

Hybrid modeling for materials processing: combining physics-based simulations and data-driven models

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Acknowledgments:

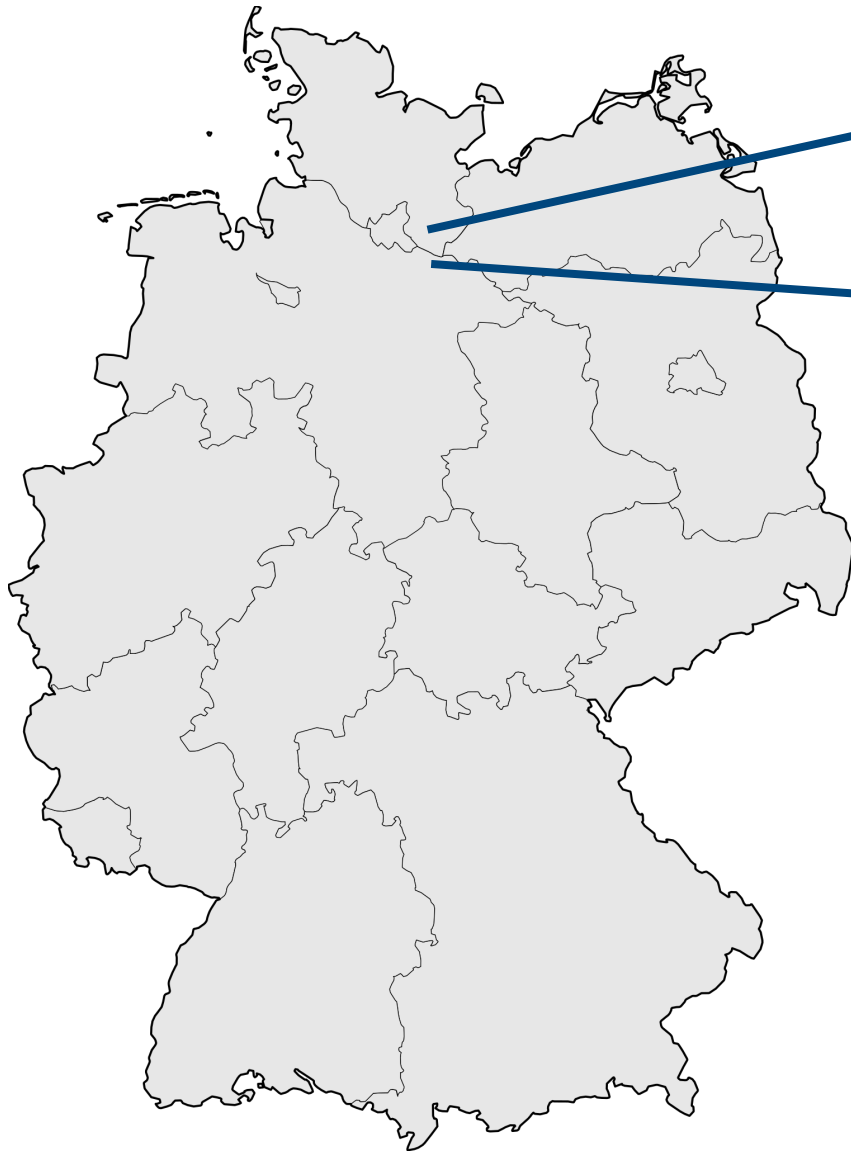
F.E. Bock, S. Keller, P. Campos,
S. Chupakin, N. Huber, N. Kashaev,
A.Hashemzadeh, C. Soyarslan,
T.van den Boogaard

IMSI Workshop
*Application of Digital Twins to
Large-Scale Complex Systems*

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Department Solid State Materials Processing

Refill Friction Stir Spot Welding:

Similar Joints | Dissimilar Joints: Al/Mg, Al/Steel, Ti/Al, Al/Cu, Mg/Ti, Mg/Steel

Friction Stir Welding and Hybrid Processes:

FSW of Bi-metallic pipes | Stationary Shoulder FSW | Stationary and Semi-Stationary Bobbin-Tool

Additive Manufacturing and Local Modification:

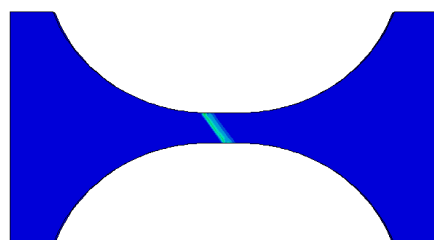
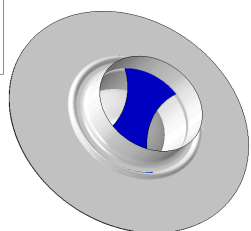
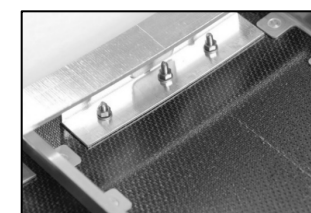
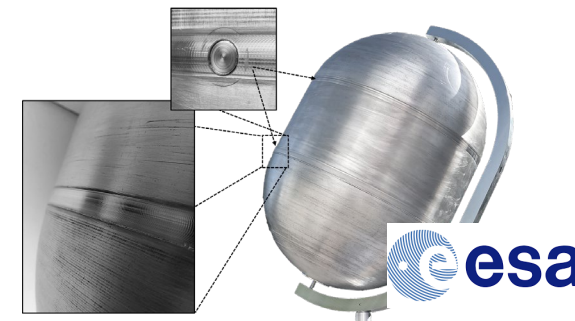
Solid State Layer Deposition

Friction Extrusion

Solid State Materials Development

Process Simulation & Material Modelling

Thermo-mechanical coupled models | Multiscale modelling | Data-driven models

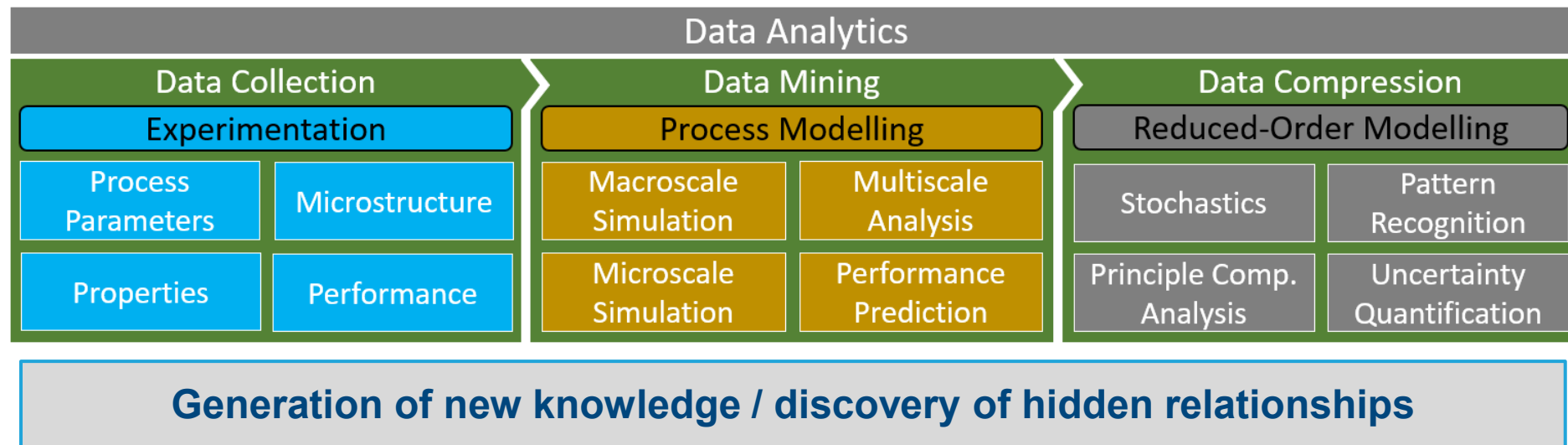


Introduction

Motivation

Machine learning and data mining as **key enablers**

- Accelerate development of novel materials, processes and techniques
- High-throughput identification of dependencies along the process-structure-property performance chain
- Description, prediction and prescription of essential features



Introduction

Physics-integration into machine learning

Level of integration

Surrogate modelling of physical process simulations

Physics-based feature engineering

- Physical relationships between features
- Physical normalization of inputs and outputs via dimensionality analysis

Hybrid / discrepancy modelling

- Using underlying physics that show discrepancies to target
- Compensating discrepancies with machine learning

Physics-informed artificial neural networks

- Loss function formulated with respect to governing equations
- Required knowledge of governing equations (i.e. nonlinear PDEs)
- Via data-driven solution of nonlinear PDEs: they are fulfilled at sample points

Upadhyay, V., Jain, P. K., and Mehta, N. K. Conf. Proc. of SocProS 2011, 761–768 (2012).

Xiong, J., Zhang, G., Hu, J., and Wu, L.; J. Intell. Manuf. 25, 157–163 (2014).

Sahu, N. K., Andhare, A. B., Andhale, S., and Abraham, R. R. IOP Conf. Ser. Mater. Sci. Eng. 346:12037 (2018).

Verleysen, M.; François, D.; Simon, G.; Wertz, V. IWANN 2003, LNCS 2687, pp. 105-112, (2003).

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Moya, B.; Badías, A.; Alfaro, I.; Chinesta, F.; Cueto, E.; Int. J. Numer. Methods Eng. 25, 87 (2020).

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Raissi, M.; Perdikaris, P.; Karniadakis, G.E. arXiv:1711.10561 (2017).

Linka, K.; Hillgärtner, M.; Abdolazizi, K.P.; Aydin, R.C.; Itskov, M.; Cyron, C.J.; J. Comput. Phys. 429, 110010 (2021).

Haghighat, E.; Raissi, M.; Moure, A.; Gomez, H.; Juanes, R. Comput. Methods Appl. Mech. Engrg. 379, 11374 (2021).

Introduction

Motivation – Physics and Data Science

Process parameters

(Micro-)structure

Mechanical properties

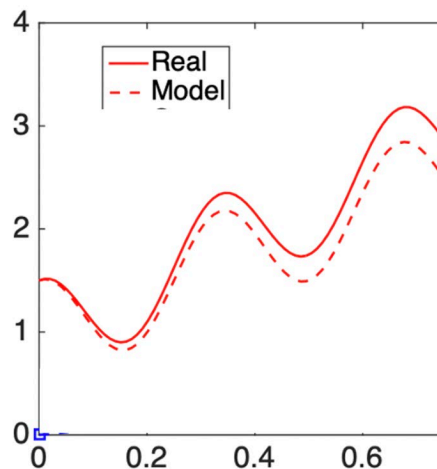
Performance

Physics

Experiments

Analytical modeling

Numerical modeling



Pro's:
Explanation
Extrapolation
Validated

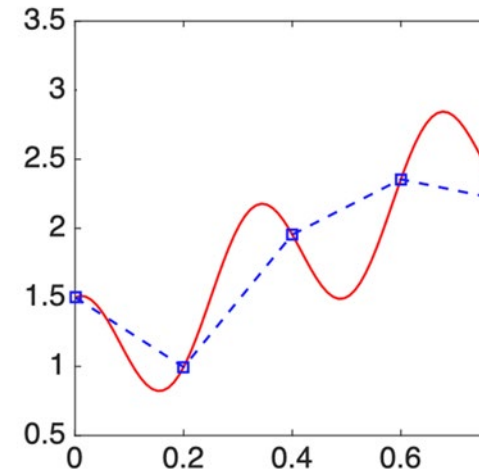
Con's:
Contain simplifications
Need calibration
High computing cost

Data science

Data analysis

Feature engineering

Machine learning

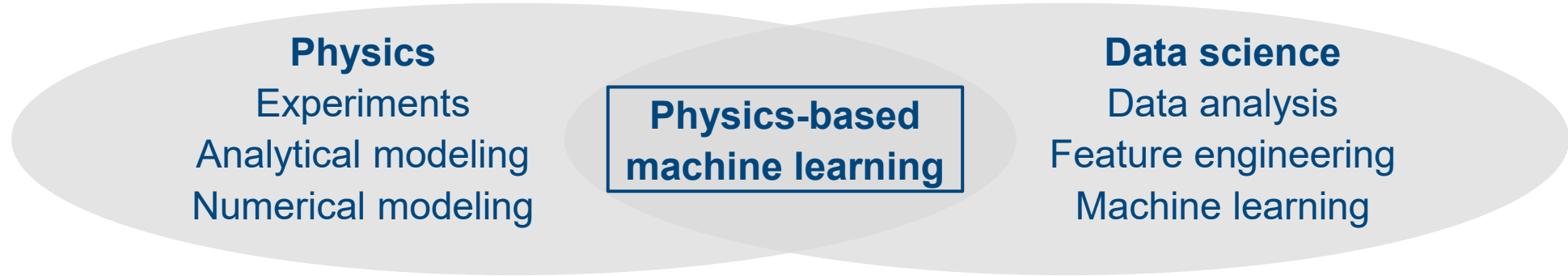


Pro's:
Accuracy
Generality
Identify relationships

Con's:
Amount of data
Physically inconsistent
Explanation difficult

Introduction

Motivation – Physics and Data Science



Use physics and data to

- Enhance prediction performance & generality
- Increase data efficiency
- Reduce experimental & computational efforts
- Increase physical consistency

Introduction

Hybrid modeling

Combine physics with data

Low-fidelity model

- Physics-based
- Prediction errors

Introduction

Hybrid modeling

Combine physics with data

Low-fidelity model

- Physics-based
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Discrepancy model

- Data-driven
- Correction of prediction errors
- Discrepancy is less complex than complete problem
- Fewer samples required than to map complete problem

Introduction

Hybrid modeling

Combine physics with data

Low-fidelity model

- Physics-based
- Prediction errors



Discrepancy model

- Data-driven
- Correction of prediction errors
- Discrepancy is less complex than complete problem
- Fewer samples required than to map complete problem

High-fidelity hybrid model

- Physics-based
- Data-driven
- Low prediction errors
- Good generalization

Introduction

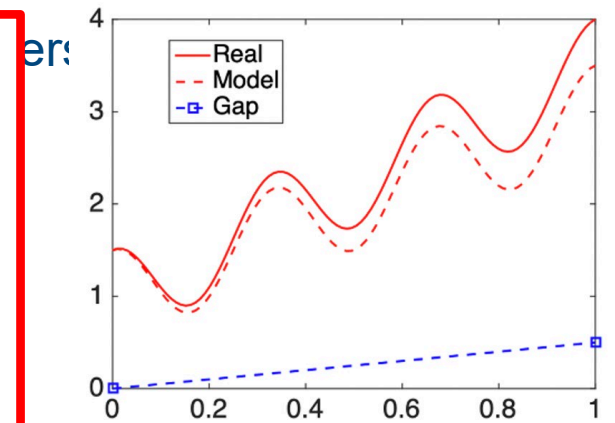
Hybrid modeling / Hybrid twin

A fundamental equation that governs a hybrid twin describes the change rate of the system's state at time t via

$$\dot{X}(t; \mu) = A(X, t; \mu) + B(X, t) + C(t) + R(t)$$

with different contributions from

Reality
=
Physics-based model "The Art of Modelling"
+
The part of the reality that the model ignores "The Ignorance"



Chinesta, F; Material forming digital twins: the alliance between physics-based and data-driven models. ESAFORM plenary lecture 2022.

Introduction

Hybrid modeling

We focus on two components of a hybrid twin:

- Physics-based model $A(X; \mu)$
- Data-driven discrepancy model $B(X)$

with X as the system's inputs and as μ as the physical model parameters

Where a system's state Y can be described either via addition

$$Y(X; \mu) = A(X; \mu) + B(X)$$

or multiplication

$$Y(X; \mu) = A(X; \mu) \cdot B(X)$$

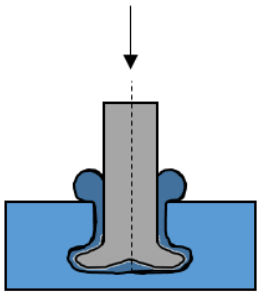
of those two components.

Case studies

Overview

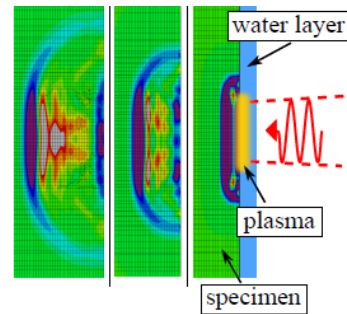
Case study 1

Ultimate tensile strength prediction for joints made by Friction Riveting



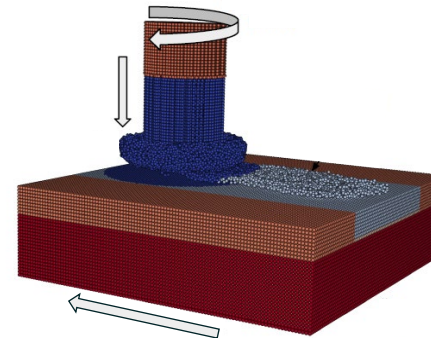
Case study 2

Prediction of residual stresses induced by Laser Shock Peening



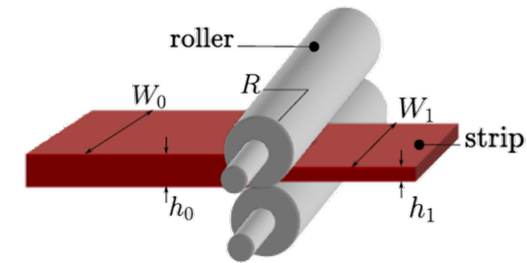
Case study 3

Prediction of layer geometry deposited via Friction Surfacing



Case study 4

Prediction of slab spread forming via Hot Rolling

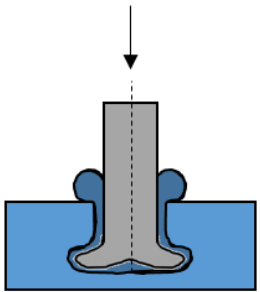


Case studies

Overview

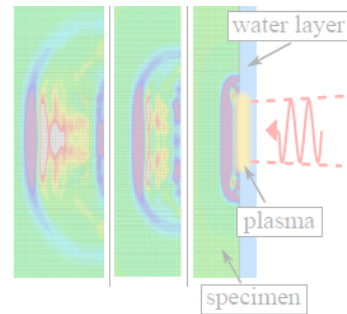
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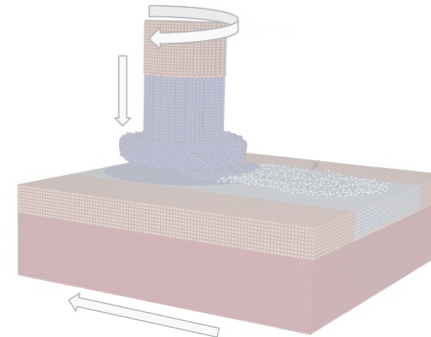
Case study 2

Prediction of residual stresses induced by Laser Shock Peening



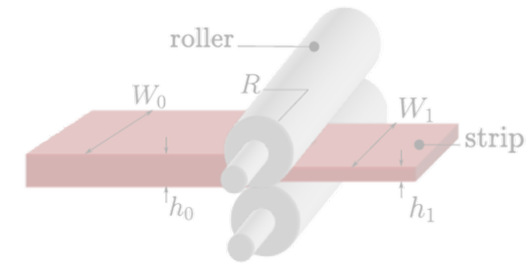
Case study 3

Prediction of layer geometry deposited via Friction Surfacing



Case study 4

Prediction of slab spread forming via Hot Rolling



Case study 1: Introduction

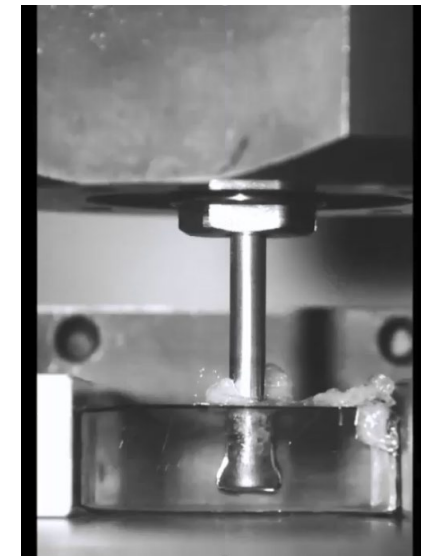
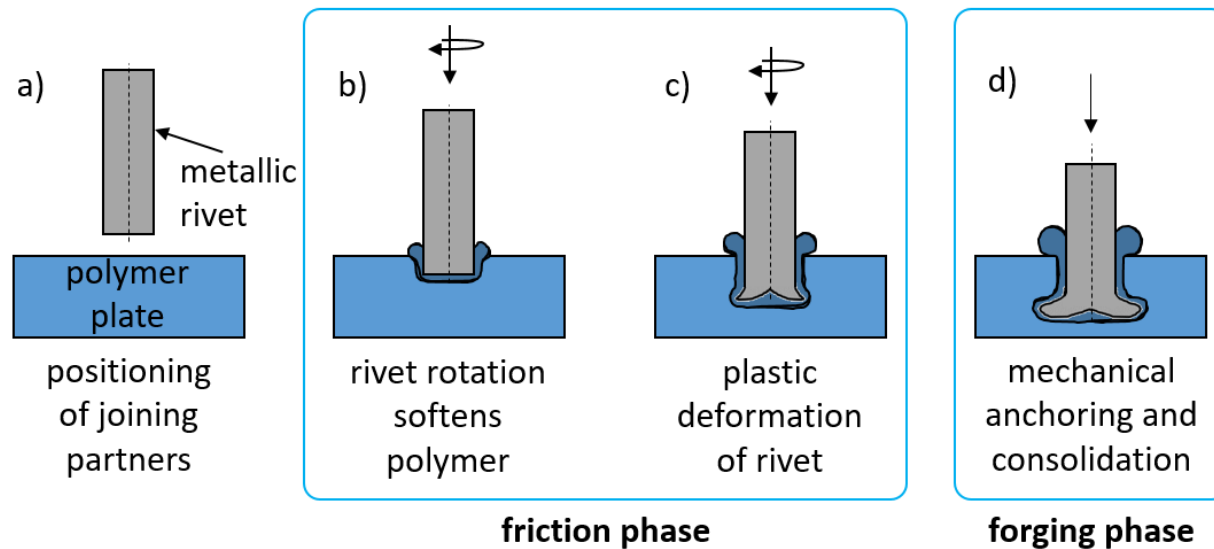
Friction Riveting – a solid state joining process

