Research-oriented Project/Master topics in Nanomechanics and new Materials NTNU Nanomechanical Lab (NML) Department of Structural Engineering

NTNU Nanomechanical Lab

Faculty

Researcher

Adjunct Profs

Postdoc

- Nanomechanics
- Interface mechanics
- Advanced mechanics

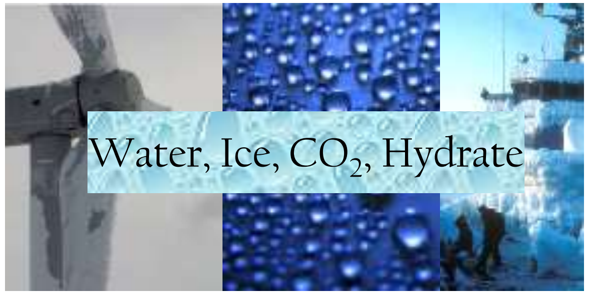
16 PhD students in 2020

~ 30 international journal papers in 2019

Nanostructured materials

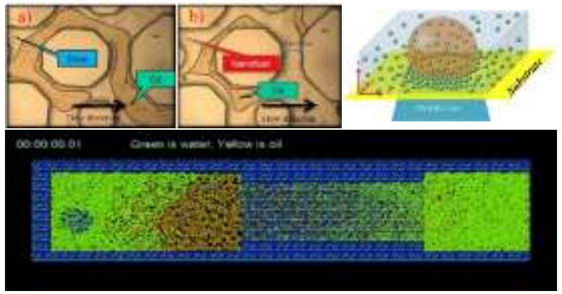
Advanced Functional Materials (2019)
Applied Materials Today (2019)
Small (2019)

Surface Design



Materials Horizons (2019)
Soft Matter (2019)
Nanoscale (2019)
Chemical Engineering J (2019)

Nano EOR



Environ Sci Nano (2019)
Phys Chem Chem Phys (2019)
AIP advances (2019)

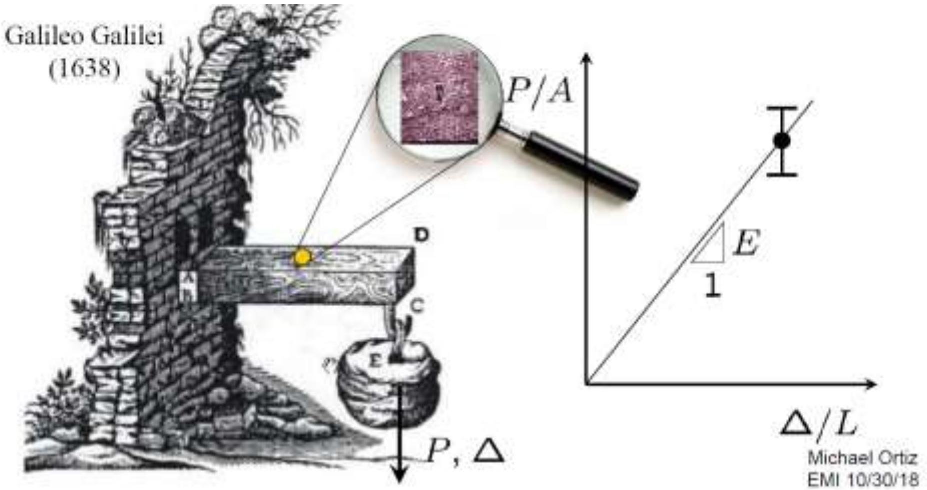
Fracture Mechanics
Hydrogen embrittlement
Advanced mechanics

Mat Sci Eng A (2019)
Engineering Failure Analysis (2019)
E J Mechanics A (2019)
Engineering Fracture Mechanics (2019)

List of project/master Topics

- Data-driven computational mechanics
- Predictive additive manufacturing
  - Development of novel patterns
  - Machine learning based thermal field predictions
  - Digital twinning of additive manufacturing
- Existing gas pipelines for future hydrogen transport? – modelling of hydrogen embrittlement

Data-driven computational mechanics



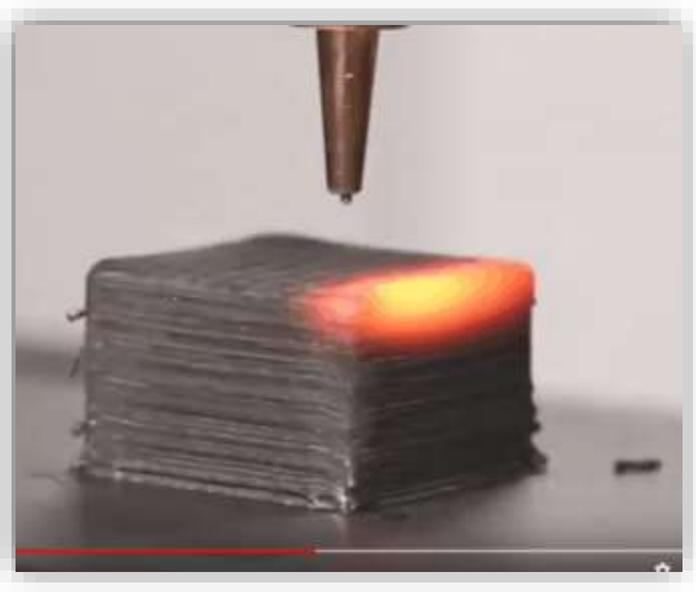
- Mechanics is built up by three fundamental relations, the so-called KLM relations
  - **Compatibility (K)** – exact
  - **Equilibrium (L)** - exact
  - **Material law (M)** – approximate and empirical
- ***Traditional***: Fit data, use calibrated empirical material models
- ***Data-Driven computational mechanics*** (*model-free*):
- Use material data directly (no fitting by any name, no loss of information, no broken link between material and manufactured data)

