POLITECNICO MILANO 1863 | DIPARTIMENTO DI MECCANICA

In-situ Monitoring in AM:

Challenges and Opportunities to Unlock Real-time Qualification

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Bio/1

Data & Manufacturing

Politecnico di Milano (since 1863)
Largest technical university in Italy

Visiting professor (spring 2024) – MechE - MIT
Professor –Mech. Eng - Polimi
PostPhD – Penn State

QS Manufacturing and Mech Eng (2025)
- 1st in Italy
- 4th in Europe
- **12th worldwide**

QS Engineering & Technology (2025)
- 1st in Italy
- 7th in Europe
- **21th worldwide**

Senior Editor- Department Editor:
- Progress in Additive Manufacturing
- Additive Manufacturing Letters
- Informs Journal of Data Science
- IISE Transactions
- Journal of Quality Techology

Recent Awards:
- Royal Swedish Academy of Engineering Sciences 2023
- 2023 ENBIS Box Medal Award
- among the top 100 Italian woman scientists in STEM

Co-founder of the AddMe Lab, and 3D cell Lab
IC Labs

Bio/2

Labs

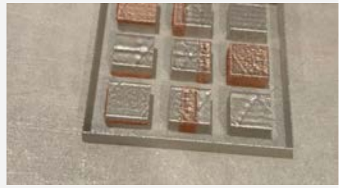
AddMeLab

IC LABS

3DCellLAB

PBF

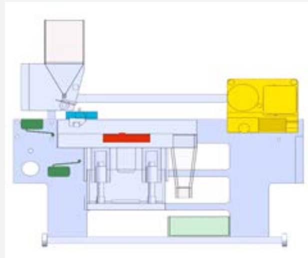
- Aconity Midi+
  - multi-material
  - high preheating



- Renishaw AM250
- 3D-NT LPBF system

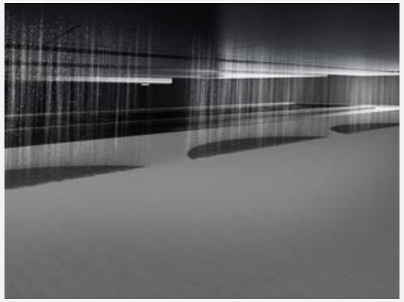
- Arcam A2

- LPBF prototypes



Binder-based AM

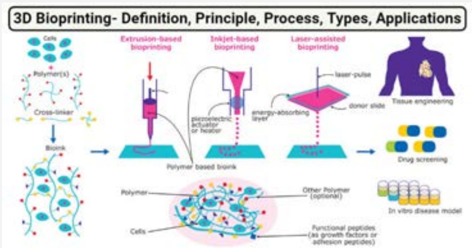
- Metal EXtrusion
- Shop System
- ExOne Innovent



DED

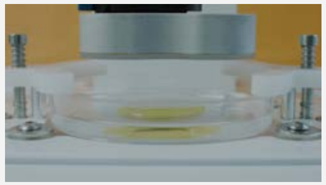
- Laser-DED
- WAAM

BIOPRINTING

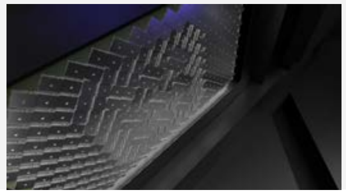


Extrusion

Digital light processing



2PP



Bio/3

Projects on insitu monitoring for AM

In-situ Monitoring in AM:

Opportunities and Challenges to Unlock Real-time Qualification

01

Opportunities

02

Challenge1: Effectiveness

03

Challenge 2: Trustiness

Opportunities

Why?

In-situ monitoring landscape

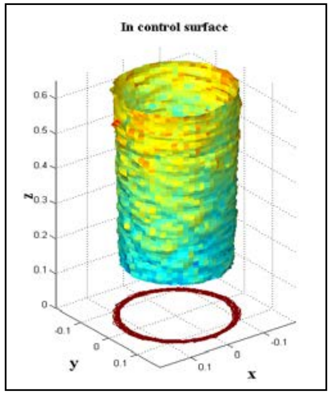
01

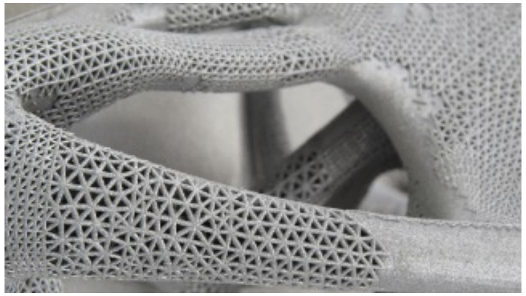
Why?

AM: Complexity «for free»

Traditional manufacturing

Additive manufacturing





Complexity vs inspectability

«The limited stability and repeatability of the process still represent a major barrier for the industrial breakthrough of metal AM systems»

(Mani et al., 2015; Tapia and Elwany, 2014; Everton et al., 2016; Spears and Gold, 2016)

Why?

PROCESS

CONTROLLABLE
Laser velocity
Laser Power
Laser Beam Diameter
Layer thickness
Inert Gas Flow Rate
Inert Gas Flow Pattern
Scanning Pattern

PREDEFINED
Powder Size
Layer thickness
Packing Density
Absorptivity
Reflectance
Build Plate

Source: NIST –NISTIR 8036

«Process mapping»

PRODUCT

GEOMETRIC
Dimensional deviations
Geometric deviations

MECHANICAL
Strength
Hardness
Thoughness
Fatigue Resistance

PHYSICAL
Residual Stresses
Surface Roughness
Porosity

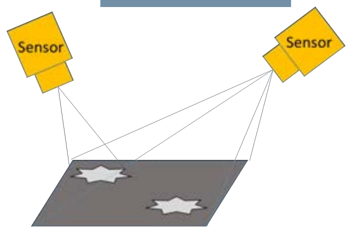
AM: costs, times, sectors

From **product data** to **process data**
(in-situ in-line)

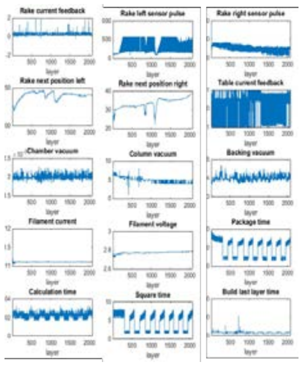
PROCESS

PRODUCT

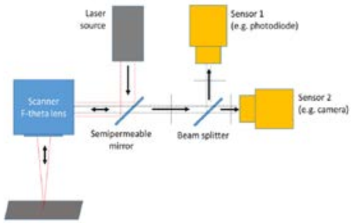
Off-axis



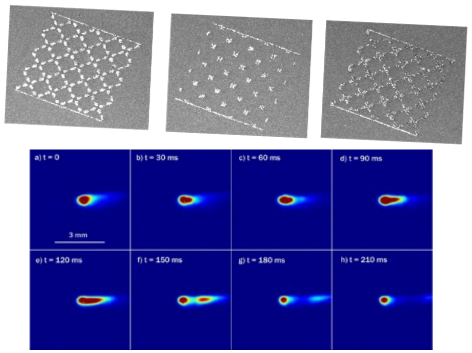
signals



Co-axial

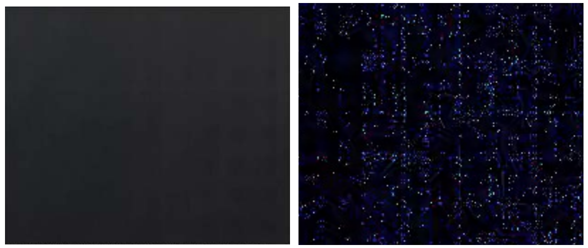


images



Acoustic emission

video-images



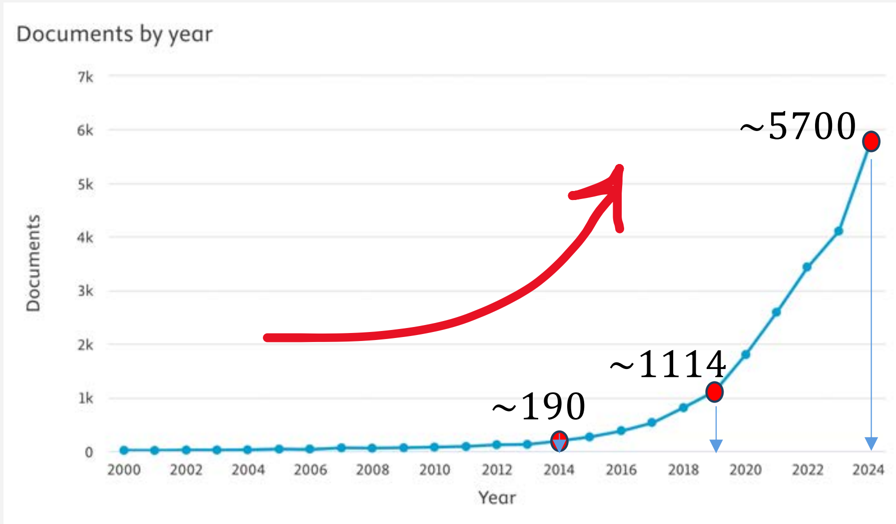
Why not?

