Digital Twin-enabled Collaborative Data Management for Metal Additive Manufacturing Systems

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Abstract

Metal Additive Manufacturing (AM) has been attracting a continuously increasing attention due to its great advantages compared to traditional subtractive manufacturing in terms of higher design flexibility, shorter development time, lower tooling cost, and fewer production wastes. However, the lack of process robustness, stability and repeatability caused by the unsolved complex relationships between material properties, product design, process parameters, process signatures, post AM processes and product quality has significantly impeded its broad acceptance in the industry. To facilitate efficient implementation of advanced data analytics in metal AM, which would support the development of intelligent process monitoring, control and optimisation, this paper proposes a novel Digital Twin (DT)-enabled collaborative data management framework for metal AM systems, where a Cloud DT communicates with distributed Edge DTs in different product lifecycle stages. A metal AM product data model that contains a comprehensive list of specific product lifecycle data is developed to support the collaborative data management. The feasibility and advantages of the proposed framework are validated through the practical implementation in a distributed metal AM system developed in the project MANUELA. A representative application scenario of cloud-based and deep learning-enabled metal AM layer defect analysis is also presented. The proposed DT-enabled collaborative data management has shown great potential in enhancing fundamental understanding of metal AM processes, developing simulation and prediction models, reducing development times and costs, and improving product quality and production efficiency.

Key words: Metal Additive Manufacturing; Digital Twin; data management; data model; machine learning; product lifecycle management.

1. Introduction

Additive Manufacturing (AM) refers to the technologies used to manufacture objects from 3D model data, in which materials are accumulated layer by layer via specific techniques such as extrusion, sintering, melting, photopolymerization, jetting, lamination, and deposition [1,2]. AM allows the manufacturing of products with complex geometries, heterogeneous materials, and customisable material properties [3]. Compared to traditional subtractive manufacturing, AM enables higher design flexibility, shorter development time, lower tooling cost, and fewer production wastes. The long-term impact of AM is expected in highly customized manufacturing, where AM can be more cost-effective than traditional manufacturing [4].

In recent years, metal AM has been attracting a continuously increasing attention in both academia and industry. Currently, there exist various types of metal AM technologies. Based on the distinctions of AM processes, the international standard ISO/ASTM 52900:2015 [5] identifies seven categories of AM technologies, including 1) powder bed fusion, 2) directed energy deposition, 3) material jetting, 4) sheet lamination, 5) material extrusion, 6) binder jetting, and 7) vat photopolymerization. With regard to metal AM, the first four technologies can be applied to manufacture pure metal parts; the other three can be used to produce metallic composite parts. While each technology has its distinct pros and cons, this paper focuses on the most mature and widely used metal AM technology, i.e. metal Powder Bed Fusion (PBF). PBF uses laser or electron beam to selectively fuse areas of a layer of powders, and then moves the powder bed downwards, adding another layer of powders and repeating the process until the part has built up. Commonly used metal PBF techniques include Direct Metal Laser Sintering (DMLS), Selective Laser Melting (SLM) and Electron Beam Melting (EBM). Compared to traditional subtractive manufacturing which has been developed and significantly improved for over two centuries [6], metal AM, which was first introduced in the 1990s [7], is relatively new. Though metal AM has shown great potential and advantages, many problems still exist that seriously limit its broad acceptance. The highly variable product quality (geometry, mechanical properties, physical properties, etc.) and the lack of process robustness, stability and repeatability have been recognised as the main barriers for the industrial breakthrough of metal AM systems [8]. Identifying the complex relationships between material properties, product design, process parameters, process signatures, post AM processes and product quality remains a major challenge [4].

In order to address the aforementioned issues and challenges in metal AM, a prerequisite is to collect and analyse the metal AM data from all product lifecycle stages. A typical metal AM product lifecycle involves several different stages such as product design, process planning, manufacturing, post processing and quality measurement. Each stage generates huge amounts and various types of metal AM data that influences the final product quality. Since the development of standards and certification for metal AM is still in the early stage, there is an urgent need to develop efficient and collaborative data management systems for metal AM.

Recently, the advancements of Digital Twin (DT) have been extensively studied in the domain of manufacturing. The implementation of DT technology in manufacturing systems has shown great potential in enabling advanced manufacturing data management. In this context, this paper proposes a novel DT-enabled collaborative data management framework for metal AM systems, which comprises a Cloud DT and distributed Edge DTs in different product lifecycle stages. The proposed framework allows metal AM data from all product lifecycle stages to be collaboratively managed in the cloud, and hence enabling various types of advanced data analytics and product quality control to be realised. As a critical component for both data management system and DT, a metal AM product data model is developed by identifying and categorising the critical metal AM product lifecycle data that has influence on the final product quality. To demonstrate the feasibility and advantages of the proposed approach, an early implementation of the DT-enabled collaborative data management in a real metal AM system is introduced. A representative application scenario enabled by the proposed data management system, i.e. cloud-based and deep learning-enabled metal AM layer defect analysis, is also developed and demonstrated. Results have shown that the proposed DT-enabled collaborative data management plays an important role in enhancing fundamental understanding of metal AM processes, developing simulation and prediction models, reducing development times and costs, and improving product quality and production efficiency.

The remaining of this paper is organised as follows. Section 2 reviews the state-of-the-art research on data management for metal AM and DT-supported data management and identifies the research gaps. Section 3 proposes a conceptual framework of the DT-enabled collaborative data management for metal AM systems. Section 4 presents the developed metal AM product data model. Section 5 demonstrates the early implementation of the DT-enabled collaborative data management in a real metal AM system as well as a representative application scenario. Section 6 concludes the paper and discusses the future work.

2. Literature Review

Current research on metal AM focuses mainly on the material science, processing science and process monitoring technologies [9–11]. Data management in the domain of metal AM has not been extensively studied due to the relatively short development history of metal AM. On the other hand, Digital Twin technology has just gained attention in manufacturing field in the last several years. Since this paper proposes a novel DT-enabled data management concept for metal AM, this section reviews the related work from two aspects: data management for metal AM and DT-supported data management in manufacturing. The research gaps are then identified and discussed.

2.1 Data management for metal AM

In the context of Industry 4.0 where information and communication technology (ICT) plays a vital role, data management becomes a critical issue for any type of manufacturing system. In metal AM, it is estimated that PBF systems involve more than 130 variables [12], while over 50 different process parameters in metal AM processes have influences on the final product quality [4,13]. The complex relationships between product design, process parameters, process signatures, post AM processes, and product quality present an urgent need for efficient data management in metal AM systems.

Since metal AM data comprises data from various sources in different product lifecycle stages, collaborative data management systems are required for metal AM. Müller et al. [14] identified three main requirements for a metal AM product lifecycle data management system: 1) easy accessibility of the entire product knowledge, 2) traceability of individual product information, and 3) automation of information flow. Aiming to capture, store and manage data through the entire metal AM lifecycle and value chain, the National Institute of Standards and Technology (NIST) [15,16] developed a collaborative AM data management system using the NoSQL (Not Only Structured Query Language) database technology. The cloud-based database is structured by an AM data schema which enables meaningful data curation and data retrieval. An ontology-based web graphical user interface is developed for the data management system, allowing users to perform data curating, exploring, and downloading. The data management system also provides a Representational State Transfer (REST) interface for the integration with other applications. Uhlmann et al. [17] developed a data management system that can store data from different sources, such as the energy system (regarding power consumption), internal machine tool sensors (platform temperature, process chamber pressure, etc.), external sensors (microphone) and machine controller (process data). Their experimental results have proven that the developed data management system enables the analysis of the links between SLM machine status and AM process conditions, though it works only in the local environment and there is no data model to organise the data from different sources. Müller et al. [14] developed a demonstrator tool as a metal AM product lifecycle data management system, where the design, simulation, manufacturing, post processing and measurement data of each individual product are stored. However, their demonstrator provides only basic database and data visualisation functions without data analytics functions. Based on the material data repository named MAPTIS, NASA [18] developed a metal AM database that contains various types of metal AM data including build parameters, material conditioning, test environment, tensile results, fracture toughness and fatigue. They claimed that the developed database serves as the foundation of the metal AM data management, which strongly complements the development of standards and protocols for metal AM. Mies et al. [19] provided an overview of the current status of AM informatics, in which the key technical requirements, the available AM informatics tools and the existing applicable solutions have been summarised. They concluded that while metal AM standards and certification are in the early development stage, advanced data management for metal AM plays an important role in reducing development times and costs and improving product quality and production efficiency.

