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DIGITALISATION AND SENSING IN ADDITIVE MANUFACTURING: DATA COLLECTION FOR PRODUCT(ION) OPTIMISATION

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Abstract: *Additive Manufacturing (AM) has evolved into a robust industrial production technology, but its inherent process complexity poses significant challenges to ensuring consistent part quality and repeatability. Traditional quality control methods often take place in the post-process phase, being time-consuming and costly. This paper argues that the future of AM lies in the adoption of real-time, in-situ monitoring and closed-loop control systems and offers several examples to fundament this claim. The AM systems leverage a network of sensors to collect vast amounts of data during the build process, enabling immediate analysis and corrective measures to prevent defect propagation. The methodology of this data-driven approach is explored, distinguishing between different in-situ monitoring solutions (optical, acoustic, and infrared sensors) and their practical implementation. A robust data management pipeline, incorporating advanced data reduction and AI/ML models, is essential to make this approach viable. The paper is discussed through four key research projects—CUSTODIAN, QuaL-DED, WAVETAILOR, and crystAIr—to illustrate these concepts in practice. These projects collectively demonstrate the importance of sensor fusion, AI-driven models and digital twins in establishing a self-optimising ecosystem that can significantly reduce scrap, accelerate development, and pave the way for a zero-defect manufacturing paradigm in AM. The conclusion is that digitalisation in AM is a critical shift that will secure the technology's future in advanced industrial production.*

Keywords: *additive manufacturing, digital technologies, monitoring, sensors*

1. INTRODUCTION

Additive Manufacturing (AM), commonly known as 3D printing, has transitioned from a rapid prototyping technology to an established industrial production method, covering the applications that conventional processes cannot attend. This shift is particularly evident in processes like Laser Powder Bed Fusion (L-PBF) and Laser Directed Energy Deposition (L-DED), which together accounted for a significant portion of the global AM market in 2025, that is 74% of all installed systems [1].

The increasing adoption of AM in critical sectors, such as aerospace, medical devices, and energy, highlights the need for robust quality assurance and process control [2]. However, the complexity of AM processes, which involve numerous interdependent parameters like laser power, scan speed, powder flow, and temperature, makes it challenging to ensure part quality and repeatability [3, 4].

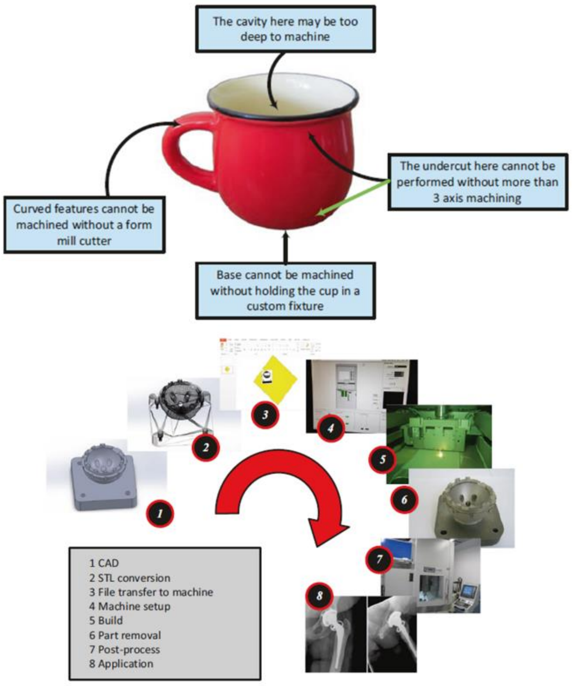

Figure 1. The niche of AM technologies [2] and the AM production steps [3]

The fundamental challenge in AM is the link between process variables, part quality, and machine health. Traditional quality control methods, such as post-process inspection using Computed Tomography (CT) or metallography, are time-consuming and costly, making them unsuitable for large-scale production. This has driven the industry towards real-time, in-situ monitoring and closed-loop control systems. These systems rely on a network of sensors to collect vast amounts of data during the build process, enabling instantaneous analysis and decision-making. Real-time monitoring can detect critical errors and stop the process, thereby preventing further defects from propagating. Alternatively, by non-critical errors, it can register an alert and notify the end user that an error has occurred at a specific location. The ideal scenario, as illustrated in a simplified closed-loop model (**Figure 2**), involves sensors providing real-time feedback to a data processing unit, which in turn can implement corrective measures on the AM machine to prevent defect propagation and ensure the production of zero-defect components.

