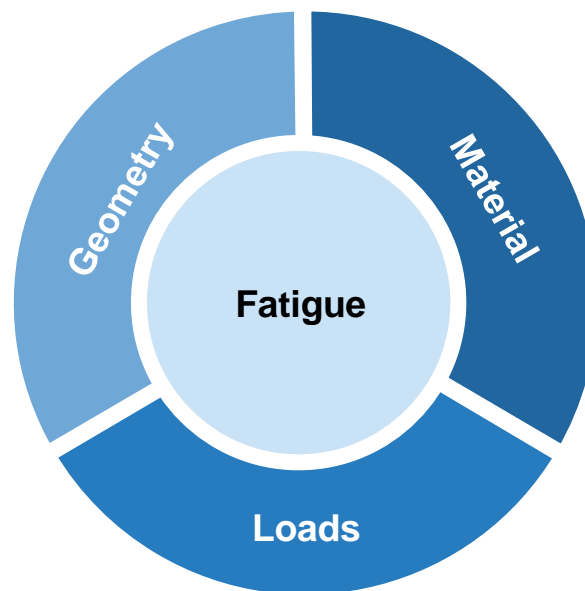


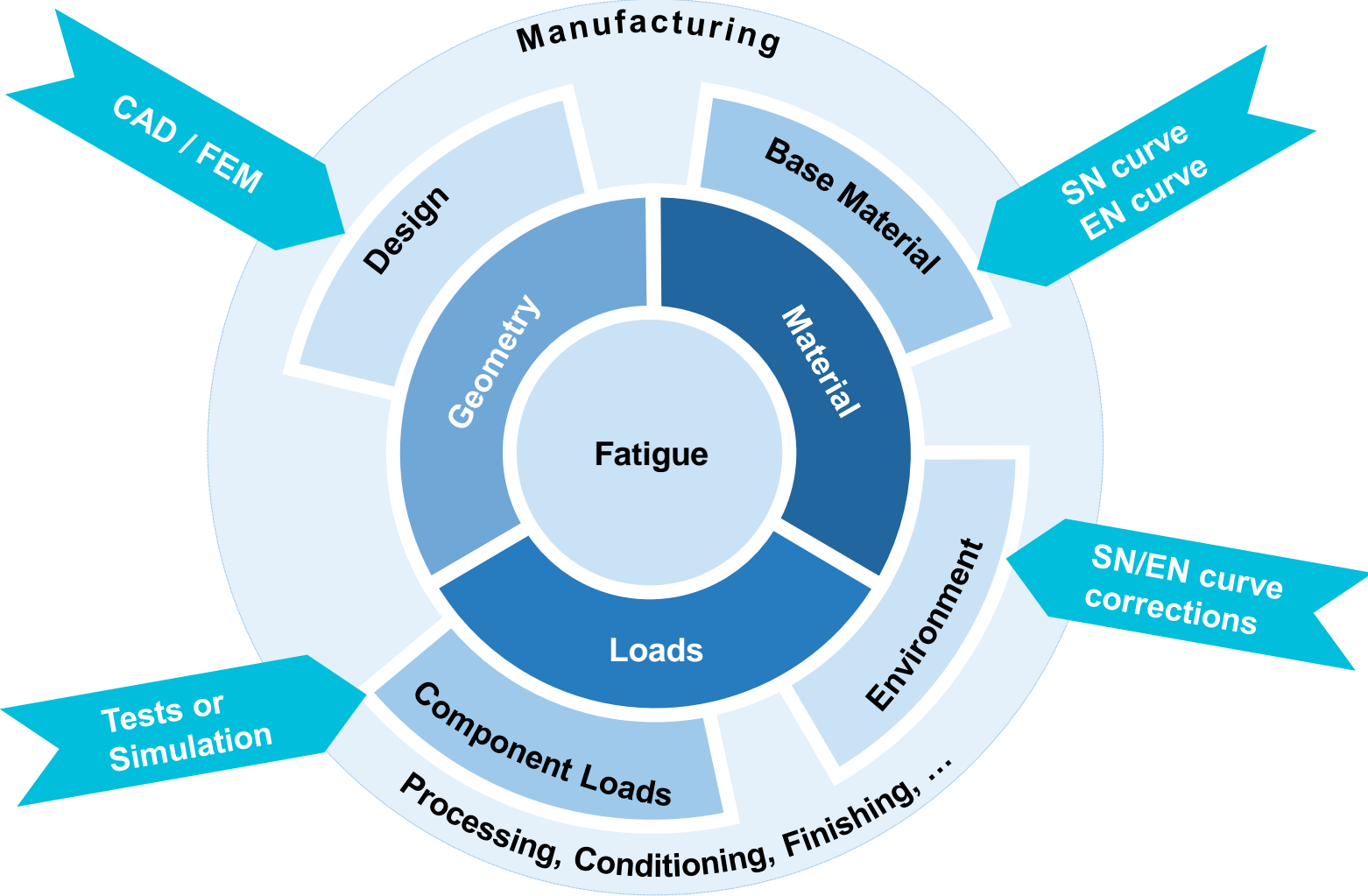
How to account for influence factors in fatigue – independent influence factors vs. machine learning

Nicolas Lammens, Matthias Schulz, Michael Hack, Hunor Erdelyi

Influences on Fatigue



Influences on Fatigue (detailed)



Approaches

Traditional (fatigue codes like BS, EC, FKM, ...)

- Analyse influence of different factors independently (e.g. surface roughness)
- Create influence factor for SN curve
- Use worst case (aka multiply influence factors) for the whole (sub-) structure

Problem

May lead to large influence factors

Does not take into account local influences

Cannot account for dependencies between the influence factors.

Example size effect

Concept	Correction factor $n_x = \frac{K_t}{K_f}$
Stress gradient	$n_\chi = f(R_p, \chi^*)$ $\chi^* = \frac{1}{e_{\sigma_{\max}}} \left \frac{d^e \sigma(x)}{dx} \right $
Adjustment for macro-yielding	$n_p = \sqrt{1 + \frac{\varepsilon_{E,p}}{\varepsilon_{E,e}}}$
Weakest-link concept	$n_w = n_w(1 \rightarrow 2) = \left(\frac{I_{A,1}}{I_{A,2}} \right)^{k_w}$ $I_A = \int_A \left(\frac{e_{\sigma(x)}}{e_{\sigma_{\max}}} \right)^{k_w} dx$
Neuber's approach to micro-yielding	$n = \sqrt{1 + \frac{s \rho^*}{\rho}}$

Approaches

Mathematical model (MaBiff project for casting)

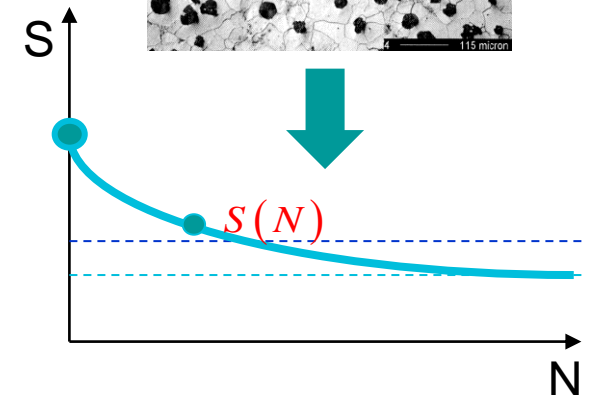
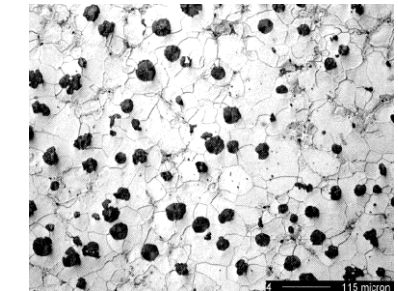
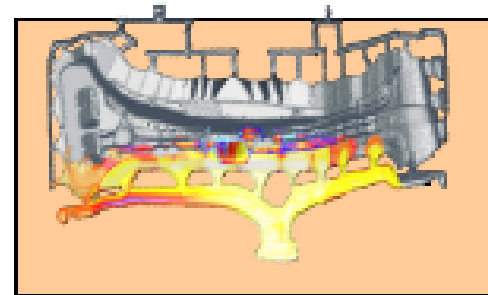
- Analyse influence of different **manufacturing** factors
- Perform mathematical analysis on dependency
- Find most influencing factors
- Define mathematical formula for the influence