Data model is considered as the backbone of a data management system, especially in the case of metal AM where various types of data from different lifecycle stages are involved. Utilising a Product Lifecycle Management (PLM) data modelling method named PPR (product, process and resource), Lu et al. [20] proposed a conceptual metal AM integrated data model where the AM data are modelled as entities under three categories, i.e. product, process and resource, and the fundamental relationships among the entities are defined. Based on the conceptual data model, Lu et al. [16] further developed an AM database schema using Unified Modelling Language (UML), which was used as the foundation of the metal AM data management system introduced previously. To address the data interoperability issue in metal AM, Feng et al. [21,22] developed an activity model for structuring process-related PBF data, by decomposing the entire PBF process (including design, process planning, fabrication, inspection and quality control) into specific activities and identifying the inputs, outputs, mechanisms and controls of each activity. Later, Kim et al. [23] developed AM data models in the form of data packages (in XML format) upon the activity model. Three case studies have been conducted to demonstrate how the data models improved data manageability, traceability and accountability in the metal AM processes. Based on the object-oriented modelling method, Bonnard et al. [24] proposed a new AM digital chain model named Hierarchical Object-Oriented Model (HOOM), which comprises seven levels corresponding to seven stages of the AM process from product design to post-production and validation. The model was implemented in a STEP-NC platform and tested through the manufacture of two parts. Their experimental results proved that the proposed AM model improves transparency, interoperability and scalability of the AM project data. Qin et al. [2] provided a comprehensive review of the existing representations of AM data. The data modelling strategies are categorised into six methods: STEP standards, coding system method, digital thread method, integrated data schema method, unified storage file format and relational database method. Comparisons among the different strategies were conducted in terms of the coverage, simplicity, interoperability, extensibility, inspectibility, accessibility and application.

2.2 Digital Twin-supported data management in manufacturing

Recently, the Digital Twin concept has attracted great research interests in the domain of manufacturing. DT is considered as a key enabling technology for the envisioned Cyber-Physical Production Systems, Smart Factory and smart manufacturing systems in the context of Industry 4.0 [25–29]. The potential of utilising DT to improve product design [30], manufacturing processes [31], process monitoring [32,33], Prognostics and Health Management (PHM) [34,35], production management [36] and PLM [37,38] has been extensively discussed and studied.

It has been identified that currently, some problems in manufacturing systems have impeded the development of efficient data management systems, including: 1) information islands between different phases of product lifecycle caused by various data types and tasks of different product lifecycle phases; 2) data waste and sharing problems due to duplicate data in different product lifecycle phases; and 3) the absence of interaction and iteration between advanced data analytics and various activities in the entire product lifecycle [26].

To overcome these problems, recent advancements in DT technology have shown great potential and advantages in the form of DT-supported product/manufacturing data management. In a comprehensive review on the development methods for DT, the enabling technologies and tools for DT data management have been investigated in six categories, including data collection, data transmission, data storage, data processing, data fusion, and data visualisation [39].

Applications of DT-supported data management for manufacturing systems have been widely reported. Lu and Xu [40] proposed a DT-driven approach to enabling cloud-based manufacturing equipment and big data analytics. A DT for a roll forming machine, which mirrors its near real-time status in the shop floor, was developed in the cloud to support various types of cloud-based data analytics such as machine status monitoring and production reporting. Based on data modelling methods provided by the open communication standards MTConnect and OPC UA, Liu et al. [41] developed DTs for CNC machine tools. The DTs enable an interoperable data management environment where data from different types of CNC controllers and sensors can be efficiently managed, visualised and analysed. Cheng et al. [42] proposed a digital twin enhanced Industrial Internet (DT-II) reference framework towards smart manufacturing. Taking the production of a steam turbine as an example, the authors claim that DT enables the interaction and convergence between physical and virtual product, and hence shortens production preparation time and production period, reduces production cost, and improves production efficiency and processing quality. Wang et al. [43] developed a shop-floor DT that reflects real-time production status in the shop floor. Advanced data analytics functions were integrated in the DT to analyse the key production performance indicators and predict the remaining processing time of work-in-processes.

In the context of Smart Manufacturing and Industry 4.0, data management is closely correlated with PLM and PHM [44,45]. Applications of DT-supported PLM and PHM have also been extensively developed. Kaewunruen et al. [46] developed a DT-enabled lifecycle management system for railway turnout systems using the Building Information Modelling (BIM) technology. Data from different lifecycle stages of the railway turnout system was integrated into a 6D model, such that various lifecycle management functions (visualisation of product design/material/component/project/schedule information, cost prediction and carbon foot-print estimation) were realised in a big data sharing platform. Wang and Wang [31] developed a DT-based system for the waste electrical and electronic equipment (WEEE) recovery to support the manufacturing/remanufacturing operations throughout the product's lifecycle, from design to recovery. International standard-complaint data models were developed to support the DT-based PLM with high data interoperability. Aiming to improve the process planning for optimized machining solutions, Botkina et al. [38] developed a digital twin of a cutting tool that could represent the properties of the cutting tool and perform precise process simulation, control and analysis. The data format and structure of the digital twin are based on the international standard ISO 13399 (Cutting tool data representation and exchange). Zheng and Sivabalan [47] proposed a novel tri-model-based approach for product-level DT development. A DT of a 3D printer that works concurrently to simulate real-world physical behavior and characteristics of the digital model was developed.

2.3 Research gaps

The literature review has revealed several research gaps. First, few studies have been conducted on data management for metal AM systems. There is a lack of collaborative data management systems for metal AM. Second, the literature review shows that data model is critical for both data management system and DT. However, there is a lack of a metal AM product data model which contains a comprehensive list of specific data that has influence on the product quality. Third, the data communication between the field-level data sources and the data management system has been rarely studied in the domain of metal AM. Furthermore, though there has been a considerable amount of literature on DT in manufacturing field, in the domain metal AM, very few studies (e.g. [48,49]) have applied the DT concept, and they all focus on the metal AM processes instead of data management.

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This paper attempts to bridge these research gaps by proposing a novel DT-enabled collaborative data management framework for Metal AM. A metal AM product data model is developed by identifying and categorising the critical metal AM data in different product lifecycle stages. Early implementation of the proposed framework in a real metal AM system developed in the project MANUELA is conducted. Cloud-based and deep learning-enabled metal AM layer defect analysis is also demonstrated as a representative application scenario.

3. Conceptual framework of the Digital Twin-enabled collaborative data management for metal AM systems

Broadly, DT refers to an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin [50]. Based on different types of physical objects and their functional requirements, the DT of a specific object may be defined in different ways. For example, Mukherjee and DebRoy [48] defined the DT of 3D printing hardware as an integration of a mechanistic model, a sensing and control model, a statistical model, big data and machine learning that can potentially improve part quality and shorten time between the design and production; while Knapp et al. [49] claimed that a DT of the AM process should provide accurate predictions of the spatial and temporal variations of metallurgical parameters that affect the structure and properties of components.

