Aluminium alloys recycling enhancement via X-ray Transmission and Artificial Intelligence

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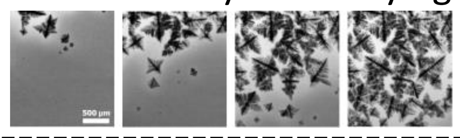
INTRODUCTION

Aluminium production uses ~3.5% of global electricity and causes ~1% of global CO^2 emissions [1].

	SORTING	SOLIDIFICATION	
• Recycling is essential for sustainability, but:	Alloys are mixed because of the difficulty in identifying the elemental composition[2]	Fe-rich intermetallic impurities accumulate during solidification	Material quality degrades at each cycle.
• X-ray transmission using a hyperspectral pixelated detector allows for:	Analysis of material bulk on conveyor belts 	Observation of phases formation while the alloy is solidifying[3] 	
• Artificial Intelligence enables:	Real-time sorting of alloys	Real-time phase identification leading to adjustment of furnace parameters to effectively control impurities	

[1] https://globalabc.org/sustainable-materials-hub/resources/mapping-global-flow-aluminum-liquid-aluminum-end-use-goods
[2] https://www.recycling-magazine.com/2020/07/14/addressing-the-challenges-of-aluminium-recycling/
[3] S. Feng, E. Liotti, M.D. Wilson, *et al.*, "In situ mapping of chemical segregation using synchrotron x-ray imaging.", MRS Bulletin 45, 934–942 (2020). https://doi.org/10.1557/mrs.2020.270

X-RAY TRANSMISSION THEORY

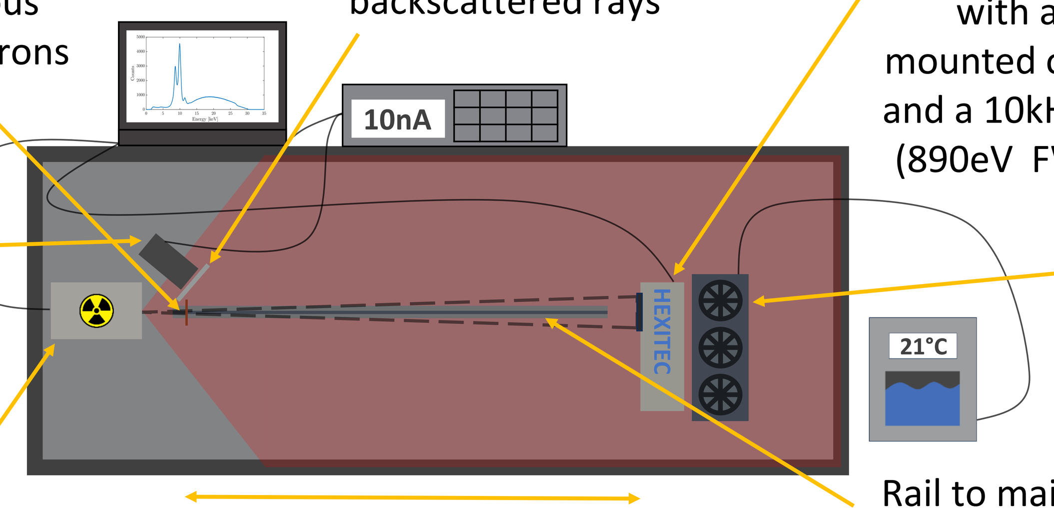
$$log\left(\frac{I_0}{I}\right) = \rho \cdot t \cdot \sum_i w_i \cdot \mu_{m_i}(E)$$

I_0: X-ray tube spectrum
I: transmitted spectrum
ρ: density
t: thickness
μ_m: mass attenuation coefficient
w: mass fraction

WHY HYPERSPECTRAL TRANSMISSION IMAGING

- Both morphological and spectroscopic information
- Real-time data during sorting or solidification
- Bulk analysis → less sensitive to coating paints or dirt
- X-ray cone beam to control magnification (no need of synchrotron)

EXPERIMENTAL SETUP



Sample holder and Al alloy foil with homogeneous thickness of ~100 microns

Al shielding to stop backscattered rays

2mm thick CdTe crystal with an 80×80 matrix of pixels with a 250µm pitch mounted on a HEXITEC ASIC and a 10kHz readout system (890eV FWHM @59.9keV)

Silicon diode to measure the flux at the edge of the cone beam

Liquid cooling radiator connected to a chiller

Micro-focused X-ray tube with tungsten anode operating at 30kV and 0.1W

Max detector to source distance: 1.12m

Rail to maintain the alignment at different magnifications (biggest mag.: 1pixel = 2x2µm²)

