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Manufacture using Advanced Powder Processes
EPSRC Future Manufacturing Hub

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Prevention is better than Cure
In-situ Monitoring and Machine Learning

Iain Todd
Director, MAPP EPSRC Future Manufacturing Hub
RAEng / GKN Aerospace Research Chair
Department of Materials Science and Engineering
The University of Sheffield

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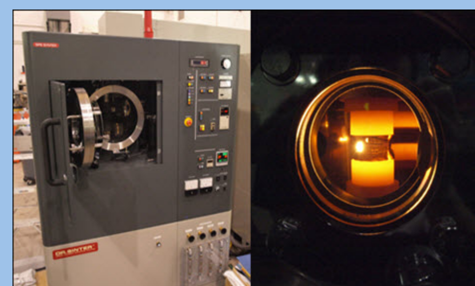
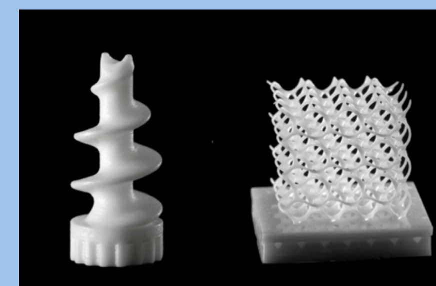
Current situation

Input



Process



Output

Variable

Fixed

Limited or no monitoring

Variable

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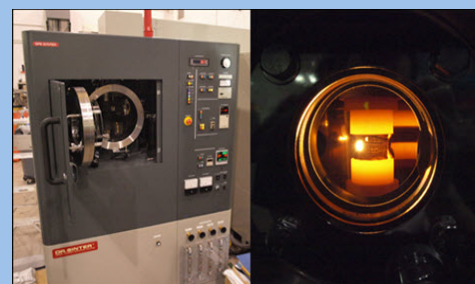
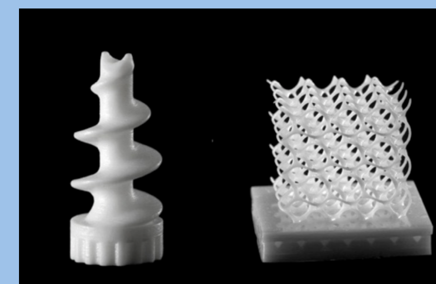
MAPP Approach

Input



Process



Output

Designed for process

Monitored

Dynamic control via machine learning

Designed

Quality built in

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Defects

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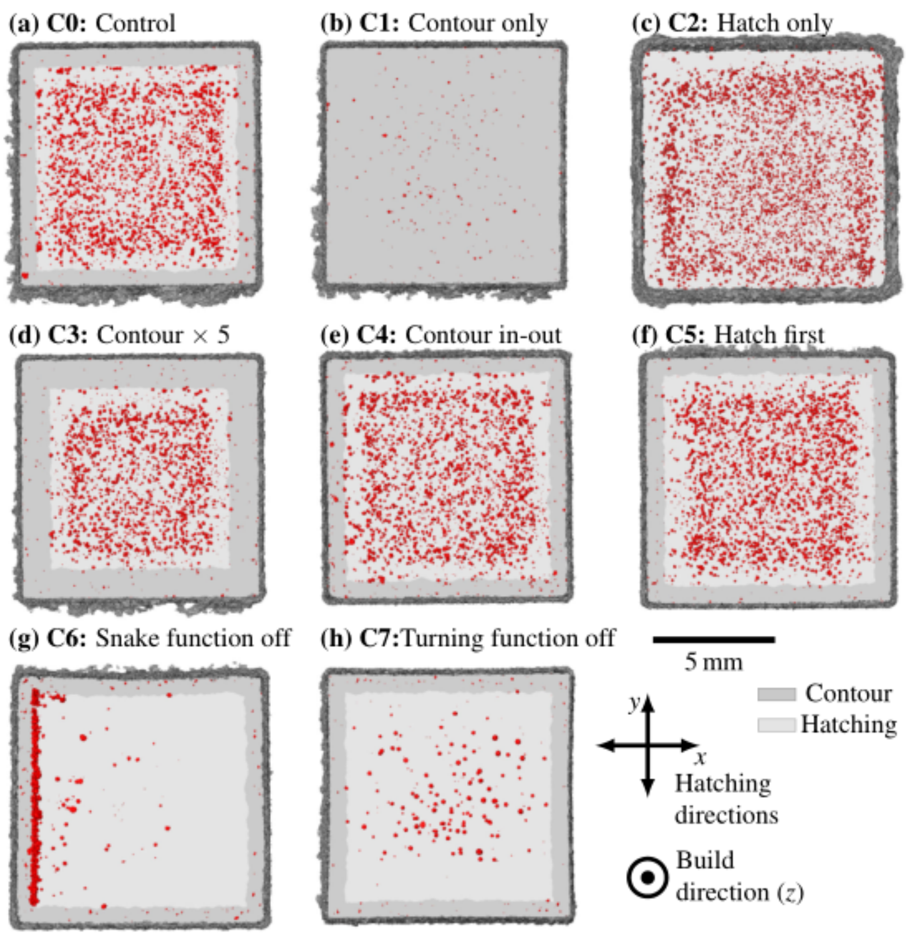
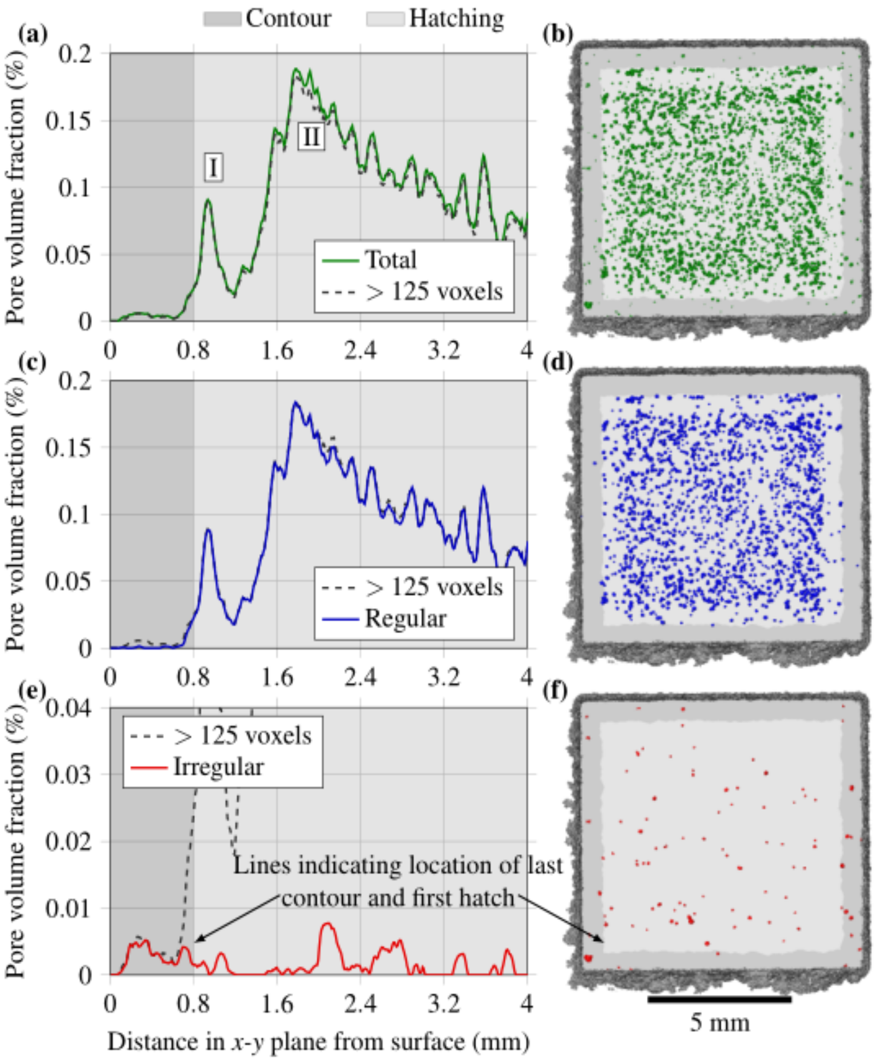
"Defects" are clearly a function of process parameters

