A quality-oriented decision support framework: cyber-physical systems and model-based design to develop Design for Additive Manufacturing features

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Abstract. Metal Additive manufacturing (AM) is a complex operation, which requires the fine-tuning of hundreds of processes parameters to obtain repeatability and a good quality design at dimensional, geometric, structural levels. Therefore, to be used as final product, metal AM parts must go through advanced quality control processes. This implies large capital equipment investment in measurement systems (i.e., tomography and lengthy inspection operations that adversely impact costs and lead times). A large amount of data can be collected in metal AM processes, as most industrial AM systems are equipped with sensors providing log signals, images and videos. This paper develops and proposes an innovative quality-oriented decision support framework, composed by a Model-based Design tool providing Design for Additive Manufacturing features, and a Cyber-Physical System created by integrating an AM asset with a real-time smart monitoring software application. Such framework caters to process engineers and quality managers needs to improve a set of quality and economic KPIs.

Keywords: metal additive manufacturing, model-based design, design guideline, cyber-physical systems, digital innovation hub.

1 Introduction

Metal Additive Manufacturing (AM) is a complex operation, which requires the fine-tuning of hundreds of processes parameters to obtain repeatability and a good quality design at dimensional, geometric, structural levels (Frazier, 2014). To be used as final product, metal AM parts must go through advanced quality control processes. This implies large capital equipment investment in measurement systems (i.e., tomography and lengthy inspection operations that adversely impact costs and lead times) (Wang et al., 2021). A large amount of data can be collected in metal AM processes, as most industrial AM systems are equipped with sensors providing log signals, images, and videos (Slotwinski et al., 2014). In particular, small and medium enterprises (SMEs) are increasingly applying data analytics to extract useful information (Lamperti et al., 2023) (e.g., by creating quality-oriented models and integrating them within their production processes (Baijens et al., 2022)). In this context, Digital Innovation Hubs (DIHs) and innovation districts act as one-stop-shop to support SMEs in benefitting from advanced digital technologies and industrial processes (Sassanelli and Terzi, 2022). The development of novel decision support frameworks help raising the benefits to SMEs, by clarifying the information flows, the development sequences, and the models and tools' target objectives and benefits. Accordingly, the objective of this research is to develop and propose a quality-oriented decision support framework, composed by a MBD tool providing Design for Additive Manufacturing (DfAM) features and a CPS.

The structure of the paper is the following. Section 2 presents the research context. Section 3 shows the research method adopted. Section 4 presents the results and Section 5 discusses them. Finally, Section 6 concludes the paper.

2 Research context and main gaps

2.1 Metal Additive Manufacturing

Latest metal AM assets are equipped with several sensors capable to inspect operations. For example, Laser Powder Bed Fusion (LBPF) (known also as Direct Metal Laser Sintering (DMLS) or Selective Laser Melting (SLM)) machines (Aboulkhair et al., 2019), not only builds the desired part by melting thin layers of metal powder on which a laser beam acts (selectively melting the powder only in the areas of interest and functional to the construction of the component) but also relies on advanced sensors suited for detailed process monitoring (Slotwinski et al., 2014). However, data, due to the long process timeframe and their heterogeneity (e.g., process chamber % Oxygen, % Inert Gas, Pressure and Temperature, Laminar Gas Flow Speed, Laser Power, Platform Temperature), are stored but not analysed in real time to monitor the production quality. While the role of the human process specialist is key, a solution is needed to support the quality acceptance decision by means of smart, real-time process monitoring. In fact, there are no consolidated solutions in the industrial practice capable to analyse this data in real-time for quality control and to provide useful information to improve the part and process design (Sames et al., 2016). The LBPF can be equipped with an Optical Tomography (OT) system that can be flanked by software platform allowing to manage all sensors inside the system, the related process data and the current powder bed.