Advantage

- Can be applied locally as manufacturing simulation gives local parameters
- At high stresses areas local safety factor

Disadvantage

- High effort
- Mathematical Model often not clear



Approaches

Machine learning approach

- Define manufacturing/fatigue influence factors
- Perform tests for combinations of the factors
- ML can identify mathematical model
- ML can identify the relevant factors (and therefore efficient tests for similar materials)

We show this on the example of

Large freedom of design



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Additive
Manufacturing (AM)
enables production of
optimal designs

which could not be
achieved before with
conventional
manufacturing methods

SIEMENS

Large freedom of design



**Additive
Manufacturing (AM)
introduces fatigue
influencing factors**

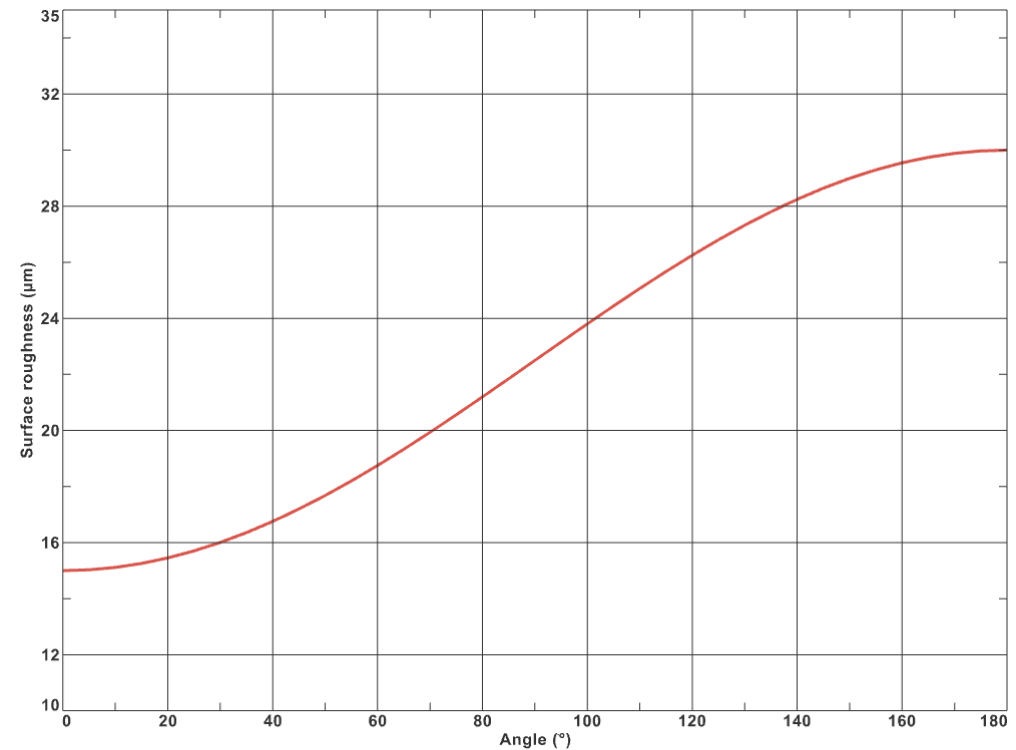
Less controlled than for
conventional manufacturing
Highly dependent on
geometry
Exhibit a local nature

Some of the most important AM process induced fatigue influencing factors

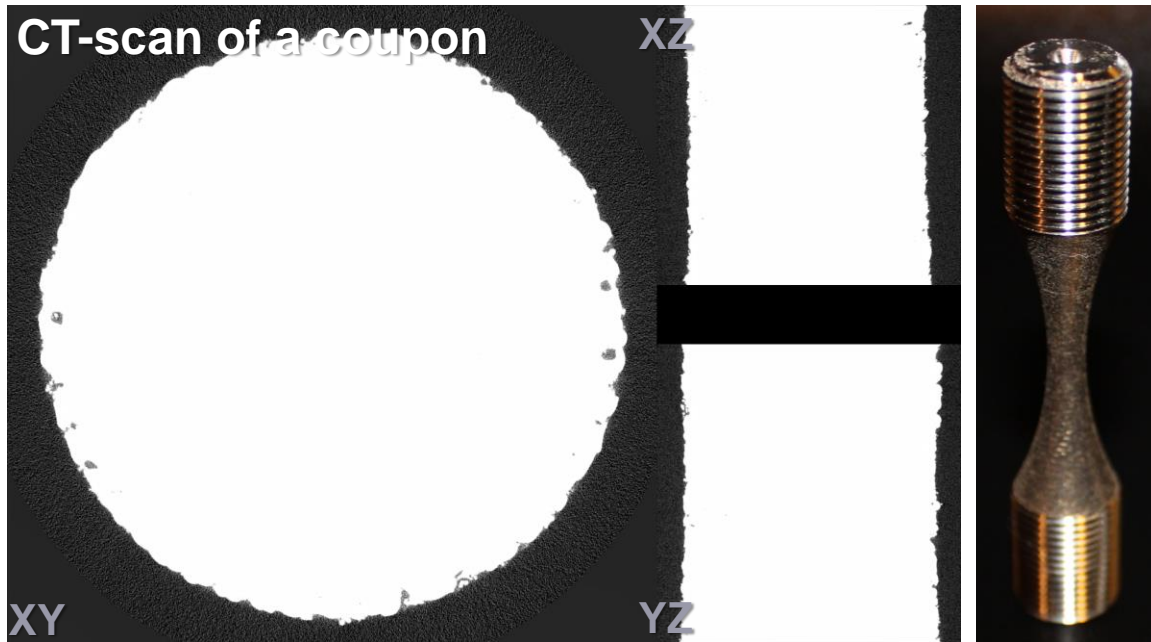


Surface roughness

- Depends on the AM process as well as on the geometry (e.g. the local overhang angle)



Some of the most important AM process induced fatigue influencing factors



Porosities

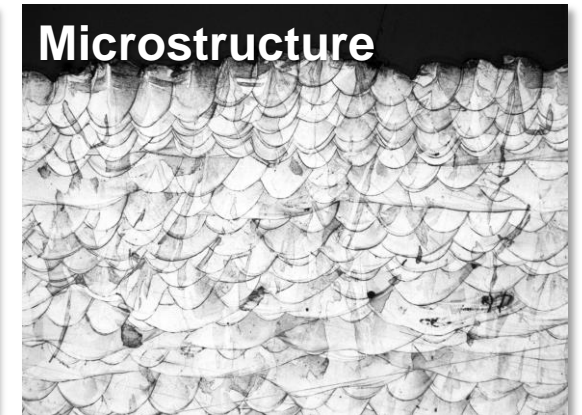
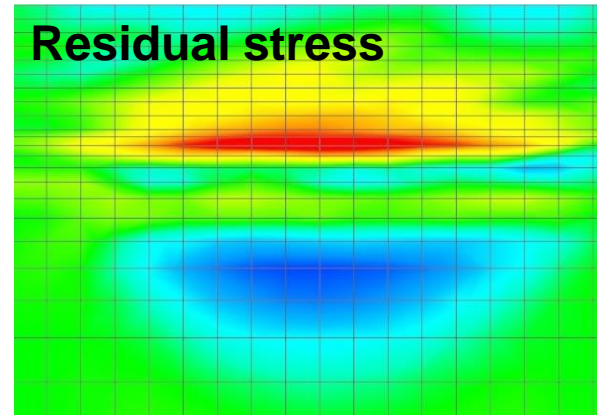
- Depend on the local conditions of the melt-pool, influenced by the hatching strategy, process parameters, local temperatures etc.

