MCR Centre for Metal Cutting Research

CHALMERS UNIVERSITY OF TECHNOLOGY

A framework for the physics-based estimation of tool wear in machining process

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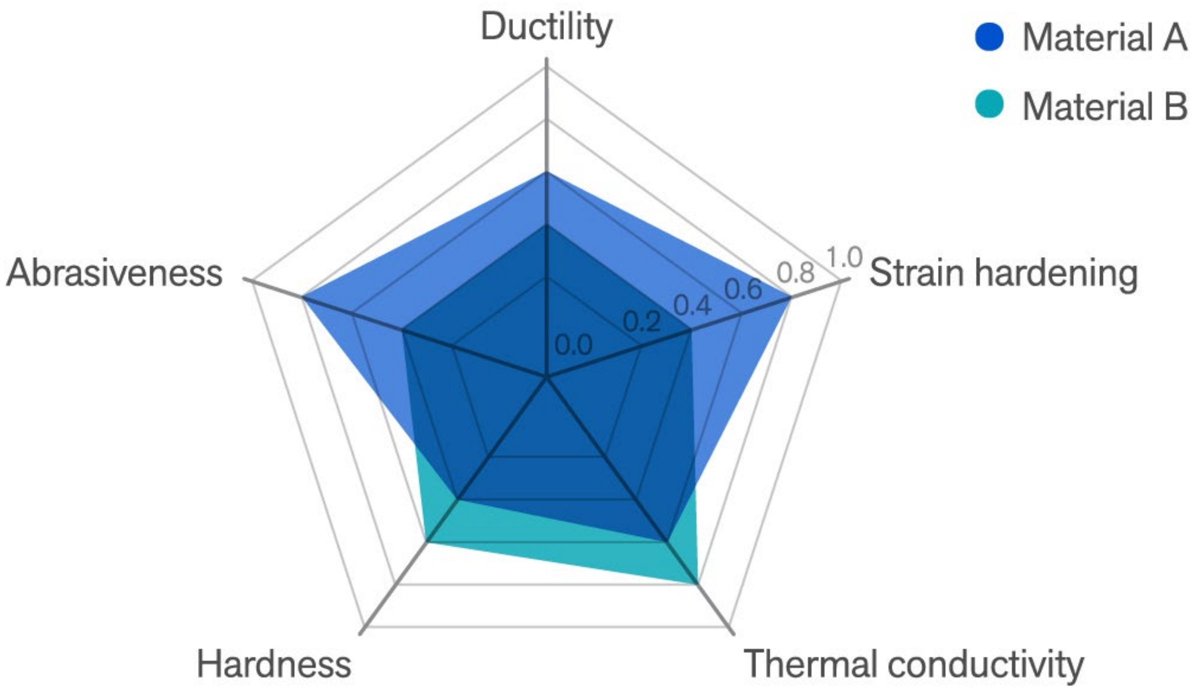
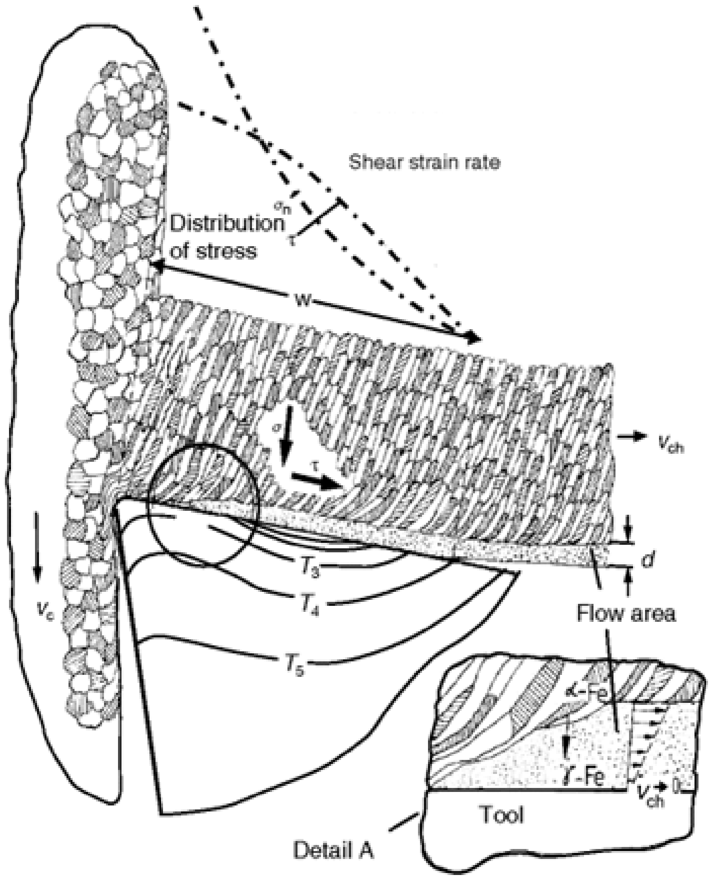
Machinability

The machinability of an alloy is similar to the palatability of wine – easily appreciated but not readily measured in quantitative terms.

Edward M. Trent



Source: Adapted from Metal cutting theories in practice, Jan-Eric Ståhl and Partick De Vos



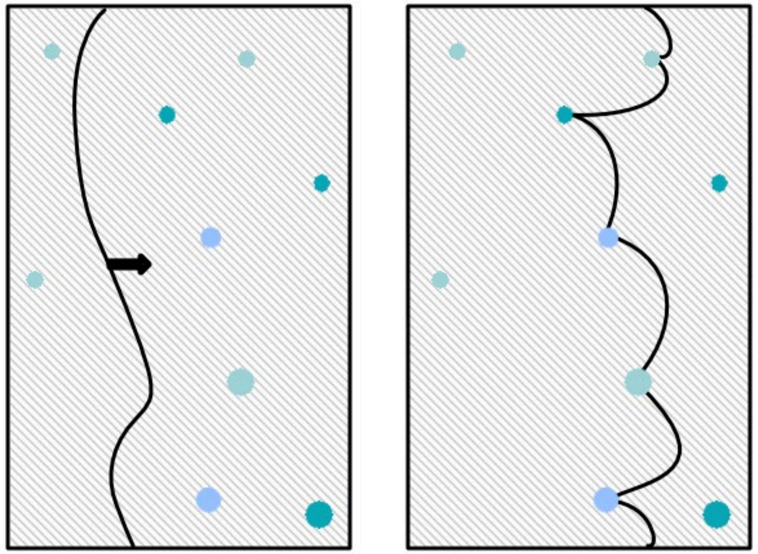
H Opitz, W König, 1968

Batch-to-batch material variation in a micro-alloyed steel

- Up to 17% variation in yield strength ($Rp_{0.2}$)
- Up to 15% variation in tensile strength (Rm)
- Variations in hardness
- Variations in oxide type/amount according to ASTM E45
- Variations in amount of carbo-nitride former elements

(Ti,V)(C,N) precipitates:

- Control grain growth during austenitisation & forging
- Influence mechanical properties



Casting

- **Non-metallic inclusion** type, size & amount
- Amount of free nitrides

Do not have major impacts on mechanical properties.

Thermo-mechanical processes

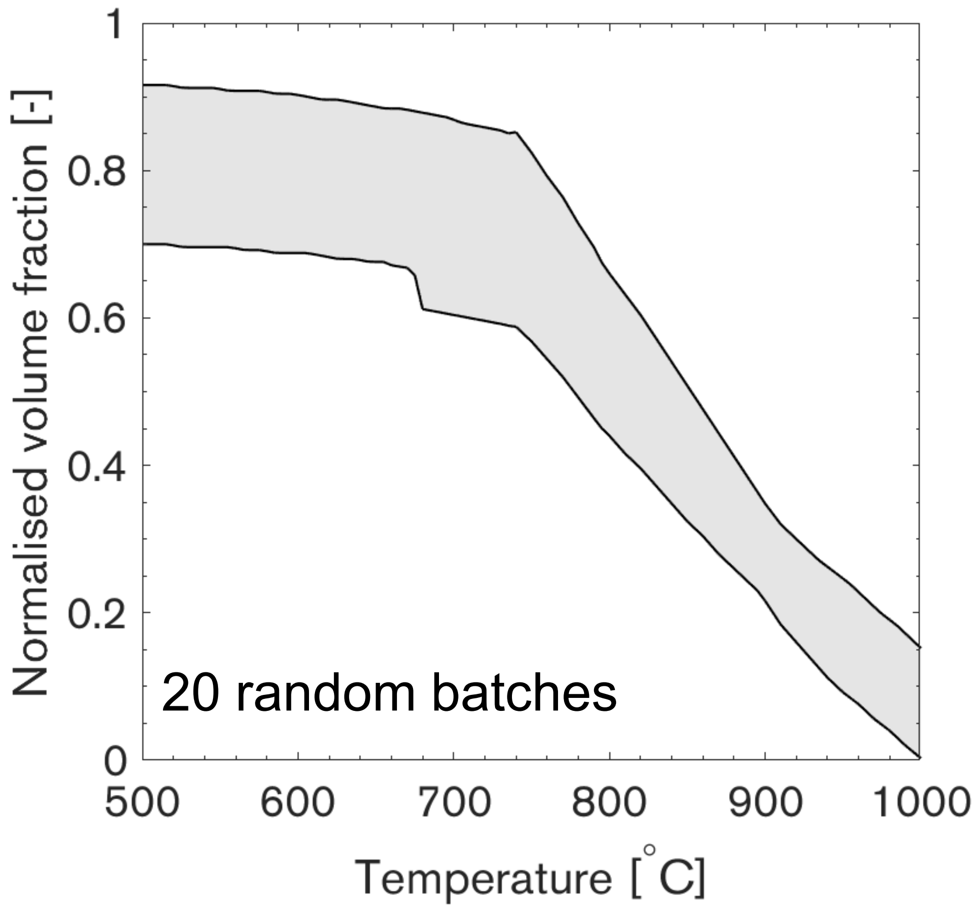
- Pearlite lamellar spacing
- Pearlite colony size
- Prior-austenite grain size
- Amount of precipitants
- Prior work-hardening