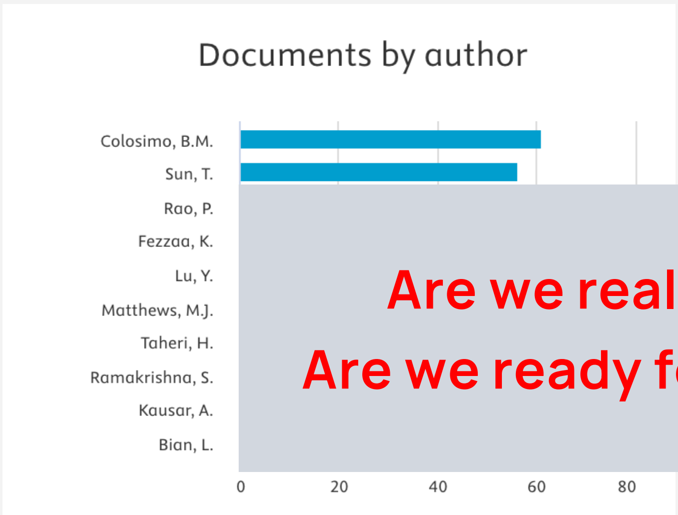
- Anomaly detection (waste and time savings)
- Increase process understanding and support process optimization
- Supporting "unmanned AM"

In-situ monitoring in AM: why?

«in-situ» AND « monitoring» AND «additive » AND « manufacturing » (Scopus)

March 11 2025





Are we really creating impact?

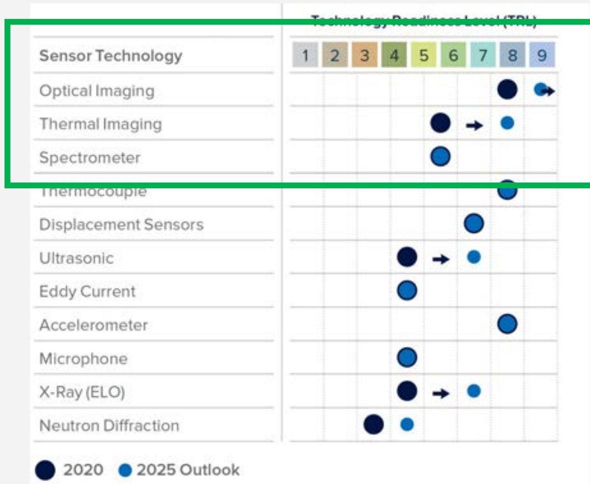
Are we ready for insitu qualification?

01/11/24

In-situ monitoring for qualification

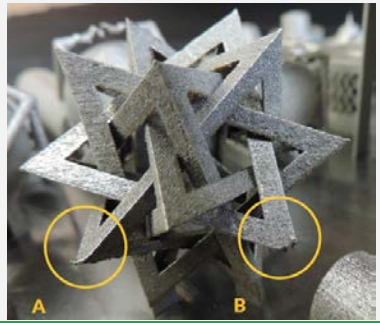
Validated in environment

Sensing

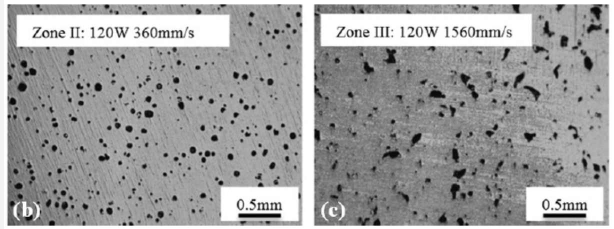


DETECTION/ACTION

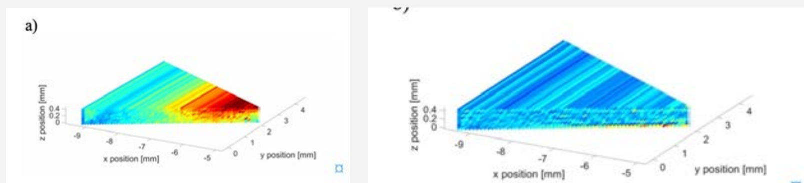
Geometrical and dimensional errors



Volumetric errors



From monitoring to control



Effectiveness

It should be worth

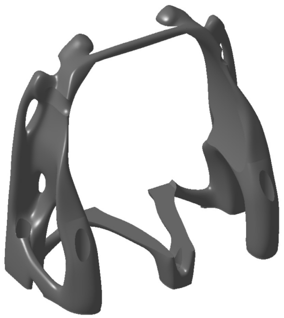
Realistic conditions/case studies

Controlled false positive and false negative rates

02

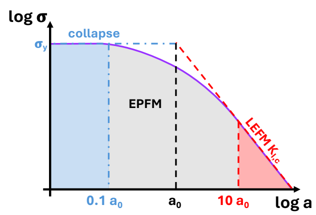
Effectiveness of insitu monitoring in real industrial settings

Main Mirror Support of the High-Resolution Spectrometer for the Flex Mission
Material: AlSi10Mg



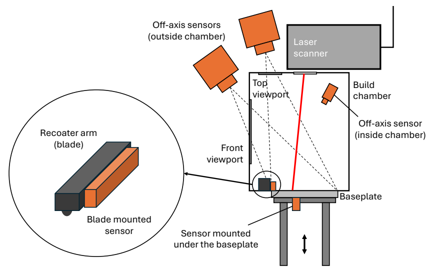
Thrust chamber of M10 liquid rocket engine for VEGA-E launch system
Material: In718

Phase 1: structural integrity



- Define **maximum allowed defect sizes** for a highly loaded, mission critical part through fracture mechanical methods

Phase 2: in-situ monitoring



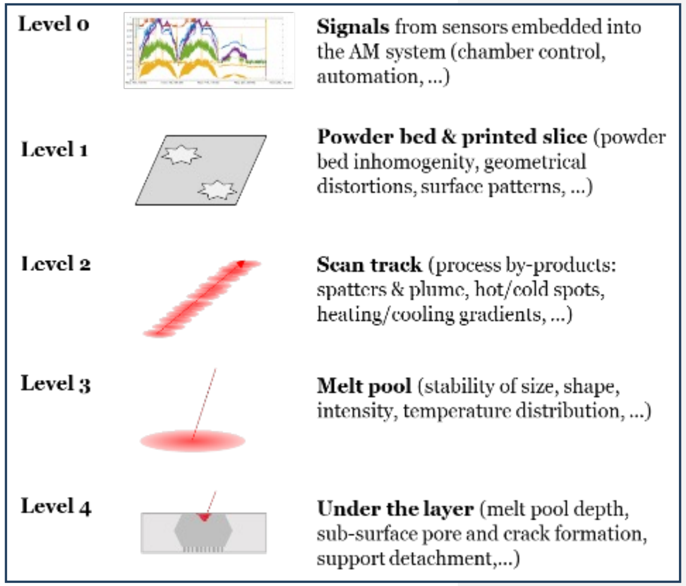
- Develop an **enhanced insitu process monitoring method (PMMs)** to detect the critical defects size