Microstructure

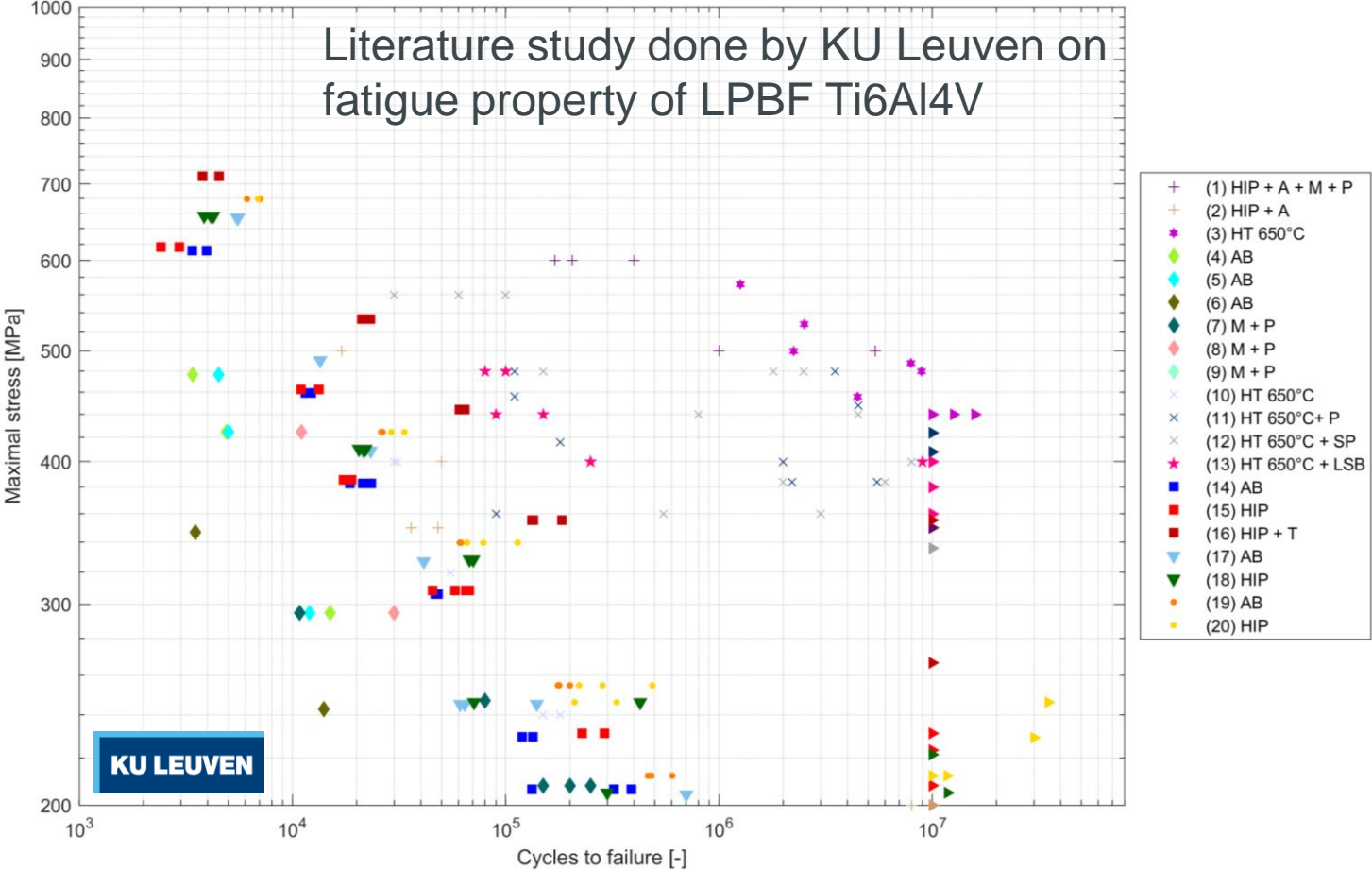
- The AM process induces unique microstructure
- The different local temperature histories will lead to local variations

Residual stress

- The layer-by-layer deposition of the material builds up residual stress in the AM component



A wide spread in fatigue data of AM material reported in literature



The AM process induced local fatigue influencing factors make fatigue performance prediction **challenging**

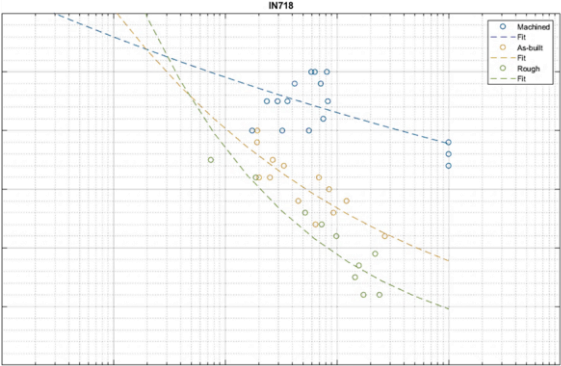
How to handle fatigue



Fatigue performance of AM components, a major challenge in the industrialisation of additive manufacturing

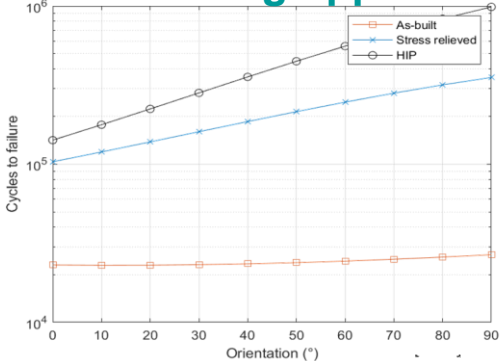
AM-enhanced durability calculation with local fatigue parameter prediction using Machine Learning

