

Fast Prediction of the Injection Molding Process Using Machine Learning

Data-Driven Product Engineering and Design
Institute of Materials Resource Management

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October 1 2026

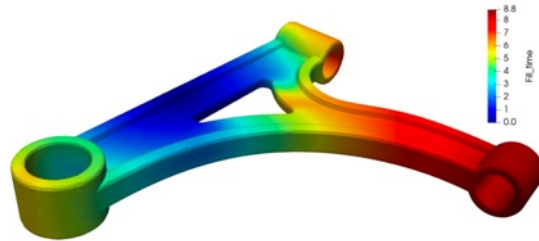
01 Introduction

Motivation

Full conventional simulation

- Established
- Robust
- Accurate

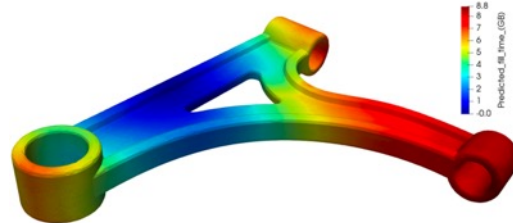
→ Validate design, mold, and process.



Fast surrogate model

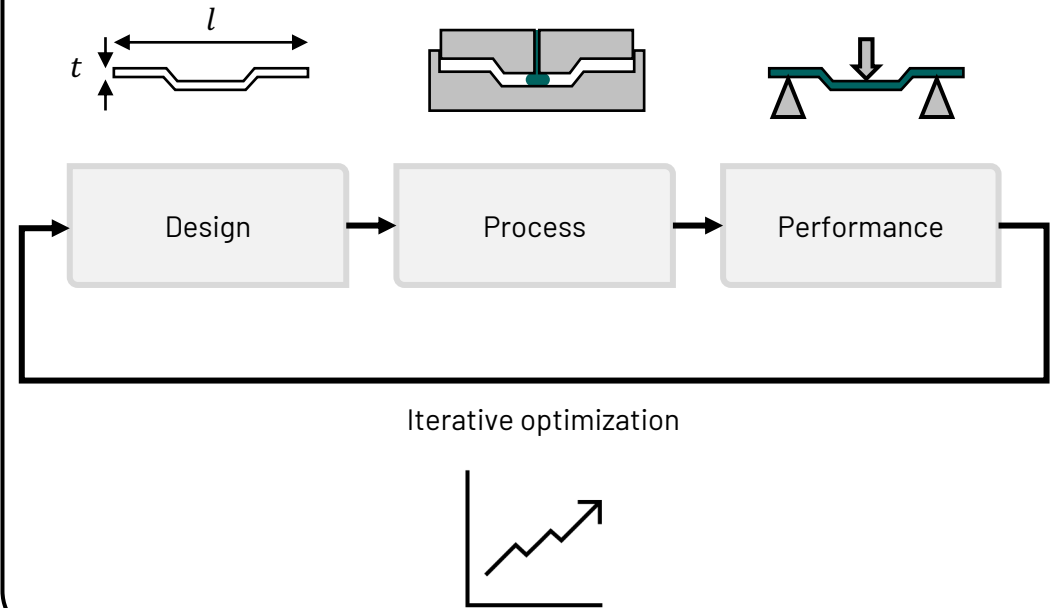
- Should trade some accuracy for speed
- Should generalize

→ Approximation for early stages



Potential use

- Accelerate initial design concepts
- Holistic optimization of the entire process chain



01 Introduction

Objective

Inputs

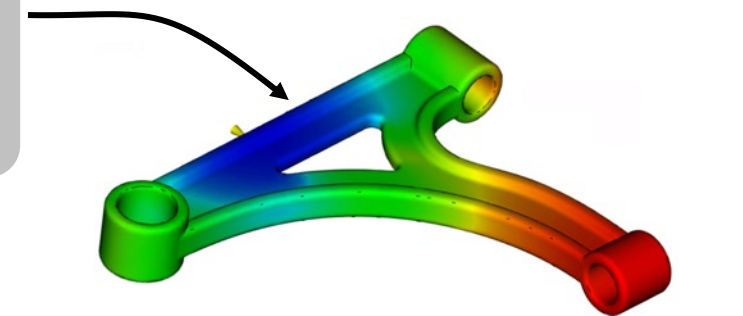
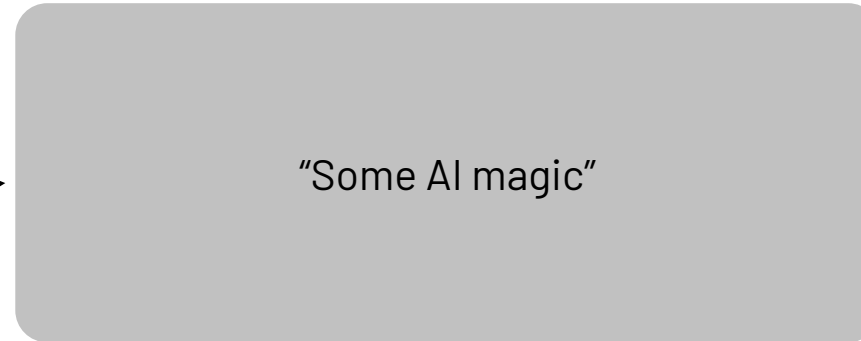
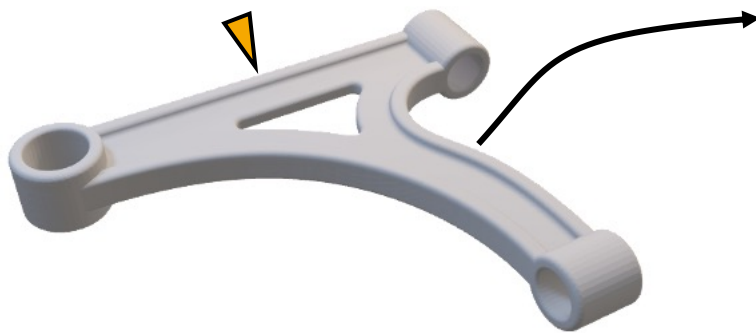
- Geometry
- Boundary conditions
- Initial conditions

Model

"Some AI magic"

Predicted outputs

- Fill pattern
- Fiber orientation
- ...



