Towards the Digitalization of Additive Manufacturing

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Abstract. Additive manufacturing (AM) is a trending technology that is being adopted by many companies around the globe. The high level of product customization that this technology can provide, added to its link with key green targets such as the reduction of emissions or materials waste, makes AM a very attractive vehicle towards the transition to more adaptive and sustainable manufacturing. However, such a level of customization and this fast acceptance, raise new needs and challenges on how to monitor and digitalize the AM product life cycles and processes, which are essential features of a flexible factory that address adaptive and first-time-right manufacturing through the exploitation of knowledge gathered with the deep analysis of large amounts of data. How to organize and transfer such amounts of information becomes particularly complex in AM given not just its volume but also its level of heterogeneity. This work proposes a common methodology matching with specific data formats to solve the integration of all the information from AM processes in industrial digital frameworks. The scenario proposed in this work deals with the AM of metallic parts as a specially complex process due to the thermal properties of metals and the difficulties of predicting defects within their manipulation, making metal AM particularly challenging for stability and repeatability reasons but at the same time, a hot topic within AM research in general due to the large impact of such customized production in sectors like aeronautical, automotive, or medical. Also, in this work, we present a dataset developed following the proposed methodology that constitutes the first public available one of multi-process Metal AM components.

Keywords: Additive manufacturing · Digitalization · Dataset

1 Introduction

The transition from a mass production model to a mass customization approach has brought a new landscape for manufacturing frameworks, triggering the evolution from the classic production lines into real adaptive systems. These

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systems are composed of large collections of different elements along the factory, interacting through information flows composed of different types of data. Such interactions make possible the reconfiguration of production lines or processes responding to different customer demands, design improvements, or the detection of product failures related to manufacturing parameters. Considering that such adaptability of manufacturing systems is possible thanks to the efficient exchange of large amounts of heterogeneous data, it is fair to say that the digitalization of manufacturing processes is responsible for the emergence of fully automated and connected factories, and consequently, the existence of smart systems and smart manufacturing [1].

Additive manufacturing (AM) is a manufacturing process capable of producing complex parts through the layer-by-layer deposition of a material, which increases the design freedom of the desired part when compared to conventional methods. AM is driven by computational methods, which is a key point for its development due to the ease of computing, data manipulation, and product prototyping in the development phase [2–4]. Some of the advantages of this process are, e.g., making parts on-demand, reducing storage needs, less waste of materials, and fewer pollutant emissions. For all these reasons AM is one of the best-known actors in the current digitalization of factories and the transition to smart manufacturing.

Nowadays, the presence of AM in the industry is a reality. One can have an intuition about how wide the spectrum of AM applications can be just by taking a look at the different length scales and materials used in the manufacturing of parts by additive technologies. Many examples of the application of AM can be found in sectors such as aeronautics, automotive, medical, biotechnology, or consumer products [5,6]. However, the high level of customization that AM brings, results also in a large amount of data whose heterogeneity in terms of software, operations or process, makes complex the extraction knowledge. The knowledge that can be extracted from such a vast amount of data coming from different branches of the whole AM process like simulation, quality, path planning, or process, can be exploited to improve the manufacturing itself through the use of advanced data analytics or even machine learning methods within different phases of the manufacturing process from design to quality control [7]. But the definition of a common ontology that relates all the elements involved in such a complex process in a digital layer, and a methodology to exploit a common data architecture based on it is still missing.

This work presents a common ontology based on product, process, and resources relations (PPR) for the optimization of information flows within the AM of metallic parts. The work develops such ontology in a digital framework and integrates all the elements in a data architecture. Relying on the exposed approach, an open dataset is presented as the first available in an open format of multiprocess AM of metallic parts. The outcome of this work can be exploited for the optimization and interoperability of AM processes in the industry in general.

