Karlsruhe Institute of Technology

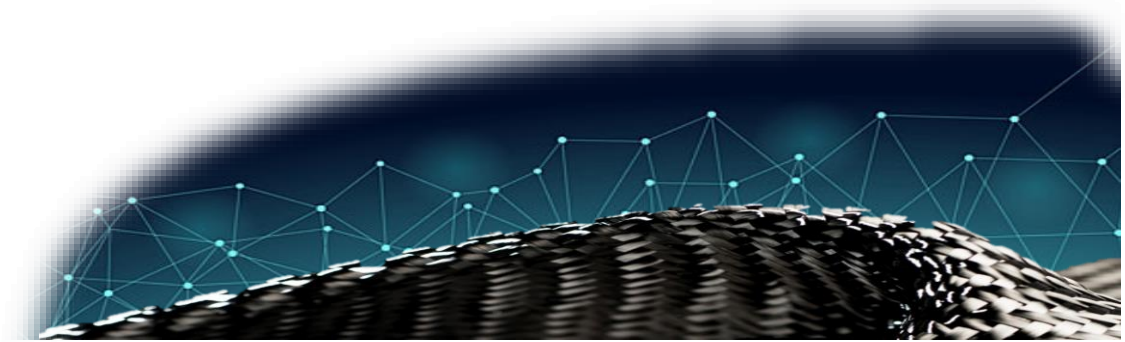
FAST Institute of Vehicle System Technology

AI and Simulation for Efficient Composite Manufacturing Process Development

SAMPE Summit

04 March 2024

Paris, France



Dr.-Ing. **Clemens Zimmerling**

Karlsruher Institute of Technology (KIT)
Institute of Vehicle Systems Technology – Lightweight Design

AI in Manufacturing

State of the Art

Now: Process surveillance

- Sensor monitoring
- Process control
- Quality inspection,...

→ *Maintaining* an intended state

Next: Process development

- Feedback on ideas
- Issue recommendations
- Efficient Optimisation

→ *Generating* an intended state

Engineering & Simulation

Virtual process engineering with AI

Data science

AI-based process development

Motivation

Lightweight Engineering

- Lightweight potential ↔ Engineering efforts

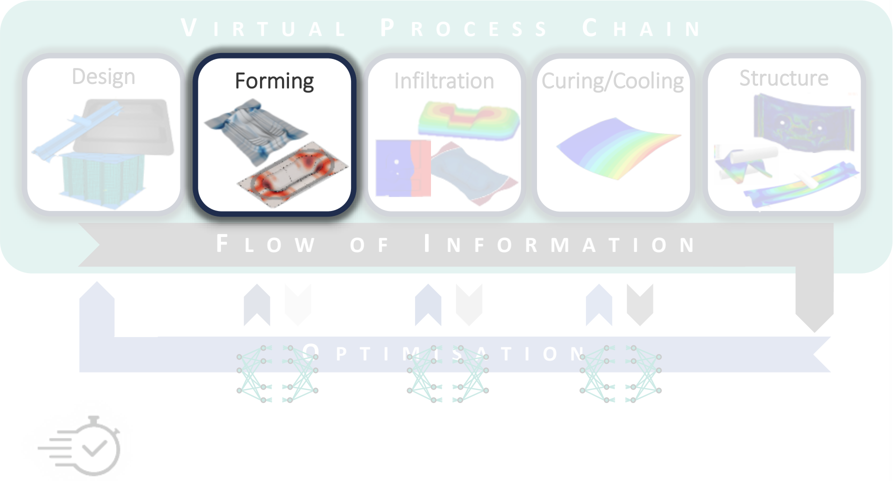
Process simulation for engineering design

- Reduction of expensive prototype trials
- Computation efforts (iterative optimisation!)

Goal

- Accelerate virtual process development by AI

adapted from [Kärger et al. 2015]



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

AI-based process development

Conceptual view

Example: virtual process optimisation

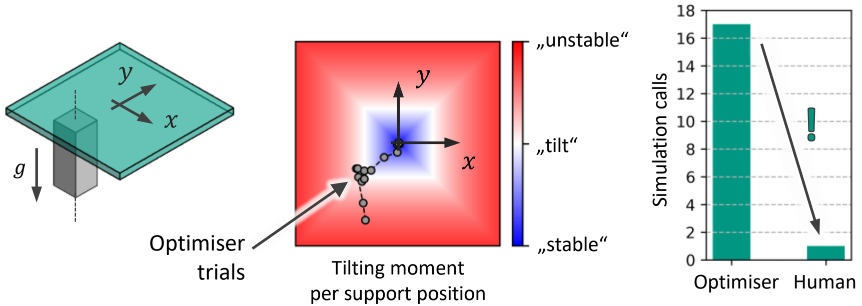
- Goal: $\boldsymbol{p}_{\text{opt}}$ with $q_{\text{opt}} = q(\boldsymbol{p}_{\text{opt}}) \overset{!}{\rightarrow} \min$
- Classical approach: Optimisation algorithms