Project/master study in Date-driven computational mechanics

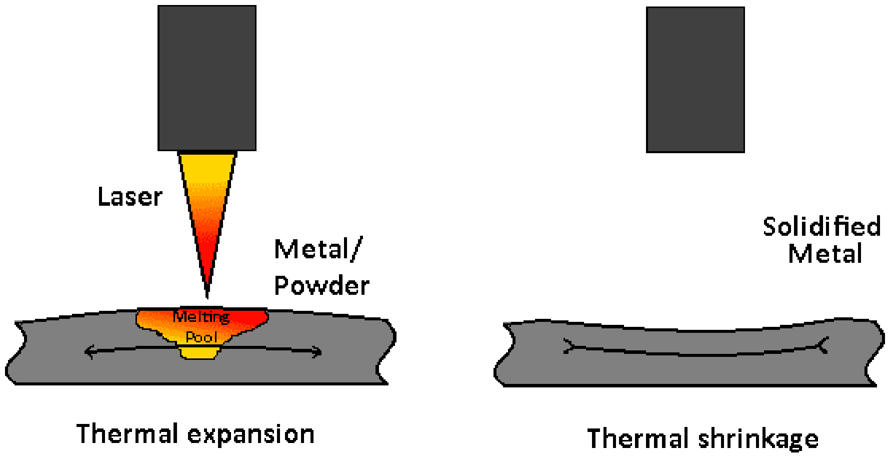
- Literature survey
- Familiar with data-driven codes
- Repetition of literature examples

- Further literature study
- Modification of the data-driven codes
- Solving of relevant engineering problems

Additive manufacturing (AM)



The future manufacturing technology



- High temperature gradient
- High heating and cooling rate

- Distortion
- Residual stresses
- Cracking

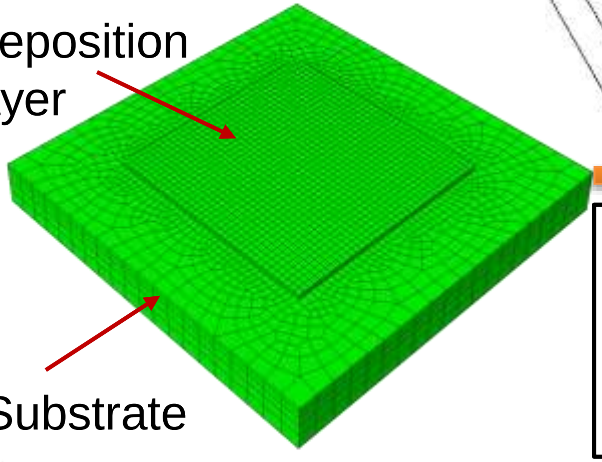
AM has been transiting from demonstrative prototypes to functional products that are impacting a wide variety of sectors, from biomedical, electronic, and automotive to renewable energy industries

Predictive AM Modelling

Based on many years thermal-mechanical-material modelling experience, NTNU Nanomechanical Lab is targeting the so-called Predictive AM

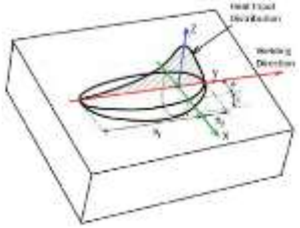
Process

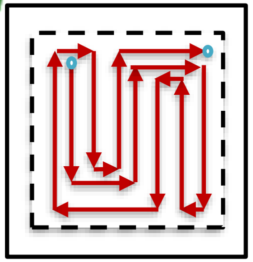
Deposition layer



Substrate

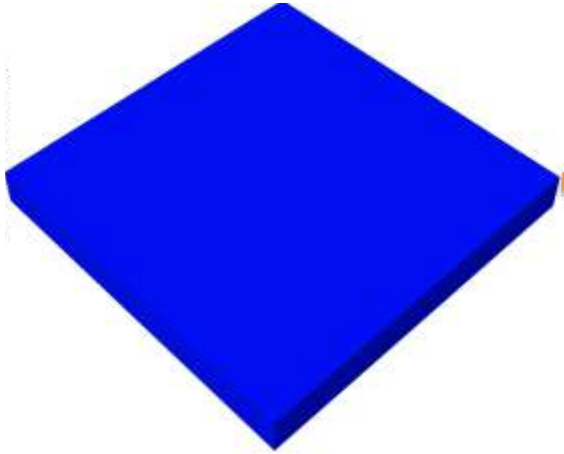
Heat source model





Patterns

Thermal Field



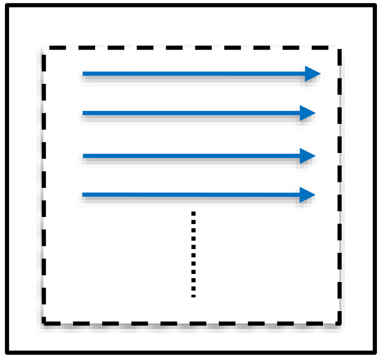
Mechanical field

- ❖ Process parameters
- ❖ Scanning patterns
- ❖ geometry

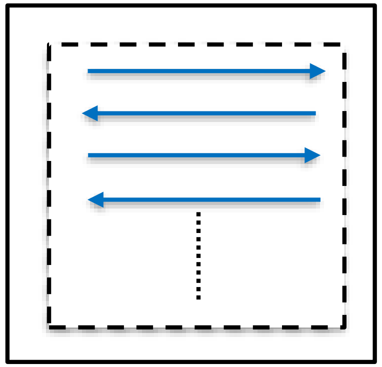
- ❖ Temperature distribution
- ❖ Temperature history