In this work, focusing specifically on data management for metal AM systems, we propose a novel DT-enabled collaborative data management system that comprises a Cloud DT and distributed Edge DTs in different product lifecycle stages. This section introduces the concepts of Cloud DT and Edge DT and proposes a conceptual framework of DT-enabled data management for Metal AM systems.

3.1 Cloud Digital Twin and Edge Digital Twin

The collaborative data management system needs to manage data generated in all product lifecycle stages in metal AM. Different stages contain different types of devices and software tools and perform different tasks. Each stage may generate a huge amount of raw data (e.g. sensor signals) that needs to be processed locally. Hence, it is inefficient or even not possible to transfer all the field-level data to the cloud to build a DT of the metal AM product. Inspired by the implementation of cloud computing [51], edge computing [52] and fog computing [53] in manufacturing systems, we propose the concepts of Cloud Digital Twin and Edge Digital Twin that communicate with each other to enable a collaborative data management system.

In general, the Edge DTs focus on specific computing tasks of different product lifecycle stages locally and transfer the processed data to the Cloud DT; while the Cloud DT stores all the product lifecycle data in the cloud and provides data access as well as advanced data analytics to different users and applications. The definitions and main functions of Edge DT and Cloud DT are explained as follows:

- *Edge DT*: An Edge DT is a DT of a specific product lifecycle stage which resides in a distributed shop floor and focuses only on the functions of that lifecycle stage. The Edge DTs have their own computing power (or local intelligence) to support various types of local real-time data processing tasks such as machine control, process monitoring, in-process optimisation, simulation and prediction. The Edge DTs store the raw data of a product lifecycle stage in local databases and transfer the processed data which has influence on the product quality to the Cloud DT through the Internet, thus enabling efficient data communication by reducing the data traffic between shop floors and the cloud.
- *Cloud DT*: The Cloud DT collects all the product lifecycle data from the Edge DTs and records it in the cloud database which is structured by a metal AM product data model. It resides in the cloud and communicates with the Edge DTs as well as different users to allow collaborative data management for metal AM systems. Advanced data analytics are integrated in the Cloud DT to support analysing the relationships among the various historical product lifecycle data. Application interfaces are also embedded in the Cloud DT such that other applications can take advantage of the product lifecycle data.

3.2 Conceptual framework

The main objective of the Cloud DT and Edge DT is to support collaborative data management for metal AM. To provide guidance for practical development and implementation, we propose a conceptual framework of DT-enabled collaborative data management for metal AM systems, as shown in Figure 1. The conceptual framework comprises six modules, i.e. a cloud-based collaborative data management platform and five product lifecycle stages, including product design, process planning, manufacturing, post processing and quality measurement. Each product lifecycle stage has an Edge DT that performs specific computing tasks to support its users and communicates with the Cloud DT to establish the collaborative data management for metal AM systems.

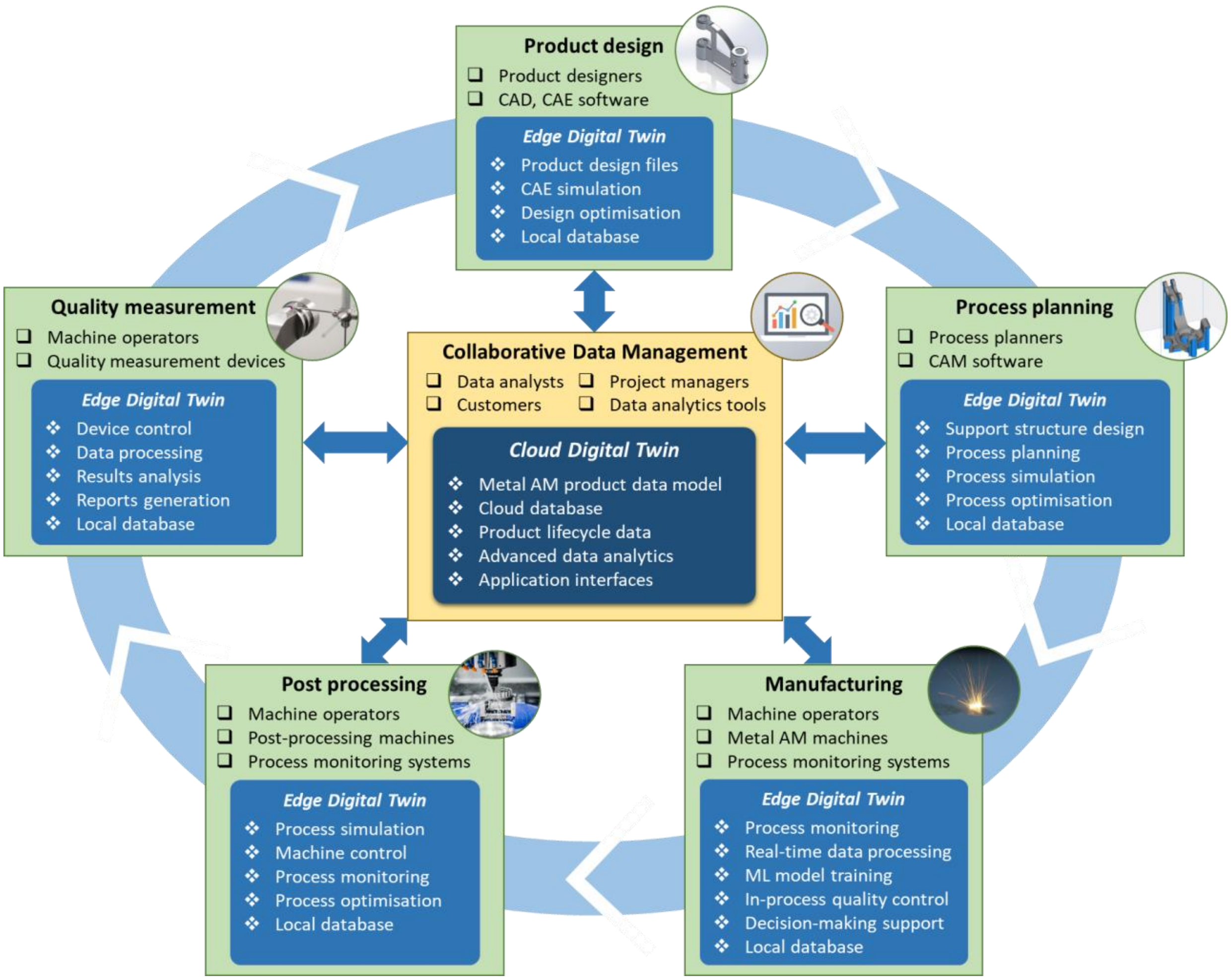

Figure 1. Conceptual framework of DT-enabled collaborative data management for metal AM

In product design stage, the Edge DT supports the product designers to design the metal AM product and perform CAE simulations with CAD and CAE software. The design files and simulation results are transferred to the Cloud DT to be recorded and shared. The Edge DT can also retrieve other data such as product quality data from the Cloud DT to aid the product designers in design optimisation.

In process planning stage, the Edge DT supports the process planners to generate support structures and conduct process planning (model slicing, selection of position, orientation, scan strategy, process parameters, etc.), process simulation and process optimisation. The process plans, process parameters and simulation results are transferred to the Cloud DT.

In manufacturing stage, the Edge DT focuses on the AM building processes of a specific metal AM product and performs various types of data processing tasks such as process monitoring and control, in-process optimisation, machine learning model training and real-time decision-making support. The monitored process signatures (machine logs, sensor signals, images, etc.) are processed locally and the results are transferred to the Cloud DT. The raw data which is usually large in size is stored in the local database for further analysis.