→ Should accept any geometry

→ Should predict ~100 x faster than simulation

→ Should have an error < 10%

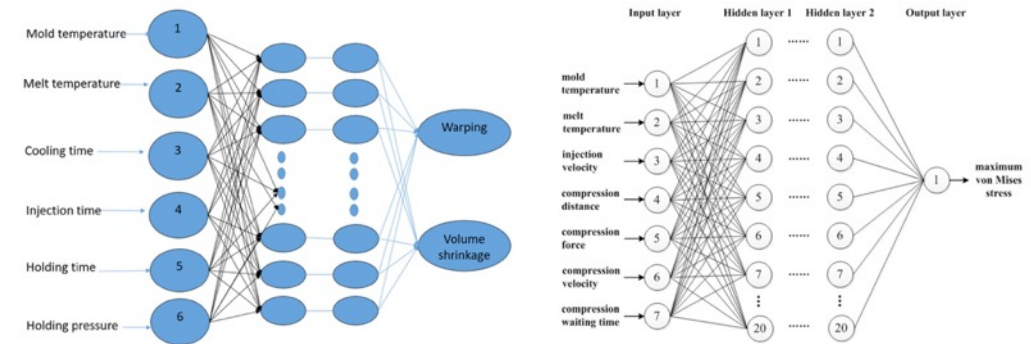
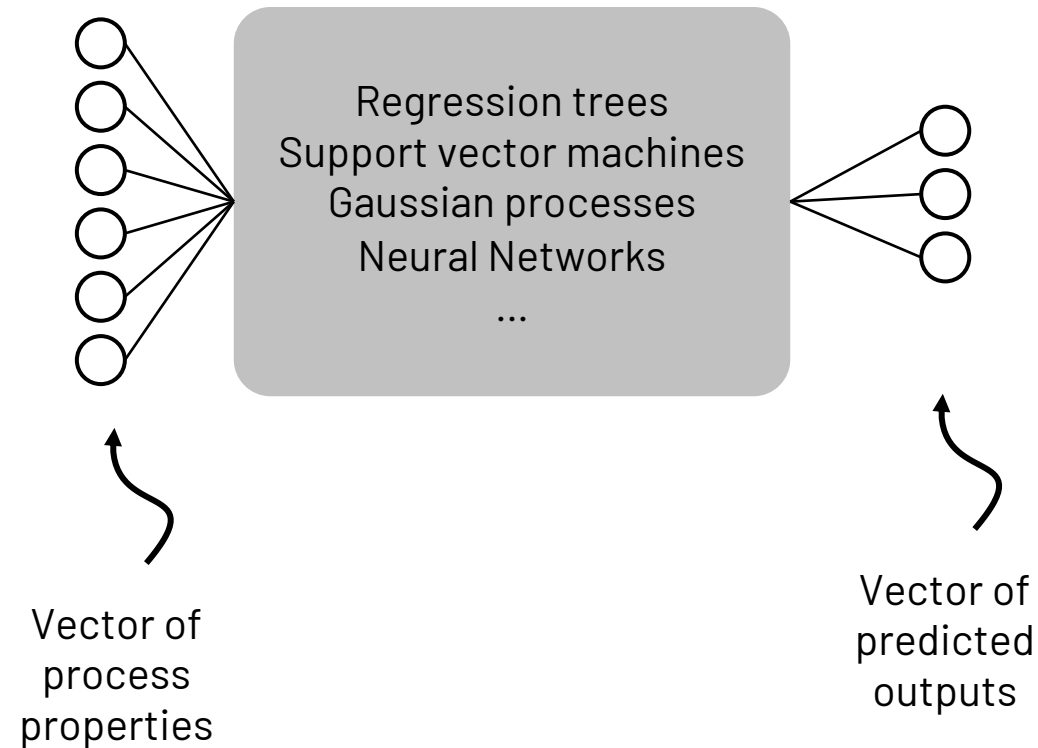
Potential Machine Learning
Approaches

02

02 Potential Machine Learning Approaches

Direct regression

Learn direct relations between processing parameters and outcomes via trainable regression models.



Song et al., *J. Adv. Manuf. Technol.*, **109**, 755-769, 2020
Xu et al. *J. Adv. Manuf. Technol.*, **76**, 2199-2208, 2015

Advantages

- Simple to build
- Fast to evaluate

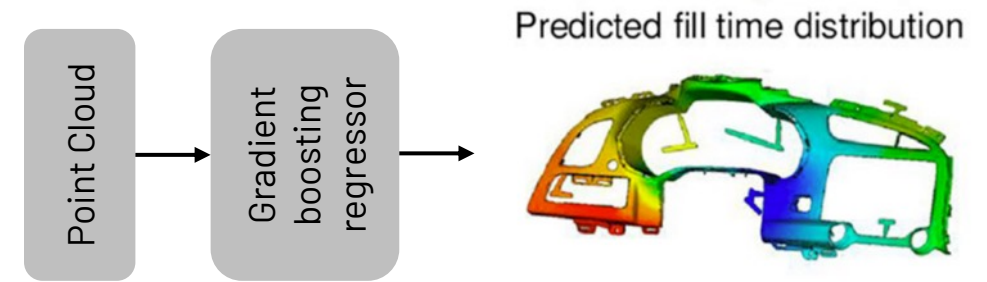
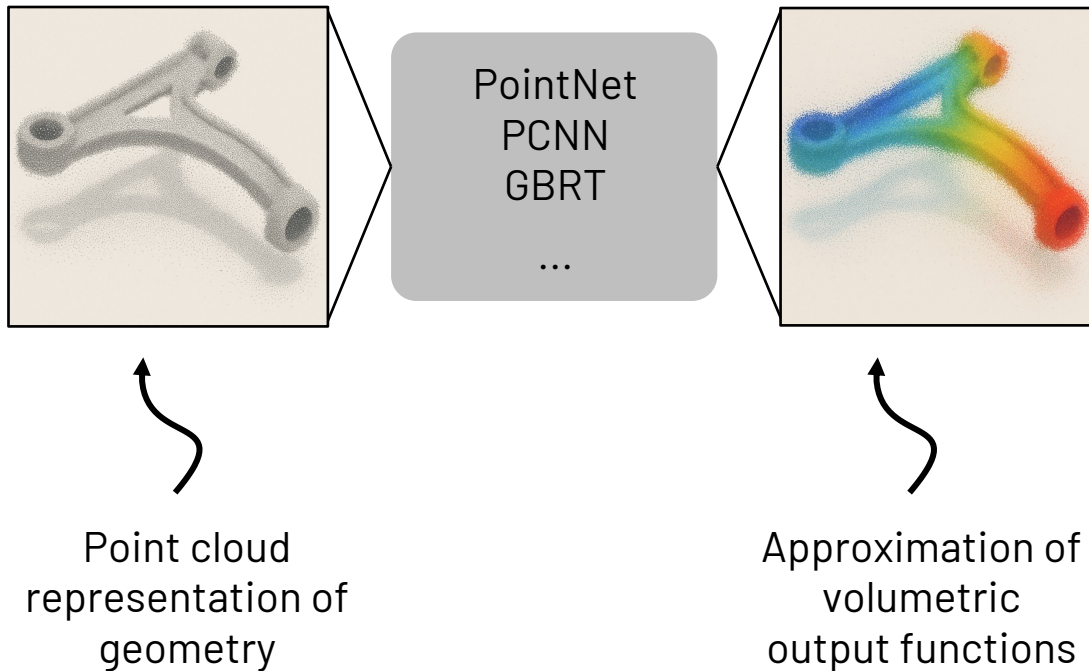
Disadvantages

- Does not account for physics
- Does not generalize to arbitrary geometries

02 Potential Machine Learning Approaches

Point clouds

Represent a domain with a set of points with features at each point and train a mapping from point clouds to volumetric functions.