Challenge

- Complex objectives → computation time grows

Increase efficiency by AI

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



AI-based process development

Idea: Combine simulation and AI

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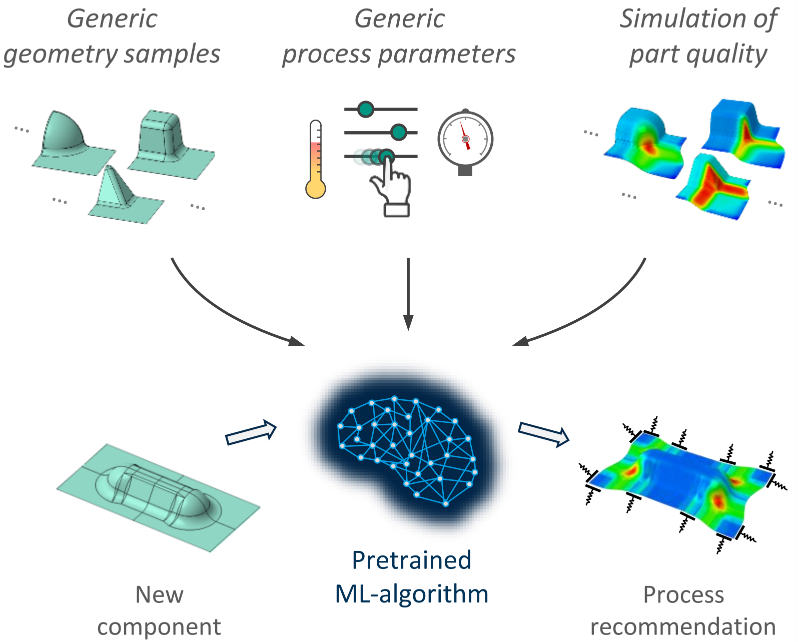
Virtual ‚process experience'

- Physics-based simulations
  as a proxy of actual experiments

- AI learns governing process dynamics

  → after training, AI gives
  recommendations for new geometries



AI-based process development

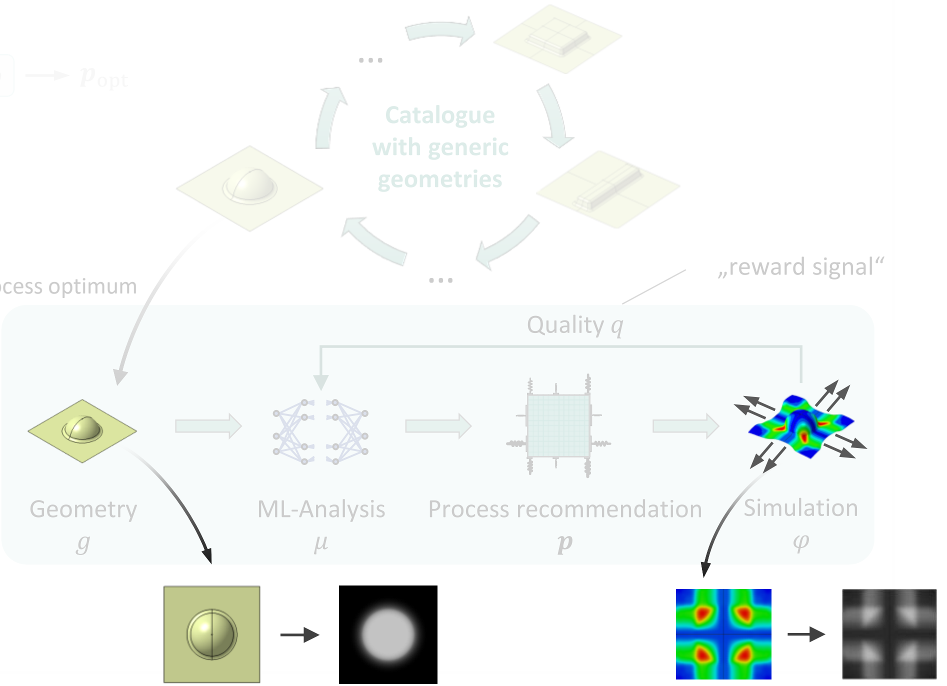
Approach: Reinforcement Learning

Idea

- Replace the iterative optimisation

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

New part geometry
Process optimum



Reinforcement Learning [Sutton and Barto, 2018]

- Trial-Error-Training in a simulation environment
- Algorithm is rewarded if part quality improves

AI-based process development

Visualisation of learning

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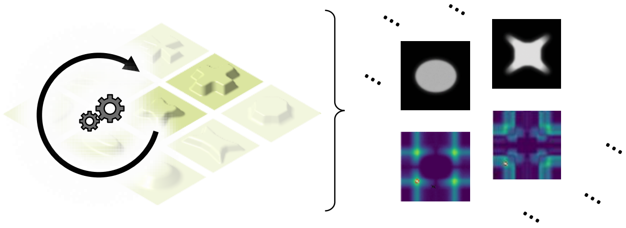
Training