MEASURED VS THEORETICAL CURVES COMPARISON

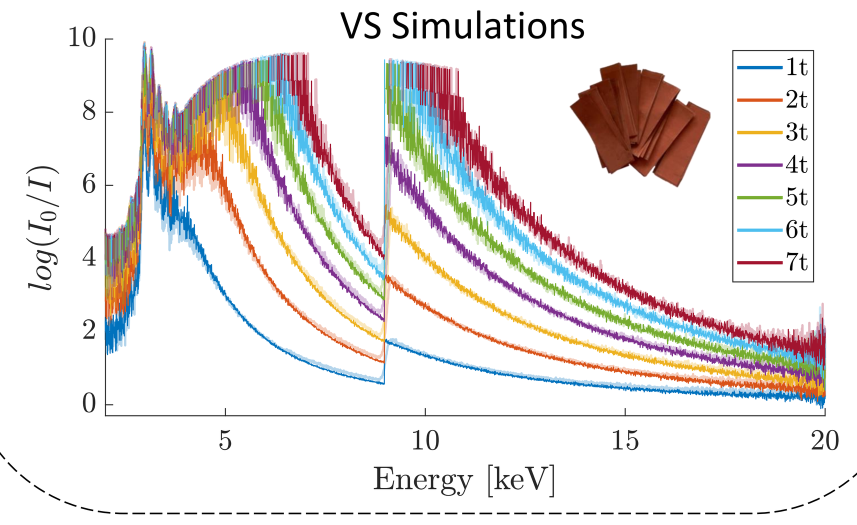
- Foils of known chemical composition; 2 minutes acquisition at low flux (~3·10⁴ counts/cm²/s) summing over all pixels

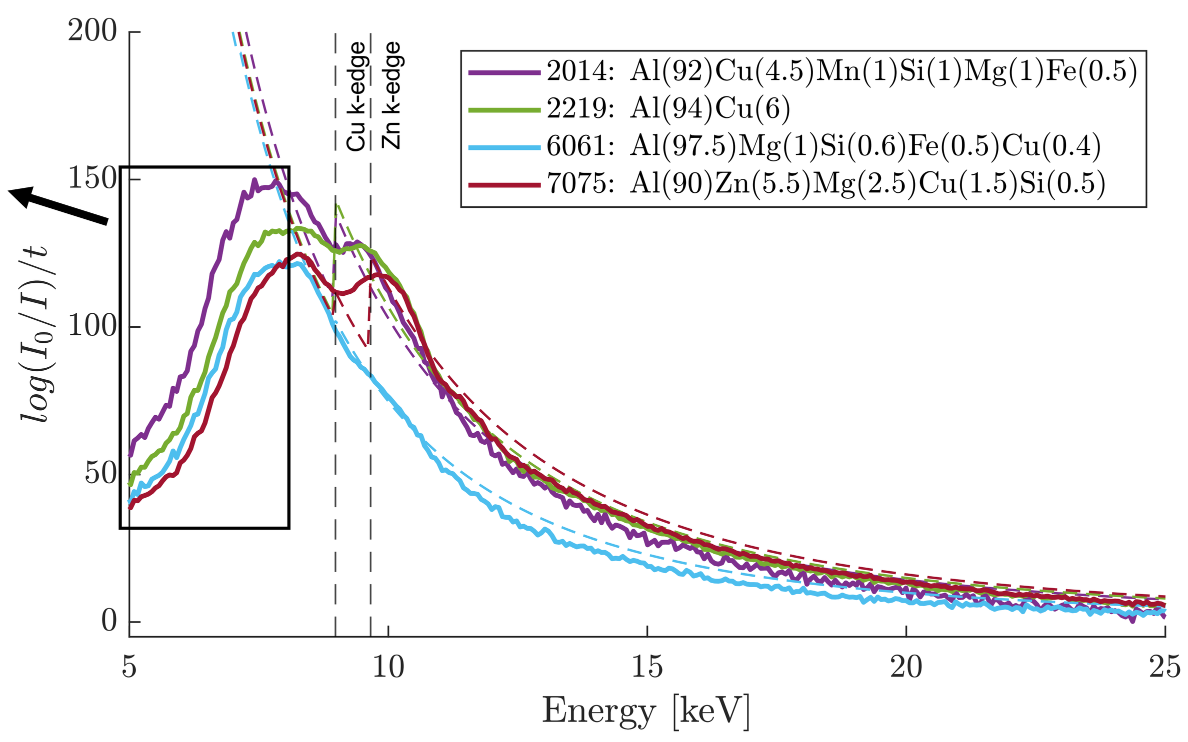
Low-energy bending study

Different setup:
- Si-drift detector for best energy resolution and no charge sharing
- Low flux and pile-up rejection
- Collimation to limit scattering