Process steps and characteristics:

- Metallic rivet rotates under axial force
- Frictional heat between rivet and polymeric plate
- Polymer processed above glass transition/melting temperature
- Mechanical anchoring via plastized and deformed rivet tip

Advantages:

- Processing below metal melting temperature
- No pores or hot cracking
- Bonding via mechanical anchoring and adhesion
- No need for pre-treatment or post-processing



Case study 1: Methodology

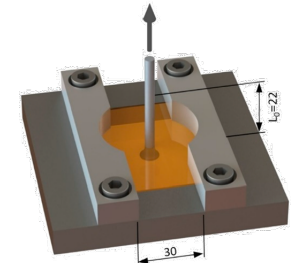
Property prediction via physics-based features

Process parameters

- Rotation speed
- Friction force
- Friction time
- Forging force
- Forging time

Mechanical property

Ultimate tensile force(N)



T-pull test setup

Rivet: AA2024-T351

Plate: Polyetherimide (PEI)

Image: Cipriano et al. (2018)

Case study 1: Methodology

Property prediction via physics-based features

Process parameters

- Rotation speed
- Friction force
- Friction time
- Forging force
- Forging time

Data: experimental & analytical

Central Composite DOE

- 5 varying parameters
- 5 increments
- 36 samples
- Linear prediction model:
 $R^2 = 77.9\%$; $\sigma = 1065 \text{ N}$

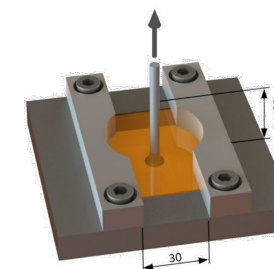
9 Replicates

- Constant parameters
- $UTF = 5041 \text{ N} - 9304 \text{ N}$
- $\sigma_{exp} = 1373 \text{ N}$

Significant
scatter

Mechanical property

Ultimate tensile force(N)



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Case study 1: Methodology

Property prediction via physics-based features

Process parameters

- Rotation speed
- Friction force
- Friction time
- Forging force
- Forging time

Physics-based feature engineering

- Friction energy E_f
- Deformation energy E_d

$$E_M = E_f + E_d =$$

$$\int M \cdot \omega \cdot dt + \int F \cdot \vartheta \cdot dt$$

M : resulting torque

ω : rotational speed

F : forging force

ϑ : plunging rate

Data: experimental & analytical

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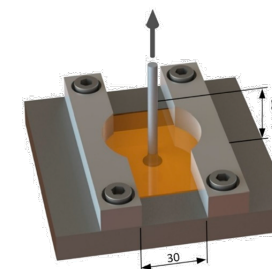
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T-pull test setup

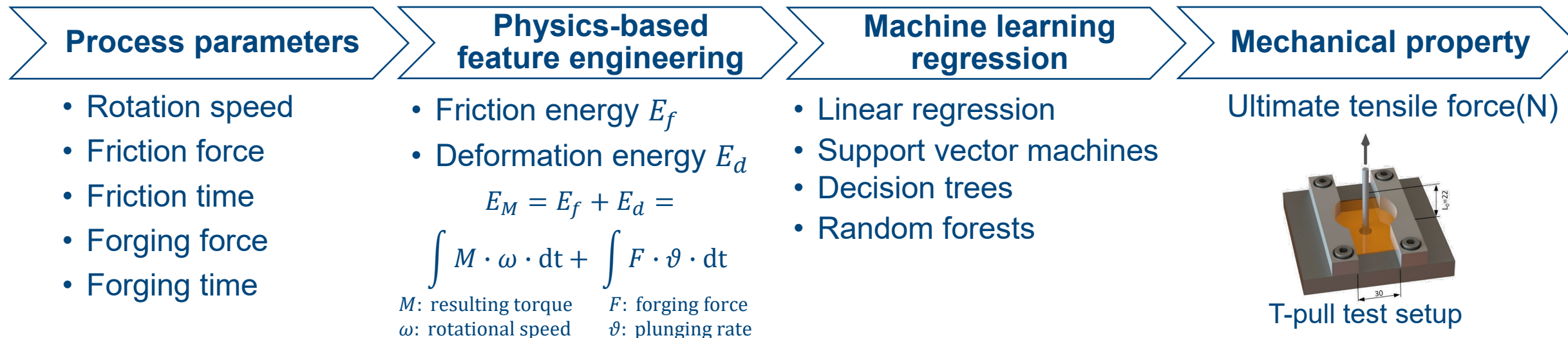
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Case study 1: Methodology

Property prediction via physics-based features



T-pull test setup

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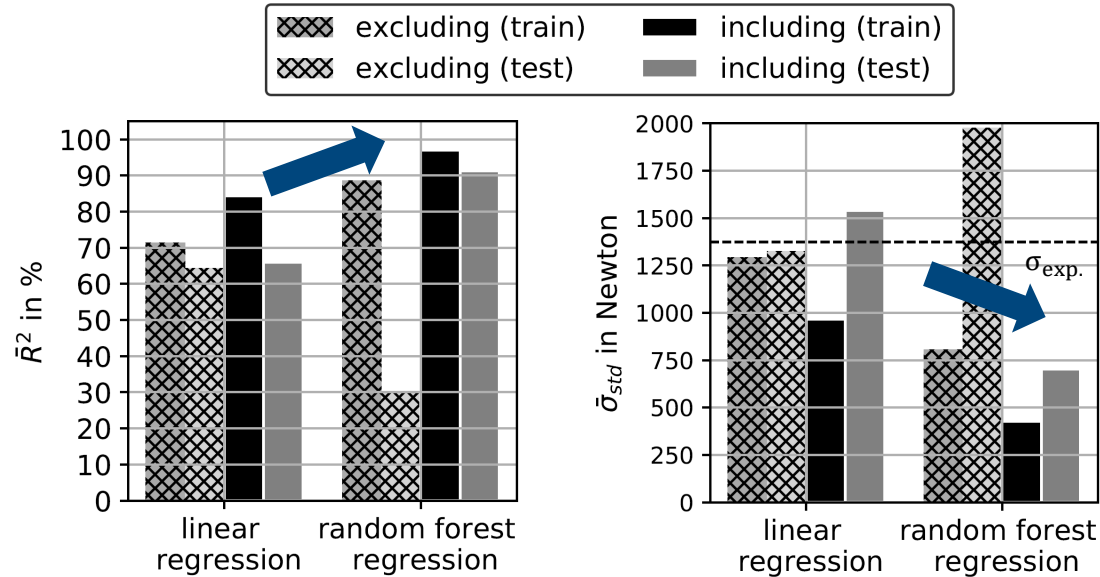
9 Replicates

- Constant parameters
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Significant scatter

Case study 1: Results

Input features: process parameters and mechanical energies

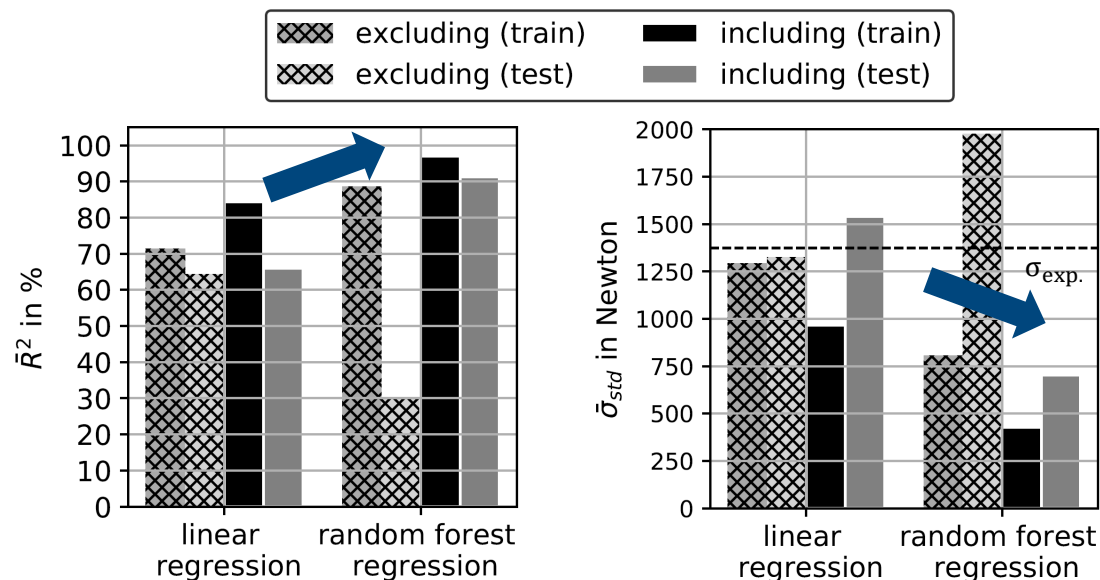


Main effect by including mechanical energy:

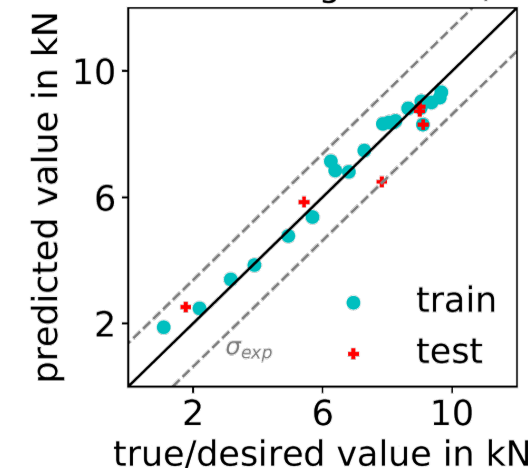
- R^2 is increased
- σ_{std} is reduced

Case study 1: Results

Input features: process parameters and mechanical energies



Random forest regression (incl. E_M)



Main effect by including mechanical energy:

- R^2 is increased
- σ_{std} is reduced

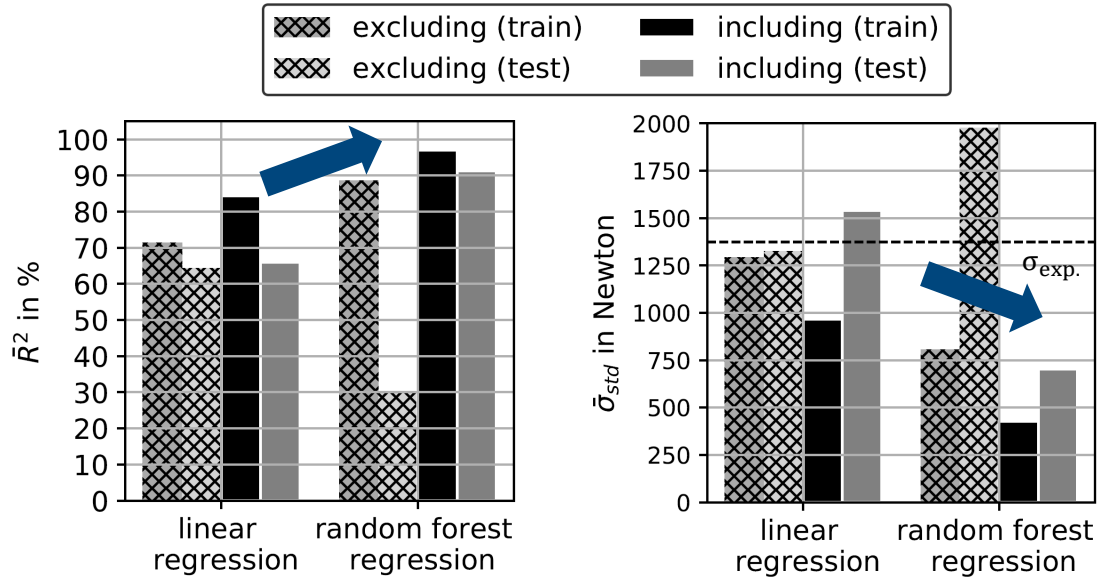
Best model: RFR

- Train set: $\bar{R}_{adj}^2 = 88.7\%$; $\bar{\sigma} = 428\text{ N}$
- Test set: $\bar{R}^2 = 91\%$; $\bar{\sigma}_{std} = 704\text{ N}$

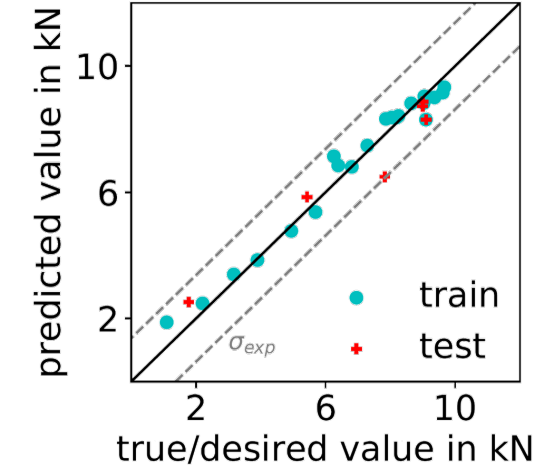
Success
Improved ML-prediction

Case study 1: Results

Input features: process parameters and mechanical energies



Random forest regression (incl. E_M)



Main effect by including mechanical energy:

- R^2 is increased
- σ_{std} is reduced

Benchmark: published linear model is exceeded

- Train set: $R^2_{adj.} = 79.4\%$
- Test set: $R^2 = 77.9\%$; $\sigma = 1065\text{ N}$

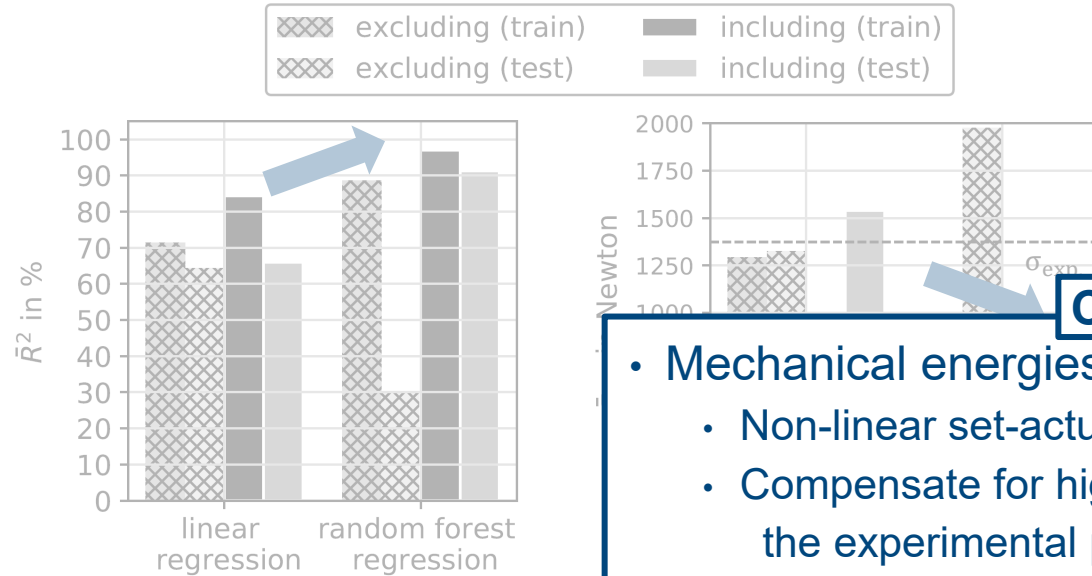
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Case study 1: Results

Input features: process parameters and mechanical energies



Main effect by including mechanical energies

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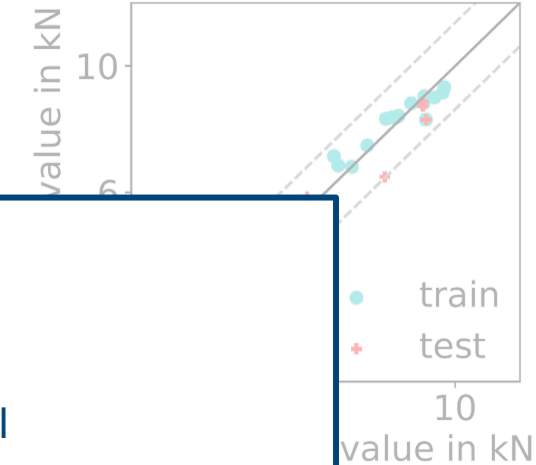
Benchmark: published linear model is exceeded

- Train set: $R^2_{adj.} = 79.4\%$
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Conclusion

- Mechanical energies
 - Non-linear set-actual corrective
 - Compensate for high uncertainty of the experimental process and its control
- RFR selected as best model
- Quality control is enabled

Random forest regression (incl. E_M)



adj. $R^2 = 88.7\%$; $\bar{\sigma} = 428\text{ N}$

- Test set: $\bar{R}^2 = 91\%$; $\bar{\sigma}_{std} = 704\text{ N}$

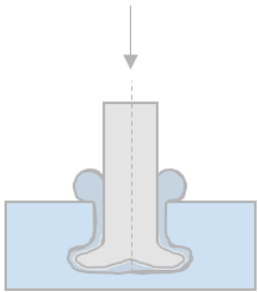
Success
Improved ML-prediction

Case studies

Overview

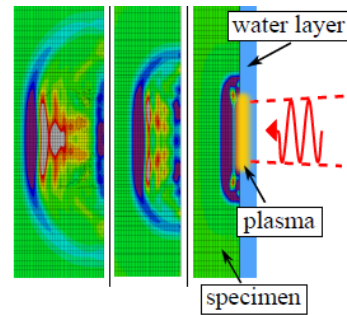
Case study 1

Ultimate tensile strength prediction for joints made by Friction Riveting



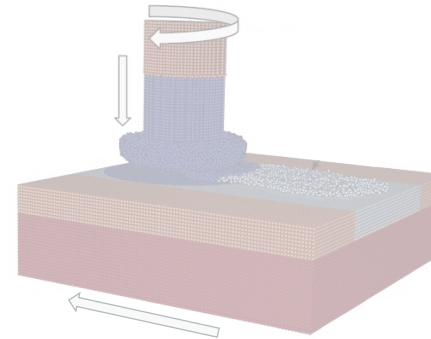
Case study 2

Prediction of residual stresses induced by Laser Shock Peening



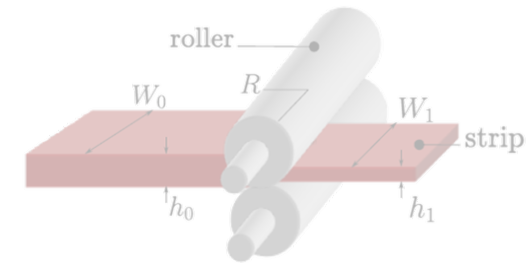
Case study 3

Prediction of layer geometry deposited via Friction Surfacing



Case study 4

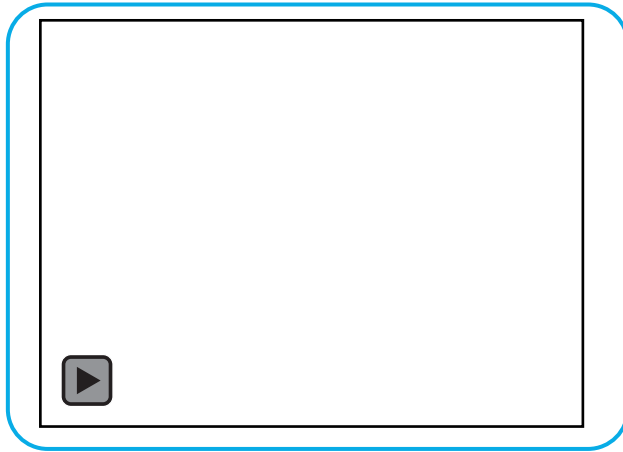
Prediction of slab spread forming via Hot Rolling