2.2 Process Simulation for AM

AM process simulation tools are a relatively new set of computer-aided engineering tools, introduced into the market over the past few years. These AM process simulation tools can predict residual stress, distortion, microstructure, porosity, and other characteristics of an AM part prior to its creation (Song et al., 2020). By simulating the effects of an AM process on a specific geometry, build failures can be reduced, and shape changes that occur in the part can be compensated before production, so that the part can be produced to a higher tolerance and with a higher probability of success. A detailed simulation of the whole process is typically infeasible (scanning length ranges from 10 to 1000 km for build volumes in the order of $10^4 \div 10^6$ mm^3). Numerical models can be classified on the basis of the dimensional scale of simulated phenomena in powder-scale modelling ($10^{-9} \div 10^{-6}$ m), layer-scale modelling ($10^{-6} \div 10^{-3}$ m) and part-scale modelling ($10^{-3} \div 1$ m). Several finite element analysis tools have been developed using average assumptions to form a solution for large, complex geometries. Multi-scale simulations alone are still too slow to enable a complete part simulation. New computational approaches for AM are still in development to reduce the solution time for large-scale AM problems (McMillan et al., 2017). Process simulation at part-scale can be used before part production to evaluate the additively part itself, since, if a failed build is predicted, it is possible to adapt the print by adding/strengthening support structure or by printing the part oversized and machining with specific design requirements.

3 Research methodology

The research has been carried out in two overlapping steps (Fig.1 and Table 1). The first step was aimed at creating and tuning the quality-oriented MBD/CPS framework. In it, the MBD approach contributes to make an abstraction of the technical requirements and to create the project file containing all the necessary instructions for the CPS, so to print the designed parts. Therefore, a quality check with CT-Scan, OT and metallography cut-up, has been conducted to obtain quality information. Finally, quality-oriented predictive models were created and integrated into the CPS. The second step was aimed at validating the framework in operation. To support the MBD approach, the CPS supplies the information useful to improve the project file and prints the part by maximizing the part quality based on the design specifications. Decision support is enabled by the process data analysis and through advanced data analytics, to provide information of the expected quality outcomes of a specific setup. Finally, AM production has been carried out, monitored and validated (to check the improved design).

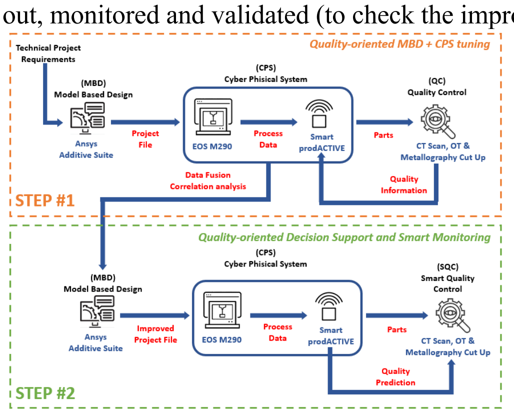

Fig. 1. Project implementation steps, and information flow

Table 1. Research steps: Activities and details

Step	Activity	Details
1	Preparation of a catalogue	of the features for aluminum parts printed with a LBPF, and of defects, to capture the available design know-how about this technology limits.
1	Definition of the targeted defects, and defects-parameters correlations a-priori identification	the MBD tool defines part geometry, machine, and process parameters (to identify defect risks), and generates a project file containing the machine instructions (e.g., AM part oriented geometry). The part geometry includes simple parts (e.g., a cylinder, to allow an efficient inspection process with the available technologies and accurate measures of the defect grade), and complex parts to induce feature-related defects (e.g., rugosity, deformations).
1	CPS creation and setup	connecting the smart monitoring solution to the AM system, to acquire machine and process data.
1	Definition of a production plan	for the defined parts (including manufacturing and inspection activities). The actual AM process is carried out according to the Design of Experiment (DOE) (machine and process data are collected by the CPS at real time).
1	Quality information collection	traceability information by the OT and CT-Scan allows to link the quality information to the relevant job and part number. Collected quality information need to be consistent with the targeted KPIs.
1	Advanced data analytics	a data fusion approach is evaluated (e.g., by integrating hot spots data and defects data). Quality-oriented predictive models are created, suitable to be executed in real-time. Data fusion consists of a multiple data elaboration to obtain a quality index (e.g., the volumetric energy supplied to the metal powder bed to be correlated to the material densification).
1	Models and CPS integration	to enable a smart process monitoring
2	Part design improvement	the MBD tool are applied to production parts representative of common AM challenges (e.g., a structural component) utilizing the information provided by the CPS to support decisions and improve the design.
2	Improved parts monitoring and inspection	though the application of the quality-oriented models, to validate the improved design and the smart monitoring features.
2	Approach contribution evaluation	to check business objectives achievement and plan future development activities accordingly.

