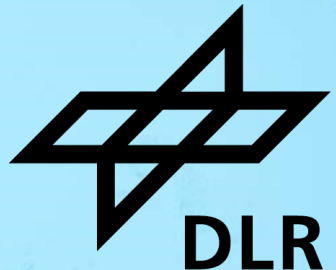


TOWARDS A PARAMETRIC RELATIONSHIP OF CRACK FRONT TWISTING ON FATIGUE CRACK GROWTH BEHAVIOR

Mixed Mode AG 2025

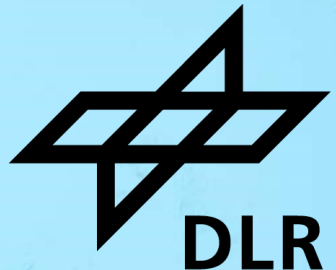
Jesco Talies, Eric Breitbarth, David Melching, Vanessa Schöne, Florian Paysan



SYSTEMATISCHE IDENTIFIKATION UND PARAMETRISCHE BESCHREIBUNG VON MECHANISMEN DER RISSFRONTVERDREHUNG BEI ZYKLISCH BELASTETEN, DÜNNWANDIGEN ALUMINIUMBLECHEN

Mixed Mode AG 2025

Jesco Talies, Eric Breitbarth, David Melching, Vanessa Schöne, Florian Paysan

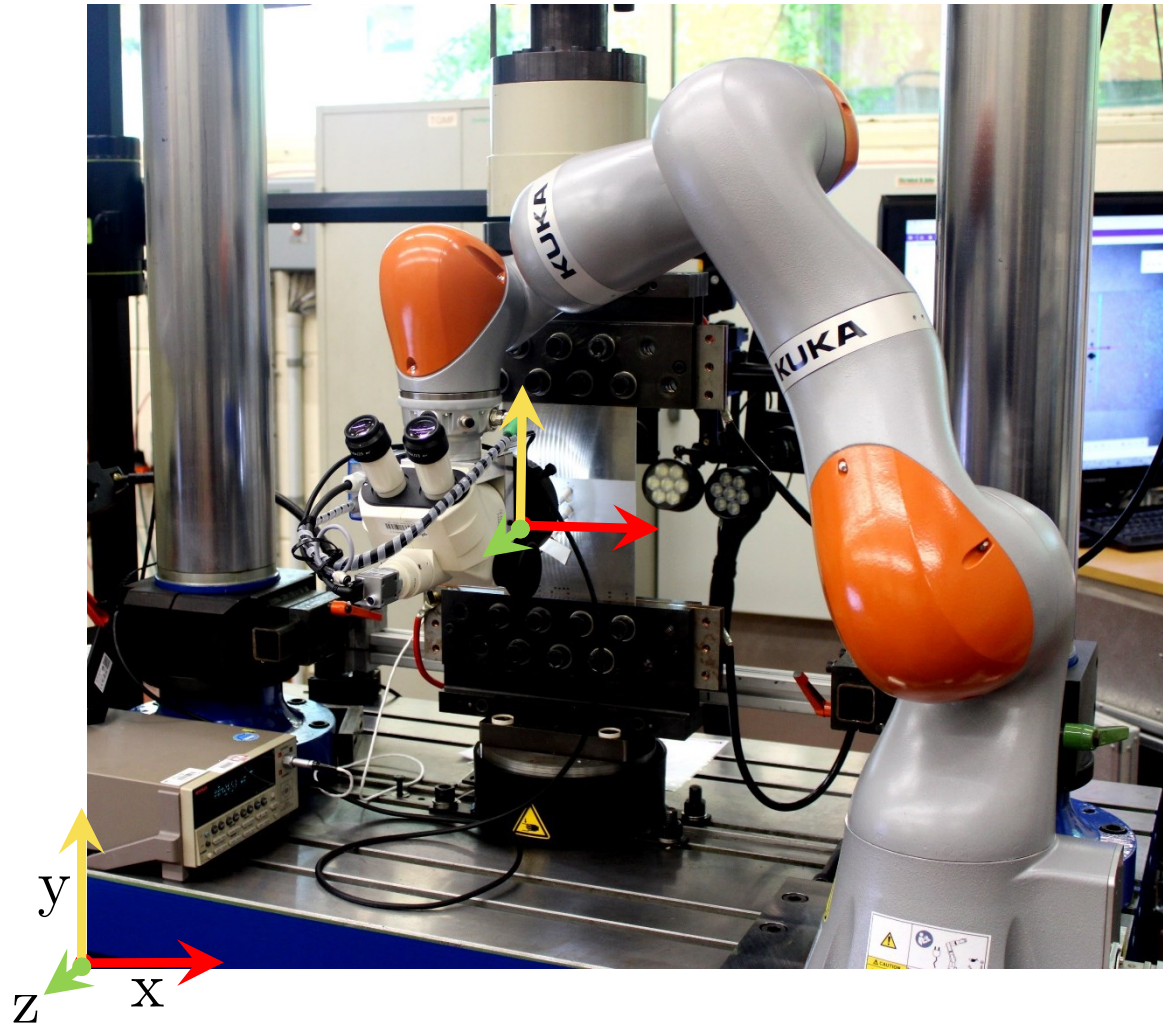


WORK IN PROGRESS

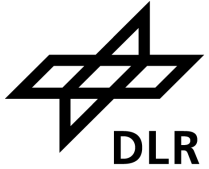


Motivation

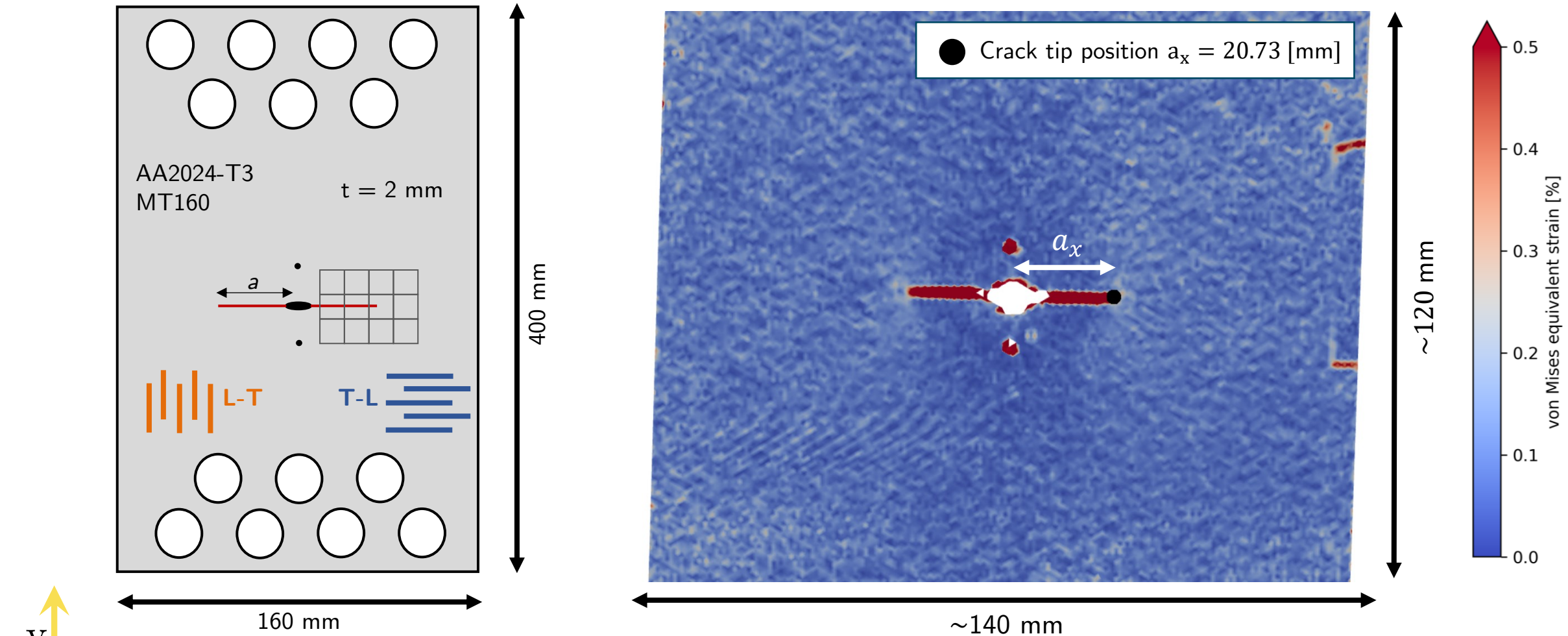
Uniaxial fatigue tests



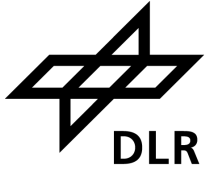
Experimental data – 3D digital image correlation



