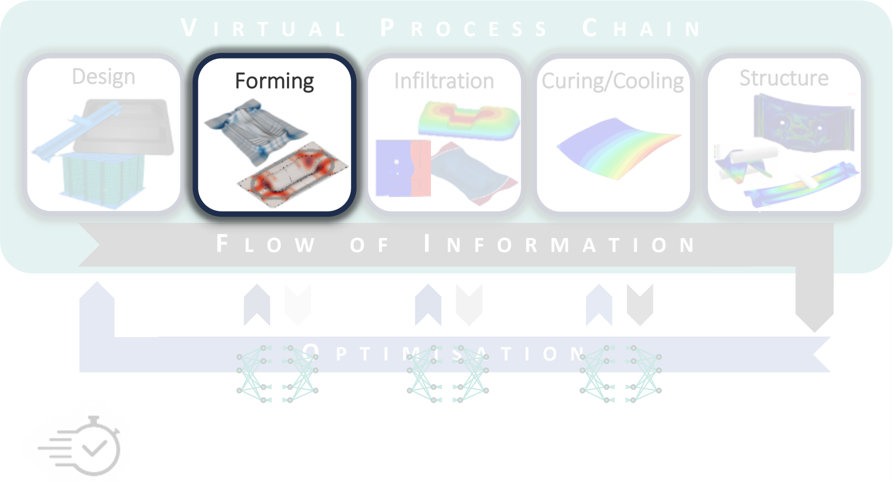
- Structural simulation with manufacturing effects
- ✓ Reduction of expensive prototype trials
- Computation efforts (iterative optimisation!)

Goal: Accelerate process optimisation

- Integration of prior knowledge from similar components via Machine Learning (ML)
- Studied example: Forming of engineering textiles

adapted from [Kärger et al. 2015]



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

Agenda

State of the Art

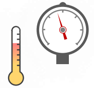
Research outset

Virtual process optimisation

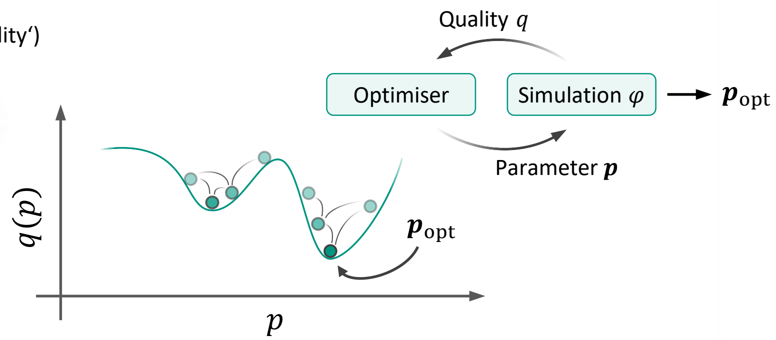
- Process simulation as function $\varphi : P \mapsto Q$

Process response (‚quality')

Process parameters



- Goal: Optimal parameters $\boldsymbol{p}_{\mathrm{opt}}$ with $q_{\mathrm{opt}} = q(\boldsymbol{p}_{\mathrm{opt}}) \overset{!}{\rightarrow} \min$
- Classical approach: Optimisation algorithms

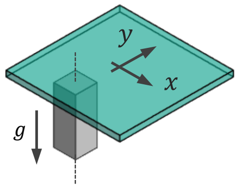


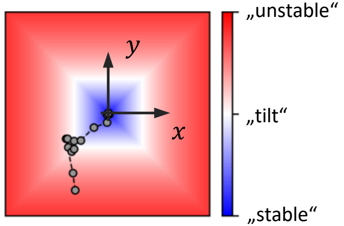
Challenge

- Complex objective, multiple parameters
  → numerous iterations → computation time grows

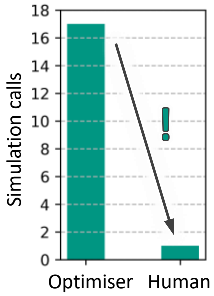
Option to increase efficiency

- Integration of "prior knowledge" into optimisation
- Thought experiment





Tilting moment per support position



State of the Art

Surrogate-based optimisation

Prior knowledge

- Numerically efficient approximation (‚Surrogate‘)