Uglov et al., *Struct. Multidiscip. Optim.*, **65**, 305, 2022

Advantages

- Powerful generalization
- Easy to obtain from nodes of meshes

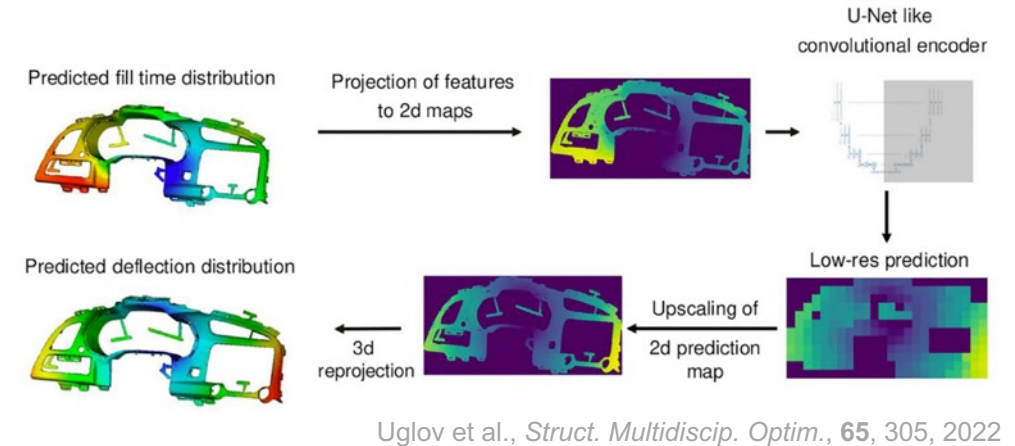
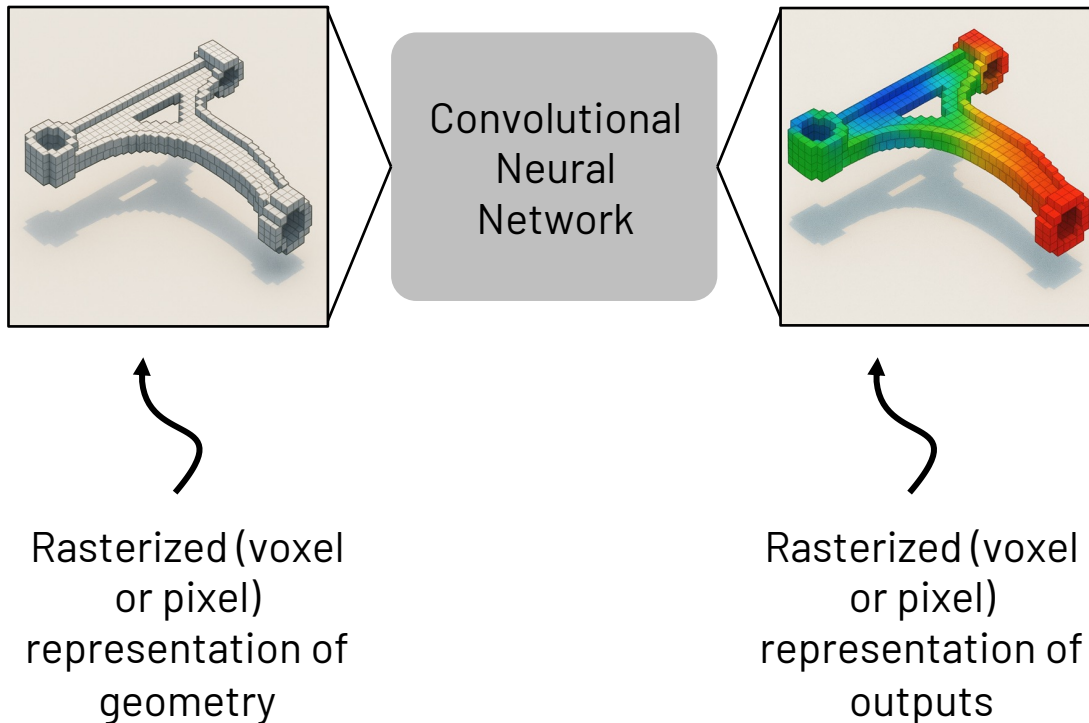
Disadvantages

- Considers only local information
- Does not account for linkage of points

02 Potential Machine Learning Approaches

Rasterized domains

Represent domain with voxels and employ Convolutional Neural Networks to learn fields directly. Alternatively, use projection to pixels and subsequent reprojection.



Advantages

- Well understood and effective for images
- Powerful generalization

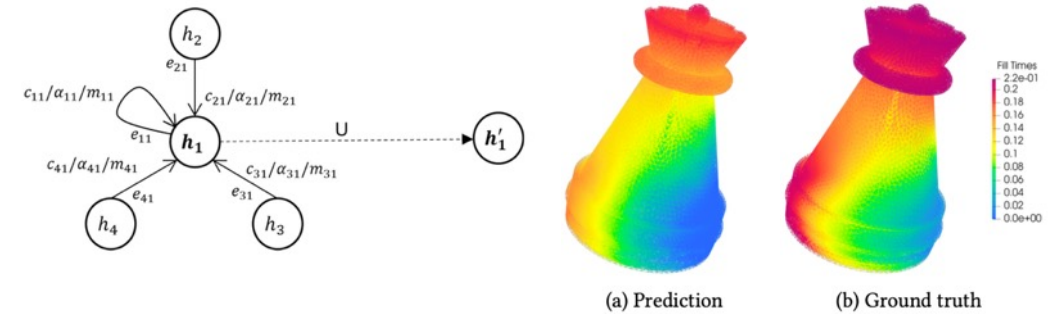
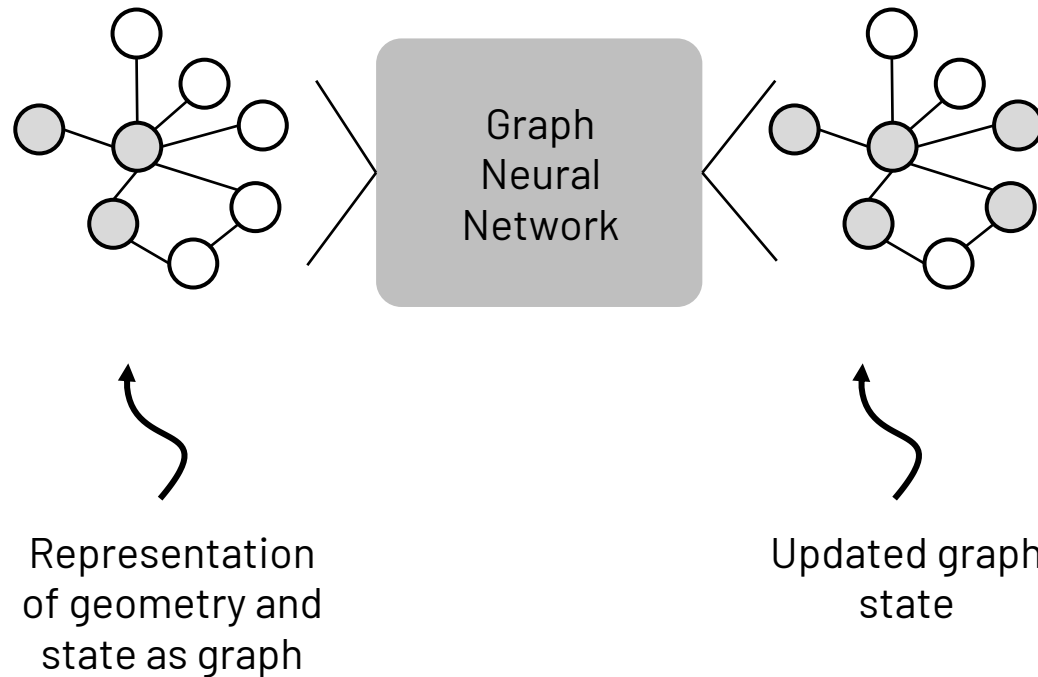
Disadvantages

- Does not account for physics
- Requires massive amount of training data

02 Potential Machine Learning Approaches

Graphs

Graph Neural Networks learn message passing rules to update the state of a graph.