Material testing

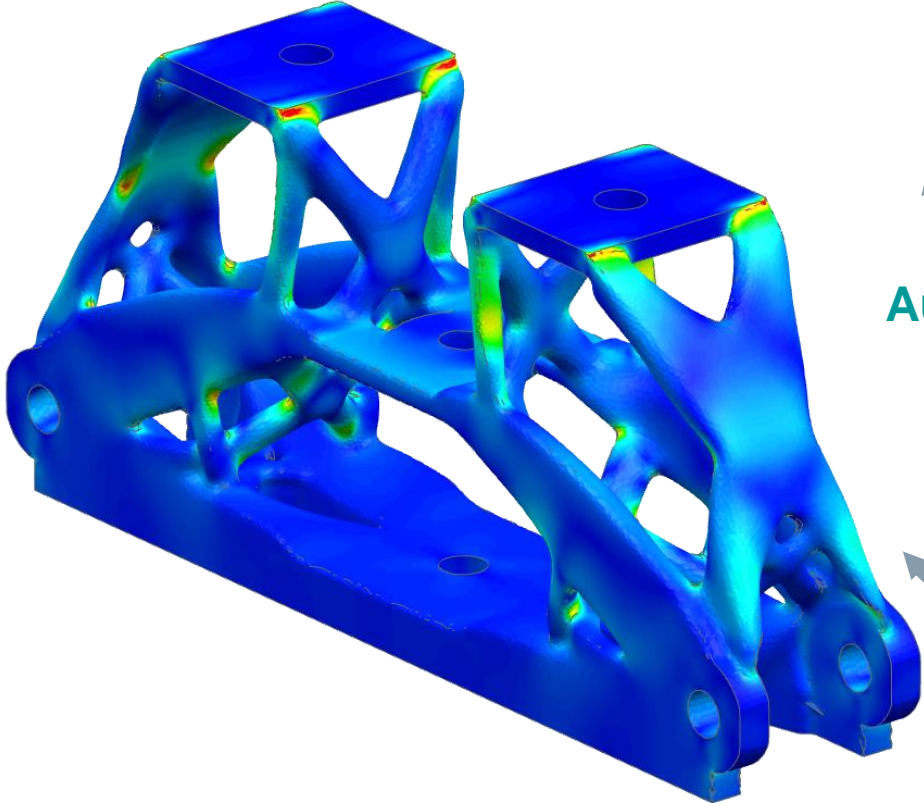


Material database

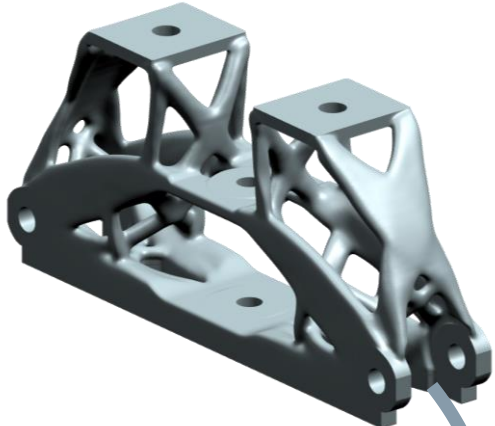
Machine Learning App



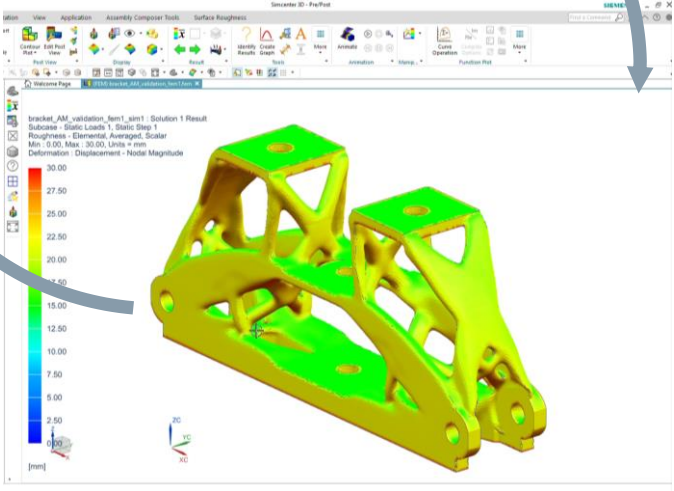
AM-aware Durability simulation



Component CAD model

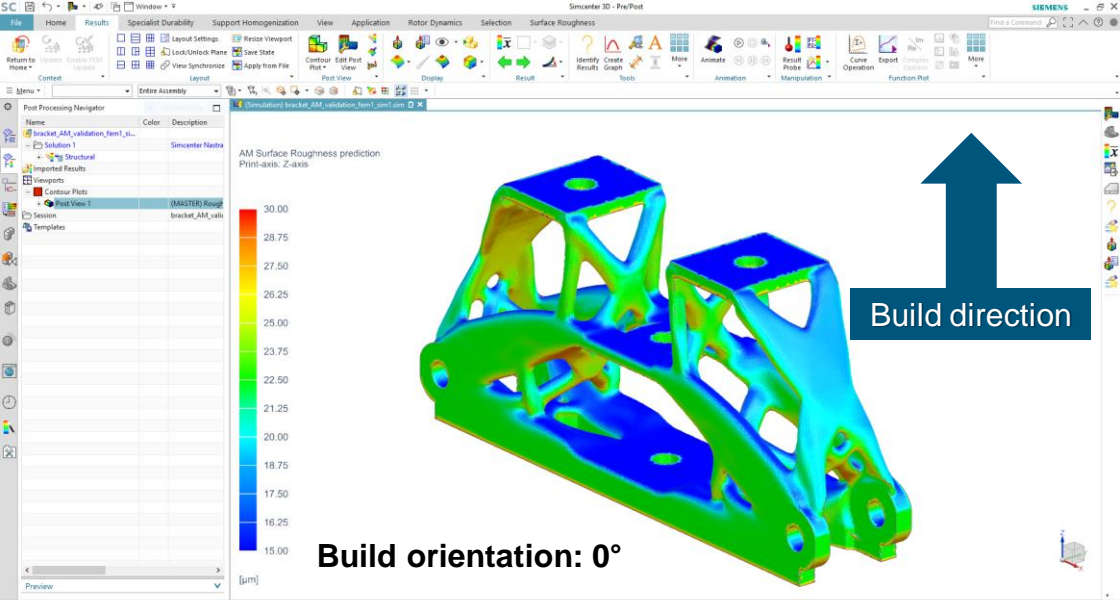


Automated feature extraction

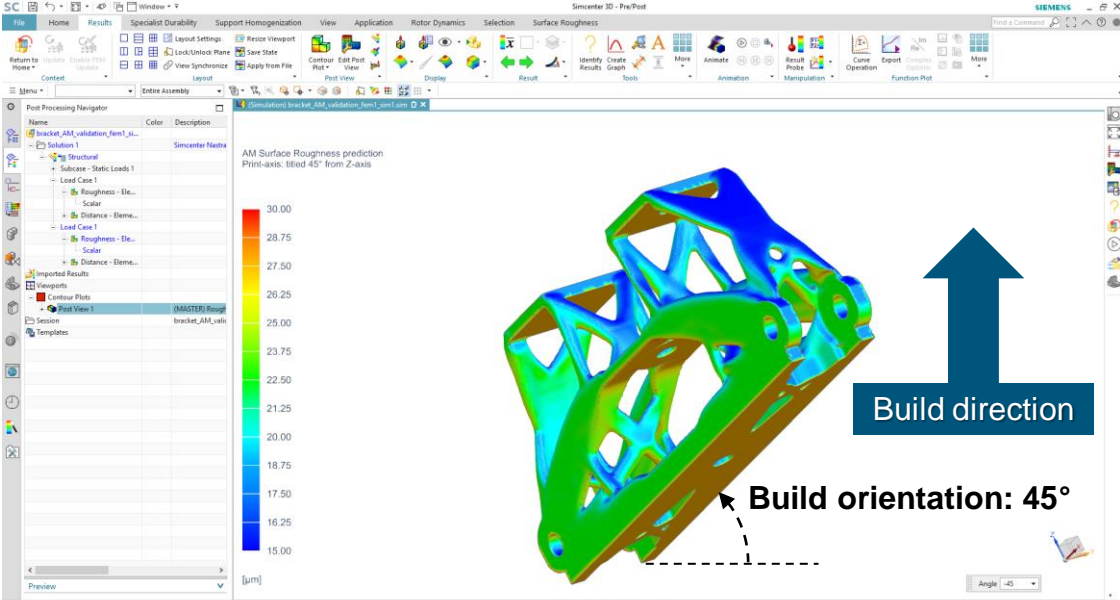


Geometry-based artefact assignment: surface roughness as a function of overhang angle in Simcenter 3D