Defect catalogue

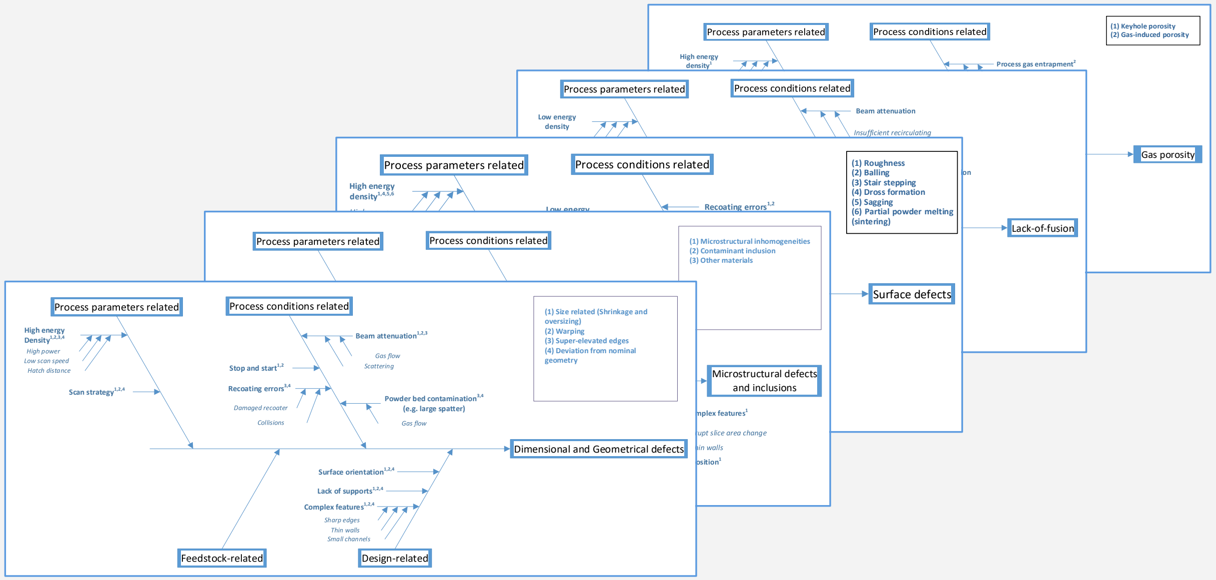
Phase 1

Defect class	Defect subclass
Macro-geometrical (dimensional and geometrical)	shrinkage, oversizing, super-elevated edges, warping, geometrical/dimensional deviations from nominal
Micro-geometrical (Surface)	roughness, balling, stair-stepping, dross formation, sagging, partial powder melting (sintering)
Microstructure and inclusions	microstructural inhomogeneity, contaminants inclusions, other material inclusions
Residual stress-induced	thermal stresses, cracks, delamination
Volumetric (porosity)	lack-of-fusion, keyhole porosity, gas-induced porosity

- Atlas of the defects
- Root cause analysis
- In-situ sensing



Grasso & Colosimo, 2017, 2021



In-situ process monitoring method (PMM) selection

To identify the **most suitable PMMs**, a **scoring system** (1 to 5 – 5 being the most mature solution for anomaly detection) was developed considering:

- Maturity of the sensing solutions
- Defect detection probability (based on literature, industrial practice)
- Techno-economical gains
- Applicability to the IAMSPACE objective (phase 1)

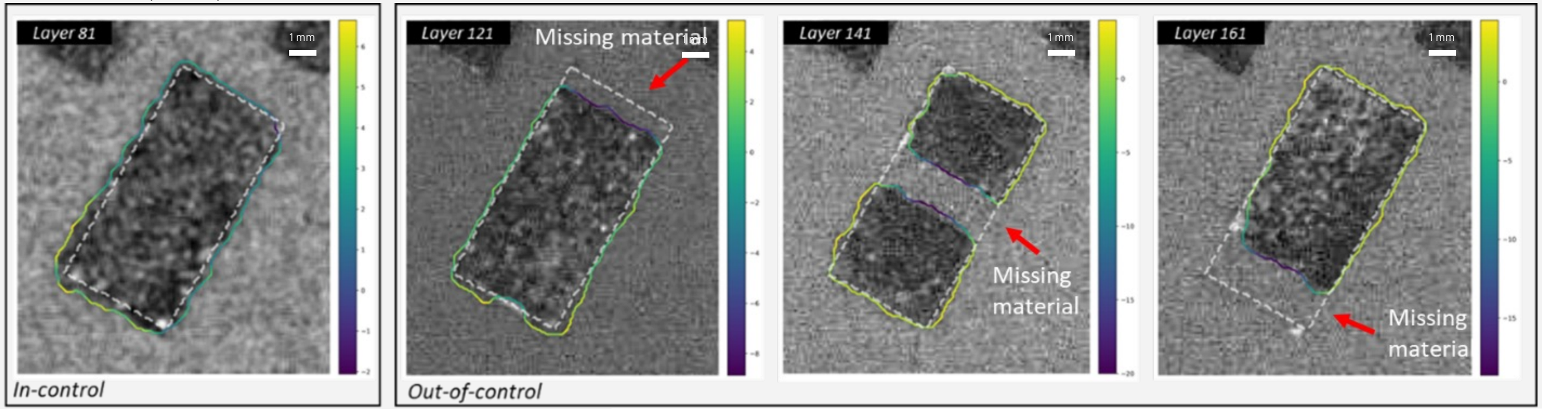
LEVEL	PROCESS MONITORING METHOD	PROCESS SIGNATURES	SENSING METHODS	COMPATIBILITY WITH PROCESS CONTROL		MATURITY		RELATED DEFECTS	PROBABILITY OF DETECTING A DEFECT		TECHNO-ECONOMICAL GAINS		APPLICABILITY TO CASE STUDY		SCORE	Selected PMM	COMMENTS
1	*Powder bed inhomogeneity*	Powder bed image	Off-axis imaging in visible range	High - layerwise imaging - recoating errors deposition is detected.	5	High (implemented in most industrial systems)	5	Dimensional and geometrical defects Surface defects Porosity	High - but affected by lighting conditions	5	Medium-High	4	High	5	**4,8**	YES	Selected because of highest score
	Printed slice geometry	Printed slice image	Off-axis imaging in visible range	High - layerwise imaging - Possibility to reject defective parts or to stop their manufacturing if the process gets out of control	5	Low (not implemented in industrial system, but with high potential)	1	Dimensional and geometrical defects	High - but affected by lighting conditions/Shrinkage and thermal-induced distortion may not be captured on a layer-by-layer basis	5	High	5	High	5	**4,2**	YES	Selected because of high score, same equipment of Powder bed inhomogeneity and high potential in commercial systems
2	*Slice dynamic signature*	Slice thermal map	Off-axis NIR/IR video imaging (EOS Optical Tomography)	Low - long time exposure image - Possibility to mark outlying behaviors of the printed parts during the process	1	Medium-Low (implemented only in one industrial system)	2	Dimensional and geometrical defects (linked to the presence of hot spots)	Low - high variability of thermal map intensities may mask actual anomalies	1	High	5	Medium - Low	2	**2,2**	NO	
3	*Melt pool monitoring*	Size and shape	Co-axial video imaging in visible and NIR/IR range	Medium - High - Simple video structure - computational time compatible with fast process dynamics	4	Low (not implemented in industrial system, but with high potential)	1	Surface defect (Dross, sagging, roughness)	Medium - the defect is indirectly correlated with the signature	3	Medium	3	High	5	**3,2**	NO	
		Radiation intensity	Co-axial video imaging in the visible range/Co-axial pyrometry	Medium - High - Simple 1D-signal/Simple video structure - computational time compatible with fast process dynamics thanks to simple image structure	4	Medium - Low (Co-axial pyrometry implemented in some industrial systems)	2	Porosity	Low - the defect is indirectly correlated with the signature	1	Medium	3	Medium	3	**2,6**	NO	
					4		2	Surface Defects (Dross, sagging, roughness)	Medium - the defect is indirectly correlated with the signature	3	Medium	3	High	5	**3,4**	YES	Selected because of the high potential

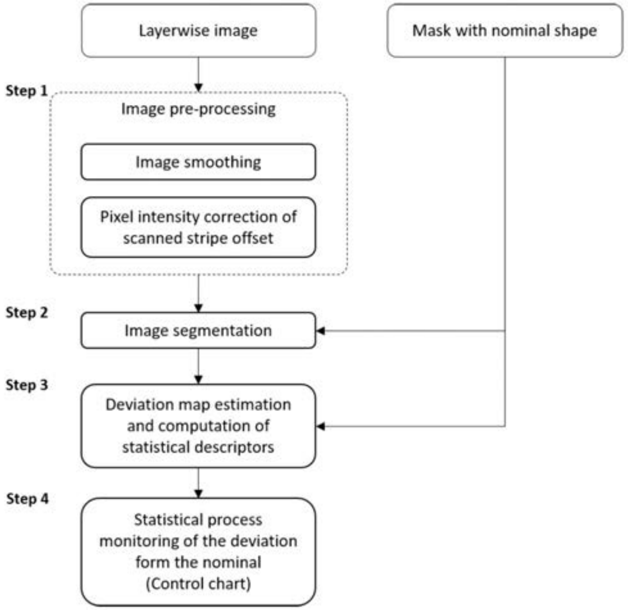
Geometrical deviation from the nominal shape:

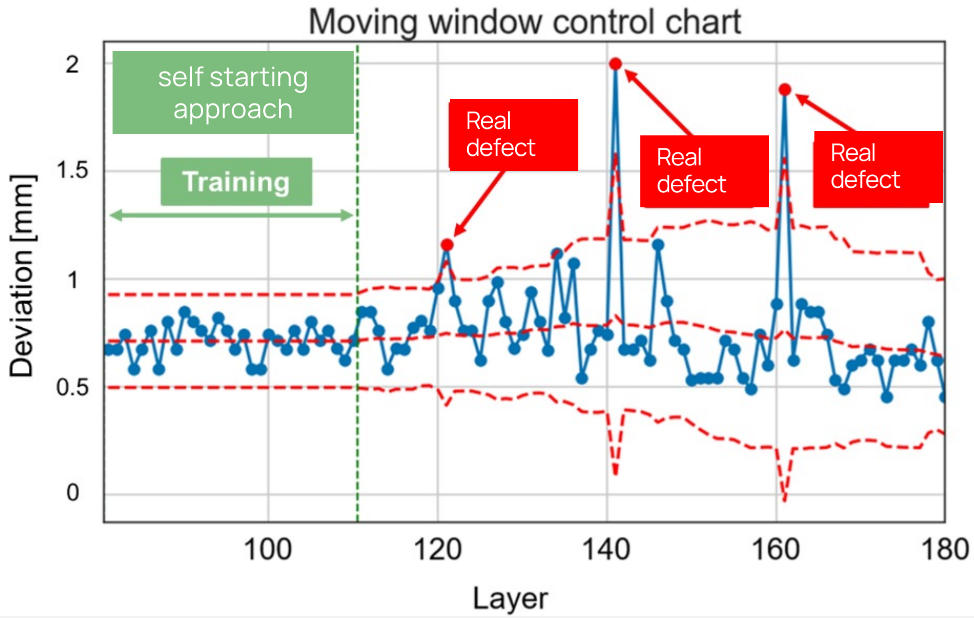
1. A **shape-agnostic** image analysis approach

2. Deviation from the nominal shape and related **uncertainty**

3. **Self-starting** anomaly detection procedure developed







The approach is able to avoid false positive and false negative!

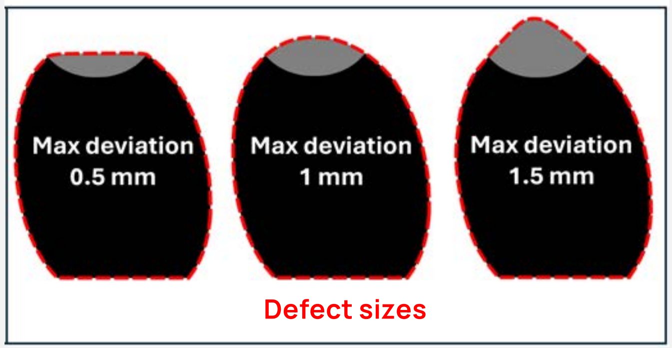
PPM for geometrical deviation

:

- Sensitivity
- Robustness
- Effectiveness

Defect

Sensitivity to Defect size



Robustness

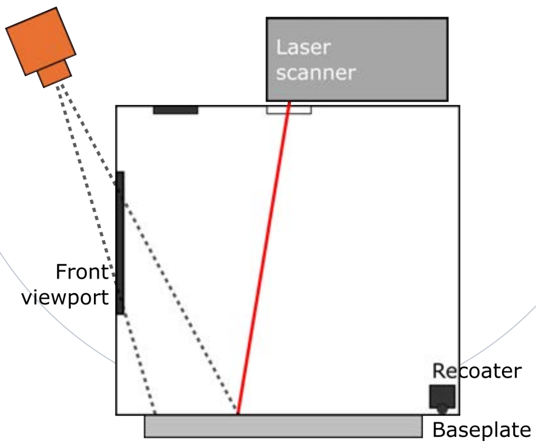
1. Machines:
   - EOS M 400,
   - Customized Prima Additive@POLIMI)
2. Sensor configuration
   - camera location
3. Materials (AlSi10Mg*)

*similar campaign on In718

Camera setting and architecture – the existing solutions

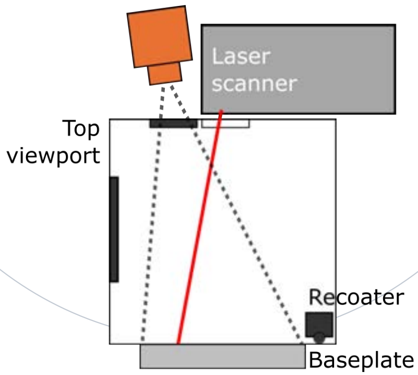
Industrial AS-IS

Machine	EOS M 400
Camera model	iDS UI-5490SE
Focal length	25 mm
Working distance	600 mm
Resolution	50 µm/px
Configuration	Off-axis (front viewport)



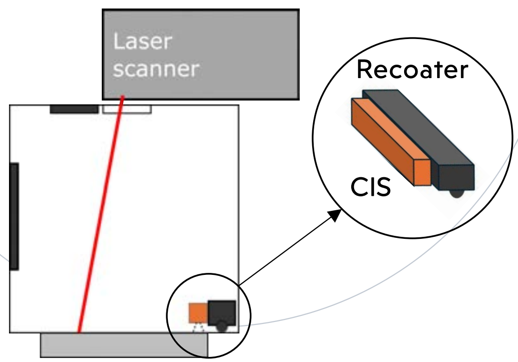
Industrial improved

Machine	3DNT @Polimi
Camera model	iDS UI-5490SE
Focal length	8.5 mm
Working distance	400 mm
Resolution	80 µm/px
Configuration	Off-axis (top viewport)



Novel

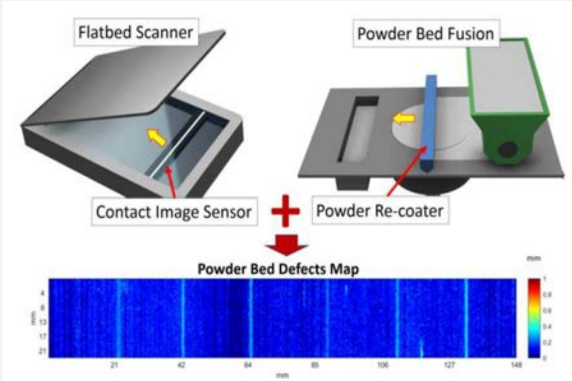
Machine	3DNT @Polimi
Camera model	Line scanner
Working distance	15 mm
Resolution	21 µm/px
Configuration	Blade-mounted

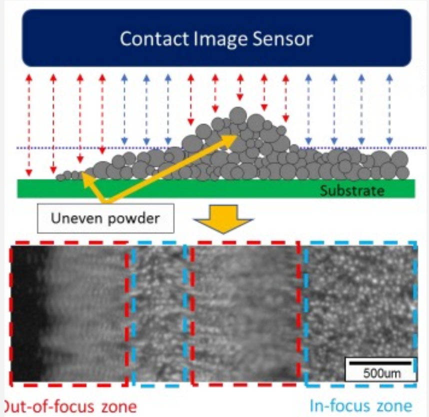


Scan it: The intelligent recoater

Size and sensing matter!