- ❖ Stress/strain fields
- ❖ Mechanical properties
- ❖ Life time performance

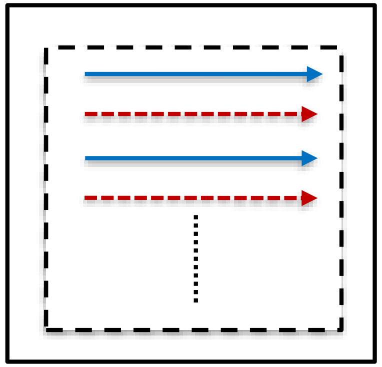
Traditional deposition patterns in AM



Raster



Zig-zag



Alternate-line

Direction-parallel

Patterns

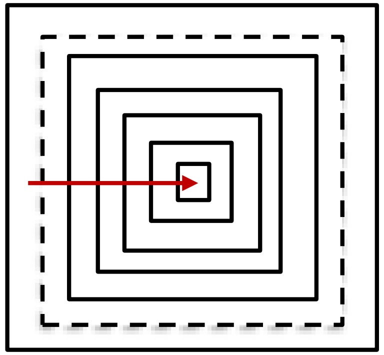
❖ Not Continuous

❖ High residual stress and distortion

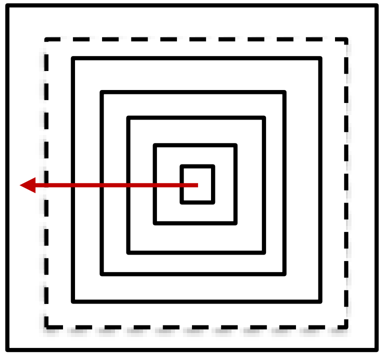
Contour-parallel

Patterns

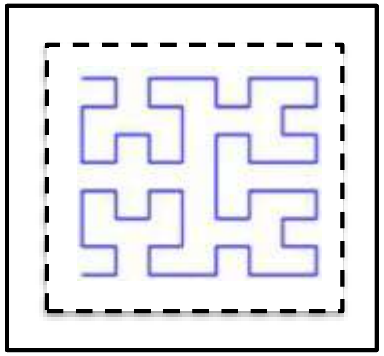
❖ Not weave pattern



Outside-in spiral