Simulations, which include:
- Multi-scattering escape events modelled from geant4 data
- Statistics

Stacked layers of Cu (1t = 5µm): Measurements (semi-transparent lines) VS Simulations





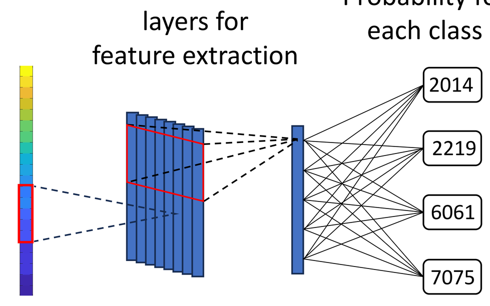
- Good agreement above 8 keV
- Visible k-edges for elements in quantities >3%
- Low-energy bending:
  - Sample thickness dependent
  - Due to charge sharing, fluorescence escapes and multi scattering events

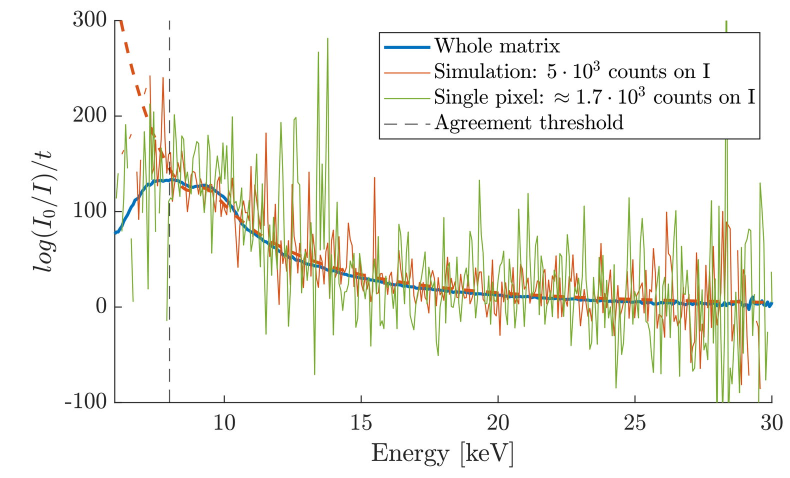
  → only part of the photon energy detected

NEURAL NETWORK CLASSIFICATION

- Training on simulated curves* and test on measured ones

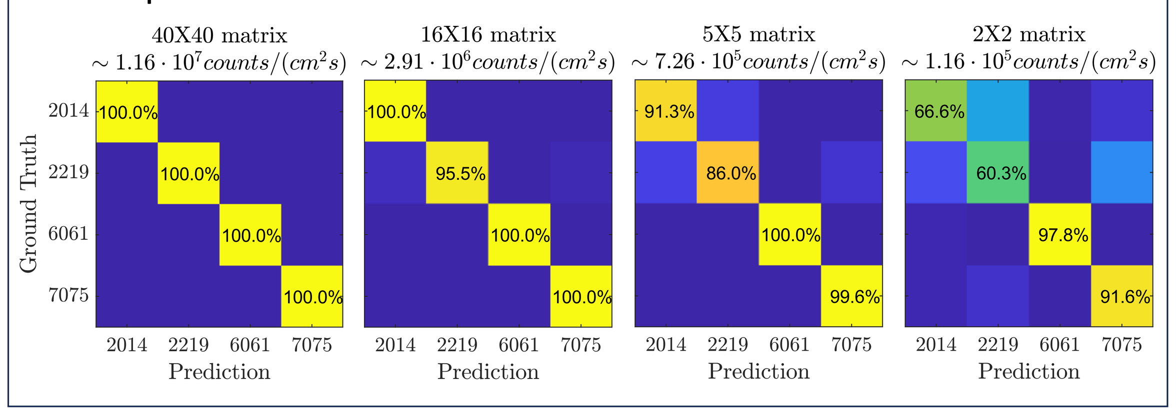
*theoretical curves + gaussian convolution and different statistics





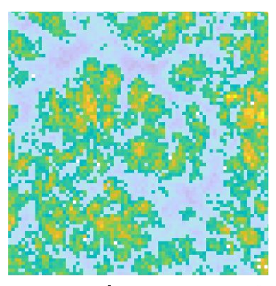
Not enough counts on single pixel spectrum!