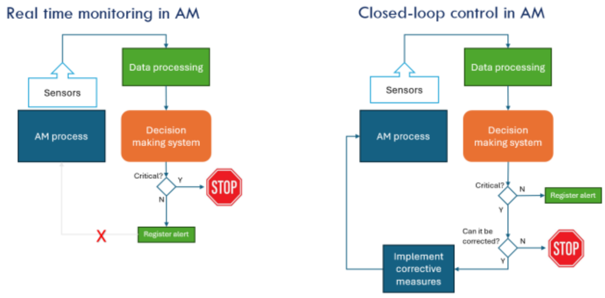

Figure 2. Schematic view and comparison of real-time monitoring and closed-loop control in AM.

The present paper outlines a data-driven approach to enhance AM process control. It details the methodologies for data collection and analysis and presents a discussion of four key research projects that demonstrate the application of these concepts in real-world scenarios.

2. METHODOLOGY

Effective data collection in AM is a multi-faceted process that can be broadly categorized into two main types of monitoring: *in-situ* and *ex-situ*. Ex-situ monitoring concepts, such as Computerized Tomography (CT), metallography, surface profilometry are limited, given that they offer an analysis when the possibility of intervention during the process is already gone. In-situ Monitoring, on the other hand, involves collecting data *during* the AM process itself and, as such, allows for a swift intervention when the process gets affected by an event. The goal is to capture transient process events and material behavior in real time. Common sensors used for in-situ monitoring include:

- Optical sensors: High-speed cameras and pyrometers are used to capture images of the melt pool, spatter, and thermal behavior. This data can reveal inconsistencies in melting, potential defects, and temperature gradients [6,11].
- Acoustic sensors: Microphones or acoustic emission sensors can detect sound waves generated by the process, such as spatter or

keyhole formation, which are often correlated with defect formation [7].

- Infrared sensors: Thermal cameras and photodiodes measure temperature distribution on the powder bed and within the melt pool, providing crucial feedback on energy input and heat dissipation [8].
- Piezoelectric sensors: Generation of impulse or signal by the collision between raw material and piezo crystal can also be successfully used for monitoring in AM [10]

The successful implementation of a data-driven approach requires robust data collection, processing and management. Raw sensor data, often in the form of high-resolution images or high-frequency signals, can be enormous. Advanced data reduction and processing techniques are useful to extract meaningful information without losing critical detail. This data is used for direct process evaluation in Real-Time, but also to train Machine Learning (ML) and Artificial Intelligence (AI) models to correlate process parameters and quality metrics. These models perform tasks such as defect prediction, process anomaly classification, and predictive maintenance [9]. The goal is to move from a *reactive* quality control paradigm to a *proactive* one, where the process is dynamically adjusted to prevent defects before they occur.

3. RESULTS & DISCUSSION

The concepts of digitalization, sensing, and data-driven process control have been demonstrated in several key research projects, which are discussed in the following section, highlighting their unique contributions to the field of AM monitoring.

3.1. Project CUSTODIAN: Real-Time Laser-Matter Interaction Monitoring

The CUSTODIAN project [12] is an example of an advanced laser-matter interaction. Its objectives were to study the role of laser beam shaping in L-PBF. The project's focus, among other challenges, was to develop advanced sensing techniques to monitor the melt pool dynamics and the flow of material and energy during laser-based AM. The project leverages an MWIR camera based on an uncooled PbSe sensor to collect data on the melt pool geometry, temperature, and spectral emission. The data is then analyzed in real-time to identify anomalies (size, shape, etc.) that could lead to porosity or improper fusion. These sensory inputs are then linked with the final mechanical properties of the part, aiming at a data-driven feedback loop that ensures part quality without extensive post-process inspection. Additional to monitoring, a closed-loop control of the laser source was established, trying to control the melt pool properties by changing the laser power in RT. Although in the case of L-DED process this has worked correctly [13], in case of L-PBF the high process speed was a relevant obstacle.