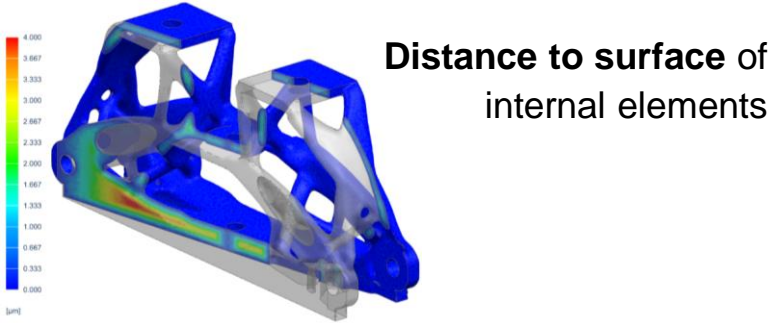
Standard print orientation



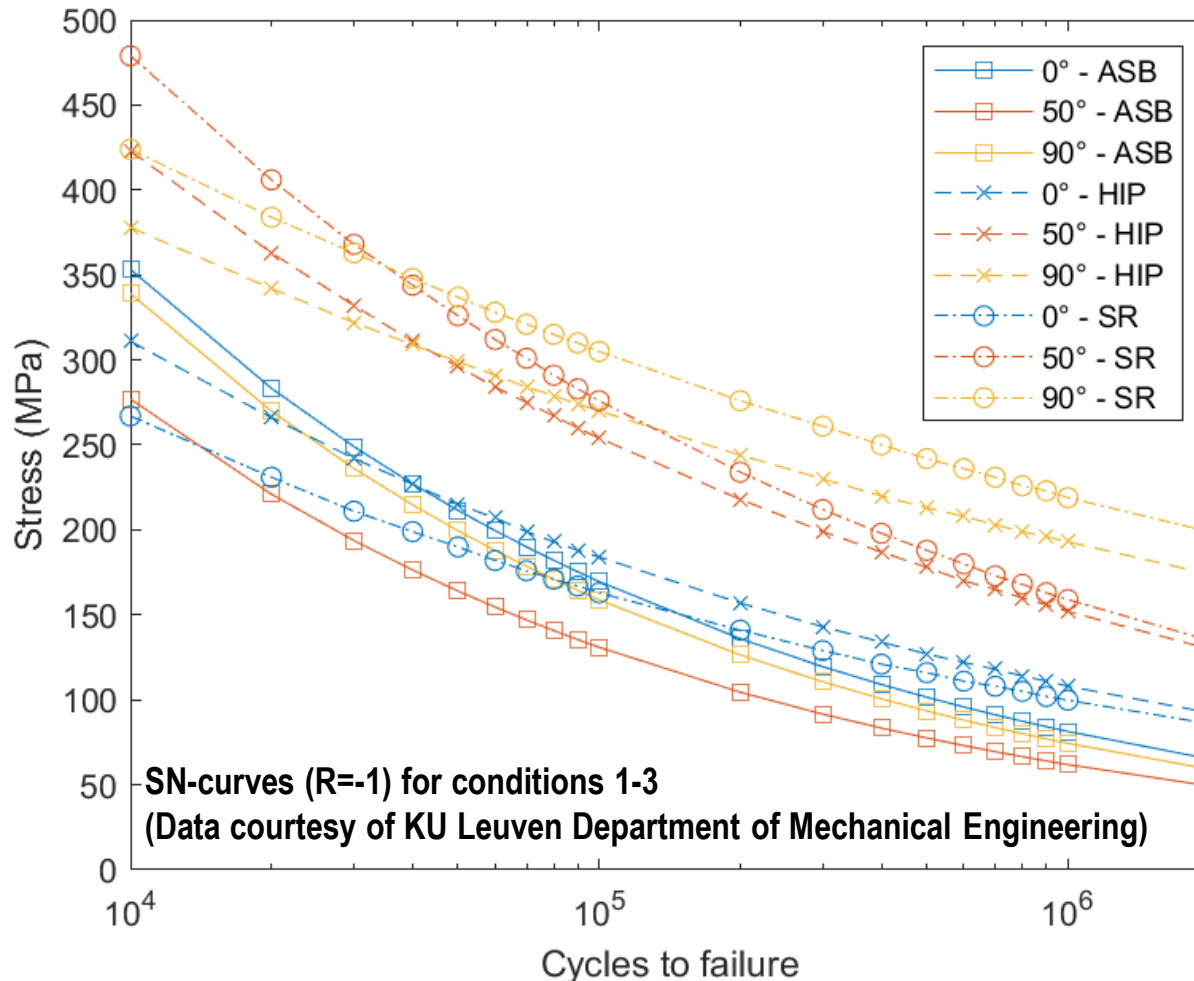
Custom print orientation



Analyze a printed geometry and assign (geometrically driven) artefact maps to be used in the durability solver



A Machine Learning database for fatigue life considering local properties of AM components



The problem

- Fatigue life is always a result of **combined influence of multiple local factors** (surface roughness, porosity, microstructure etc.)
- One cannot afford to test for all possible combinations
- And it is impossible to separate these factors and to describe the interaction and separated impact of these factors

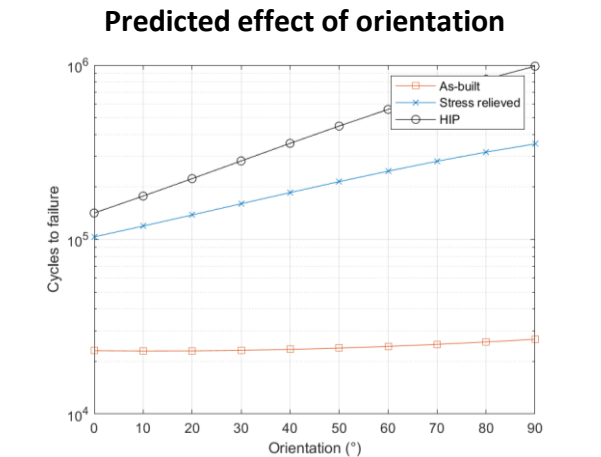
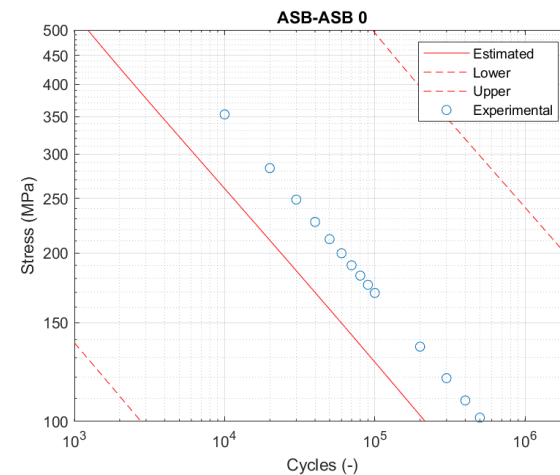
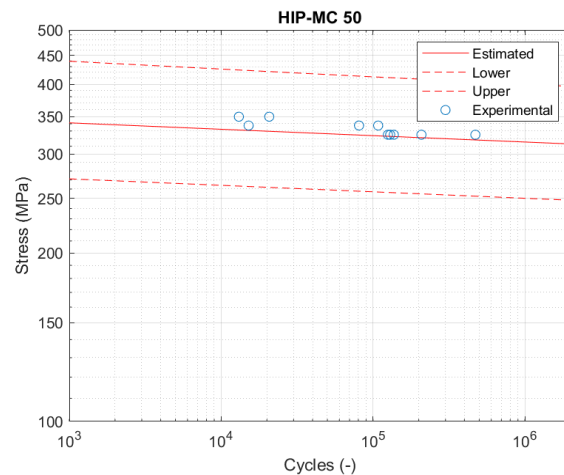
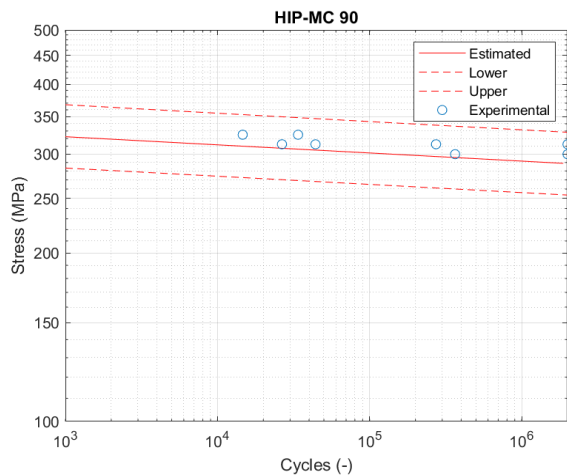
How to derive a valid mathematical model that can predict the impact of any combination of fatigue influencing factor?