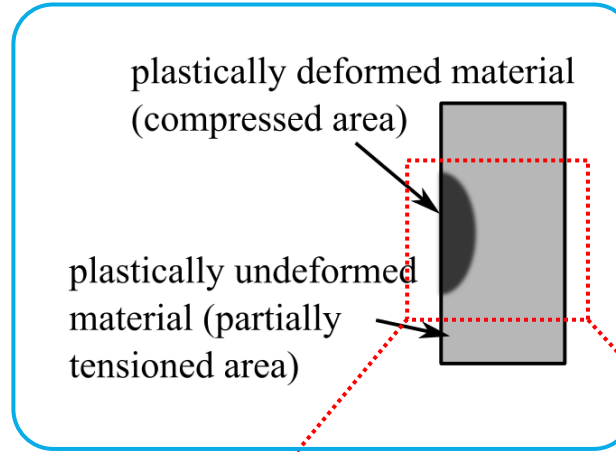
Case study 2: Introduction

Laser shock peening

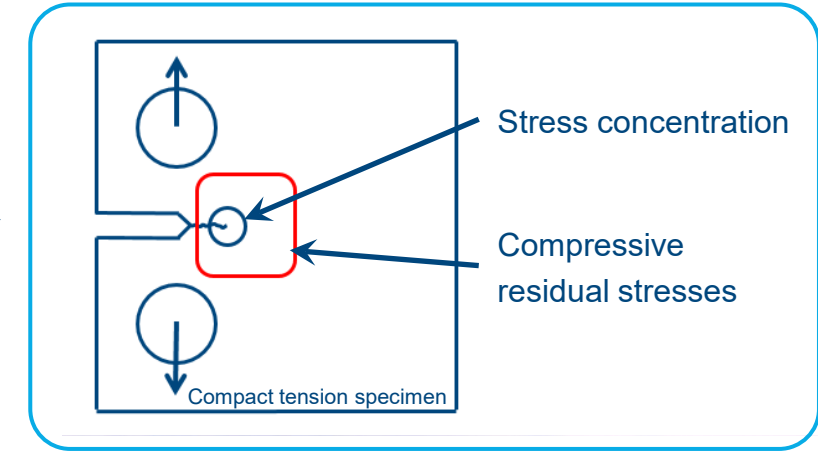
Process



Result



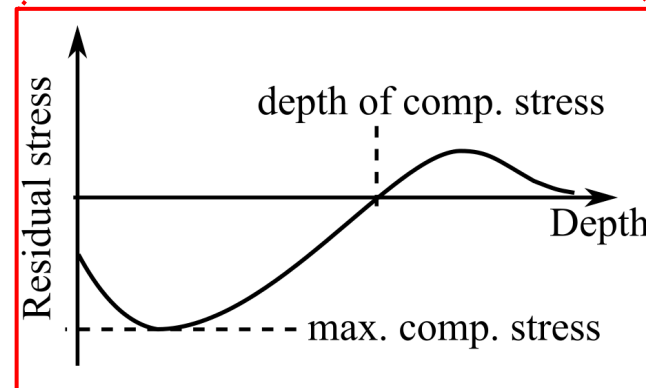
Improving damage tolerance



Process advantages

- Locally induced residual stresses
- Flexible controllability
- Minimal material changes

Induced stress distribution



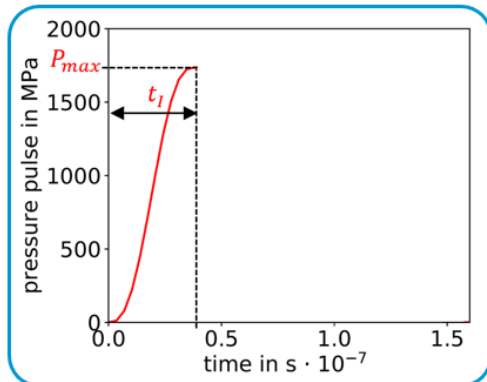
Residual stress fields can

- Slow down crack growth
- Increase fatigue resistance

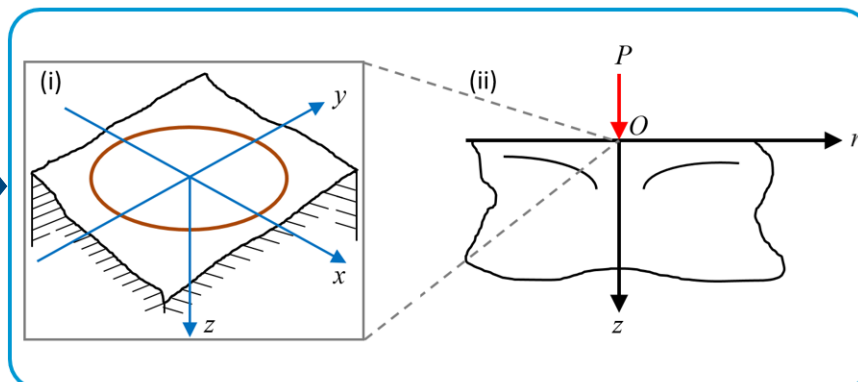
Case study 2: Problem statement

Enhance analytical model via ML to reach FE solution

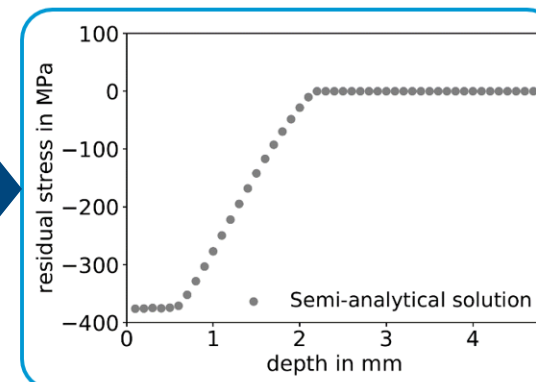
Input: Pressure pulse



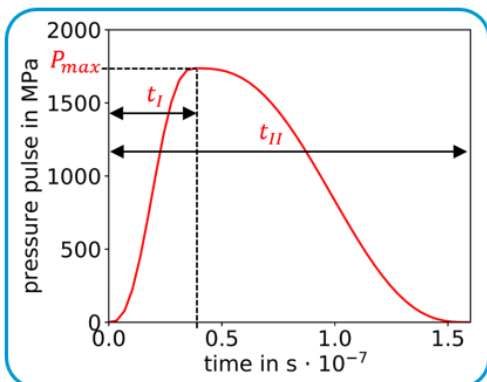
Low fidelity semi-analytical model



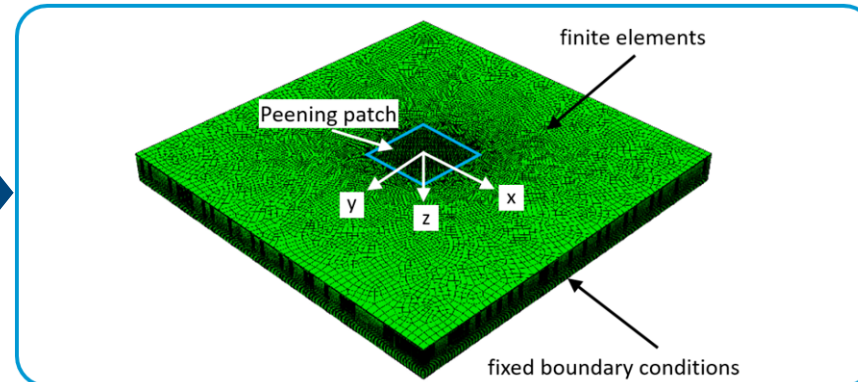
Output: Residual stress



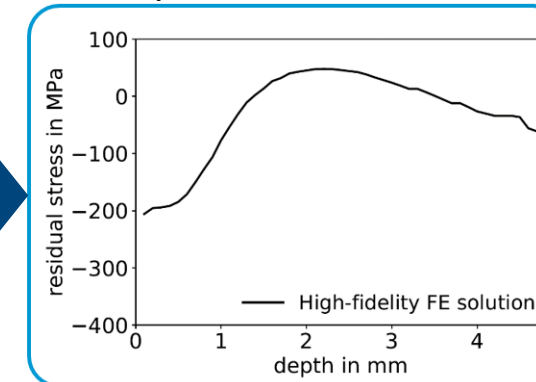
Input: Pressure pulse



High-fidelity finite element model



Output: Residual stress



Case study 2: Methodology

Hybrid modeling of residual stresses induced by laser shock peening

Process parameters

- Max. pressure
- Time of max. pressure
- Pulse duration

Physics-based features & model

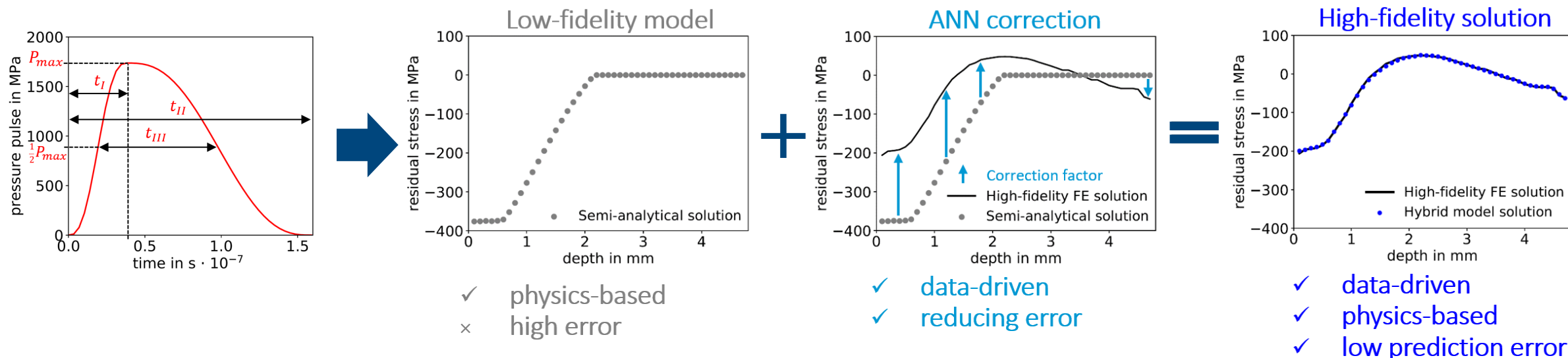
- Dimensionless inputs
- Dimensionless outputs
- Semi-analytical model

Machine learning correction

- ANN as regressor
- Data split: 80/10/10

Mechanical property

Residual stress distribution



Case study 2: Methodology

Dimensionality analysis

- Perform dimensionality reduction based on the Buckingham - Π Theorem
- Goal:** Find minimum number of dimensionless parameters Π to describe the problem

General function of physical quantities a_i^*

$$f(a_1^*, a_2^*, \dots, a_n^*) = 0$$

$f(\dots)$ only functional relationship and
 $f(\dots)$ independent of particular physical units

Dimensionless formulation

$$F(\Pi_1, \Pi_2, \dots, \Pi_{n-m}) = 0$$

n = number of physical quantities
 m = rank of dimensionality matrix



5 - steps to find
relevant variables

R1	Target variable
R2	Geometry variable
R3	Process variable
R4	Material variable
R5	Constants

Case study 2: Methodology

Dimensionality analysis

$$\sigma_i = g(E, \rho, A_{peen}, P_{max}, t_I, t_{II}, t_{III})$$

Residual stresses Material parameters Pressure pulse parameters

Anticipated function

Unit	σ_i	A_{peen}	P_{max}	E	ρ	t_I	t_{II}	t_{III}
N	1	0	1	1	1	0	0	0
mm	-2	2	-2	-2	-4	0	0	0
s	0	0	0	0	2	1	1	1

rank 3

Number of dimensionless parameters:

$$n - m = 8 - 3 = 5$$



$$\Pi_1 = \frac{\sigma_i}{P_{max}}, \Pi_2 = \frac{t_I}{t_{II}}, \Pi_3 = \frac{t_{III}}{t_{II}}, \Pi_4 = t_{III} \sqrt{\frac{E}{\rho \cdot A_{peen}}}, \Pi_5 = \frac{P_{max}}{E}.$$



$$\Pi_1 = g^*(\Pi_2, \Pi_3, \Pi_4, \Pi_5)$$



$$\frac{\sigma_i}{P_{max}} = g^*\left(\frac{t_I}{t_{II}}, \frac{t_{III}}{t_{II}}, t_{III} \sqrt{\frac{E}{\rho \cdot A_{peen}}}, \frac{P_{max}}{E}\right)$$

Dimensionless parameters ☺

Case study 2: Methodology

Dimensionless inputs & outputs for correction task

Dimensionless output

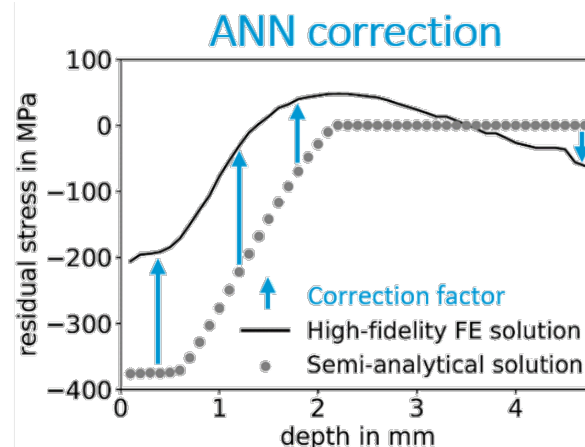
$$Y^i := \left\{ \frac{\sigma_{ana,j}^i + 2\sigma_y}{\sigma_{FE,j}^i + 2\sigma_y} \right\}$$

$$\frac{\sigma_i}{P_{max}} = g^* \left(\frac{t_I}{t_{II}}, \frac{t_{III}}{t_{II}}, t_{III} \sqrt{\frac{E}{\rho \cdot A_{peen}}}, \frac{P_{max}}{E} \right)$$

Dimensionless input

$$X^i := \left\{ \frac{\sigma_{ana,1}^i + 2\sigma_y}{P_{max}^i}, \frac{\sigma_{ana,2}^i + 2\sigma_y}{P_{max}^i}, \dots, \frac{\sigma_{ana,47}^i + 2\sigma_y}{P_{max}^i}, \frac{t_I^i}{t_{II}^i}, \frac{t_{III}^i}{t_{II}^i}, t_{III}^i \sqrt{\frac{E}{\rho \cdot A_{peen}}}, \frac{P_{max}^i}{E}, \frac{j}{47} \right\}$$

Complete stress
distribution over
depth



Point-wise
prediction

→ smooth curve!

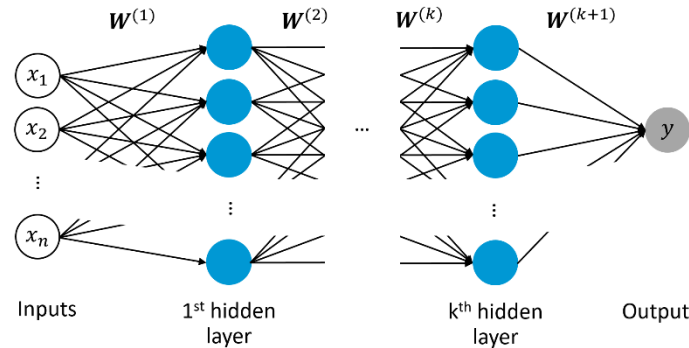
Case study 2: Methodology

Data preparation, preprocessing and ANN implementation

Dimensionless input

$$\mathbf{X}^i := \left\{ \frac{\sigma_{ana,1}^i + 2\sigma_y}{P_{max}^i}, \frac{\sigma_{ana,2}^i + 2\sigma_y}{P_{max}^i}, \dots, \frac{\sigma_{ana,47}^i + 2\sigma_y}{P_{max}^i}, \right. \\ \left. \frac{t_I^i}{t_{II}^i}, \frac{t_{III}^i}{t_{II}^i}, t_{III}^i \sqrt{\frac{E}{\rho \cdot A_{peen}}}, \frac{P_{max}^i}{E}, \frac{j}{47} \right\}$$

ANN-Implementation



Dimensionless output

$$\mathbf{Y}^i := \left\{ \frac{\sigma_{ana,j}^i + 2\sigma_y}{\sigma_{FE,j}^i + 2\sigma_y} \right\}$$

Advantages of dimensionless inputs and outputs (via dimensionality analysis)

- Predictions of wider range of physical parameters than that used for training possible
- Reduction of prediction scatter + inaccuracies

Data: analytical & numerical

82 samples pairs (Pulse → Stress)[from both models]

Since point-wise prediction for **47 depth steps**:

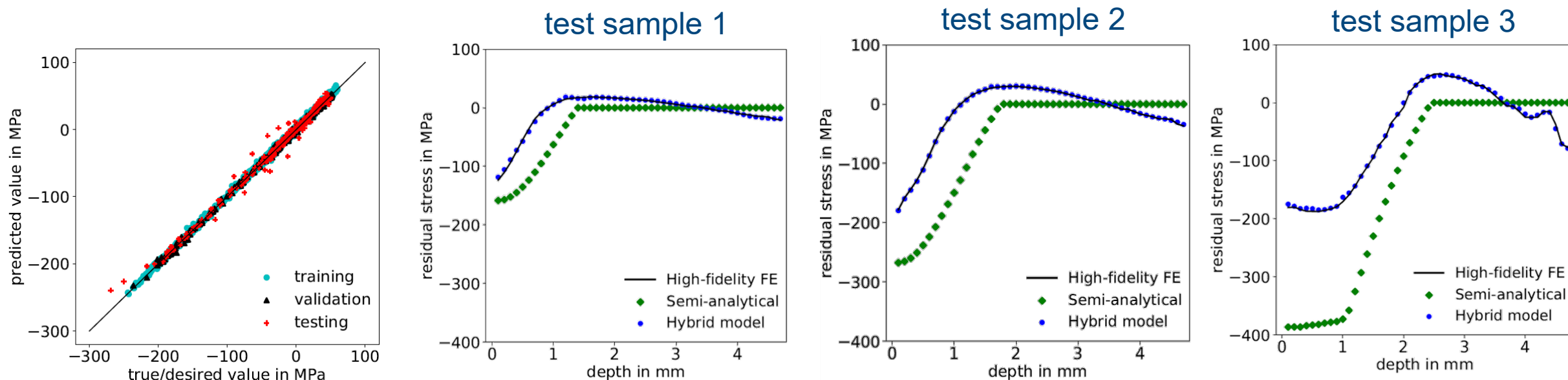
→ A total of **82 x 47 = 3854 patterns** are available for ANN

Process parameter space

	P_{max} in MPa	t_I in ns	t_{II} in ns
Min.	800	12	43
Max.	2200	66	300

Case study 2: Results

Residual stress predictions



Residual Stresses		
Data Set	R^2 in %	MSE in MPa ²
Training	99.90	4.33
Validation	99.86	7.38
Test	99.15	28.63

Main observations

- No overfitting
- Excellent performance measures
- Very good agreement between corrected prediction and desired solution

Case study 2: Benchmark

Hybrid vs. data-driven model

Model differences

Hybrid model

Input: Analytical stress

$$X^i := \left\{ \frac{\sigma_{ana,1}^i + 2\sigma_y}{P_{max}^i}, \dots \right\}$$

Output: Correction factor

$$Y^i := \left\{ \frac{\sigma_{ana,j}^i + 2\sigma_y}{\sigma_{FE,j}^i + 2\sigma_y} \right\}$$

Data-driven ANN

Input: Pressure pulse

$$X_{direct}^i := \left\{ \frac{P_1^i}{P_{max}^i}, \dots \right\}$$

Output: High-fidelity stress

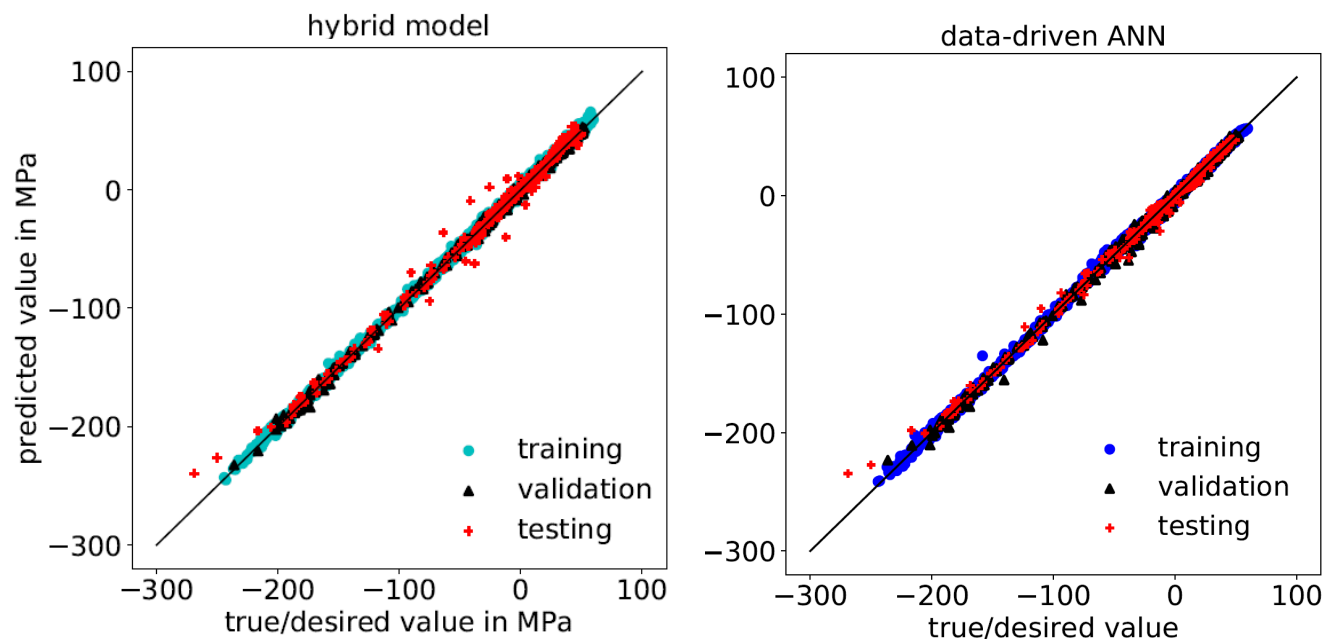
$$Y_{direct}^i := \left\{ \frac{\sigma_{FE,j}^i + 2\sigma_y}{\sigma_y} \right\}$$



Anything else remained identical
(e.g. ANN hyper-parameters etc.)