Gätje, Master's thesis, KIT, 2023

Advantages

- Good generalization potential
- Graph is easy to obtain from meshes

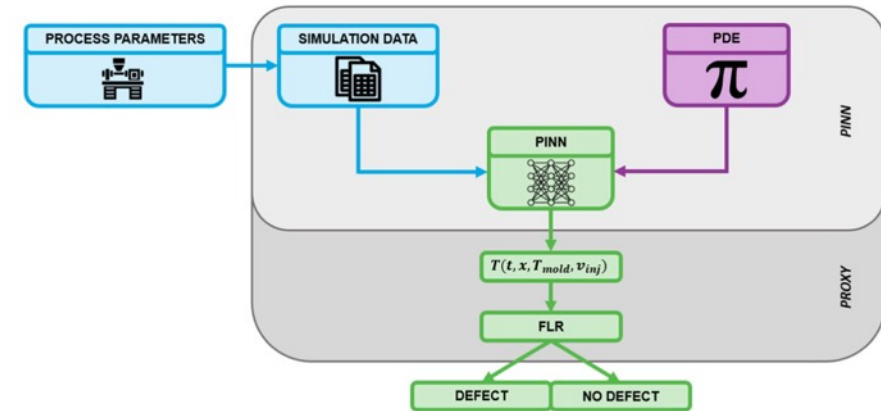
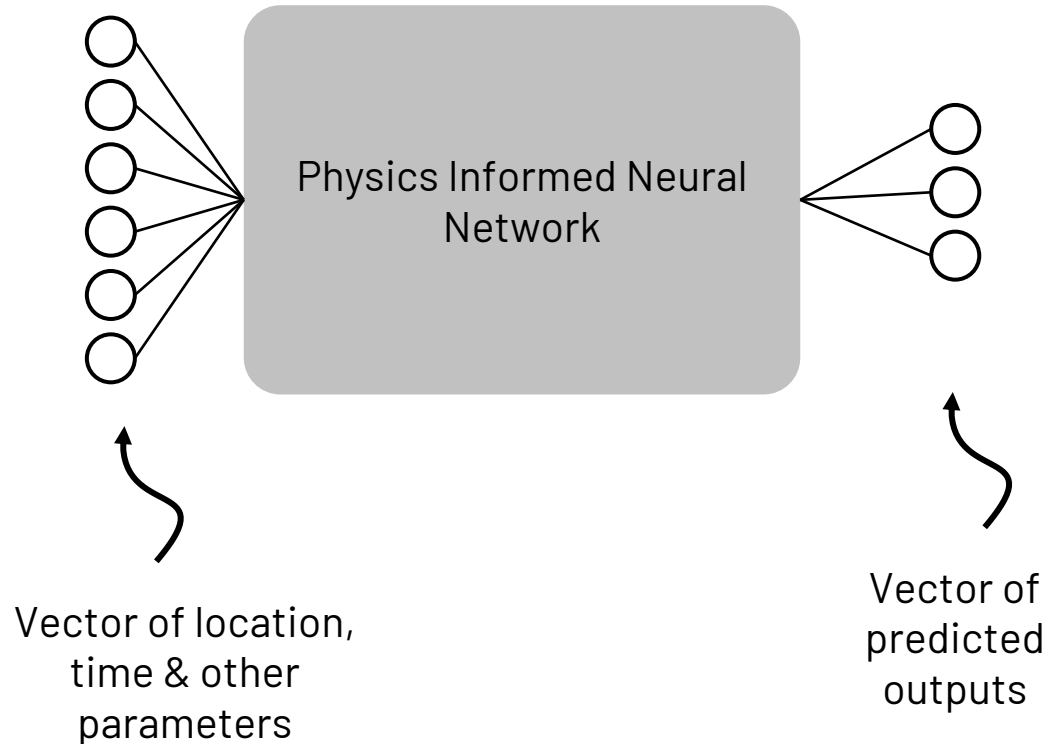
Disadvantages

- Information passing limited by network depth
- Roll-out inference slow

02 Potential Machine Learning Approaches

Physics Informed Machine Learning

Physics Informed Neural Networks, Deep Operator Nets, etc. are trained to minimize the residual of physical equations and data points.



Pieressa et al., *J. Intell. Manuf.*, 2024

Advantages

- Very little data needed
- Include known physical equations

Disadvantages

- Limited generalization
- Training times can be quite significant

Fast surrogate base model

03

03 Fast surrogate base model

Node encoding

Geodesic distance to walls D_w

$$|\nabla D_w(\mathbf{x})| = 1 \quad \mathbf{x} \in \Omega$$

$$D_w(\mathbf{x}) = 0 \quad \mathbf{x} \in \partial\Omega_w$$

Geodesic distance to injection gate

$$|\nabla D_i(\mathbf{x})| = 1 \quad \mathbf{x} \in \Omega$$

$$D_i(\mathbf{x}) = 0 \quad \mathbf{x} \in \partial\Omega_i$$

Modified distance to injection gate

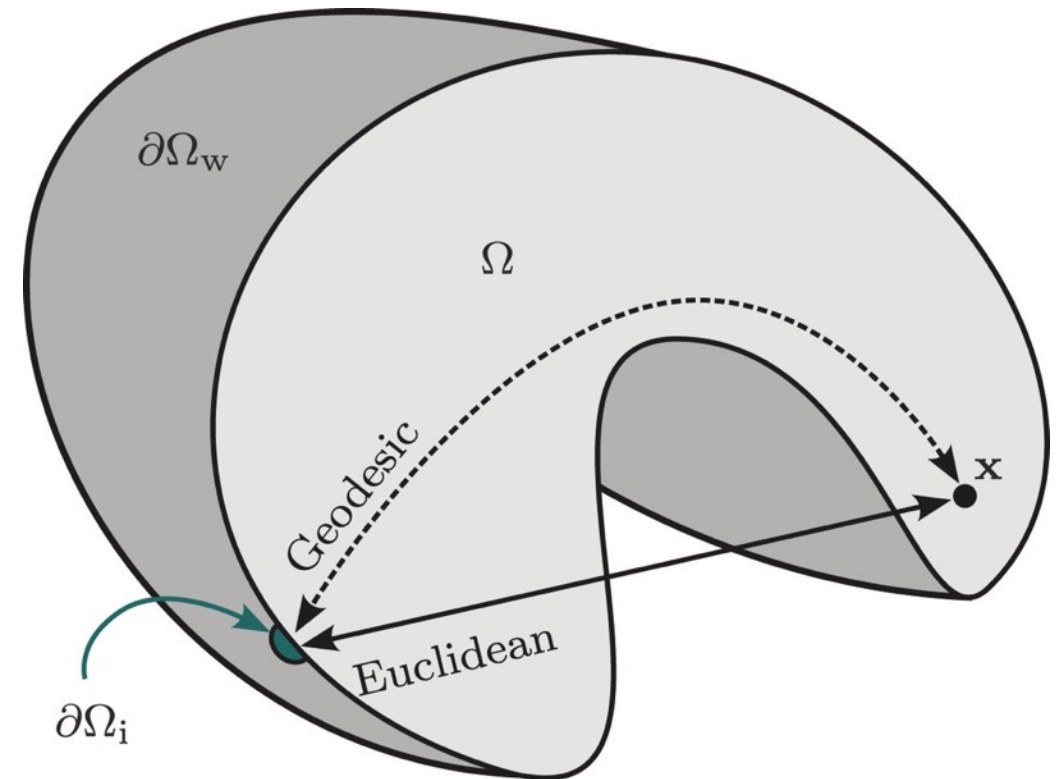
$$|\nabla \hat{D}_i(\mathbf{x})| = 1/D_w(\mathbf{x}) \quad \mathbf{x} \in \Omega$$