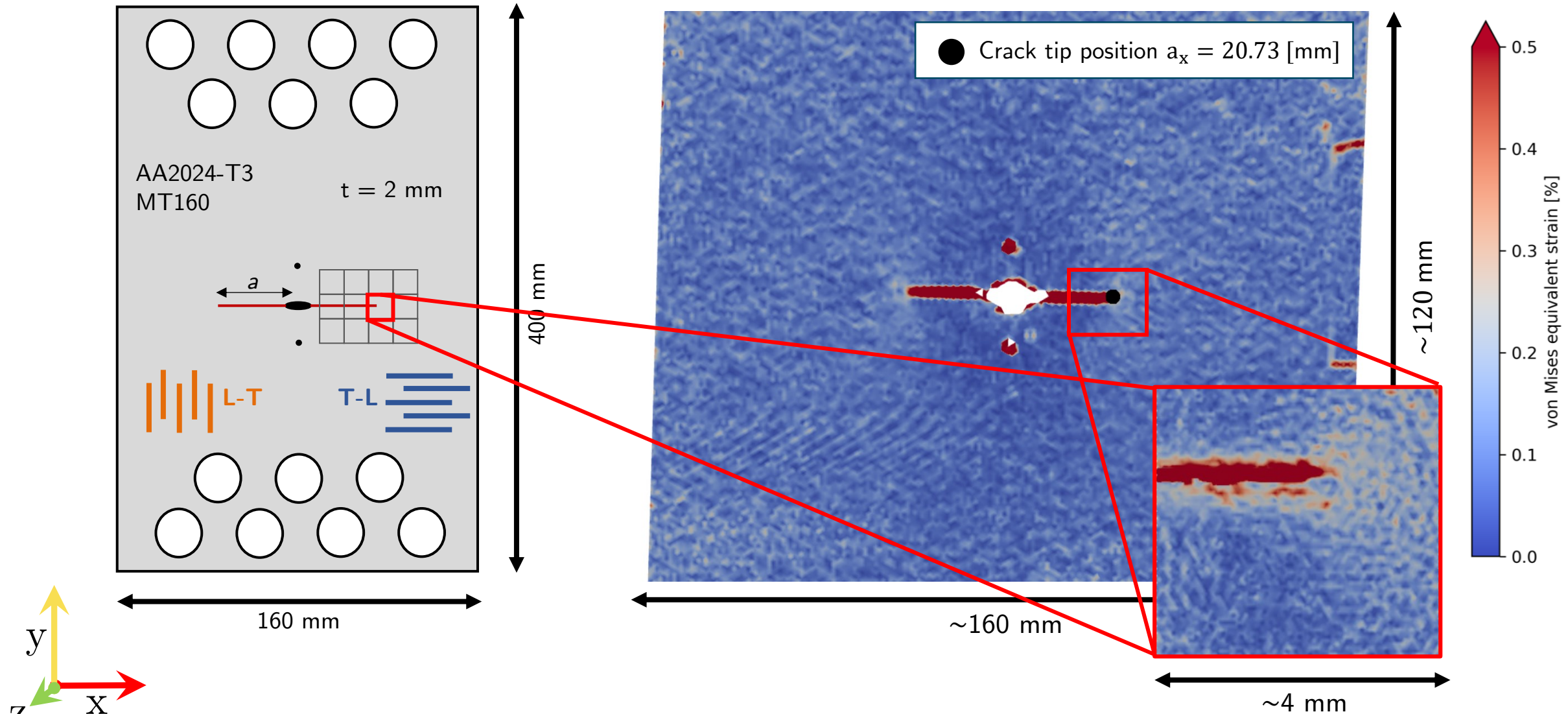
$R = 0.1$, $F_{\max} = 15$ kN



Experimental data – high res. digital image correlation

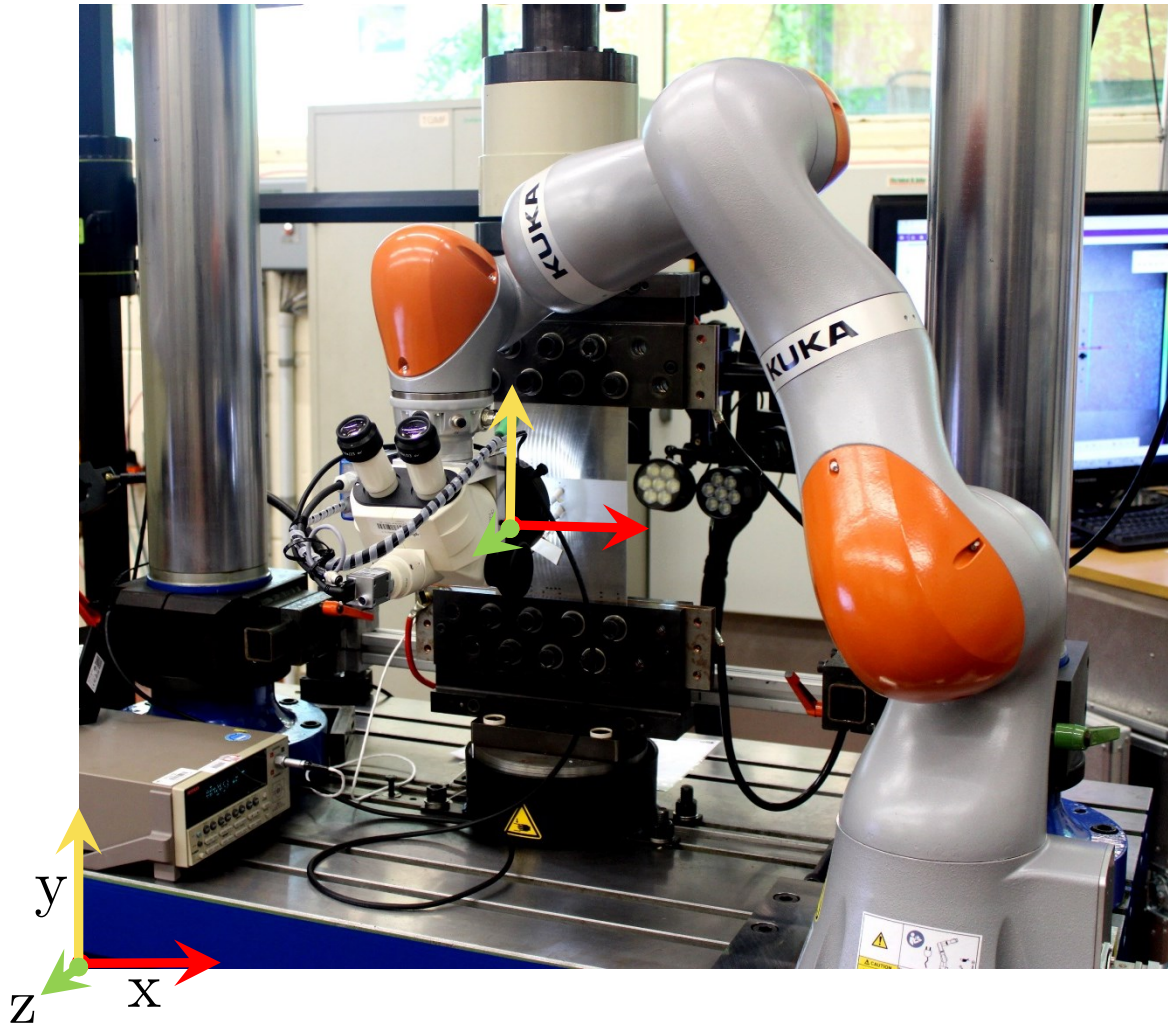


$R = 0.1$, $F_{\max} = 15$ kN

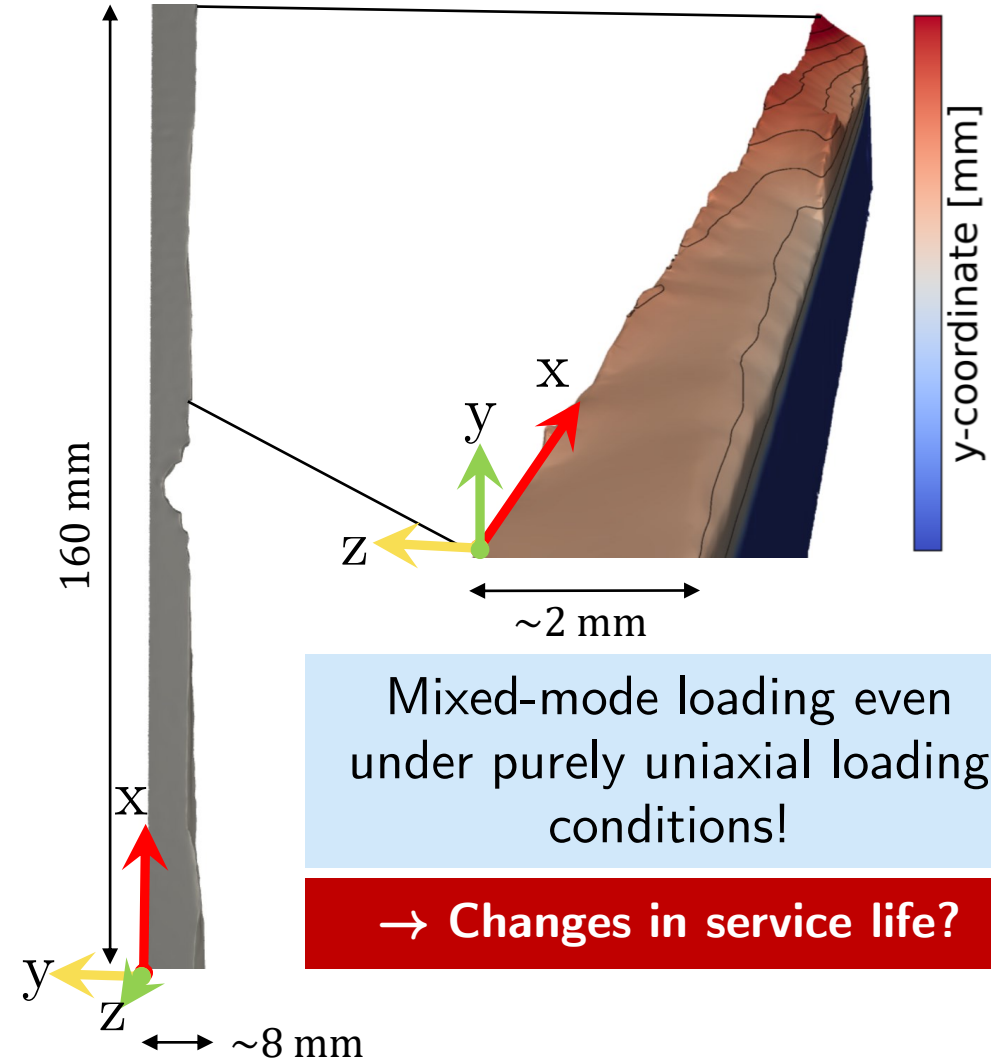


Motivation

Uniaxial fatigue tests



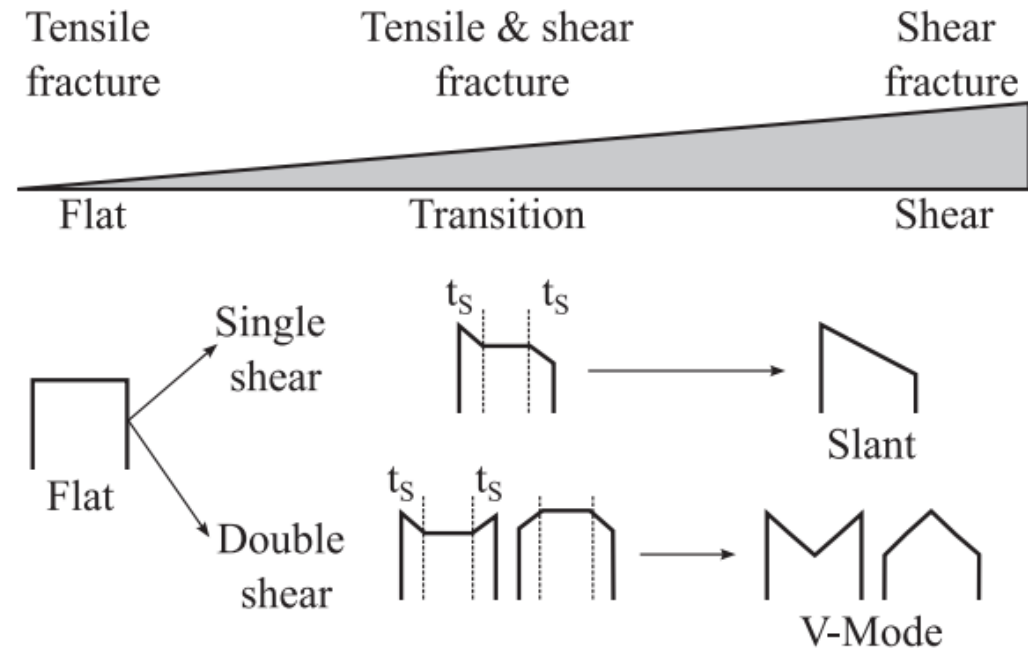
Post-mortem analysis



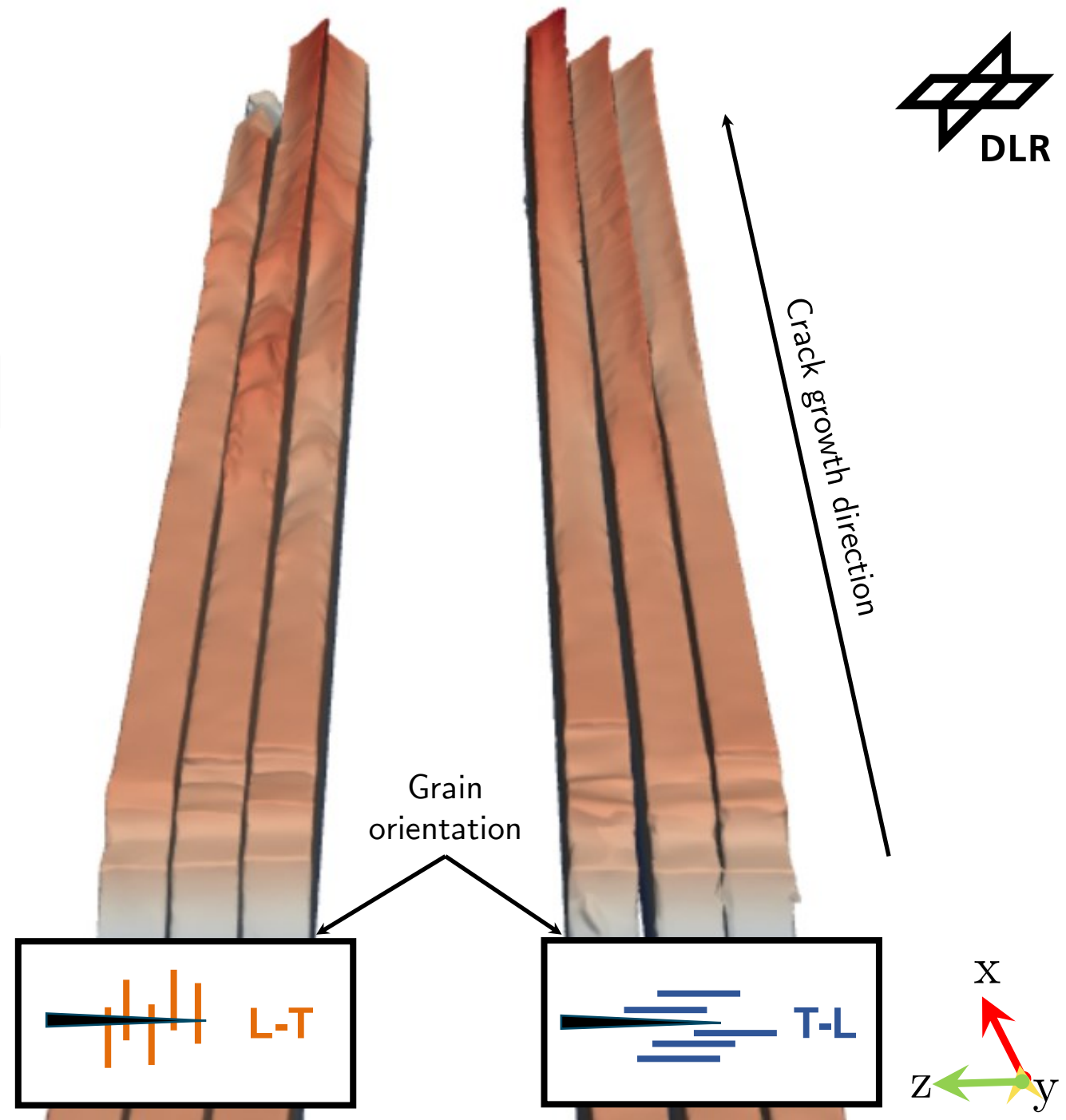
Mixed-mode loading even under purely uniaxial loading conditions!