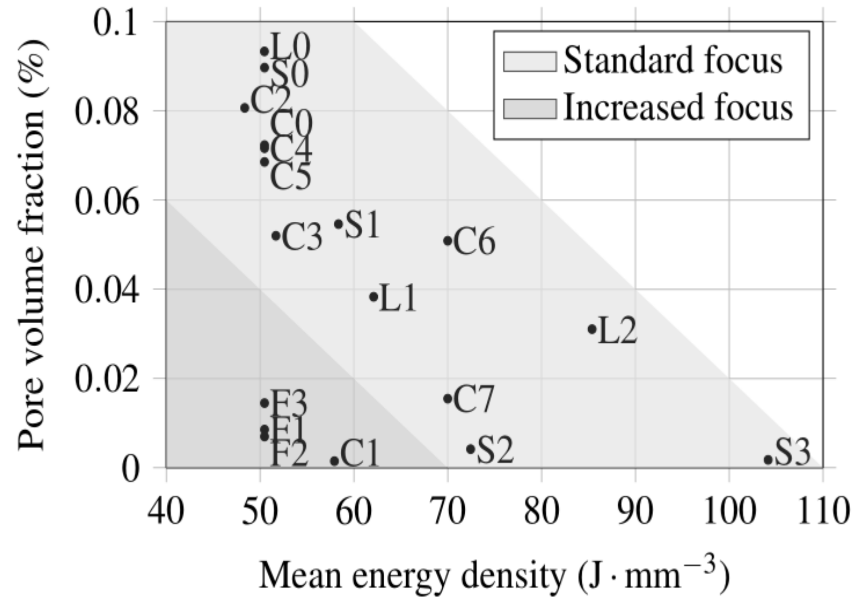


In a single build, the number of defects (red) can be altered by changing the melt strategy.

Red = high circularity defects (gas pores)

S. Tammas-Williams, H. Zhao, F. Léonard, F. Derguti, I. Todd, P.B. Prangnell, XCT Analysis of the Influence of Melt Strategies on Defect Population in Ti-6Al-4V Components Manufactured by Selective Electron Beam Melting, Mater. Charact. 102 (2015) 47–61.



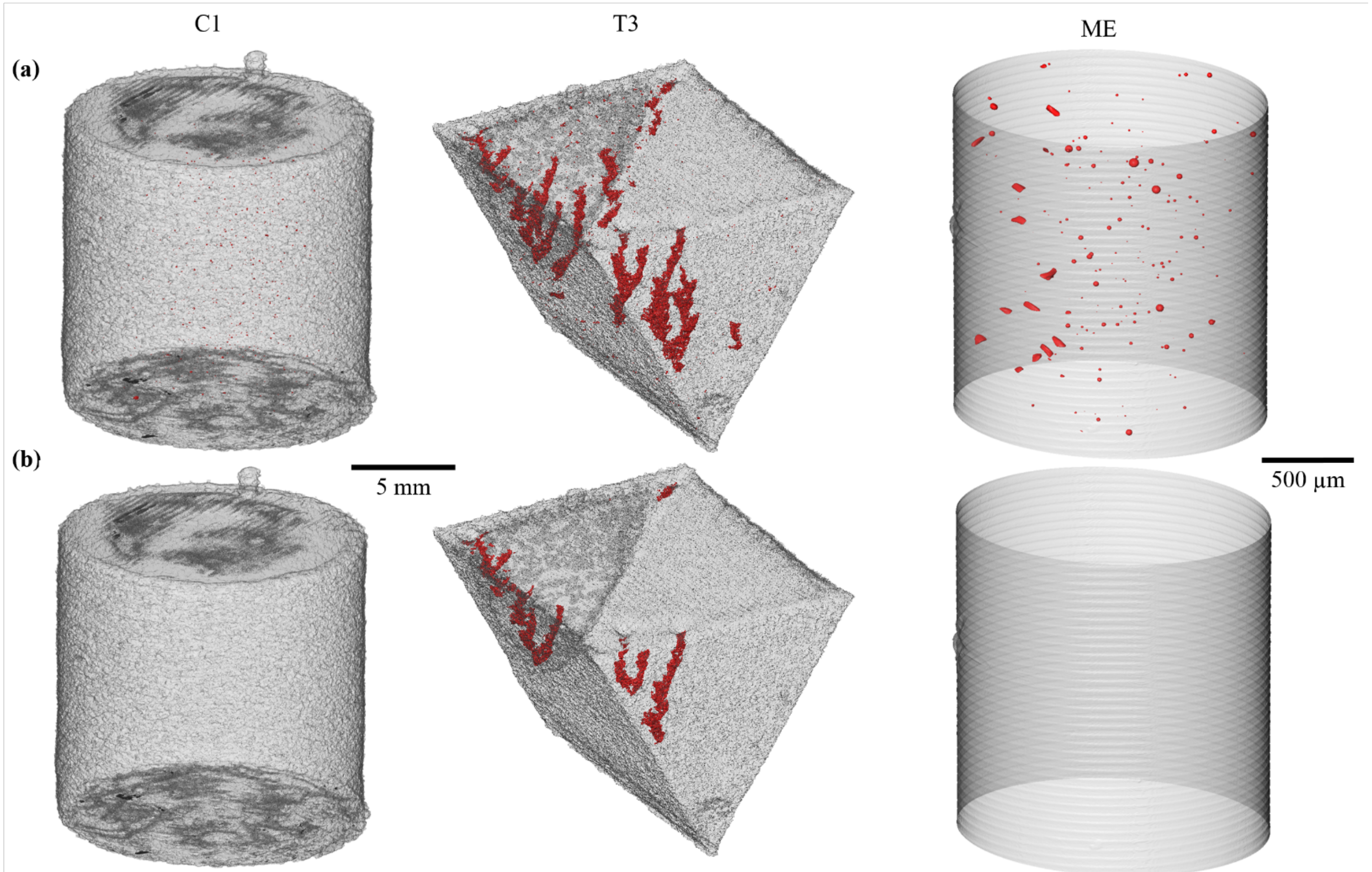


$$E.D = \frac{q}{v.l.h}$$

Where:
q = Beam power
v = Beam traverse rate
l = Layer thickness
h = Hatch offset