A Machine Learning database for fatigue life considering local properties of AM components

The solution: use *machine learning* to *more accurately model fatigue* life performance of additive manufactured components

Validated with a blind test

- Model trained with 6 SN curves corresponding to different **combinations** of factors
- Prediction and comparison to **3 new and unseen combination of factors**



No a-priori assumptions on how different artefacts affect fatigue life, flexible, accounts for local phenomena, limited testing required, enables extrapolation

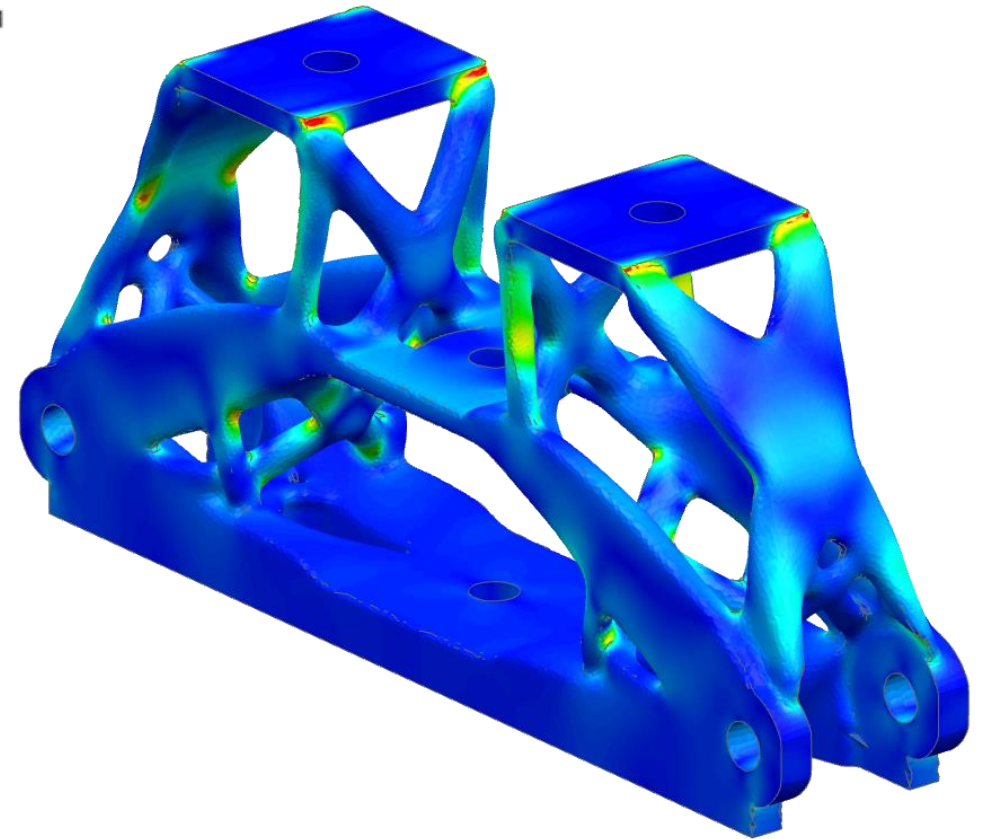
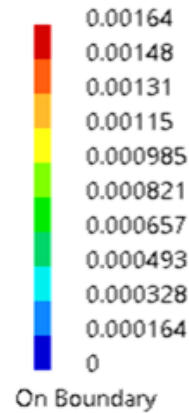
AM aware Durability analysis

Durability Simulation for AM in Simcenter 3D

- Uses Simcenter 3D Specialist Durability Open Solver
- Including automatic training tool for ML
- Methodology can rely on experimental and/or simulation data
- Mean stress compensation using Walker equation
- Accounting for fatigue-influencing factors, including localized phenomena
 - Surface roughness, Void-rich areas, residual stress from AM, stress concentrations etc.

The **only fatigue solver** able to consider AM process induced local properties in part scale durability analysis.

Fatigue Damage (Fringe).1
Occurrence 1



Proof-of-concept demonstrator

Specimen geometry with multiple identical failure points

- Traditional fatigue solvers Unable to discriminate which hole will lead to failure

By taking the processing into account, proposed fatigue solver can uniquely identify the failure location

- Processing will be varied deliberately in small amounts to create different types of samples and illustrate the robustness of our solution
- Accuracy of methodology to be proven through experimental fatigue testing and instrumentation

TYPE I (Reference)

- Outer surface shot peened
- Both holes printed and shot peened

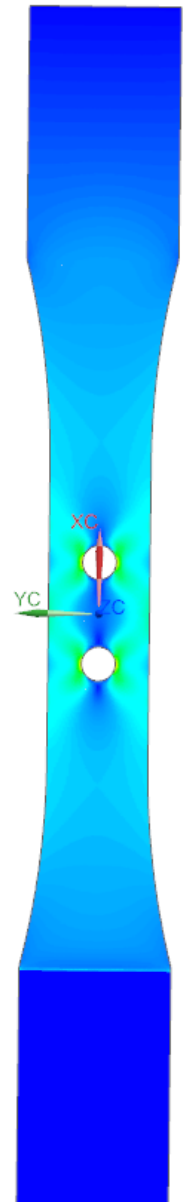
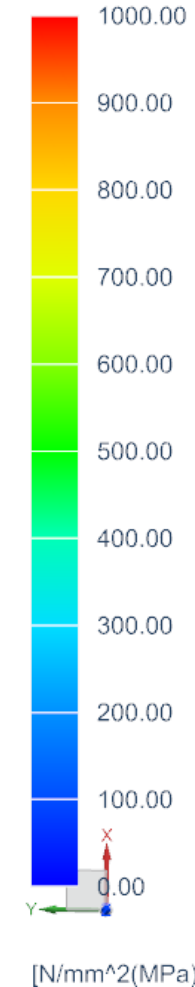
TYPE II (Shot peened)

- Outer surface shot peened
- Top hole shot peened internally
- Bottom hole as-built

TYPE III (Drilled)

- Outer surface shot peened
- Top hole as-built and then shot peened
- Bottom hole not printed but drilled and then shot peened