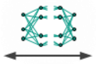
$$\mu_{\mathrm{srg}}: \quad P \mapsto Q$$

$$\text{mit} \qquad \mu_{\mathrm{srg}} \approx \varphi$$

- Data-driven

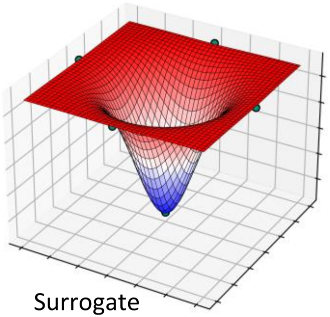
ID	p_1	p_2	...
1	0.1	2.3	...
2	4.2	0.8	...
...	...	...	...
n	9.5	2.8	...

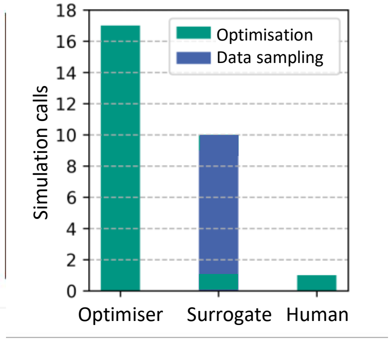
Input P



ID	q_1	q_2	...
1	0.1	2.3	...
2	4.2	0.8	...
...	...	...	...
n	9.5	2.8	...

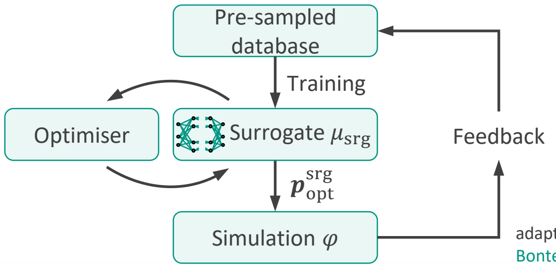
Output Q





Surrogate-based optimisation (SBO)

- Surrogate guides the optimiser in the search space
- Concentrate simulations on most promising regions
- Feedback of new observations



adapted from
Bonte et al. 2007

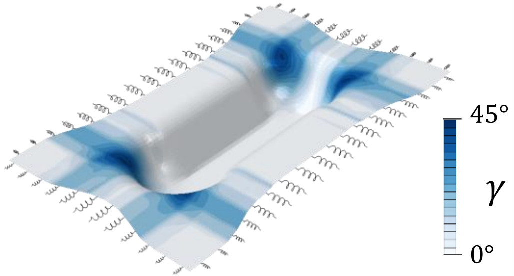
State of the Art

Surrogate-based Optimisation | Application example

Gripper-assisted textile forming [Zimmerling et al. 2021]

- FE forming simulation (Fabric model [Poppe et al. 2018, 2019])
- Optimisation of material intake (60 adjustable grippers)
- Goal: Minimisation of shear strain γ

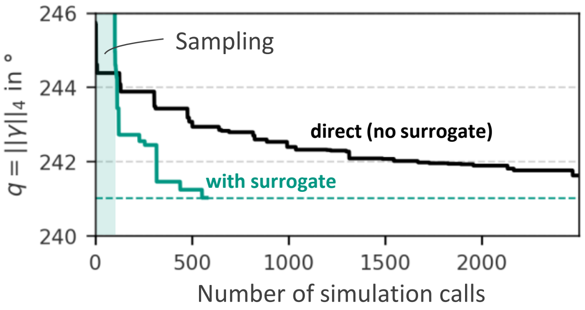
Clamping frame with grippers [Albrecht et al., 2019 (Fh ICT)]



Example plot of the shear strain γ after forming

Comparison: with and without surrogate

- SBO converges faster than direct optimisation
- Fewer simulations calls to reach optimum



[Zimmerling et al. 2021]

