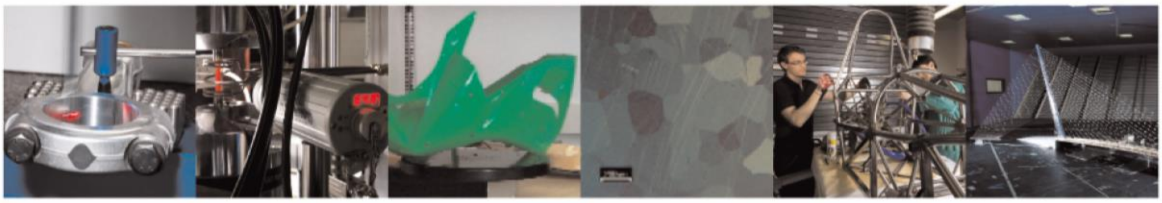

# Open data for open science in Industry 4.0: In-situ monitoring of quality in additive manufacturing

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# Open data for open science in Industry 4.0: in-situ monitoring of quality in additive manufacturing

*Abstract.* Open science has the capacity of boosting innovative solutions and knowledge development thanks to a transparent access to data shared within the research community and collaborative networks. Because of this, it has become a policy priority in various research and development strategy plans and roadmaps, but the awareness if its potential is still limited in industry. Additive manufacturing (AM) represents a field where open science initiatives may have a great impact, as large academic and industrial communities are working in the same area, enormous quantities of data are generated on a daily basis by companies and research centres, and many challenging problems still need to be solved. This paper presents a case study based on an open science collaboration project between TRUMPF Laser- und Systemtechnik GmbH, one of the major AM systems developers and Politecnico di Milano. The case study relies on an open dataset including in-line and in-situ signals gathered during the laser powder bed fusion of specimens of aluminium parts on an industrial machine. The signals were acquired by means of two photodiodes installed co-axially to the laser path. The specimens were designed to introduce, on purpose, anomalies in certain locations and in certain layers. The dataset is specifically designed to support the development of novel in-situ monitoring methodologies for fast and robust anomaly detection while the part is being built. A layerwise statistical monitoring approach is proposed and preliminary results are presented, but the problem is open to additional research and to the exploration of novel solutions.

*Keywords*: Open science; open data; industry 4.0; additive manufacturing; 3d printing; process monitoring; in-situ; powder bed fusion; profile monitoring; functional data

## 1 Introduction

In the current industrial context, which is more and more characterized by Industry 4.0 approaches, data availability at every level has literarily exploded. Within the value chain of a product, data are generated at every possible step, from part design through all processing and assembly phases, to qualification inspections and acceptance testing. Data availability is not only improving in terms of data volume, but also in terms of structured data collection methods and efficient data storage solutions, like data lakes and cloud resources. An example that well represents this context regards the continuously growing industrial adoption of additive manufacturing (AM) technologies. Indeed, AM is one of the pillars of the Industry 4.0 paradigm where the “four Vs” commonly used to describe big data, i.e., volume, velocity, variety and veracity, well fit the large and complex datasets generated on a daily basis by end-users, machine builders and researchers. The layerwise production paradigm enables the collection of a large variety of signals on a layer-by-layer basis, during the entire AM process (Grasso et al., 2021; Colosimo et al., 2018; Colosimo, 2020). These signals range from high resolution images to high-speed videos, from surface topography reconstructions to thermographic measurements, etc. In addition, large volumes of data are generated during the design, optimization and simulation of products characterized by novel geometrical complexity levels. The increased geometrical complexity also imposes the adoption of appropriate inspection techniques, like x-ray computed tomography, which, in turn, further increase the volume and variety of data collected during the whole production and qualification chain.

Such big data generation and collection is typically associated to strict data security policies aimed at protecting intellectual and industrial properties, which is at the basis of traditional industrial innovation procedures. Nonetheless, policy makers and national/supranational institutions included open science, which involves a transparent access to shared data and knowledge within collaborative networks, among their innovation strategies and roadmaps (an example is the 2020-2024 research and innovation strategy program of the European Commission[*]). Similarly to the several benefits enabled by open innovation policies, the open science approach allows industry to face complex problems and accelerate the adoption of innovative solutions by taking advantage of variegated knowledge backgrounds of researchers who have access to shared data. Besides that, the research community can strongly benefit from shared data in the development of benchmark case studies for testing, validating and comparing novel methodologies, but the availability of shared real datasets to this aim is still quite limited. In the AM field, recent initiatives highlighted an increasing awareness of industrial actors about the great opportunities potentially enabled by sharing data and knowledge within the research community. A few examples include the creation of a format for open beam path data[†], the adoption of open software platforms like Open Machine Control™, which enable full parameter control, software tool customization and plugin development[‡], and the creation of open material databases, like the ones from NIST[§] and NASA (Prater, 2017).

This paper presents a case study originated from an open science collaboration between TRUMPF Laser- und Systemtechnik GmbH, one of major AM system developers and market leader for machine tools used in flexible sheet metal processing and industrial laser-based manufacturing, and Politecnico di Milano[**]. The framework of the case study regards in-line monitoring of the AM process using signals gathered via in-situ installed sensors to detect anomalies and process unstable states. A continuously increasing interest has been devoted to this problem, which also represents a playground where AM system

[*] https://ec.europa.eu/info/research-and-innovation/strategy/strategy-2020-2024/our-digital-future/open-science_en (last access: 14/07/2021)
[†] https://freemelt.com/join-the-game/ (last access: 13/07/2021)
[‡] https://openadditive.com/wp-content/uploads/2021/01/PANDA_Machine_Control.pdf (last access: 13/07/2021)
[§] https://ammd.nist.gov/ (last access: 13/07/2020)
[**] https://www.ic.polimi.it/open-data-challenge (last access: 13/07/2020)

developers are investing notable resources to develop robust and effective solutions (McCann et al., 2021; Grasso et al., 2021). The final aim consists of anticipating the detection of defects and undesired deviations while the part is being produced, reducing costs and time devoted to post-process inspections and qualification operations. Moreover, in-situ sensing and monitoring tools allow the operator to stop the process if unrecoverable anomalies are detected, with consequent waste reduction. When possible, real-time process data may also enable either closed loop control methods, to avoid or mitigate the onset of defect, or in-situ defect repair solutions (Liu et al., 2020; Renken et al., 2019; Colosimo et al. 2020).

The case study here presented relies on an open dataset that consists of in-situ signals gathered during laser powder bed fusion (L-PBF) of aluminium specimens. The signals were acquired by means of two photodiodes installed co-axially to the path of the laser. The specimens were specifically designed to introduce, on purpose, anomalies in certain locations and in certain layers. A layerwise statistical monitoring approach is proposed and preliminary results are presented, but the problem is open to additional research. The dataset, which is openly available[††], is designed to support the design, benchmarking and validation of novel in-situ monitoring methodologies, which possibly outperform the layerwise approach here presented.