2 Problem Definition

Conventional manufacturing (CM) processes to produce metallic parts such as subtractive manufacturing, electrical discharge machining (EDM), or laser cutting, share a set of common steps in their workflow as design, path planning, simulation, manufacturing, quality inspection, and product validation. However, in contrast with the lack of freedom to fabricate free-form shapes [8] through CM methods, AM represents a revolutionary process that builds objects by adding material one layer at a time until the desired part is complete. For instance, one can characterize AM processes in terms of the feed stock, namely powder bed, powder feed, and wire feed systems, possessing energy sources like electron beam, laser, or arc [9] with all their characteristic parameters in terms of materials and also thermodynamics of the system to be considered. Which means that it introduces a remarkable level of complexity in all the data associated with all those steps within the workflow. The integration of all this information result crucial to ensure traceability and repeatability.

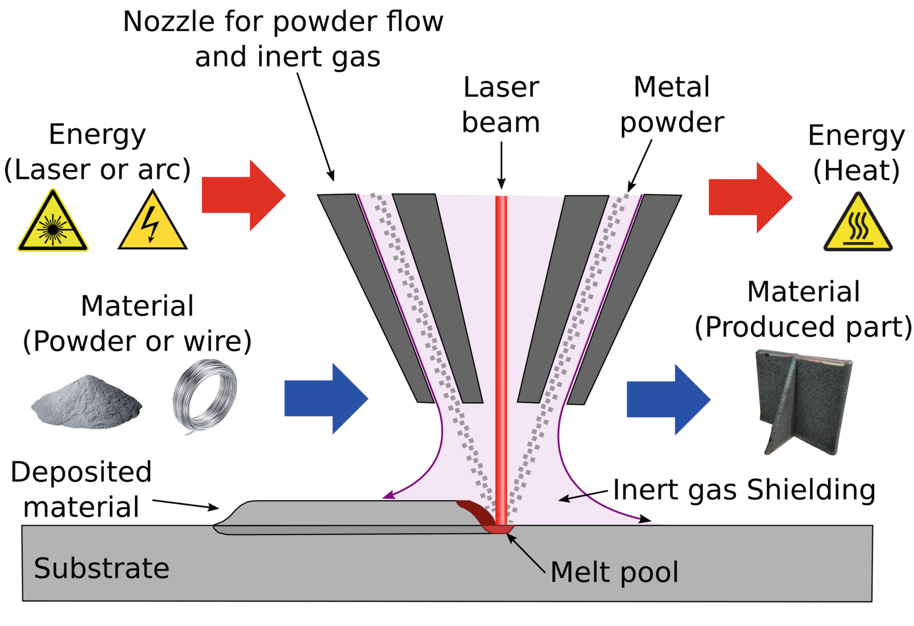

Fig. 1. The central part of the figure shows a typical DED machine nozzle, which is mounted on a multi-axis arm. It deposits powder or wire material onto the specified surface and into the path of an energy beam, where it melts and solidifies. Data collection of DED processes relies on the kind of energy employed (laser or arc), the feedstock (material and shape), and sensors to acquire heat information (infrared) and produced part shape (tomographic data).

In particular, the complexity of AM of metallic parts has led to intense developments in very different areas of knowledge. One evident point of remarkable research is related to the clear need for advanced analytical and computational methods to address the study of temperature flows along the pieces within the manufacturing process that results critical. This thermal response and the thermal leaks within the AM have been identified as one of the main reasons for the emergence of defects such as pores or cracks [10], but also instabilities within the process that lead to issues to achieve the repeatability of processes. This first step leads to other areas of research such as the quality control methods for the analysis of the manufactured pieces, the path planning that optimizes the manufacturing of the piece, or the correlation through disparity analysis of the final piece and its design. All these areas have associated different models and data that need to be integrated into a common Masterfile that follows a well-defined data architecture [11,12]. This way, such vast and heterogeneous information involves for instance material's data containing its type, form, and feed lot; part geometry's data containing feature variability, and CAD tools; processing data, holding the parameters that control the build process; post-processing for the machining of surface roughness, and heating to reduce residual stresses; testing data containing physical and non-destructive testing, and physics-based simulations for certification; end-of-life data for recyclability, and maintenance, can be efficiently exchanged and exploited.