Do have significant impacts on mechanical properties.

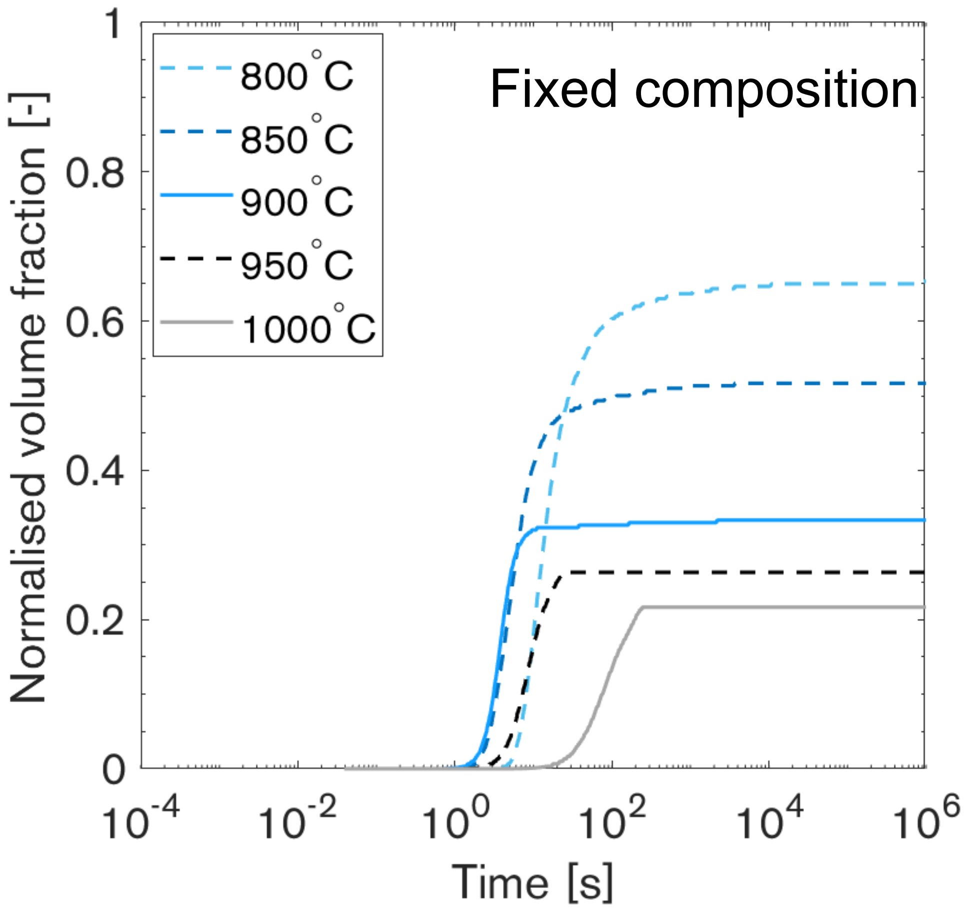
Effects of thermo-mechanical processes

Batch-to-batch variations

Variations in the equilibrium amount (volume fraction) of (**V**,Ti)(C,N) precipitates



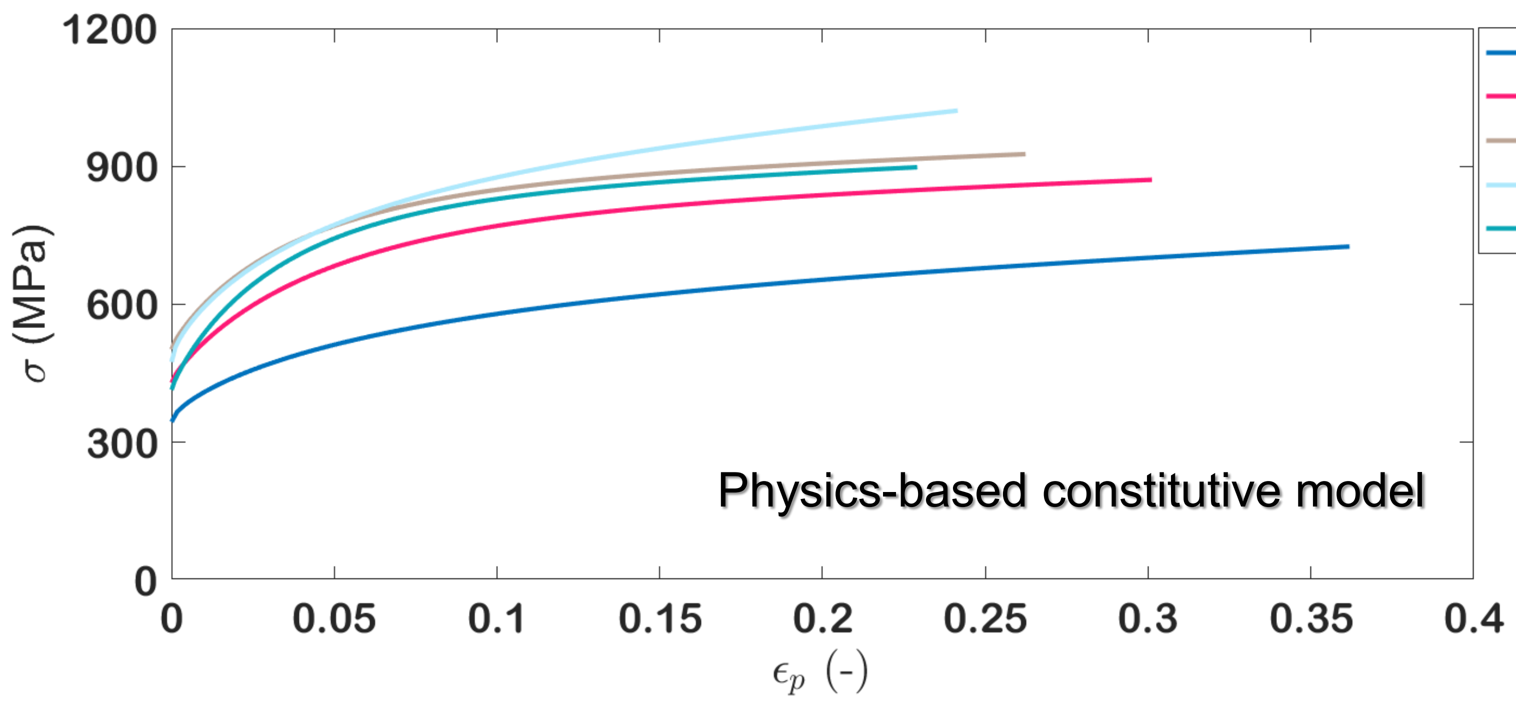
Normalised volume fraction of (**V**,Ti)(C,N) with aging time under different isothermal conditions