State of the Art

Research Gap

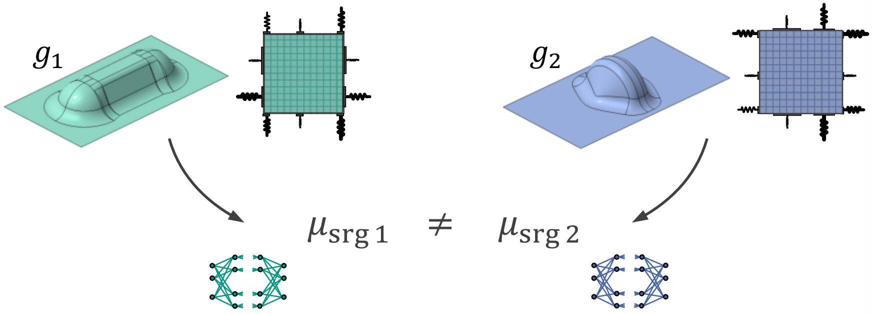
Surrogates …

✓ … support convergence in many cases, …

…but they are typically task-specific “one-off” models

→ task variations difficult to capture (geometry change, …)

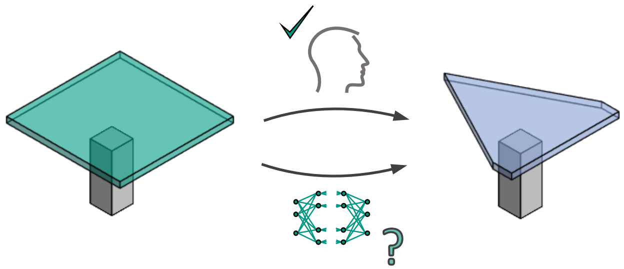
→ each component requires re-sampling and re-training



Idea

- ML-techniques can learn complex system dynamics

  → suitable for a generalised surrogate?



State of the Art

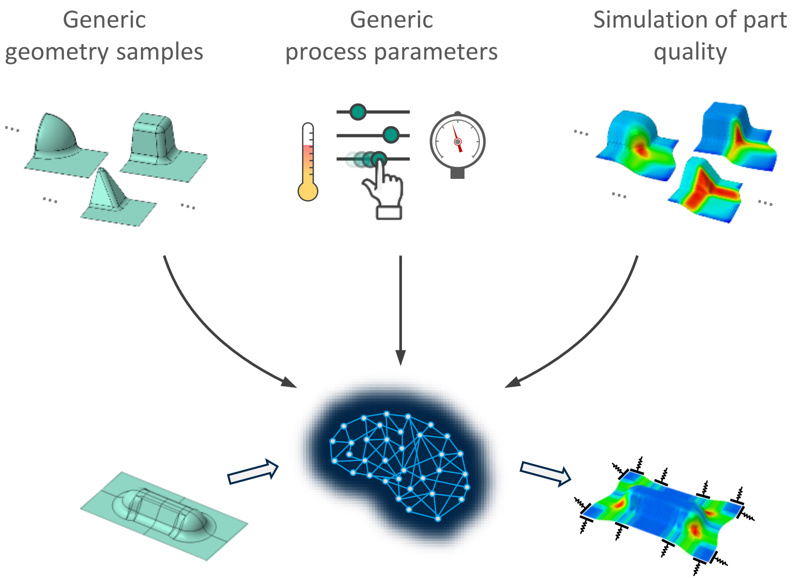
Research hypotheses

Hypothesis 1

ML and process simulation can be combined to extract knowledge from generic process samples and apply it to a new geometry

Hypothesis 2

Once trained, such a generalised ML-model speeds up an optimisation like a classical, geometry-specific surrogate