In post processing stage, the Edge DT performs similar functions as in the manufacturing stage. Various types of post AM processes are monitored, controlled and optimised with local computing power. Process signatures and results are processes and transferred to the Cloud DT, while the raw data is stored in local database.

In quality measurement stage, the Edge DT retrieves the measurement tasks and product design files from the Cloud DT and supports the machine operators to measure the product qualities, analyse the measured results and generate measurement reports. The processed product quality data is then transferred to the Cloud DT.

In the collaborative data management platform, the Cloud DT collects all the product lifecycle data from the Edge DTs and stores it in the cloud database structured by a metal AM product data model. Different users (data analysts, project managers, customers, etc.) can access the Cloud DT through the Internet to collectively manage the metal AM product data. Various types of functions such as project management, production planning, progress monitoring, advanced data analytics can be developed to improve the product quality and the production efficiency.

It is worth mentioning that this framework focuses on the metal AM product quality and its related production processes, though a full product lifecycle may also include product usage stage and end-of-life treatment stage [54]. Furthermore, the proposed conceptual framework can also be used as a generic reference framework for developing collaborative data management for other types of manufacturing systems.

4. Metal AM product data model

Data model is a critical element for both DTs and data management systems. The proposed DT-enabled collaborative data management system requires a data model as the underlying database structure in the Cloud DT which can organise the data acquired from all the Edge DTs of different product lifecycle stages in a clear and logical manner, such that advanced data analytics can be efficiently applied to analyse the complex relationships among the product lifecycle data.

In this work, we propose a metal AM product data model by identifying and categorising the critical metal AM product lifecycle data that has influence on the final product quality, based on a review of existing literature as well as experts' knowledge. To ensure the data model can be easily implemented in the data management system, a product-centric and object-oriented modelling strategy is utilised.

The structure of the proposed data model is shown in Figure 2. The data model is developed as a tree structure. The highest-level root element represents a metal AM product which contains five categories of data (design parameters, process parameters, process signatures, post processing parameters and product quality), divided based on the five product lifecycle stages mentioned in the conceptual framework (Figure 1). Each category contains several sub-categories representing different aspects of that category. Finally, each sub-category contains a comprehensive set of specific critical metal AM data. The details of the critical data in each category are listed and explained in the following subsections.

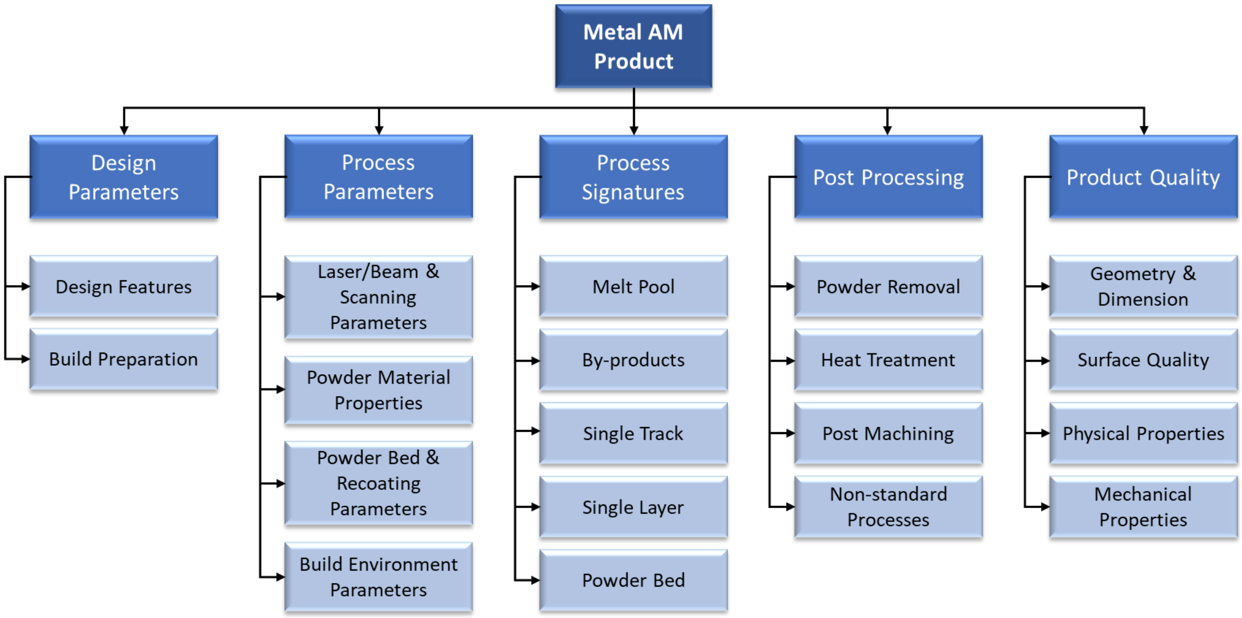

Figure 2. Structure of the metal AM product data model

4.1 Design parameters

Design parameters refer to the product design parameters that are defined in the product design stage. Design parameters can only be modified at the design stage before manufacturing processes. The critical data of the design parameters include two sub-categories: 1) design features, and 2) build preparation.

Design parameters have a significant influence on the product quality, especially in metal AM processes where inappropriate designs can directly lead to build failures and damage to machine components. The data items of design parameters, along with their description and data format, are listed in Table 1.

Table 1. Data items of design parameters in the data model

Sub-category	Data item	Description	Data format
Design Features	CAD file	CAD file of the designed product	CAD file
	Part Material	Material of the product	string
	Part Volume (cm^3)	Volume of the designed part	number
	Minimum Feature Size (mm)	Minimum feature size of the product in x, y, z axis	number
	Surface Roughness	Required surface roughness	number
	Tolerances	Required dimensional and geometric tolerances	CAD file
Build Preparation	Supports	Designed support structure	CAD file
	Build Position	Designed build position of the part on the powder bed	number
	Build Orientation	Designed build orientation	CAD file

4.2 Process parameters

Process parameters refer to the 'input' parameters for the manufacturing processes in metal AM. They determine the rate of laser/electron beam energy delivered to the powder bed surface and how that energy interacts with the powders. Based on different components involved in the manufacturing process, the critical data of the process parameters is categorised into four sub-categories: 1) laser/beam and scanning parameters, 2) powder material properties, 3) powder bed properties and recoating parameters, and 4) build environment parameters.

The controllability of process parameters is critical for metal AM process monitoring, control and optimization. Process parameters can be characterised as either predefined or controllable. Predefined parameters are set before each build and cannot be modified during printing; while controllable parameters are possible to be continuously tuned during printing. It is noted that different machine manufacturers may provide users with different levels of access rights to control the process parameters during the build. Based on some previous summaries [55,56], Table 2 lists the data items of process parameters in the data model, including their description, controllability and data format.

