euspen's 24th International Conference & Exhibition, Dublin, IE, June 2024
www.euspen.eu

An in-process digital twin and decision support system for additive manufacturing

Cathal Hoare[1], Andrew Parnell[2] & Denis Dowling[1]

[1]*I-Form Centre, School of Mechanical and Materials Engineering, University College Dublin, Dublin, D04 V1W8, Belfield, Ireland*
[2] *Department of Mathematics & Statistics, Maynooth University, Maynooth, Kildare, Ireland*

cathal.hoare@i-form.ie

Abstract

The application of digital manufacturing technologies to additive manufacturing offers significant potential to improve process resilience, sustainability, and productivity. While Machine Learning (ML) is now widely applied in AM, the ability of operators to use and act on predictions from ML approaches in real time has been limited. Factors such as heterogeneity of data, inexpressive data models, timeliness of results, and poor contextualization of ML results have contributed to this limitation. The novel software platform described in this paper addresses this deficit in two parts; first, a digital twin outlined in this paper represents the additive manufacturing process state using a novel data model that collects and fuses various information, including real-time hardware sensor data. The second component is a Decision Support System that captures operator expertise and heuristics in the form of rules. Drawing insights from both successful and unsuccessful print runs, the system continuously learns, enhancing its ability to provide informed recommendations for remedial actions over time. Together, the digital twin and decision support system provide recommendations to operators while a print process is ongoing.

Additive Manufacturing, In-process Monitoring, Digital Twin, Recommender System, Decision Support System, Machine Learning

1. Introduction

Metal Additive Manufacturing (AM) offers significant advantages over traditional subtractive manufacturing, such as enhanced design flexibility, increased sustainability, and shorter product development times [1]. However, AM faces challenges related to process stability and repeatability [2]. In-process analysis during part printing can identify and predict anomalies using machine learning (ML) and other forms of artificial intelligence. To harness machine learning successfully, obstacles like data heterogenization, suboptimal data architectures (especially for real-time analysis), and inadequate data models must be addressed [3]. Digital twins, dynamic virtual copies of physical assets, offer a solution to these challenges, especially when employed in real-time scenarios. However, platforms providing near real-time decision support for AM processes, particularly in sensor fusion and data management applications, are still considered in their early stages [4].

This paper describes a real-time digital twin that informs an in-process decision support system, aiding operators of additive manufacturing equipment in addressing processing issues and thereby improving product quality, production line efficiency, and sustainability. Additionally, we present an example illustrating the application of the digital twin and decision support system in a production environment.

2. Platform Description

The digital twin outlined in this paper represents the additive manufacturing process state using a novel data model that collects and fuses various information, including real-time hardware sensor data. This information populates a data model describing the printing process. Our digital twin enhances the data model by employing machine learning-based analysis on the collected data to gain profound insights into the print's state. It works in conjunction with a rules-based decision support system that assesses the digital twin's described printing process state, providing real-time recommendations to guide manufacturing. These rules are tailored on a per-product basis and can be refined and reused for similar manufacturing processes. The interactions among data sources, the digital twin, and the decision support system for our approach are illustrated in Figure 1.

The digital twin's data model describes a series of tables that can be integrated into other schema, for example the NIST schema [4], to provide support for real-time reasoning about an ongoing build. The data schema is capable of capturing information in fine detail; these data can be aggregated to various levels to provide summary information about individual build layers, the build or collections of builds. Information can be represented in different forms, including image data obtained using optical sensors and camera, measurements derived from in-process data and events such as anomalies reported by analysis modules. Details of the analysis module that generates an event are also captured.

The developed system also incorporates a Recommender System framework that captures operator expertise and heuristics in the form of rules. Drawing insights from both successful and unsuccessful print runs, the system continuously learns, enhancing its ability to provide informed recommendations for remedial actions over time.

The platforms user interface is shown in Figure 2. It displays three key pieces of information. Figure 2 (A) shows summary information about the print and provides an overview of key metrics about the print. Figure 2 (B) shows sensor data,