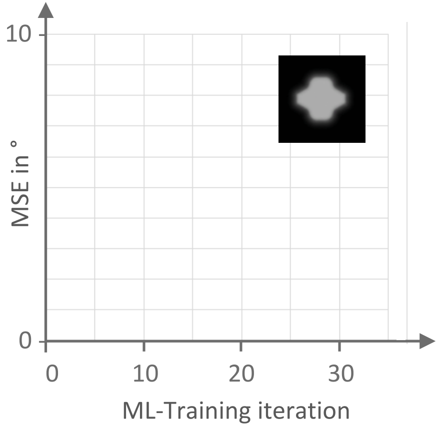
- Database with forming simulation samples
- Training: Iterative adaption of network parameters to minimise MSE

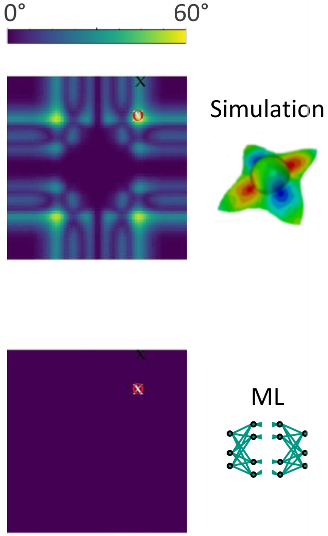
→ Images well suited to describe arbitrary forming geometries

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



Database with draping samples





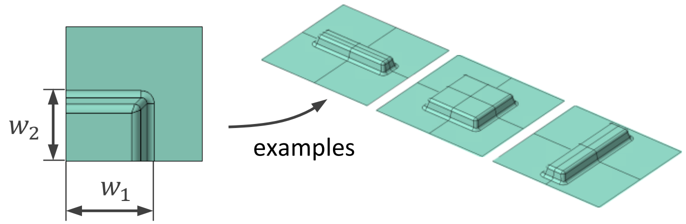
Images from [Trippe, 2019]

AI-based process development

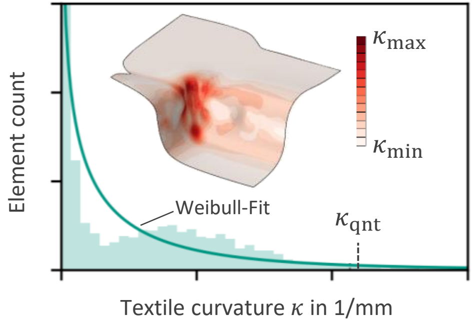
Application example

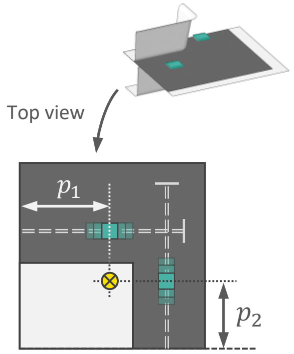
Pressure-pad assisted fabric forming [Zimmerling et al. 2020, 2022b]

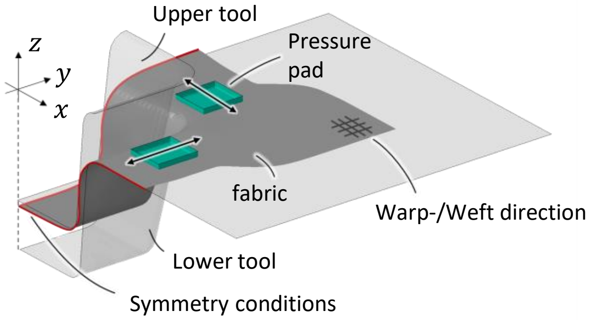
- FE fabric model [Poppe et al. 2018, 2019]
  on geometry catalogue of cuboids
- Process manipulation by pressure pads



- Goal: Smoothest possible draw-in







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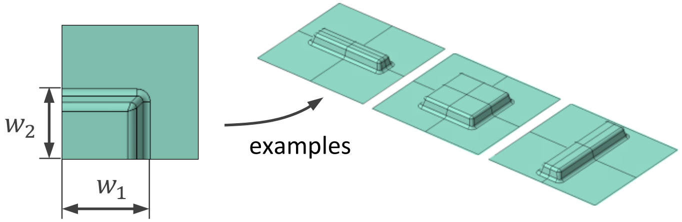