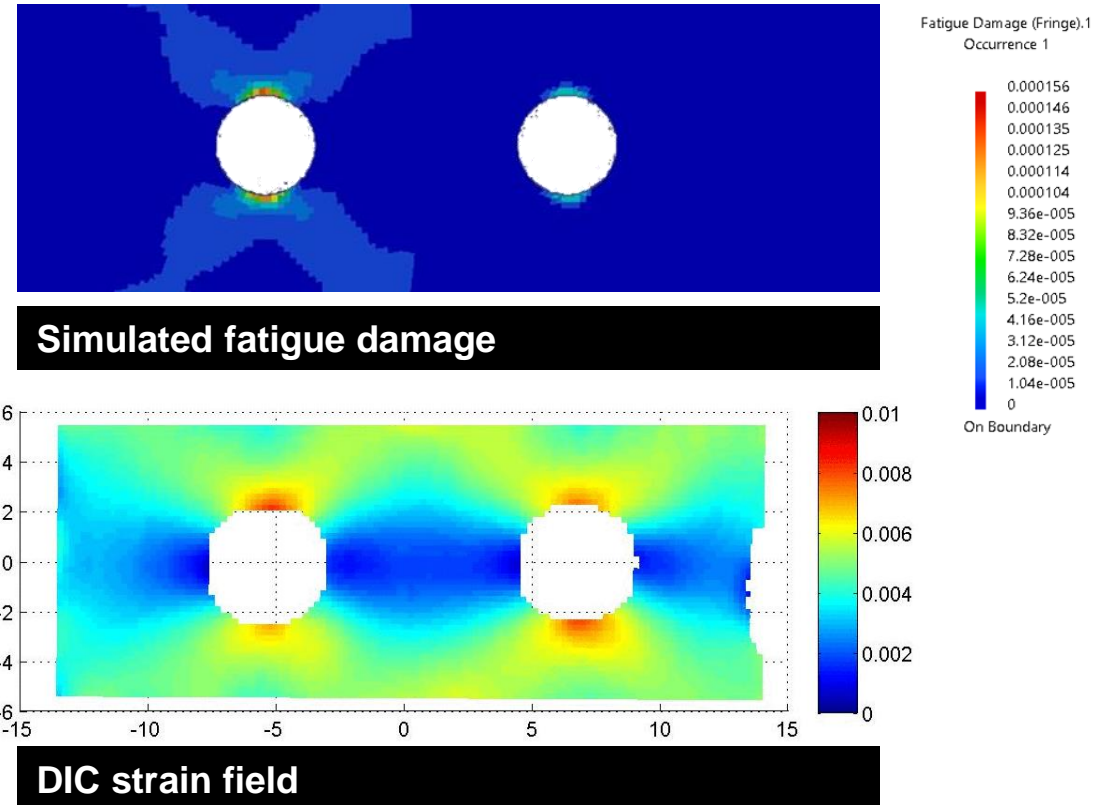
Von Mises Stress



Proof-of-concept demonstrator

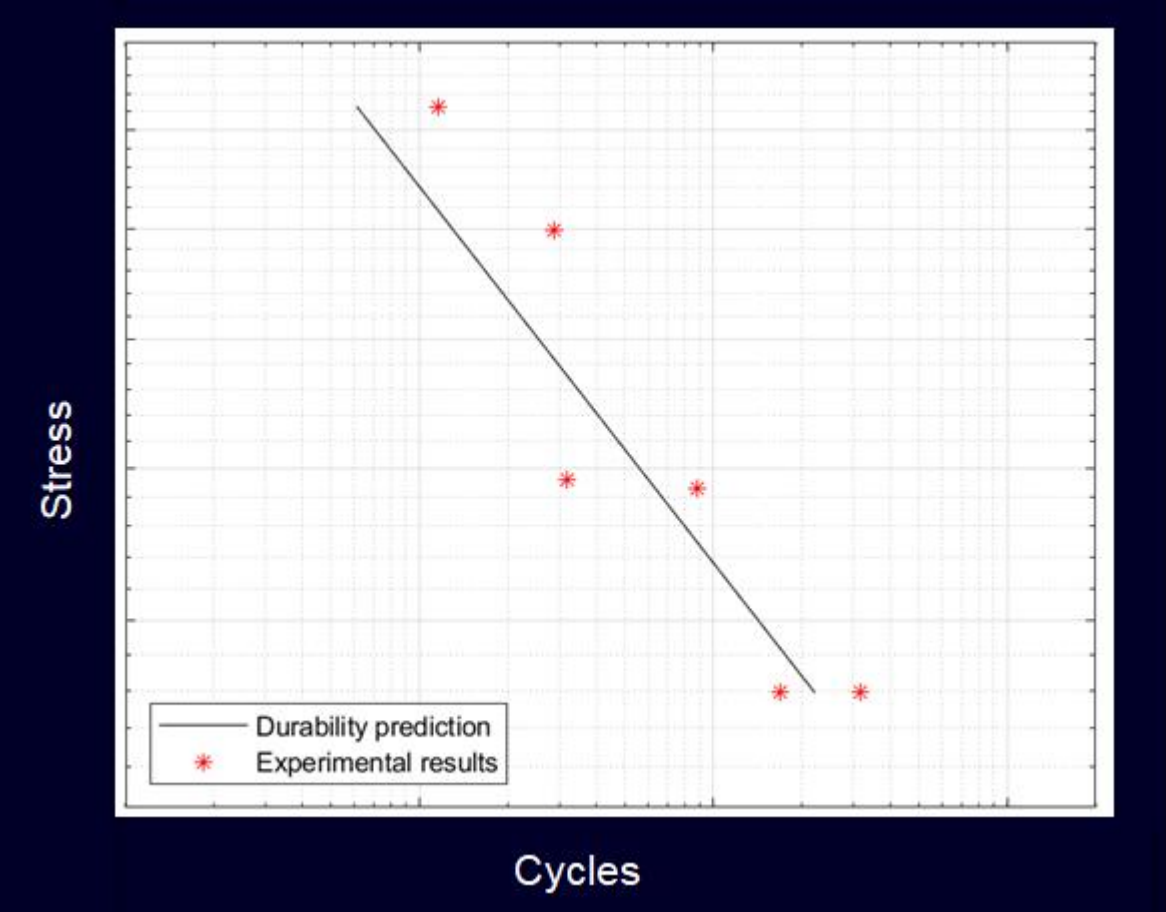
	Type 1 (random failure expected)		Type 2 (bottom failure expected)		Type 3 (top failure expected)	
	# cycles	failure	# cycles	failure	# cycles	failure
Sample 1	15.710	top	1.400	bottom	88.090	top
Sample 2	21.000	top	9.200	bottom	113.200	top
Sample 3	28.760	bottom	10.790	bottom	90.760	top
Sample 4	25.116	top	10.064	bottom	91.960	top
Sample 5	18.225	bottom	8.700	bottom	140.450	top

- Correct failure location predicted for all cases
- Higher measured cycle to failure for Type 3 coupon under investigation