Agenda

Karlsruher Institut für Technologie

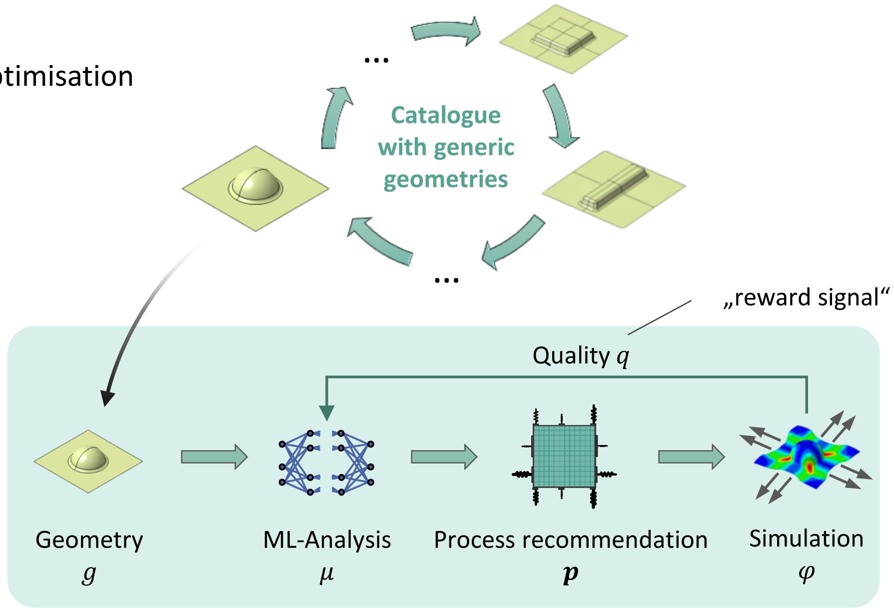
Process optimisation for variable geometries

Concept

Idea

- Replace the classical surrogate $\mu_{\text{srg}} : P \overset{G}{\mapsto} Q$ + Optimisation

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



Reinforcement Learning [Sutton and Barto, 2018]

- Trial-Error-Training in a simulation environment
- Algorithm is rewarded if part quality improves
- Goal: Maximise total „reward“

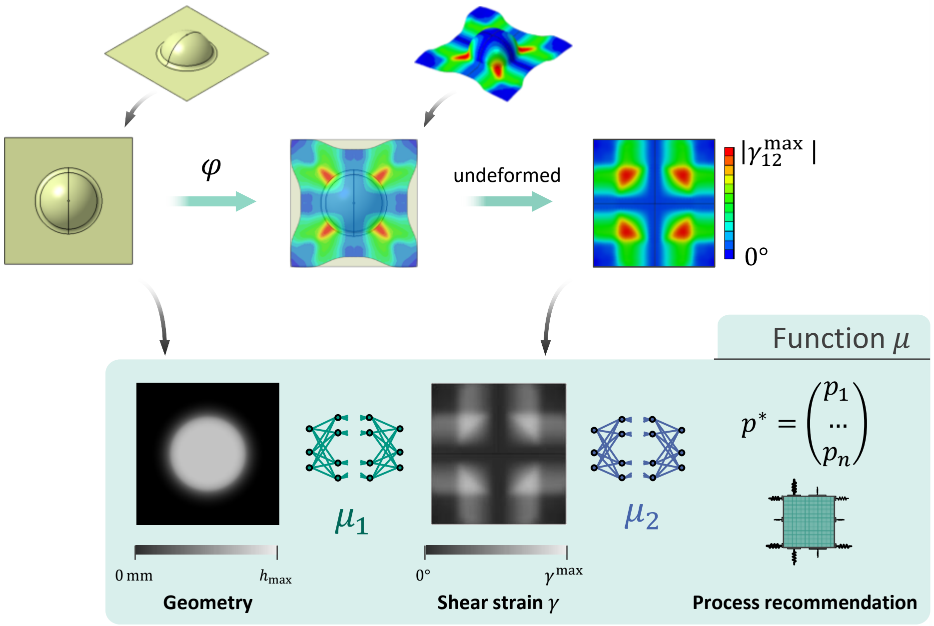
Process optimisation for variable geometries

Geometry information

Geometry encoding

- Close spatial relation between geometry and material strain [Zimmerling et al. 2019]
  - Well representable in greyscale-images
  - Usage of image processing ML-techniques (Convolutional neural networks, CNNs)

- Two-step function models μ [Zimmerling et al. 2020]
  1. μ_1 : Estimation of strain field $\boldsymbol{\gamma}$
  2. μ_2 : Interpretation of the strain field and estimation of beneficial process parameters



[Zimmerling et al. 2020]