Inside-out spiral



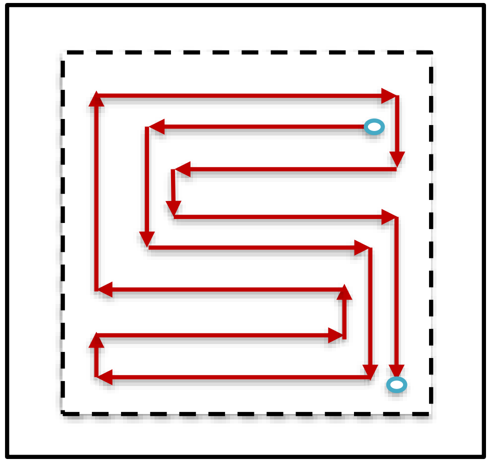
Hilbert

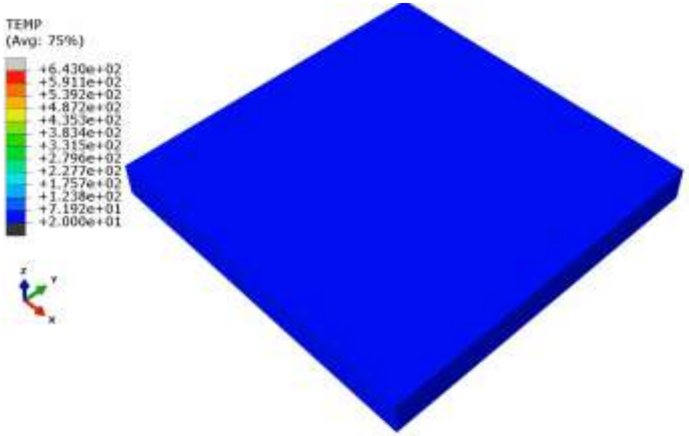
Fractal

❖ Many pattern elements

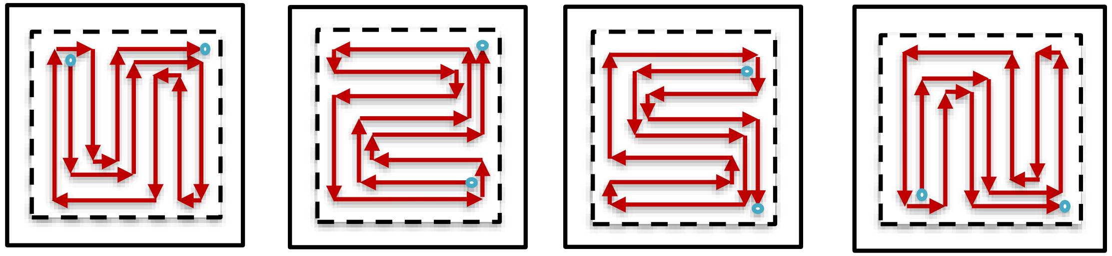
Developing novel deposition patterns

Aim: to reduce the residual stresses

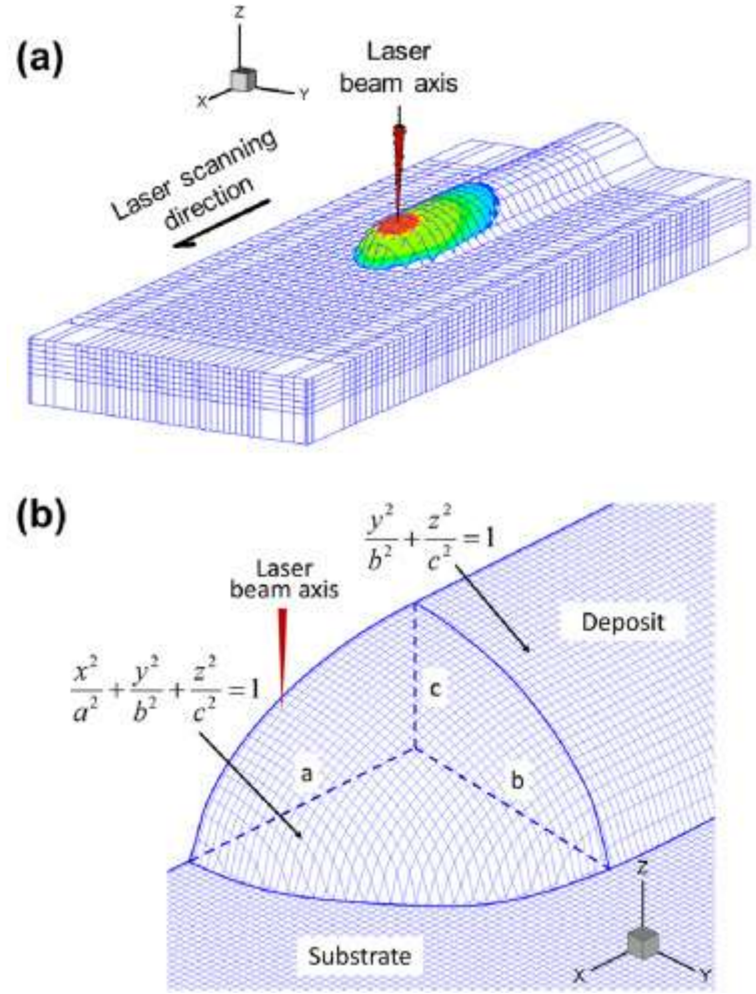




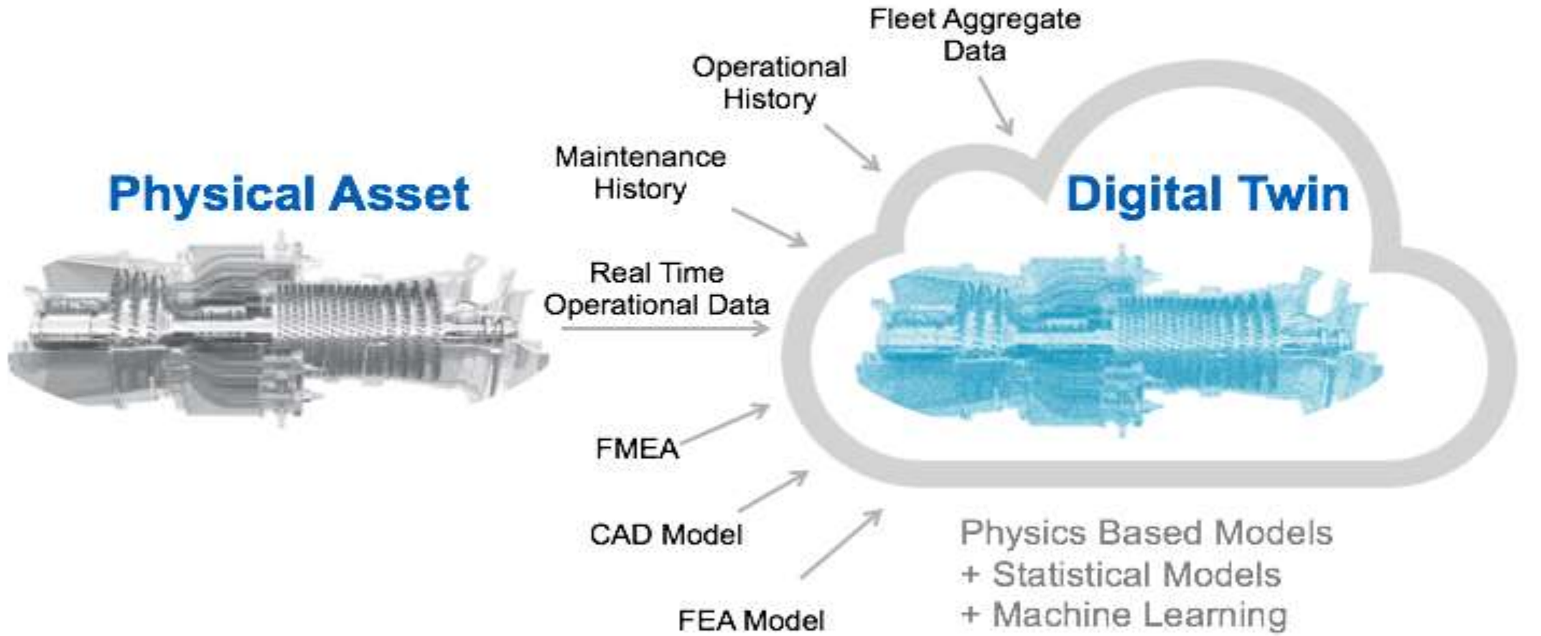
- ❖ Continuous
- ❖ Weave pattern (Multi-layer)
- ❖ Less pattern elements
- ❖ Alternate pass direction
- ❖ Adjustable pass length