→ Changes in service life?

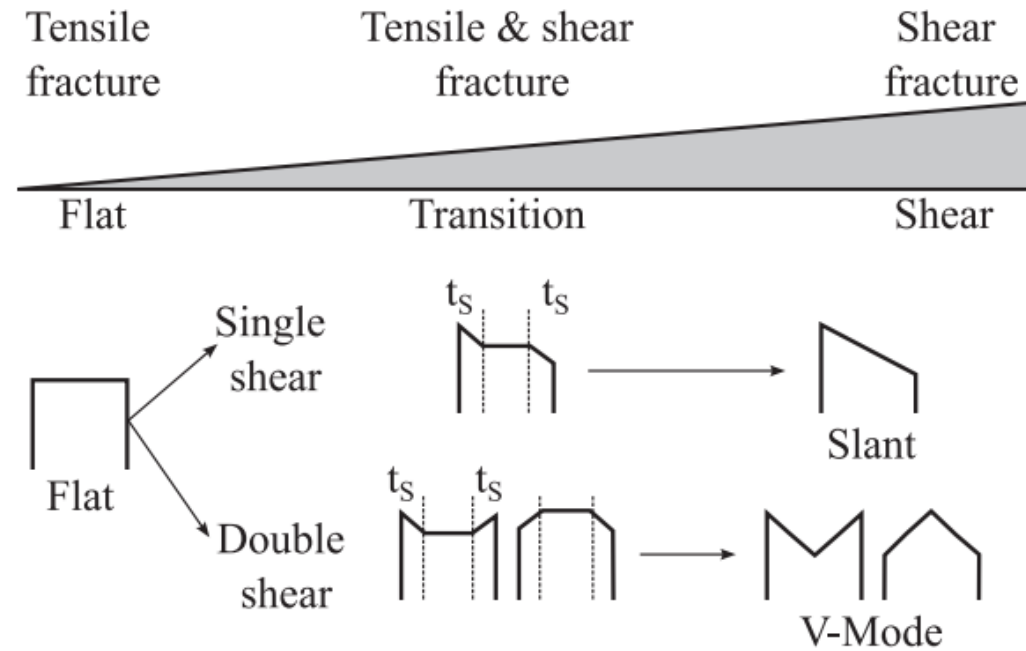
Previous research



Schöne, Vanessa und Paysan, Florian und Breitbarth, Eric
Engineering Fracture Mechanics 313 (2025) 110664



Previous research



Schöne, Vanessa und Paysan, Florian und Breitbarth, Eric
Engineering Fracture Mechanics 313 (2025) 110664

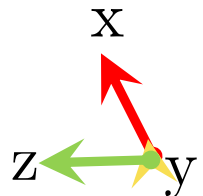
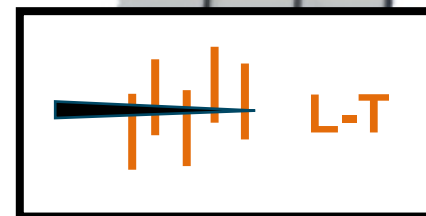
Transition
or V-Mode

Slant

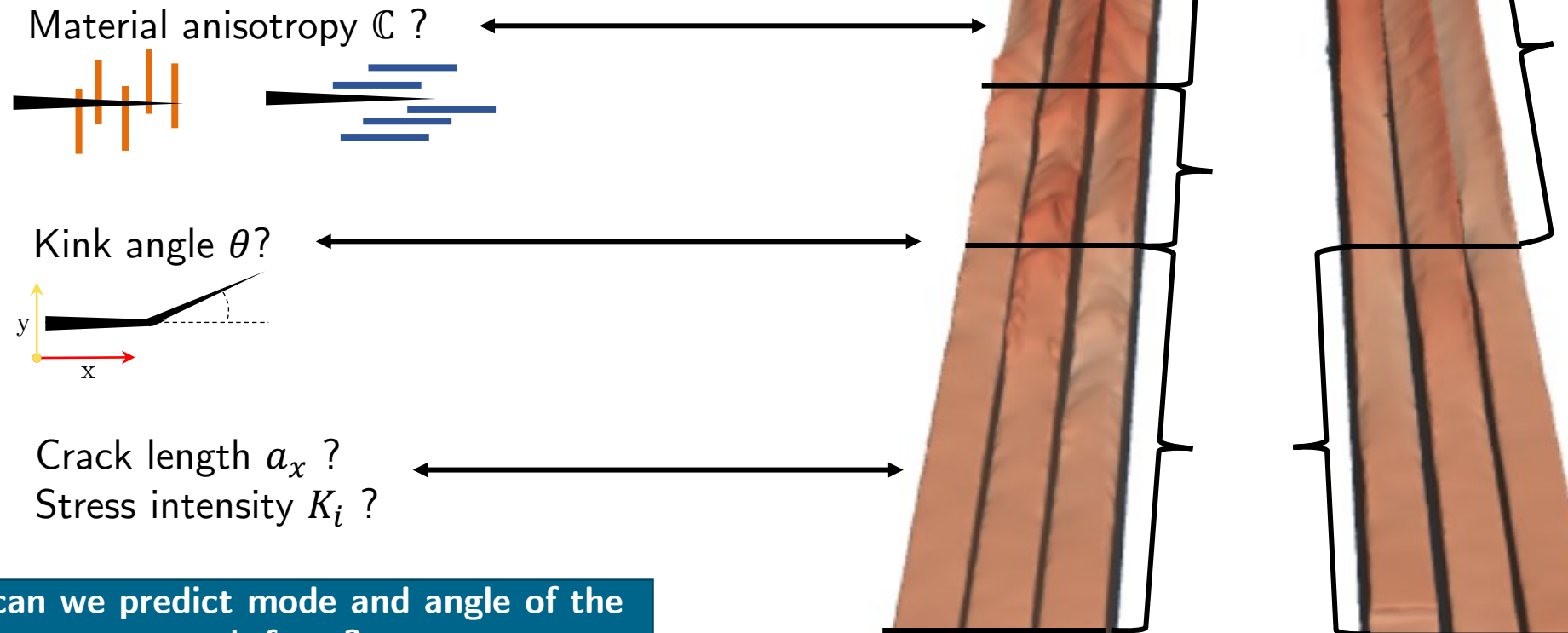
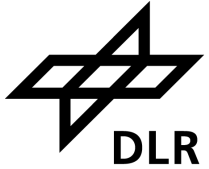
Trans.

Slant

Flat



Research question



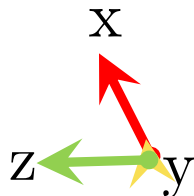
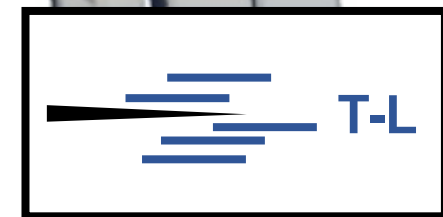
How can we predict mode and angle of the crack front?

Twist mode

$$M(a_x, t, \mathbb{C}, K_i, \sigma, R, \eta, \theta, \dots) \in \{\text{Flat}, \text{V-Mode}, \text{Trans}\}$$

Angle

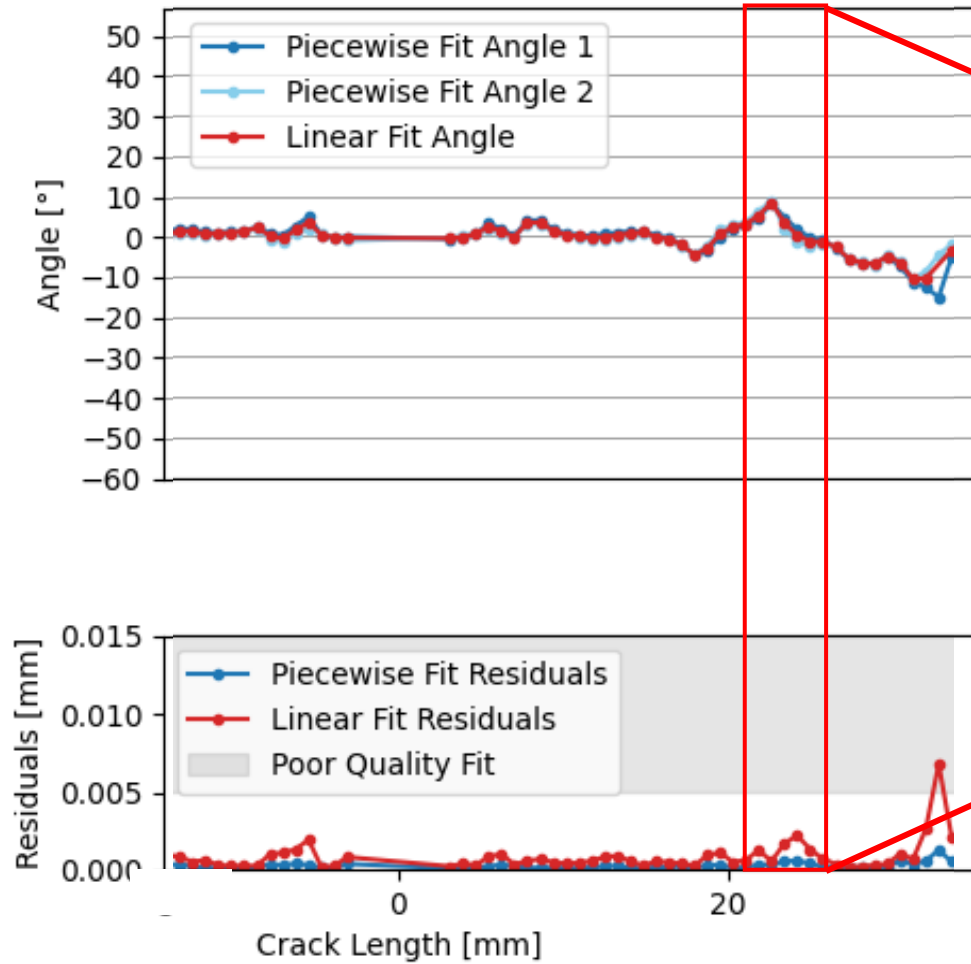
$$\varphi(a_x, t, \mathbb{C}, K_i, \sigma, R, \eta, \theta, \dots) \in [-\pi, +\pi]$$



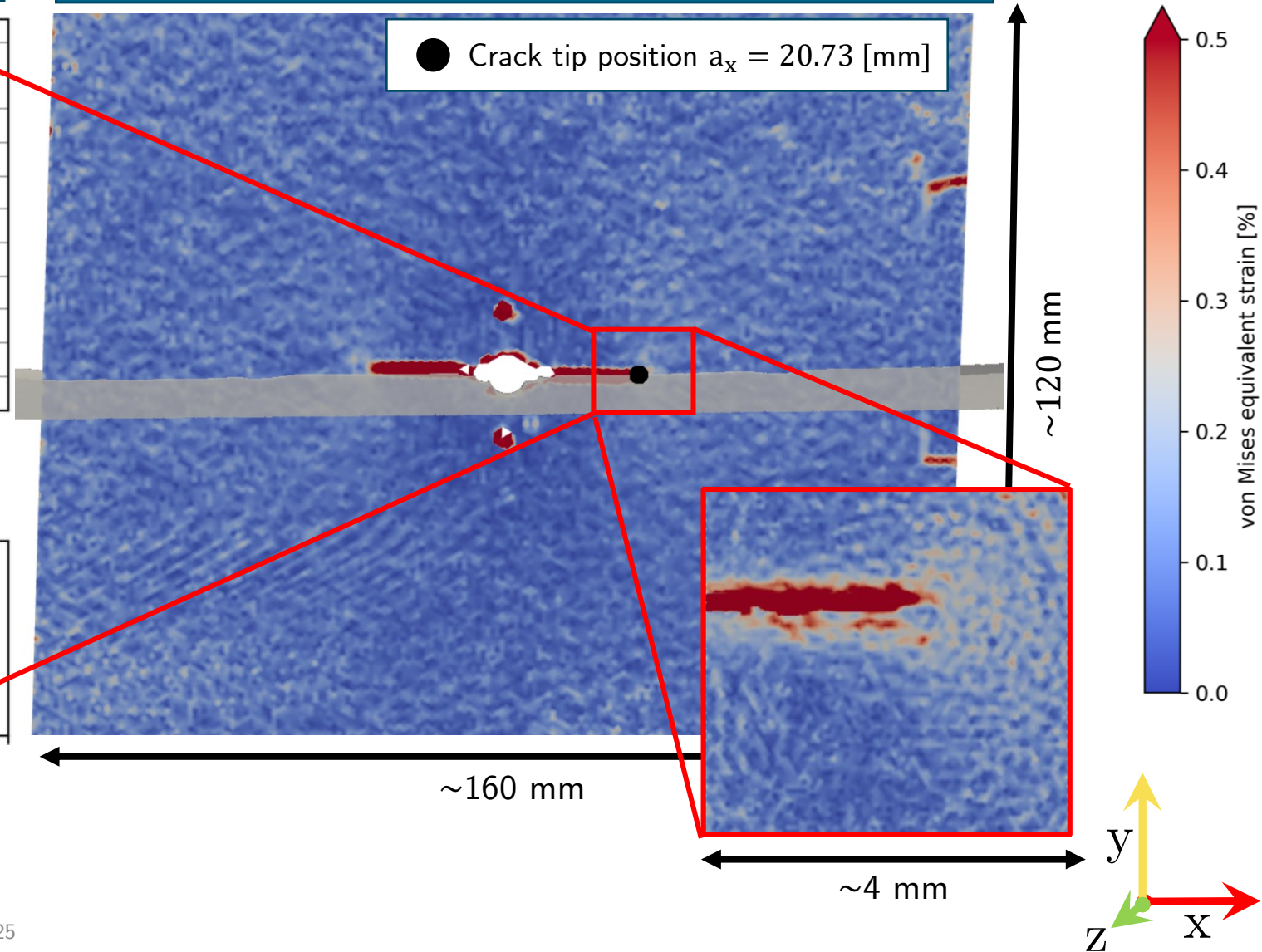
Experimental data – fracture surface angle