Process optimisation for variable geometries

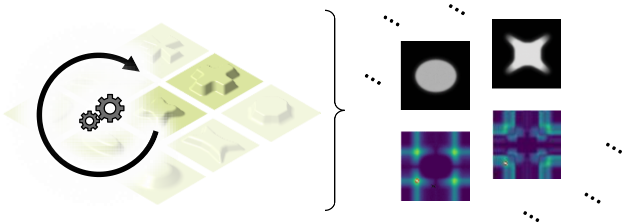
Visualisation example

Training of μ_1

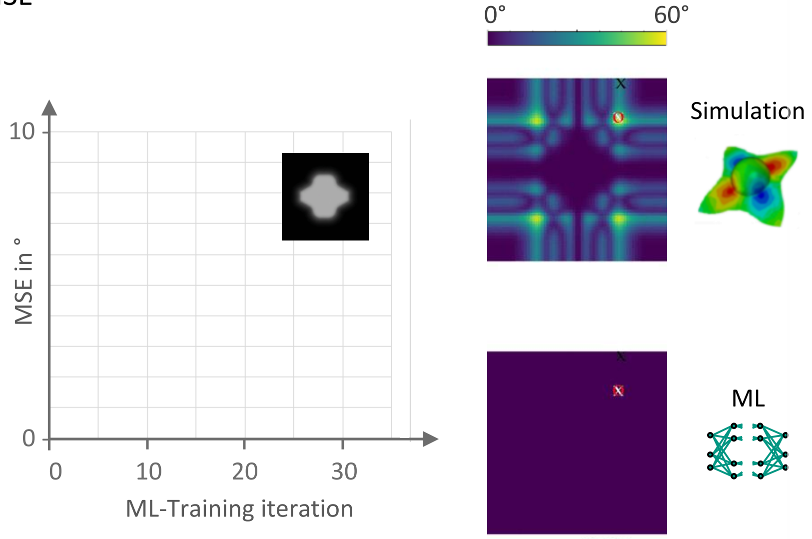
- Database with draping simulation samples
- Training: Iterative adaption of network parameters to minimise MSE

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

→ Images well suited to describe arbitratry forming geometries



Database with draping samples



Images from [Trippe, 2019]

Agenda

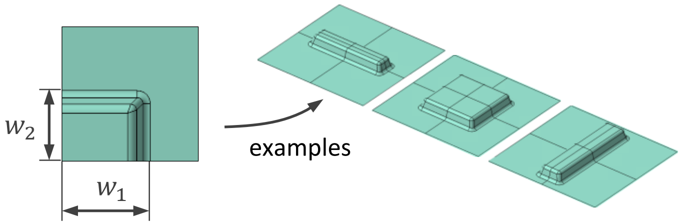
- Motivation
- State of the art and research hypotheses
- Optimisation methodology
- **Application example**
- Summary and outlook

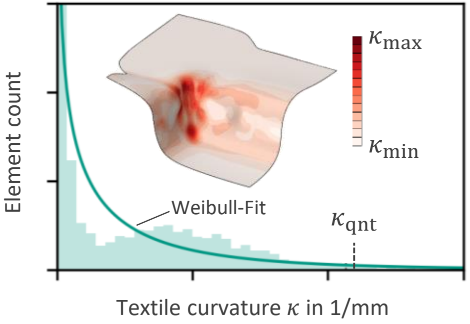
Optimisation of variable geometries

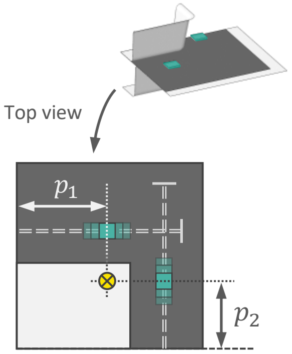
Application example

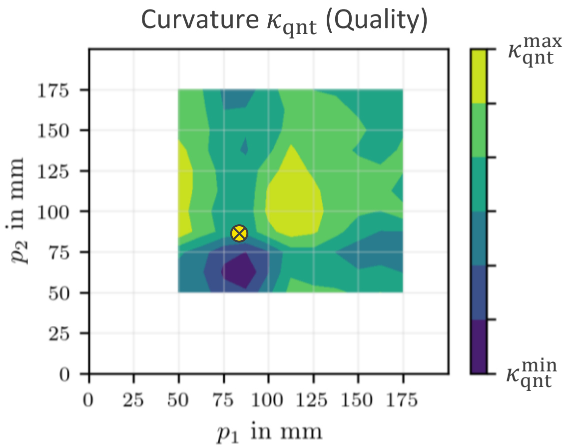
Pressure-pad assisted fabric forming [Zimmerling et al. 2020, 2022b]