Flow stress properties of (micro-alloyed) steels

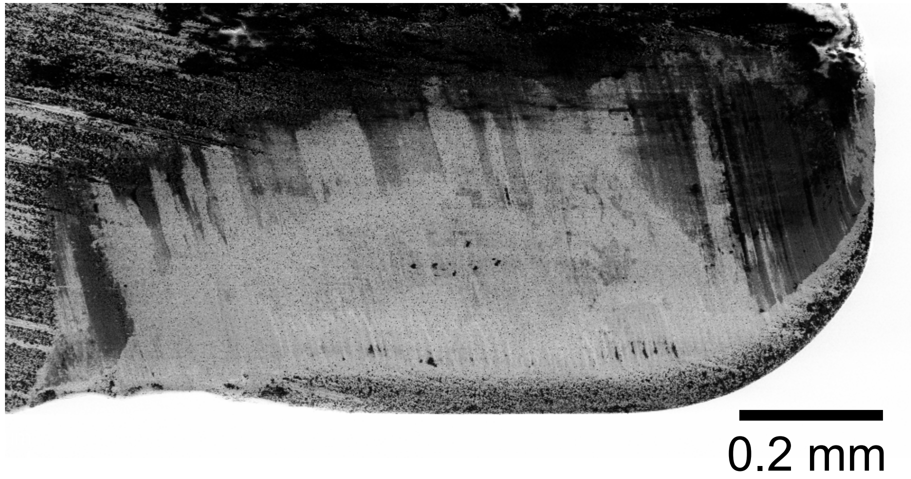
- Chemical composition (solid-solution)
- Pearlite lamellar spacing
- Ferrite grain size
- Volume fraction of (V,Ti)(N,C) precipitates
- Size of (V,Ti)(N,C) precipitates
- Prior work hardening – dislocation density

No.	$V_{Pearlite}$ (-)	$D_{Ferrite}$ (μm)	V_{TiVCN} (-)	D_{TiVCN} (nm)	$\lambda_{Pearlite}$ (μm)
1	0.2	20	-	-	0.2
2	0.5	20	-	-	0.2
3	0.5	20	0.002	10	0.2
4	0.3	5	0.002	10	0.2
5	0.6	10	0.001	10	0.4



Effects of non-metallic inclusions

Batch-to-batch material variation in steels



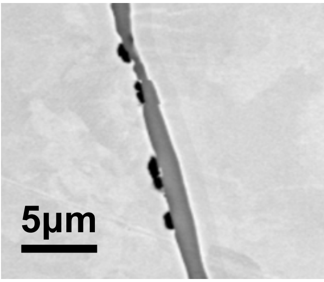
Non-metallic inclusion within the standard specifications **do not** have a major impact on mechanical properties **BUT** they can significantly influence the machinability of steels.

Non-metallic inclusions:

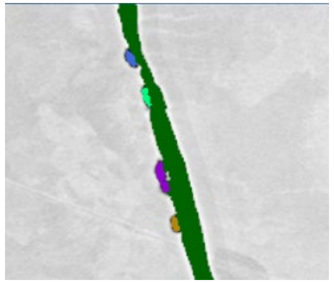
- Control the formation of a protective layer that can affect tool wear progression.
- Influence the contact length between the tool and the chip – thereby affecting the cutting temperature
- Can lead to abrasive tool wear depending on their type, size and amount.
- **Can thus improve the machinability of steels based on the deformability of the inclusions.**

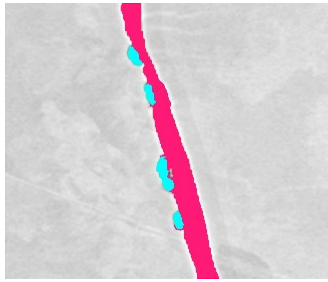
Non-metallic inclusions – an example

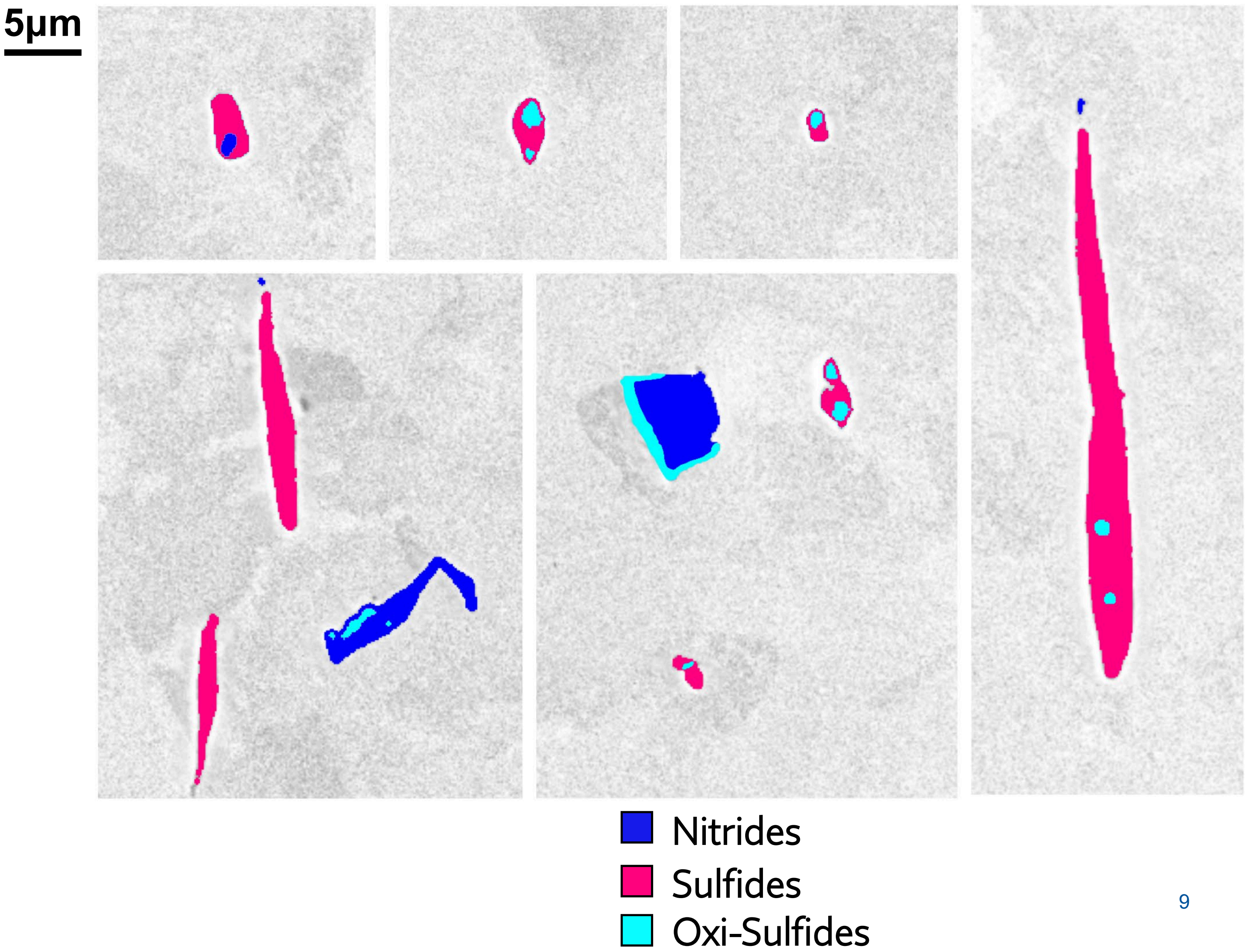
An SEM and EDS analysis of the steels shows the complexity of the inclusions within the matrix.