S. Tammas-Williams, H. Zhao, F. Léonard, F. Derguti, I. Todd, P.B. Prangnell, XCT Analysis of the Influence of Melt Strategies on Defect Population in Ti-6Al-4V Components Manufactured by Selective Electron Beam Melting, Mater. Charact. 102 (2015) 47–61.

HIP

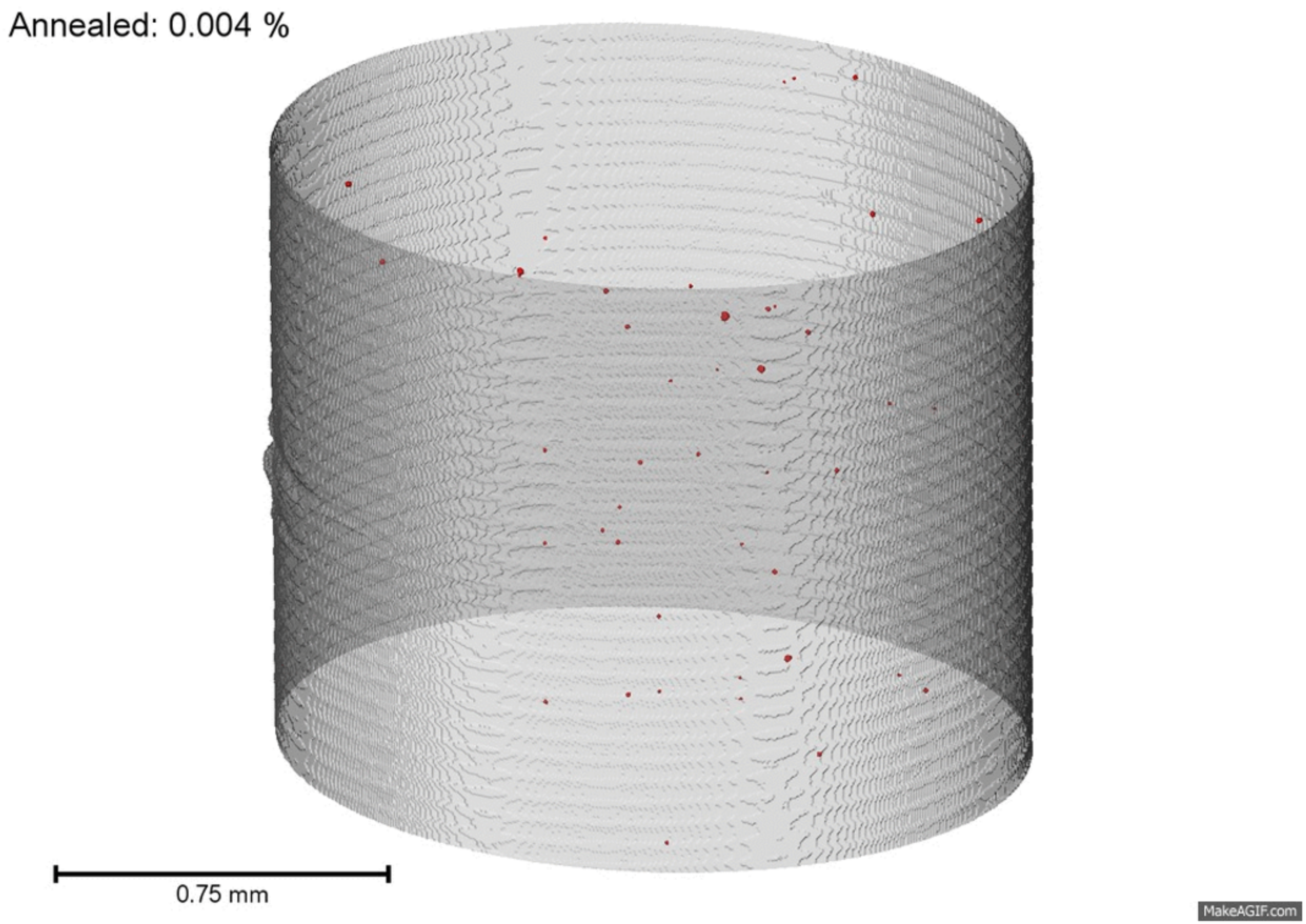


Whilst HIPing is undoubtedly good – it is not a "cure all"

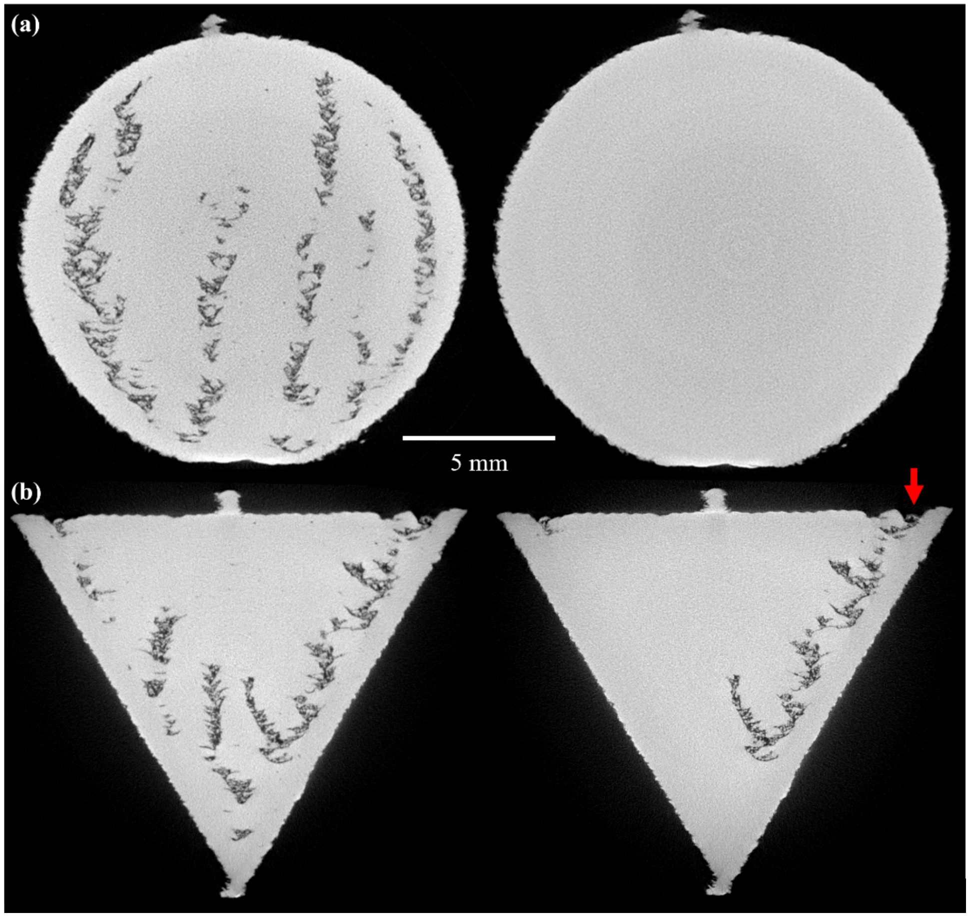
S. Tammas-Williams et al. Metallurgical and Materials Transactions A May 2016, Volume 47, Issue 5, pp 1939–1946