- Classification scores summing spectra on sub-matrixes of decreasing size to study performances at different equivalent fluxes

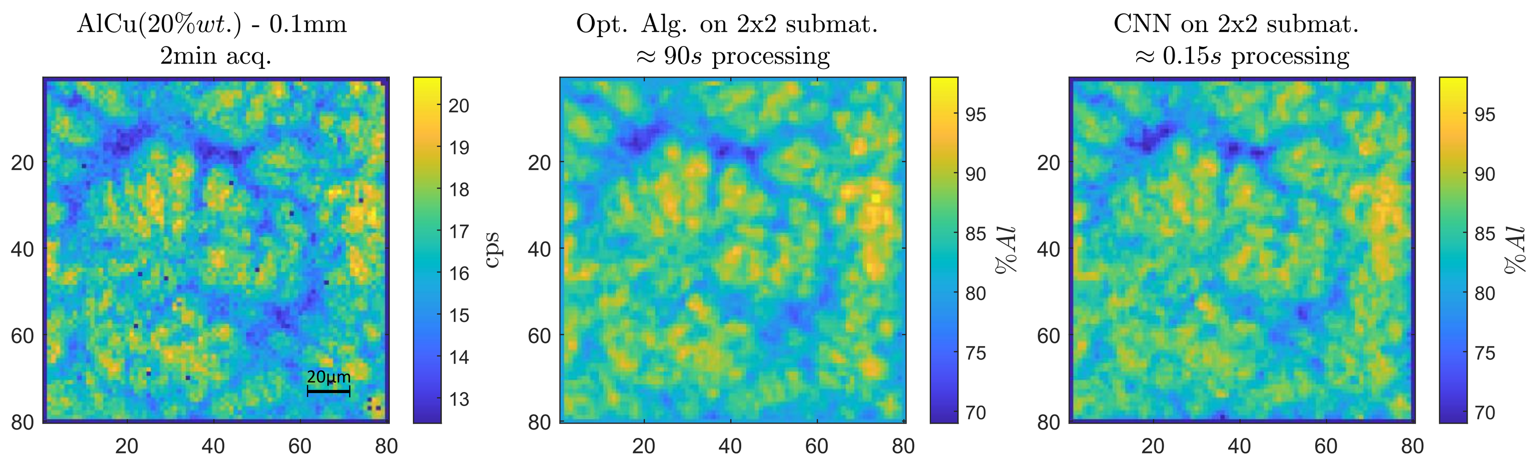


AUTOMATIC ELEMENTAL COMPOSITION LABELLING

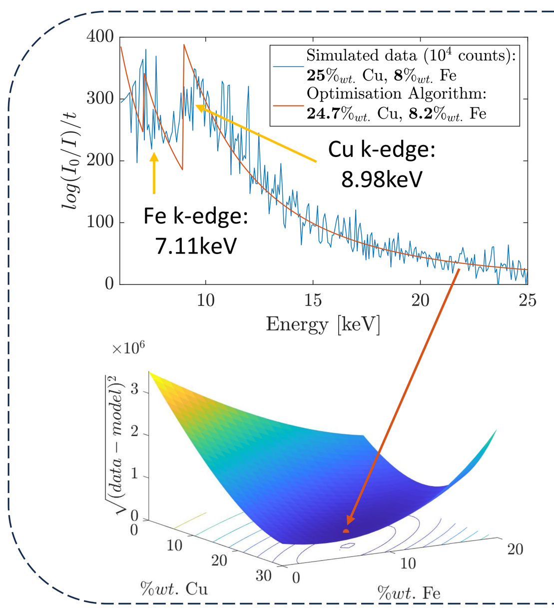
Dendrites!



Elemental composition in agreement with Energy Dispersive X-ray analysis results



- Sum of curves on 2x2 pixels to reduce noise (equivalent count rate of ~10⁵ counts/(cm²s))



- **Optimisation algorithm** to find minimum of Root Mean Squared Error between measured and theoretical attenuation curve for different % of Al and Cu (agreement above 11keV: Cu k-edge not included)
- Start from pixel in one corner and compute other pixels radially using nearest neighbors values as starting point to speed up the process

→ Image blurred but consistent with the dendritic structure

- **Convolutional Neural Network** trained on a dataset with labels coming from the optimisation algorithm
- Advantages:
  - Include Cu k-edge
  - Much less computing time, still the same increasing the number of elements

CONCLUSION AND FUTURE STEPS

- K-edges crucial for Al alloy discrimination
  - Low % elements undetectable
- Tube flux monitoring and temperature control required
- Low flux to avoid charge sharing and pile up limits time-constrained studies; new detectors (Hexitec MHz) may help
- Minimum count rate to apply AI: ~10⁵ counts/(cm²s)
- CZT: no polarisation issues, operates at room temperature
- Add pixelated detector distortion effects into the simulation tool to enhance agreement below 8-11 keV

  → Better labeling, flexibility from training on simulated curves
- Combine morphological and spectroscopic data to improve the algorithms

Are you struggling with material sorting?
Do you want to know how you can apply AI to your X-ray transmission data?
I'm open to collaborations!

Gitlab repo

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