Acquired Image

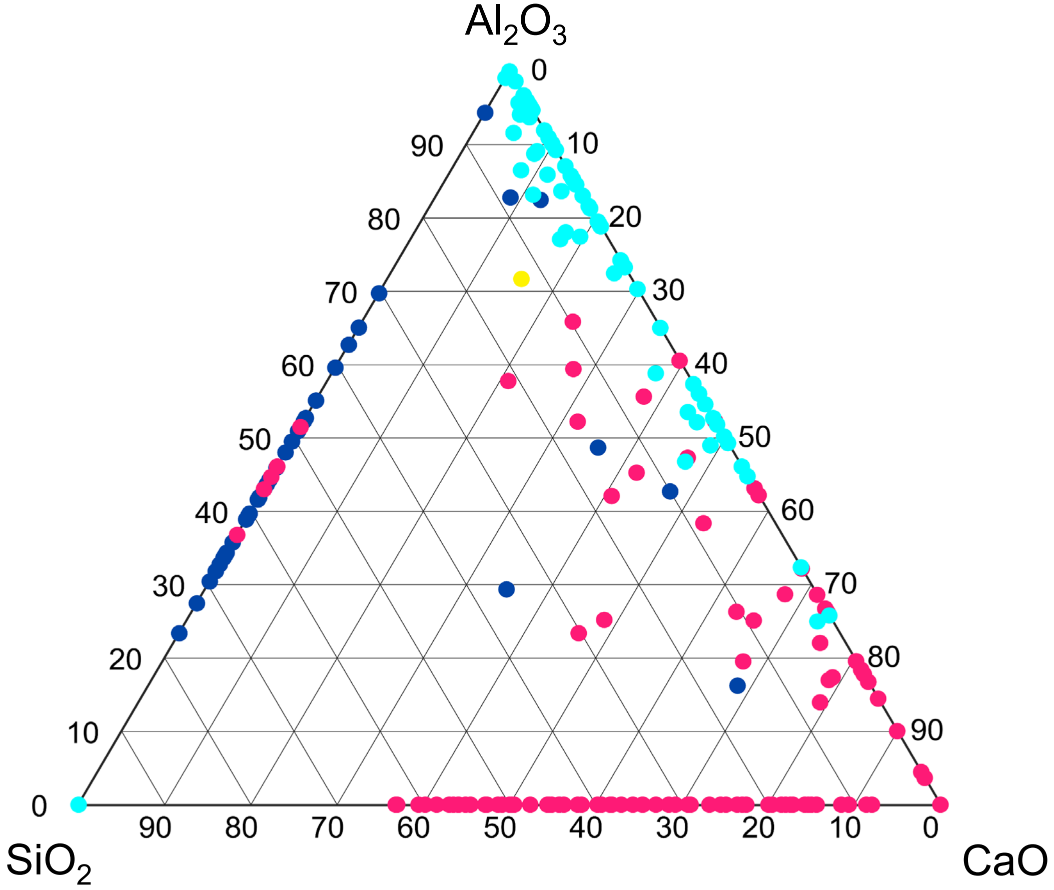

Filtered by Feature


Filtered by Class

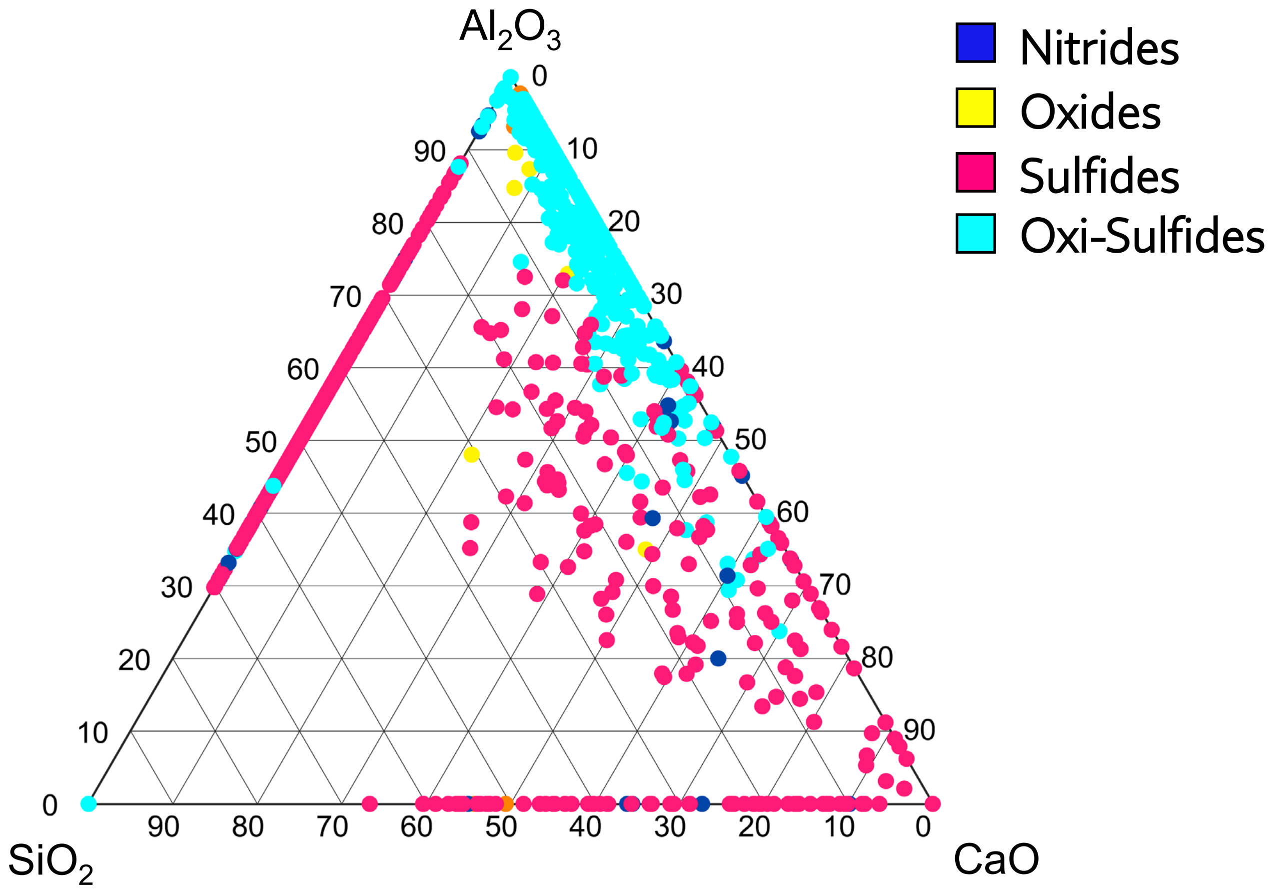


Batch-to-batch material variation in steels

AZtecSteel



Batch 1



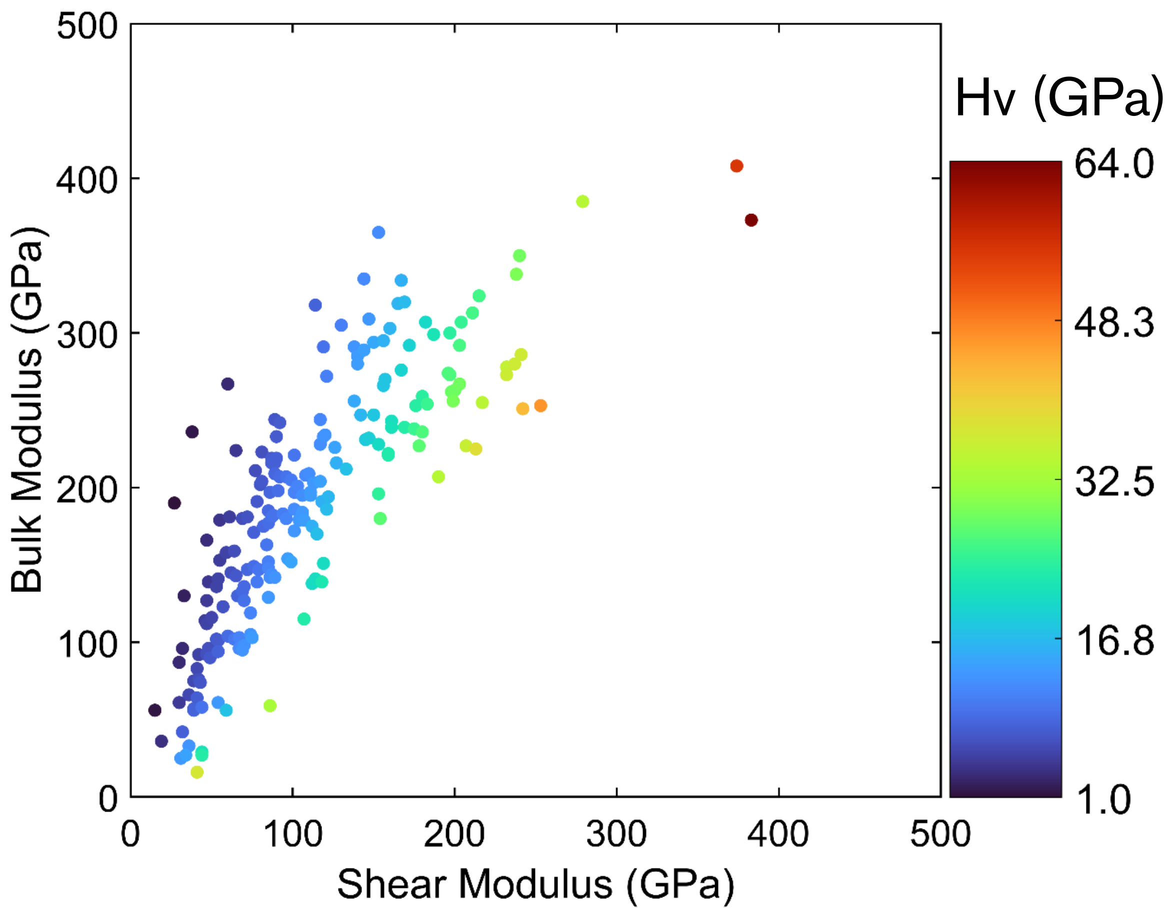
Batch 2

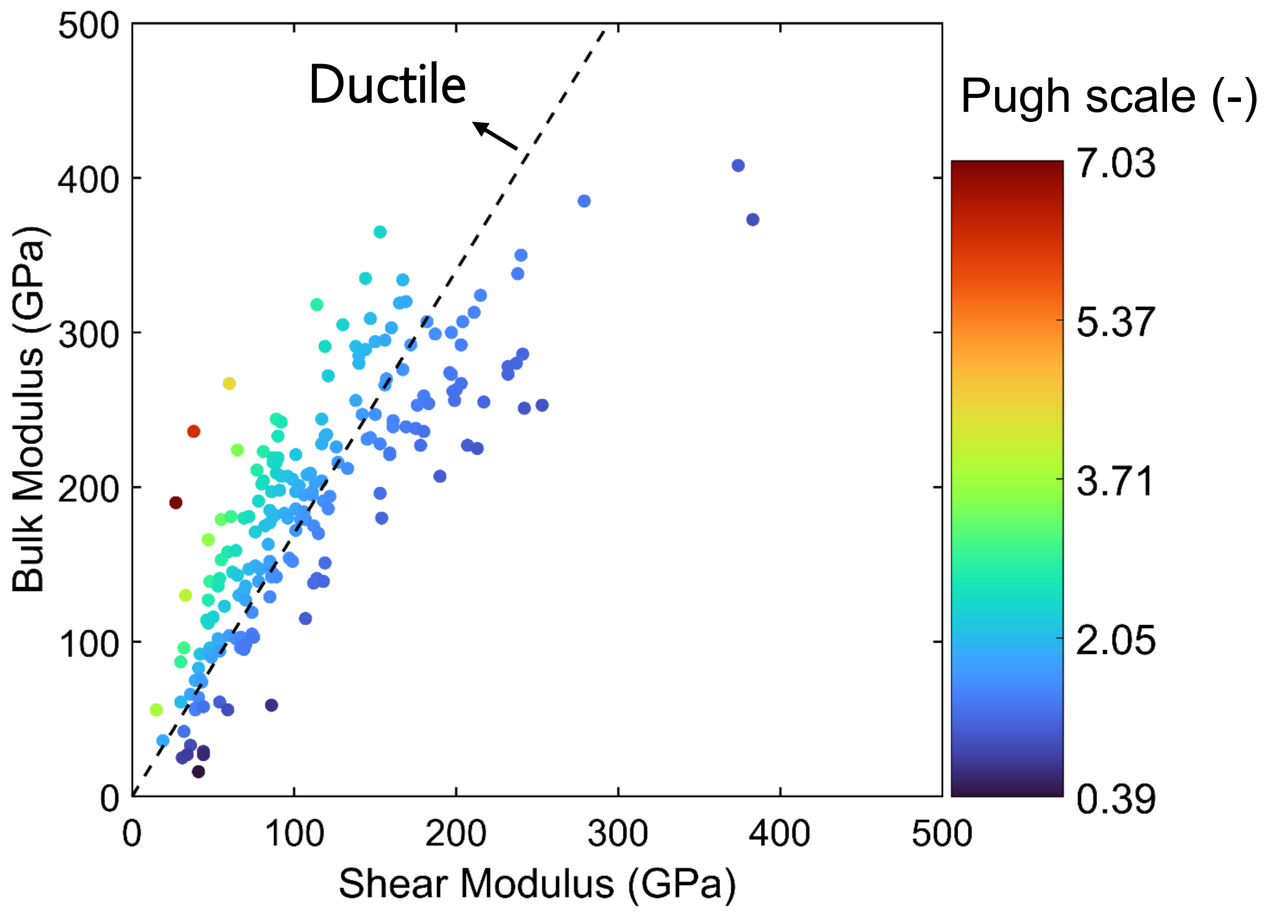
Hardness and ductility

materials design

Density Functional Theory (DFT) + Machine Learning (ML)