The case study was designed by TRUMPF Laser- und Systemtechnik GmbH, and hence it is representative of actual industrial settings used nowadays by AM system developers to calibrate, test, and tune their own in-situ sensing and monitoring toolkits before making them available on the market.

[††] The dataset described in this paper is available at the following link: https://www.ic.polimi.it/open-data-challenge/

An important usage of real datasets consists of the development of case studies to support practical learning in the framework of professional qualification programs. The potential of open science initiatives to create and consolidate sector skills in AM is therefore another potential outcome of this study, which is discussed in a dedicated section.

Section 2 describes the problem. Section 3 describes the dataset, its collection and preparation. Section 4 presents the layerwise monitoring method. Section 5 presents some guidelines for practitioners on the use of the proposed case study to investigate and test process monitoring methodologies. Section 6 presents a brief discussion about the role of open science in AM professional qualification frameworks. Section 7 concludes the paper.

## 2 Problem description

The problem addressed in this case study regards the development of in-situ monitoring solutions for AM processes. The term "in situ monitoring" refers to the use of measurements performed while the part is being produced by exploiting the layerwise production paradigm entailed in AM. Indeed, a variety of sensor signals may be gathered during the production of any given layer, enabling several benefits that motivate a continuously increasing amount of research studies and industrial developments in this field (Grasso et al., 2021).

The deployment of in-situ monitoring solutions allows anticipating quality measurements and qualification operations during the process itself, reducing costs and time devoted to post-process quality inspection or complex shapes. In addition, the capability to detect anomalies and defects in-line and in-situ enables the early interruption of the process in case of unrecoverable errors, with consequent waste reduction. Seminal studies also showed that in-situ measurements may be used as inputs for closed-loop control strategies aimed at preventing or mitigating unstable states (Liu et al., 2020; Renken et al., 2019) and for the implementation of in-line defect correction and removal methods (Colosimo et al. 2020).

Most metal AM system developers are investing notable resources in the development of in-situ monitoring solutions. Several commercial toolkits have become commercially available in the last years (Colosimo and Grasso, 2020) and most metal powder bed fusion systems are nowadays equipped with sensors and in-line data collection and visualization instruments. What is still missing is the availability of embedded intelligent methods suitable to make sense of big and fast data streams gathered during the entire duration of the process and to signal real anomalies and defects in a robust and effective way. As a matter of fact, the challenging goal of in-situ monitoring methodologies in AM, like in other industrial processes, consists of being able to detect actual anomalies as soon as possible while achieving the best compromise in terms of false positives and false negatives.

This case study specifically focuses on metal L-PBF, which is an AM process adopted in several industrial sectors to produce highly complex and near-net-shape products with high dimensional and geometrical accuracy, good surface finishing and mechanical performances comparable or even superior to the ones achieved with competing processes (Yadroitsev et al., 2021).

Among several possible in-situ sensing configurations, a very effective one, which is also largely available in industrial L-PBF systems, consists of using the optical path of the laser to measure the radiation emitted by the melt pool and its surroundings. The melt pool is the region where the laser beam exposure melts the material, and it is known to be a primary feature of interest in any process that involves a beam-material interaction aimed at achieving a local melting of the material.

The wide literature devoted to in-situ monitoring of melt pool properties in L-PBF has been reviewed by various authors (Everton et al., 2016; Grasso et al., 2017; Grasso et al., 2021). Most of the literature relies on co-axial spatially integrated pyrometry, co-axial spatially resolved video imaging or combinations of the two.

Spatially integrated pyrometry through one or multiple photodiodes is suitable to measure the melt pool radiation intensity with high temporal resolution (e.g., in the order of 100 kHz). Some authors showed the correlation between co-axial photodiode signals and salient quality features of solidified tracks (Forien et al., 2020) together with the final density of the part (Jayasinghe et al., 2020; Alberts and al., 2017). Being spatially integrated measurements, co-axial photodiode signals provide a weaker information about the melt pool properties than co-axial machine vision methods, which have been extensively investigated in the literature as well (Grasso et al., 2021; McCann et al., 2021). However, from an industrial implementation perspective, photodiodes are less intrusive sensors, and hence easier to install into the optical laser path. Moreover, the spatially integrated signal allows a much higher temporal resolution, which also results in a higher potential for being used as input for real-time closed loop control.

In this case study, an industrial setup consisting of two co-axial photodiodes monitoring the radiation in two different wavelength ranges is considered. The signals were acquired during the production of specimens specifically designed to introduce, on purpose, anomalies with different severity levels in terms of melt pool radiation in certain locations and in certain layers. This results into an open experimental dataset for testing, validating, and comparing novel in-situ monitoring solutions.

## 3 Data collection and preparation

The laser optical chain including the two co-axial photodiodes is shown in Fig. 1. The sensing equipment consists of an indium gallium arsenide (InGaAs) photodiode that measures the integral radiation in the short infrared range (1100-1700 nm) and a silicon (Si) photodiode that measures the integral radiation in the visible and near infrared range (550-950 nm).

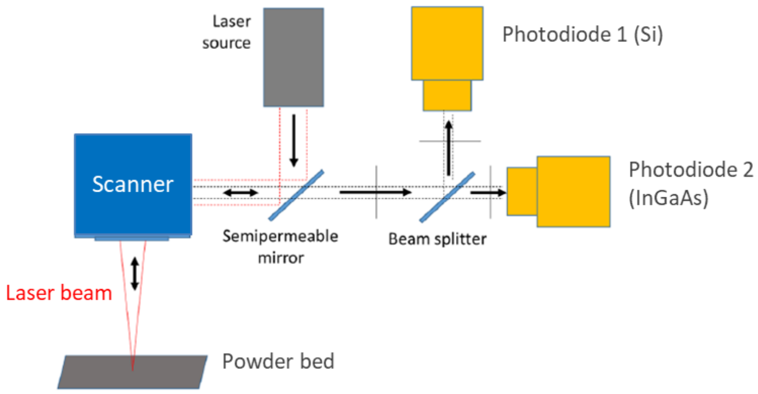



Fig. 1 – The co-axial monitoring setup that utilizes two photodiodes aligned to the optical path of the laser.

Depending on the monitored wavelength range, different phenomena may be captured and different responses to undesired process conditions and unstable states may be obtained. This motivates the adoption of multiple sensors characterized by different spectral ranges.

The sensing setup shown in Fig. 1 was available on a TRUMPF TruPrint 5000 multi-laser L-PBF production system, including three laser scanners with full field overlap and two on-axis photodiode sensors per scanner.

The photodiode signals were acquired during the manufacturing of four equal AlSi10Mg specimens produced with fixed process parameters (specifically, a scan speed of 1500 mm/s, laser power of 480 W, and laser spot diameter of 100 µm). Two specimens were produced with the same laser scanner, whereas the remaining two were produced with two other laser scanners. The shape and size of the specimens are shown in Fig. 2.