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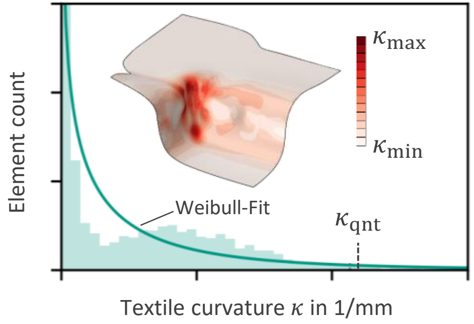
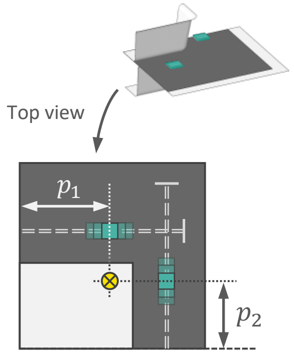
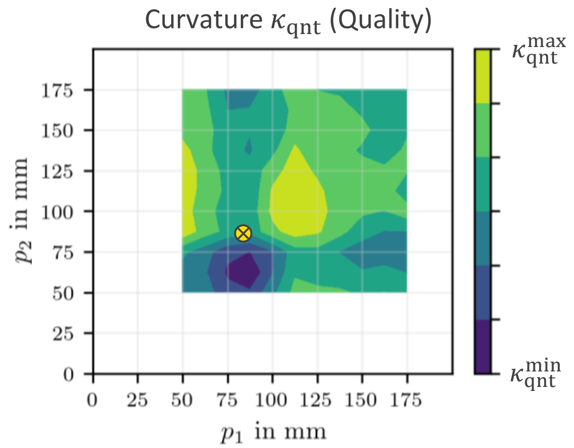
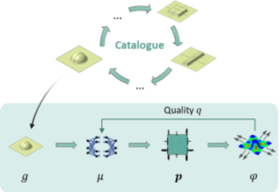






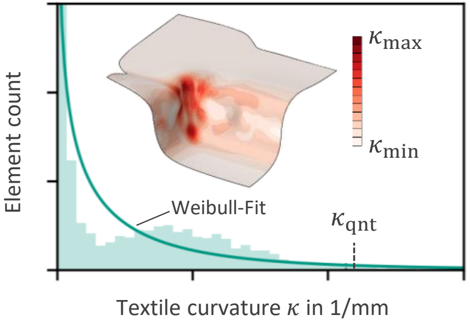
AI-based process development

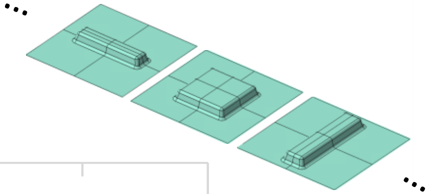
Application example | Training results

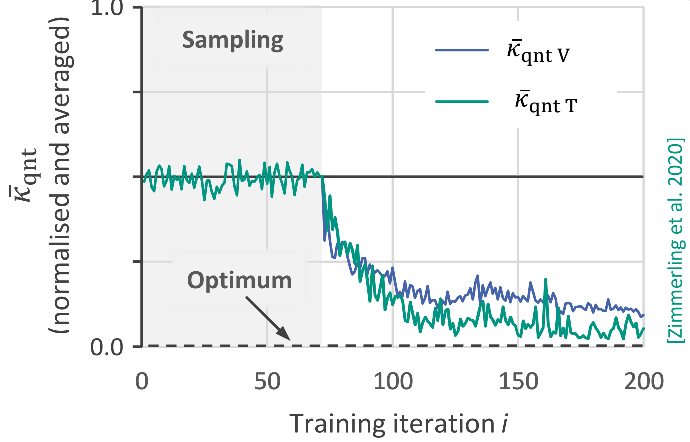


Training progress with Reinforcement Learning [Zimmerling et al. 2020, 2022b]

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







AI-based process development

Application example | Training results

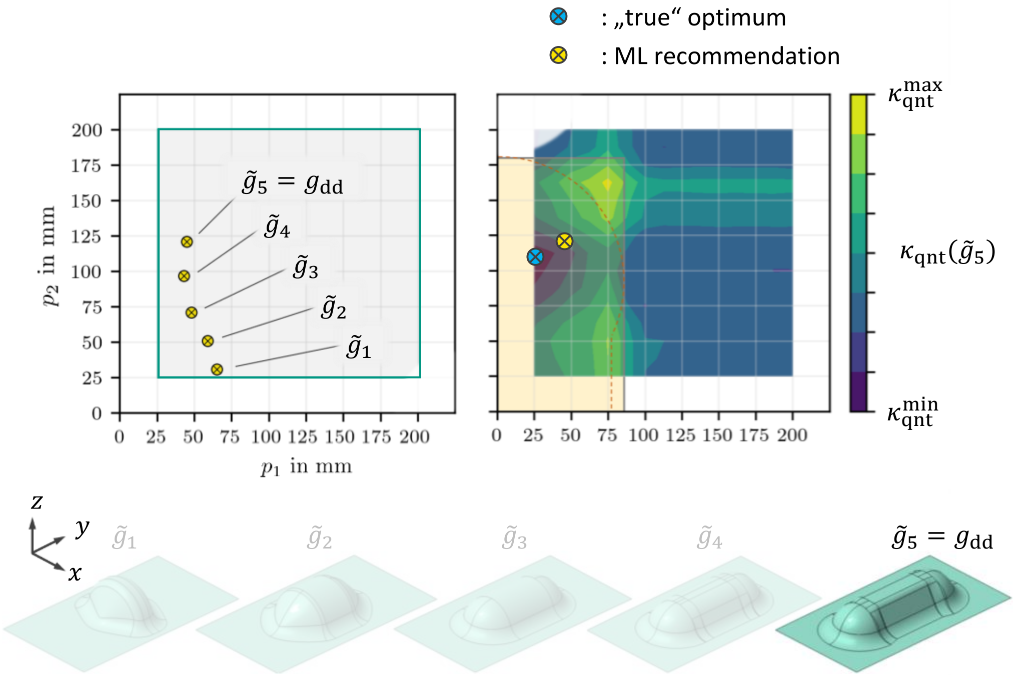
After training [Zimmerling et al. 2020, 2022b]