Contact image sensors (CIS) -
usually used in our printer scanner

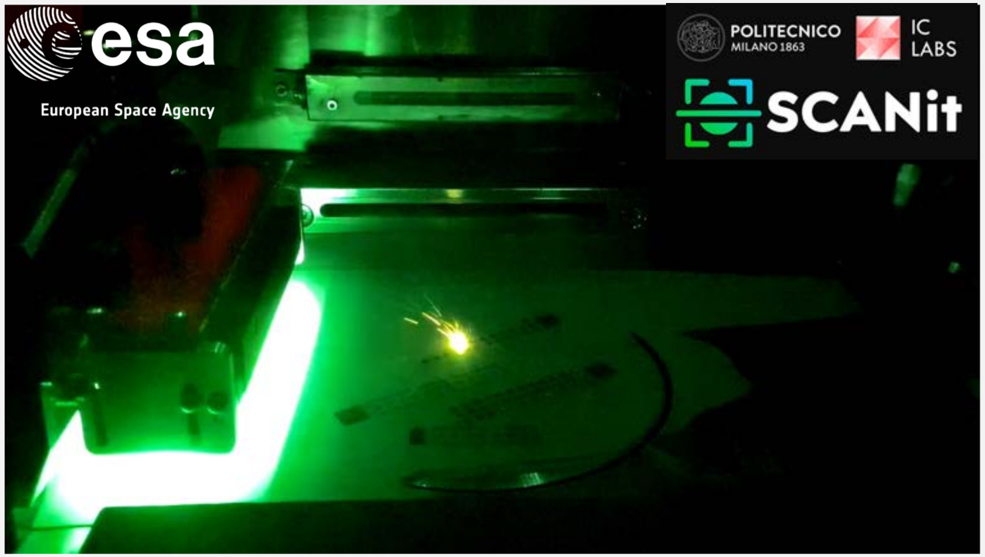


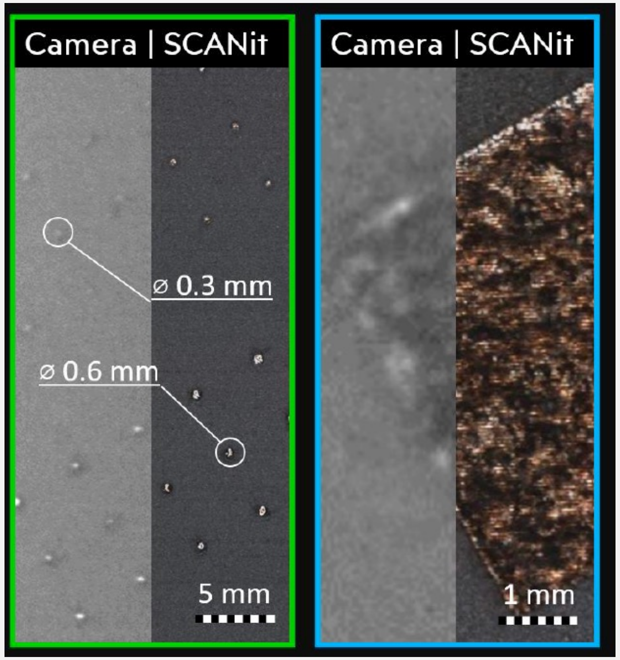


Synchronous **line scanner** mounted on powder recoater for **powder bed topography** (5 µm/pixel)

Non-uniformities in the powder bed are identified by quantifying out-of-focus regions in the raw scans

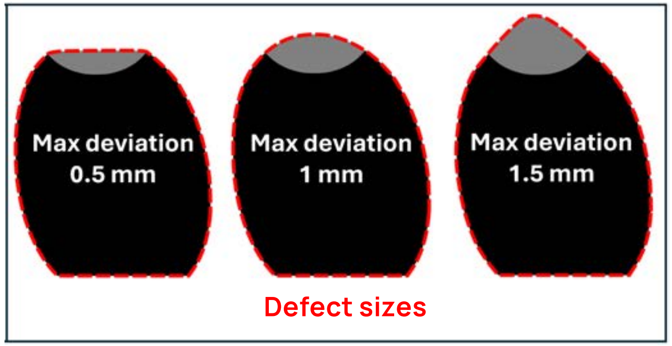
- High resolution (21 µm/px)
- Built-in illumination
- Color imaging (discoloration, oxidation can be observed)
- Line sensor (encoder is required for synchronization and 2D image reconstruction)

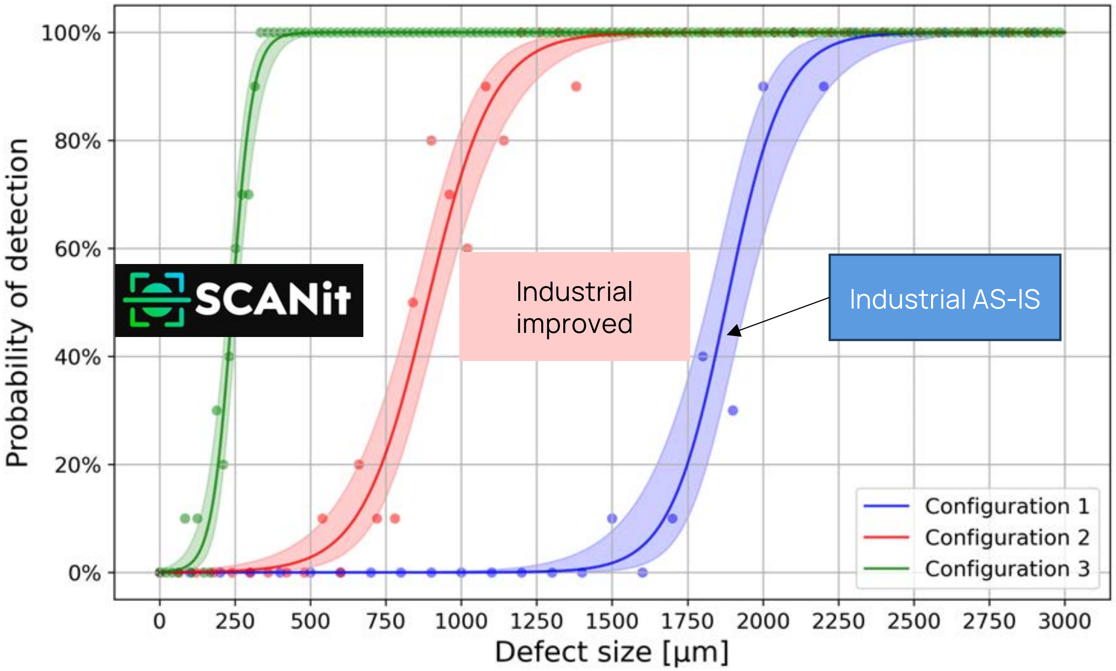


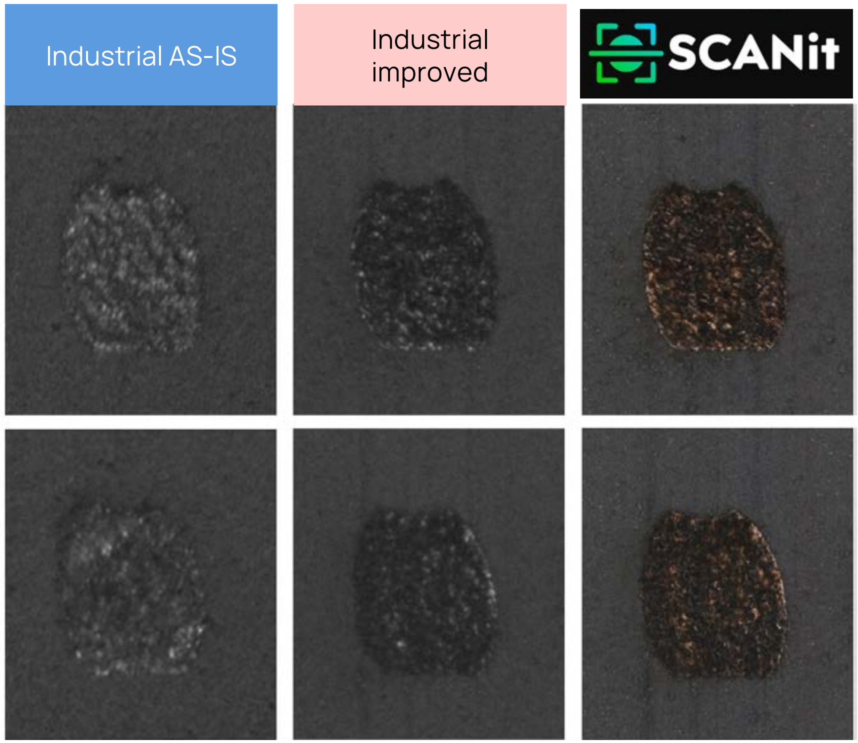


Effectiveness
(Probability of Detection – POD)

We explored the Probability of defect detection to characterize our PMM solution as a function of the defect size.