Table 2. Data items of process parameters in the data model

Sub-category	Data item	Description	Data Format	Control-ability
Laser/Beam and Scanning Parameters	Laser/Beam Type	The type of the laser/beam	string	Predefined
	Laser/Beam Mode	Continuous wave or pulsed	string	Predefined
	Spot Diameter (μm)	Diameter of the laser/beam spot	number	Predefined
	Wavelength (μm)	Laser/beam wavelength	number	Predefined
	Beam Quality Factor	The degree of variation of a beam from an ideal Gaussian beam	number	Predefined
	Pulse Frequency (Hz)	Pulses per unit time (in pulsed mode)	number	Predefined
	Pulse Width (μm)	Length of a laser pulse (in pulsed mode)	number	Predefined
	Peak Power (W)	Maximum power in a laser pulse (in pulsed mode)	number	Predefined
	Laser/Beam Power (W)	Power of the laser/beam	number	Controllable
	Scan Speed (m/s)	Velocity at which the laser/beam moves across the build surface	number	Controllable
	Hatch Spacing (μm)	Distance between the centres of two adjacent scan paths	number	Controllable
	Scan Pattern	Pattern in which the laser/beam is scanned across the build surface	CAM file	Controllable
Powder Material Properties	Powder Material	Material of the powder	string	Predefined
	Material Thermal Conductivity ($W \cdot m^{-1} \cdot K^{-1}$)	Measure of material's ability to conduct heat	number	Predefined
	Material Specific Heat Capacity ($J \cdot K^{-1} \cdot kg^{-1}$)	Measure of energy required to raise the temperature of the material	number	Predefined
	Material Melting Temperature (°C)	Temperature at which the material melts	number	Predefined
	Chemical Composition	Measured powder chemical composition	file (txt)	Predefined
	Impurity Element	Characterization of material impurity	string	Predefined
	Max Allowed Impurity Concentration (wt%)	The controlled impurity concentration	number	Predefined

	Phase Composition	X-ray diffractogram	image	Predefined
	Particle Morphology	SEM images of powder	image	Predefined
	Particle Sphericity	Measure of how closely the shape of an object resembles that of a perfect sphere	number	Predefined
	Particle Aspect Ratio	Measure of roundness of the particle	number	Predefined
	Particle Surface Roughness	Measure of surface roughness of the particle	number	Predefined
	Particle Presence of Defect	The presence of defects in particles (Y/N)	string	Predefined
	Particle Inhomogeneity	The homogeneity of particles (Y/N)	string	Predefined
	Particle Size Distribution	Particle size distribution plot	image	Predefined
	Powder Apparent Density (g/cm^3)	Apparent density of the powder	number	Predefined
	Powder Tap Density (g/cm^3)	Tapped density of the powder	number	Predefined
	Powder Cohesive Force Index	Plot of flowability as a function of rotating drum speed	image	Predefined
	Powder Hausner Ratio	Hausner ratio from packing dynamic measurements	number	Predefined
Powder Bed Properties and Recoating Parameters	Density (g/cm^3)	Measure of packing density of powder particles	number	Predefined
	Thermal Conductivity ($W{\cdot}m^{-1}{\cdot}K^{-1}$)	Measure of powder bed's ability to conduct heat	number	Predefined
	Heat Capacity (J/K)	Measure of energy required to raise the temperature of the powder bed	number	Predefined
	Absorptivity ($L{\cdot}mol^{-1}{\cdot}cm^{-1}$)	Measure of absorbed laser energy	number	Predefined
	Emissivity	Ratio of energy radiated to that of black body	number	Predefined
	Recoater Type	Type and mechanism of the recoating system	string	Predefined
	Recoater Speed (mm/s)	Velocity at which the recoater moves during recoating	number	Controllable
	Dosing per Layer (%)	Dosing of powders during recoating	number	Controllable
	Layer Thickness (μm)	Height of a single powder layer	number	Controllable
	Powder Bed Preheating Temperature (°C)	Preheating (bulk) temperature of the powder bed	number	Controllable
Build Environment parameters	Type of Shield Gas	Argon, Nitrogen, Helium, etc.	string	Predefined
	Shield Gas Molecular Weight (g/mol)	Molecular weight of shield gas	number	Predefined
	Shield Gas Viscosity (Pa·s)	Viscosity of shield gas	number	Predefined
	Shield Gas Thermal Conductivity ($W{\cdot}m^{-1}{\cdot}K^{-1}$)	Thermal conductivity of shield gas	number	Predefined
	Shield Gas Heat Capacity (J/K)	Heat capacity of shield gas	number	Predefined
	Convective Heat Transfer Coefficient	Convective cooling of just melted part by gas flowing over the surface	number	Predefined
	Surface Free Energy (mJ/m^2)	Surface free energy between melted powders and shield gas	number	Predefined
	Build Plate Material	Material of the build plate	string	Predefined
	Build Plate Thickness	Thickness of the build plate	number	Predefined
	Oxygen Level (%)	Percentage of Oxygen in the build chamber	number	Controllable
	Pressure (kPa)	Pressure in the build chamber	number	Controllable
	Gas Flow Velocity (m^3/s)	Gas flow velocity in the build chamber	number	Controllable
	Ambient Temperature (°C)	Ambient temperature in the build chamber	number	Controllable

4.3 Process signatures

Process signatures refer to the dynamic characteristics of the powder heating, melting and solidification processes occurred during the build. Unlike process parameters that can be directly set or controlled, process signatures reflect the dynamic processing results that can only be controlled indirectly by modifying the process parameters. Based on different scopes of the signatures, the critical data of the process signatures is categorised into five sub-categories: 1) melt pool, 2) by-products, 3) single track, 4) single layer, and 5) powder bed.

Measurement of process signatures is critical for process and product quality improvement. The sample rate required for measuring a process signature directly determines the feasibility, cost and efficiency of the metal AM process monitoring and optimisation. Based on a literature review on process monitoring of metal AM, the required sample rates of the process signatures are summarised. Table 3 lists the data items of process signatures in the data model, including their description, required sample rate and data format.

Table 3. Data items of process signatures in the data model

Sub-category	Data item	Description	Sample rate	Data Format
Melt Pool	Melt Pool Temperature	Temperature signatures of melt pool (maximum temperature, gradient temperature, etc.)	> 10 kHz	signal file/ image
	Melt Pool Geometry	Geometry signatures of melt pool (width, length, depth, shape, area, intensity, etc.)	> 10 kHz	signal file/ image
By-products	Plume Signature	Signatures of plume (plume consists of metal vapor and plasma)	50 Hz to 5 kHz	image
	Spatter Signature	Signatures of spatter (spatter comes from vapor jets and bubbles, generated by the ablation pressure to the vapor on the melt pool surface)	50 Hz to 5 kHz	image
	Acoustic Emission	Acoustic emission in the build chamber	> 100 kHz	signal file
Single Track	Track Width	Width of a single track	ex-situ	image
	Track Continuity	Continuity of a single track	ex-situ	image
	Track Depth	Depth of a single track	ex-situ	image
	Track Overlap	Overlap between two adjacent tracks	ex-situ	image
	Track Microcracks	Microcracks in a single track	> 50 kHz	image
	Track Consolidation Characteristics	Consolidation characteristics of a single track, such as continuous, discontinuous, weak, ball-shaped, very little consolidations.	> 10 kHz	image
Single Layer	Melt Pool Intensity Variation	Melt pool intensity variation across a single layer	> 10 kHz	image
	Layer Surface Topography	Topography of a single layer (layer geometry, height, waviness, roughness etc.)	per layer to 70 kHz	signal file/ image
	Layer/Powder Bed Surface Temperature	Temperatures of layer surface	per layer to > 10 kHz	signal file/ image
	Layer Defects	Layerwise defects (porosity, uneven, under-melt, over-melt, etc.)	per layer	image
Powder Bed	Powder Bed Surface Topography	Surface topography of the powder bed	per layer	image

Powder Bed Anomalies	Various types of powder bed anomalies (recoater hopping, recoater streaking, debris, super-elevation, part failure, incomplete spreading, etc.)	per layer	image

4.4 Post processing parameters

Post processing parameters refer to the designed post processes and their related process parameters. Post processing is an optional process depending on specific requirements. There exist various types of post processing technologies that can be generally divided into four sub-categories: 1) powder removal, 2) heat treatment, 3) post machining, and 4) non-standard processes. Table 4 lists the data items of post processing parameters in the data model, including their description and data format.