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

Observation

- ML recommendations follow geometry variation
- Useful process recommendation
- Continuation of training for refinement

✓ Successful extraction of process experience and application to new geometries



[Zimmerling et al. 2022b]

AI-based process development

Application example | Training results

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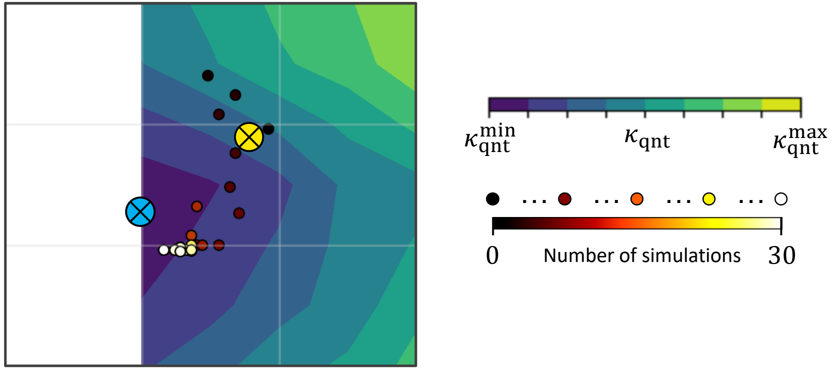
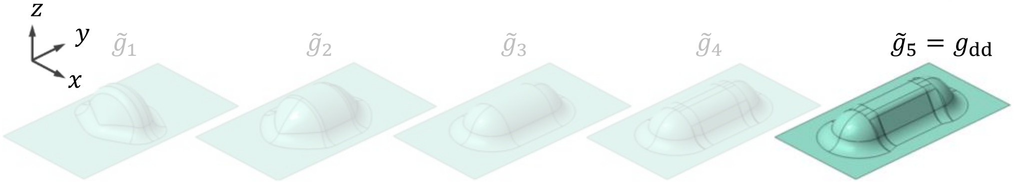




[Zimmerling et al. 2022b]

AI-based process development

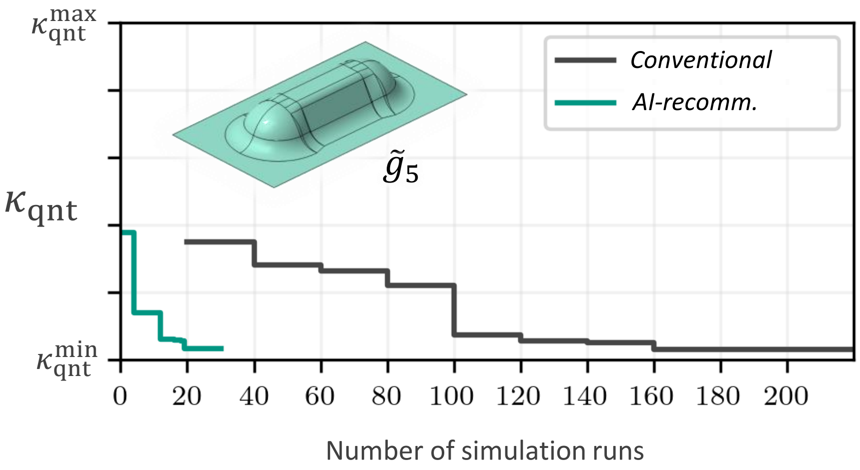
Application example | Training results and Summary

Performance comparison

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

Observation

- Fewer simulations required for optimum
- *AI* more efficient than *conventional*
  → Utilise 'knowledge' from previous, generic samples



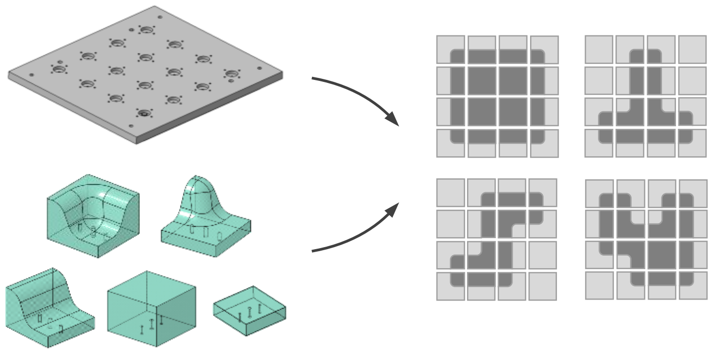
Once trained, such a generalised ML-model guides the optimiser and overall speeds up the optimisation