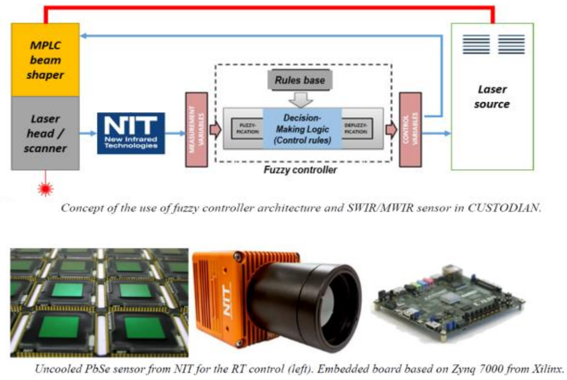

Figure 3. Concept of the use of fuzzy controller architecture and MWIR sensor in CUSTODIAN (up). Uncooled PbSe sensor by NIT Europe for the RT control, together with the embedded board based on Zynq 7000 from Xilinx.

3.2. Project QuaL-DED: Towards Zero-Defect Components

The QuaL-DED project [14], aimed to develop a full Quality Assessment (QA) system for the L-DED process. The project's central objective was to ensure process stability and pave the way for manufacturing zero-defect metallic components. The system integrated three key concepts:

- Beam Quality Monitoring: Constant real-time monitoring of the laser beam's quality and stability using MWIR camera approach.
- Energy Input Control: A monitoring system for both the melt pool and powder flux. The novelty was the combined monitoring of the energy-per-mass input, measuring the powder flux by laser scattering principle and the melt pool aspect by the MWIR images reconstructed in 3D.
- Inline Quality Monitoring: A special novelty was the use of Laser-Induced Breakdown spectroscopy to monitor the composition of the consolidated material as it is being built layer-by-layer, being this performed in near real time.

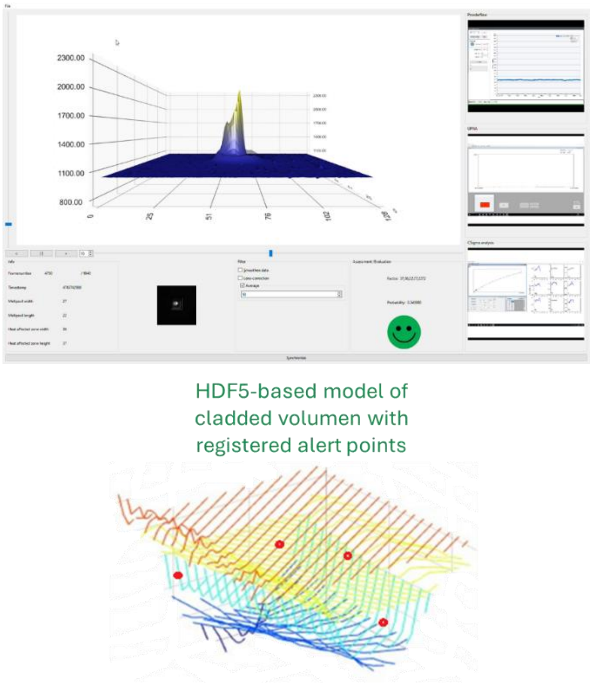

Figure 4. A 3D reconstruction of the melt pool, shown together with the powder flow values and momentaneous values of main chemical constituents in the recently deposited material.

This approach, which leverages big data analytics and machine learning to analyze process parameters and sensor data, has two aims. The first one is to record all events, that is, mismatches in the process parameters, in an HDF5 data structure, and to enable the L-DED technician to analyze what went wrong after the job, helping also the certification of the part. Another goal was to identify behavioral patterns for process optimization and analyze the influence of component design on process stability.

3.3. Project WAVETAILOR: Digital Twins and Sensor Fusion

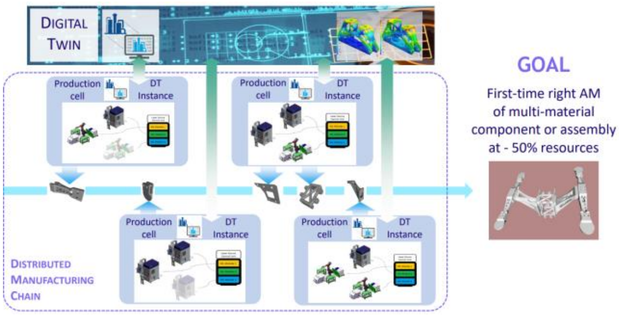

Figure 5. A schematic view of a digital twin concept operating over a delocalized LBAM facility.