$$\hat{D}_i(\mathbf{x}) = 0 \quad \mathbf{x} \in \partial\Omega_i$$

GPU-Implementation

We use a tetrahedral Fast Iterative Method (tetFIM) for solving the equations on linear tetrahedral domains.

Fu et al., *SIAM J. Sci. Comput.*, 35(5), C473-C494, 2013
Grandits, *J. Open Source Softw.*, 6(66), 3641, 2021.



03 Fast surrogate base model

Node encoding

We compute a volume weighted spatial moment of the neighborhood

$$\mathbf{s}_i = \frac{1}{V_i} \sum_{j \in \mathcal{N}_i} v_j \mathbf{d}_{ij} \otimes \mathbf{d}_{ij} \text{ with. } V_i = \sum_{\mathcal{N}_i} v_j$$

as a metric to encode directionality of the material distribution. For example:

$$\mathbf{s}_{\text{rod}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \mathbf{s}_{\text{plate}} = \frac{1}{2} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \mathbf{s}_{\text{sphere}} = \frac{1}{3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

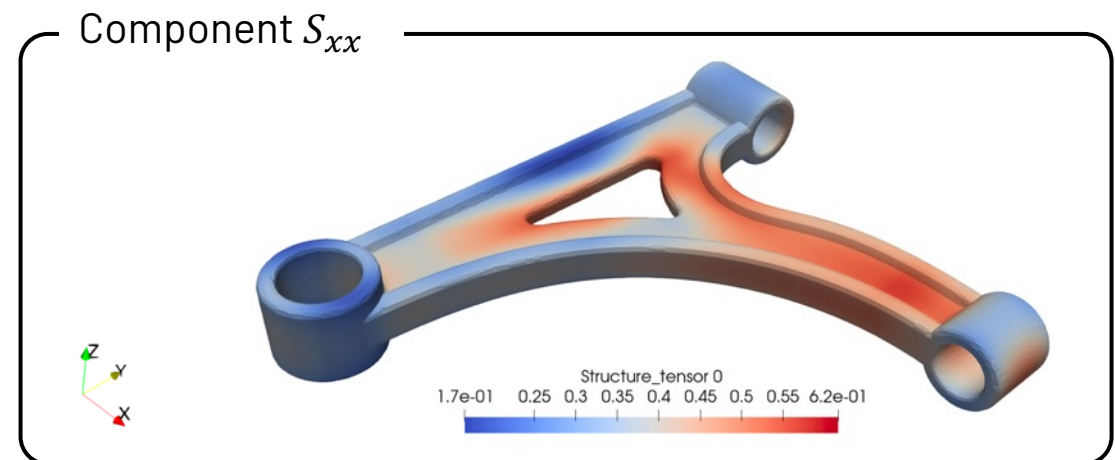
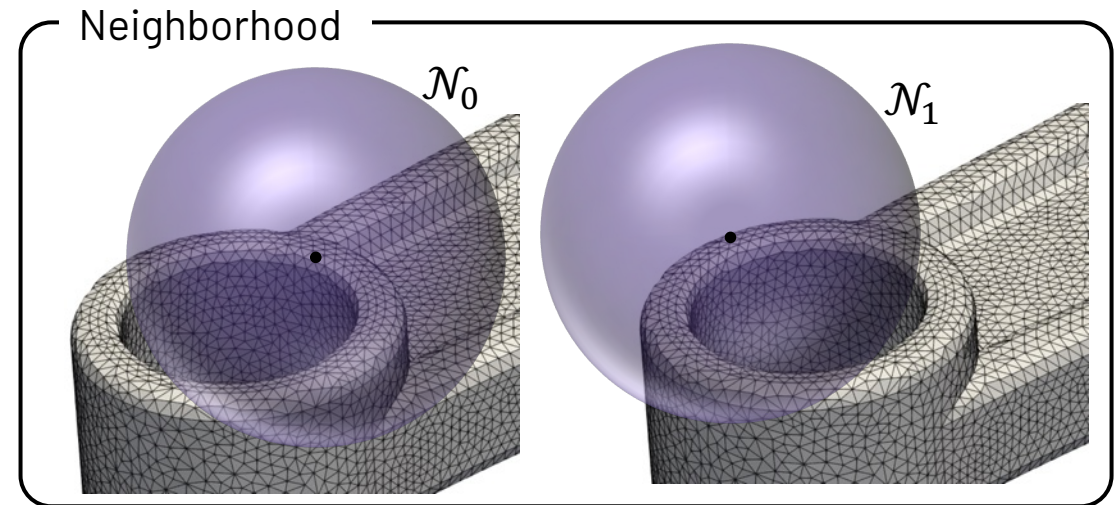
The efficient neighborhood-search is performed with a Ball-Tree algorithm.