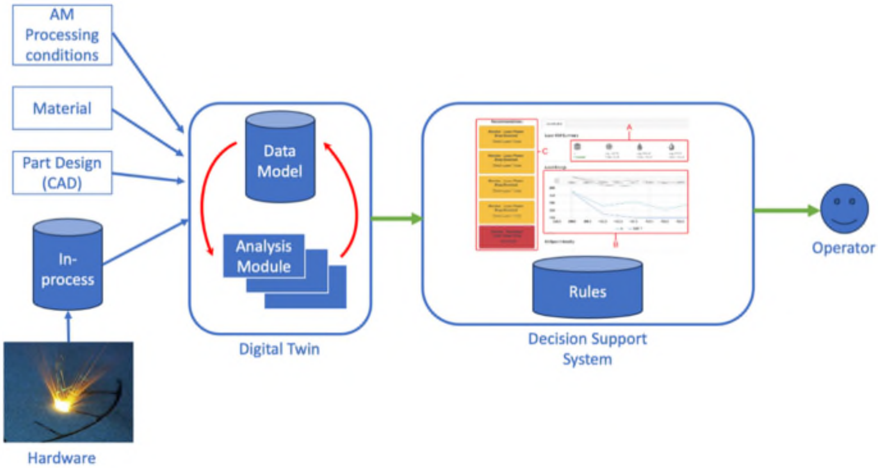

Figure 1. Overview of the I-Form Digital Twin/Decision Support Platform, including data collection, analysis and generation of recommendations.

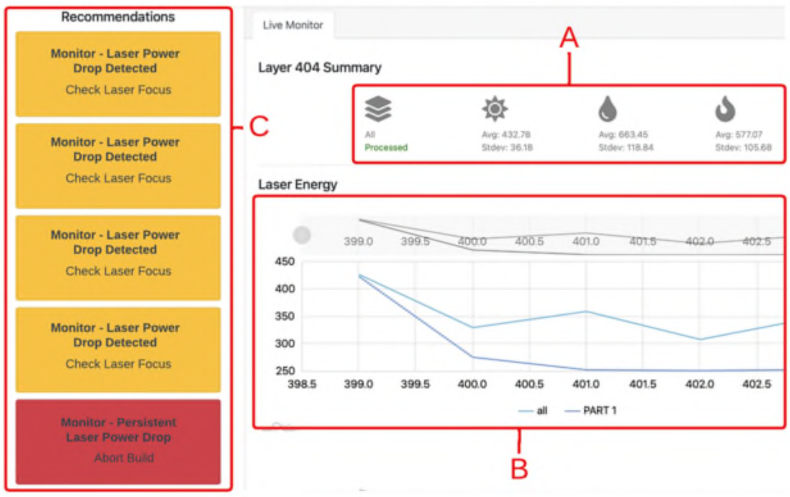

Figure 2. Screenshot of Web-based Decision Support Interface showing (A) a summary of the AM processes' current status (B) Monitor for Laser Energy Output (C) a series of recommendations.

displayed as a series of graphs, displaying aggregated values per layer for the overall build area and each of the observed volumes. In this view of the print, the mean value of the laser output are displayed. The graph of the laser output shows a fall in laser output has occurred. This drop began at layer 400 and continued over three contiguous layers. Figure 2 (C) shows generated recommendations; here analysis modules associated with an observed volume noted the laser power drop for a layer. This triggered a recommendation with advice to check the laser focus. When this anomaly was detected over three layers, the second FSM generated a second recommendation type that advised that the print be abandoned.

The versatility of the developed digital twin and decision support system extends beyond L-PBF processes, making it applicable to a broader spectrum of manufacturing processes. This is attributed to its flexible structure, capacity to consume data from various sources, and the application of diverse analysis methodologies to this data. However, it's imperative to note that, for each process application, defining and applying rules to the outputs of the analysis is essential.

3. Conclusions

In conclusion, the outlined digital twin and decision support platform not only addresses the intricacies of additive manufacturing but also holds promise for broader manufacturing applications, thanks to its adaptable architecture and robust analytical capabilities. Having been successfully deployed in an industry setting, the platform seamlessly processed high-volume and high-velocity sensor data in near real time. For instance, in the L-PBF process discussed in this paper, each print layer generates approximately 450 MB of data. Despite this substantial volume, the system defines and delivers recommendations to operators before the next layer completes. This rapid processing speed coupled with operator decision support represents a distinctive advantage within the realm of AM processing.

References

[1] Atzeni E and Salmi A 2012 Economics of additive manufacturing for end usable metal parts *The International Journal of Advanced Manufacturing Technology*. **62** 9 1147–1155

[2] Grasso M and Colosimo B M 2017 Process defects and in situ monitoring methods in metal powder bed fusion: a review *Meas Sci Technol.* **28** 4

[3] Zhang L *et al.* 2020 Digital Twins for Additive Manufacturing: A State-of-the-Art Review *Applied Sciences*. **10** 23

[4] Razvi S, Feng S, Narayanan A, Lee Y T, and Witherell P 2019 A Review Of Machine Learning Applications In Additive Manufacturing *Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*