3D Fracture surface angle data



Optical high-resolution crack tip data



Numerical model - Setup



Ansys mechanical model

Linear elastic

$E = 74.1 \text{ GPa}$

$\nu = 0.33$

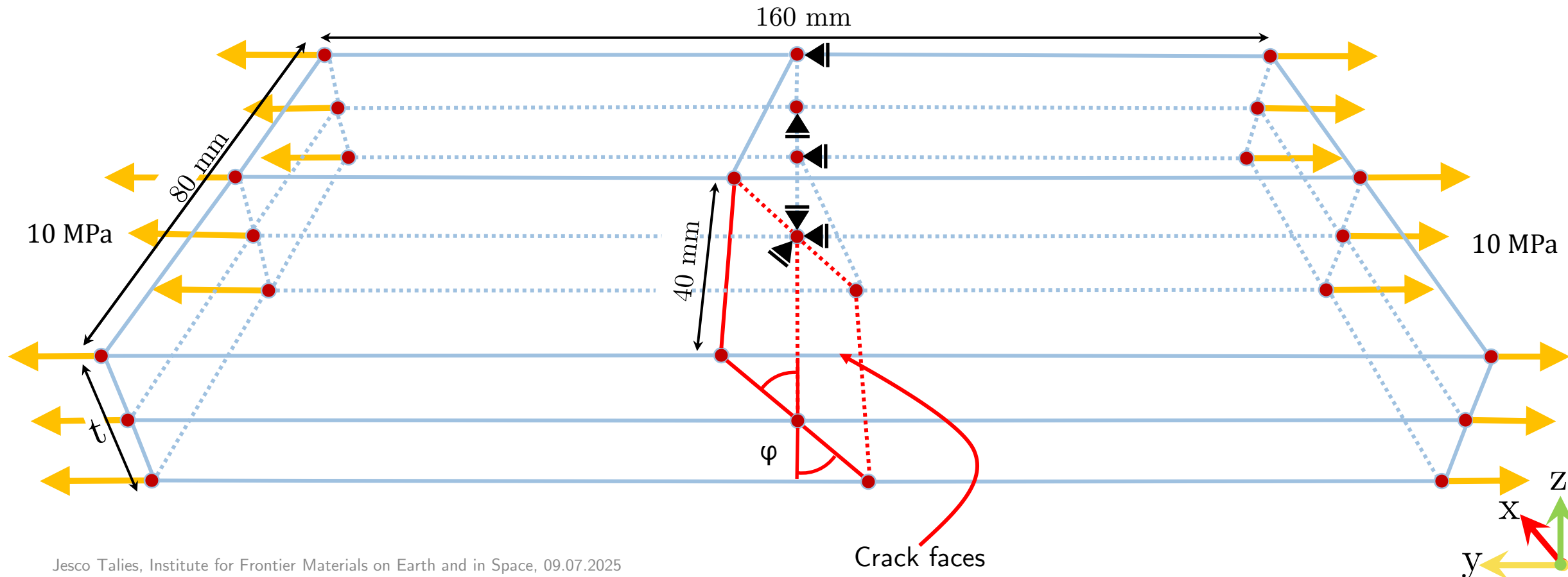
$a/w = 0.5$

Ele. Size = 2 mm

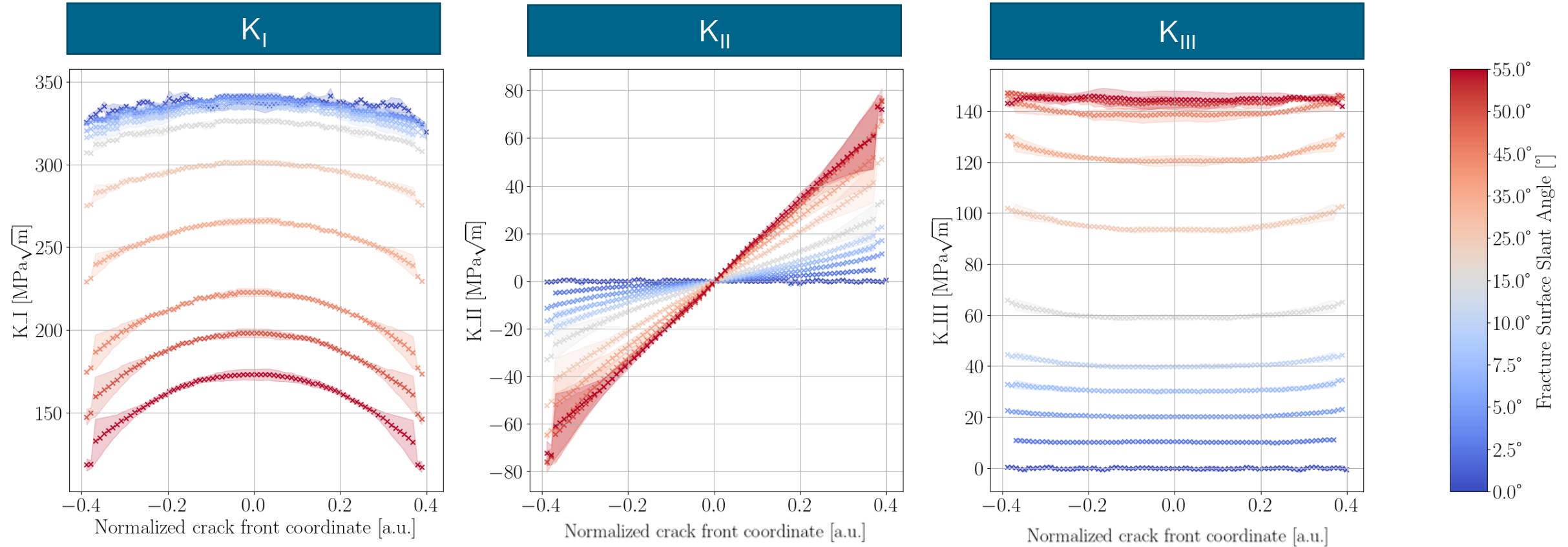
Ele. tip = 0.125 mm

$t \in [2, \dots, 10] \text{ mm}$

$\varphi \in [0, \dots, 55]^\circ$



Numerical model – stress intensity factors



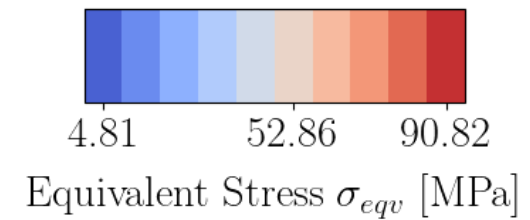
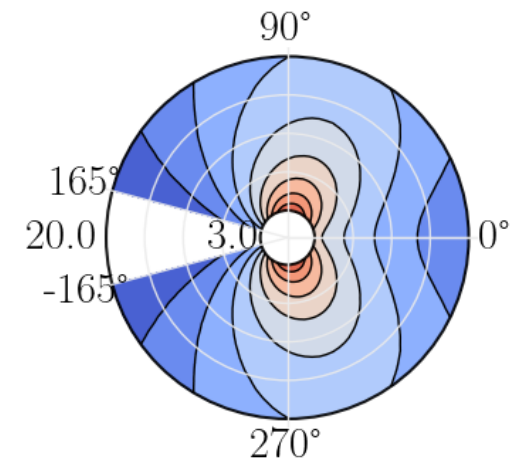
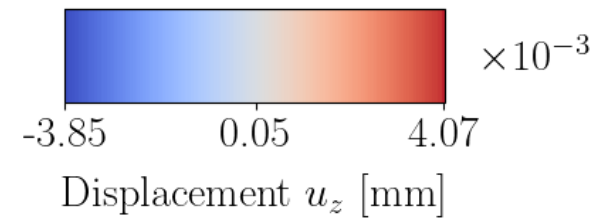
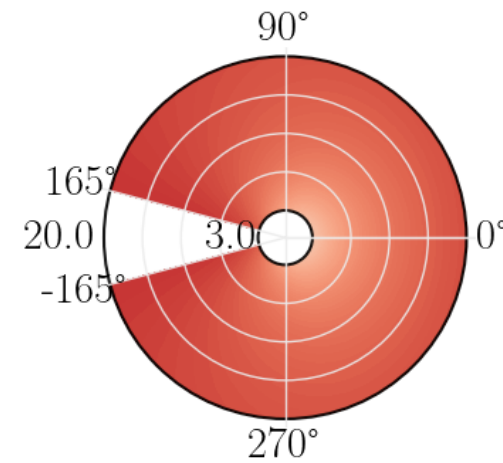
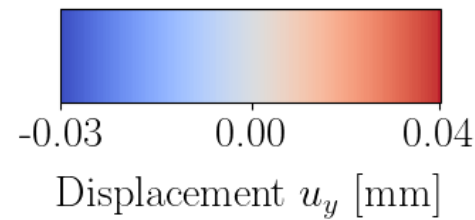
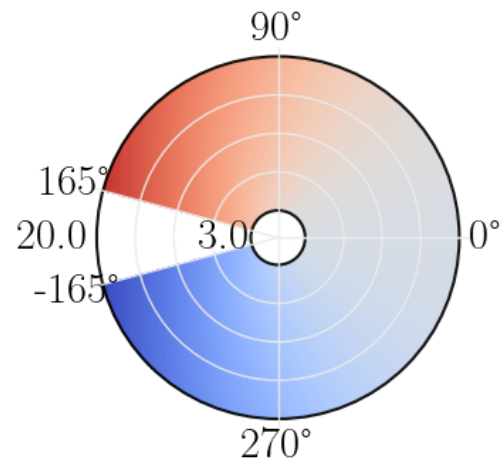
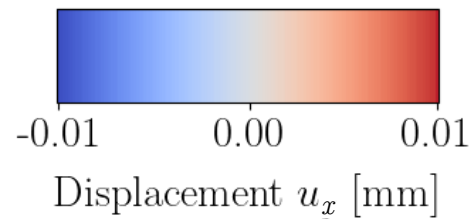
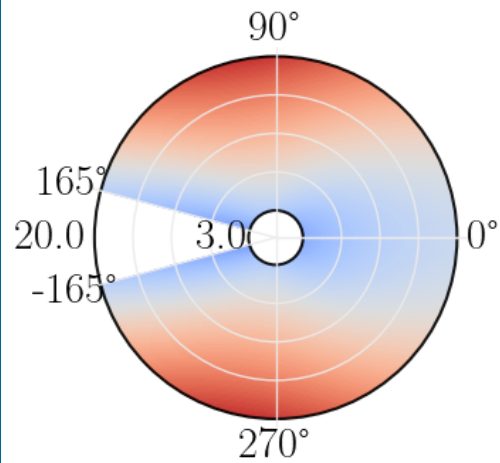
Twisted crack fronts lead to complex stress at the crack front even under purely uniaxial loading conditions