Table 4. Data items of post processing parameters in the data model

Sub-category	Data item	Description	Data Format
Powder Removal	Vibration Setting	Machine vibration settings	string
	Rotational Setting	Machine rotational settings	file (txt)
	Time (min)	Time of the removal process	number
Heat Treatment	Heat Treatment Sequence	Sequence of heat treatment steps for a single component	file (txt)
	Technique	The heat treatment technique used (e.g. annealing, quenching, case hardening)	string
	Atmosphere	Media (nitrogen, argon etc.) and pressure	string
	Heating Rate (K/min)	Heating rate	number
	Final Temperature (°C)	Final temperature	number
	Holding Time (h)	Holding time at final temperature in hours	number
	Cooling Rate (K/min)	Cooling rate	number
	Cooling Medium	Air, Nitrogen, Argon, Water, etc.	string
Post Machining	Machining Operation	Milling, drilling, fly cutting, grinding, turning, shaping, slotting, planning etc.	string
	Process Plan	Process plan of the machining operation, including the machining strategy, tool path plan, G code, and all process parameters such as cutting speed (m/min), feed rate (mm/min), depth of cut (mm), etc.	CAM file
	Tool Geometry	Specification of cutting tool geometry.	CAD file
	Tool Material	Specification of cutting tool material.	string
Non-standard Processes	Process Name	For example, painting, etching, plasma treatment etc.	string
	Process Specification	A description of the non-standard processes and process parameters used.	file (txt)

4.5 Product quality

Product quality refers to the final quality of the metal AM product. It is the joint results of all the other critical data introduced previously. Product quality can be categorised into four sub-categories: 1) geometry and dimension, 2) surface quality, 3) physical properties, and 4) mechanical properties. Accurate and efficient measurement of the product quality is critical for product quality control, design optimisation and process optimization. Commonly used measurement devices/methods for each data item are summarised from literature. Table 5 lists the data items of product quality in the data model, including their common measurement devices/methods and data format.

Table 5. Data items of product quality in the data model

Sub-category	Data item	Common measurement devices/methods	Data Format
Geometry and Dimension	Dimensional Accuracy	CT dimensional metrology; coordinate measuring machine (CMM); 3D laser scanner	measurement reports (PDF, CSV, XLS)
	Geometric Accuracy	CT dimensional metrology; CMM; 3D laser scanner	measurement reports (PDF, CSV, XLS)
Surface Quality	Surface Roughness (μm)	Contact/optical surface profilometers	number; profile graphs
	Surface Waviness (μm)	Contact/optical surface profilometers	number; profile graphs
	Surface Deformation (μm)	Contact/optical surface profilometers	number; profile graphs
	Surface Chemical composition	X-ray photoelectron spectroscopy; scanning electron microscopy	report (image, table)
Physical Properties	Part Density (g/cm^3)	Archimedes drainage method; Gas pycnometry; Microscopy of cross-sections; X-ray scanning of cross-sections	number
	Part Porosity	Archimedes method; gas pycnometry; microscopic analysis of cross-sections; X-ray CT	CT scan images; 3D model (STL)
	Residual Stress (MPa)	Diffraction based methods; Mechanical strain relaxation-based methods	number/report
	Cracks and Delamination	Camera; Visual observation	image
	Part Microstructures	SEM, transmission electron microscopy (TEM)	image
Mechanical Properties	Yield Strength (N/m^2)	Tensile tests based on standards	number
	Tensile Strength (N/m^2)	Tensile tests based on standards	number
	Elongation (%)	Tensile tests based on standards	number
	Fatigue	Fatigue tests based on standards	report
	Hardness (kgf/mm^2)	Rockwell/Brinell/Vickers/Knoop hardness testing; Instrumented Indentation Testing	number
	Toughness (J/m^3)	Fracture Toughness Testing	number

4.6 Summary

The features and advantages of the proposed metal AM product data model are summarised as follows:

- The data model contains a comprehensive set of specific metal AM product data and divides them into five categories corresponding to five product lifecycle stages, thus allowing collaborative data management and advanced data analytics to be realised efficiently.
- The data model is designed to be product-centric and object-oriented. Each specific metal AM product can be generated as a new instance based on the data model, which contains only the product-specific data while omitting the data items that are not of interest or not available.
- The data model allows data of different formats to be stored, including number, string, CAD file, CAM file, image, signal file, reports, and so on. Database developed based on

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this data model needs to be able to store data in different formats. For large data sets such as stacks of images, a link to another database could be stored under the data item.

- The data model can be easily extended by adding additional data items or sub-categories into their related categories.
- Implementation of the data model in databases or data management systems is flexible due to its simple hierarchical structure.

5. Early implementation of DT-enabled collaborative data management in MANUELA metal AM system

To demonstrate the feasibility and advantages of the proposed approach, this section introduces an early implementation of DT-enabled collaborative data management in a metal AM system established under the European Union's H2020 project MANUELA, which involves 20 partner organisations from both research institutions and industrial companies. The goal of MANUELA is the development of a metal AM pilot line service covering the full AM development cycle including simulation, robust AM manufacturing and on-line process control, characterization, real-time feedback, post-treatment, AM qualification protocols and associated business model. MANUELA contains all the five product lifecycle stages described in the conceptual framework. However, the shop floors and hardware equipment are geographically distributed in several countries in Europe. Thus, to realise collaborative data management among all partners throughout the product lifecycle, the DT-enabled collaborative data management is implemented in MANUELA metal AM system in an early stage.

First, the system architecture of the DT-enabled collaborative data management in MANUELA is introduced. Detailed data communications in each product lifecycle stage are explained. Examples of early implementations are also demonstrated. Second, a representative application scenario of the collaborative data management system, i.e. cloud-based and deep learning-enabled layer defect analysis, is presented.

5.1 System architecture and early implementations

The conceptual framework proposed in Section 3.2 describes the general functions and high-level data communication structures. To implement the DT-enabled collaborative data management in a real metal AM system, specific data communication and storage strategies in the field level must be developed correspondingly to establish the connections among the field-level data, the Edge DTs, the Cloud DT as well as different users. Based on the shop floors and hardware equipment involved in MANUELA, the overall system architecture of the DT-enabled collaborative data management in MANUELA metal AM system is developed as shown in Figure 3.