Digital Twin of AM soon a reality



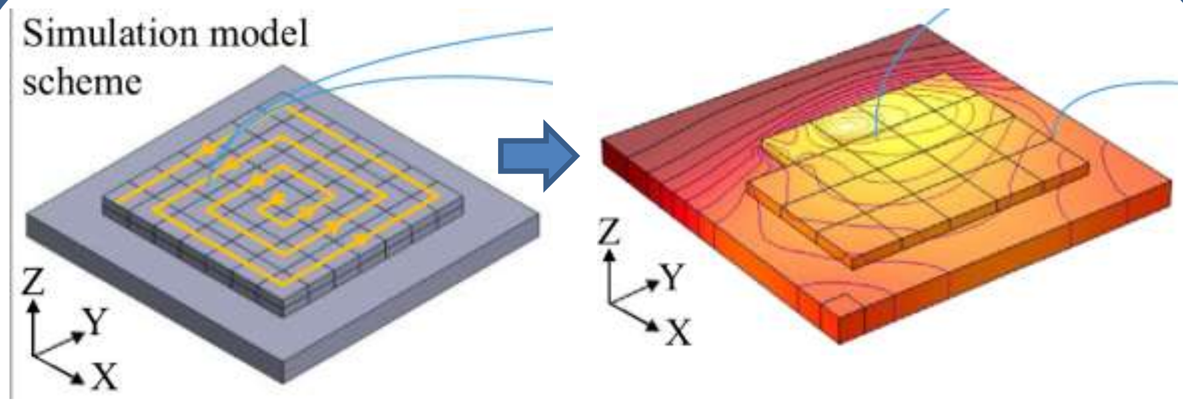
- Digital twin of AM does not yet exist
- Extensive research world wide!
- You can contribute to add building blocks of a digital twin to AM

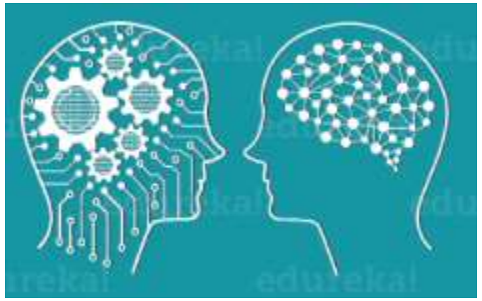


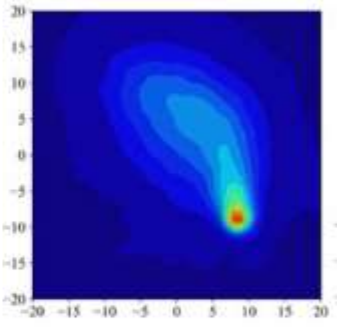
Predicting AM Thermal field for any geometry ant scanning pattern by FEM+ML

- Residual stresses and final material properties are controlled by the thermal field
- If we can predict the thermal fields, we can link to the mechanical properties
- For arbitrary geometry, it is very time consuming
- Machine learning plays an important role here

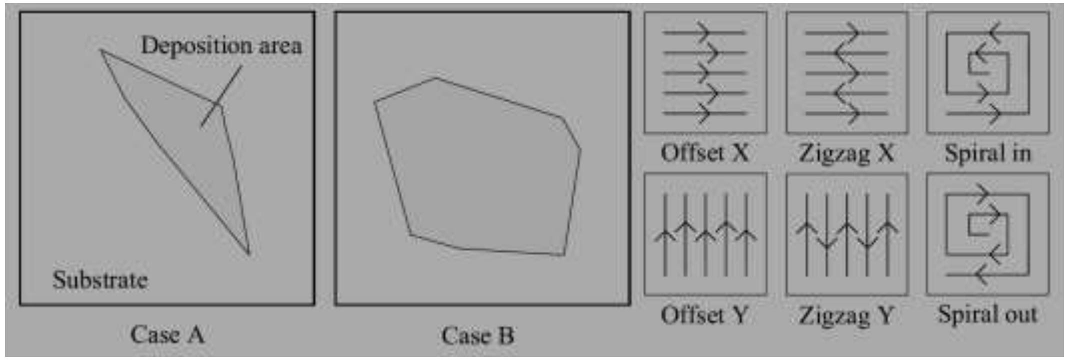
Predicting AM Thermal field for any geometry ant scanning pattern by FEM+ML