$\mathbf{s}$: Spatial moment

v_j : Volume of element j

$\mathcal{N}_i$: Neighborhood of node i

$\mathbf{d}_{ij}$: Normalized direction to element center j

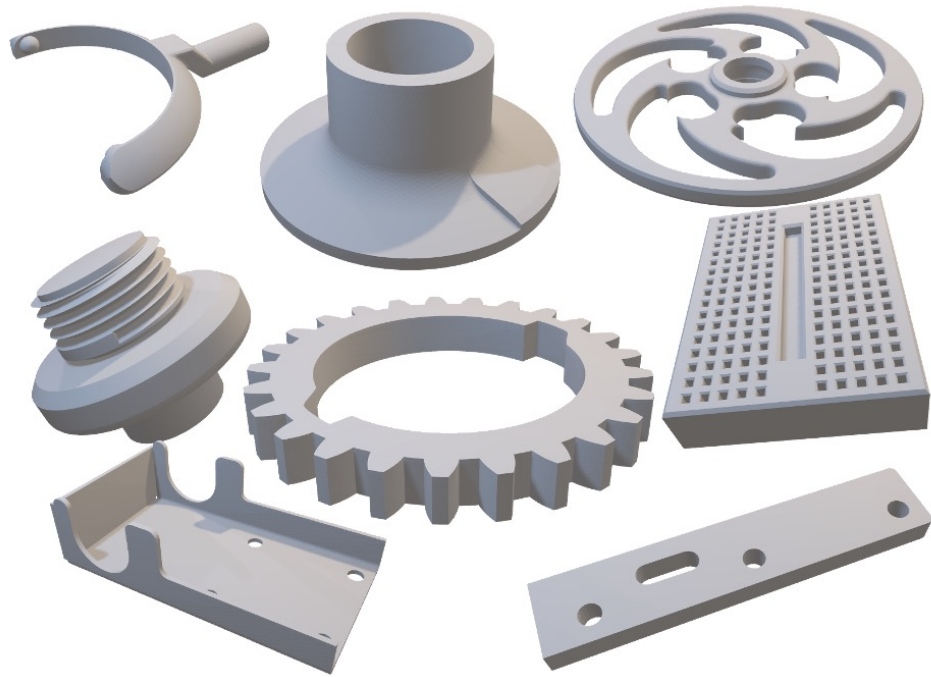


03 Fast surrogate base model

Training data

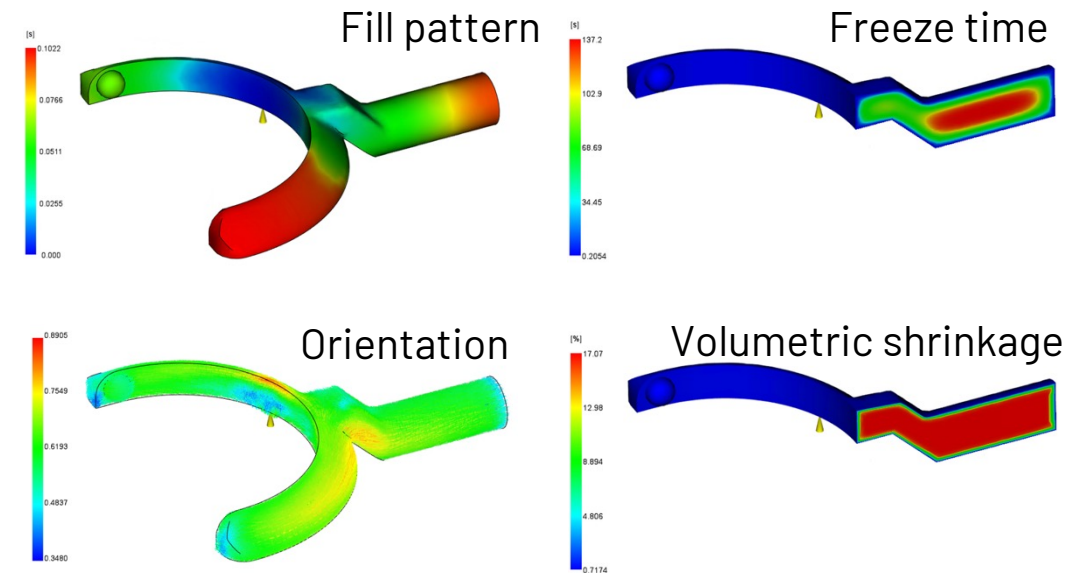
CAD Model Dataset For Geometric Deep Learning

Koch et al., IEEE CVPR, 2019



Autodesk Moldflow Simulations

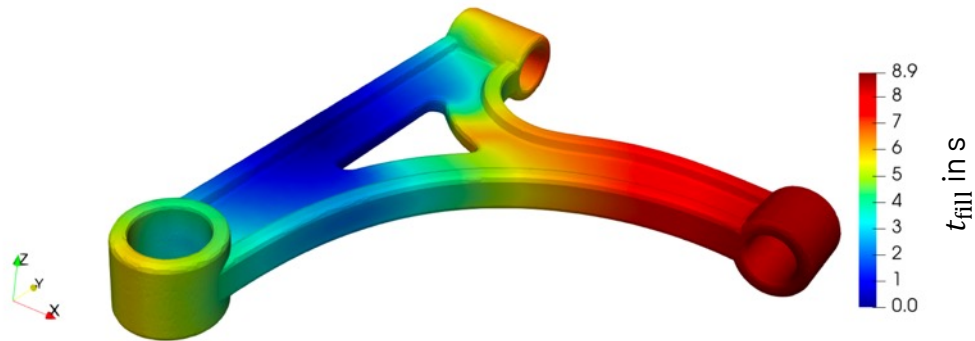
Run for each geometry with a random injection gate at the surface.



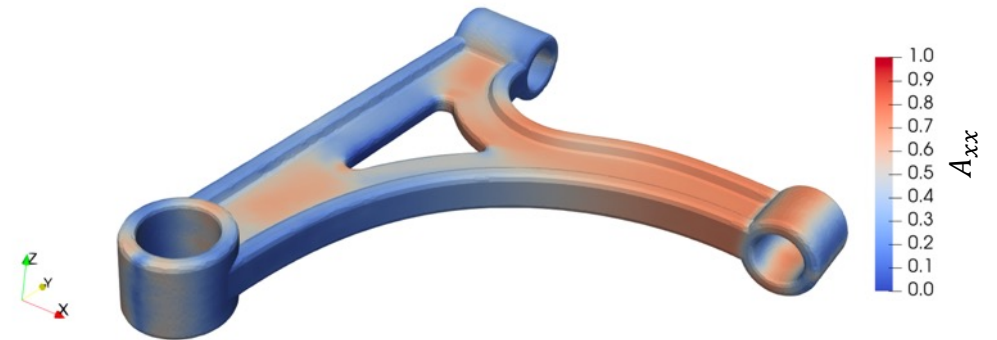
03 Fast surrogate base model

Performance on generic sample (not part of training)

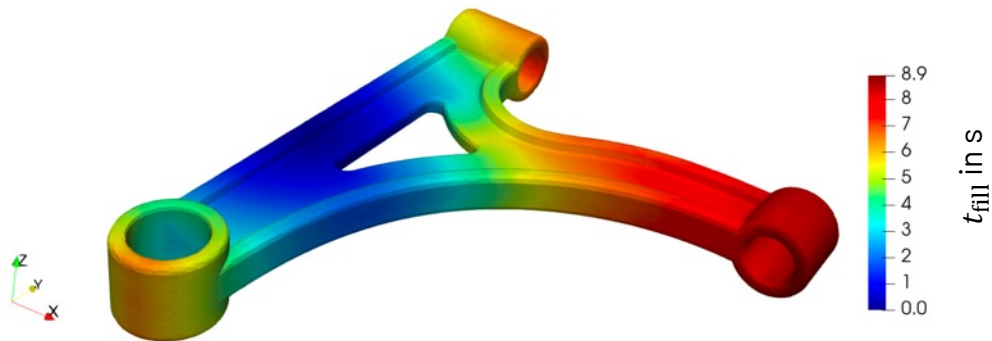
Ground truth (Fill pattern)



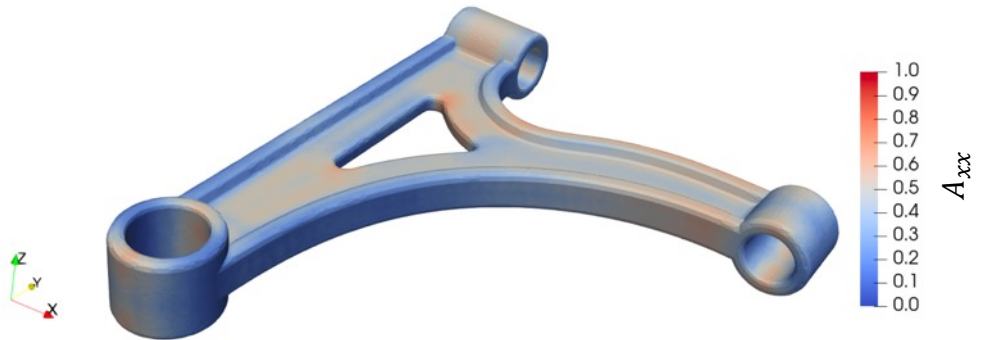
Ground truth (Orientation)