AI-based process development

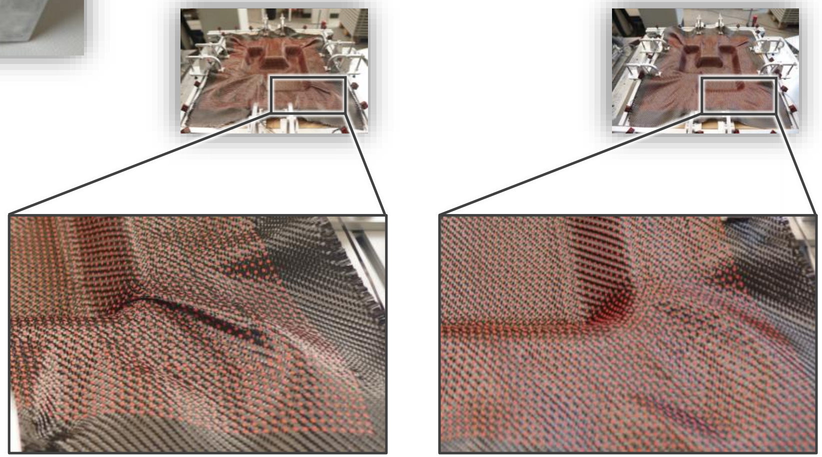
Following AI-recommendations…

Reconfigurable tool

- Base plate to mount tool blocks
  → multiple geometries possible
- Frame-mounted clamps control draw-in
- Conclusion: AI gives useful process advise*



‚Neutral‘ ‚ML‘



*: but is extremely data-intensive

The Asterisk

Reading the smallprint…

Reconfigurable tool

- Base plate to mount tool blocks
  → multiple geometries possible
- Frame-mounted clamps control draw-in
- Conclusion: AI gives useful process advise*

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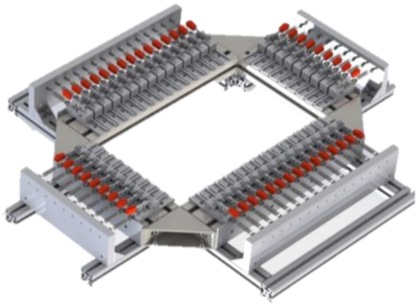
AI-assisted process modelling

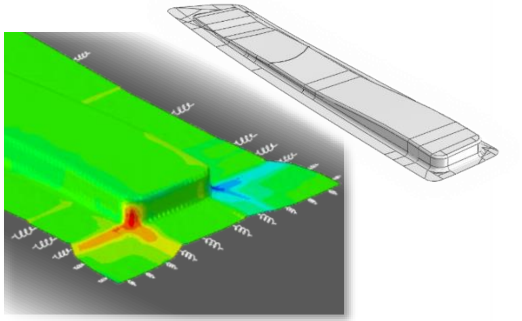
Not all data are created equal...

AI training data for process modelling

- Neural networks require expensive training data...

  → Data-efficiency decisive!



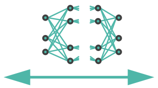


Textile forming with a clamping frame [Albrecht et al., 2019]

- 60 spring-guided grippers control the process
- Goal: Data-driven model $\mu: C \mapsto Q$
- Accurate model with little data possible?

ID	c_1	c_2	...
1	0.123	2.384	...
2	4.241	0.853	...
...	...	...	...
n	9.565	2.853	...

Clamping C



ID	q_1	q_2	...
1	231.2	241.8	...
2	235.6	231.2	...
...	...	...	...
n	239.1	229.9	...

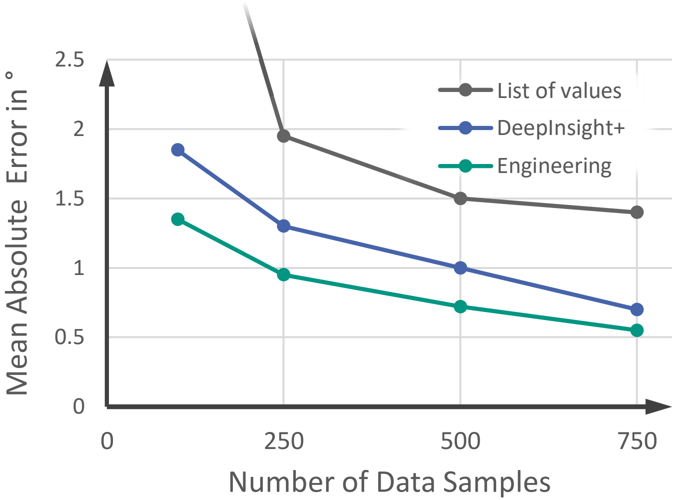
Quality Q

AI-assisted process modelling

Not all data are created equal…

Observation

- All models improve with more data
- Preprocessing the data improves model accuracy
- Domain knowledge outperforms data-science