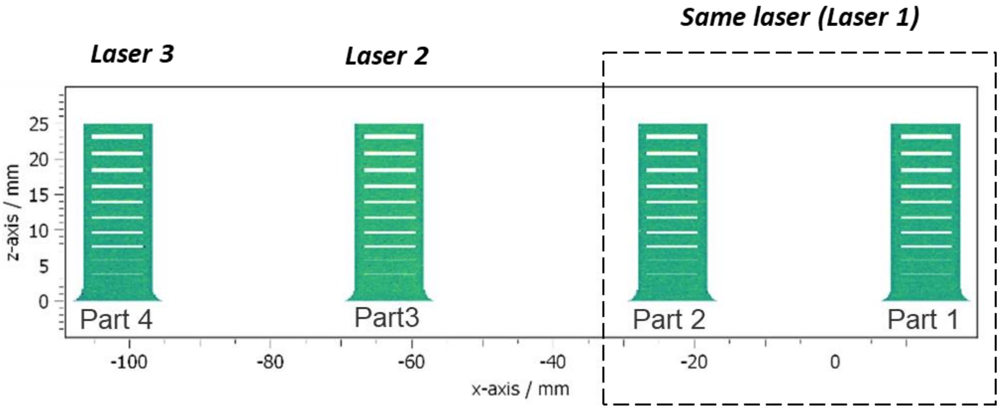



Fig. 2 – Specimens produced in the same build with different laser scanners

The specimens are parallelepipeds of size $10 \times 10 \times 25$ mm. They were placed in different locations of the build area and built vertically (i.e., the *z* direction is the build direction) during the same L-PBF process. In the bottom layers, corresponding to the tapered base area, the process was still not in its regime conditions, and so data collected during the production of such bottom layers are not included in the dataset.

Within each specimen, anomalies were purposely introduced in specified layers by designing some unexposed blocks, i.e., inner regions of the specimen in which no laser scan occurred for a number of consecutive layers ranging between 1 and 10, with the number of unexposed layers that increases along the build direction. The first layer after an unexposed block has a large overhanging area with loose powder underneath. The heat exchange in this overhanging layer (and possibly in few of the layers that follow it) is altered by the fact that the loose powder has much less conductivity than the bulk material. Therefore, unexposed blocks tend to force heat conduction anomalies with increasing severity as the number of unexposed layers increases. Therefore, the first fully exposed layer produced on top of an unexposed block is assumed to be out-of-control. The anomalous heat exchange may also affect a few following layers, especially when the unexposed block consists of many consecutive layers. Fully exposed layers produced on top of previously fully exposed layers are referred to as “bulk layers”, and the process is assumed to be in-control during the production of such layers.

The photodiode signal was initially acquired with a sampling rate of 100 kHz and then down-sampled in order to have one datapoint every 30 μm along the laser scan path. The orientation of the laser scan direction and the laser scan path were changed every layer, as is commonly done in L-PBF. The dataset includes the X and Y coordinates of the laser spot (i.e., the coordinates of the centre of the photodiodes’ field of view) recorded synchronously to the photodiode signals.

Another signal included in the dataset is the measured laser power, acquired with a synchronous sampling with respect to laser beam location and photodiode signals.

Fig. 3 shows a detail of the specimen shape and an example of the laser scan path in consecutive layers including unexposed ones.

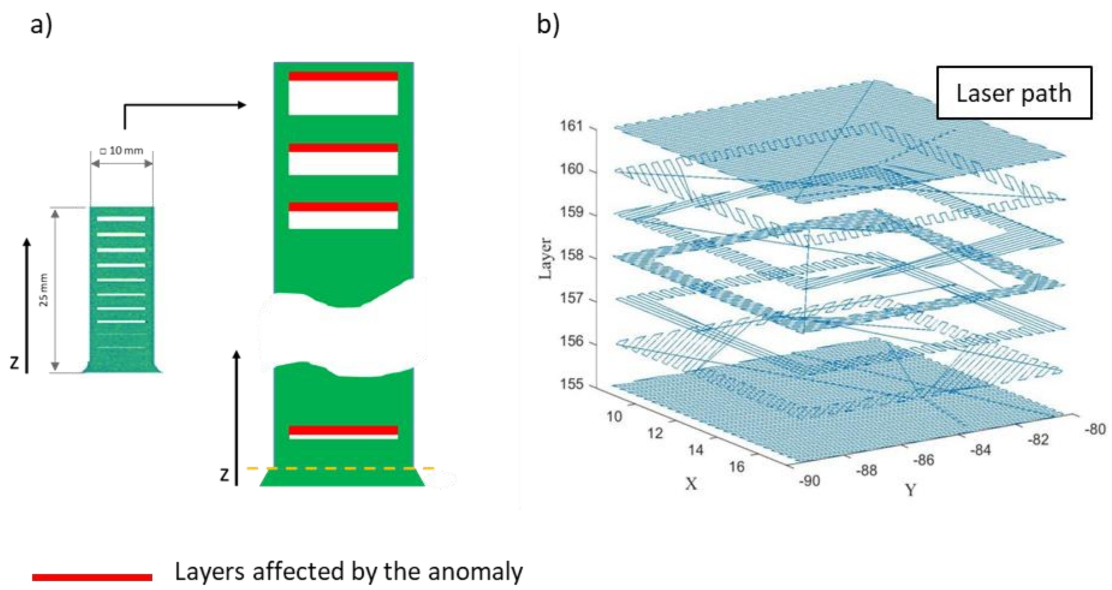
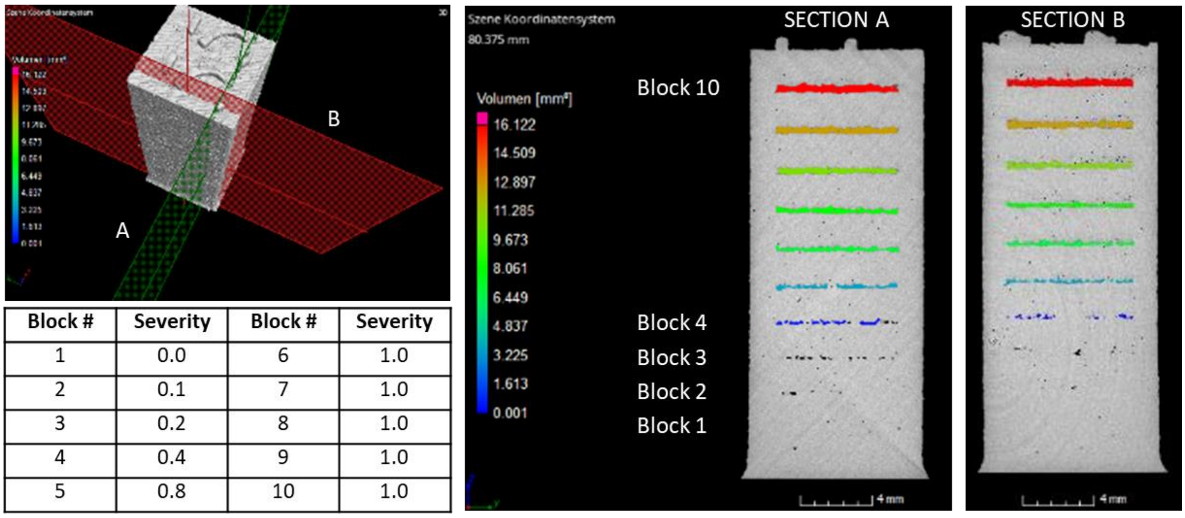