Prediction (Fill pattern)



Prediction (Orientation)



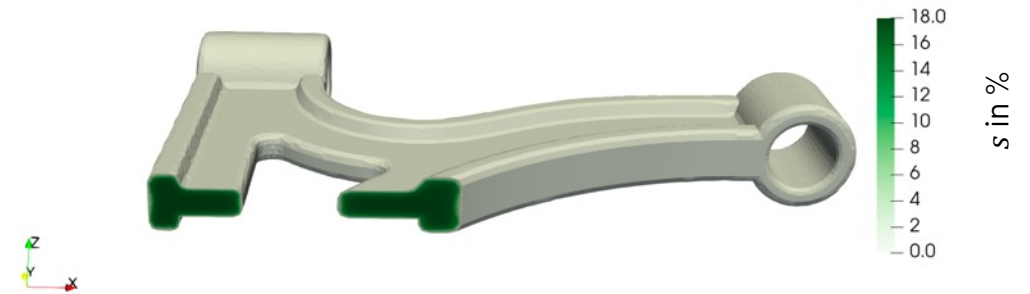
03 Fast surrogate base model

Performance on generic sample (not part of training)

Ground truth (Cooling time)



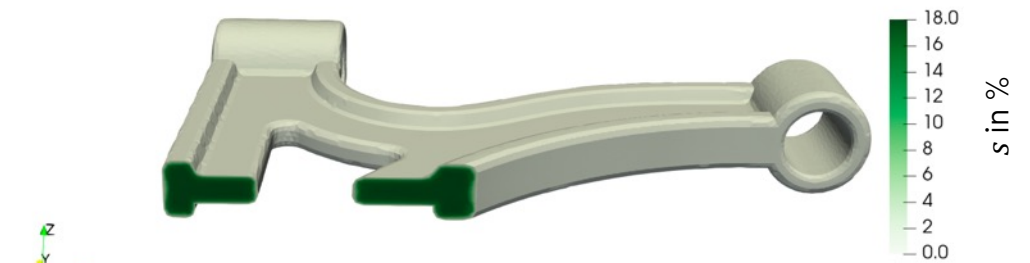
Ground truth (Shrinkage)



Prediction (Cooling time)



Prediction (Shrinkage)



03 Fast surrogate base model

Computational performance

Computational domain

Elements: 694 049

Nodes: 127 737



Computational resources

CPU: AMD Threadripper Pro 5995WX
(64 Cores @ 2.7GHz with 4.5GHz Boost)

RAM: 512GB (DDR4-3200)

GPU: NVIDIA RTX 4090 (24GB VRAM)

Speed up

Overall: ~ 20x

New gate: ~ 275x

Software	Task	Full Simulation	Approximation
Moldflow	Meshing	62 s	62 s
Moldflow	PDE Solver	1647 s	-
tetFIM	Initialization	-	12 s
tetFIM	D_i	-	3.3 s
tetFIM	D_w	-	1.6 s
tetFIM	D_f	-	2.8 s
SciPy, NumPy	Spatial Moment	-	4 s
		1709 s	85.7 s



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Composites Part A

journal homepage: www.elsevier.com/locate/compositesa

Fast approximation of fiber reinforced injection molding processes using eikonal equations and machine learning

Julian Greif^a, Philipp Lechner^{a,b}, Nils Meyer^{a,b,*}

Warpage

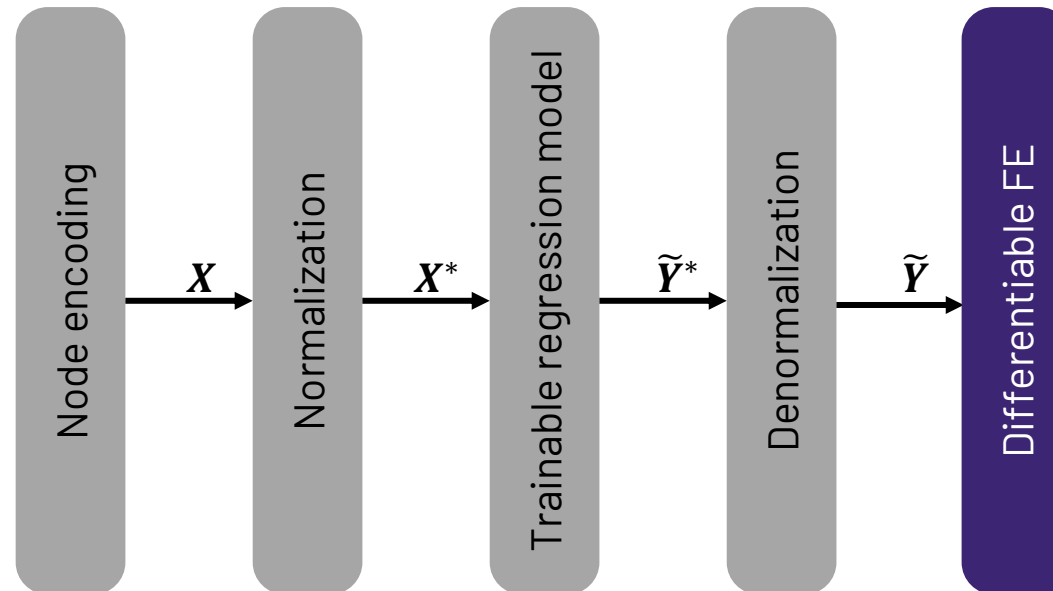
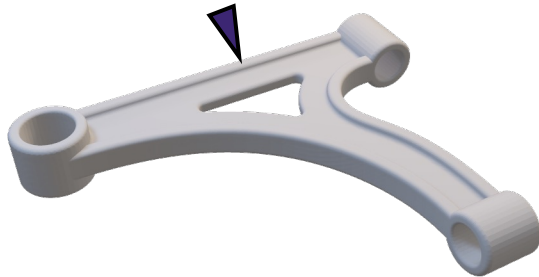
04