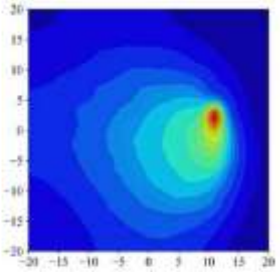






Case A: Prediction Spiral out

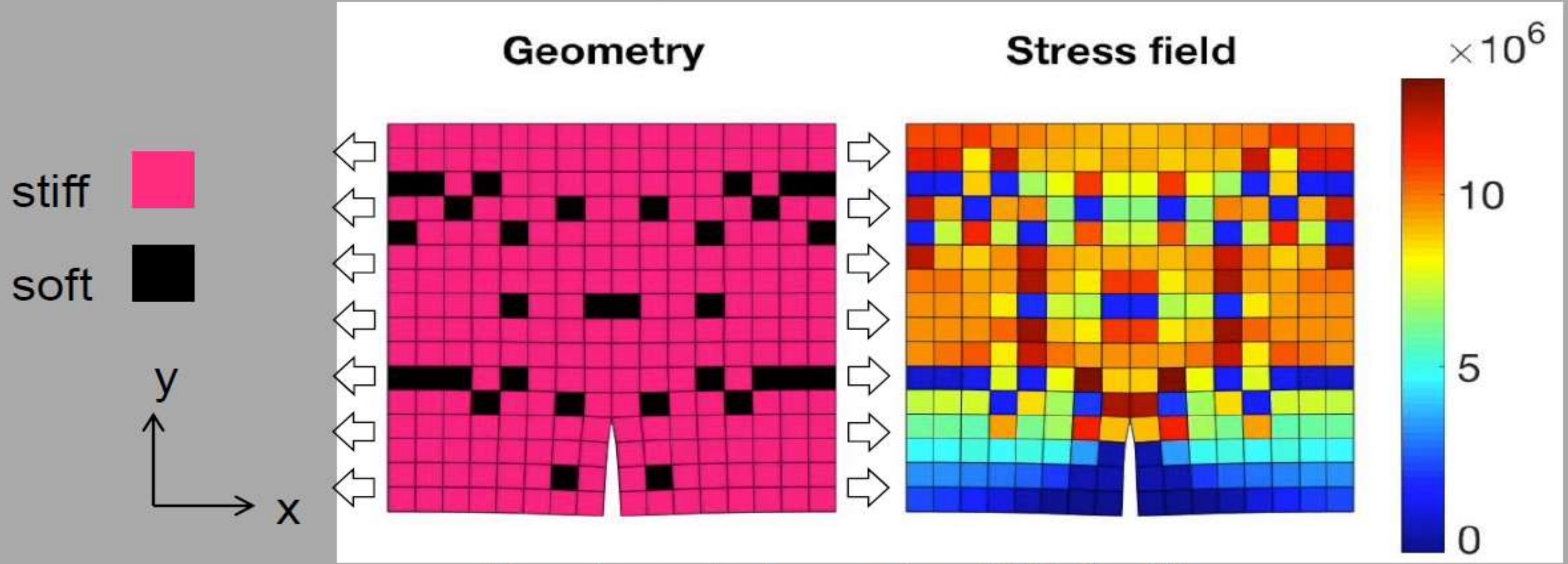




Case B: Prediction Zigzag Y

FEM+ML for Material Design

How to distribute stiff and soft elements to achieve the highest toughness for the composite under Mode I fracture?



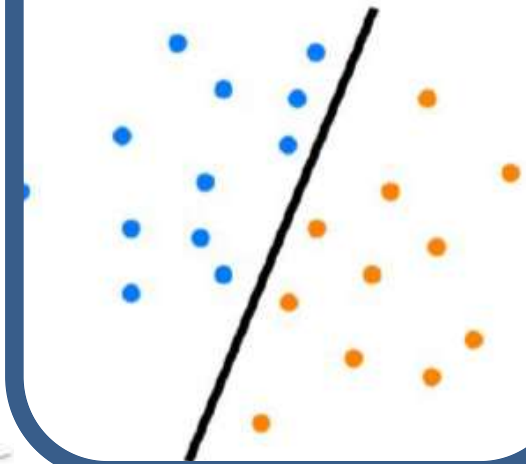
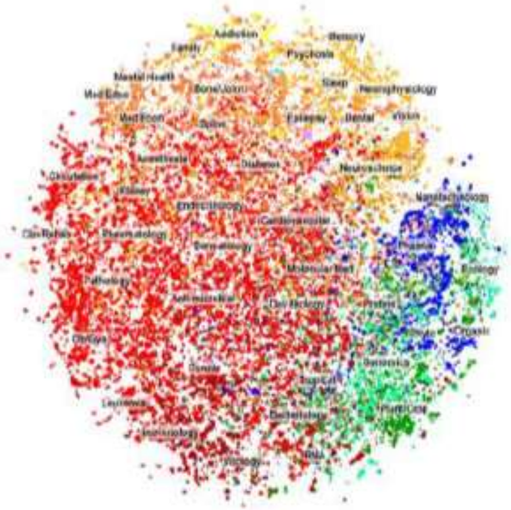
- Number of elements: 128 (half)
- Geometry constraint: 12.5 % soft
- Number of combinations: $\sim 10^{20}$
- Computational cost: 20 samples/sec
- Brute-force: 158 billion years

FEM and Machine Learning

Prediction of top performing geometries

- Without knowing any mechanics, without even knowing that the geometry has a given edge crack, the ML model discovers the kind of pattern that leads to high-performance scores

Three types of learning

Supervised	Unsupervised	Reinforcement
Learning known patterns	Learning unknown patterns	Generating data Learning patterns
		

Project/master in predictive additive manufacturing

- Project
  - Literature study on AM
  - Learning simple FEM modelling of additive manufacturing process
  - Literature study of ML, basic knowledge of Tensorflow