Case study 2: Results

Benchmark: Predictions via hybrid vs. data-driven model



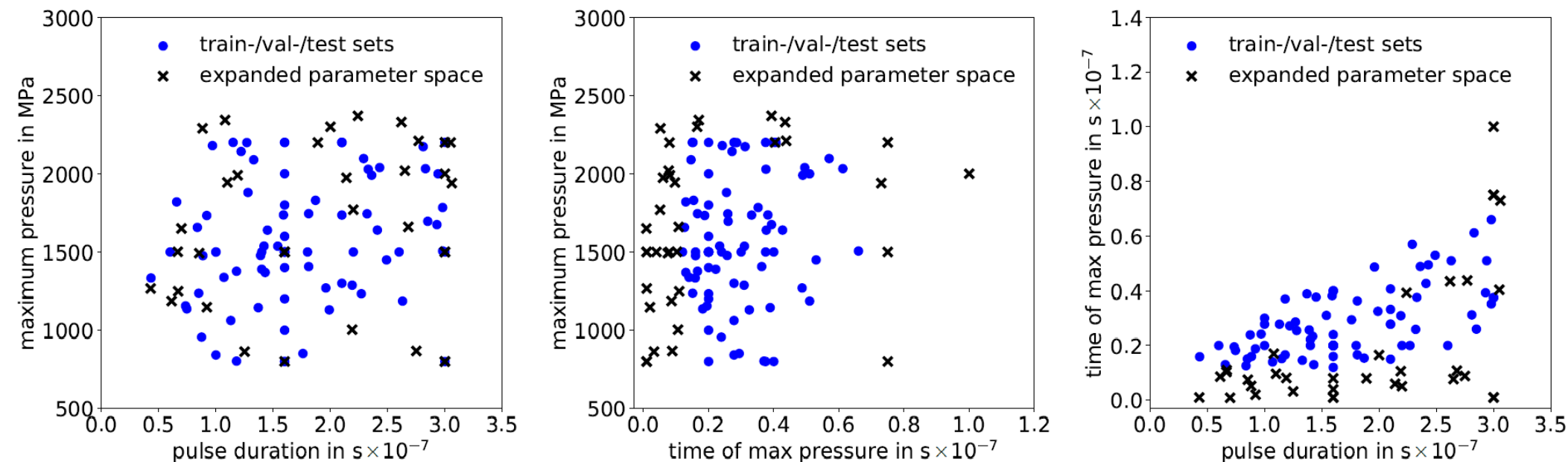
	Hybrid Model	Data-Driven ANN
Data Set	R^2 in %	R^2 in %
Training	99.90	99.86
Validation	99.86	99.76
Test	99.15	95.89

Main observations

- Both models are well trained
- Data-driven model: slightly reduced generalization

Case study 2: Results

Expanded process parameter space

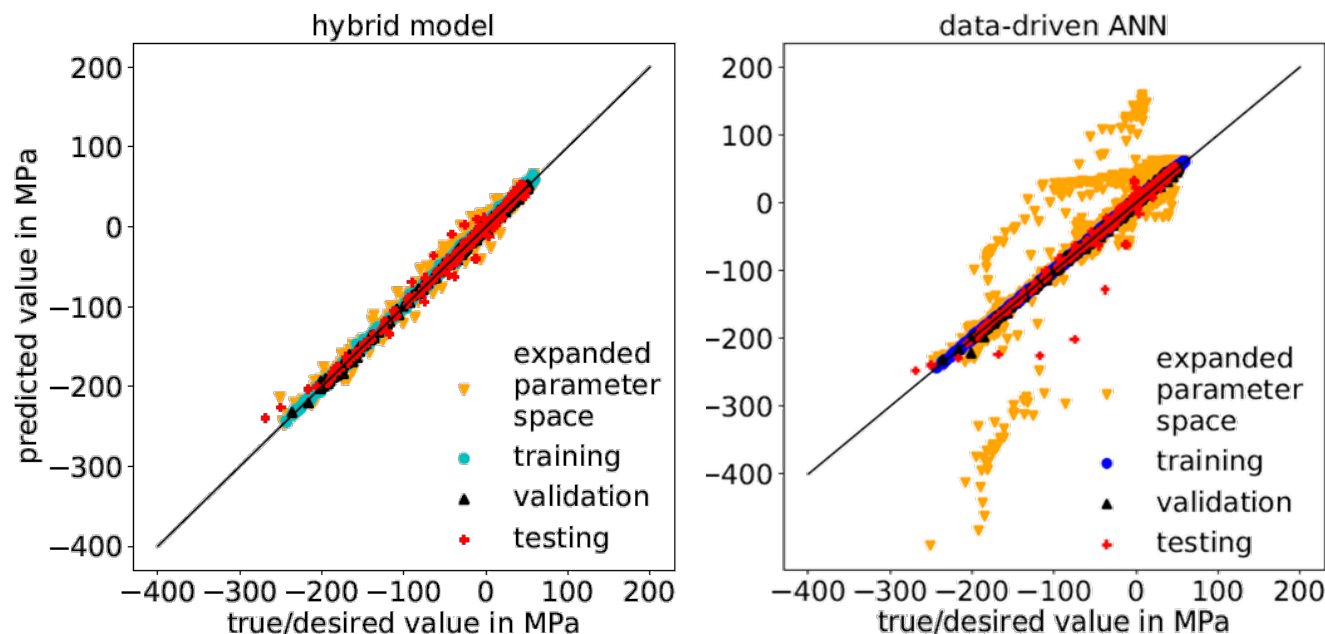


		P_{max} in MPa	t_I in ns	t_{II} in ns
Training, validation, test	Min.	800	12	43
	Max.	2200	66	300
Expanded parameter space	Min.	800	1	43
	Max.	2400	100	306

Remaining within
 range of correction factors
 [0.5090-1.1189]

Case study 2: Results

Benchmark: Physical extrapolation via hybrid vs. data-driven model



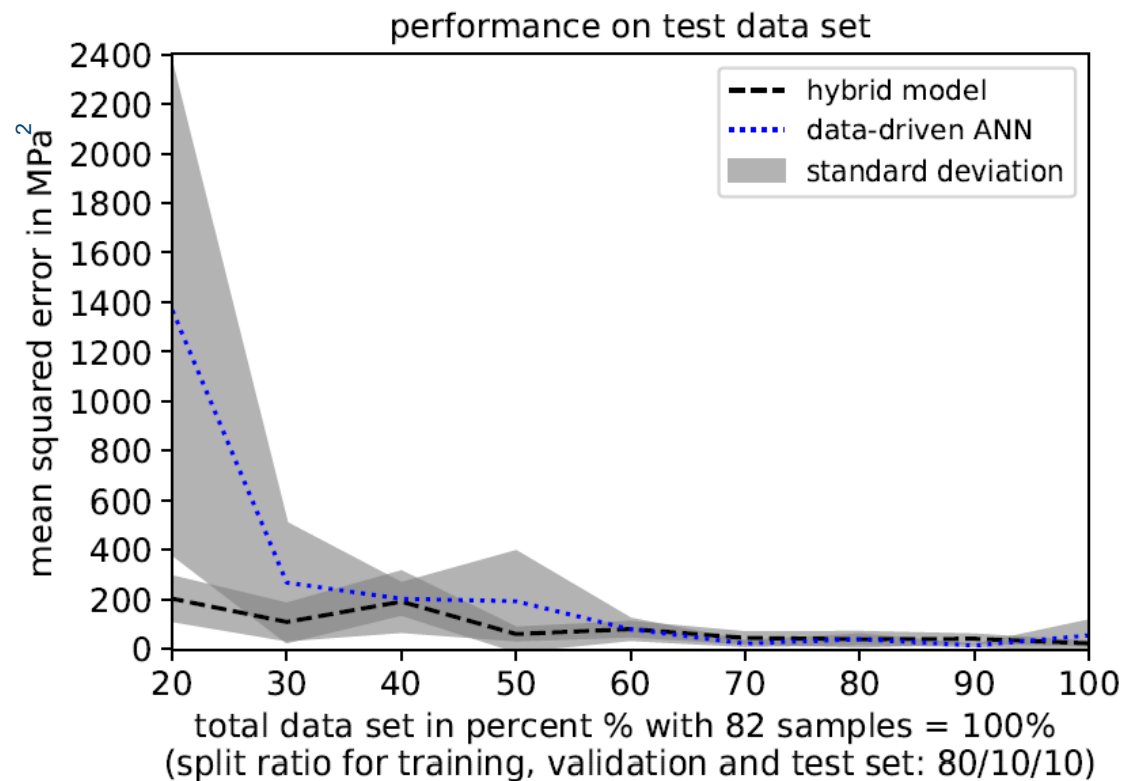
	Hybrid Model	Data-Driven ANN
Data Set	R^2 in %	R^2 in %
Training	99.90	99.86
Validation	99.86	99.76
Test	99.15	95.89
Expanded space	99.39	65.00

Main observations

- Hybrid model: Very good performance
- Data-driven: inferior generalization

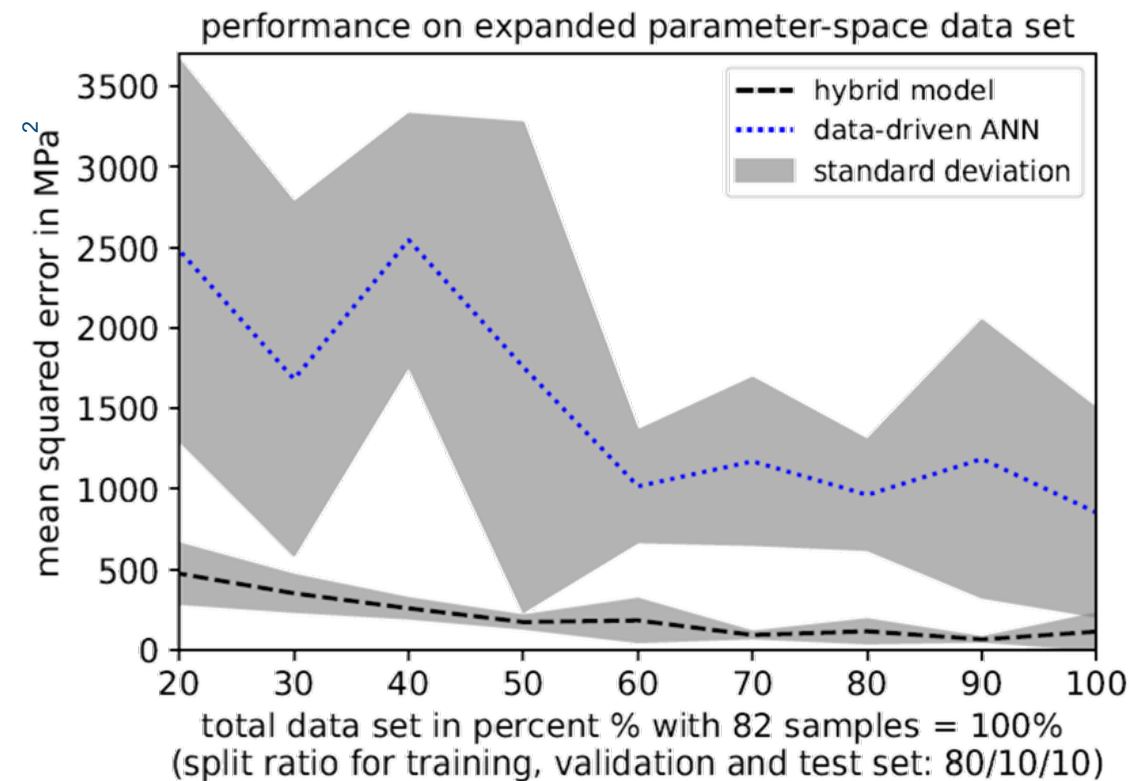
Case study 2: Results

Benchmark: Data reduction study



Main observations

- Lower MSE for hybrid model below 60 %
- Greatest MSE difference at 20 % (13/1/1)



Main observation

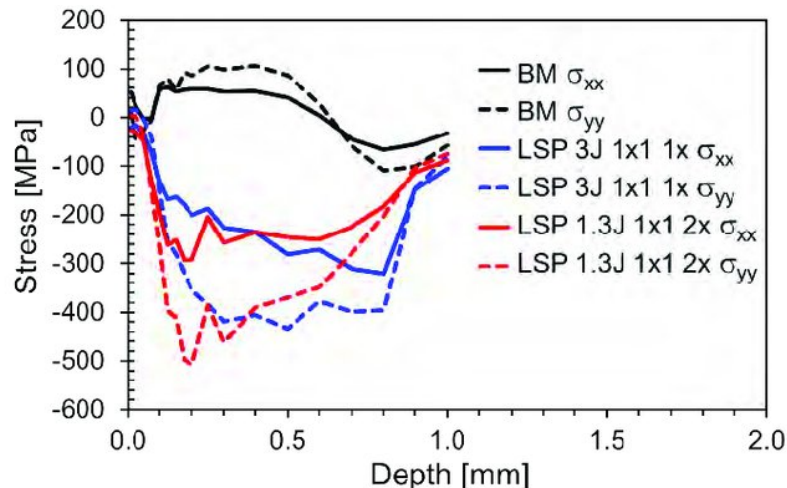
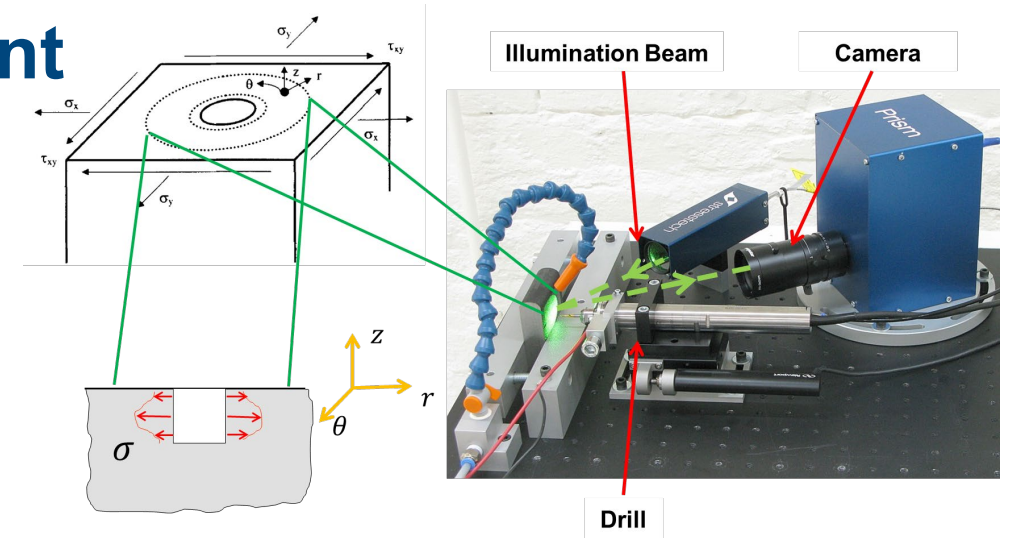
- Lower MSE for hybrid model throughout

Case study 2: Further Problem statement

Residual stress determination

Assumptions in hole drilling method:

- Maximum hole depth is half of the hole diameter
- At the scale of measurement, the specimen is essentially infinitely thick
- Spatial in-plane residual stresses are uniform within the area of 3 hole diameter
- All deformations are linearly elastic



AA2024-T3

Yield strength ~350MPa

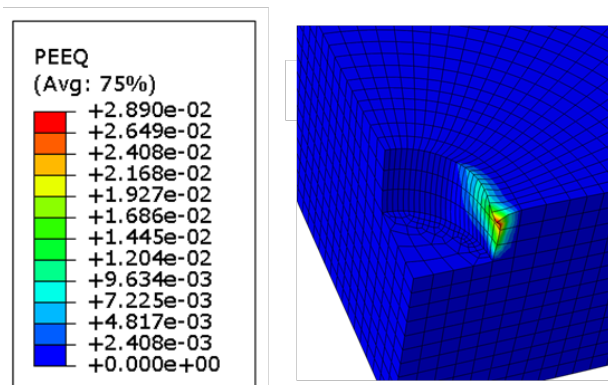
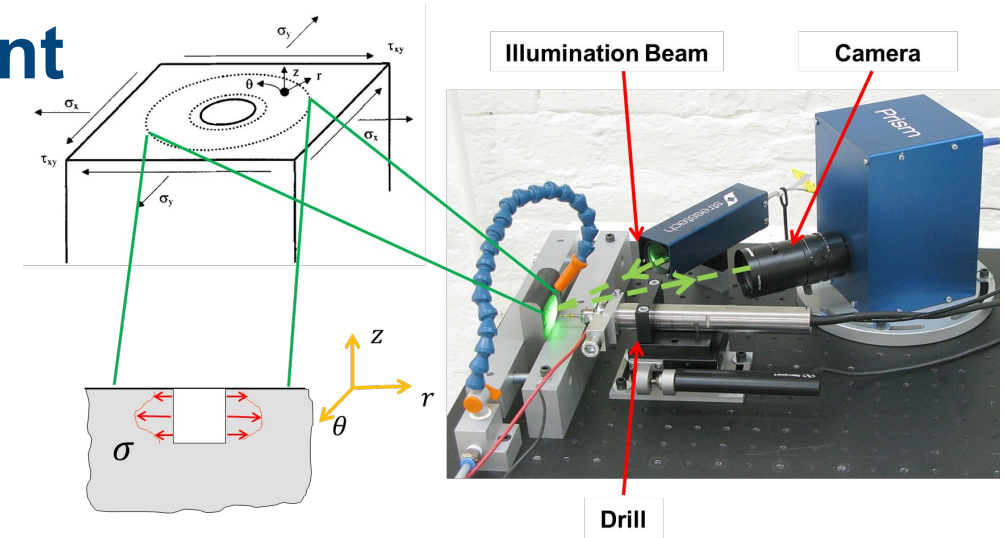
Ultimate tensile strength ~475

Case study 2: Further Problem statement

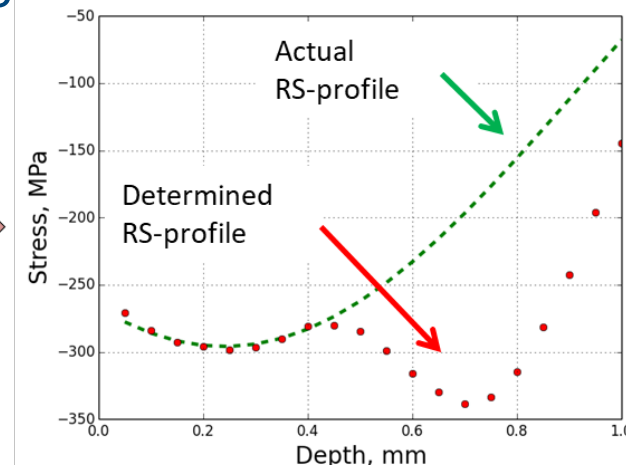
Residual stress determination

Assumptions in hole drilling method:

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- Spatial in-plane residual stresses are uniform within the area of 3 hole diameter
- All deformations are linearly elastic