04 Warpage

Extended approximation model

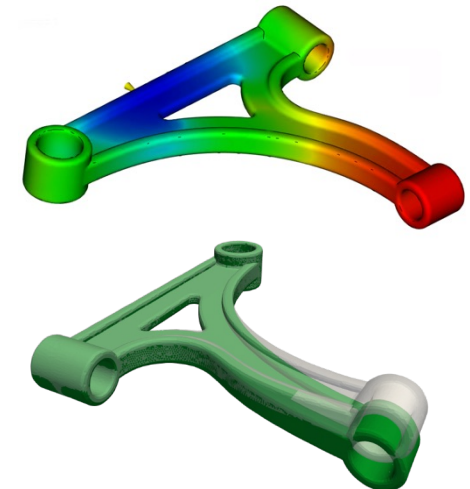
Inputs

- Meshed geometry
- Injection points
- Flow rate at inlets



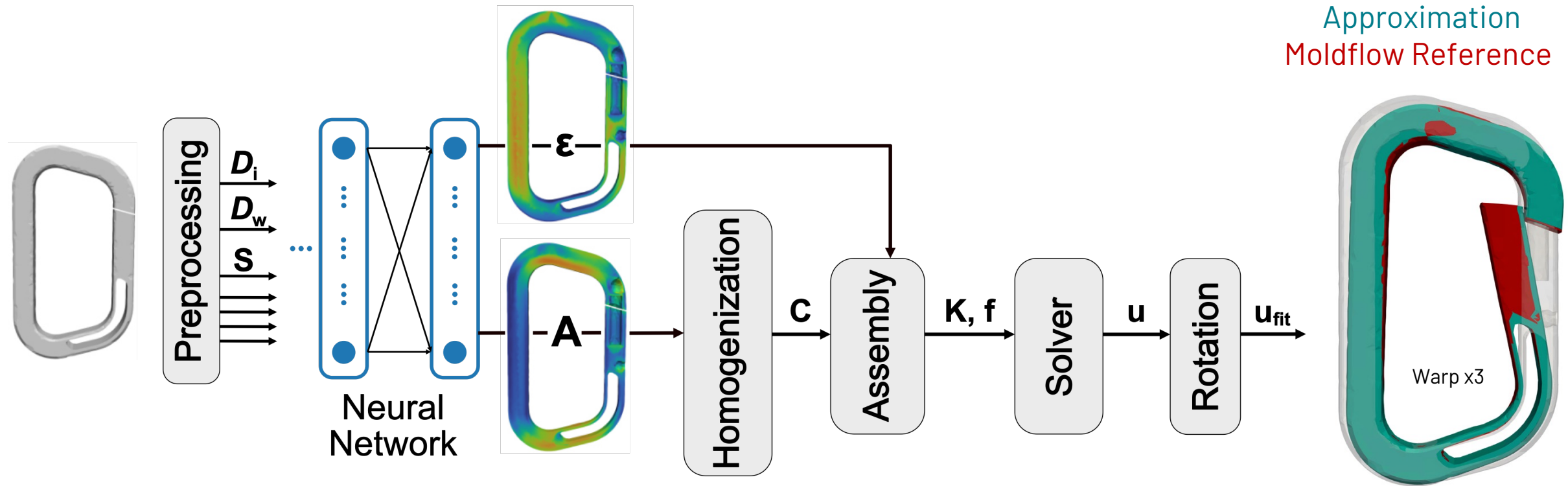
Predicted outputs

- Fill pattern
- Volumetric shrinkage
- Freeze time
- Fiber orientation
- Warpage



04 Warpage

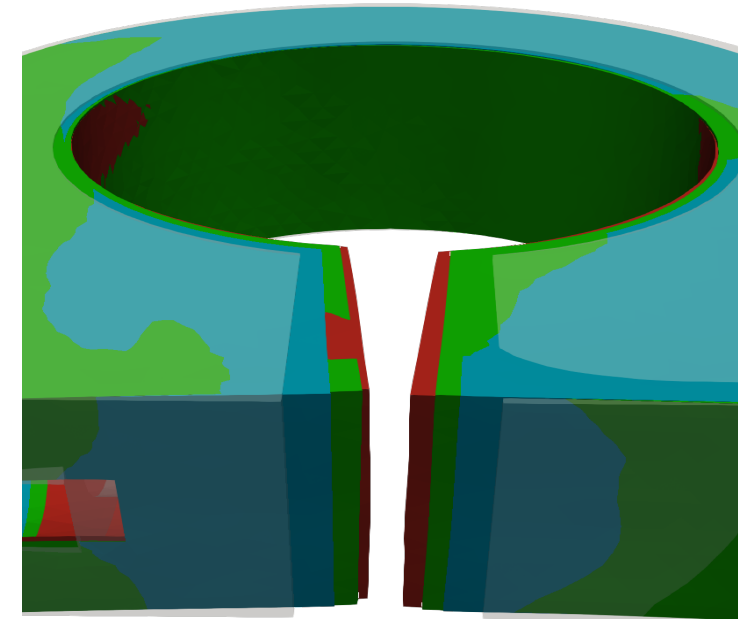
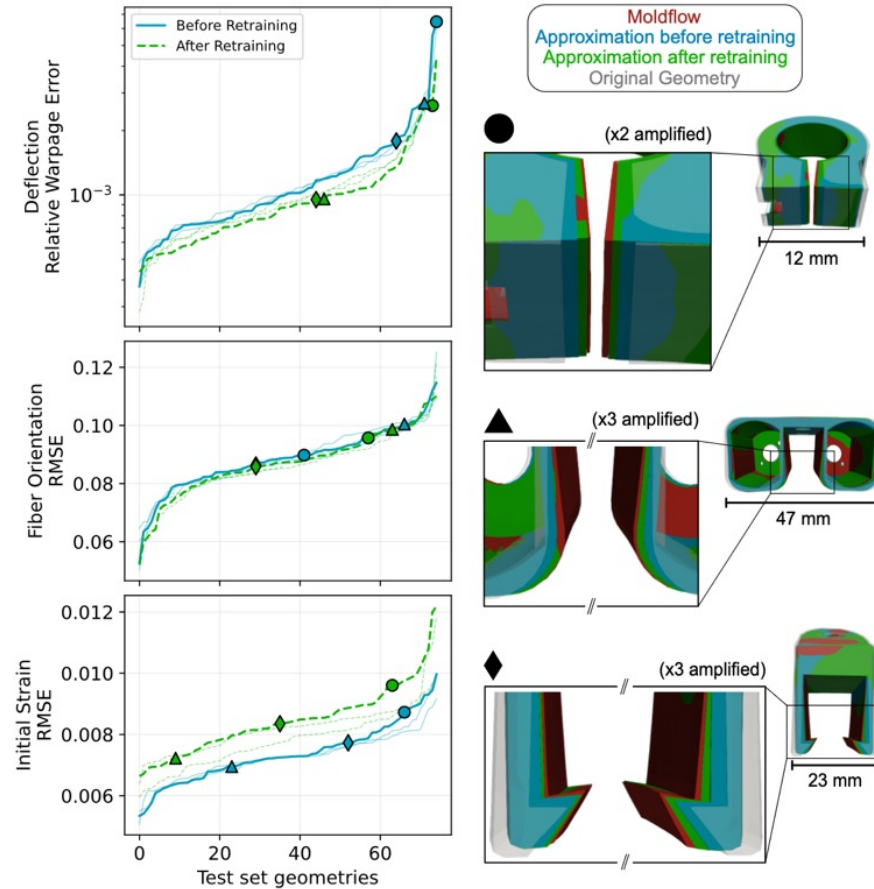
Extended approximation model



$$\text{Relative Warpage Error } (u_{fit}, u_{ref}) = \sqrt{\frac{1}{N} \left\| \frac{u_{fit}}{L} - \frac{u_{ref}}{L} \right\|_2^2}$$

04 Warpage

Results



Warpage prediction for fiber reinforced injection molding via geometric feature learning and differentiable FEM[☆]

Julian Greif^{a,*,}, Nils Meyer^{a,b}



Nils Meyer



Julian Greif



Leon Böhmer

Thank you for your attention

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