In this work, we will refer to only two AM techniques, laser metal deposition (LMD) wire and powder, and wire arc additive manufacturing (WAAM), which were the technologies used to generate the digitalized data present in the dataset. LMD and WAAM are AM processes categorized as direct energy deposition (DED) [13]. DED processes use a focused beam possessing thermal energy to melt the material as long as it is deposited onto a surface. In LMD, the metallic powder is injected at a surface and a laser beam melts it, forming a molten pool. The continuous motion of a robot makes possible the layer-by-layer deposition along the designed path, enabling the manufacture of the desired part, see Fig. 1. On the other hand, WAAM is a technology that uses an arc welding process to melt a metallic wire using an electric arc as the heat source [14,15].

3 Methodology

The essential goal of this work is to present a methodology that provides a full digital representation of the life-cycle of AM products. Such representation will hold all the data from design to the manufacturing and use, in order to create a holistic information model that can be used to, on the one hand, ensure process repeatability, and on the other improve the manufacturing process itself by means of further methods relying on advance analytics or even artificial intelligence that are our of the scope of this work.

Our proposed methodology is based on two main pillars: on one side, the modeling and traceability of all the digital assets produced during the design, engineering, and production of AM components, and on the other side the generation of a common digital representation of the physical operations in distinct AM processes.

3.1 Digitalization of the AM Data Chain

One of the direct consequences of the use of AM is the flexibility introduced in the production lines and processes. Where the engineering phases of traditional manufacturing are more streamlined, the different options in AM results in multiple ways of producing the same pieces. Also, the freedom of design associated with AM results in new ways to optimize the manufacturing of pieces. These characteristics result in a much more iterative and unstructured engineering process, where, the results of the fabrication can introduce new changes in the process parameters or the piece's physical design. To be able of representing the AM products' life-cycle it is needed to capture these feedback loops and iterative operations in a consensual format.

To achieve this goal, we propose the use of an information model derived from the commonly used in CM Product, Process, and Resource (PPR) Modeling, adapted for the digital assets produced during the different phases of AM. In traditional PPR, as shown in Fig. 2, we have three basic structures: products, that represent the physical items in a manufacturing domain; resources, that represent the assets in a manufacturing plant; and processes, that represents an action performed by a resource on a product. Using these three blocks, it is possible to model most of the manufacturing processes.

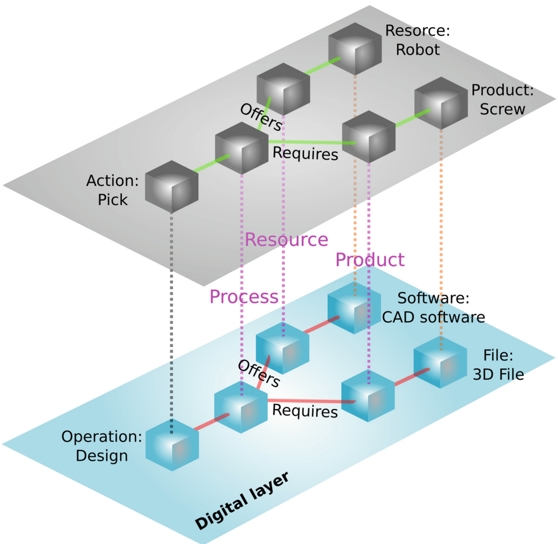

Fig. 2. Representation of the translation of the PPR model in the upper layer in gray to a digital domain in the blue lower layer. (Color figure online)

However in AM, many of these operations are performed in a digital domain, so PPR Modeling needs to be adapted to this type of cycles. In the modified PPR for AM, the files created along the engineering phases are considered products, that are generated and consumed by the processes, or the digital operations associated with the files (e.g., Design). Finally, these operations are related to the Resources, that correspond to the software tools used for that digital operation.

Using this information model, we can represent the flow of data and information in the engineering and production phases while keeping track of the feedback loops where, for example, the results of the simulation force the re-design of the piece, or a defect in production causes the re-evaluation of the production phase. The aggregation of this information can help to identify patterns and optimize the operations needed in the pre-production of an AM piece.