- Master
  - FEM simulations of AM
  - Database building for training with ML
  - Prediction and Verification

Safe Pipelines for Hydrogen Transport (HyLINE) (2019-2022)

Forskningsrådet

GASSCO

equinor

KYUSHU UNIVERSITY

TechnipFMC

Air Liquide creative oxygen

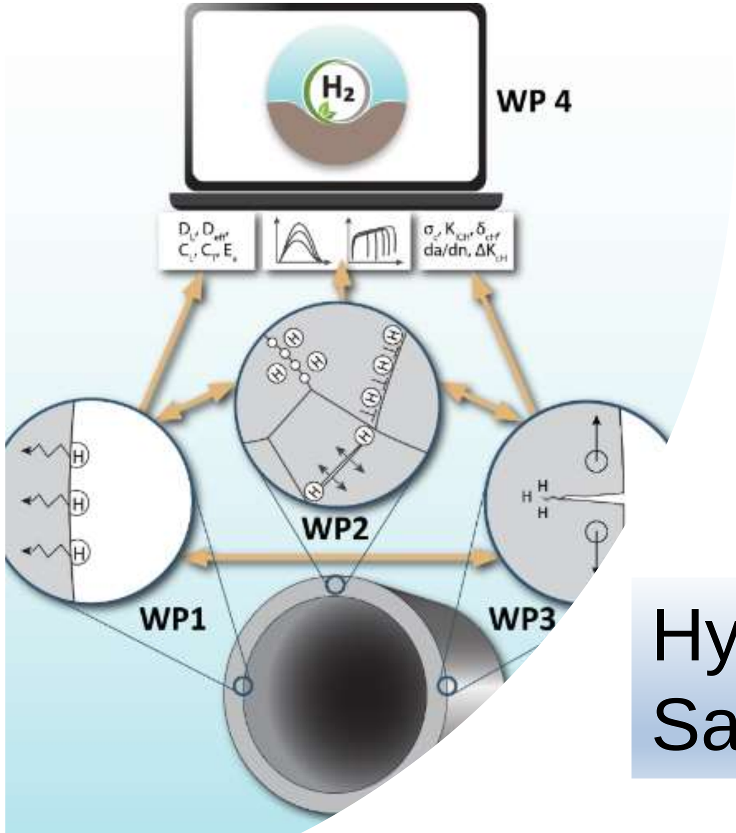
nel

Tenaris

Université de Poitiers

SINTEF

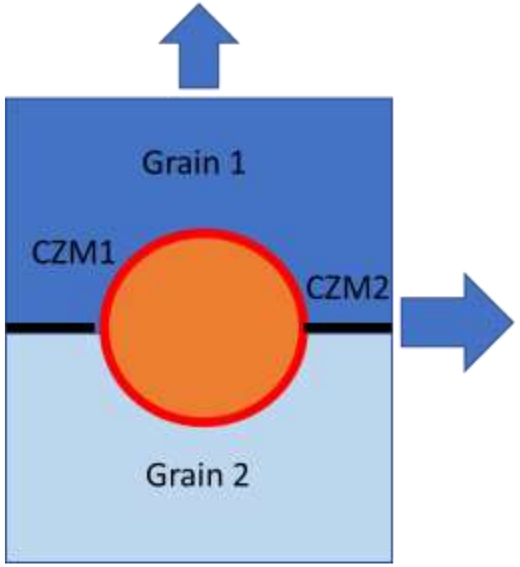
NTNU

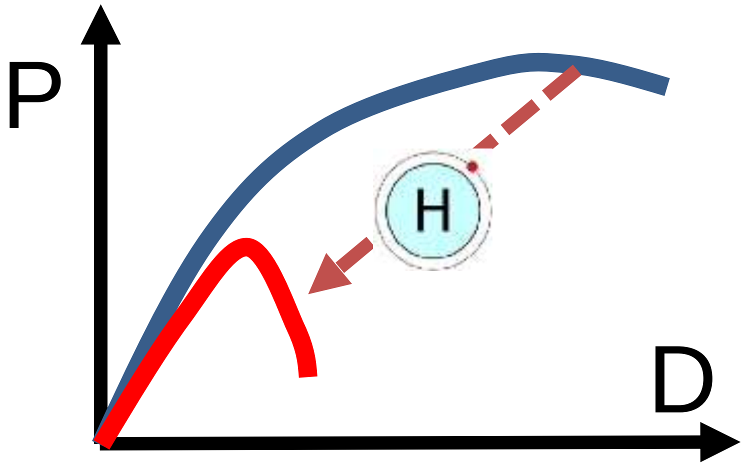


Hydrogen energy
Safe transport

Challenges of transporting H2 instead of gas from Norway to Europe?

Predicting of Hydrogen embrittlement





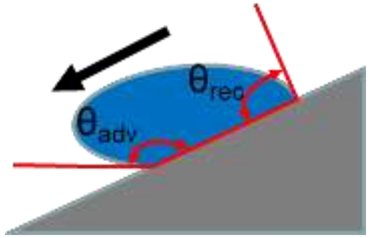
- ABAQUS
- Cohesive zone model (CZM)
- Industrial relevant project

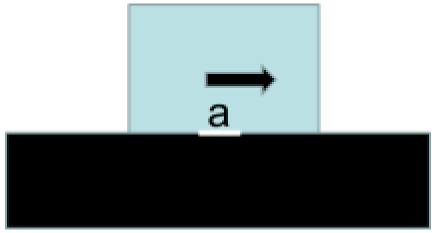
Hydrogen embrittlement (HE): **Ductile** materials under clean environment becomes **brittle** under H environment

Other Topics

- We have several ongoing research projects financed by the Norwegian research council and Norwegian industrial partners, related to nanomechanics, multiscale modelling and new materials using both experimental methods and numerical approaches.