- 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



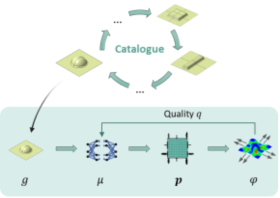






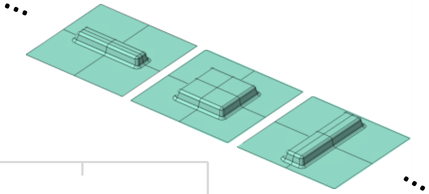
Optimisation of variable geometries

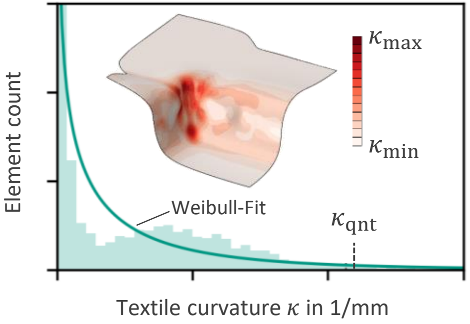
Application example | Training results

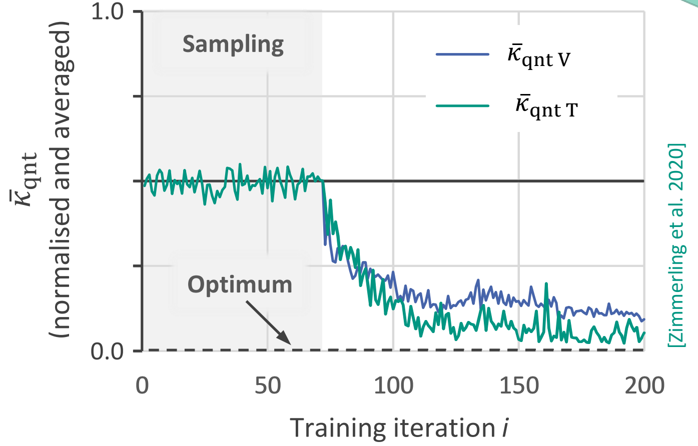


Training progress with Reinforcement Learning [Zimmerling et al. 2020, 2022b]

- 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

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

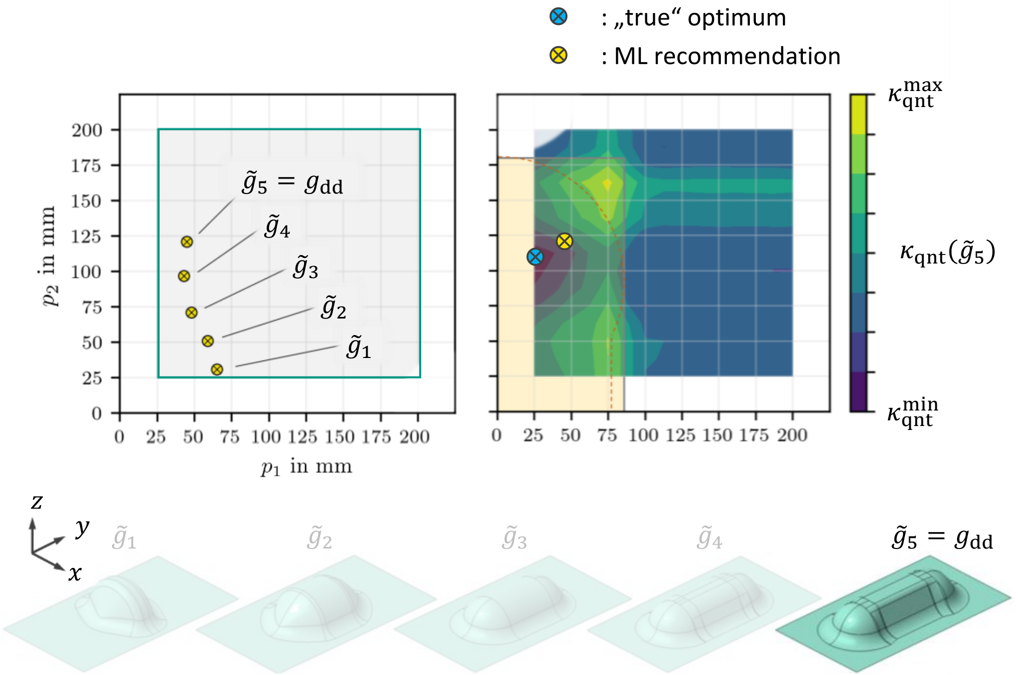
- Testing on new geometry variants
  - Doubly symmetric and mostly convex
  - No subset of the cuboids