Defects

After HIPing and heat treatments



As-built HIP



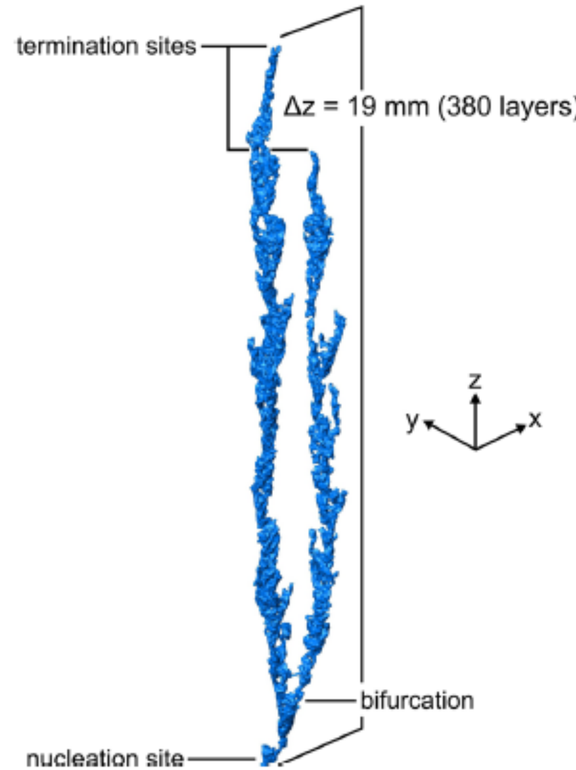


Figure 3 Chimney pore that split into two branches soon after it nucleated.

From Cordero et al.J Mater. Sci 52, (2017), 3429-3435

Prevention is better than Cure (1): In-situ Detection

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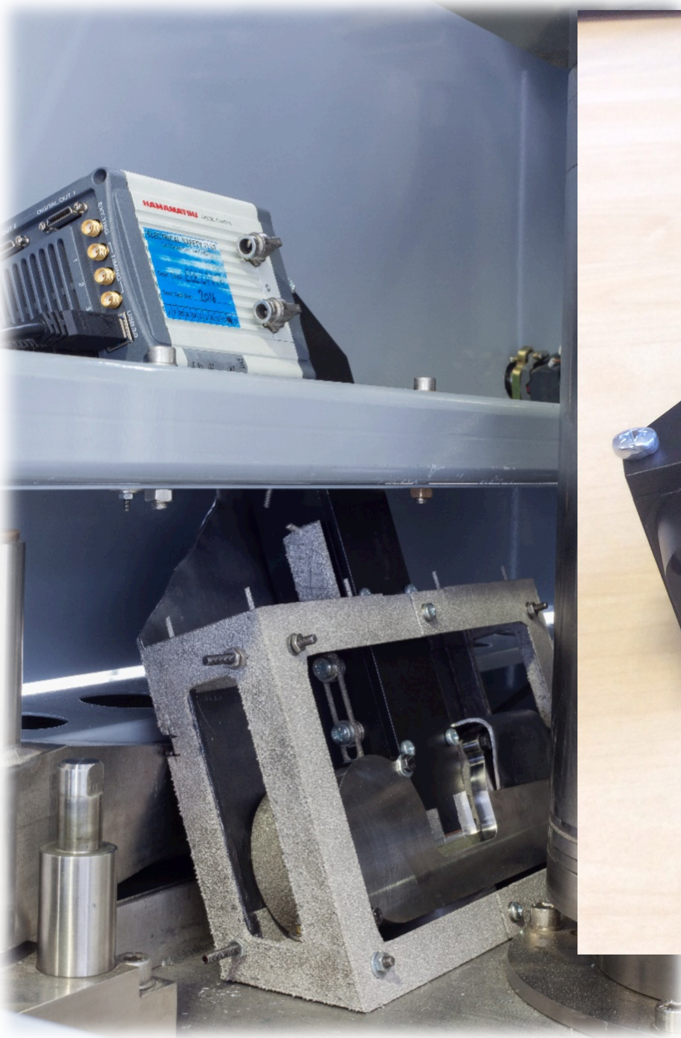
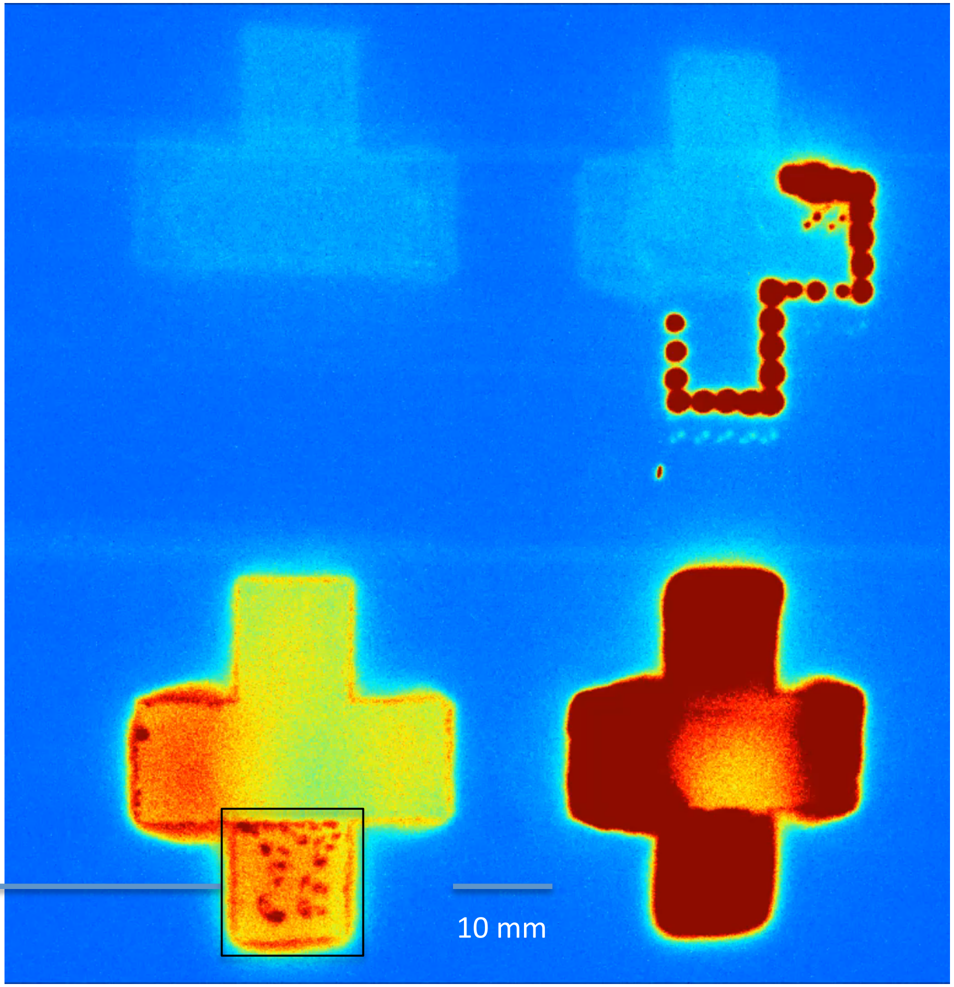
Thermal camera