To implement this information model in an interoperable and flexible format, we have used AutomationML [18], a known XML schema for industrial systems. While AutomationML is specialized in the modeling of cyber-physical systems, it also offers support for PPR models, which makes it suitable for this application. Using this format we are able to represent the proposed model as interrelated collections of Operations, Files and Software that represent the flow of information in those phases (see Fig. 3). Therefore, all the information related to an AM component can be summarized in a single AutomationML file, also known as Masterfile, where the relationship between the different files and a link to the files themselves are kept in a way that facilitates the location and traceability of the designs.

Since the Masterfile only contains a link to the digital files with the data from the stages, the resultant file is light and can be easily used for the exchange of information. Most of the related files contain some kind of 3D information, based on the same coordinate system, which facilitates to establish casualty relationships between the stages and files.

3.2 Digitalization of the AM Process Data

In order to establish relationships between the produced pieces and the other stages of the production it is critical to model and monitor the physical AM process with a representation that fully captures the dynamics of the system. This digitalization of the physical processes of additive manufacturing raises several challenges due to the nature of the produced data.

- The representation of distinct AM processes is very heterogeneous, due to the different technologies that are used for both manufacturing and monitorization. In order to create an interchangeable data model capable of representing multiple types of AM processes, it is needed to structure this data following the abstract model of AM.
- Due to the flexible nature of AM processes, different types of sensors and systems can be used to monitor the processes. This raises the need for a flexible data structure capable of aggregating multi-modal information from different sources or with different sample rates.

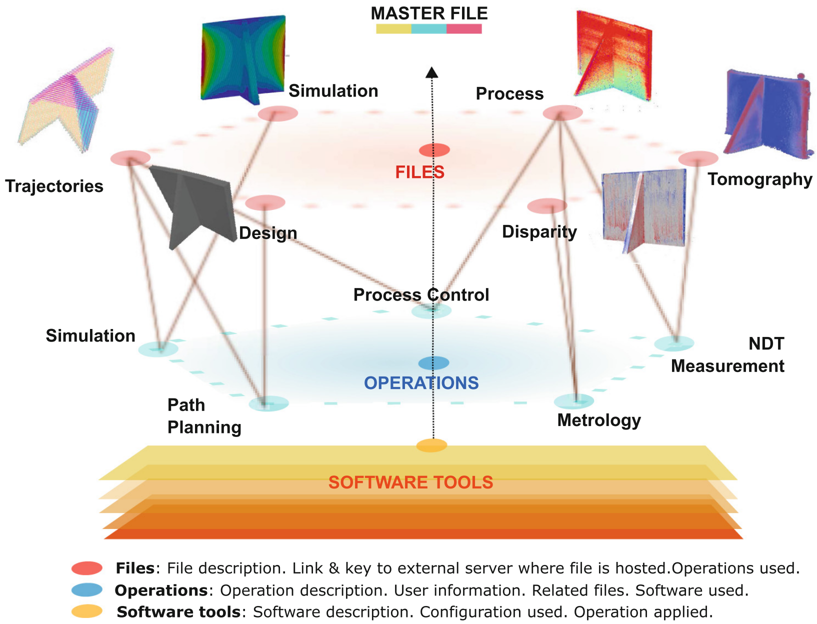

Fig. 3. Representation of the proposed main structure of the Masterfile to ensure the complete traceability of an AM process. Three main blocks of information describe all the processes. All the operations (blue layer) have a correspondence with a given software (orange layers) that drives those operations and at the same time are translated into files (red layer) where operations turn into digital information. These files are self-descriptive. The operations hold information about their relations with different types of files and their location and software tools information provides details on parameters configuration among the corresponding software and at the same time relations with different operations. (Color figure online)

– It is needed to establish a correlation of the monitorization data with specific regions of the produced piece, in order to link this production information with other stages of the piece's life-cycle like dimensional or quality control.

To address these challenges, we propose the use of a hierarchical data structure to model the AM process as a sequence of synchronized measurements over the duration of the process. To that end, the proposed format uses a dynamic array to represent the temporal axis associated with the sequential nature of AM processes. This array stores common attributes of AM processes such as position, power input, or speed, which are then related by a link to other tables that contain measurements of the process structured in their own types and formats (e.g. thermography imaging). As shown in Fig. 5, the end result is a main structured array of "snapshots" of the process associated with a set of 3D coordinates with references to other tables of sensor data that can be recorded synchronously or asynchronously to the process (Fig. 4).