+ switch meshing to hexahedral elements

Numerical model – crack tip field

$\varphi \in 0^\circ$

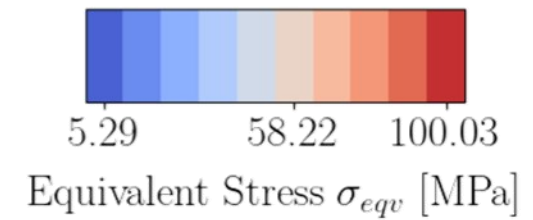
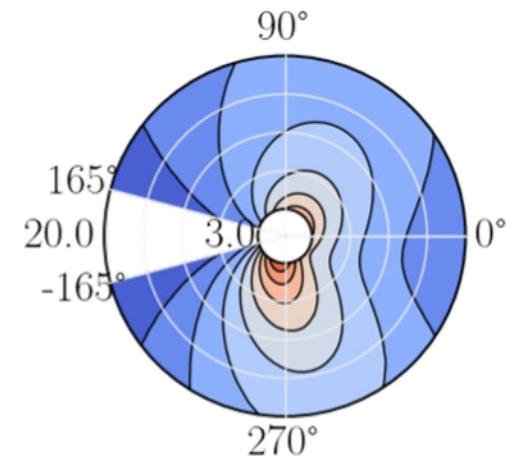
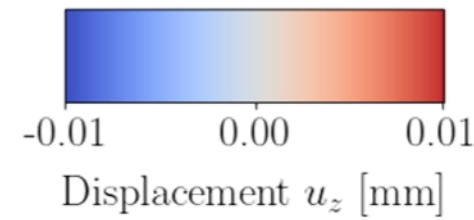
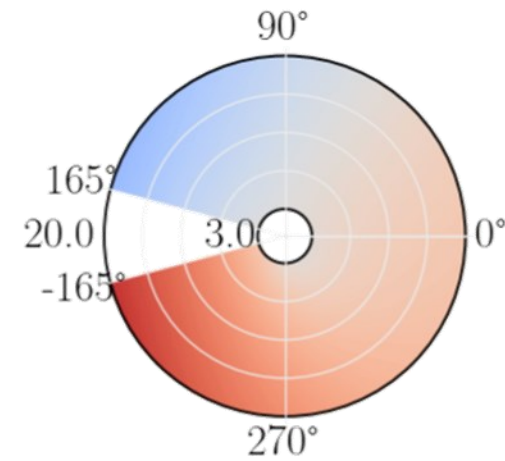
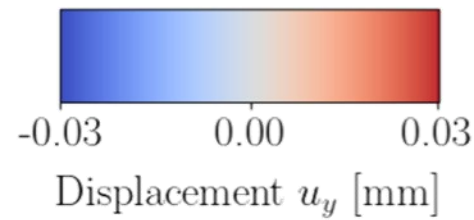
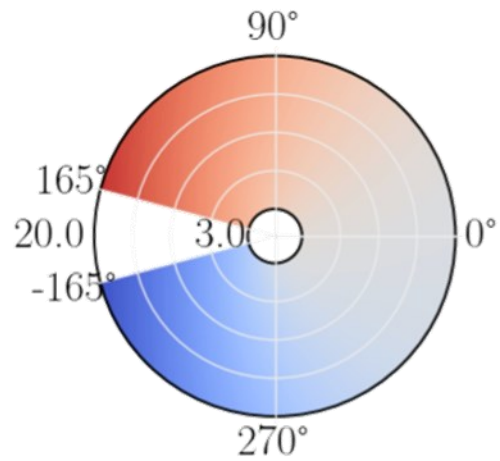
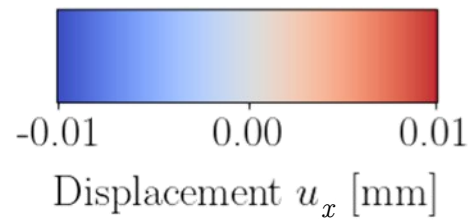
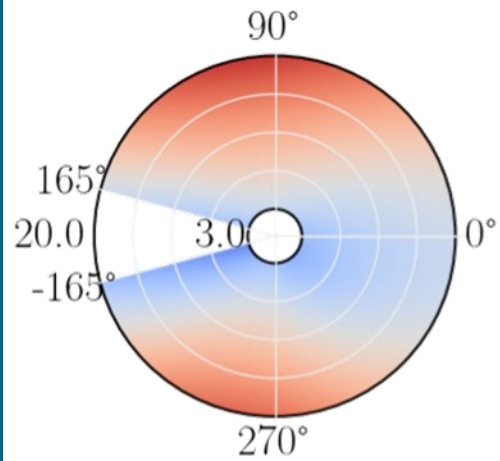
$t = 10 \text{ mm}$



Numerical model – crack tip field

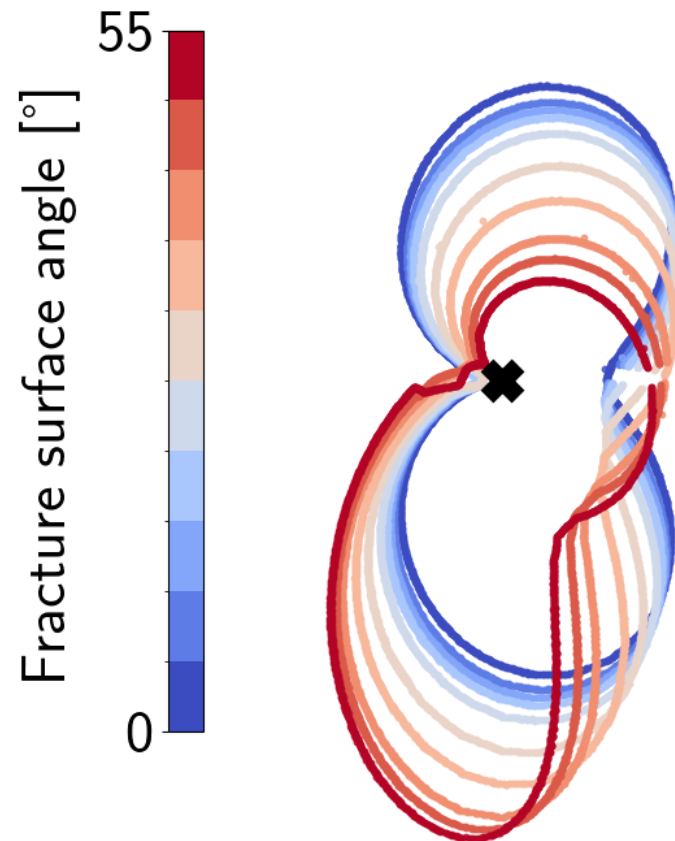
$\varphi \in 35^\circ$

$t = 10 \text{ mm}$



Crack tip field characterization

Contours for $\sigma_{eqv} = \text{const.}$



Quantitative characterization

Williams series expansion

Stress

$$\sigma_{ij}(r, \varphi) = \sum_{n=1}^{\infty} r^{\frac{n}{2}-1} \left[\underbrace{a_n \tilde{M}_{ij}^{(n)}(\varphi)}_{\text{Mode I}} + \underbrace{b_n \tilde{N}_{ij}^{(n)}(\varphi)}_{\text{Mode II}} + \underbrace{c_n \tilde{L}_{ij}^{(n)}(\varphi)}_{\text{Mode III}} \right]$$

Displacement

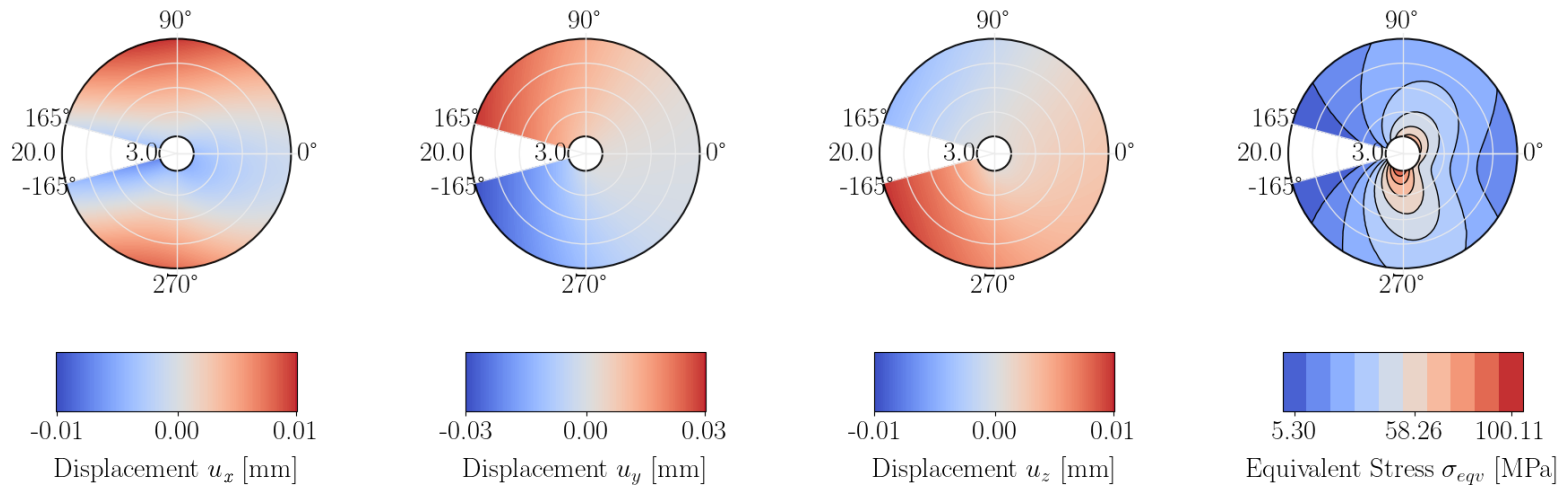
$$u_i(r, \varphi) = \frac{1}{2\mu} \sum_{n=1}^{\infty} \left[a_n \tilde{F}_i^{(n)}(\varphi) + b_n \tilde{G}_i^{(n)}(\varphi) + c_n \tilde{H}_i^{(n)}(\varphi) \right]$$

$$\mu = \frac{E}{2 \cdot (1 + \nu)}$$



Williams fitting

Finite element simulation crack tip field data



Truncated Williams series

$$u_i(r, \varphi) \approx \frac{1}{2\mu} \sum_{n=-M}^N \left[\underbrace{a_n \tilde{F}_i^{(n)}(\varphi)}_{\text{Mode I}} + \underbrace{b_n \tilde{G}_i^{(n)}(\varphi)}_{\text{Mode II}} + \underbrace{c_n \tilde{H}_i^{(n)}(\varphi)}_{\text{Mode III}} \right]$$

Least squares fit

$$\arg \min_{a_i, b_i, c_i} \sum_i^{x,y,z} [w_i (u_{y,data} - u_{y,williams})]^2$$

Using weights w_i to balance contributions

Quantitative descriptors

a_i, b_i, c_i for $i \in [-M, \dots, N]$

Relate to fracture mechanics

$$\begin{aligned} K_I &= 2\pi a_1 \\ K_{II} &= -2\pi b_1 \\ K_{III} &= 2\pi c_1 \end{aligned}$$

Williams fitting - example

$$\varphi \in 35^\circ, t=10 \text{ mm}$$

$$r_{min} = 3 \text{ mm}, r_{max} = 20 \text{ mm}$$

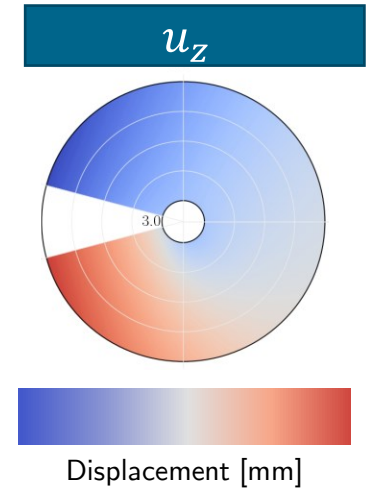
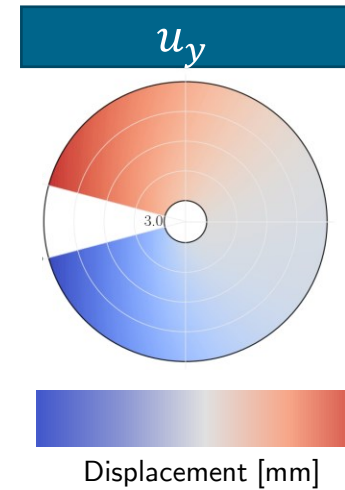
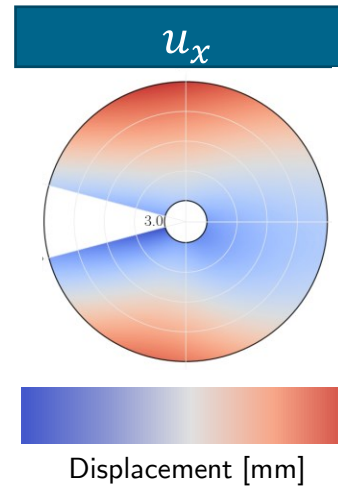
$$R_r = 17 \frac{\text{points}}{\text{mm}}, R_r = 1 \frac{\text{points}}{\text{deg}}$$

$$\text{Terms: } i \in [-1, 0, 1, \dots, 9]$$

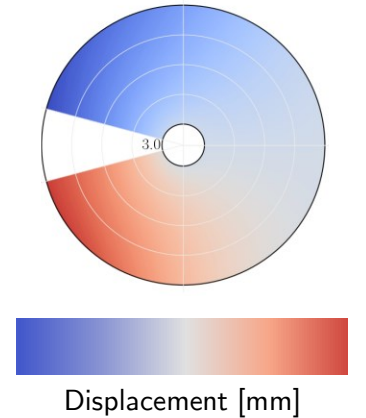
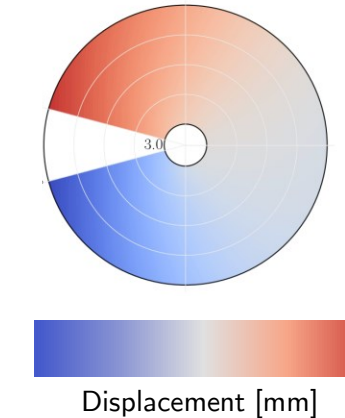
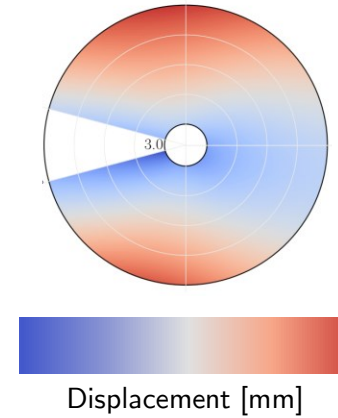
$$w_i = 1 \text{ for } i \in [x, y, z]$$

Preliminary parameters.
Convergence studies for optimal
fitting parameters are in
preparation.