Fig. 3 – Detail of the specimen shape with indication of layers affected by the purposely introduced anomaly (a); example of laser path in some consecutive layers including unexposed ones

Specimens were inspected after the L-PBF process by means of x-ray computed tomography to determine the presence and volume of voids within the unexposed blocks. An example of such tomographic reconstructions along two perpendicular planes is shown in Fig. 4. This inspection highlighted that when one single layer was not exposed, no pores were generated within the part, thanks to the remelting that occurs in few underneath layers when the next fully exposed layer is produced. Because of this, a severity rating equal to zero was set for the first anomaly following a block of only one unexposed layer. Anomalies following blocks of two to five unexposed layers were given severity ratings between 0.1 and 0.8. All anomalies following blocks with more than five unexposed layers were given the maximum severity rating equal to 1.0. Severity ratings are shown in the bottom-left panel of Fig. 4. Such severity ratings can be used to evaluate the performances of in-situ process monitoring methods.




| Block # | Severity | Block # | Severity |
|---|---|---|---|
| 1 | 0.0 | 6 | 1.0 |
| 2 | 0.1 | 7 | 1.0 |
| 3 | 0.2 | 8 | 1.0 |
| 4 | 0.4 | 9 | 1.0 |
| 5 | 0.8 | 10 | 1.0 |

Fig. 4 – Presence of pores and their corresponding volume along two perpendicular planes, A and B, virtually sectioning the specimen resulting from post-process x-ray computed tomography; based on these inspections, severity ratings reported in the bottom-left table were defined

## 4 Analysis and Interpretation

### 4.1 A layerwise monitoring approach

The proposed approach consists of monitoring synthetic statistics computed layerwise. In particular, we show the monitoring performance of a statistical process monitoring approach based on the layerwise mean of the photodiode signal and we compare it against the statistical process monitoring of the layerwise standard deviation of the same signal.

The method includes a 1) pre-processing phase, aimed at reducing undesired track boundary effects on the variability of the signal, 2) the estimation of synthetic layerwise statistics and 3) the design of a univariate control chart that exploits few initial layers as phase I (training phase).

The method has been applied to the InGaAs photodiode signal, which is known to be more sensitive to variations in the heat dissipation process, like the ones induced by the unexposed blocks included into the specimens. However, extensions of the method as well as different approaches may possibly consider also the information content of the Si photodiode signal.

Subsection 4.2 presents the proposed approach, whereas subsection 4.3 presents the results.

### *4.2 Methodology*

The first step of the proposed approach consists of getting rid of sources of variability related to transient effects in the boundaries of each scanned track and along the external contours. As shown in Fig. 5, the laser power quickly drops to zero (or to low power values) when the laser reaches the end of one track, then it quickly rises to the nominal level at the beginning of the next track. These transients result in a drop of the radiation measured by the photodiode, and they may represent an undesired source of variability and a nuisance factor in the following process monitoring. In addition, contours are scanned with process parameters that are different from the ones used in the inner scanned area, also known as internal hatching area. The aim of contour scans is to improve the surface finishing of external surfaces, but such contours are not of interest for the in-situ monitoring problem addressed in this study. Therefore, a preprocessing step consists of filtering out both the contour scan phase and the transient patterns in the boundaries of scanned tracked from the monitored signal. To this aim, a threshold $t = 440$ W was set such that photodiode signals were filtered out when the measured laser power signal was lower than the threshold $t$. The threshold was selected being known the nominal laser power during the melting phase, i.e., $P = 480$ W, and being known a natural fluctuation of the measured power signal within a range of about 20 – 30 W. Thus, datapoint acquired when the laser power was lower than $t$ correspond to datapoints where no melting was occurring.

Fig. 6 shows an example of InGaAs photodiode signal in one layer before and after this filtering operation. A 3D representation of the same signal before and after the filtering operation is shown in Fig. 7.

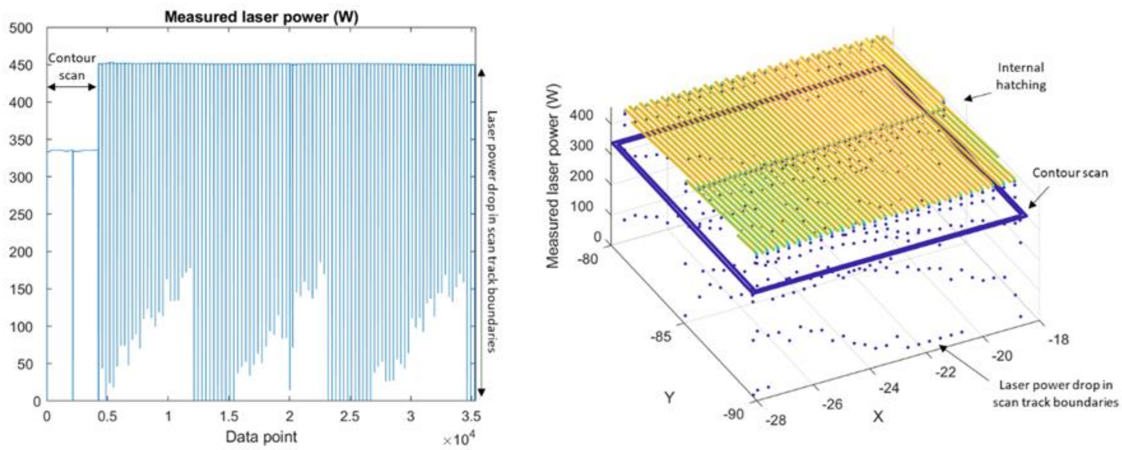



Fig. 5 – Example of measured laser power signal in one layer: time series pattern in the left panel, 3D scatterplot as a function of X and Y laser coordinated in the right panel

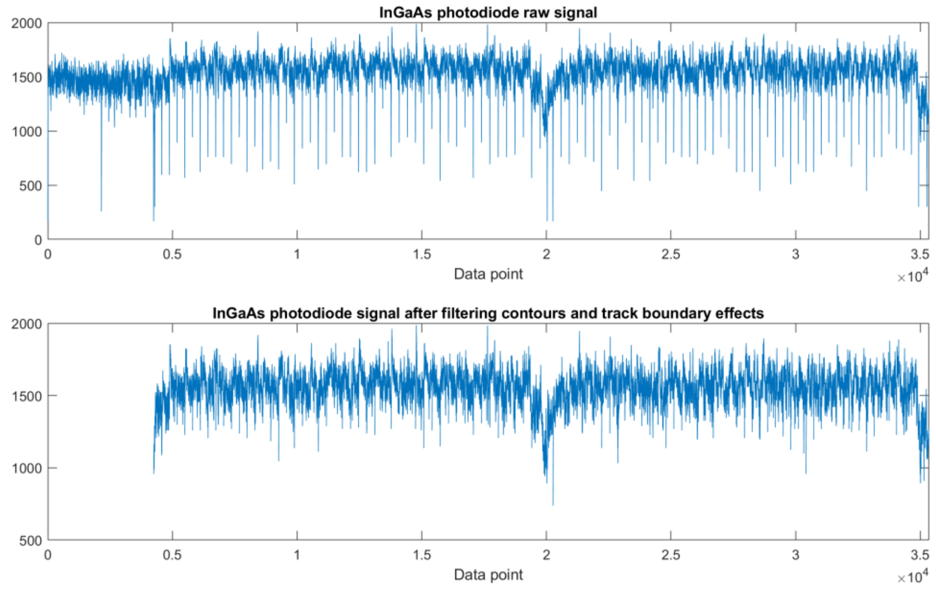



Fig. 6 – Example of raw InGaAs photodiode signal in one layer (top panel) and the corresponding signal after filtering out the contouring phase and the track boundaries with laser power lower than the threshold (bottom panel). The intensities of the photodiodes are coarsely proportional to the recorded heat radiation.