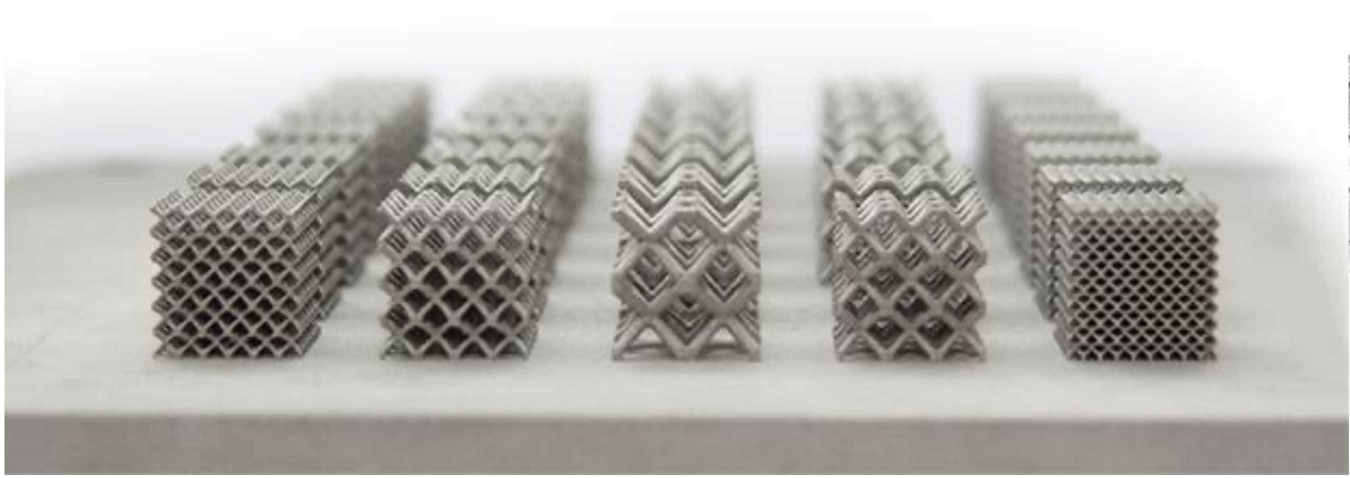


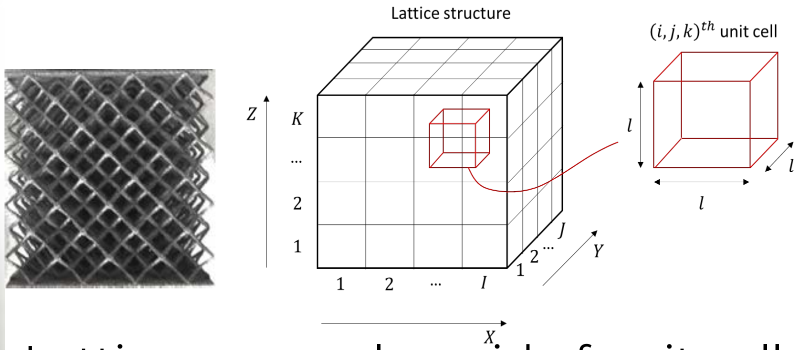


Significant improvement in the POD can be achieved by improving the sensing solutions

Metamaterial or lattice structures

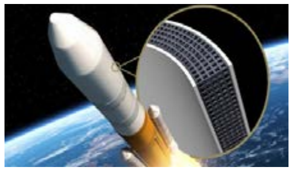
Colosimo and Grasso, JQT 2022 -ASQ Brumbaugh





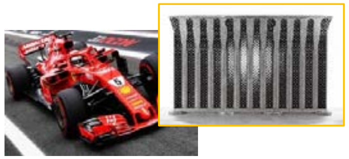
Lattice – a regular grid of unit cells

Main applications (weight, vibration, cooling, cell integration)



SPACE

AERO



RACING

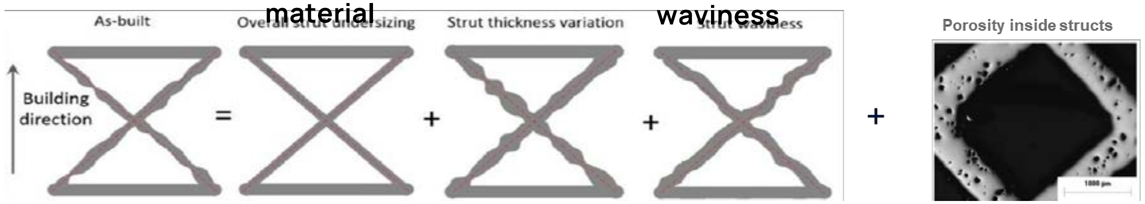
MACHINERY

BIO

Examples of **defects** in lattice structures

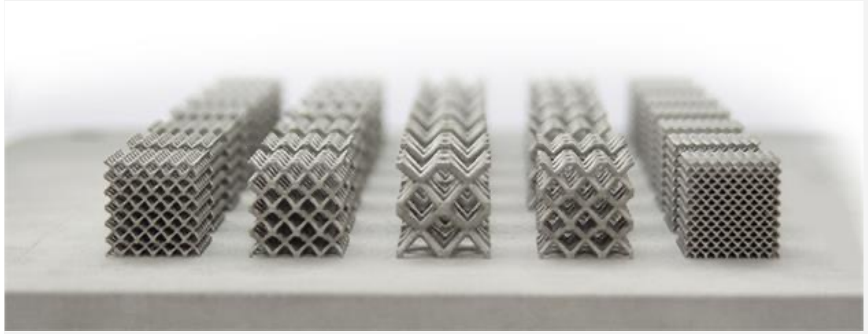
(Liu et al., 2017; Melancon et al., 2017; Dallago et al., 2019)

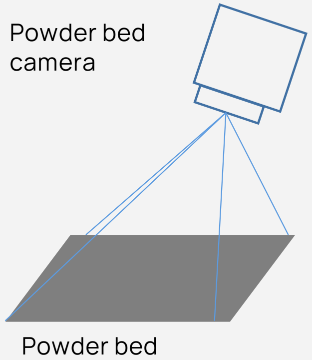
As-built | **Undersizing and lack of material** | **Excess of material** | **Irregular thickness, waviness** | **Porosity and cracks**

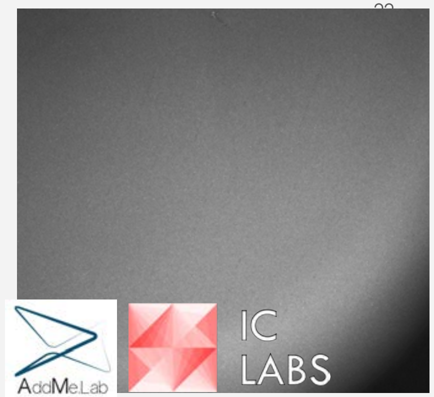


Geometrical deviation via off-axis imaging

Lattice structure

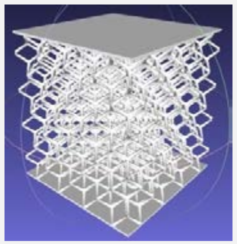




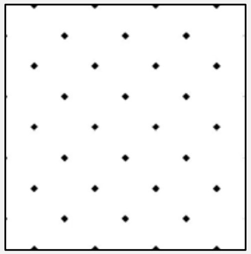


Real printed part

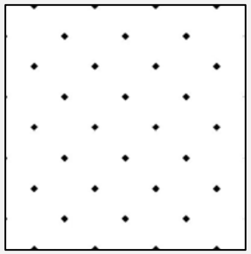
Nominal geometry (CAD)



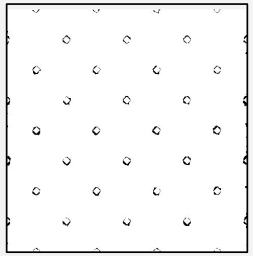
Layerwise evolution of the
***real** geometry* (Xray CT/insitu imaging)



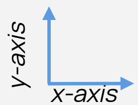
Layerwise evolution of
*the **nominal** geometry* (CAD)



Layerwise evolution of the deviation
Real (printed) vs nominal shape (CAD)



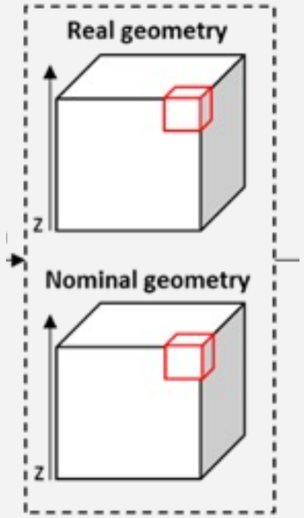
Deviation index



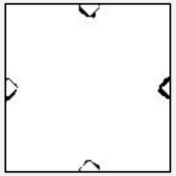
Colosimo and Grasso, JQT 2022 –ASQ Brumbaugh Award