Specifications



Thermal camera

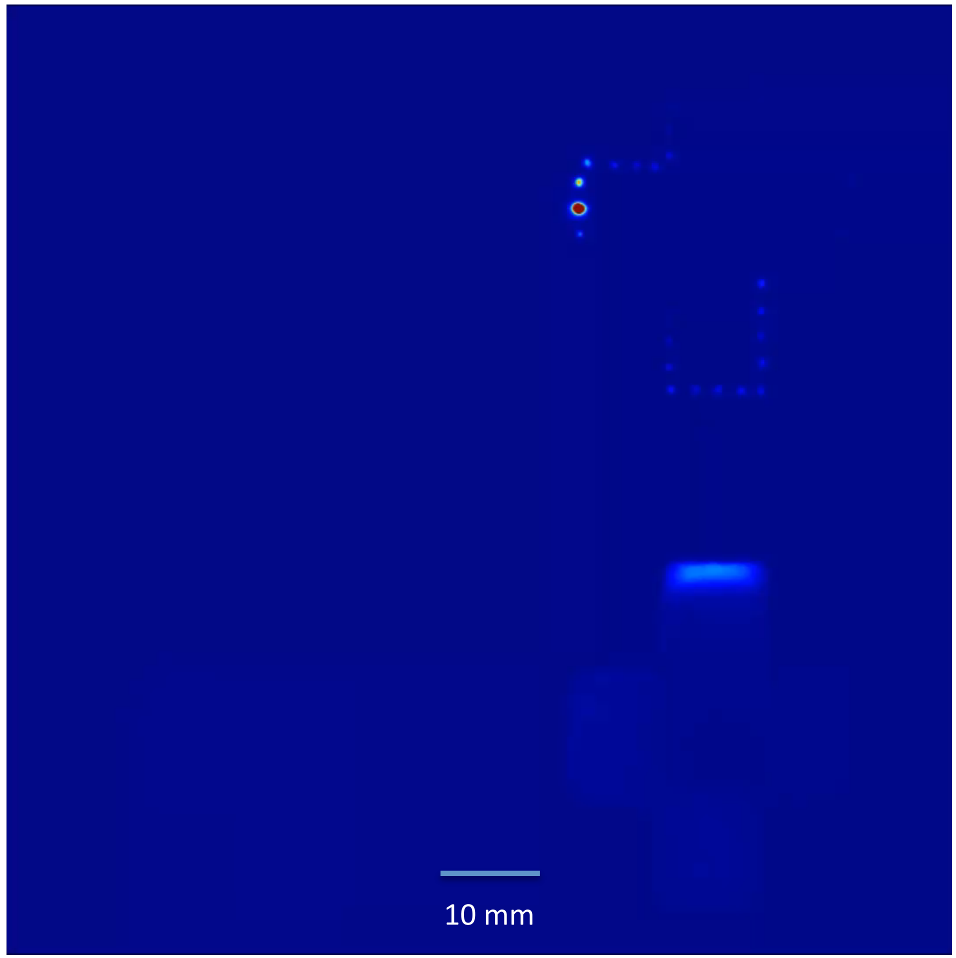
Example Footage

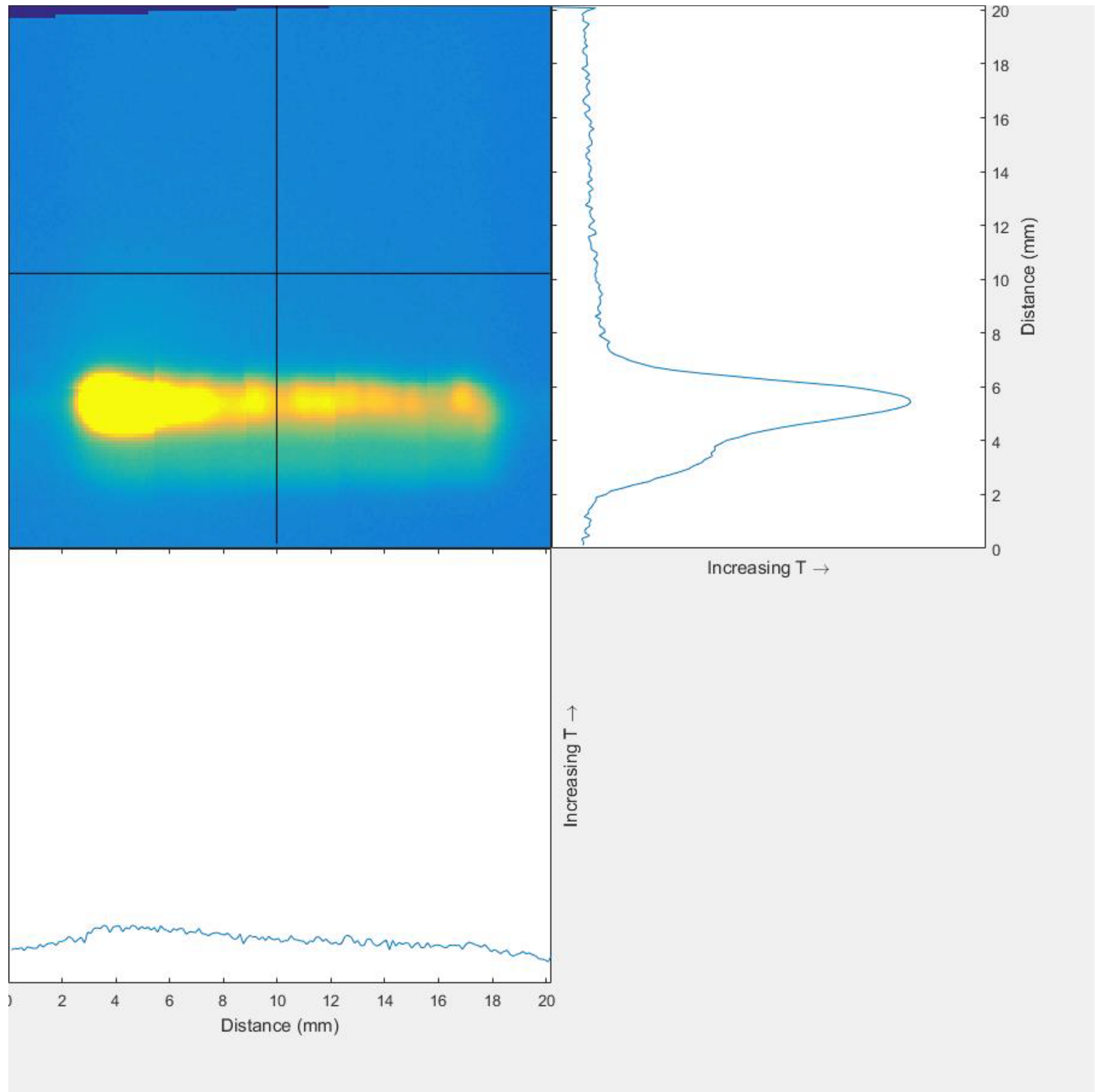


Tunnel Defects

Thermal camera

Example Footage

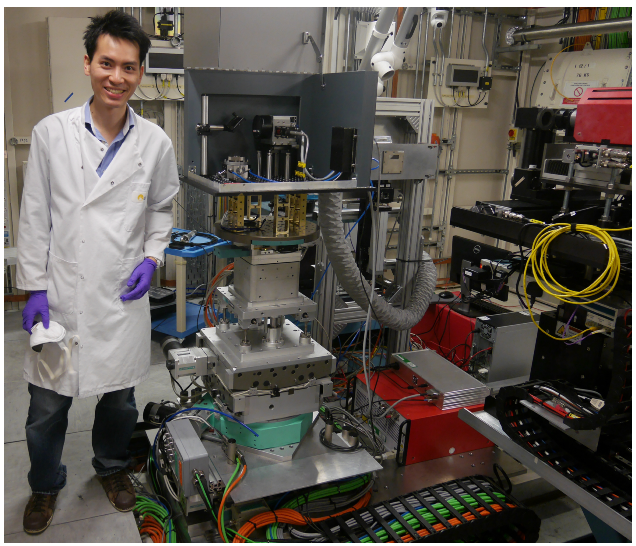




20
18
16
14
12
10
8
6
4
2
0
Distance (mm)
Increasing T →
Increasing T →
0
2
4
6
8
10
12
14
16
18
20
Distance (mm)

In situ AM Synchrotron Setup