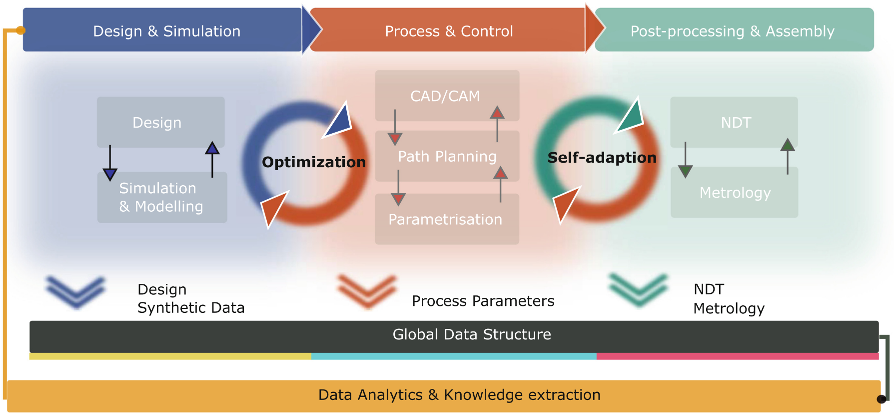

Fig. 4. Representation of the different feedback loops involved in the life-cycle of an AM product. The whole cycle can be divided into different blocks as Design & Simulation, Process and Control and Post-processing & assemble. Each of these blocks can hold internal interactions. A clear example might be within the Design & Simulation block where the outcome of simulation might feed different designs for their optimization. Also, interactions among the blocks take place. A clear example, in this case, can be the interactions among Process & Control and Post-processing blocks, where the outcome of NDT testing might feed process control to correct parameters related to the emergence of a given defect. All these interactions take place within a digital layer that relies on a common data structure (black box). Such a Global data structure has all the elements to perform advanced statistics or machine learning methods to optimize the whole AM process.

The use of this ontology to model the data from AM processes offers several technical advantages while being compatible with most databases and data collection systems. The use of a structured format facilitates the storage, compression, and access of the tables, which can reach considerable size, while keeping a flexible and scalable structure. Also, its abstract design makes it able to represent any type of AM process regardless of the machines and sensors being used for the modeling.

The representation of an AM process as a series of multi-modal "snapshots" provides also more insights about the status of the process, allowing the representation of one or multiple modes of information as a temporal series or a 3D structure. These methods of representing the process information create a straightforward way to find correlations between the modes of the information, like for example, thermodynamics of the process and the manufactured geometries.

This structure was implemented using the Hierarchical Data Format (HDF) standard, which supports the hierarchical relationships needed by the model and allows us to keep the "one file per piece" mentality present in the holistic data model. Another big advantage of this standard is that is widely supported by scientific communities and libraries.

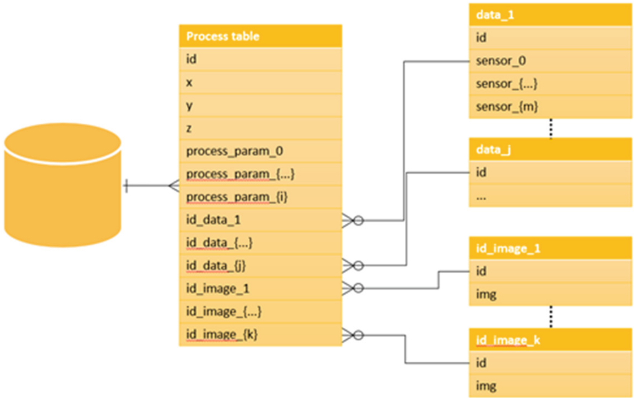

Fig. 5. Hierarchical structure of the AM process data. The overall AM recording contains a group of processes, that are tables that contain a series of 3D points referenced to the piece origin of coordinates. Besides, the process table contains relevant process parameters that are measured directly (such as speed) and references to sub-tables indexes that contain measurements from sensors and cameras. This decoupling from the process and the sensors, introduces a lot of flexibility in the pattern, since the sensor tables can be recorded at a different rate and removes any limitation in the number of sensors to monitor the process. Following the sequence of points in the main table it is possible to completely reproduce the process and all the related data, which enables the use of this structure for the analysis of the manufacturing afterwards.