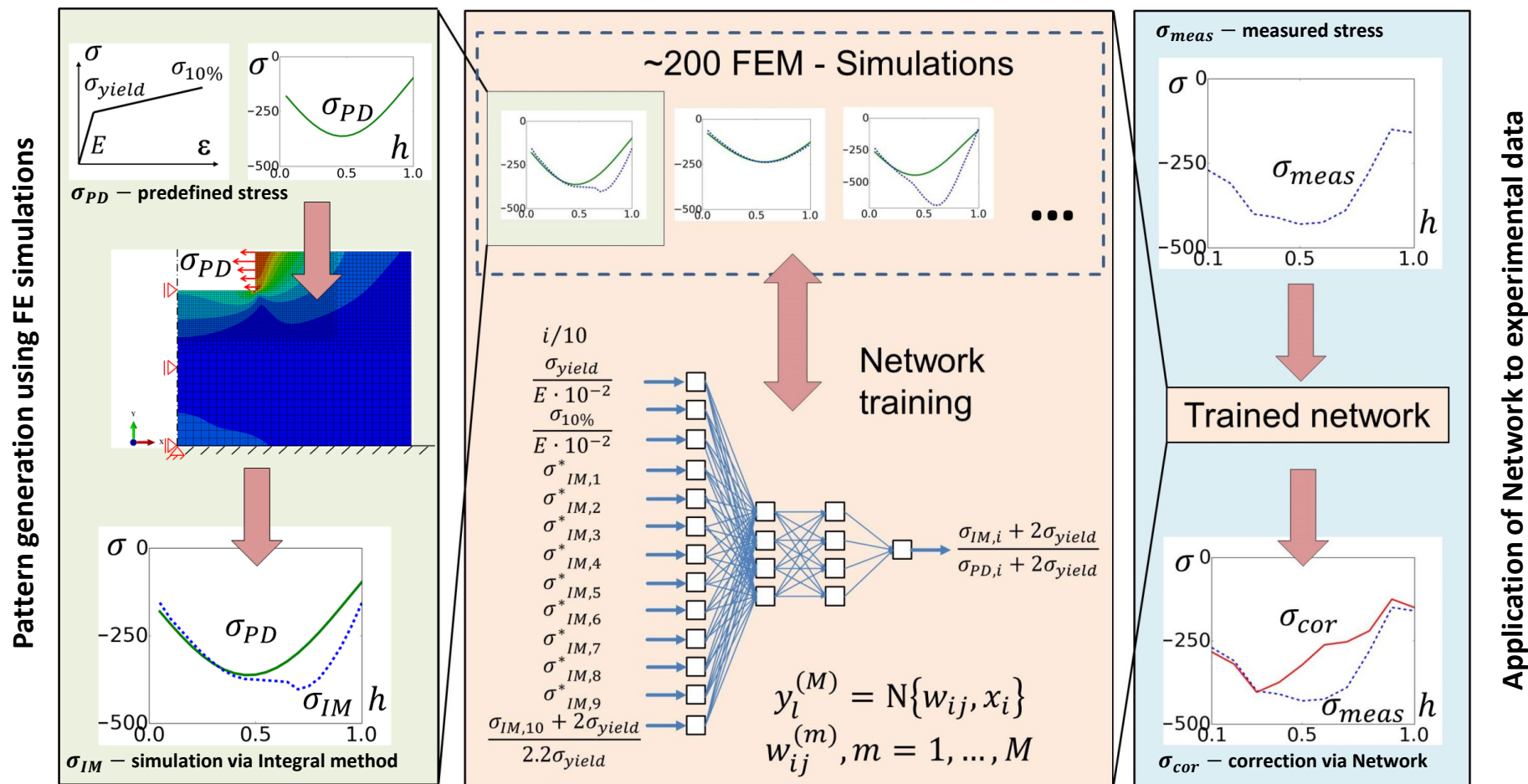


plasticity effect



Case study 2: Residual stress determination

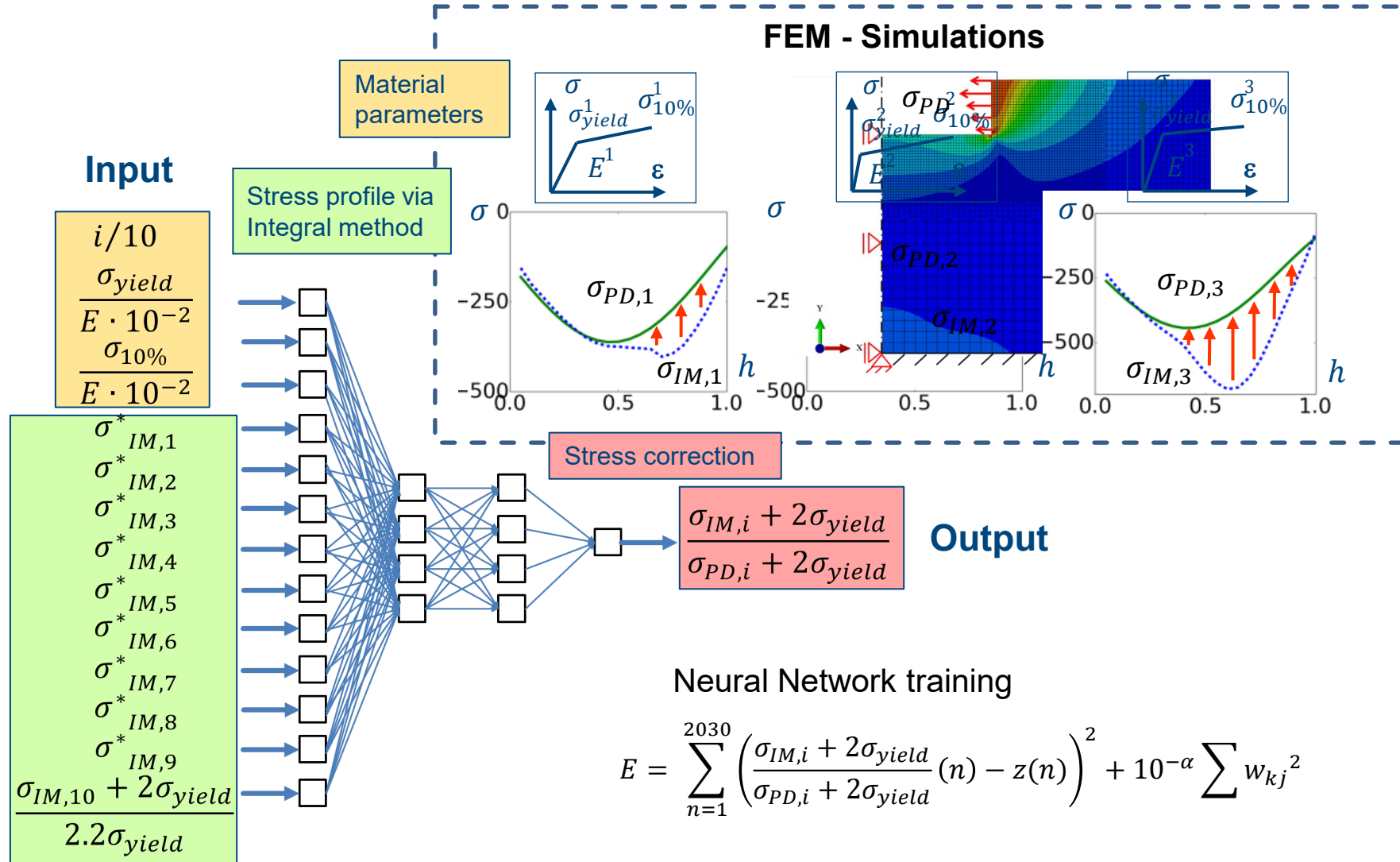
Stress Correction Methodology



Publication: S. Chupakhin, N. Kashaev, B. Klusemann, and N. Huber. Artificial neural network for correction of effects of plasticity in equibiaxial residual stress profiles measured by hole drilling. The Journal of Strain Analysis for Engineering Design, 52(3):137–151, 2017.

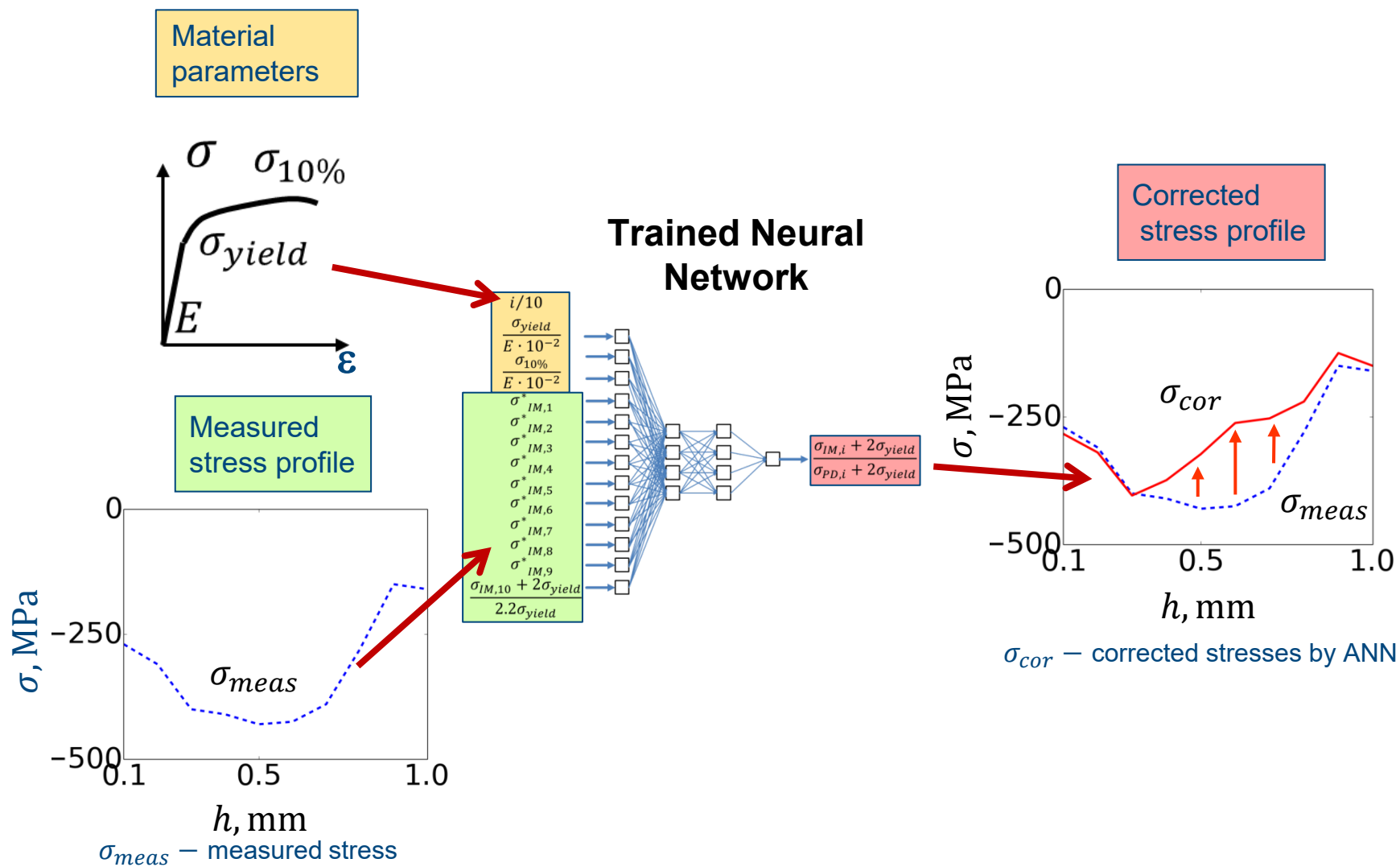
Case study 2: Residual stress determination

Stress Correction Methodology



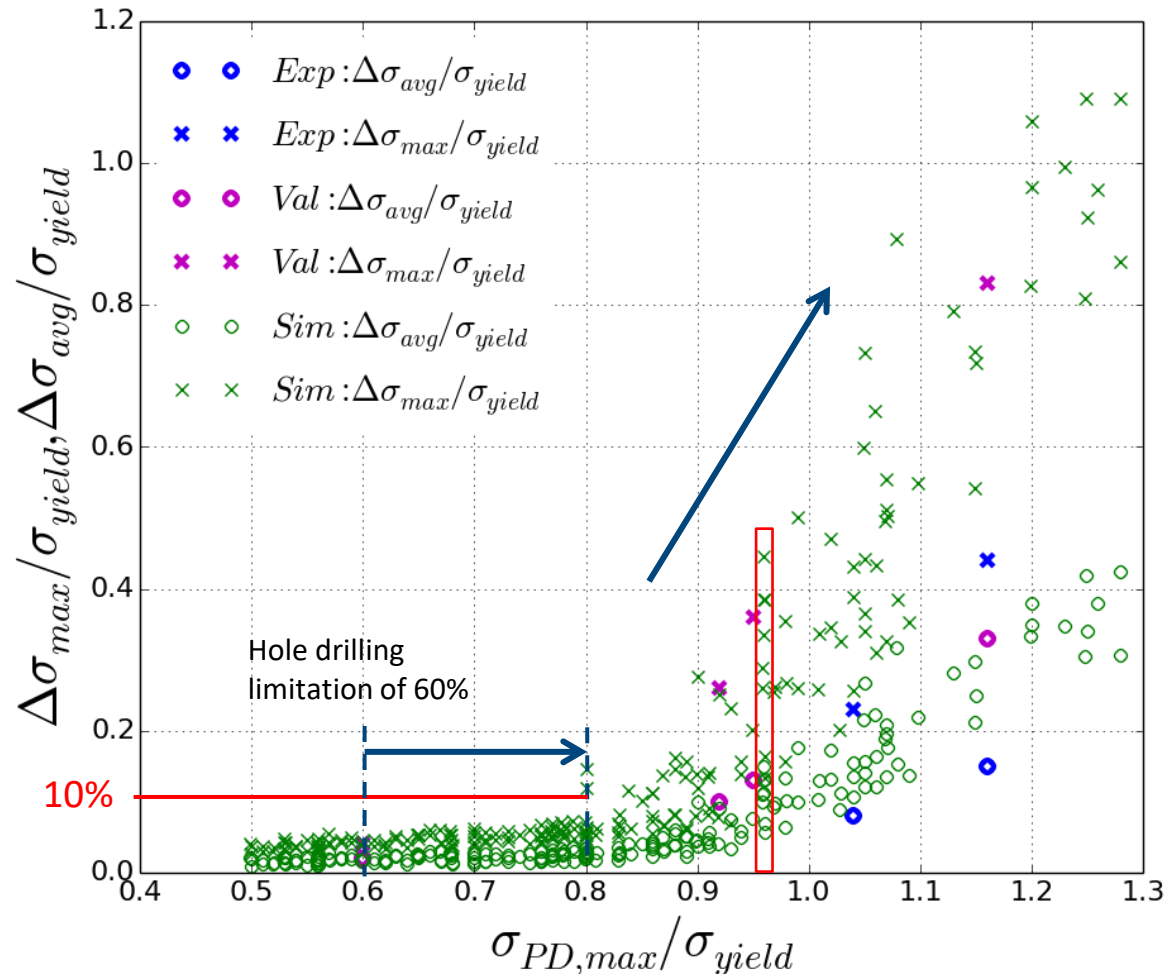
Case study 2: Residual stress determination

Stress Correction Methodology



Case study 2: Residual stress determination

Results Stress Correction Methodology



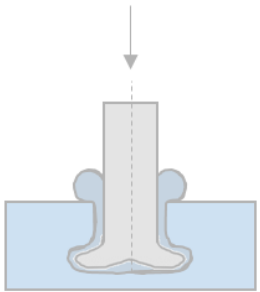
- LSP-shaped stress errors are less than 10% as long as $\sigma_{max}/\sigma_{yield} \leq 0.8$
- When $\sigma_{max}/\sigma_{yield} > 0.8$ the normalized errors $\Delta\sigma_{avg}/\sigma_{yield}$ and $\Delta\sigma_{max}/\sigma_{yield}$ grow progressively
- Errors' scatter shows that the effect of plasticity depends on combination of stress profile shape and the depth of peak values

Case studies

Overview

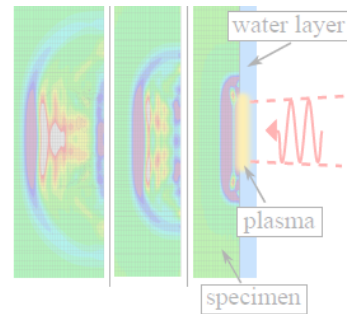
Case study 1

Ultimate tensile strength prediction for joints made by Friction Riveting



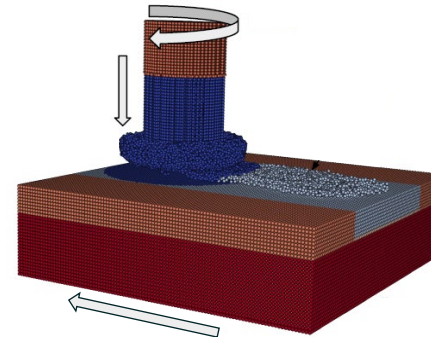
Case study 2

Prediction of residual stresses induced by Laser Shock Peening



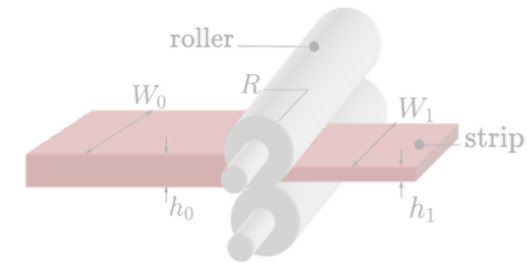
Case study 3

Prediction of layer geometry deposited via Friction Surfacing



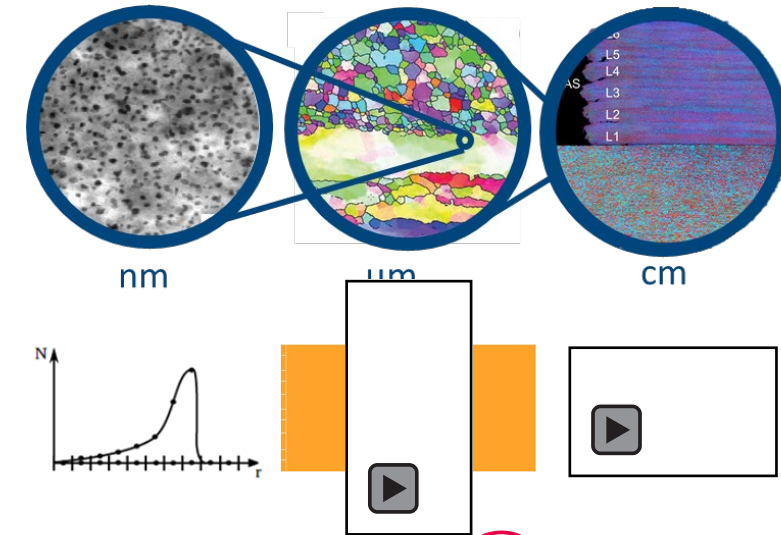
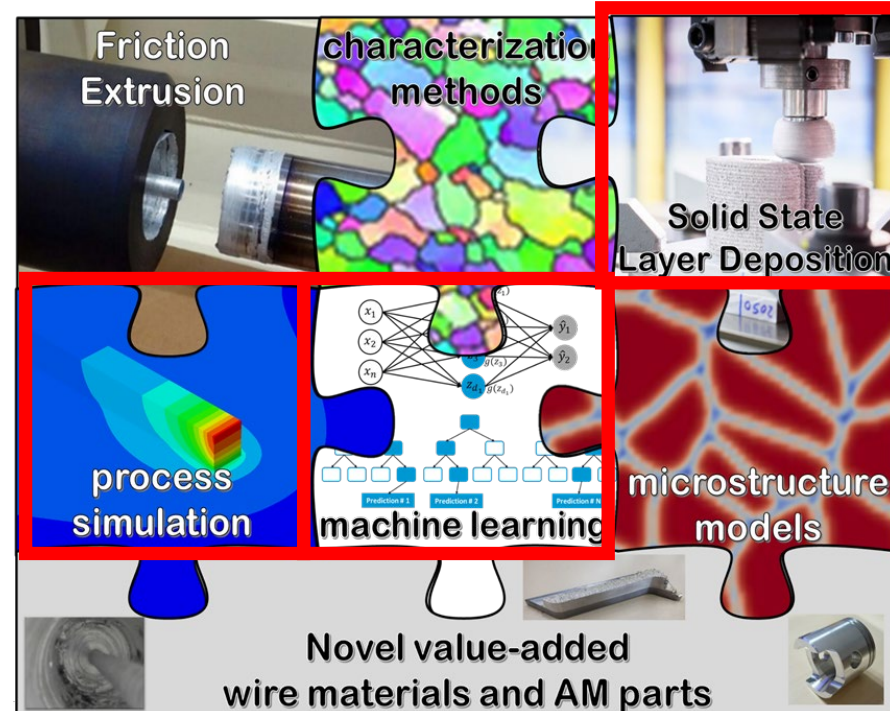
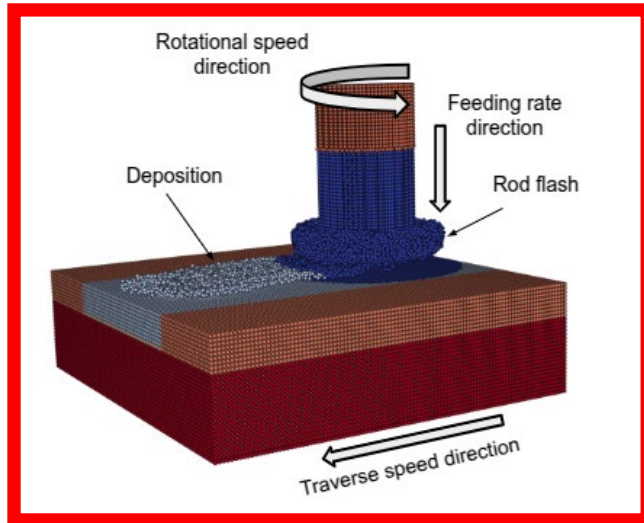
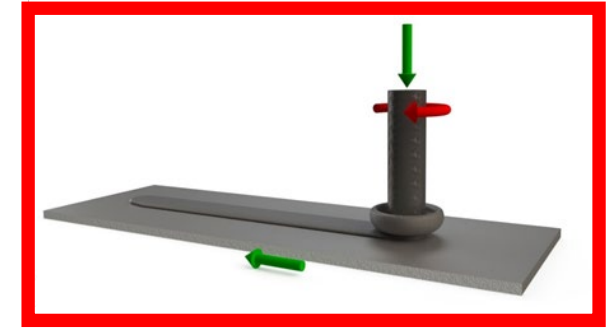
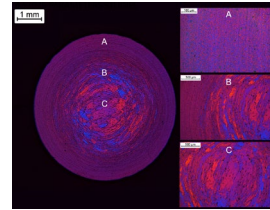
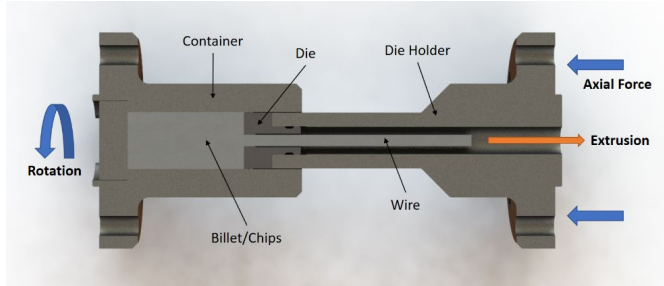
Case study 4

Prediction of slab spread forming via Hot Rolling



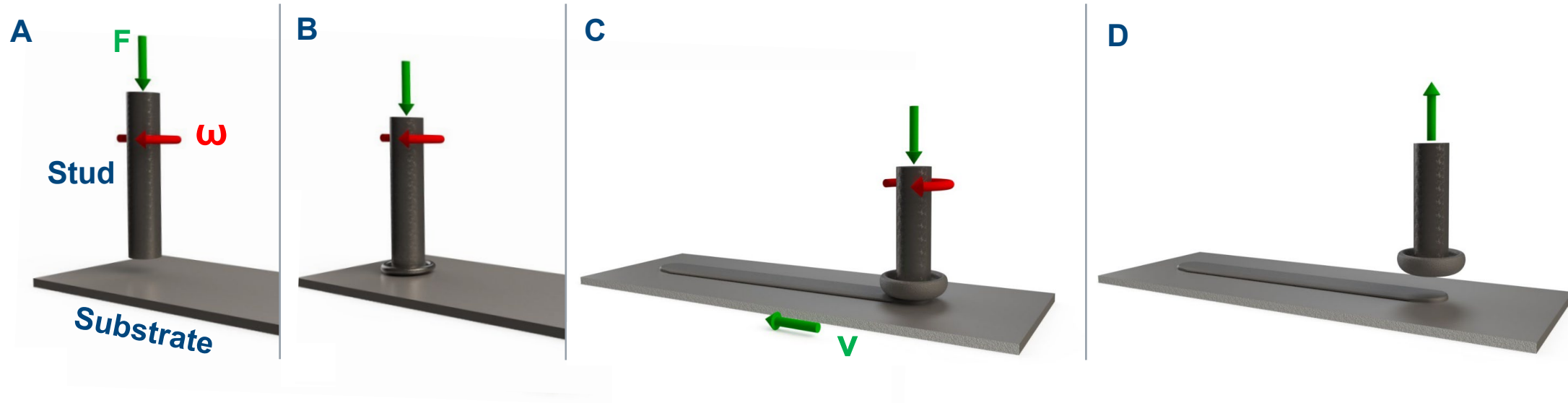
Case study 3: Introduction

MA.D.AM - Modelling Assisted Solid State Materials Development and Additive Manufacturing