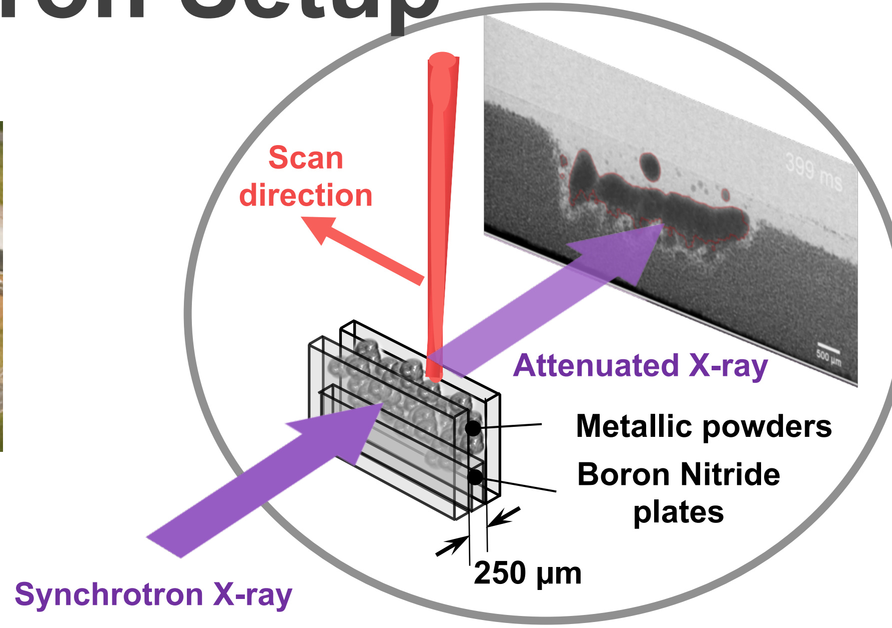
Diamond Light Source

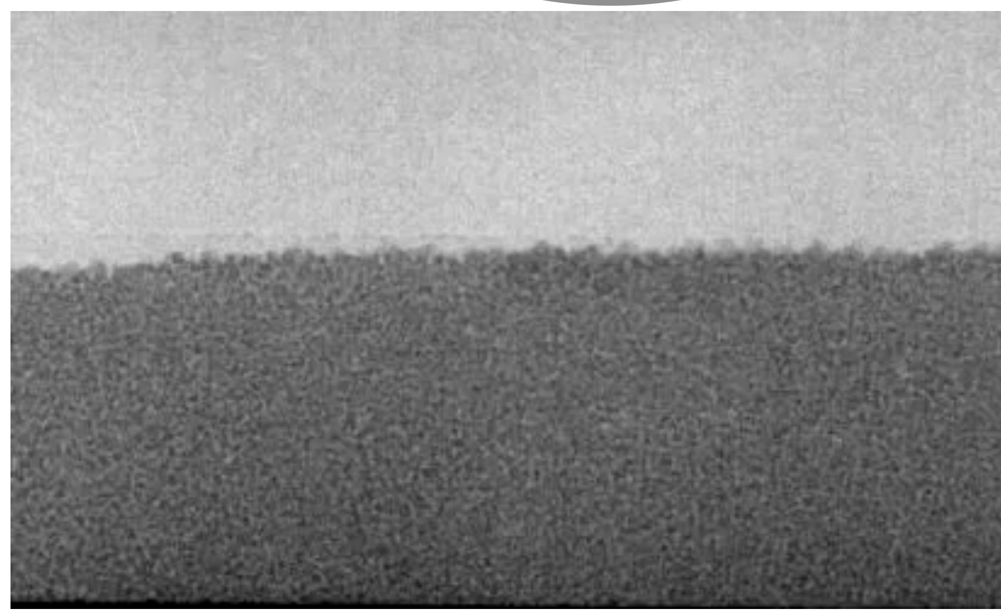


In situ AM on Beamline I12

Leung, Lee, Towrie et al,
Funding EPSRC (RCaH&MAPP), FP7

EPSRC Engineering and Physical Sciences Research Council
diamond
AMAZE
mapp Manufacture using Advanced Powder Processes
Research Complex at Harwell