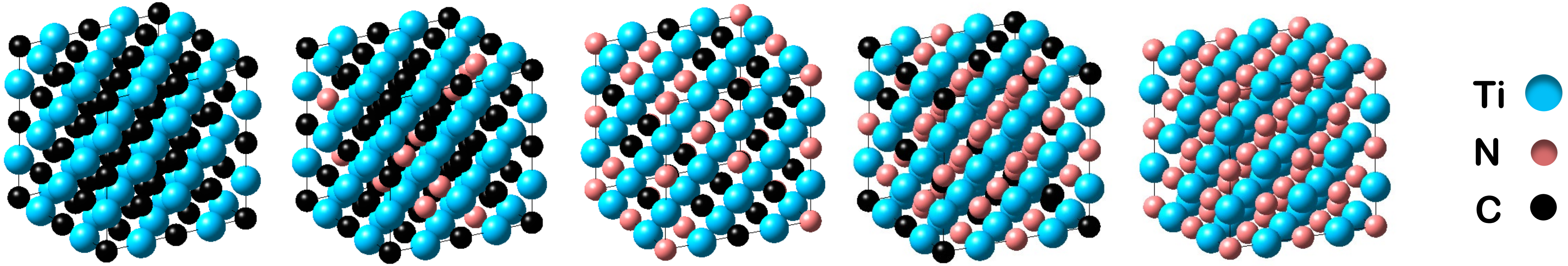
~220 oxides, carbides, nitrides and sulfides have been analysed so far!

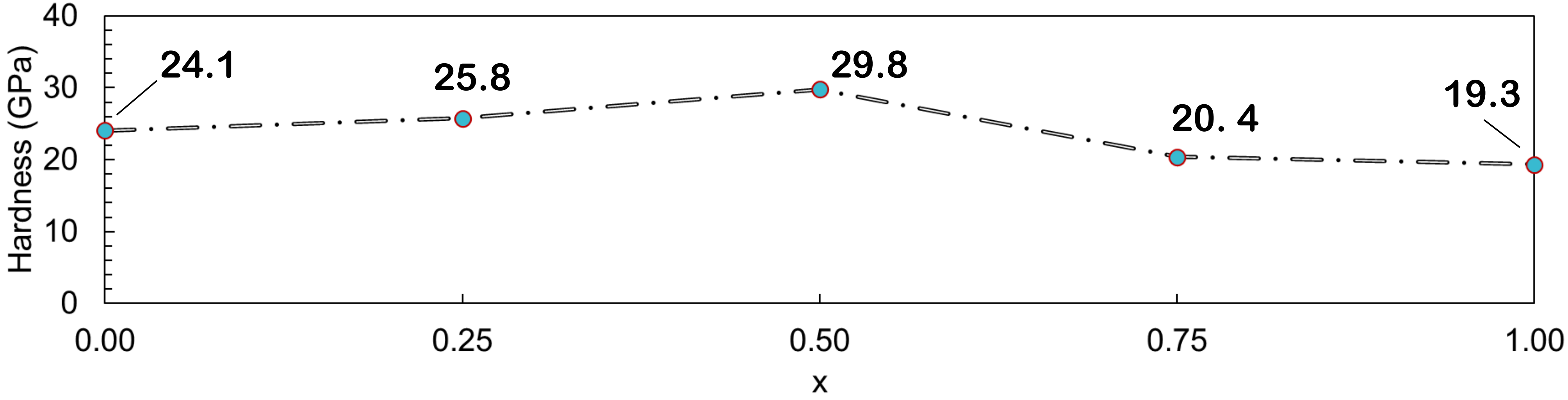




Hardness estimation of $TiC_{1-x}N_x$ carbo-nitrides

- A supercell including 32 **Ti** and 32 **C** atoms!
- 25%, 50%, 75% and 100% of **C** atoms (in **TiC** supercell) were replaced by **N** atoms (**randomly distributed**)!