4 Dataset

Following the methodologies described in Sect. 2, we have created the first dataset [16] of AM components that contains not only information regarding the building of the piece, but also information from the previous (design and engineering) and posterior (Inspection and validation) phases. Each component of the dataset contains information regarding the design, path planning, manufacturing, inspection, and validation of the produced pieces.

This dataset also provides a baseline to compare the effects of process parameters on the overall process dynamics and the quality of the resulted pieces. Furthermore, the dataset comprises pieces from three different AM processes recorded in the same format, which allows a direct comparison between both the produced pieces and the manufacturing data. The process data is stored in the HDF format specified in Sect. 3, and a software tool is provided to interact with the process data [19].

As shown in Table 1, the dataset is structured as a series of components. Each one of these components corresponds to a global data chain and contains the files generated during the engineering and production of the pieces. For each of the components, several pieces were manufactured using the same or different processes, and each one of these pieces was tested using NDT tomography inspection and scanned to check its dimensional tolerances. Images of the pieces of the dataset can be found in Appendix A.

The goal of the presented dataset is to validate the methodology exposed in the present paper and to showcase the possibilities of the data model for production and quality control in AM scenarios. Using the process data model we can easily compare the state and dynamics of the process with the quality and tolerances of the resulted product, which makes it possible to develop automatic methods for the prediction of anomalies and defects. Also, by using the global information model, it is also possible to trace back these anomalies and defects to the engineering stages, which makes possible the implementation of methodologies and checks to preventively assert the good quality of the components.

Table 1. Specimens of pieces found in the dataset

Name	Number of pieces	Process type
T Coupons	3	LMD - Powder
Jet Engine	2	LMD - Powder
CC Coupons - A	13	LMD - Powder
CC Coupons - I	3	LMD - Wire
CC Coupons - M	8	WAAM
CC Coupons - W	4	WAAM

5 Conclusion

This work has presented a methodology to optimize the flow of information within AM of metallic parts. An assessment of a PPR ontology has been done to find its equivalent in a digital domain where our methodology has been implemented. In addition, as a validation of this methodology, a dataset has been presented representing the very first one made open for AM of metal components based on multiple processes. Predictive analysis for the emergence of defects within metallic manufactured parts, design optimization to overcome systematic process issues or trajectory optimization could be some of the immediate ways of exploitation of the presented data structure. Also, the optimization in terms of data storage and transferring, that this methodology offers might provide significant progress in terms of traceability that would trigger relevant breakthrough towards repeatability of the AM process. While the methodology presented was conceived and might be directly useful for the AM in metalworking, the data structure would be valid for the manufacturing of parts using any other material.

Particularly interesting might be how this type of structure opens the door to materials development that, based on generative approaches [17], could address material discovery based on desired properties or fitness with AM processes. Also as a future step, physical models of the system might be added to the master file to promote interactions with process and simulation data in order to promote the exploitation of Physics Informed Systems for the optimization of the manufacturing process.

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Appendix A

Pieces on Metal Additive Manufacturing Open Repository

In this appendix, Fig. 6 shows some pictures of the physical specimens manufactured for the dataset are displayed to facilitate the visual understanding of the manufactured components.

- The T-Coupon is a simple geometry that combines a curved wall with a rib manufactured with stainless steel as a first demonstrator of the capabilities of the presented methodology. Three unique specimens with different process parameters were manufactured.
- The Jet Engine is a complex geometry that combines a cylindrical body with smaller subcomponents around it manufactured with stainless steel to showcase the use of the methodology with large real-world components. Two unique specimens were manufactured in different sizes.
- The CC-Coupon is a simple geometry that combines two curved walls with three flat walls manufactured with stainless steel to demonstrate the capabilities of the presented methodology and formats to represent different processes and machines. These coupons were manufactured in four unique machines and locations, making a total of 28 different coupons created with completely different processes.

Fig. 6. Pictures of the pieces in the Metal Additive Manufacturing Open Repository

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