SS316, 200W, 7.5mm/s, 5000fps

Prevention is better than Cure (2): Control (Machine Learning)

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Model-Based Feature Selection Based on Radial Basis Functions and Information Theory

George Panoutsos

g.panoutsos@sheffield.ac.uk

COMBILASER

EU H2020: Factories of The Future
Agreement no. 636902

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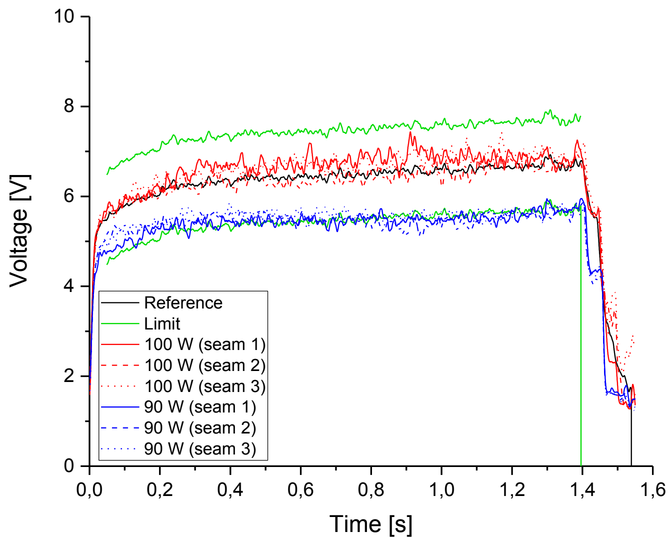
Human-Centric Systems

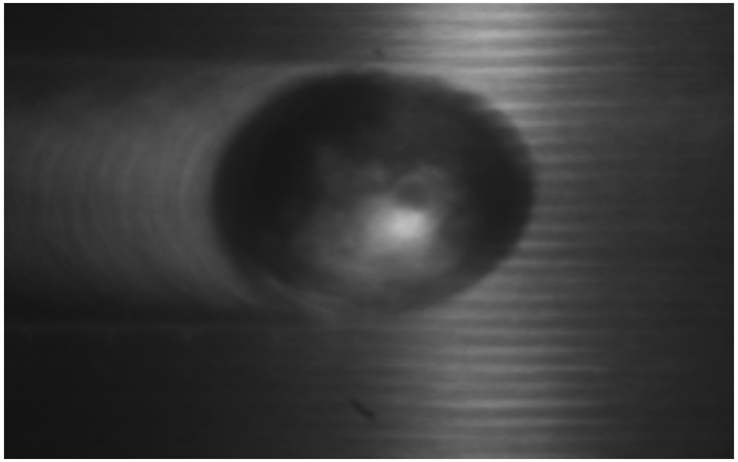
- Human-Centric Systems: Computational Systems designed for user-centred information processing
  - Frameworks that mimic human cognition, i.e. incremental learning, learning from examples etc.
  - Systems that are easy to interpret and interact with – by non-experts i.e. linguistic interpretability

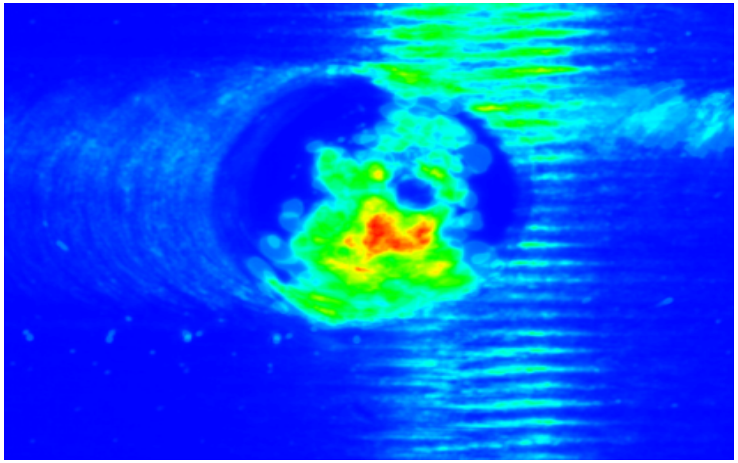
Process monitoring

- High-speed imaging and bespoke illumination system for melt pool monitoring
- Spectral monitoring



Courtes:y LZH, CAVITAR



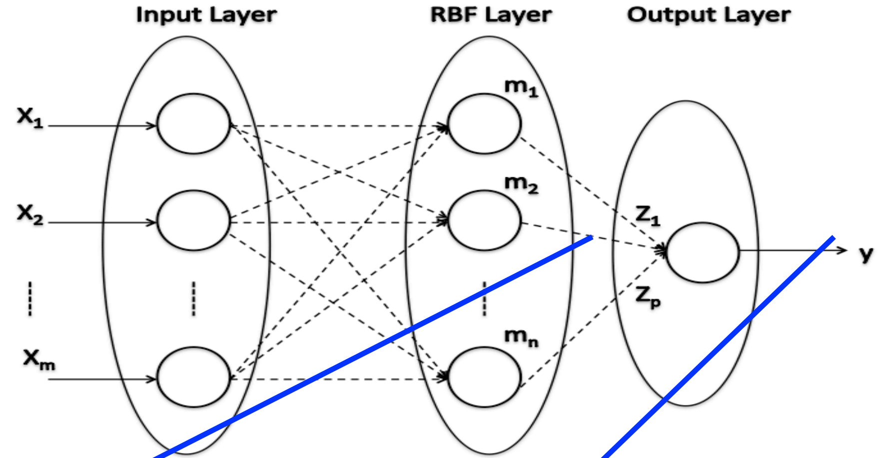


Courtesy: 4D

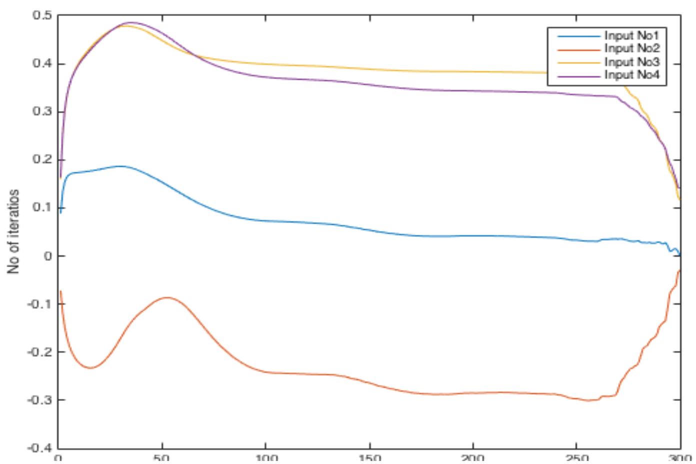
Methodology

- Construct a modelling framework based on a data-driven approach (model output: defects)
- Develop a fast, but transparent 'learning' methodology for the model
- Observe (algorithmically) how the model learns from data
- Use information theory to link the learning performance of the model to the input signals (process monitoring)