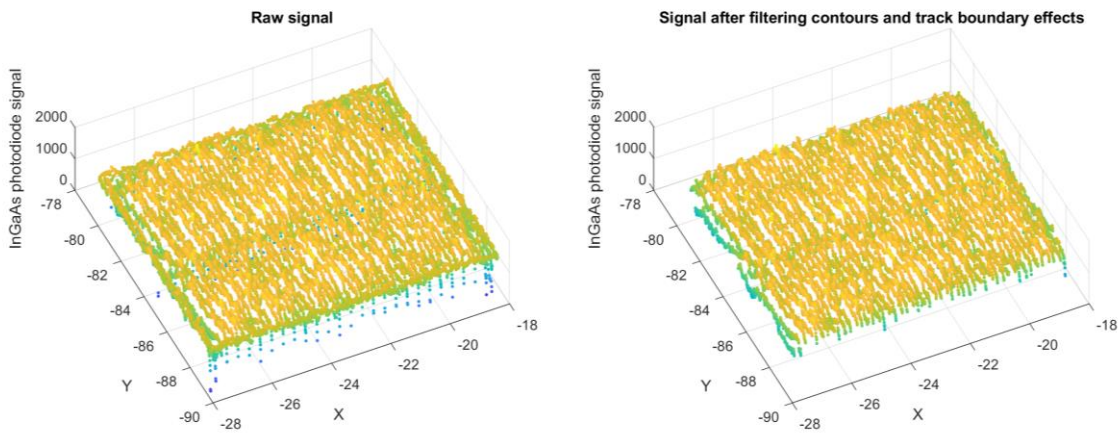



Fig. 7 – 3D scatterplot representation of the raw InGaAs photodiode signal in one layer (left panel) and the corresponding signal after filtering out the contouring phase and the track boundaries with laser power lower than the threshold (right panel)

Once the photodiode signal has been pre-processed, the sample mean of the signal is computed in every layer. The proposed layerwise monitoring approach consists of designing a control chart to monitor the stability of the sample mean radiation measured by the photodiode using as Phase I (training phase) the signals in a small number of first initial layers. In this case study, we used the first $m = 25$ bottom layer of the specimens. Probabilistic control limits were estimated as percentiles of the empirical probability density distribution smoothed by means of a gaussian kernel density estimation (Bowman and Azzalini, 1997). The target type I error was set at $\alpha = 0.0027$. In Phase II, only bulk layers, i.e., fully exposed layers, were considered, and empty spaces in the control chart were left in correspondence of unexposed layers.

The use of initial layers of the same part in the control chart design phase prevents from the need to collect historical data in previous builds. Although heat exchanges may vary during the process, the melt pool properties within bulk regions are expected to stay stable over time, under in-control conditions, and this applies even in parts where the geometry of the bulk changes from layer to layer. Because of this, a training phase performed on few initial layers enables the design of a process monitoring tool suitable to detect anomalous patterns in the bulk material. Moving from bulk regions to contours, overhang areas and thin walls, instead, would modify the melt pool "signature", imposing the study of more general and adaptive techniques (see also Section 6 for further discussion). It is evident that, following this route, anomalies occurring in the first few layers may be not detected and they may have detrimental consequences on the control chart effectiveness. A competitor approach consists of designing and applying the same control chart on other layerwise descriptive statistic of the photodiode signal. In this study, we considered the same control charting scheme applied to the layerwise standard deviation of the signal.

### 4.3 Results

A preliminary exploration of data patterns is shown for one single specimen, i.e., the specimen labelled as part 2 in Fig. 2. Process monitoring results including all four specimens are shown later.

Fig. 8 and Fig. 9 show the InGaAs photodiode signals in the first layer after an unexposed block for all the blocks, represented as a time series or by means of a 3D scatterplot as a function of laser coordinates X and Y, respectively.

Fig. 8 and Fig. 9 show that the effect of the purposely introduced anomaly is hardly visible in the radiation measured by the InGaAs photodiode in the first layer following unexposed blocks from 1 to 5, whose severity ranges between 0 and 0.8. The effect of the anomalous heat exchange starts to be visible after unexposed blocks with severity equal to 1. When the laser exposes portions of the track within the anomalous area, the measured radiation exhibits a clear increase. Along the border of the scanned area, where no anomaly is present, the photodiode signal intensity drops to intensity levels observed in bulk (in-control) layers.

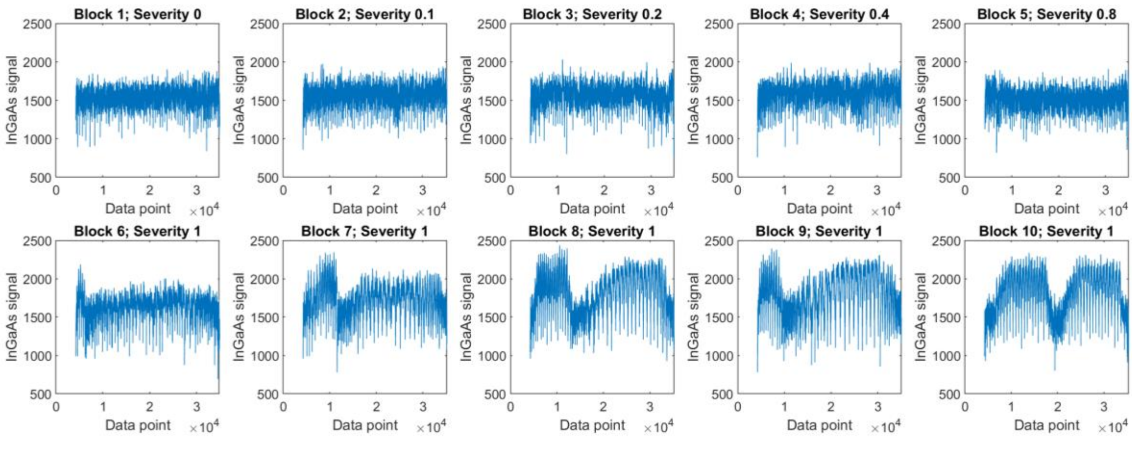



Fig. 8 – Time series of InGaAs photodiode signal in the first layer after each unexposed block