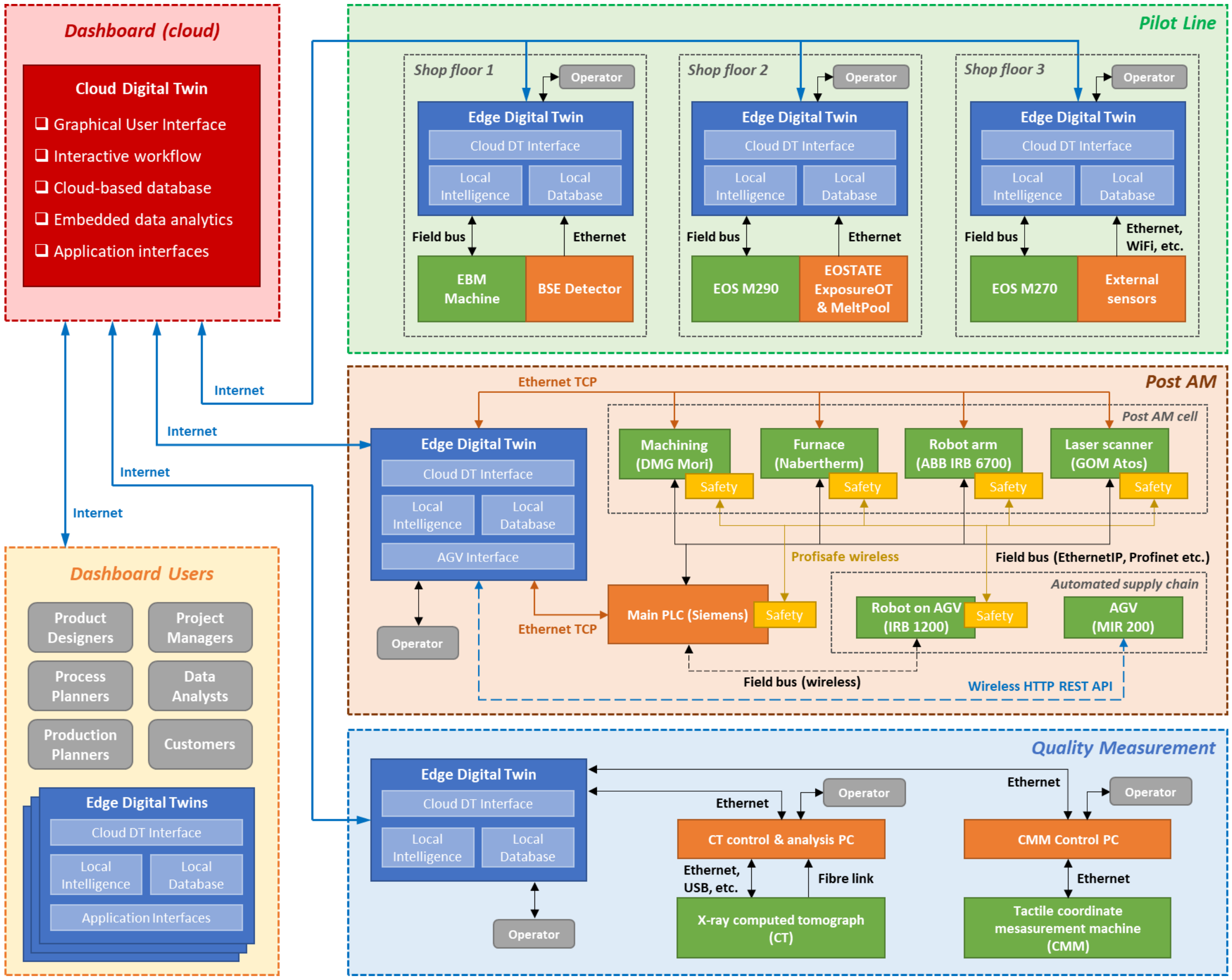

Figure 3. Overall system architecture of DT-enabled collaborative data management in MANUELA

The system comprises five main modules: 1) Dashboard, 2) Dashboard Users, 3) Pilot Line, 4) Post AM, and 5) Quality Measurement. In correspondence with the conceptual framework (Figure 1), the Dashboard module represents the cloud-based collaborative data management platform. The Dashboard Users module represents different users who utilise software tools and local intelligence of their Edge DTs to collaboratively manage the metal AM product lifecycle data in the cloud. The product design and process planning stages described in the conceptual framework are integrated in the Dashboard Users module since they do not directly work on the field-level manufacturing equipment. The other three modules, i.e. Pilot Line, Post AM and Quality Measurement, are respectively corresponding to the manufacturing stage, post processing stage and quality measurement stage in the metal AM product lifecycle. The following sub-sections explain the detailed functions and data communications in each module.

5.1.1 *Dashboard and Dashboard Users*

The Dashboard resides in the cloud and communicates with Dashboard Users through the Internet to achieve collaborative data management in MANUELA. Figure 4 illustrates the main functions

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and tasks of the Dashboard and different Dashboard Users. The Dashboard provides five main functions as follows:

1) The Dashboard provides a Graphical User Interface (GUI) that allows efficient data management and data visualisation. Customised GUIs are developed for different users based on specific requirements.
2) An interactive metal AM workflow is designed in the Dashboard for each product/project by the project managers. The workflow, based on the product lifecycle stages, defines the specific tasks and access rights for each type of Dashboard Users to establish a safe and collaborative project management platform.
3) The Dashboard contains a cloud-based relational database which is structured by the metal AM product data model introduced in Section 4. This database stores all the product lifecycle data retrieved from the Edge DTs.
4) Advanced data analytics tools can be embedded in the Dashboard to provide cloud-based decision-making support, such as analysis of material-geometry-process-property relationships and non-real-time product quality control.
5) The Dashboard also provides application interfaces for a wide range of software (CAD/CAM/CAE software, data visualisation and analytics software, etc.) that allow different Dashboard Users to perform various types of specialised data analysis.

There are mainly six types of Dashboard Users, including 1) product designers, 2) process planners, 3) production planners, 4) project managers, 5) data analysts, and 6) customers. These users utilise the local intelligence of their Edge DTs to perform their tasks and interact with the Dashboard through the Internet. The main tasks of each type of Dashboard Users are summarised in Figure 4.

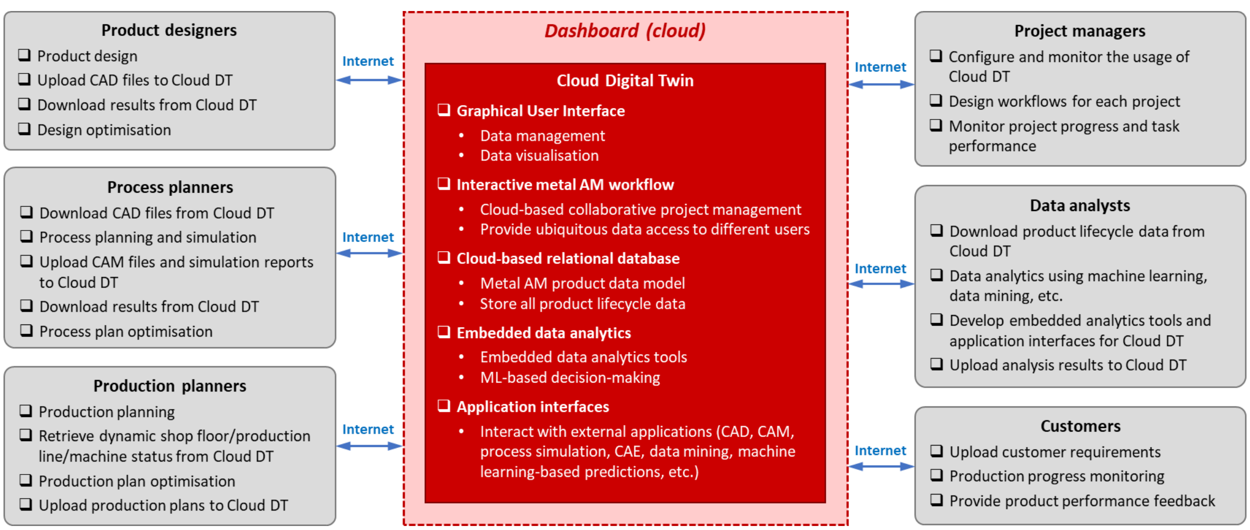

Figure 4. Main functions of Dashboard and Dashboard Users

The Dashboard application for MANUELA project is developed using MSC's product lifecycle management software named MaterialCenter. MaterialCenter perfectly meets the requirements of the proposed DT-enabled collaborative data management since it provides flexible and efficient

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functions for 1) developing customised Graphical User Interfaces (GUIs) and databases, 2) integrating customised data analytics functions, and 3) interfacing with external software applications. In addition, MaterialCenter allows secure cloud-based collaborative data management by granting different administration rights to different users.

The database in the Dashboard is developed based on the metal AM product data model introduced in Section 4. XML schema files are developed for MaterialCenter to define the structure as well as the name, data type, description and properties of each individual data item of the database. The Dashboard allows users to upload data to the database in two manners, i.e. manual input and bulk upload. Figure 5 shows the developed Dashboard GUI for manual data input where users can input values or files to each individual data item in the database.