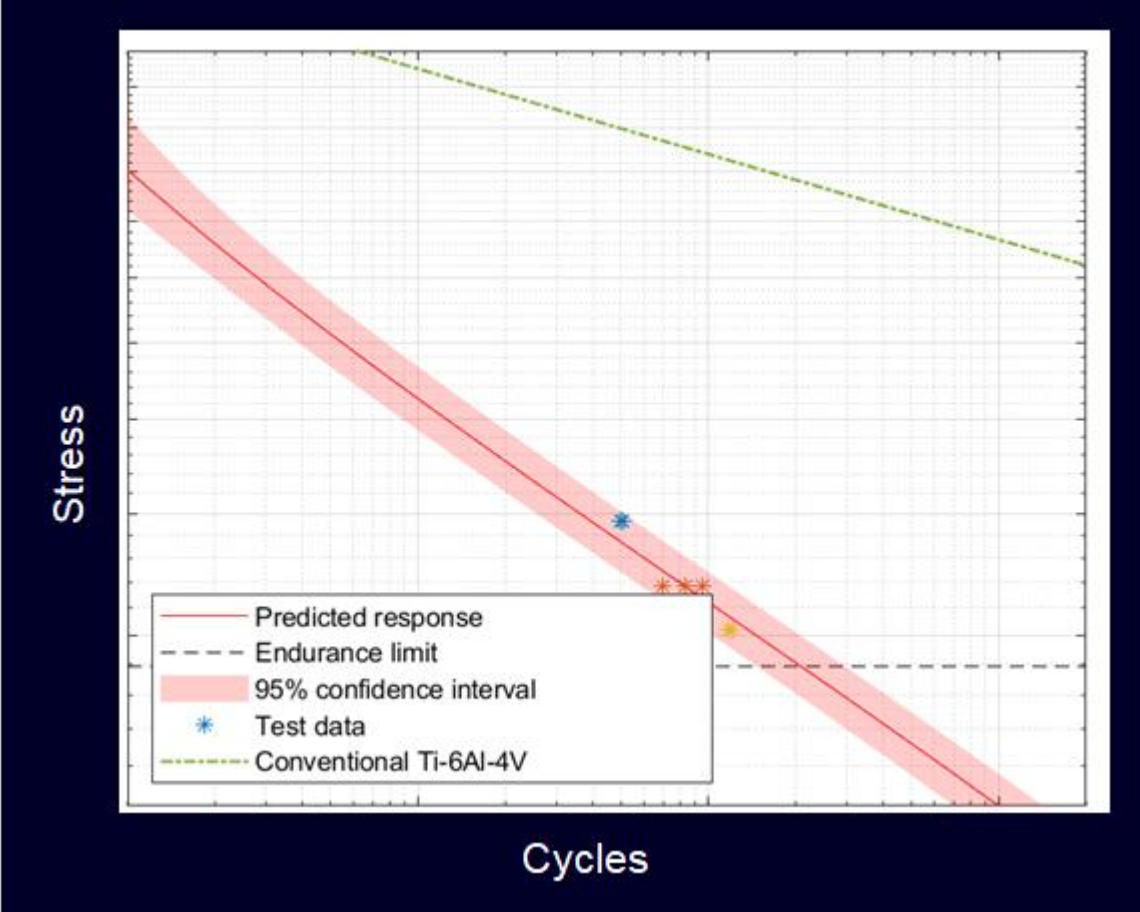


Validated with test results

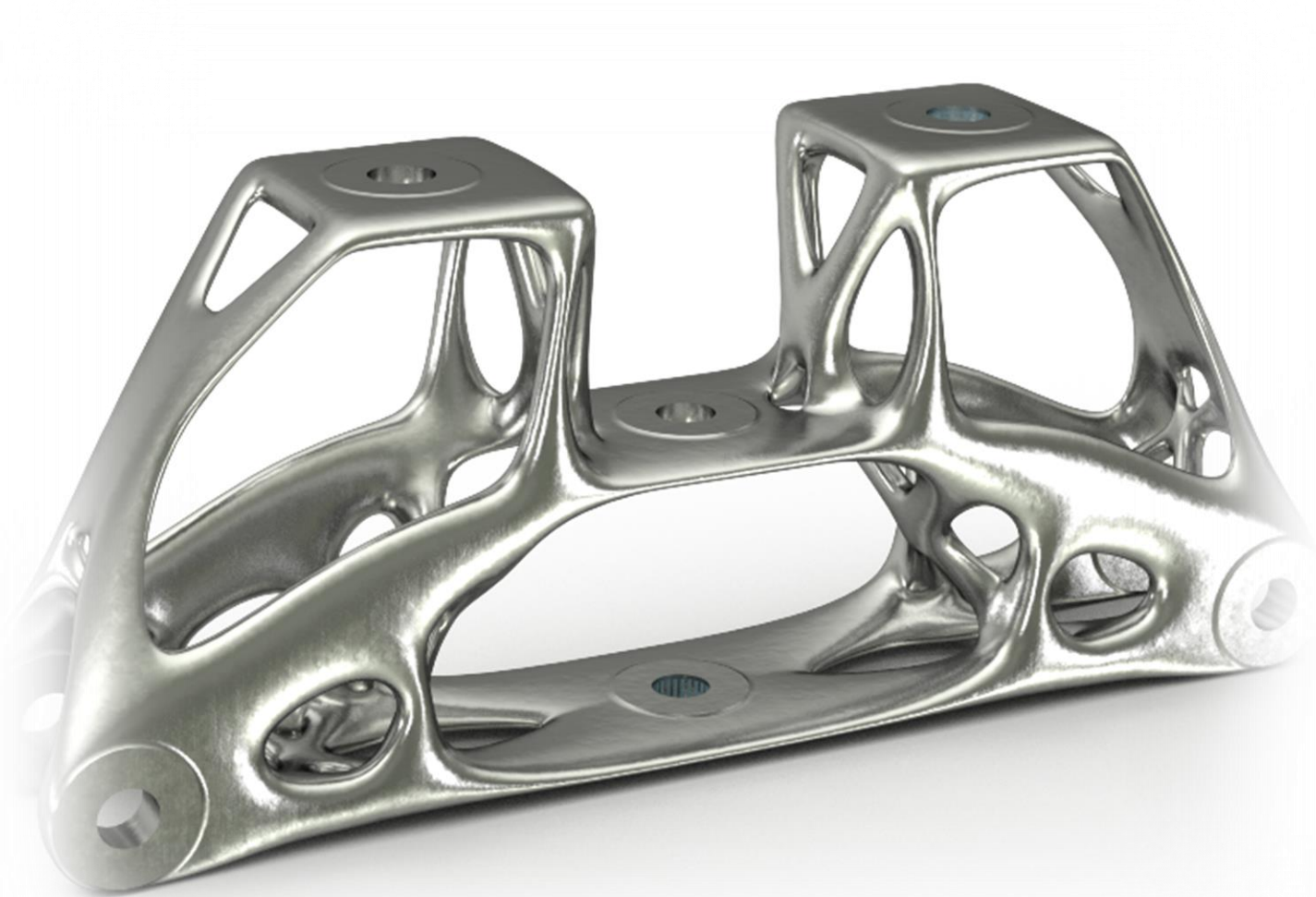
LPBF SS316L



LPBF Ti6Al4V



Outlook



Method available

Integrated in standard software

For projects

ML based material data for
several metals available

Can be achieved in projects

Ongoing work

Further improve ML process

Probabilistic analysis

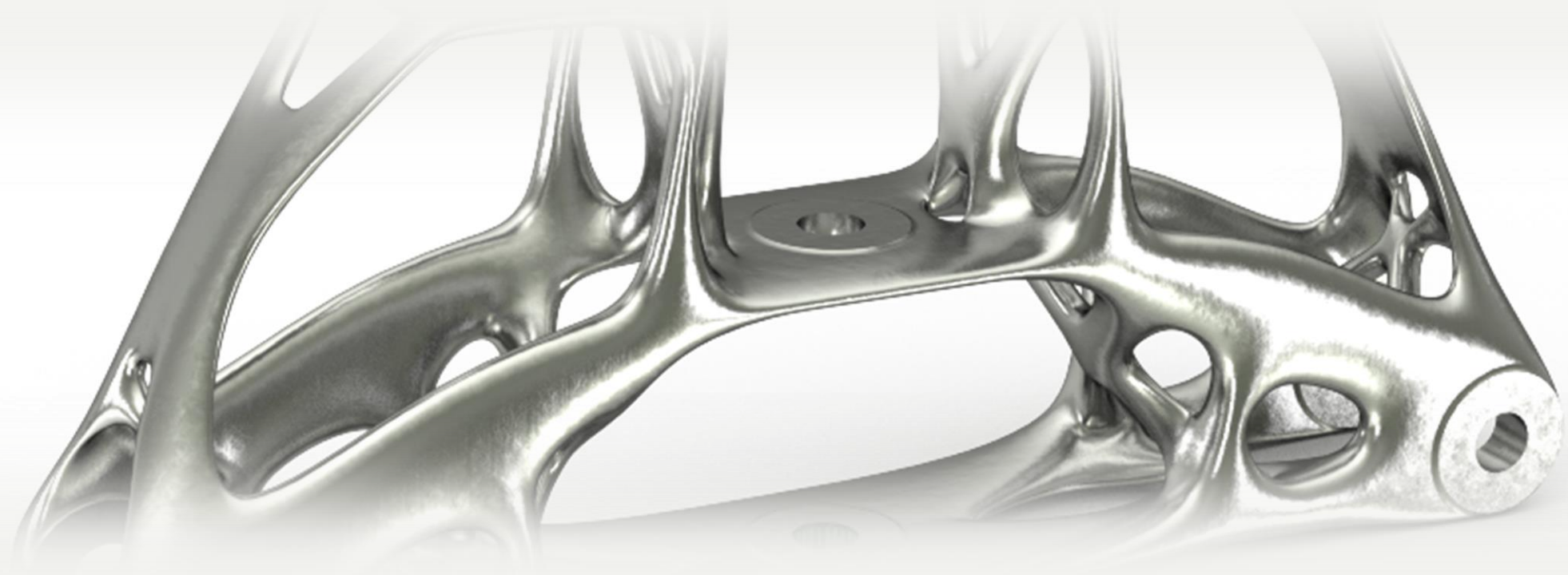
Further studies on microstructure

Validate, Validate, Validate

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(Siemens Digital Industries Software, Belgium).
<http://www.sim-flanders.be/research-program/m3>

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