3.1 The case and its partners

The partners of this research are three SMEs: EnginSoft (the technology provider), and KM Rosso and Pres-X (as technology adopters). EnginSoft role included the research coordination, MBD tool application, development of the CPS and framework integration. Kilometro Rosso role included performing DfAM activities, providing the AM asset and carrying out the actual prototyping production, and act as a testbed for the framework. Pres-X dealt with the AM processes, and in particular quality control & post processing processes, and materials characterization activities.

4 Results

The main result of this paper is a quality-oriented decision support framework, composed by a MBD tool providing DfAM features (i.e., ANSYS additive suite), and a CPS (created by connecting the EOS M290 machine with the Smart ProdACTIVE smart monitoring solution) (Fig. 2), also applied and validated in a pilot application case.

Fig. 2. Quality-oriented decision support framework: main elements

The Ansys Additive Suite delivers the critical insights required for the development and analysis of an AM product to avoid build failure and create parts that accurately conform to design specifications. This comprehensive solution spans the entire AM workflow (from DfAM through validation, print design, process simulation and exploration of materials). Related to the MBD, it offers dedicated tools to support the design of a product suitable to be realized with metal AM (in particular, LPBF).

The EOS M290 machine uses a LPBF process, combined with a software (EOS connect), that relies on advanced sensors suited for detailed process monitoring.

Smart ProdACTIVE is an integrated smart monitoring solution that connects production processes data sources (machines, sensors) with software modules offering smart features. It provides a centralized production monitoring via a network of data acquisition agents, a flexible database to persist and manage production processes data, a web-based application for remote monitoring of the process stability, and KPIs such as efficiency and costs, smart monitoring features enabling production optimization, active real-time application of predictive models (e.g., quality-oriented models). Data analysis approach have been performed on the data to create quality-oriented predictive models: such models have been integrated into the Smart ProdACTIVE system to integrate real time smart monitoring features, in turn enabling a better decision making.

4.1 Features and defects catalogue for Metal AM

A catalogue of the features for aluminum parts that can be printed with a LBPF, and of typical defects, has been created. It aims to capture the available design know-how regarding the advantages and limits of the metal AM technology. A specific focus has been given to LBPF process, and to the material used for project activities (AlSi10Mg). The catalogue is subdivided into 3 main sections: (i) process description, workflow and advantages; (ii) material details (with information on chemical and mechanical properties); (iii) aspects related to DfAM (about what may be the features to be controlled and verified in the components). These guidelines are useful to reduce the errors that could bring to the failure of the manufacturing process. Following these instructions, suggestions, and strategies, it is possible to achieve the best results in AM with fewer iterations. In this study, a qualitative comparison between MBD simulation output (e.g., stress concentration, final deformation, errors in post processing) and the actual process data and results (as evaluated by means of CT scan and metallographic inspections datasets) has been performed. The catalogue substantiates the link between the MBD and the CPS and can be generalised and applied to different AM processes and materials.

4.2 Application to the pilot application case

The framework developed has been applied to the pilot case shown in sub-section 3.1 going through a series of steps, as follows.

Definition of the targeted defects and a-priori identification of the potential correlations. First, the targeted defects have been defined, focusing on porosity (as expressed by DMQ) and on shape variation from the nominal one. The a-priori identification of the potential correlations between such defects and parameters has been carried out by discussing process experience, reviewing nominal process parameters for the targeted alloy and the information available in literature, and by MBD DOEs execution.

Starting from the standard process parameters for the selected alloy, and qualitative considerations, multiple DOEs have been defined and executed using the MBD tool (ANSYS Additive Suite), to identify potential areas of interest for the subsequent physical DOEs. MBD simulation allowed to explore areas of the parameter space that are relatively distant from the standard parameters suggested for a given process-machine-alloy combination. The solver can predict lack-of-fusion porosity via the powder-solid state tracking but does not predict balling or keyhole phenomena. The simulations helped to identify areas of the parameters space where lack-of-fusion porosity would happen, providing relevant information about meltpool size and the resulting density.

Initial CPS setup. The CPS has been created (installing Smart ProdACTIVE on a virtual machine connected to the EOS M290 system through the EOS CONNECT Core OPC UA interface module) and configured to acquire all available endpoints (49 tags).

Physical DOE setup. Starting from the virtual DOEs results, the physical DOEs have been defined for machine and process constraints (e.g., the maximum laser power available for the EOS M290 of 370 W). Cylindrical specimens have been selected for the physical DOEs, being the most suitable shape to conduct inspection activities and to determine the quality output (i.e., DMQ). The first physical DOE has been defined by varying laser power and laser scan speed while keeping the other parameters constant.