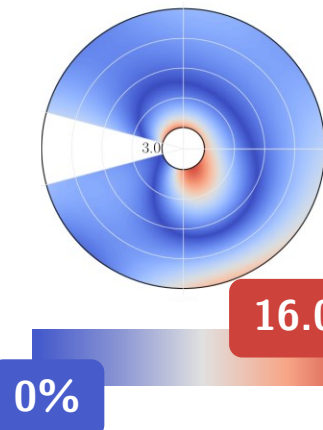
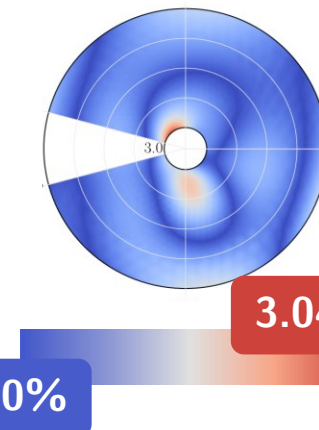
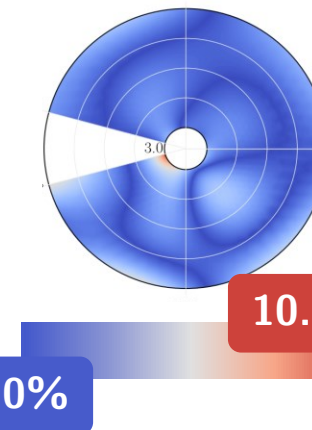
FE data



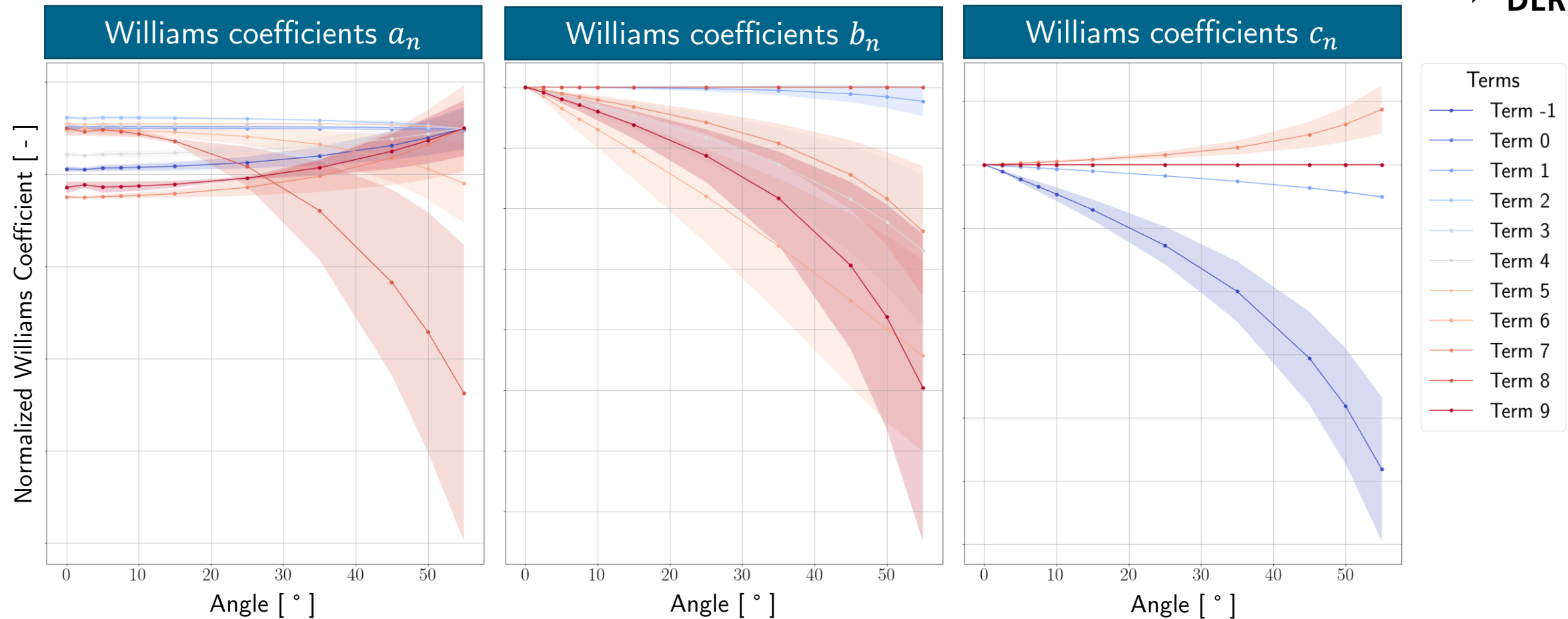
Williams data



Error in %



Williams fitting - summary



Intermediate research question: How does the Williams field relate to the crack front angle?

~~$$\varphi(a_x, t, \mathbb{C}, K_i, \sigma, R, \eta, \theta, \dots) \in [-\pi, +\pi]$$~~

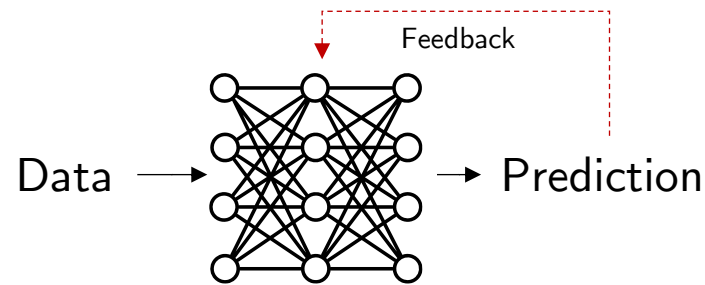


$$\varphi(a_n, b_n, c_n) \in [-\pi, +\pi]$$

Symbolic regression - introduction

Machine learning

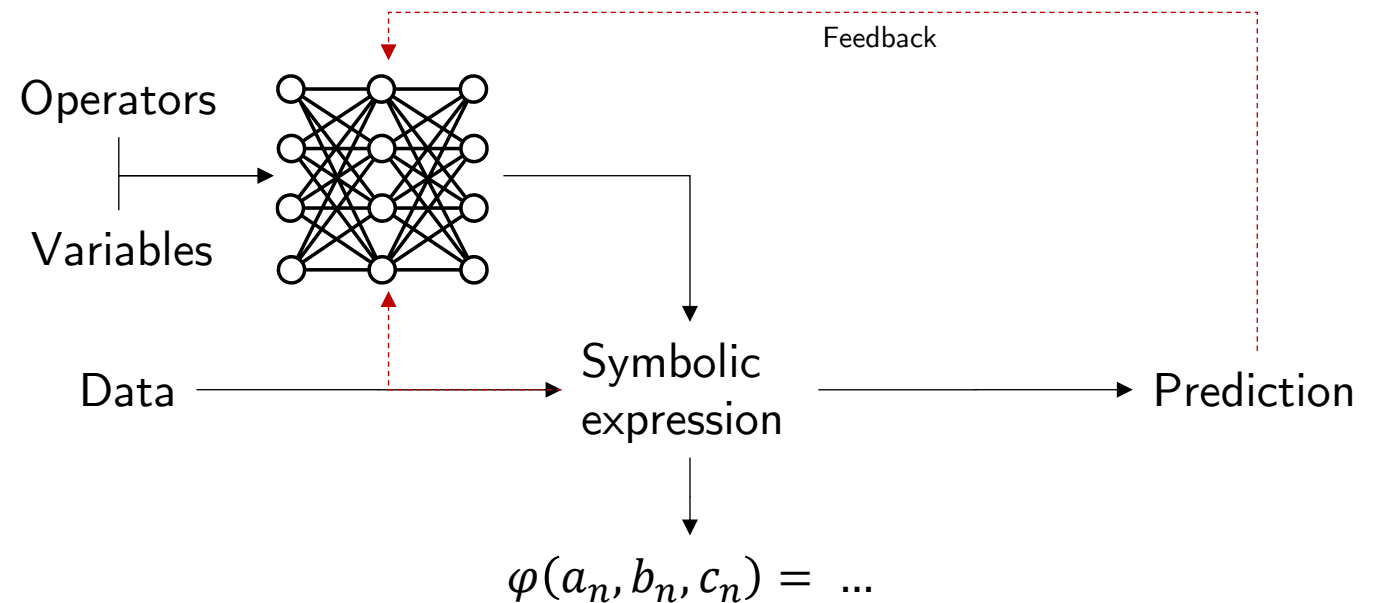
Train a model f to predict values from data



- Usually opaque black-box
- Not interpretable
- Rarely transferable to new domains
- Prone to overfitting / poor generalization

Symbolic regression (part of ML)

Train a model f to predict functions of varying complexity that fit the data



- Interpretable
- Potentially analytically derivable from known expressions
- Potentially general (within assumptions)

Symbolic regression - introduction

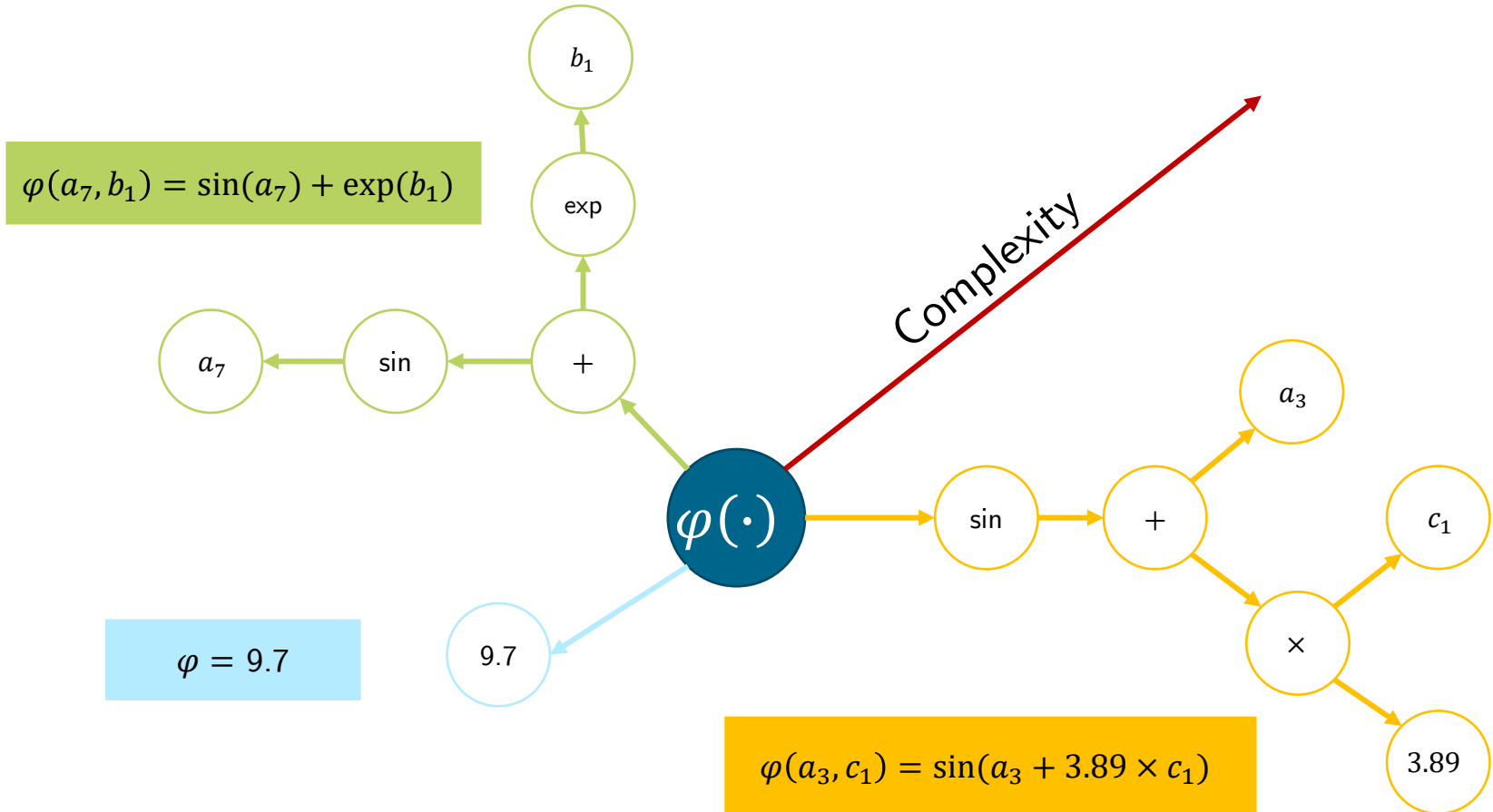
Operators

$\sin(\cdot)$
 $\cos(\cdot)$
 $\exp(\cdot)$
 $\log(\cdot)$
 $\cdot + \cdot$
 $\cdot - \cdot$
const.
...