Geometrical deviation via off-axis imaging

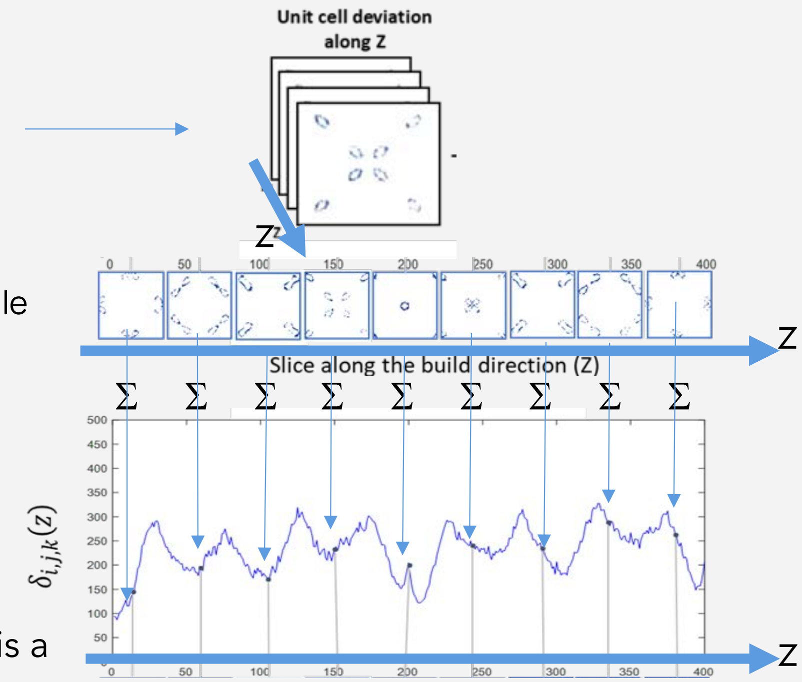
Lattice structure



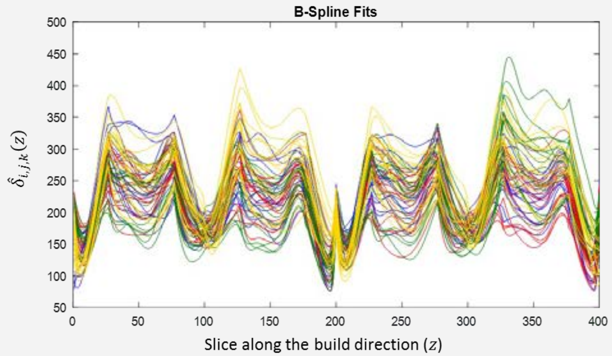
Real vs nominal



Deviation on the single cell as a function of z



Layerwise evolution of the deviation from the nominal shape in each single cell is a profile



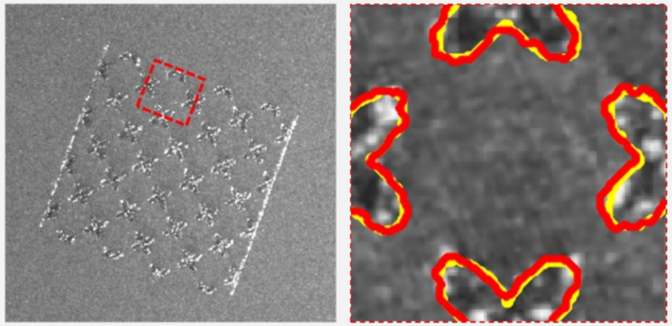
BSPLINE FUNCTIONAL DATA

MULTIVARAITE CONTROL CHARTING ON COEFFICIENTS (DIMENISONAL REDUCTION)

Geometrical deviation via off-axis imaging

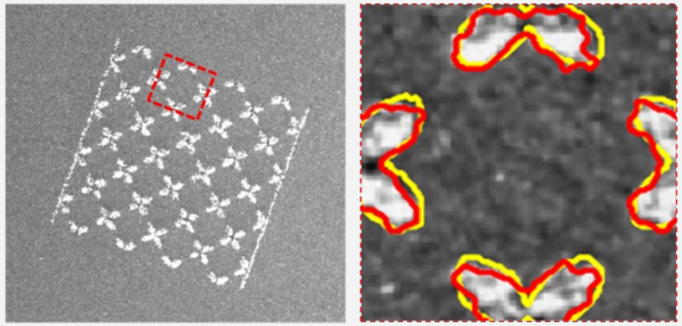
Lattice structure

Example of layer with dark-field pattern



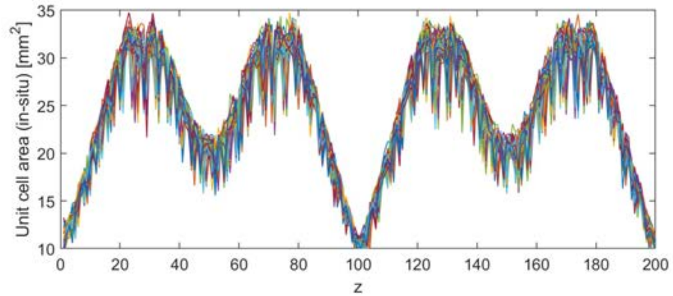
DARK-FIELD IMAGE (good reconstruction)

Example of layer with bright-field pattern

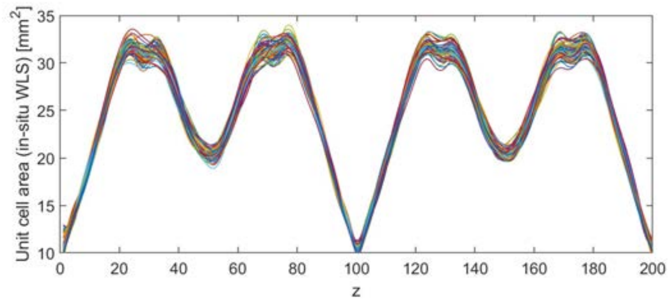


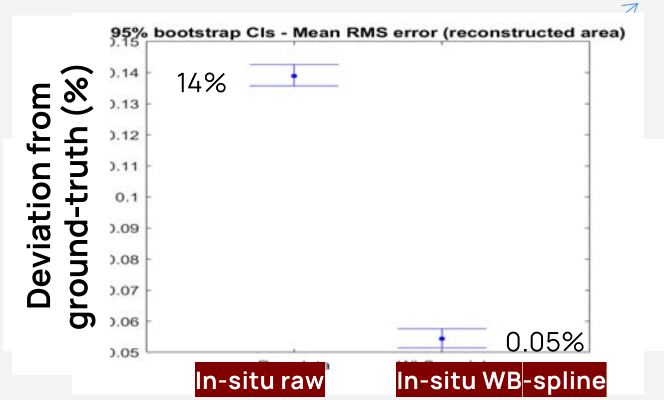
BRIGTH-FIELD IMAGE (bad reconstruction)

In-situ raw



In-situ WBspline





Weighted bspline

$$P_j = (B^T W(z) B)^{-1} B^T W(z) \delta_j(z)$$

$$\omega(z) = \frac{1}{s_b(z)^2}$$

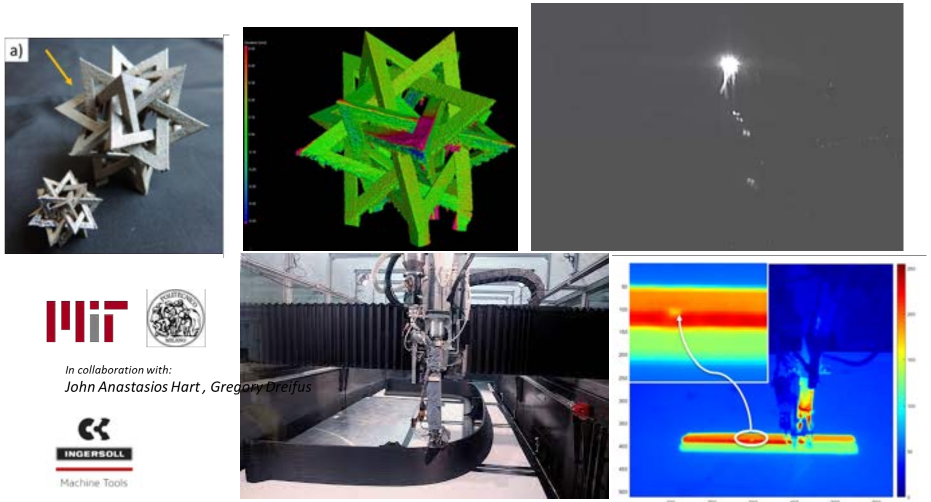
Weight = inverse of the pixel intensity variance in a band around the detected edge