Case study 3: Introduction

Friction surfacing process



Advantages

- Deposition of dissimilar and non-fusion weldable materials
- Fine-grained recrystallized microstructure
- Low requirements for the process environment
- Environmentally friendly ('green' process)
- Low heat input

Process parameters

Axial force F

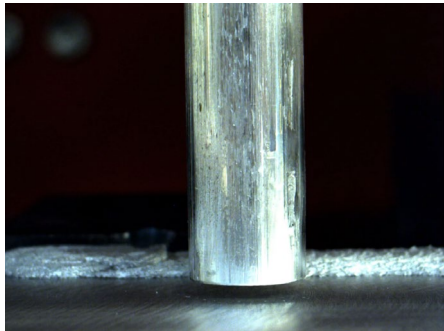
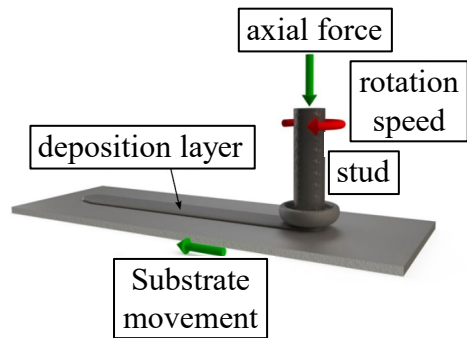
Rotation speed ω

Travel speed v

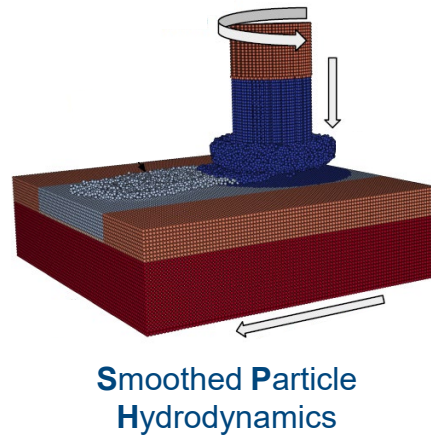
Case study 3: Problem statement

Discrepancy between numerical and experimental results

Experimental measurements



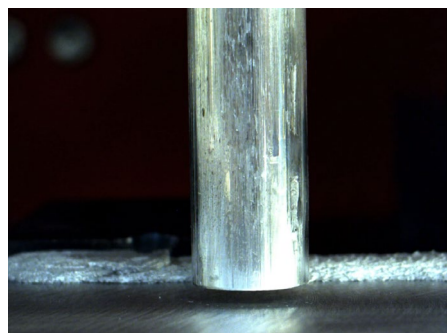
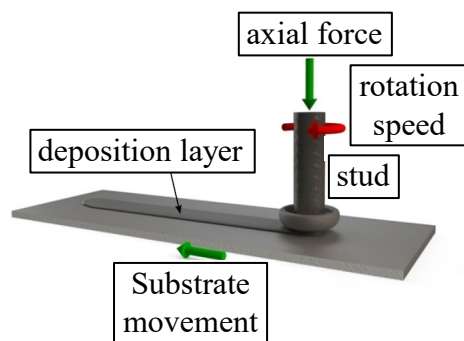
Numerical SPH model



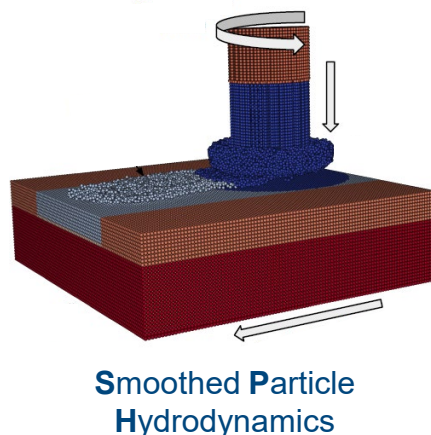
Case study 3: Problem statement

Discrepancy between numerical and experimental results

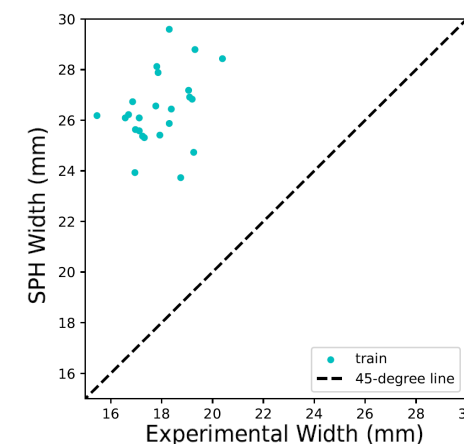
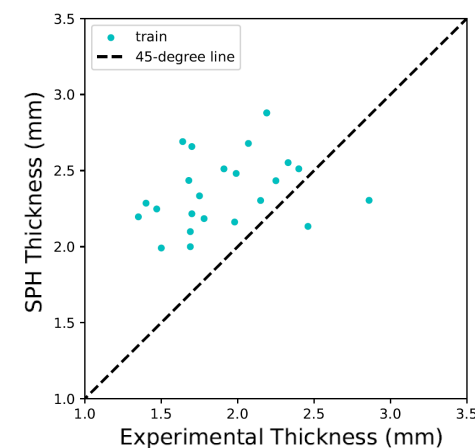
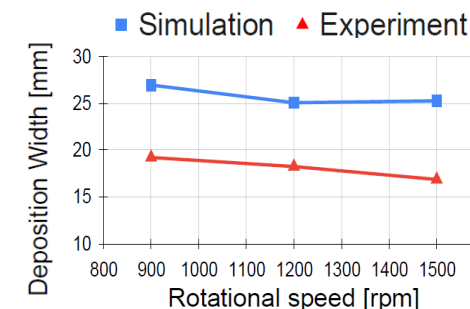
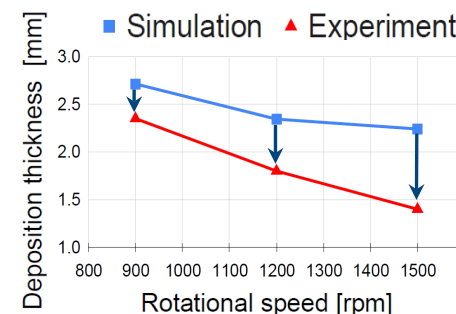
Experimental measurements



Numerical SPH model



Discrepancies of prediction targets



Case study 3: Methodology

Hybrid modeling of layer deposit geometry

Process parameters

- Axial force
- Rotation speed
- Travel speed

Physics-based features & model

- Dimensionless inputs
- Dimensionless outputs
- Numerical model (SPH)

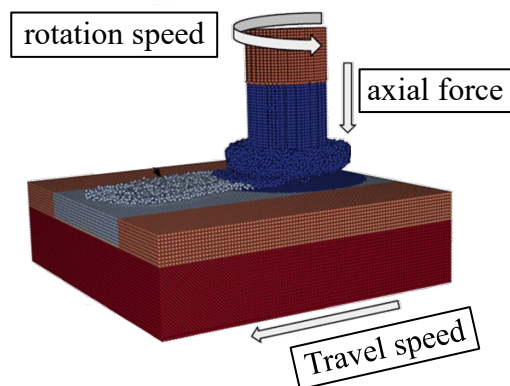
Machine learning correction

- ANN as regressor
- Leave-One-Out-Cross-Validation (LOOCV)

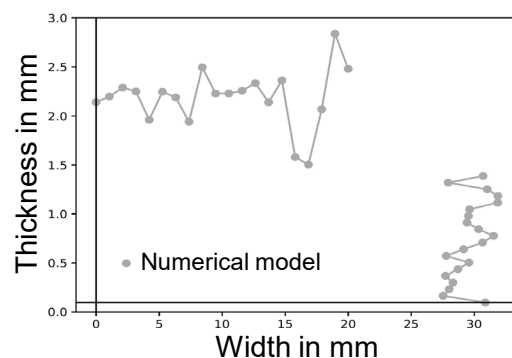
Structural properties

- Deposit thickness
- Deposit width

Parameter visualization (SPH model)

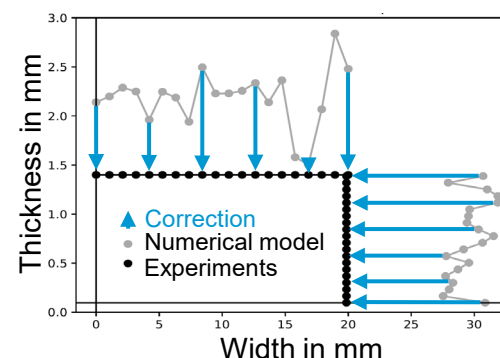


High-fidelity solution



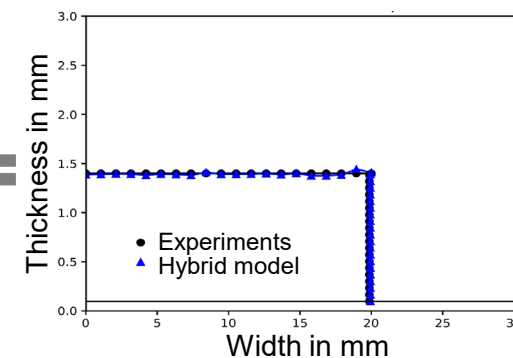
- ✓ physics-based
- × high error

ANN correction



- ✓ data-driven
- ✓ reducing error

Experimental solution



- ✓ data-driven
- ✓ physics-based
- ✓ low prediction error

Case study 3: Methodology

Data preparation, preprocessing and ANN implementation

Dimensionless input

$$X := \left(\frac{M}{F \cdot t_{sim}}, \frac{\omega^2 \cdot M \cdot T_{max}}{v_{tr} \cdot k_s}, \frac{v_{cr}}{\omega \cdot t_{sim}}, \frac{\omega \cdot t_{sim}}{v_{tr}}, \frac{k_s \cdot t_{sim}}{F \cdot T_{max} \cdot v_{tr}}, \frac{v_{cr}}{v_{tr}} \right)$$

$$X := \left(\frac{M}{F \cdot w_{sim}}, \frac{\omega^2 \cdot M \cdot T_{max}}{v_{tr} \cdot k_s}, \frac{v_{cr}}{\omega \cdot w_{sim}}, \frac{\omega \cdot w_{sim}}{v_{tr}}, \frac{k_s \cdot w_{sim}}{F \cdot T_{max} \cdot v_{tr}}, \frac{v_{cr}}{v_{tr}} \right)$$

Data: numerical & experimental

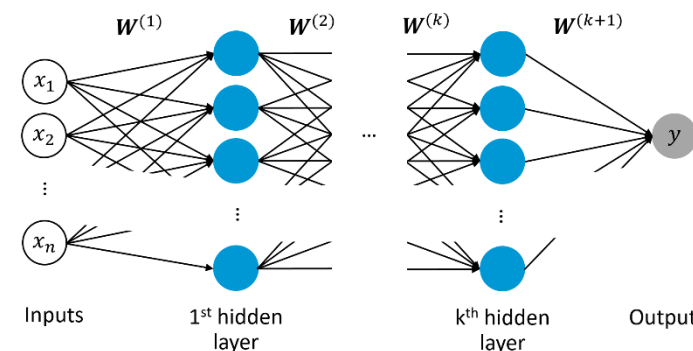
25 samples pairs (Process → Geometry)

Point-wise prediction for 20 length steps:

→ **25 x 20 = 500 patterns** available for ANN

Materials: Substate: AA7050 T7451 (t=10mm)
Backing: AA7050 T7451 (t= 8mm)
Stud: AA5083 H112 (d=20mm)

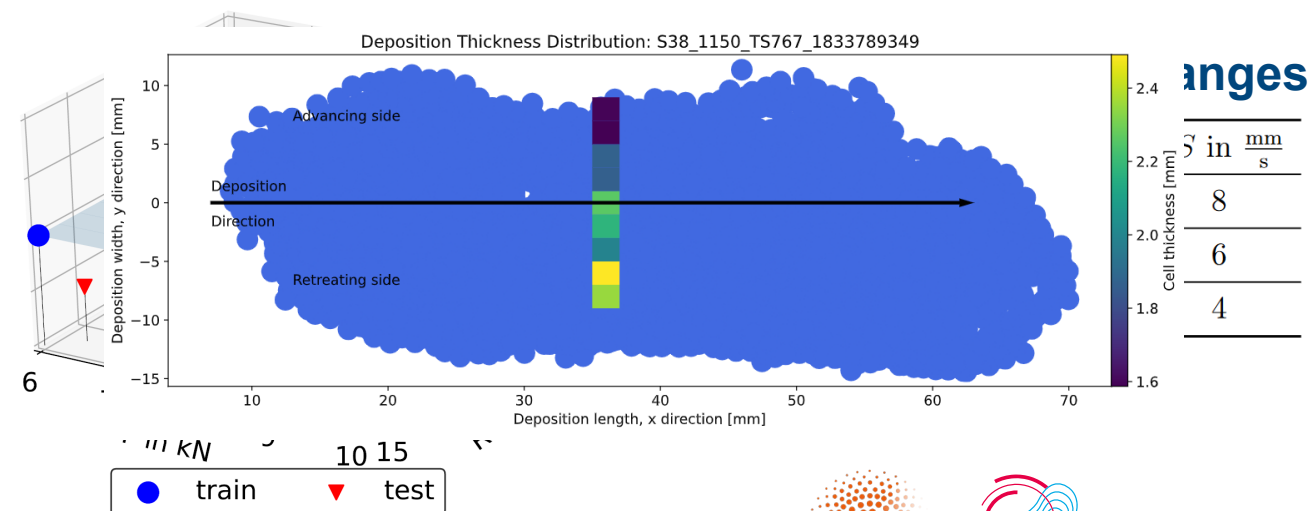
ANN-Implementation



Dimensionless output

$$Y := \left(\frac{t_{sim}}{t_{exp}} \right)$$

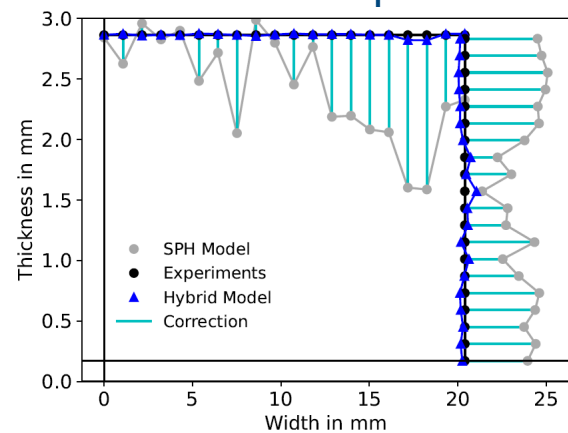
$$Y := \left(\frac{w_{sim}}{w_{exp}} \right)$$