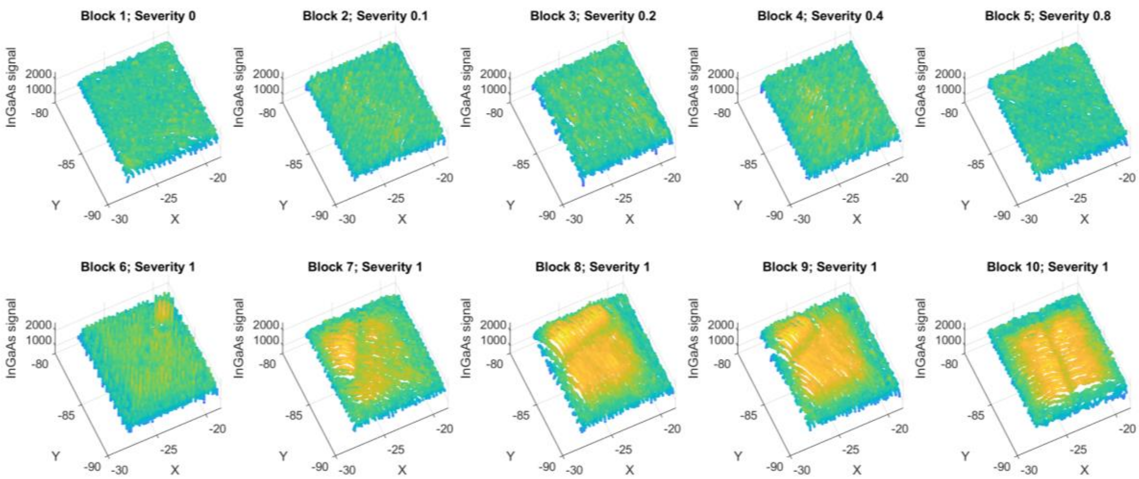



Fig. 9 – 3D scatter plot of InGaAs photodiode signal as a function of the laser X and Y positions in the first layer after each unexposed block

Fig. 10 shows how the InGaAs photodiode signal varies from the first layer after one unexposed block to the third layer after the same block for different blocks, i.e., for different severity levels. More specifically, Fig. 10 shows the InGaAs photodiode signal in the first, second and third layer after blocks 6, 8 and 10. Fig. 10 shows that the effect of the anomaly quickly mitigates starting from the second layer after an unexposed block.

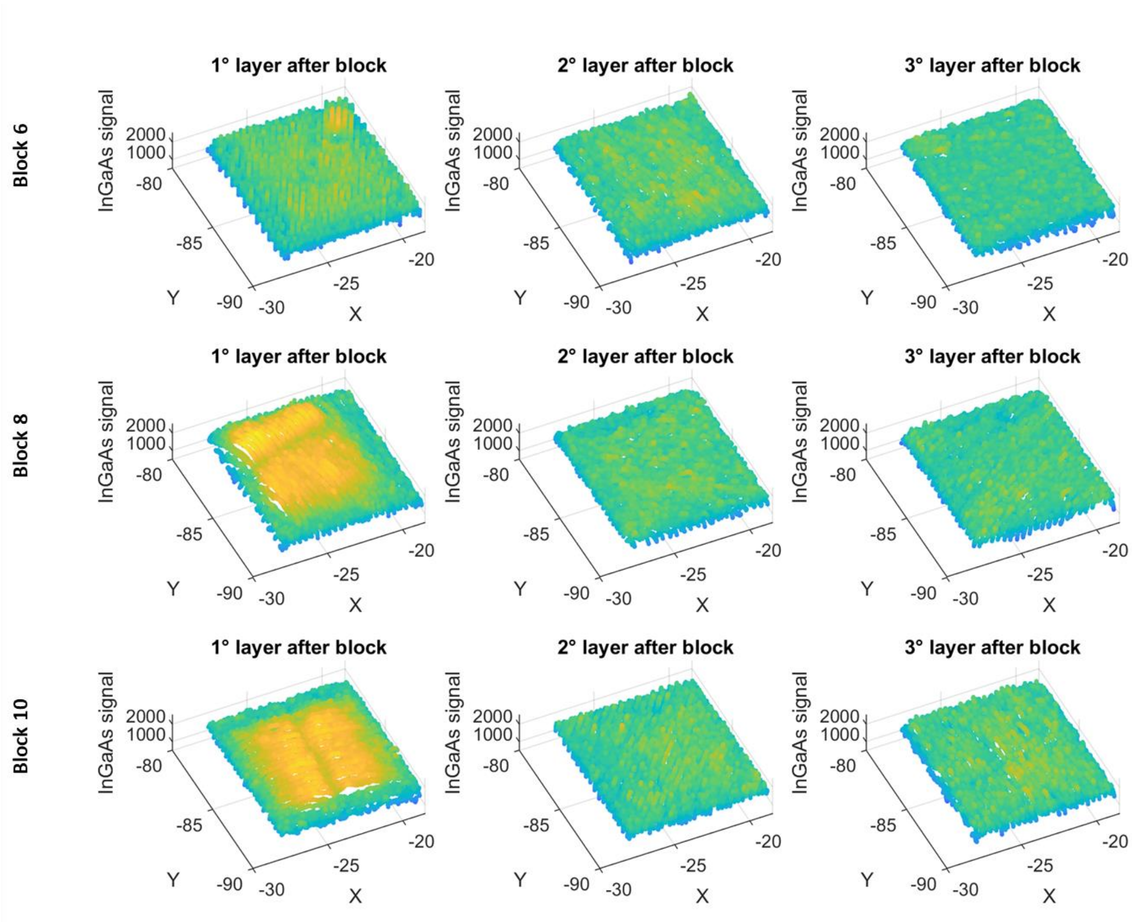



Fig. 10 – 3D scatter plot of InGaAs photodiode signal as a function of the laser X and Y positions in the first, second and third layers after unexposed blocks 6, 8 and 10

Fig. 11 shows the proposed control chart on the layerwise mean of the InGaAs photodiode signal designed and applied to one specimen (part 2). Fig. 11 shows that the control chart starts signalling the out-of-condition in the first layer after the third unexposed block, the one with severity 0.2. All following anomalies with higher severity are correctly detected, and the entity of the out-of-control shift grows as the severity increases. In most cases, only the first layer after the unexposed block is signalled, but in some cases also the second and/or the third layer after the unexposed block are signalled as well (after blocks 5, 6, 9 and 10). Fig. 11 also shows that no false alarm in bulk layers unaffected by the purposely inserted anomaly is present.