CPS adaptation and improvement. The initial CPS tests clarified the need to install, configure and connect additional process monitoring technologies to expand the scope of the monitored process data.The a-priori identification of the potential correlations, confirmed by the MBD simulations, provided evidence of the need to identify suitable process data related to the volumetric energy density not provided by the EOS CONNECT system. Therefore, to grasp these data, the EOSTATE Monitoring Suite advanced technologies has been added. It is composed of EOSTATE Exposure OT, providing OT, and EOSTATE MeltPool Monitoring, measuring the quantity of energy transferred by the laser locally. Both technologies provided grey values, representing the intensity of the light emitted by the bed fusion or meltpool, offering measures of energy deposition. To acquire the grey values, as EOSTATE data is not provided by any protocol, a Smart ProdACTIVE client has been configured to poll the CSV file during production and ingest the grey value data, together with job, part and layer information, as they are available.

Finalization of the catalogue of features and defects for Metal AM. Process defects guidelines have been augmented with qualitative considerations regarding the usage and outputs of process simulation tools. In this research, the study refers to the ANSYS product family, but can be easily expanded to include other simulation products. **Part design improvement by MBD tool application.** The structural part selected for this activity is presented in Fig. 3. This complex design presents a set of geometrical features common for metal AM parts, therefore it can be considered representative of a typical DfAM challenge. Its complexity may induce feature-related defects (e.g., rugosity, deformations). The MBD tool (ANSYS Additive Suite) has been applied to generate different project files containing the machine instructions for the selected structural component. To determine the impact of the framework, two different project files have been targeted: a baseline project file, designed without considering the catalogue of features and defects; and an improved project file, designed considering the best practice described in the catalogue. Simulation results unveil that, compared to the nominal shape, the improved project shows a relevant reduction of the residual stresses (50 MPa reduction), and a 200% reduction of the maximum deformation. A visual comparison between the nominal and the resulting shapes confirms that the baseline job may generate problematic shape variations in critical features (e.g., support holes).

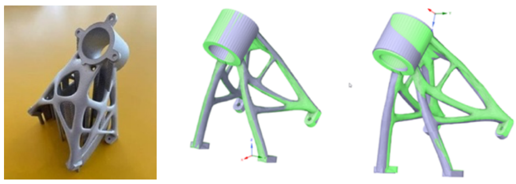

Fig. 3. Left: Structural component selected for the framework application. Center (improved job) and right (baseline job): Nominal (grey) vs resulting (green) shape comparison.

Shape variations were measured on the improved design by applying OT inspection. Results shown that the variations are limited and inferior to the values predicted by the process simulation. Table 2 describes the features catalogue applied to improve the baseline job design towards KPI4 (Reduce the complexity of design by abstraction).

Table 2. Features catalogue applied to improve the baseline job design towards KPI4

Category	Feature	Guideline	Baseline design	Improved design
Part orientation	Overall build	"… self-supporting angle between 45°/50°"	Excessive slope angles	Positioning angle has been improved
	Downfacing surfaces	"… avoid big overhang sections or large downfacing sections"	Excessive unsupported overhang	Overhang has been reduced by part orientation
	Shrink lines		Does not take into account the support structures	Considering the support structures provides a better orientation
Support generation	Thermal stresses reduction	"Support structure is needed to avoid warping and to keep part in position."	Inadequate thermal dissipation leading to increased stresses	Support structure with adequate sections help dissipating heat
Holes	Straight		Inadequate hole support	Block Support structures have been increases to prevent dross formation

Surfaces	Influence on quality	"… avoid big overhang sections or large downfacing sections"	See downfacing surfaces	See downfacing surfaces
		TOTAL BEST PRACTICES APPLIED		6

5 Discussion

5.1 KPIs of the quality-oriented decision support framework

The following KPIs (Table 3) have been monitored and evaluated. KPI1 is about DMQ and has been measured during the printing phase via metallographic analysis through a smart monitoring system integrating also a predictive MBD approach to monitor the production and to identify potential issues in-process. KPI2 measures the shape variation improvement by MBD by comparing the variation respect to the nominal shape of a geometry produced using a job not evaluated with MDB and the same geometry produced using an optimized process by application of MBD. KPI3 (Lead time reduction) wants to reduce the number of the quality control (mostly, volumetric) on parts once printed. KPI4 (Reduce the complexity of design by abstraction) tracks the number of design iterations (virtual and/or actual), that can be reduced thanks to the application of the features catalogue throughout the MBD.