Variables

a_n
 b_n
 c_n

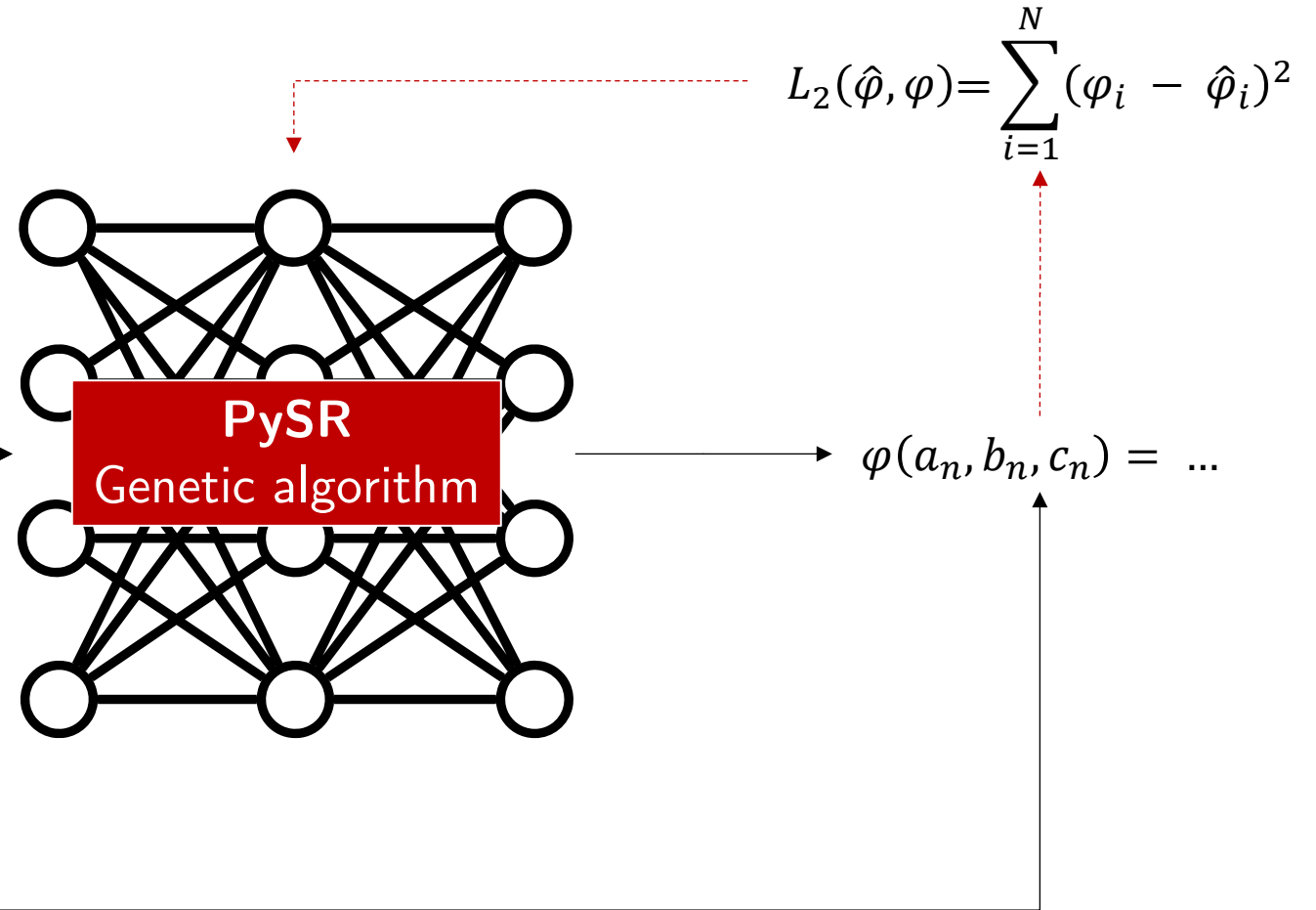
Expression Tree(s)



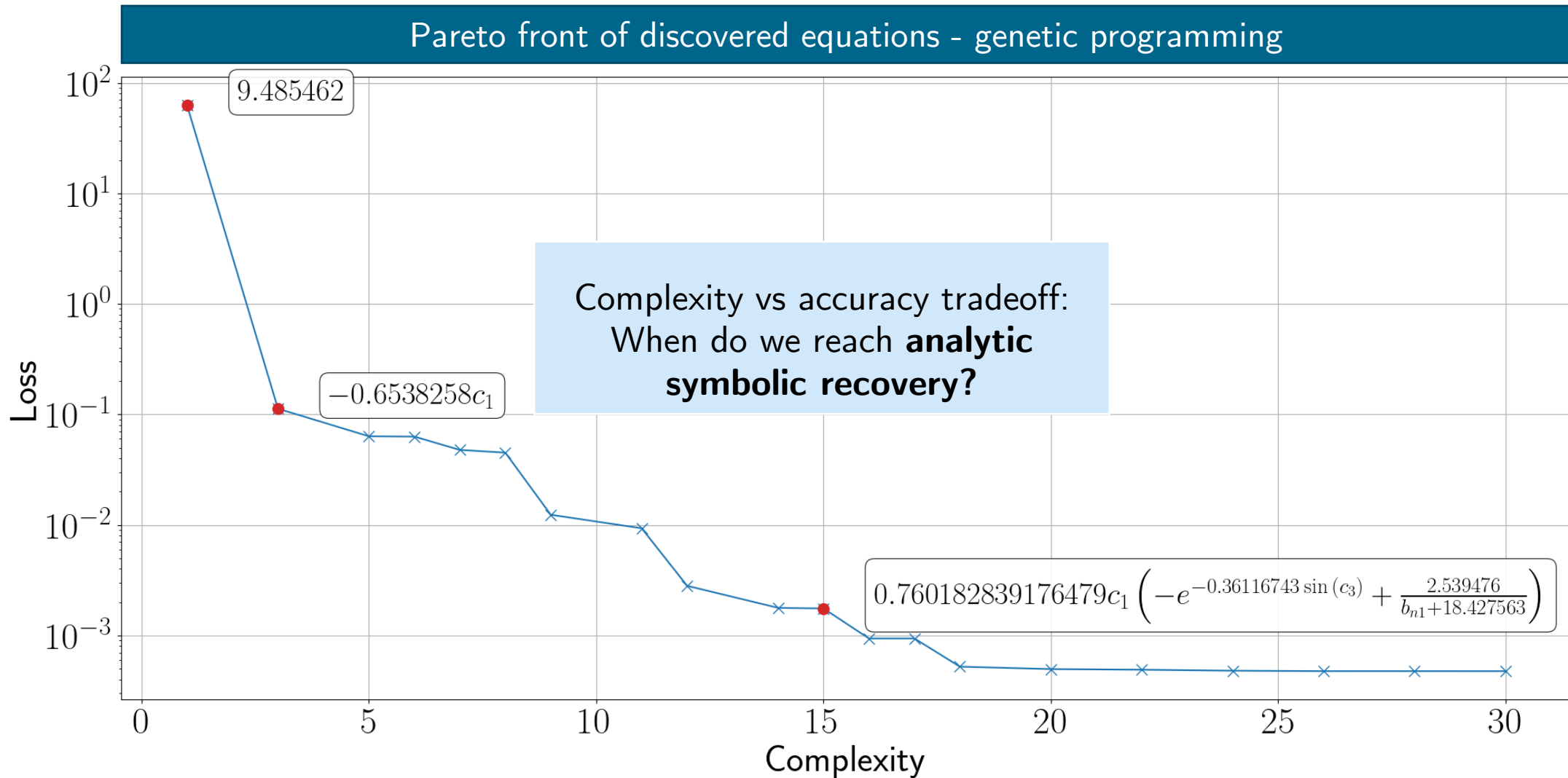
Symbolic regression – setup

Operators		Variables		
$\sin(\cdot)$	$\cdot + \cdot$	a_{-1}	b_{-1}	b_{-1}
$\cos(\cdot)$	$\cdot - \cdot$	a_0	b_0	c_0
$\exp(\cdot)$	$\cdot \times \cdot$	a_1	b_1	c_1
$\log(\cdot)$	$\cdot \div \cdot$	...	...	...
$\text{sqrt}(\cdot)$	const.			

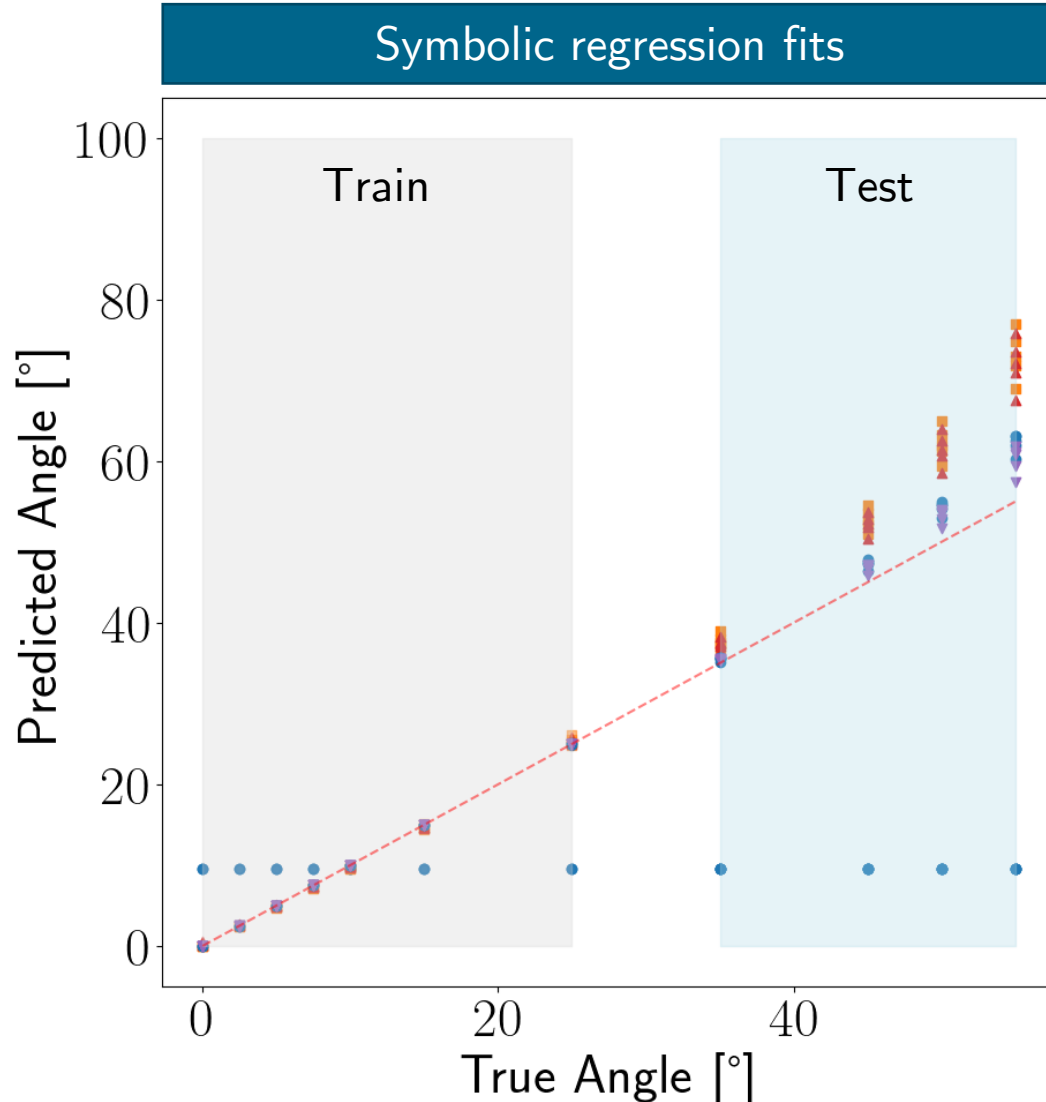
Dataset									
$\hat{\varphi}$	a_{-1}	...	a_9	b_{-1}	...	b_9	c_{-1}	...	c_9
0	3.64	...	4e-9	-0.01	...	-1e-9	0.11	...	2e-9
0	1.88	...	-3e-7	4e-4	...	2e-9	-0.02	...	1e-9
...	...	...	...	...	...	...	...	...	...
35	7.18	...	-2e-7	35.72	...	-3e-7	-83.7	...	3e-7