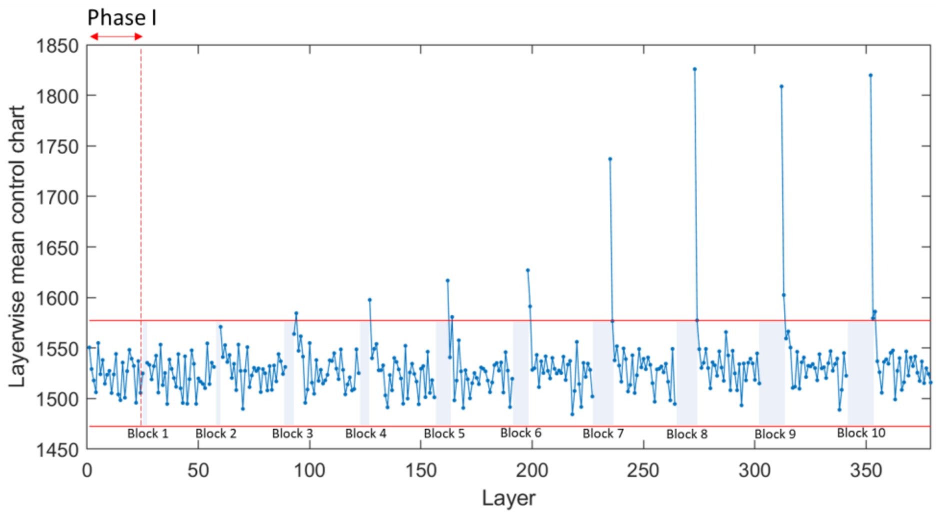



Fig. 11 – Proposed control chart on the layerwise mean of the InGaAs photodiode signal gathered during the production of the specimen labelled as part 2

A summary of results in terms of both actual anomaly detection rates for different severity levels and false alarms is shown in Fig. 12 and Table 1, where a comparison against the same layerwise control charting scheme applied to the standard deviation of the InGaAs photodiode signal is shown too. Summary results in Fig. 12 and Table 1 refer to all four specimens included into the experimentation. The performances summarized in Table 1 and Fig. 12 are based on the assumption that alarms in the first three layers following an unexposed block can be considered justified alarms, whereas any alarm in all other bulk layers are labelled as false alarms. Moreover, for each unexposed block, the anomaly is considered detected when an alarm is signalled in at least one of three following layers. Table 1 shows that the overall percentage of false alarms (0.425%) provided by the proposed approach is slightly higher than the target (0.27%). The control chart on the layerwise standard deviation of the signal yields a higher percentage of false alarms (0.935%).

Table 1 – Percentage of false alarms signalled by the proposed control chart and the same control chart applied on the layerwise standard deviation of the signal

| | **False alarms (%)** | |
|---|---|---|
| | **Control chart on layerwise mean** | **Control chart on layerwise standard deviation** |
| Part 1 | 0.00 | 0.34 |
| Part 2 | 0.00 | 2.38 |
| Part 3 | 0.34 | 1.02 |
| Part 4 | 1.36 | 0.00 |
| **Overall** | **0.425** | **0.935** |

Fig. 12 shows the percentage of anomaly detection considering the four monitored specimens (a percentage of 100% means that the anomaly was detected for all the four specimens, whereas percentages equal to 25%, 50% and 75% indicate a detection in 1, 2 or 3 out of 4 specimens only). Fig. 12 shows that monitoring the layerwise mean of the InGaAs photodiode signal is more effective than monitoring its layerwise standard deviation.

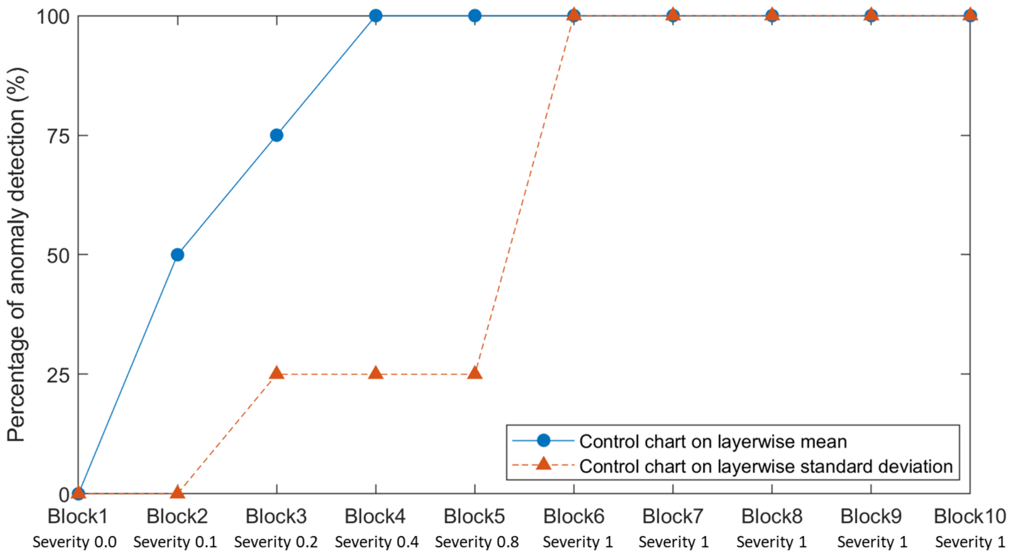



Fig. 12 – Percentage of anomaly detection: comparison between the proposed approach and the same control chart applied to the standard deviation of the layerwise signal

## 5 Guidelines for practitioners

The present case study belongs to the category of methods where the salient properties of the melt pool are monitored to detect process anomalies and deviations from a stable condition (Grasso et al., 2021). Co-axial photodiode sensors like the one used in this study are available from most L-PBF system developers and few other third-party providers. Methods tested and developed starting from the case study here proposed can be easily transferred to other platforms, aiding practitioners in filling the current lack of automated methods to detect actual anomalies with reasonable performances in terms of false positives and false negatives. The best practice in industry consists of setting a user-defined threshold on the photodiode signal intensity or its moving average. In the literature, seminal methods showed a correlation between photodiode signals and part density (Jayasinghe et al., 2020, Alberts et al., 2017), but statistical process monitoring solutions still need to be explored. Hereafter, we provide some guidelines on possible ways to use the present case study and extend the proposed methodology.

a. Data pre-processing: in this study, we pre-filtered the signal by setting a threshold on its intensity aiming to exclude from our analysis regions where the laser beam was not exposing the material. A variety of other filtering, pre-processing and/or modelling methods can be explored to get rid of irrelevant signal portions, to smooth high frequency variations or to cope with signal autocorrelation. Regardless of the adopted approach, we advocate to filter out the contouring phase, as contours are produced with different process parameters, and they are not affected by anomalies in any layer.

b. Training phase: in our proposed approach we use few initial layers as control chart design phase. The main assumption is that, under in control conditions, the process state in these initial layers remains stable in all following layers. Based on our previous experience, this assumption is met in practice as far as bulk regions of the additively manufactured part are concerned, even in the presence of layerwise varying geometries. Moving from bulk regions to contours, overhang areas and thin walls, instead, implies a change of the natural signatures of the melt pool properties. Thus, whether relying on few initial layers to estimate control limits or exploring more general and adaptive methods that require no fixed training phase, should be evaluated depending on the target application practitioners aim to address.

c. Spatio-temporal analysis: one practical limitation of our proposed layerwise methodology is that it requires the whole measurements in the current layer to be gathered before determining whether an anomaly was present in the layer itself. From an industrial perspective, it would be much more effective to signal an alarm as soon as the sensor data exhibit an anomalous pattern in space and/or time, *during* the production of the layer. The case study can be used to explore spatial and spatio-temporal techniques that go far beyond the proposed methodology.

d. Spatial extension of the anomaly: the within-layer extension of the area affected by the anomaly is quite large compared to the overall printed area. This makes layerwise synthetic methods, like the one here proposed, quite effective in practice. However, it is possible to increase the challenge complexity by testing the method and possible competitors on a reduced portion of the printed area. This would allow to vary the ratio between the anomaly-affected area and the whole area considered for the analysis. It can be regarded as a way to virtually cut the specimen and test process monitoring methods by considering just a portion of it. Depending on the analysed portion, the anomaly detection performances may vary, which allows to investigate in more depth the benefits and limitations of investigated techniques.