WAVETAILOR is another pioneering project about digitalization in AM, specifically in L-PBF and L-DED [15]. This ongoing project's key innovation is the use of a robust Digital Twin, a virtual replica of the manufacturing process that allows for real-time simulation and optimization. By integrating multi-scale models with machine learning algorithms, the digital twin can accurately predict outcomes and optimise component designs, thereby reducing the reliance on a trial-and-error approach.

The core component of WAVETAILOR is sensor signal fusion. The idea is to combine data from multiple disparate sensors to enhance the AI/ML algorithms, leading to more precise process parameter optimization with two main outcomes: less deformation in L-PBF parts and better assembly of L-PBF parts which have been manufactured in different machines at different locations (delocalized manufacturing). This approach is instrumental in ensuring a substantial reduction in scrap, by as much as 80%. WAVETAILOR's application of

Digital Twin technology and sensor fusion represents a significant step towards creating more reliable AM processes.

3.4. Project crystAIr: Sensing in Related Fields

While not directly referring to monitoring and control of AM production, crystAIr demonstrates the application of AI and sensing in a related high-tech field: *combustion burners made by L-PBF*. The project is focused on developing an AI- and sensing-driven combustion burner to address the challenges of hydrogen combustion, such as increased temperatures and faster combustion, which can lead to dangerous flashbacks. The methodology is based on a generic, data-driven three-step process: unsupervised learning of the intended combustion state, classification of different combustion states, and detection of early indicators of irregularities which could lead to a flashback. This is achieved through a distributed network of sensors, including a Piezoelectric crystal sensor with a sensitivity of 18.5 pC/bar and capable of operating up to 600°C [17].

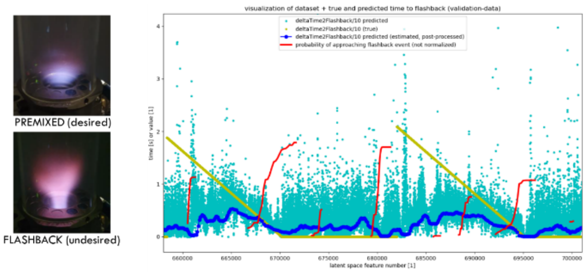

Figure 6. Hydrogen combustor in premixed and flashback mode (left). Prediction of flashback using data from a sensorized combustion burner (right) [16].

The project's approach of creating a hybrid digital twin for unsupervised mixture and flame control provides a valuable blueprint for AM. The integration of sensors, AI, and digital twin technology to monitor a dynamic, high-temperature process for early anomaly detection is a directly transferable concept to the AM environment, particularly in L-PBF and L-DED, where process stability is paramount.

4. CONCLUSION

The transition of Additive Manufacturing into an established industrial technology hinges on the ability to ensure consistent quality and process reliability. Real-time monitoring and data collection are not merely beneficial but are essential for the future of AM. The move from post-process inspection to in-situ, closed-loop control is a critical paradigm shift that enables the production of complex, high-performance parts with a high degree of confidence. Monitoring in even not so mature AM technologies is a reality, which is shown through the projects discussed in this paper provide compelling examples realized. However, the closed loop control remains a complex challenge, mostly because of process speed (e.g. L-PBF).

The examples shown collectively demonstrate that by leveraging sensor technology, Big Data analytics, Artificial Intelligence, and Digital Twins, it becomes possible to achieve unparalleled levels of production control. The conclusions drawn from these projects in terms of monitoring are clear:

1. Combining data from multiple sensor types provides a more comprehensive picture of the process than any single sensor could offer, hence, the sensor fusion is key.
2. Machine learning and AI are indispensable for making sense of the large and complex datasets generated by AM processes. They enable the detection of subtle anomalies and the prediction of potential defects, at the production and part-in-service level.
3. The use of Digital Twins creates a virtual environment and a meeting point for process monitoring data, drastically reducing trial-and-error and improving efficiency.
4. Although the ultimate goal remains to establish a closed-loop control system that can automatically adjust process parameters in real-time, moving AM closer

to a zero-defect manufacturing paradigm, the path is complex due to significant process speed.

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