Observation

- ML recommendations follow geometry variation
- Useful process recommendation
  (10% deviation from ‚true‘ optimum)

Hypothesis 1

ML and process simulation can be combined to extract knowledge from generic process samples and apply it to a new geometry



[Zimmerling et al. 2022b]

Optimisation of variable geometries

Application example | Training results

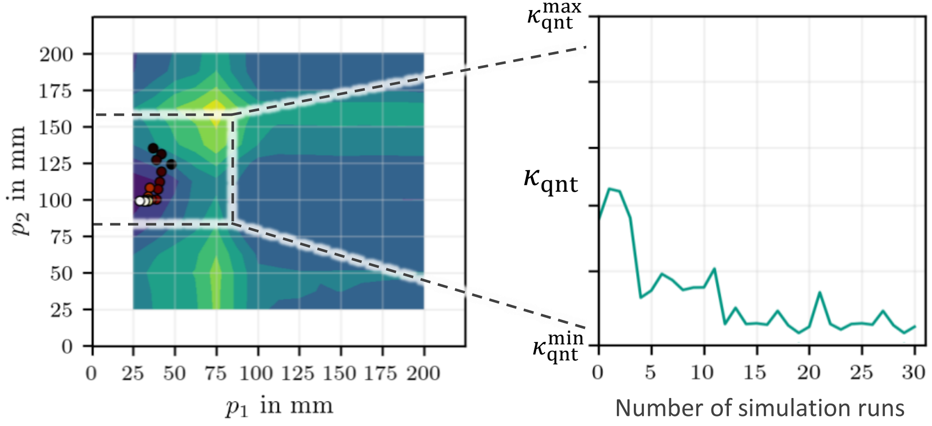
Training continuation [Zimmerling et al. 2020, 2022b]

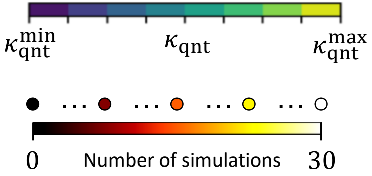
- Process recommendations useful, but not strictly optimal

Thus

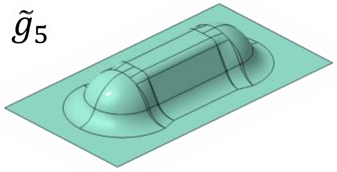
- Continuation of training on envisaged target geometry
  - Convergence towards optimum
  - Gradual reduction of textile curvature