✓ Engineering knowledge boosts AI-models
→ *Smart data beats big data*

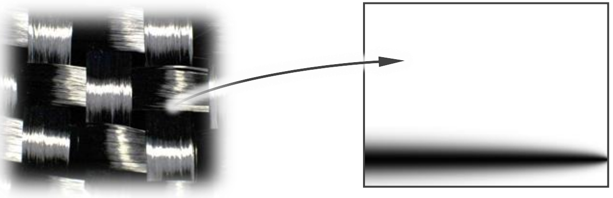
Introducing more knowledge

Physics-informed AI

Generalising knowledge

- Domain knowledge often case-specific
- Difficult to transfer between domains

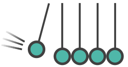
→ more general description necessary



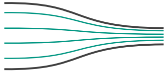
Physics-informed AI

- Integration of physics into training [Raissi et al. 2019]

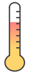
→ physically-consistent AI [Würth 2023, Würth2024]



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



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



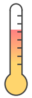
$$\frac{\partial T}{\partial t} - a\Delta T = h_{\mathrm{inh}}$$

Introducing more knowledge

Physics-informed AI

Integration of physics [Würth 2023]

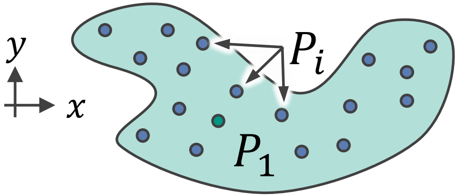
- Physical laws are expressed as PDEs
  - Example: Heat equation

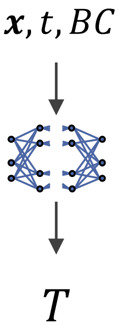


$$\frac{\partial T_1}{\partial t} = a\,\Delta T_1 + q_1 \iff \frac{\partial T_1}{\partial t} - a\,\Delta T_1 - q_1 = 0$$

- Neural network learns to solve PDEs

→ Physics-consistent AI model **without** data





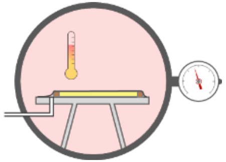
P_i	Condition	
1	$\frac{\partial T_1}{\partial t} - a\,\Delta T_1 - q_1$	$= 0$
2	$\frac{\partial T_2}{\partial t} - a\,\Delta T_2 - q_2$	$= 0$
…	…	$= 0$
	Σ	$= 0$

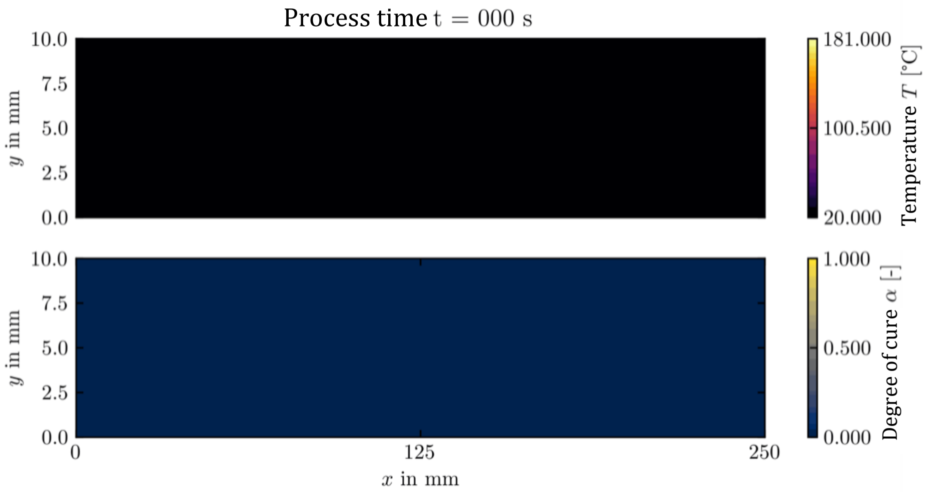
Introducing more knowledge

Physics-informed AI

Example [Würth 2023]

- Simplified autoclave curing of a thick CFRP plate
- AI predicts temperature and degree of cure over time
- Accurate solution of the physics with <2% deviation to FEM
- No simulation data required



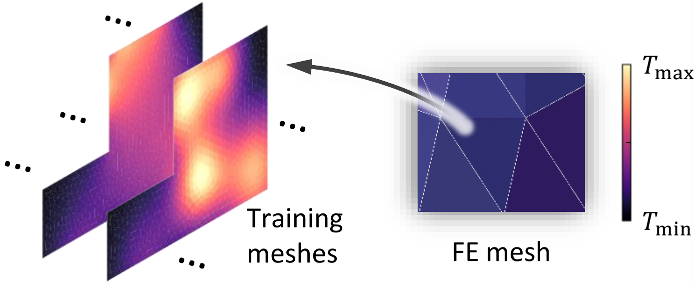


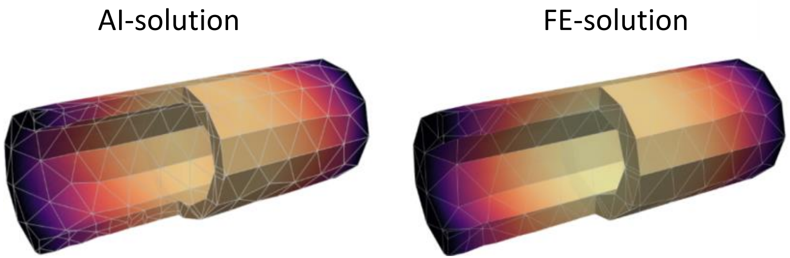
Introducing more knowledge

Physics-informed AI – Application example

Neural FE-solver [Würth2024]