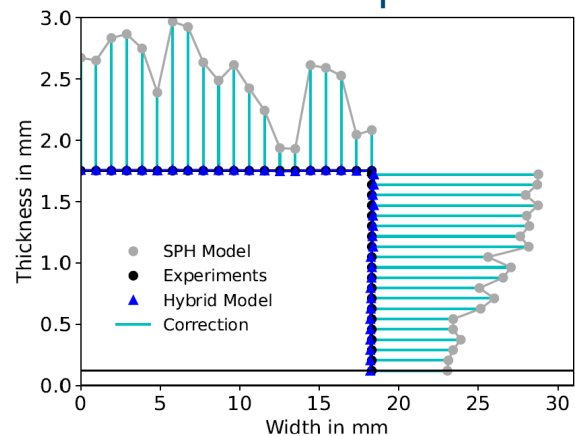
Case study 3: Results

Geometry predictions

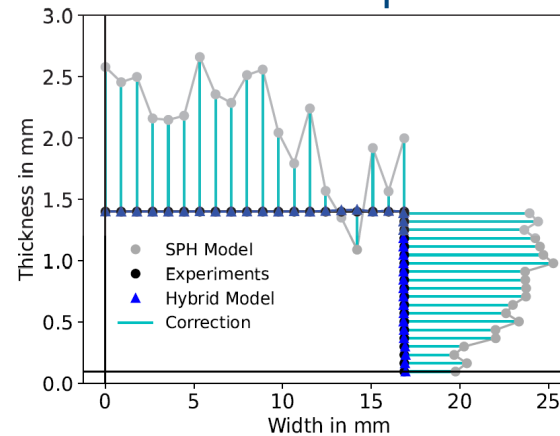
Train sample 1



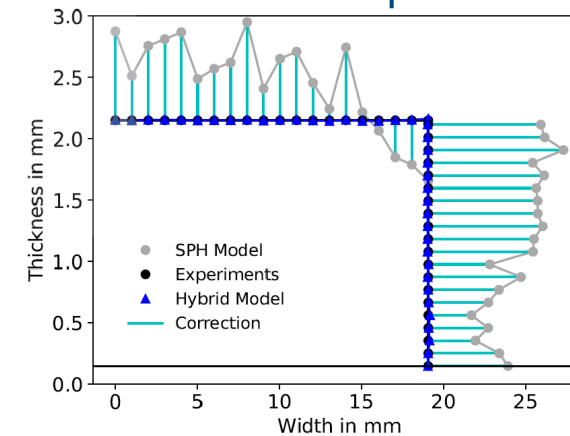
Train sample 2



Train sample 3



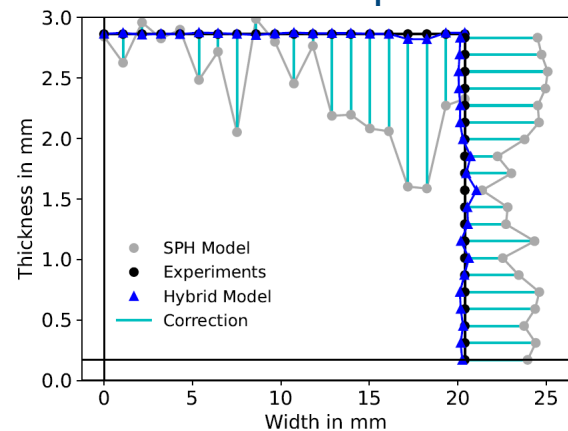
Train sample 4



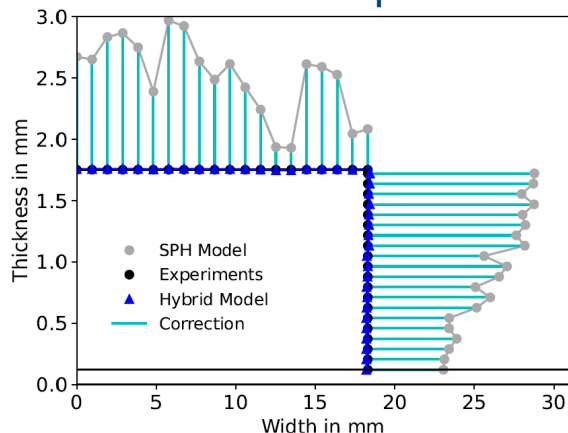
Case study 3: Results

Geometry predictions

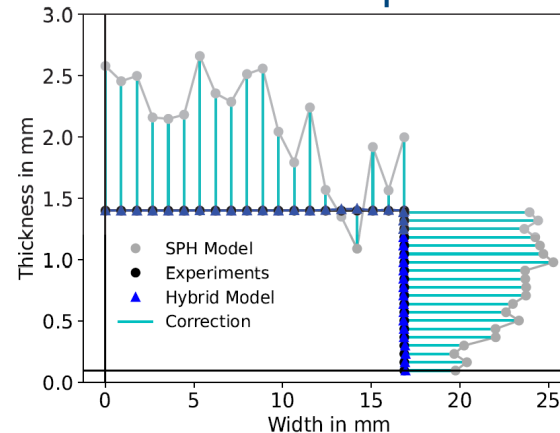
Train sample 1



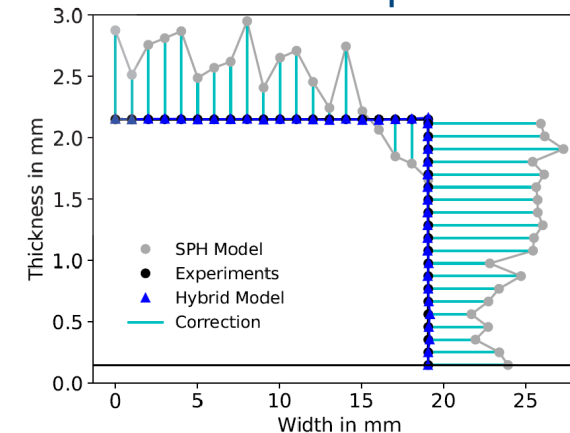
Train sample 2



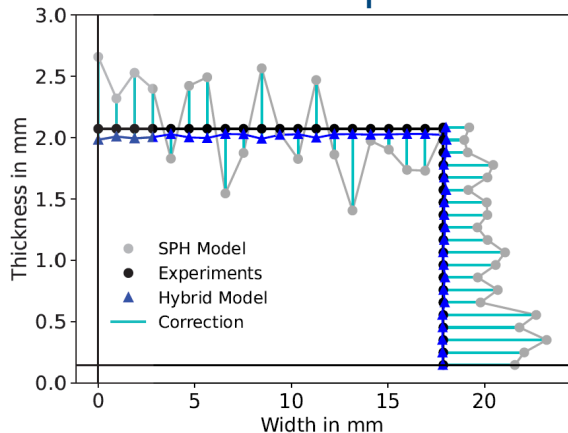
Train sample 3



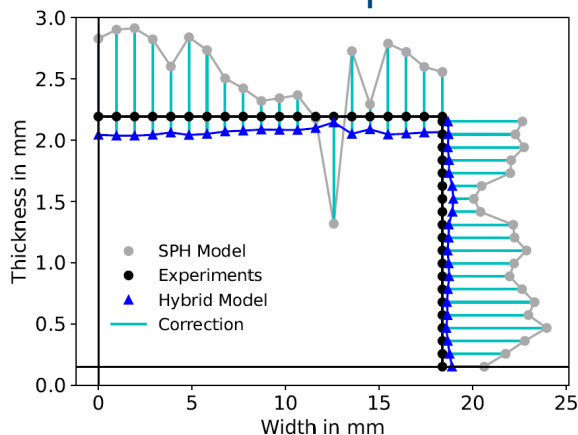
Train sample 4



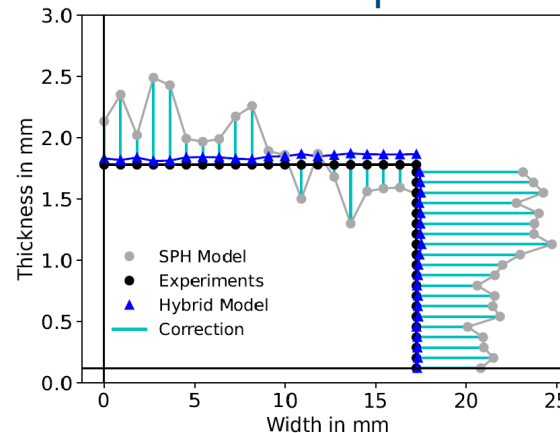
Test sample 1



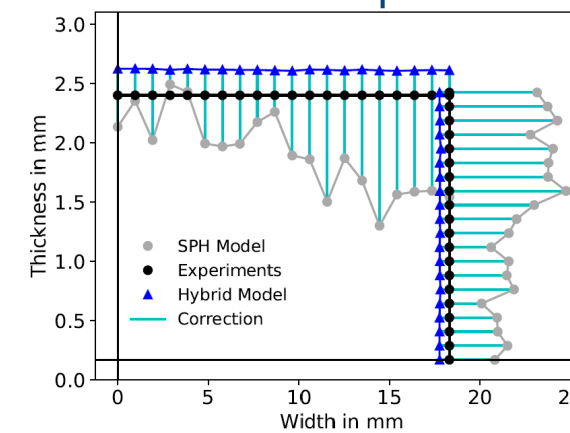
Test sample 2



Test sample 3



Test sample 4

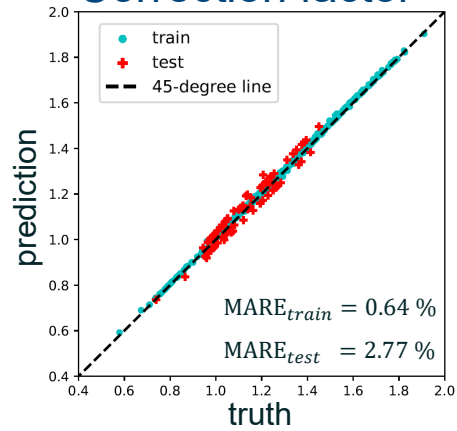


Case study 3: Results

Geometry predictions

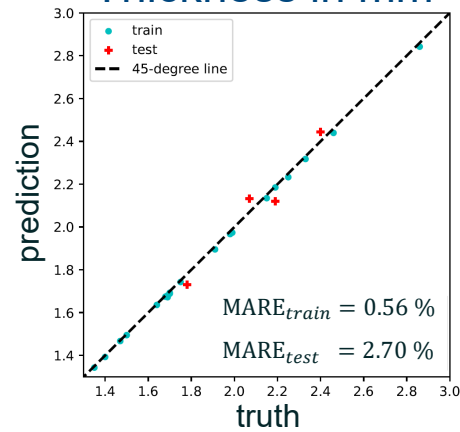
Discrepancy models:

Correction factor

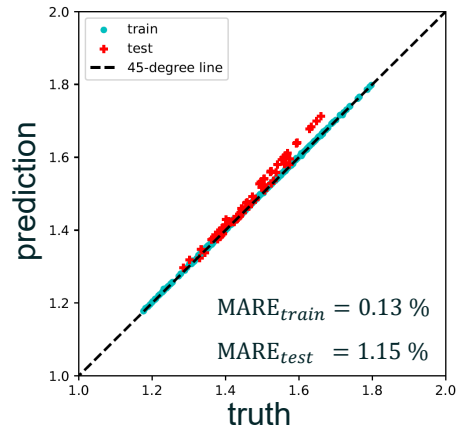


Hybrid models:

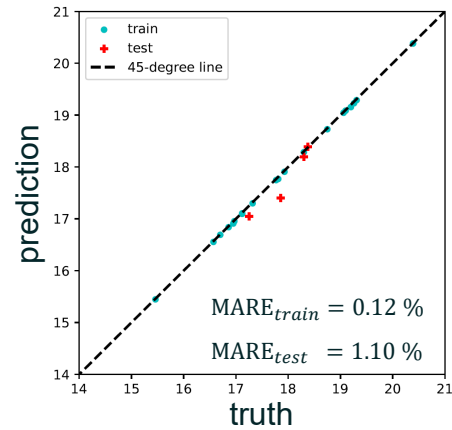
Thickness in mm



Correction factor



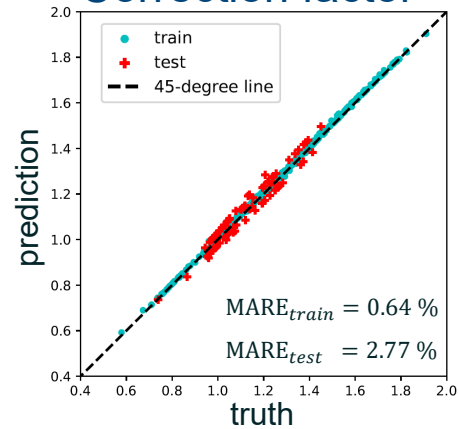
Width in mm



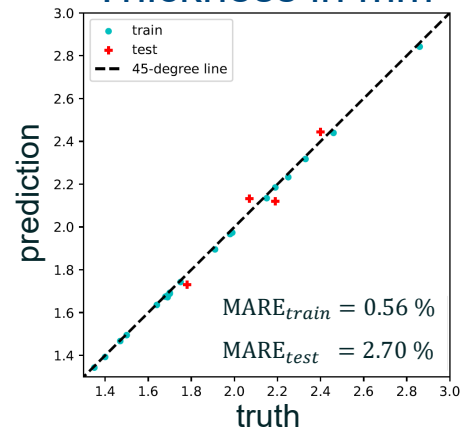
Case study 3: Results

Geometry predictions

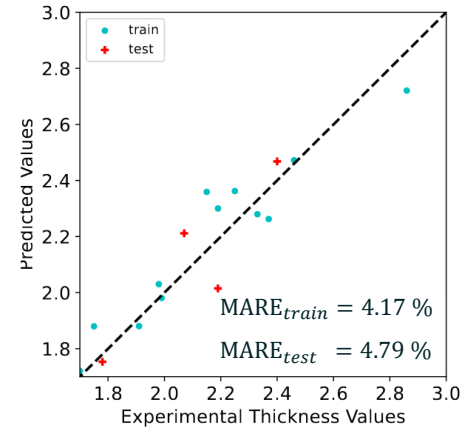
Discrepancy models:
Correction factor



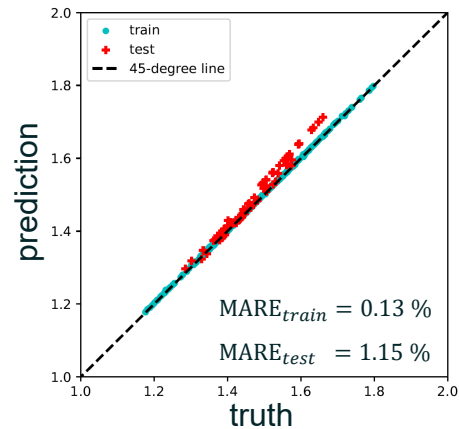
Hybrid models:
Thickness in mm



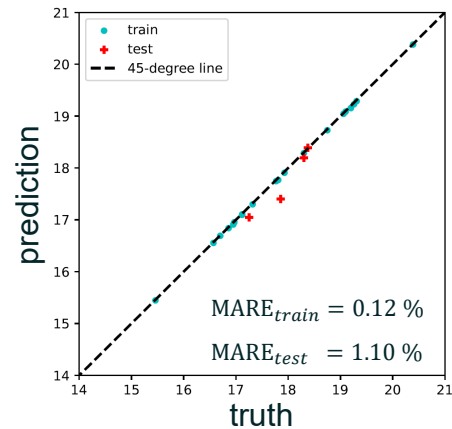
Benchmark against
data-driven models:
Thickness in mm



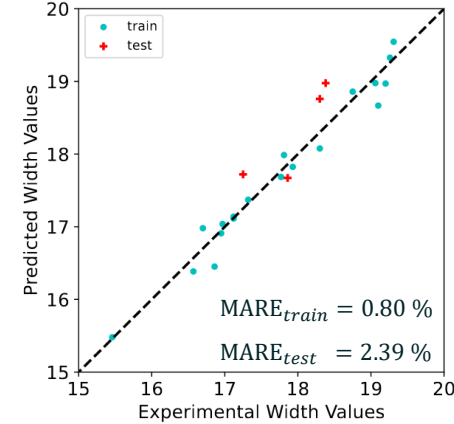
Correction factor



Width in mm



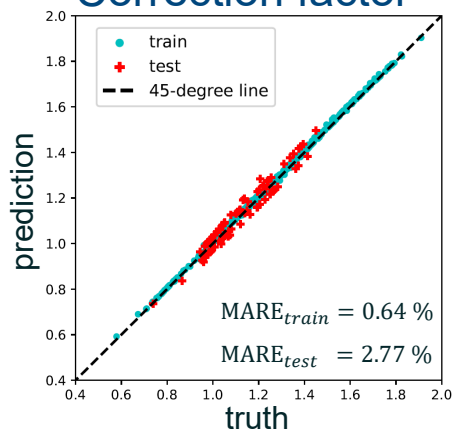
Width in mm



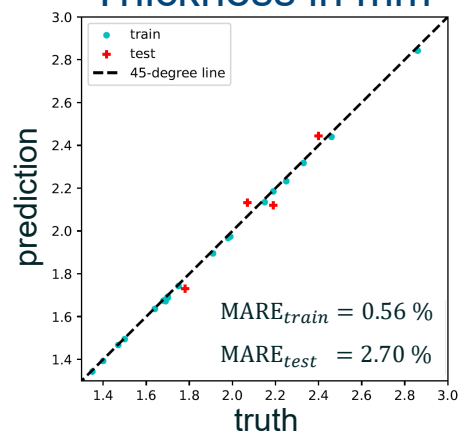
Case study 3: Results

Geometry predictions

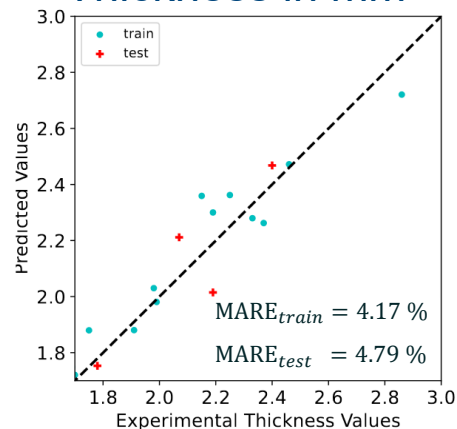
Discrepancy models:
Correction factor



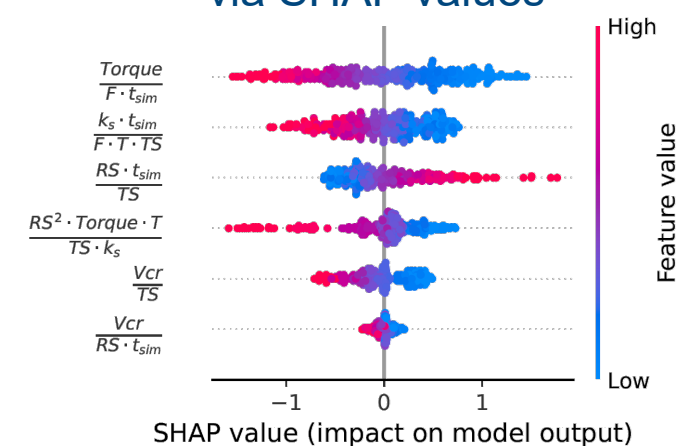
Hybrid models:
Thickness in mm



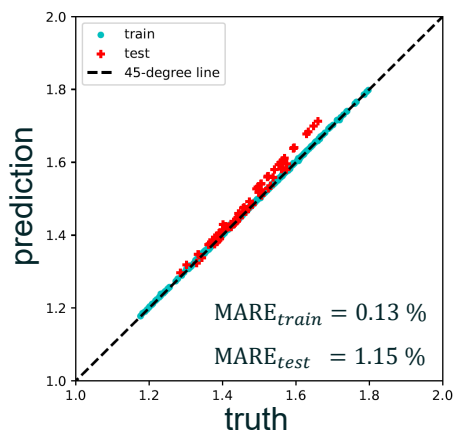
Benchmark against
data-driven models:
Thickness in mm



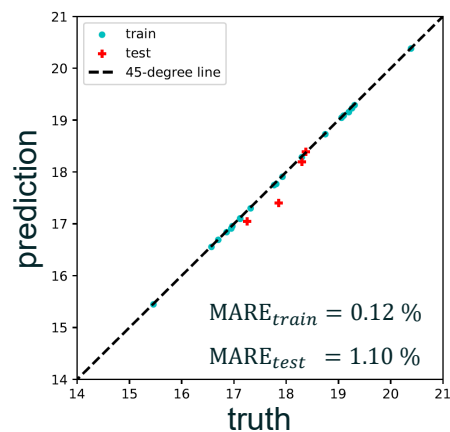
XAI of hybrid models
via SHAP values



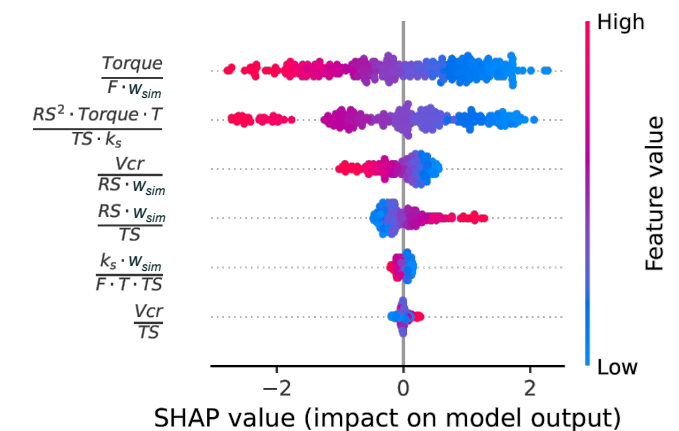
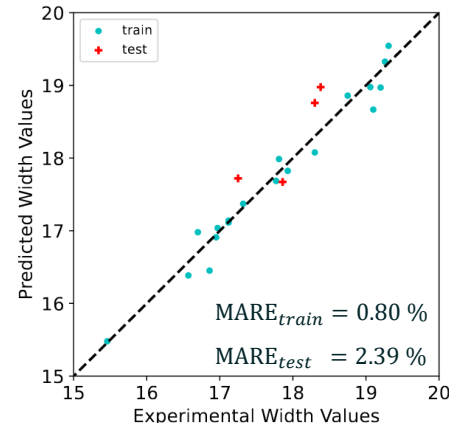
Correction factor



Width in mm



Width in mm

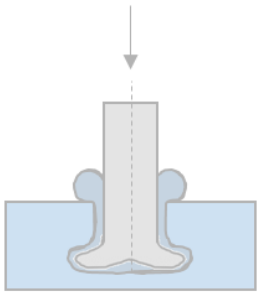


Case studies

Overview

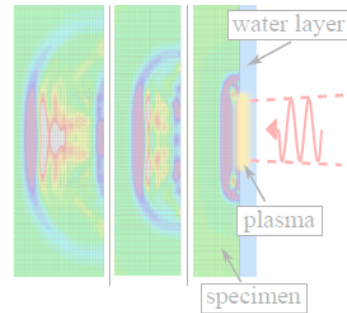
Case study 1

Ultimate tensile strength prediction for joints made by Friction Riveting



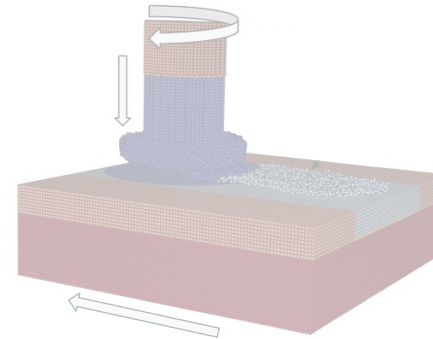
Case study 2

Prediction of residual stresses induced by Laser Shock Peening



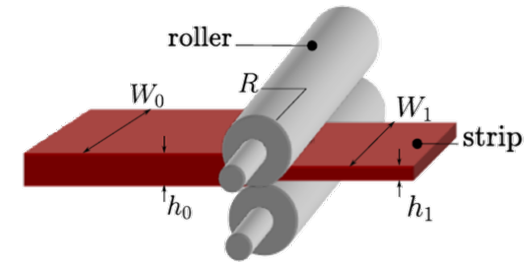
Case study 3

Prediction of layer geometry deposited via Friction Surfacing



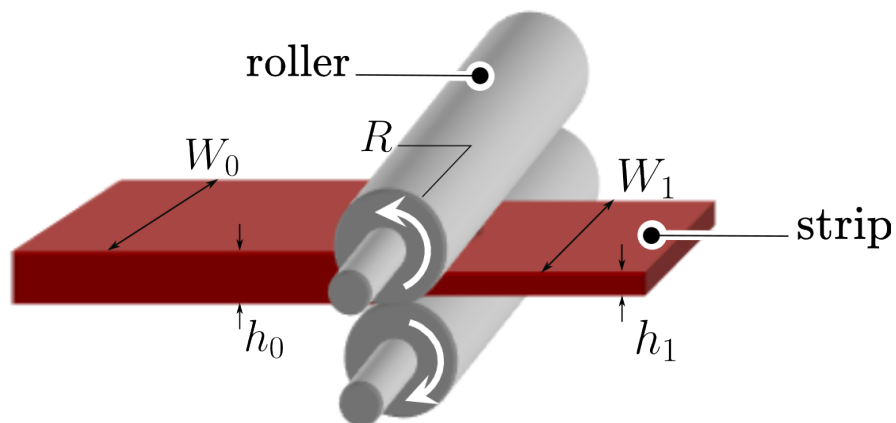
Case study 4

Prediction of slab spread forming via Hot Rolling



Case study 4: Introduction

Hot rolling of steel strip profiles



Material parameters

Initial height h_0

Initial width W_0

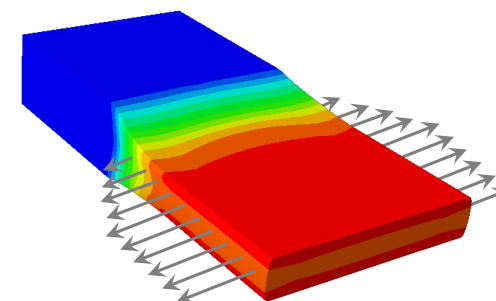
Process parameters

Radius R

Roller distance h_1

Target of interest:
Lateral flow (i.e. spread)

$$\Delta W = W_1 - W_0$$



Publication: A.Hashemzadeh, F.E. Bock, C. Hol, K. Schutte, A. Cometa, C. Soyarslan, B. Klusemann and T.v.d. Boogaard,
“An analytical predictor machine learning corrector scheme for modeling lateral flow in hot strip rolling”

57 in *Materials Research Proceedings*, vol. 54, pp. 2002-2011, 2025.