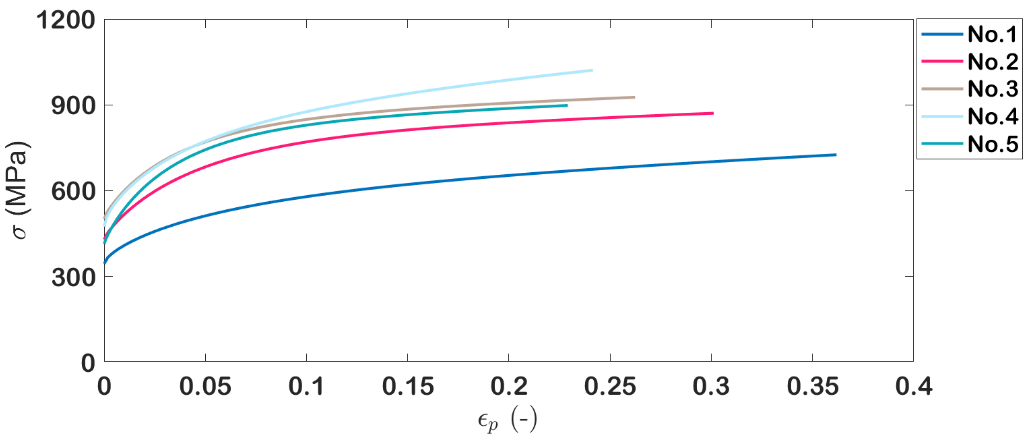




Physics-based machinability assessment

Physics-based platform

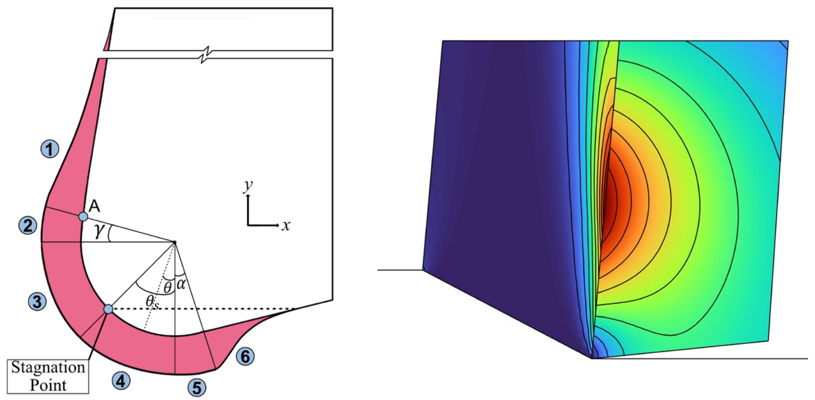
Physics-based constitutive model



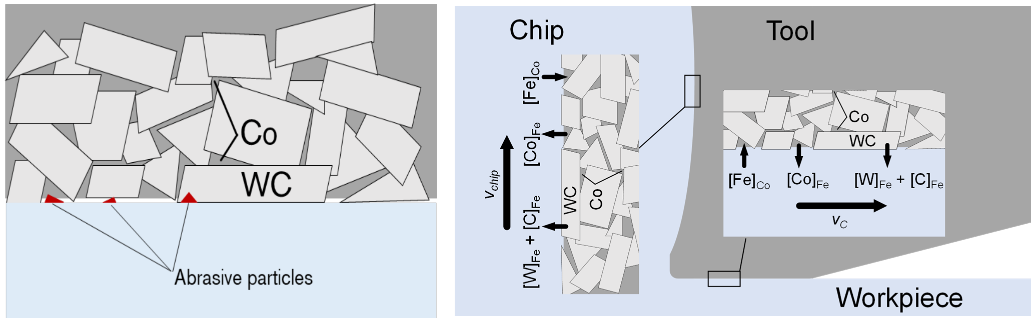
Estimation of thermo-mechanical loads

Stress distribution

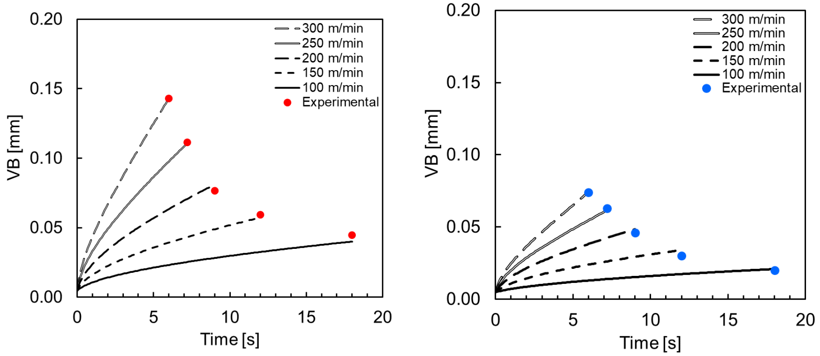
Temperature profile



Physics-based wear model



Physics-based wear estimation

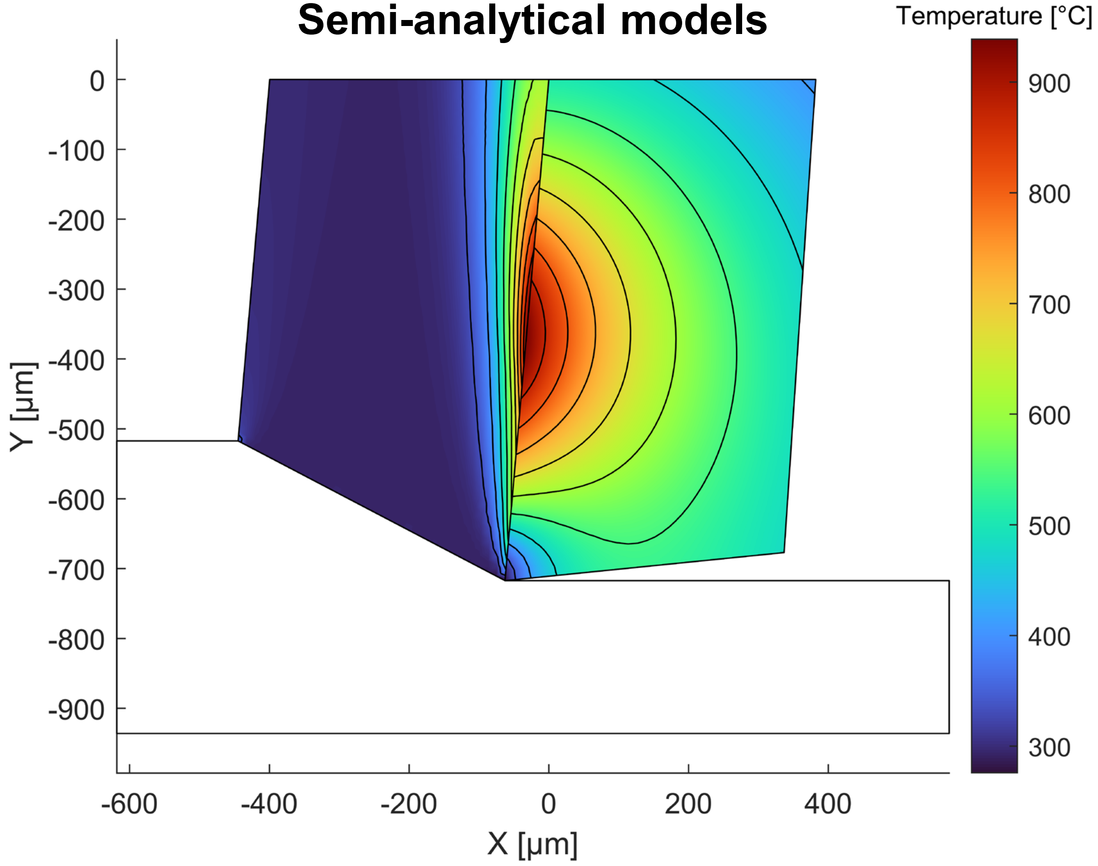


Machinability assessment

Simulation of interface temperature

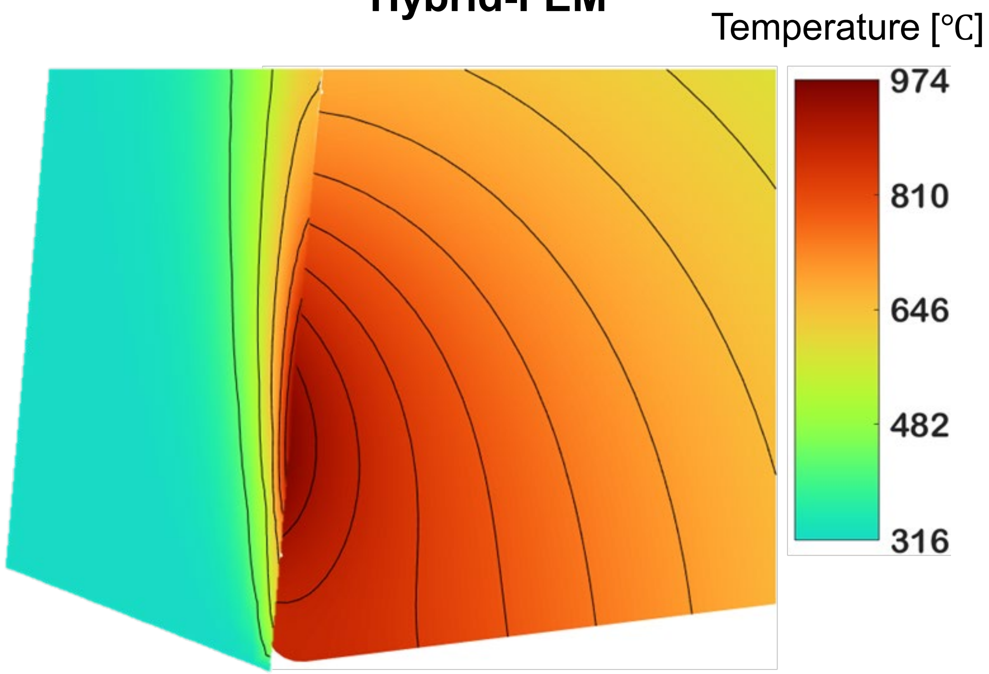
- **Value** of the maximum temperature
- **Location** of the maximum temperature