Trustiness ...and a final question

03

Assess the real TRL of all the developed solutions

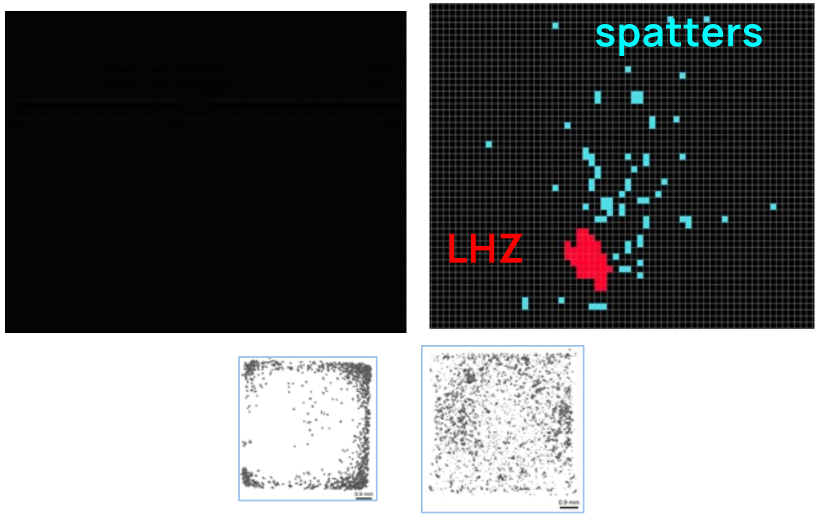
Hot-and cold- spot detection



IC LABS

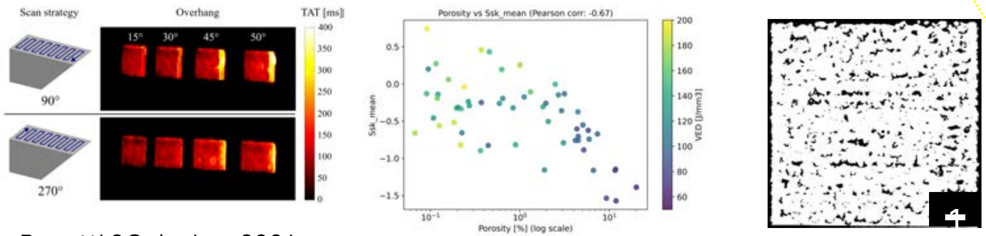
Colosimo& Grasso 2018; Yan et al. 2022; Bugatti &Colosimo 2022, Caltanissetta et al. 2022

Spattering



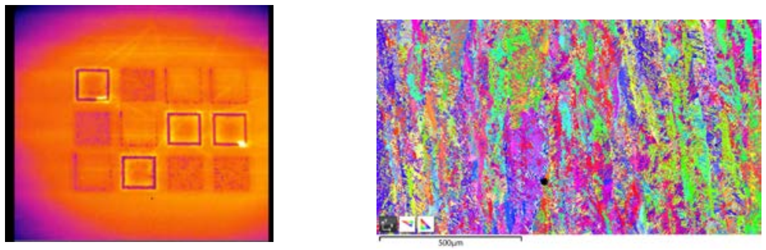
Repossini et al., 2017; Colosimo et al., 2024

Surface texturing and Roughness prediction



Bugatti &Colosimo 2024

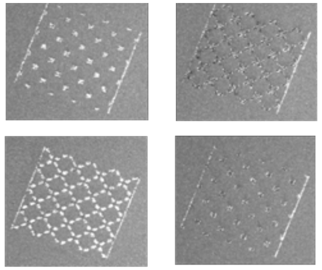
Microstructure (classification amd prediction)



Colosimo & Grasso, 2025

Data is not information and information is not knowledge

Powder bed images

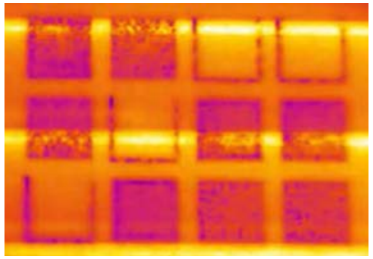


5 - 10 Gbyte

Off-axis high speed video

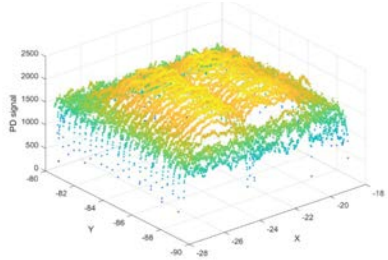
5 – 10 Tbyte

Off-axis high speed IR video



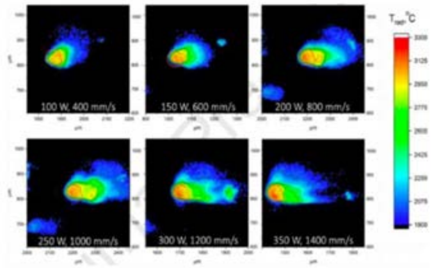
50 – 100 Tbyte

Co-axial photodiode

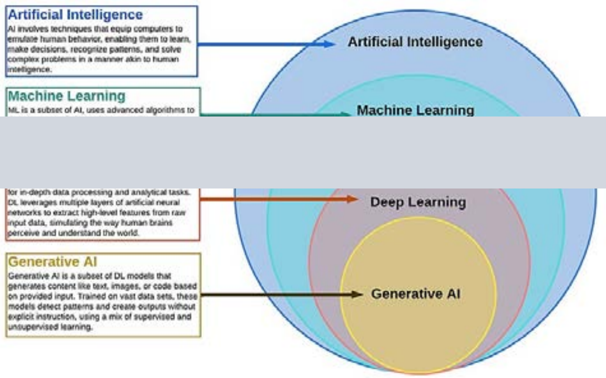


10 – 30 Gbyte

Co-axial meltpoole



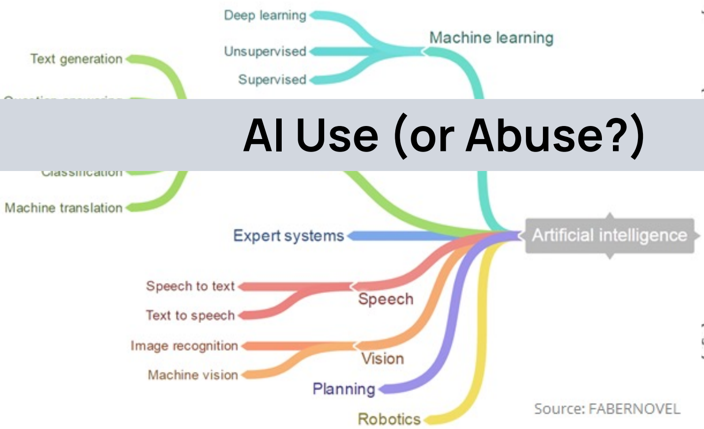
5 – 10 Tbyte



Unraveling AI Complexity - A Comparative View of AI, Machine Learning, Deep Learning, and Generative AI.

(Created by Dr. Lily Popova Zhuhadar, 07, 29, 2023)

AI Use (or Abuse?)



Source: FABERNOVEL

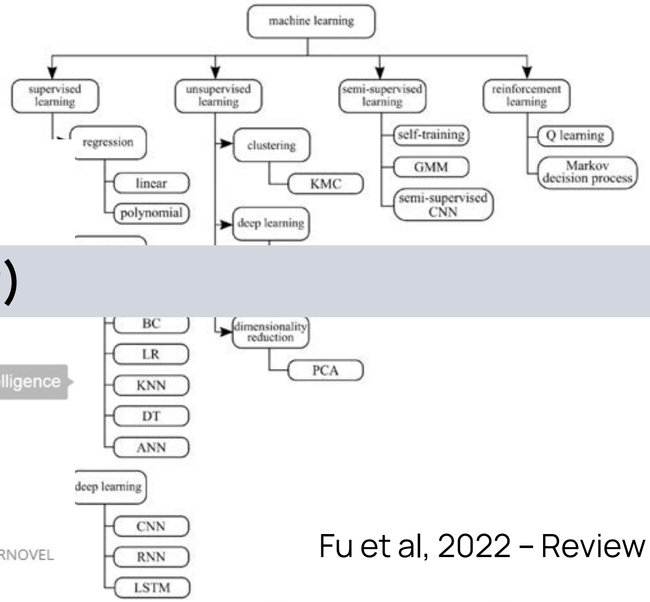
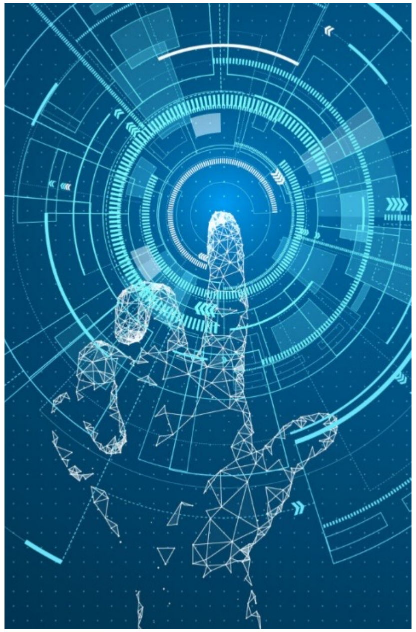


Fig. 7. Categories of different machine learning algorithms (all the abbreviations are listed in the nomenclature and can be found in the paper).

Fu et al, 2022 – Review on ML for L-AM

Digital+green= “twin” transition ?

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Thank you for the attention

Contact

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