## 6 The relevance of open data for sector skills development in AM

As mentioned in the introduction, open science represents an opportunity for the companies that share their data with the international research community and for all researchers belonging to the community. One additional benefit related to the creation of open and accessible case studies is linked to the creation and consolidation of sector skills for novel professional figures. In the framework of AM, there is a gap of competencies that may represent a barrier for the widespread adoption of these technologies in industry. Filling such a gap has been identified as a priority by several institutions and policy makers. An example of initiatives aimed at deploying a strategy in this field at regional, national and international level is represented by the SAM (Sector Skills Strategy in AM)[‡‡] project, an Erasmus+ project funded by the European Commission. The project aims to identify and anticipate the right skills for the AM sector demands in response to the increasing labor market needs. A key issue for an effective training of professionals consists of letting them work on real case studies and real problems representative of the several challenges involved in AM applications. These professionals are expected to strengthen their multi-disciplinary competences in the many aspects related to AM technologies: in this framework, practical learning plays a central role. Nevertheless, real case studies including open data provided by important industrial actors are quite rare, and access to these data is commonly restricted. This is a further motivation to encourage companies and research centers to open their real data and case studies and share them with the community

[‡‡] https://www.skills4am.eu/ (last access: 16/07/2021)

## 7 Conclusions

This paper presented an open data case study that is available for the development, test and validation of novel process monitoring methodologies in AM. A quite simple process monitoring approach was presented, consisting of a univariate control charting scheme applied to the layerwise mean of the photodiode signal to detect anomalies associated to wrong heat exchange patterns in overhang areas. The proposed approach was motivated by the nature of the out-of-control condition, which affects a large portion of the scanned area, thus resulting in a global effect on the layerwise mean of the signal. However, the dataset lends itself to the study and test of alternative solutions that can possibly outperform the proposed one in terms of reactiveness to the anomaly and compromise between false positives and false negatives. As an example, a process monitoring approach suitable to anticipate the detection of the anomaly during the production of the layer, i.e., while the laser beam is melting each single track, may have a high impact from an industrial implementation viewpoint, with a high potential for being transferred to more complex geometries and other AM applications. The training strategy can be revised as well. In this regards, in-situ monitoring methods that require a very limited training phase or even no training at all have a huge potential in AM, where geometries may vary from one part to another, but also from one layer to the next one. Despite the simple shape of the specimens foreseen in the present case study, they can be used as a benchmark to test and develop methodologies that can be lately extended to more general and complex shapes. This is actually the rationale behind the industrial design of such experimental case study, which is an example of a real industrial benchmark for calibration, testing and tuning of in-situ process monitoring toolkits. Fostering the use of this open dataset to explore and test novel solutions is specifically the aim of the present study.

**Supplemental material**: all data are available at

https://www.ic.polimi.it/open-data-challenge/

## References

Alberts, D., Schwarze, D., & Witt, G. (2017). In Situ Melt Pool Monitoring And The Correlation To Part Density Of Inconel® 718 For Quality Assurance In Selective Laser Melting. In International Solid Freeform Fabrication Symposium, Austin, TX, USA (pp. 1481-1494).

Bowman, A. W., and A. Azzalini. *Applied Smoothing Techniques for Data Analysis*. New York: Oxford University Press Inc., 1997.

Colosimo, B. M., Grossi, E., Caltanissetta, F., & Grasso, M. (2020). Penelope: A Novel Prototype for In Situ Defect Removal in LPBF. JOM, 1-8.

Colosimo, B.M., (2020), Quality Monitoring and Control in Additive Manufacturing, Wiley StatsRef: Statistics Reference Online (ISBN: 9781118445112) - https://onlinelibrary.wiley.com/doi/10.1002/9781118445112.stat08241

Colosimo, B. M., Huang, Q., Dasgupta, T., & Tsung, F. (2018). Opportunities and challenges of quality engineering for additive manufacturing. *Journal of Quality Technology*, *50*(3), 233-252.

Everton, S. K., Hirsch, M., Stravroulakis, P., Leach, R. K., & Clare, A. T. (2016). Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing. Materials & Design, 95, 431-445.

Forien, J. B., Calta, N. P., DePond, P. J., Guss, G. M., Roehling, T. T., & Matthews, M. J. (2020). Detecting keyhole pore defects and monitoring process signatures during laser powder bed fusion: a correlation between in situ pyrometry and ex situ X-ray radiography. Additive Manufacturing, 101336.

Grasso, M. L. G., Remani, A., Dickins, A., Colosimo, B. M., & Leach, R. K. (2021). In-situ measurement and monitoring methods for metal powder bed fusion–an updated review. Measurement Science and Technology, https://doi.org/10.1088/1361-6501/ac0b6b.

Jayasinghe, S., Paoletti, P., Sutcliffe, C., Dardis, J., Jones, N., & Green, P. (2020). Automatic quality assessments of laser powder bed fusion builds from photodiode sensor measurements.

Liu, C., Le Roux, L., Ji, Z., Kerfriden, P., Lacan, F., & Bigot, S. (2020). Machine Learning-enabled feedback loops for metal powder bed fusion additive manufacturing. Procedia Computer Science, 176, 2586-2595.

McCann, R., Obeidi, M. A., Hughes, C., McCarthy, É., Egan, D. S., Vijayaraghavan, R. K., ... & Brabazon, D. (2021). In-situ sensing, process monitoring and machine control in Laser Powder Bed Fusion: A review. *Additive Manufacturing*, 102058.

Prater, T. (2017). Database development for additive manufacturing. *Progress in Additive Manufacturing*, *2*(1-2), 11-18.

Renken, V., von Freyberg, A., Schünemann, K., Pastors, F., & Fischer, A. (2019). In-process closed-loop control for stabilising the melt pool temperature in selective laser melting. Progress in Additive Manufacturing, 4(4), 411-421.

Yadroitsev, I., Yadroitsava, I., Du Plessis, A., MacDonald, E. (2021). Fundamentals of Laser Powder Bed Fusion of Metals, Elsevier