Semi-analytical models



- Good efficiency
- Good accuracy – less accurate near the cutting edge

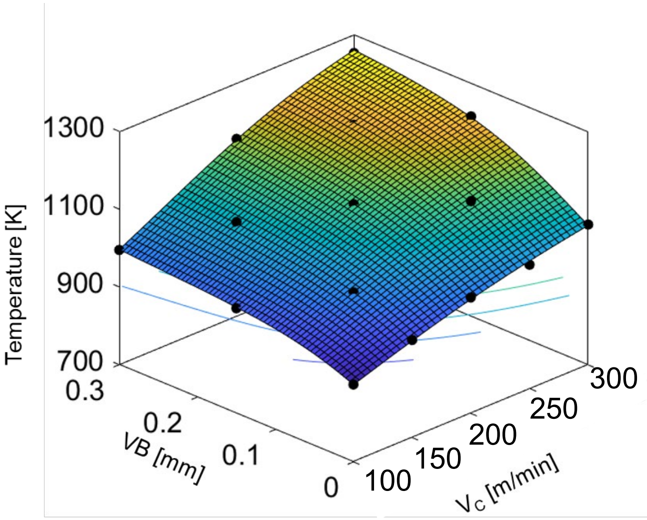
Hybrid-FEM



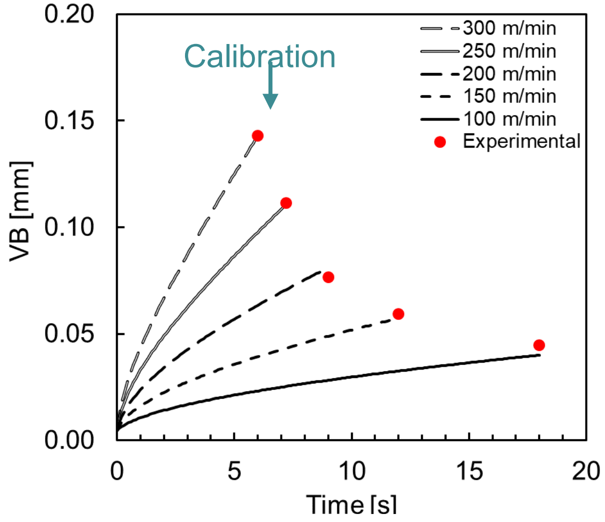
- Better efficiency – calculates in **30-60 seconds**!
- Better accuracy – improved accuracy near the cutting edge