- Integration of physics-informed AI into Finite-Element solver
  - Learn to solve PDE on small training meshes (< 1000 nodes)
  - Deployment on new meshes
    - Heat exchanger (>100 000 nodes)
    - Resin curing of a hollow cylinder (non-linear PDE)





AI solves PDE like FE-solver, …

Introducing more knowledge

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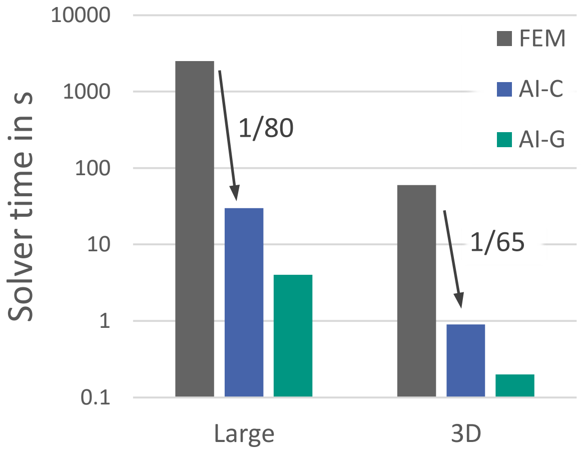
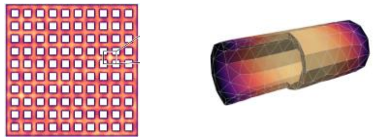




AI solves PDE like FE-solver, …

… yet much faster

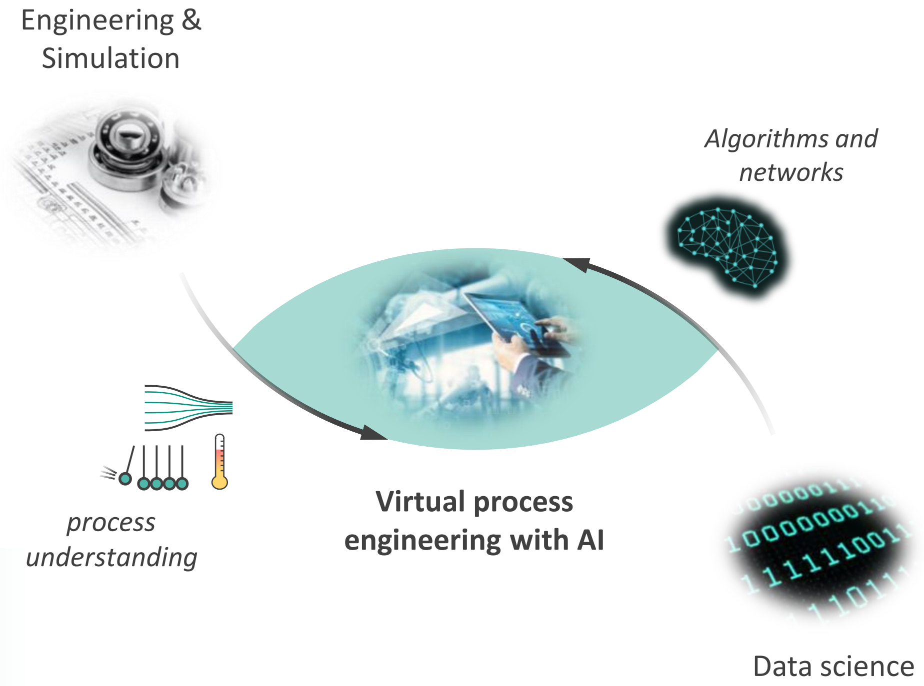
Summary & Outlook

Quo vadis, ML-based process engineering?

AI-based process engineering

- Data-driven AI offers the means to simulate and optimise processes…
- … but data acquisition is difficult
- Engineering knowledge required to make AI applicable for development

✓ AI and Engineering combined presage great potential for virtual process engineering



Sources

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Thank you!

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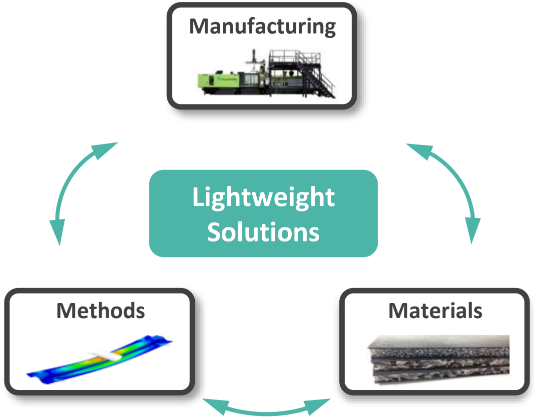

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