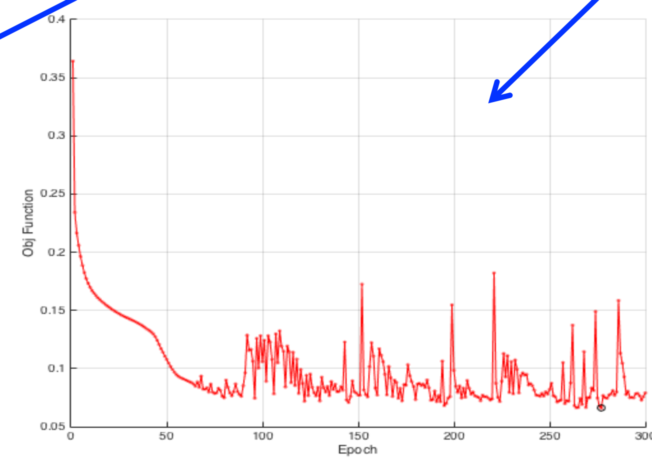
The model's learning evolution (training error) is linked directly to the model's inputs (monitoring signals)



Output layer weights



Training Error



$$Zi = w_1 x_1 + w_2 x_2 + \dots + w_j x_j + \dots + w_m x_m \qquad (11)$$

where w_j is the weight for the correspond input x_j.

Each model input 'xj' corresponds to a metric from the process monitoring signals

Hypothesis: For two data sequences (model weights – evolution of model learning) we can use information-theoretic measures to identify relevance/importance:

Cross-sample entropy is used [1]:

For two normalized sequences x(i) and y(i), 1≤i≤N, the vector sequences X_i^m and Y_j^m were formed as follows:

$$X_i^m = \{x(i), x(i+1), \ldots, x(i+m-1)\} \quad (5)$$

$$Y_j^m = \{y(j), y(j+1), \ldots, y(j+m-1)\} \quad (6)$$

where $1 \le i, j \le N-m$, N is the number of data points of each time series and m (embedding dimension) and r (tolerance limits of similarity) are fix parameters.

The distance between X_i^m and Y_j^m is defined as:

$$d_{i,j}^m = d[X_i^m, Y_j^m] = \max\left|x(i+k) - y(j+k)\right| \quad (7)$$

where $1 \le k \le m-1$.

For each $i \le N-m$, denote:

$$B_i^m(r)(x \| y) = \frac{number\_of\_j\_that\_meets\_d_{i,j}^m \le r}{N-m} \quad (8)$$

and

$$A_i^m(r)(x \| y) = \frac{number\_of\_j\_that\_meets\_d_{i,j}^{m+1} \le r}{N-m} \quad (9)$$

CSE is defined as:

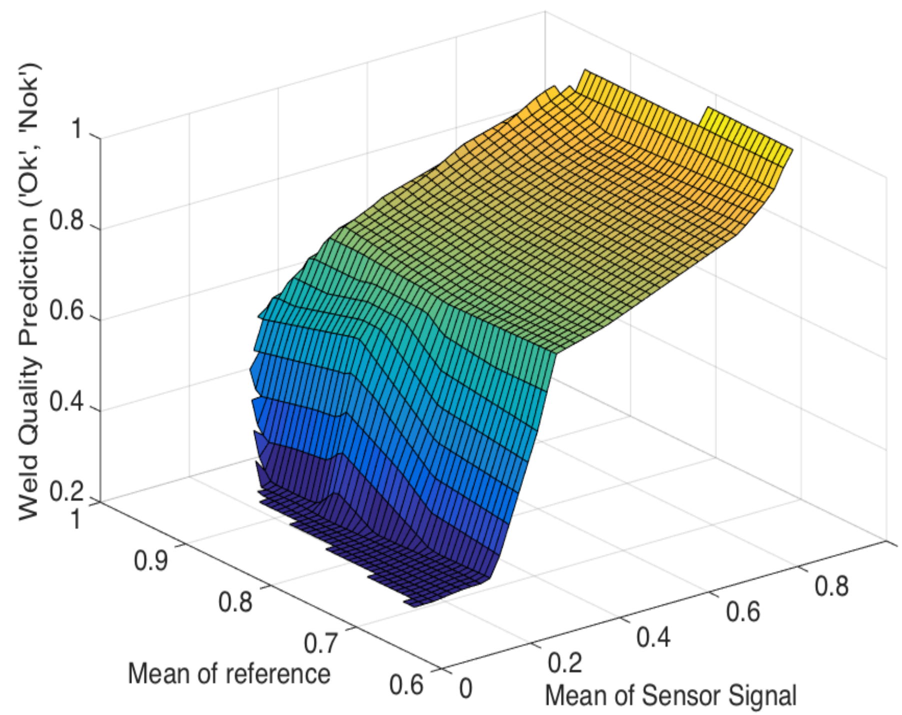
$$Cross-SampEn(m,r,N) = -\ln\left(\frac{\sum_{i=1}^{N-m} A_i^m(r)(x \| y)}{\sum_{i=1}^{N-m} B_i^m(r)(x \| y)}\right) \quad (10)$$

[1] G. Tzagarakis and G. Panoutsos, Model-Based Feature Selection Based on Radial Basis Functions and Information Measures, Proceedings of the 2016 IEEE World Congress on Computational Intelligence, Canada (2016)

Simulation results

- Simulation results on a sample of 81 welds
- 80 features from the monitoring signals were used to create the overall dataset
- Most important metric linked to defects:
  – Mean of reference width measurement (meltpool)

Example model-based defect prediction surface



What Next?

- Development of Deeper Process "rules"

- **Performance by Design** - building from / on
  - models of differing levels of complexity – generation of Axioms
  - data acquisition – *in* and *ex-situ* and *in-operando (see P.Lee talk later…)*
  - direct observation – visual, hyperspectral, resistance etc.

- Capacity to Develop "cyber-physical" manufacturing environments – Human Centric but Machine Learning enabled

- This is a clear intersection of AM and Industry 4.0 – but should enable the promise of AM (and other processes) to be fulfilled.

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