Symbolic regression – pareto optima



Symbolic regression – performance



Sampled equations

Eq. 1

$$\varphi = \text{const.} = 9.49$$

Eq. 2

$$\varphi = -0.65 c_1$$

Eq. 3

$$\varphi = -0.65 c_1 - \sin(c_2)$$

Eq. 10

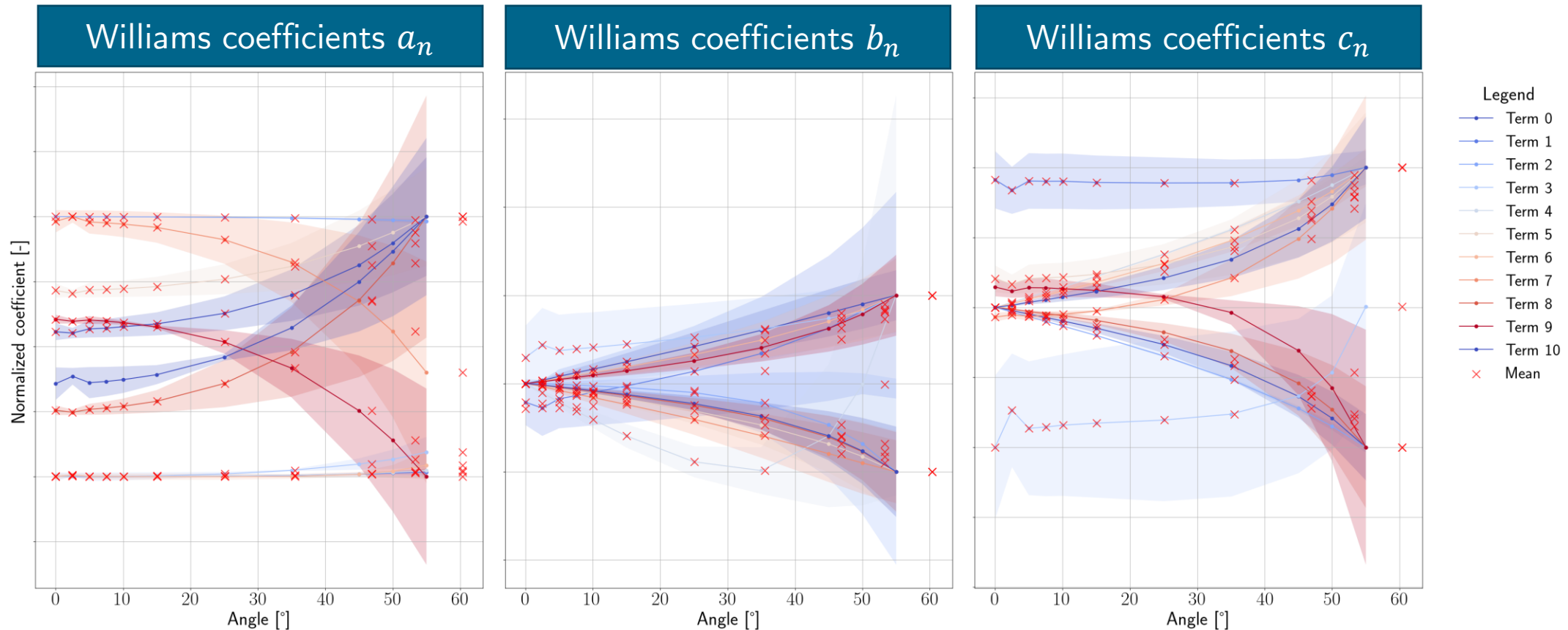
$$\varphi = -0.76 c_1 \left(-e^{-0.4 \sin(c_3)} + \frac{2.5}{b_{-1} + 18.4} \right)$$

Eq. 19

$$\varphi = -0.47 b_4 + c_1 \left(0.47 b_4 + 0.24 c_3 - 0.72 + \frac{0.72}{b_{-1} + \sqrt{c_0}} \right) + c_3 - c_4 + \dots$$

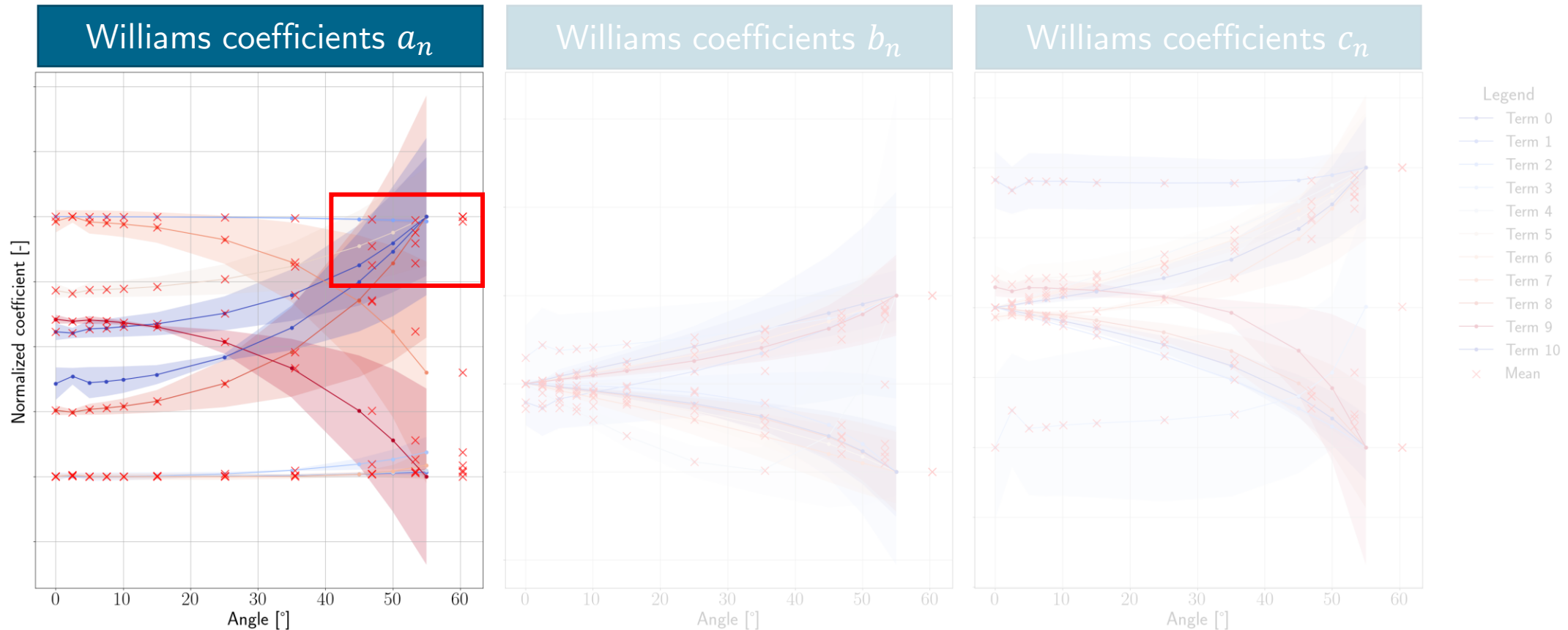
Model appears to distinguish between relevant and irrelevant coefficients and fits nicely even for lower complexity equations

Symbolic predictions – Eq. 19



The discovered equation largely is able to predict the correct angles

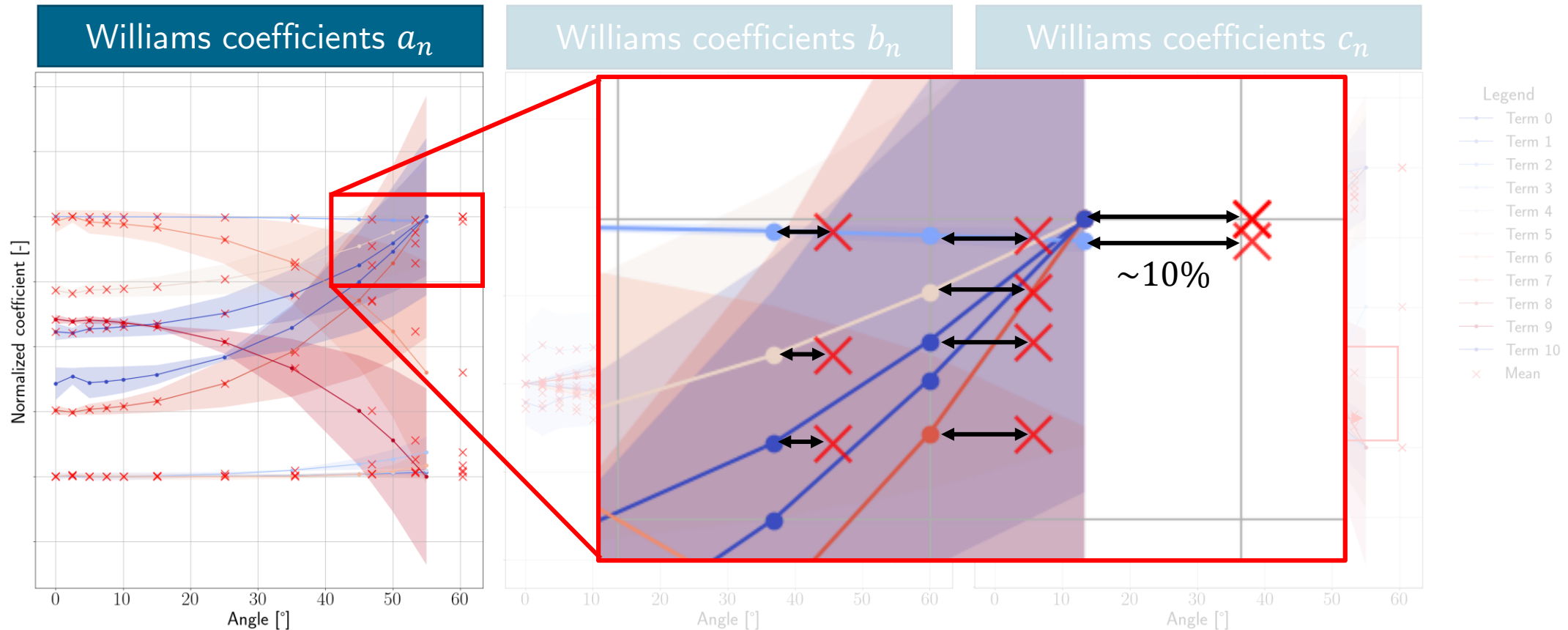
Symbolic predictions – Eq. 19



There is a remaining offset.

likely no full symbolic recovery → Improve symbolic regression approach

Symbolic predictions – Eq. 19



There is a remaining offset.

likely no full symbolic recovery → Improve symbolic regression approach

Next steps

FE Model

Hexahedral elements

Add kink angle

More sophisticated material model

Symbolic regression

Improve (Williams) series coefficient fitting

Explore DL based approaches

Add physical priors (e.g. via units)

Explore uncertainty and noise

Analytic correctness along pareto front

Experimental data

MT160 for varying thickness and varying R ratios

AA2024-T3 and AA7075-T651

Validate models on microscope DIC data

Determine more material characteristics that can be essential for the symbolic regression task

Thank you for your attention and feedback!

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DLR Cologne

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and to **Vanessa Schöne** and **Florian Paysan** for providing data and additional resources.