→ successful process optimisation for target geometry





$\tilde{g}_5$



Optimisation of variable geometries

Application example | Training results

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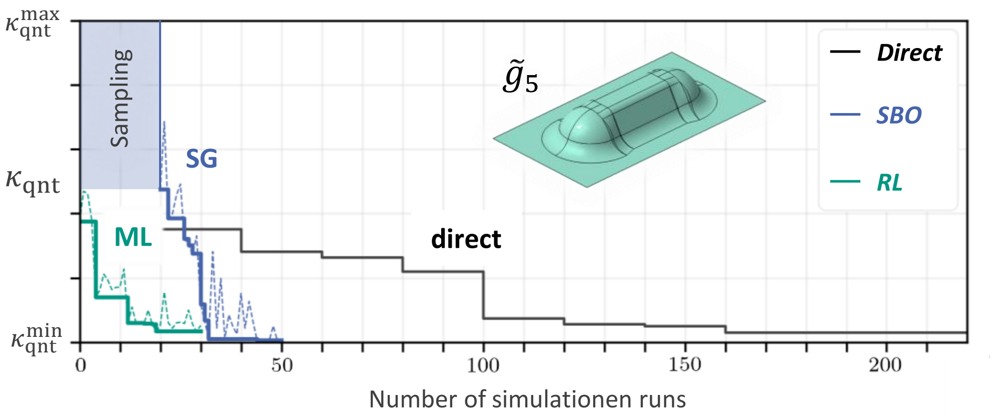
Optimisation approach comparison

- ***Direct*** ***(GA, no surrogate)***
- ***SG*** ***(classical surrogate)***
- ***ML*** ***(geometry-informed surrogate)***



Observation

- ***SG*** and ***ML*** faster than ***direct***
  → Integration of prior knowledge
- ***ML*** more efficient than ***SG***
  → Geometry-specific sampling saved

Note on ML-pretraining

- Substantial prior effort required
- Decoupling of pre-training and deployment

Hypothesis 2

Once trained, such an generalised ML-model speeds up an optimisation like a classical, geometry-specific surrogate

Agenda

- Motivation
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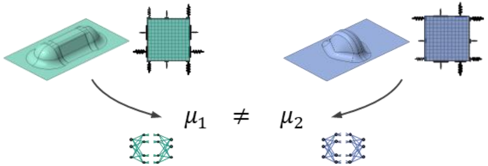
Summary

Efficient process optimisation

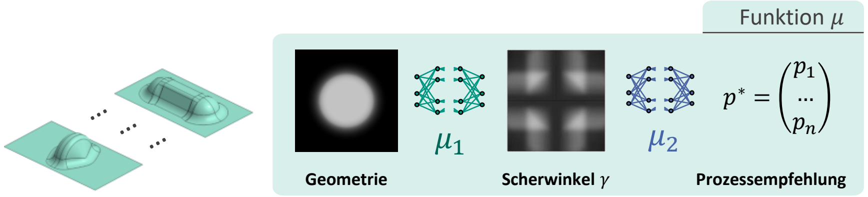
Initial situation

- Surrogate models speed up optimisation procedures, but prove unwieldy for variable geometries



Methodology

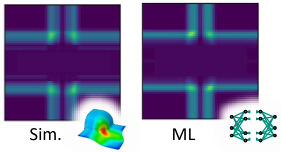
- ML-based optimisation for variable geometries
- Validation on new geometries and comparison to classical optimisers

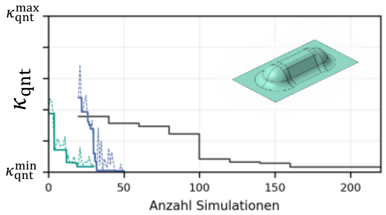


[Zimmerling et al. 2020]

Results

- Process dynamic can be learned from generic samples
  - Useful process recommendations after training
  - Recommendations converge to optimum



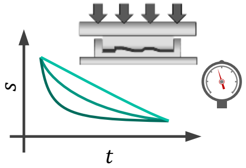


Outlook

Efficient process optimisation

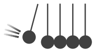
Use case

- More complex scenarios
  - Geometry, process parameters,…
  - Other manufacturing processes

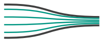


Integration of prior knowledge [Raissi et al. 2019]

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



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

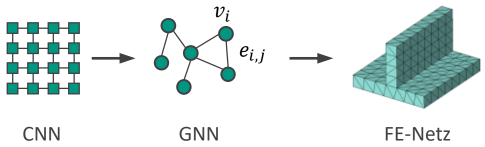


$$\frac{\partial \rho}{\partial t} + \nabla(\rho u) = 0$$

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

More advanced ML-techniques

- Graph neural networks for further generalisability



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Thank you

for the great support.