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Case study 4: Problem statement

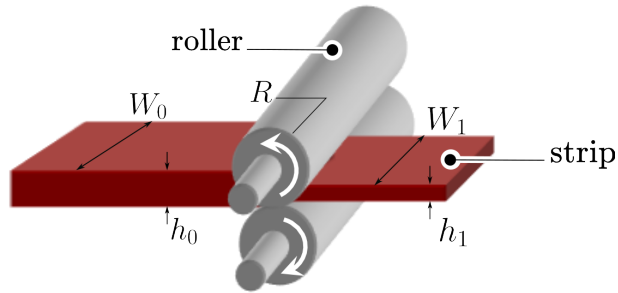
Enhance analytical model via ML to reach FE solution

Analytical model is based on

- Empirical correlations
- Analytical derivations
- Simplifying assumptions

→ Fast but inaccurate

→ Widely used by industry



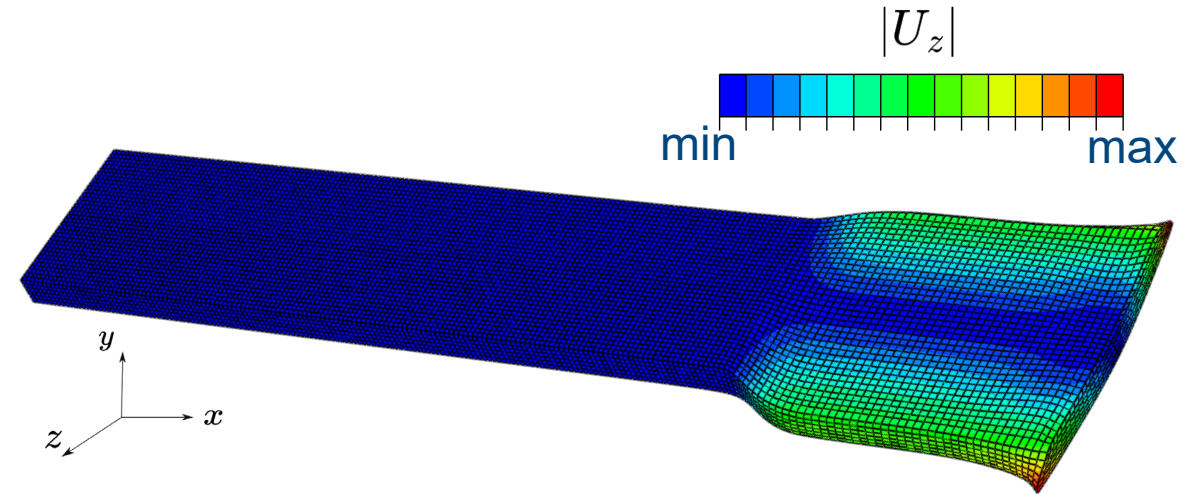
Tselikov's analytical model^{1,2}

$$\begin{aligned}\Delta W &= W_1 - W_0 \\ &= \frac{2c}{\epsilon_h^2} \left(\sqrt{R\delta} - \frac{\delta}{2\mu} \right) \left[(1 - \epsilon_h)^2 \log \left(\frac{1}{1 - \epsilon_h} \right) - \epsilon_h + 1.5\epsilon_h^2 \right]\end{aligned}$$

Numerical model is based on

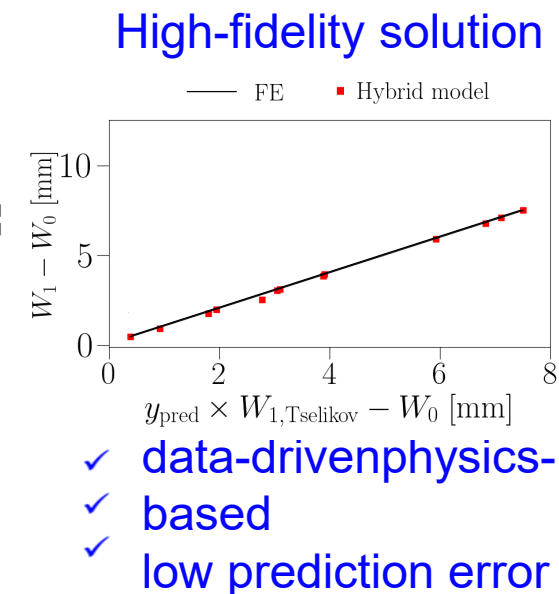
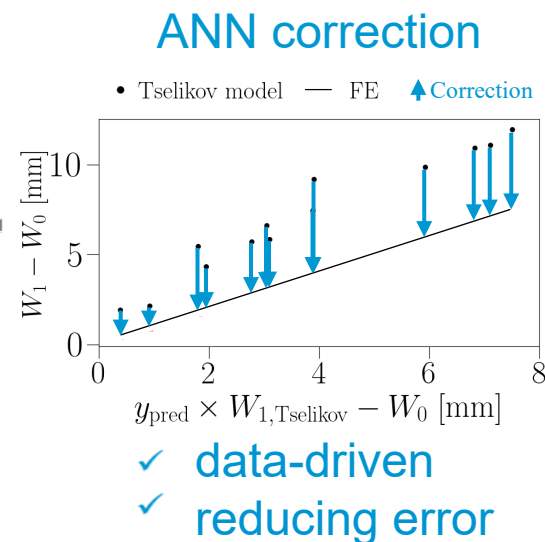
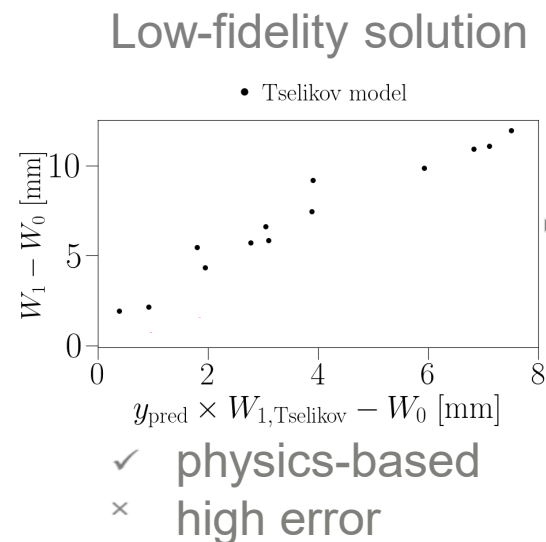
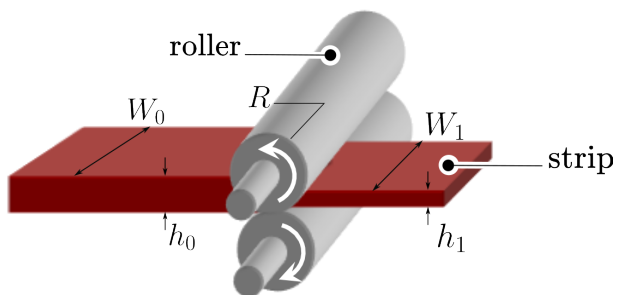
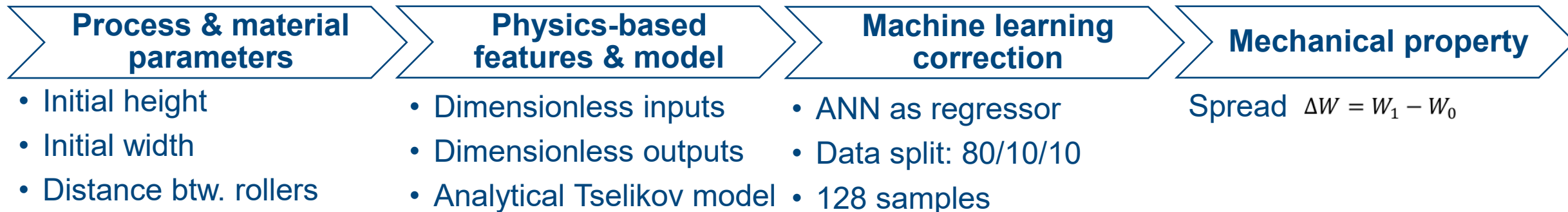
- Heat transfer modes
- 3D deformation
- Thermo-mechanical coupling
- Contact and friction

→ Accurate but slow



Case study 4: Methodology & results

Hybrid modeling of spread caused by hot rolling



Publication: A.Hashemzadeh, F.E. Bock, C. Hol, K. Schutte, A. Cometa, C. Soyarslan, B. Klusemann and T.v.d. Boogaard,
 “An analytical predictor machine learning corrector scheme for modeling lateral flow in hot strip rolling”
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Case study 4: Methodology

Data preparation, preprocessing and ANN implementation

Geometrical process parameters: W_0, h_0, R, h_1

Dimensionless inputs:

$$\mathbf{x}^i := \{x_1^i, x_2^i, x_3^i\} = \left\{ \frac{W_0^i}{h_0^i}, \frac{h_0^i}{R}, \frac{h_1^i}{h_0^i} \right\}$$

Dimensionless output:

$$y_{\text{pred}}^i = \left\{ \frac{W_{1,\text{FE}}^i}{W_{1,\text{A}}^i} \right\}$$

Value ranges: $x_1 \in [1,5], x_2 \in [0.1,0.25], x_3 \in (0.5,1)$

Data: analytical & numerical

Data split

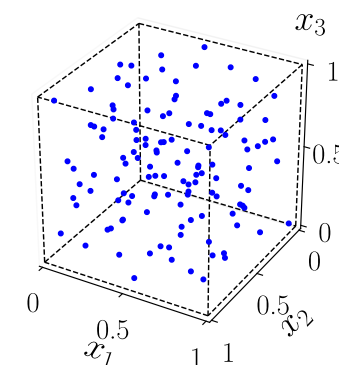
80/10/10 (train/validation/test sets)

Uniform inclusion of the input feature ranges via *stratification*

→ Per input feature x_i for $i = 1, 2, 3$

Data sampling

Sobol
Samples: 128, CD: 0.0001

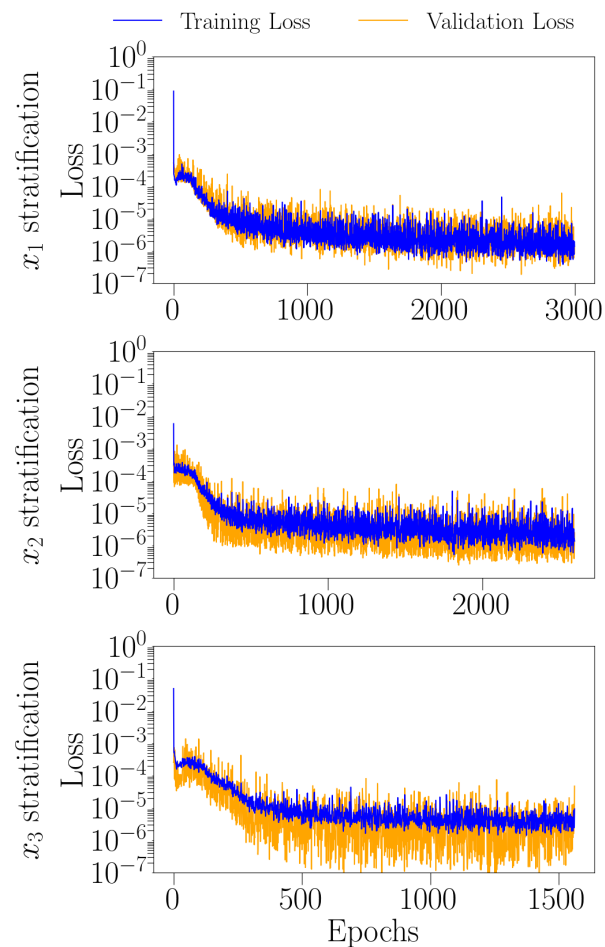


128 samples with
 $R = 200$ mm (fixed)

Case study 4: Results

Prediction performance for spread

a) Training and validation loss



Publication: A.Hashemzadeh, F.E. Bock, C. Hol, K. Schutte, A. Cometa, C. Soyarslan, B. Klusemann and T.v.d. Boogaard,

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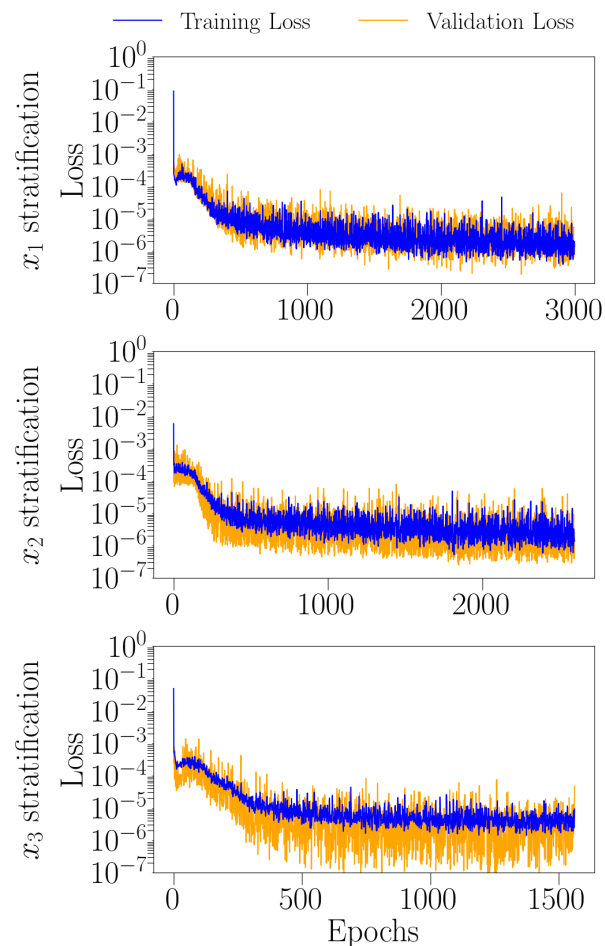
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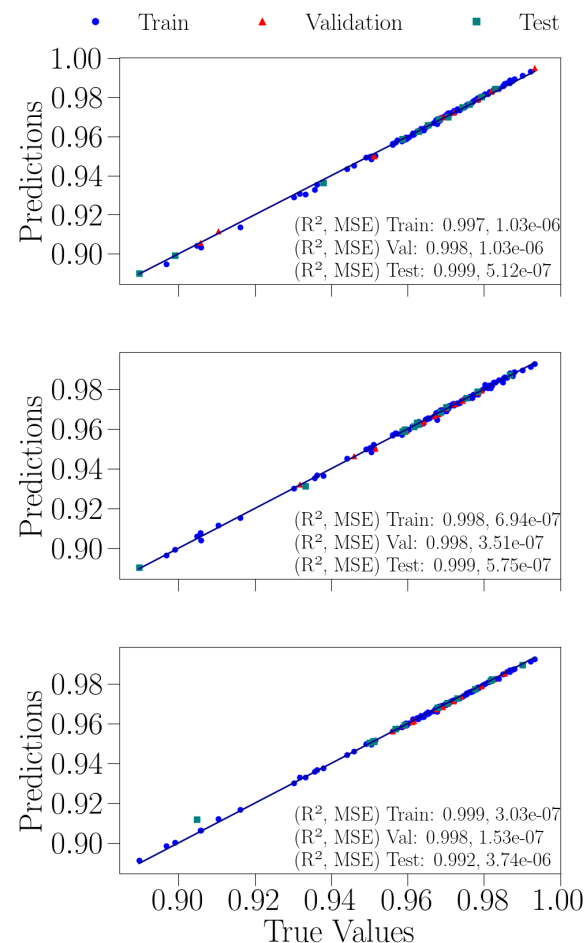
Case study 4: Results

Prediction performance for spread

a) Training and validation loss



b) Prediction vs. true values



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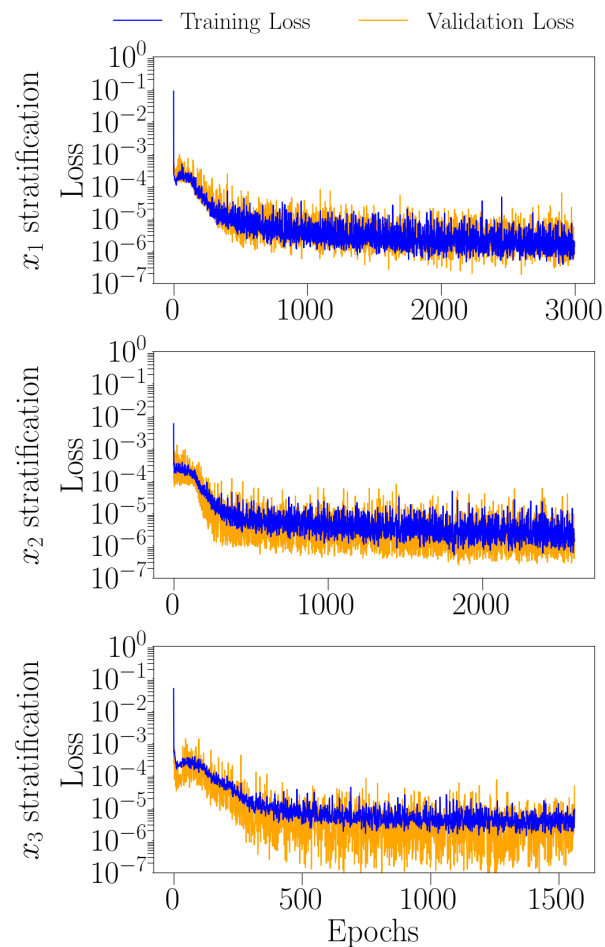
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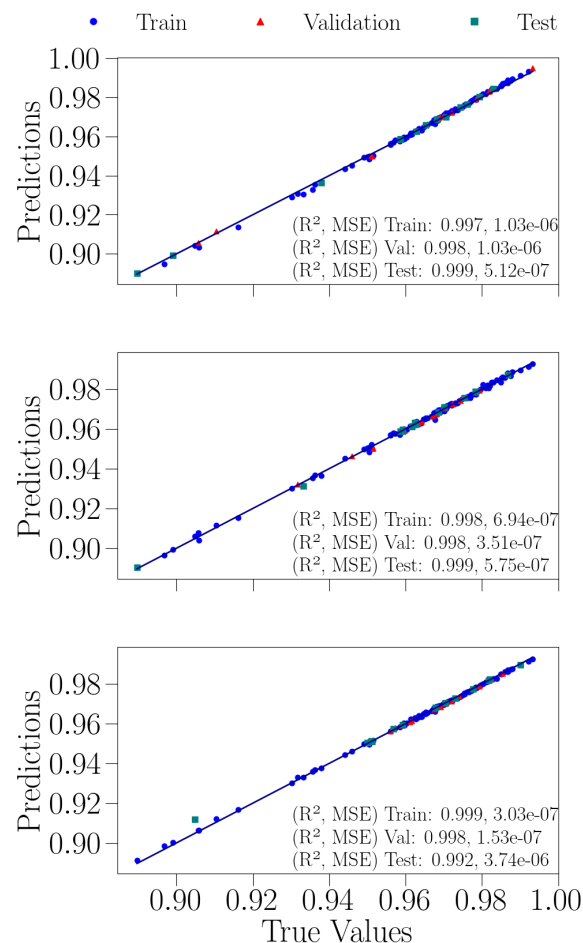
Case study 4: Results

Prediction performance for spread

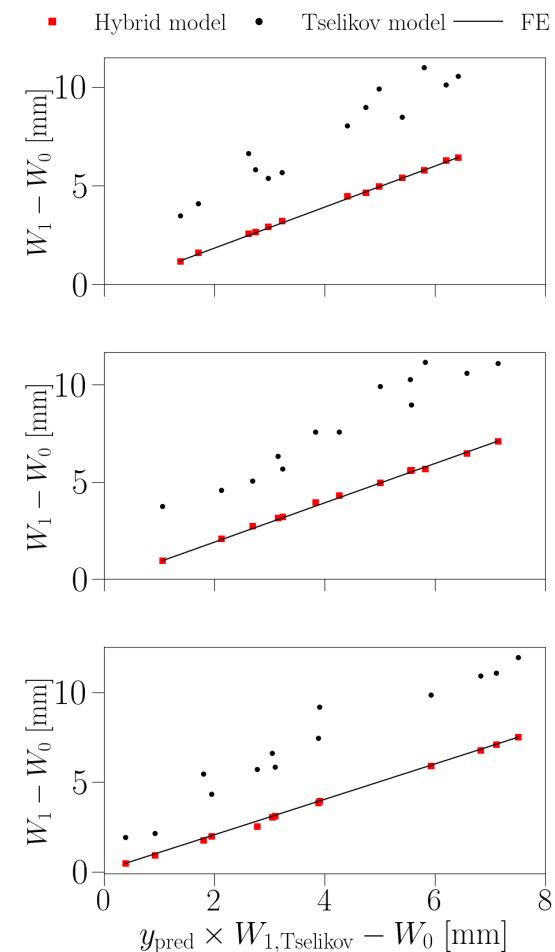
a) Training and validation loss



b) Prediction vs. true values



c) Network spread correction



Publication: A.Hashemzadeh, F.E. Bock, C. Hol, K. Schutte, A. Cometa, C. Soyarslan, B. Klusemann and T.v.d. Boogaard,

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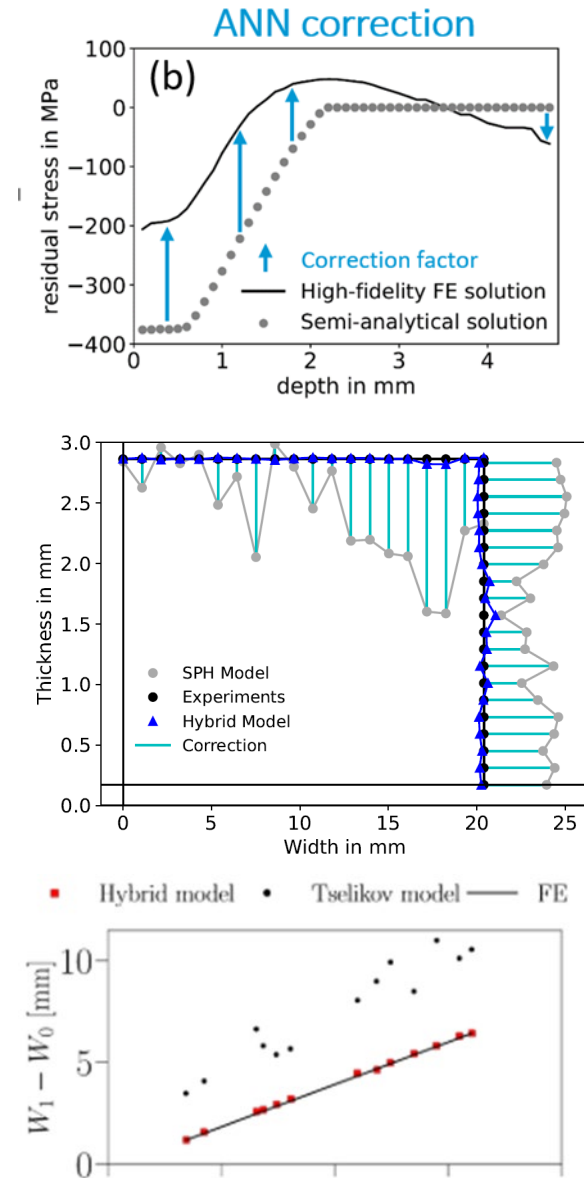


Summary

Demonstrated benefits of hybrid modeling

- Enhanced prediction performances based on physics-based model
→ Excellent agreement between hybrid predictions and targets
- Physical extrapolation can be enabled in combination with dimensionless inputs & outputs
- Data-efficiency of correction models is empowered by exploitation of physics-based models
→ Hybrid modeling outperforms data-driven modeling in scarce data settings

Thank you!



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Thank you.

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