How to Lower the Ice Adhesion?





Interface Youngs modulus

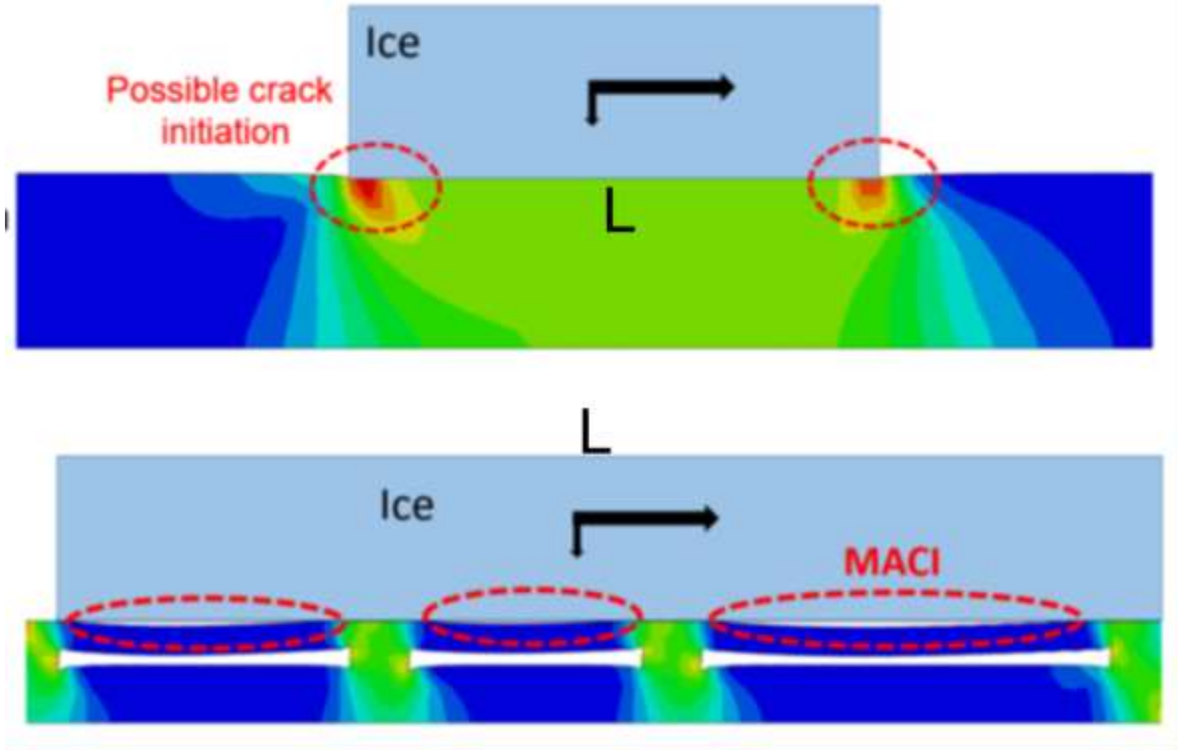
Surface energy

$$\tau_c = \sqrt{\frac{E^* G}{\pi a \Lambda}}$$

Crack size

Boundary dependent constant

Fracture Mechanics-based design to lower the ice adhesion



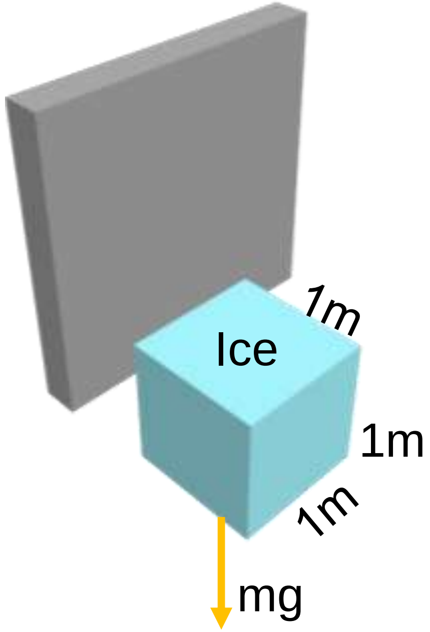
Macroscopic Crack Initiators (MACI)

- **5** ongoing research-projects on anti-icing related projects by the Norwegian research council.
- Many exciting master topics for both continuum mechanics-oriented or nanotechnology students
- Both numerical or experimental methods

How Low is Low Enough?

$$\tau_c = \frac{\rho L^3 g}{L^2} = \rho L g$$

- Metallic untreated surfaces: >~**600 kPa**.
- Non-textured fluorinated surfaces: ≥ ~**200 kPa**
- Icephobic surfaces: ≤ **100 kPa**
- Low ice adhesion surface: ≤ **60 kPa**
- US Navy wanted: ≤ **30 kPa**
- NML: Super-low ice adhesion surfaces (SLIAS) ≤ **10 kPa**
- NML: lowest: ~**1 kPa without surface additives**



NML produced world's lowest ice adhesion surfaces based on fracture mechanics theory

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