Physics-based wear prediction – an example

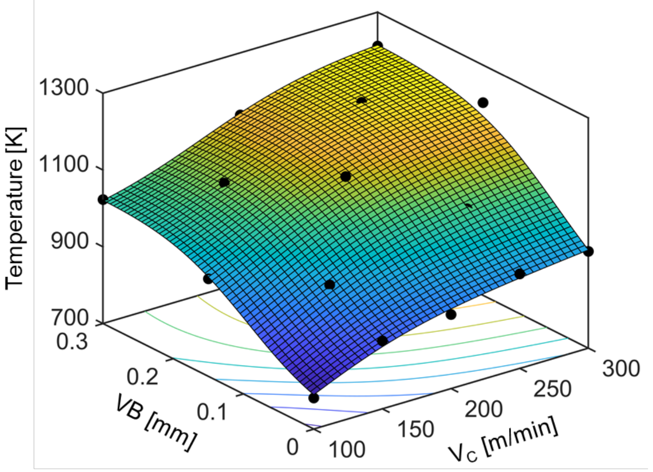
316L



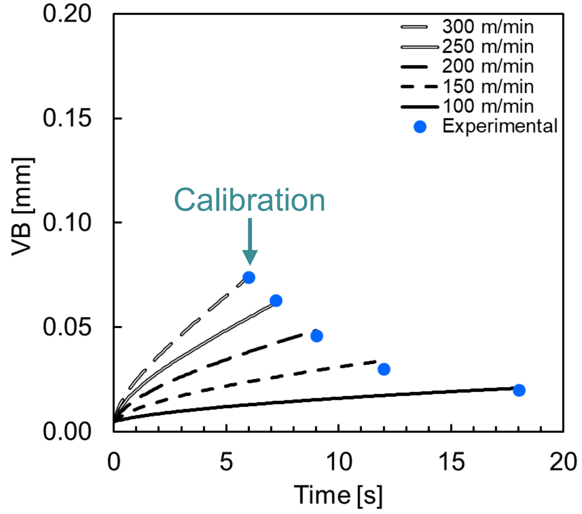
WEAR MODEL



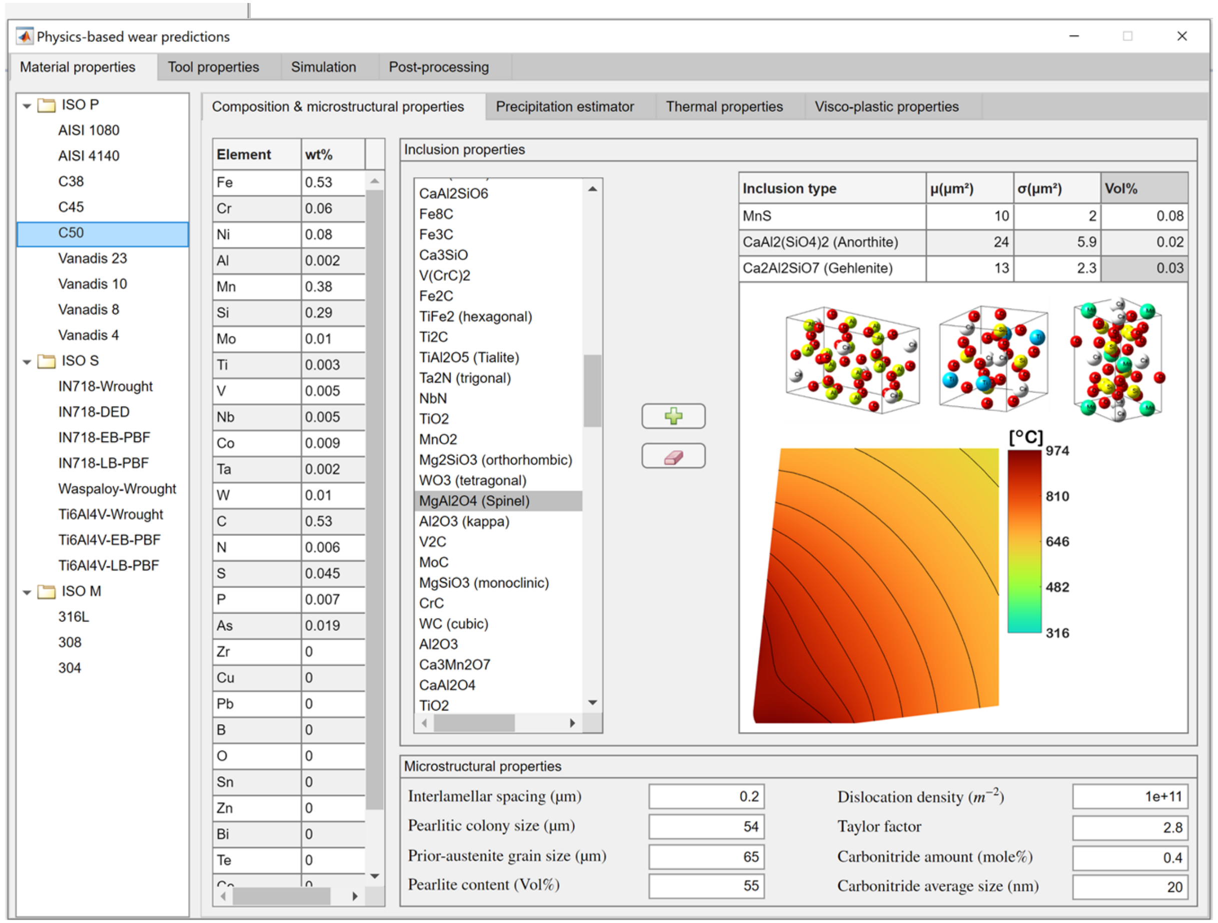
C50

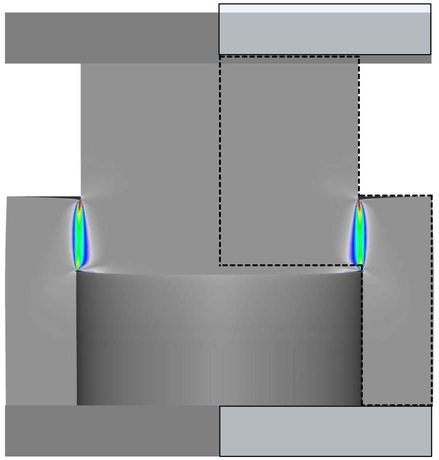


WEAR MODEL



MCutSim V1.0 – An open-source software

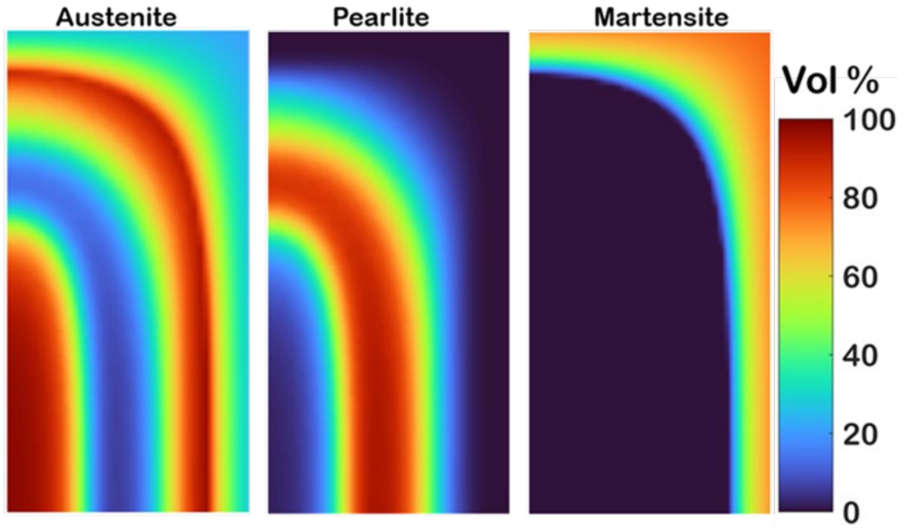


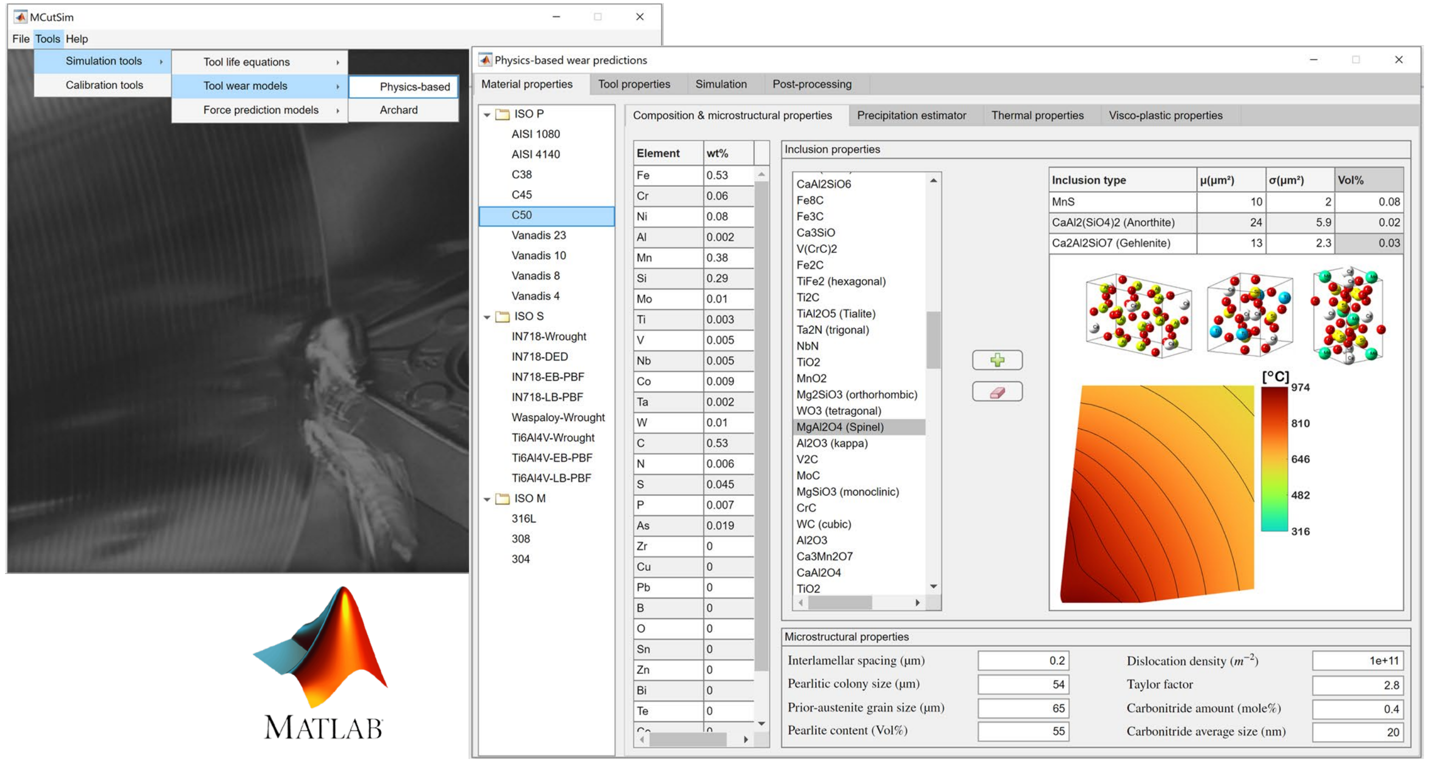


Outlook

- Physics-based tool wear estimation when using coated and uncoated tools: Abrasion, dissolution-diffusion, oxidation & chemical interaction.
- Databases are being developed for Ni-, Ti- and Fe-based alloys. Extending the models for a practical range of strain rates and temperature.
- Coupled with microstructure simulation.

15 seconds of cooling – water quenching from 850°C





Acknowledgements

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VINNOVA

FFI Fordonsstrategisk Forskning och Innovation

PRODUCTION
A CHALMERS AREA OF ADVANCE

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Microtechnology and Nanoscience

GNOSJÖ
AUTOMAT
SVARVNING

SECO

Background

Material certificates & data analytics

Material supplier A

Material supplier B

Material supplier C

Forging company A

Material supplier C

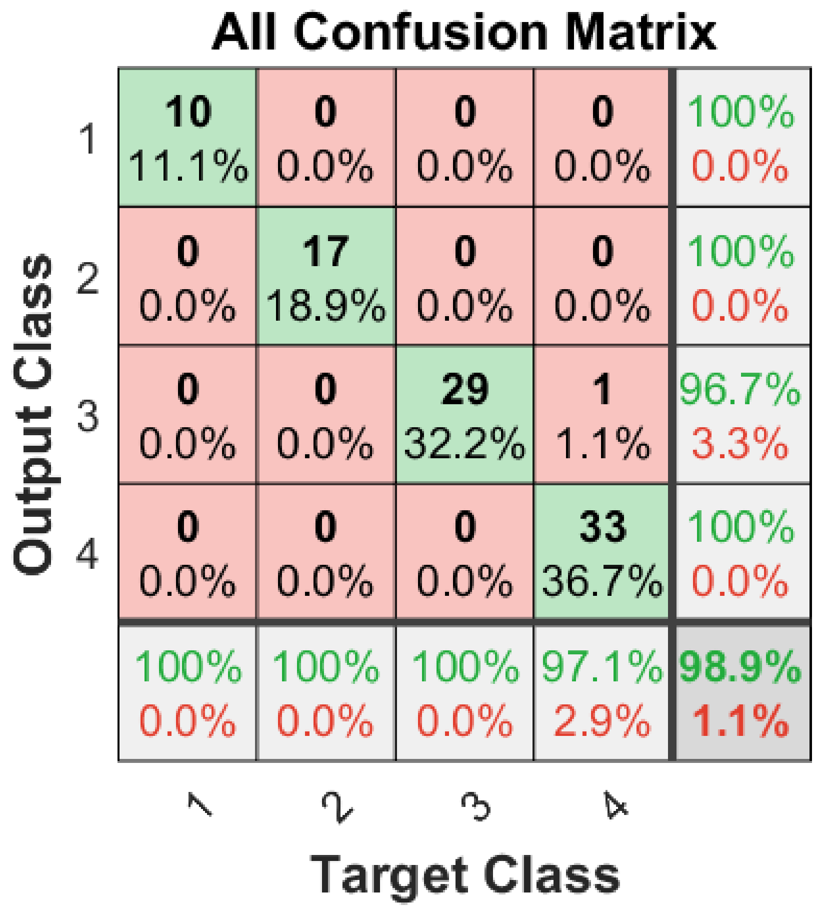
Material supplier D

Forging company B

Background

60% training dataset
20% Validation dataset
20% test dataset
Neural Network Clustering, 8 layers

Input: Chemical composition of all batches



Forging company A & B

Class 1: Steel supplier A
Class 2: Steel supplier B
Class 3: Steel supplier C
Class 4: Steel supplier D

Conclusion:
It is possible to determine the steel company based on the input materials in ~99% of the cases. There are differences in steel compositions specific to the steel mill.