Table 3. KPIs: baseline, target, and results achieved

KPI	Baseline	Target	Results achieved
KPI – Quality improvement 1 (DMQ)	DMQ ≈ 99.4 %	DMQ ≥ 99.5 %	DMQ ≥ 99.8 %
KPI2 – Quality impr. 2 (shape variation through MBD)	Baseline model shape variation	Model shape variation improved (>20%)	200% improvement observed in simulation. Estimates have been confirmed by inspection.
KPI3 – Lead time reduction	100% control on all critical printed components (32h in 4d)	80% control on all critical printed components	80% control feasible with in-process smart monitoring. 15% processing time reduction without DMQ degradation.
KPI4 – Reduce the complexity of design by abstraction	No design process checklist	≥5 guideline steps applied	6 guideline steps applied to improve the baseline design.

5.2 Value proposition of the quality-oriented decision support framework

Results end users are identified as AM process engineers and quality managers. Fig. 4 presents the Value Proposition Canvas for such roles. The framework value proposition consists of an innovative metal AM production workflow, which enables the quality optimization of the project design. The proposed approach facilitates the reduction of defects occurring during the production process, such as the distortions of the component during their realization, leading to shapes that may not comply with the original design and may eventually hit the dust spreading blade, also blocking the printing job. While foreseeing these defects, the framework enables to reduce the number of attempts needed to obtain the desired component so to reach the result in less time and cost.

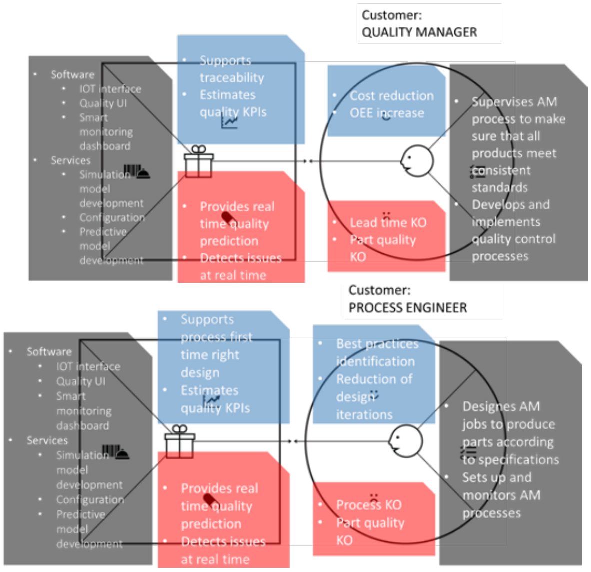

Fig. 4. Value Proposition for Quality Manager (up), and AM Process Engineer (down) user

The framework provides AM SMEs with an innovative solution to address production defects in metal AM. Defects at the macro scale can be identified by the process simulation, while defect at the meso and micro scale can be analyzed, modelled, and predicted by applying advanced quality-oriented modelling to real time process data. The proposed framework provides a significant contribution for improving the metal AM production at various stages. During the MBD stage, through process simulation and a feature catalogue enriched with experimental and virtual information, the framework provides quality-oriented support to product/process design decision leading to improved product and processes, better asset utilization, improved predictability, and lower scrap rates. During the Quality Assurance stage, applying a CPS capable of detecting quality issues at real time, improved process monitoring enabling process quality conformity declaration. Finally, in the Quality Control stage, by application of validated predictive models, a smarter process control (e.g., from wide inspection areas and range of defects to targeted areas and specific defect types) enables the implementation of different policies and cost reduction (e.g., from 100% inspection to sampling).

6 Conclusions

This research demonstrated that manufacturers can improve their metal AM processes by systematically applying an innovative quality-oriented decision support framework. Such framework assists the component design providing a checklist of best practices and qualitatively links them to DfAM MBD-tools features (e.g., through ANSYS additive suite). It also provides valuable insight regarding the manufacturing process and the relationship between process parameters combinations and quality results. Once integrated in the design process, they enable the confident selection of parameters sets different from the nominal ones. Finally, it integrates a CPS by augmenting an AM asset with a real-time smart monitoring software application. This allows to guarantee and improve a set of quality (i.e., component density) and economic KPIs (e.g., lead time). The validated quality-oriented predictive models can be further enriched by expanding the DOEs and considering additional data and parameters.

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