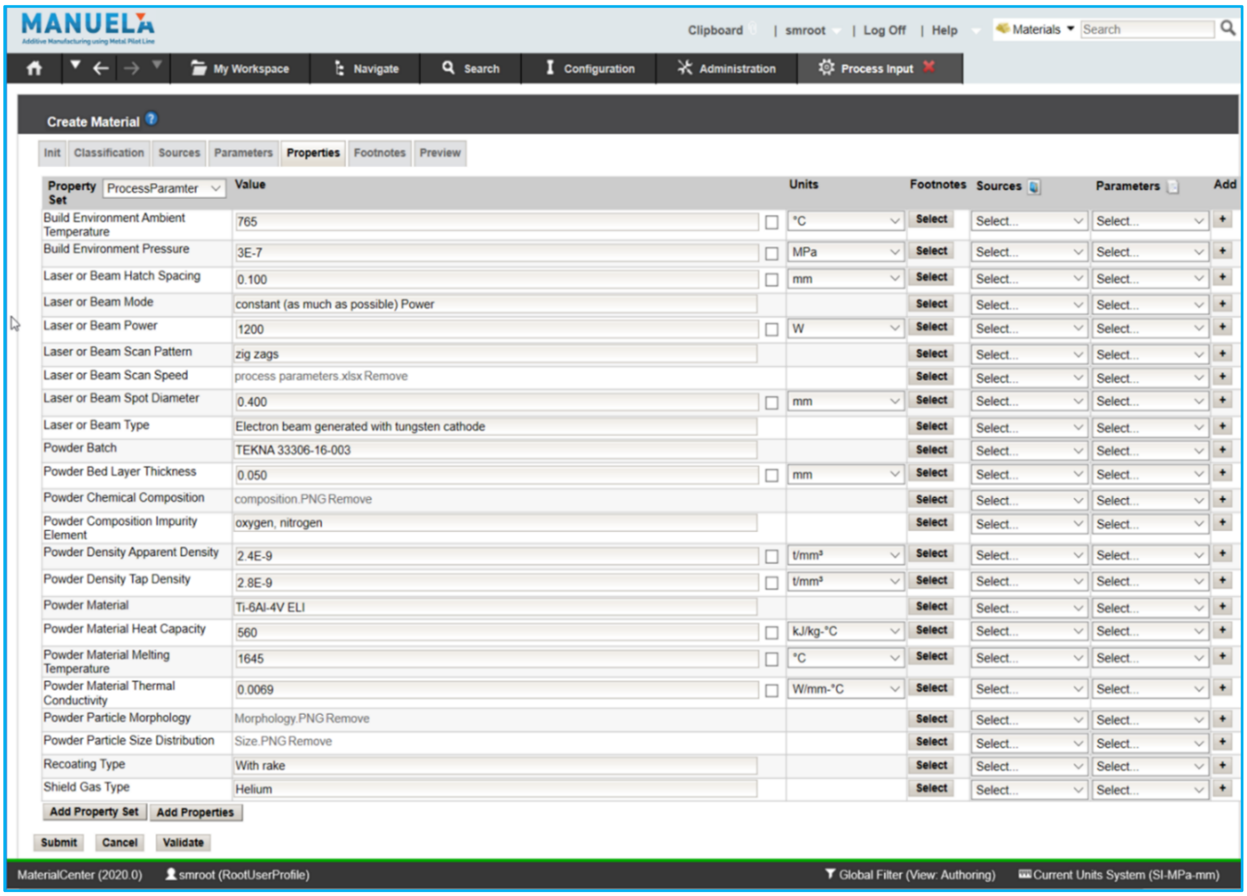

Figure 5. Manual data input using the Dashboard

The GUIs and procedures for bulk data upload using the Dashboard are described in Figure 6. A template Excel file that contains all the data items in the database is developed as shown in the bottom of Figure 6. An XML mapping schema is developed for mapping all the data in the template Excel file to the database through the MaterialCenter plugin in Excel software. In the Dashboard GUI, the user chooses the Excel file to be imported and the mapping schema to perform the bulk data upload. In this way, various types of field-level manufacturing data can be uploaded to the

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cloud database, and hence enabling efficient and collaborative metal AM product data management.

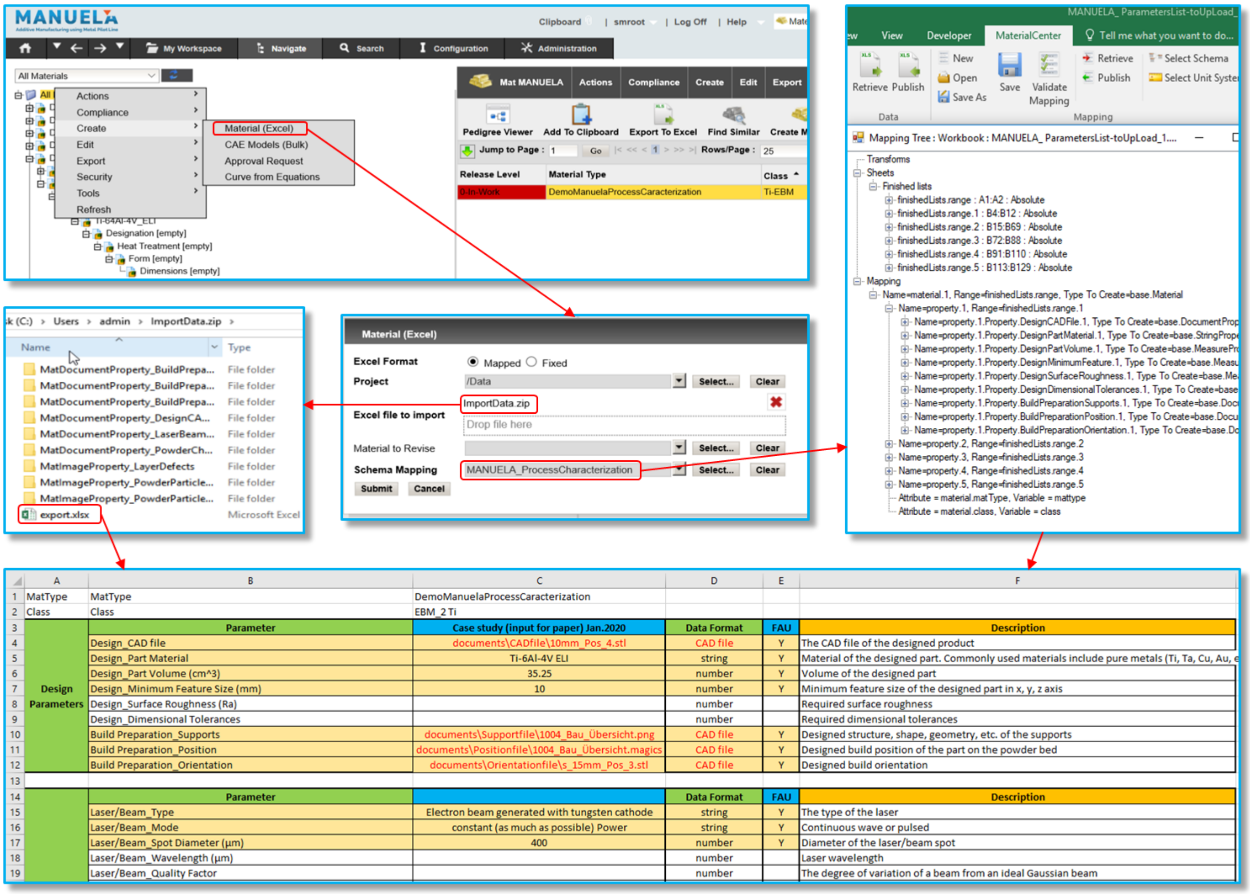

Figure 6. Bulk data upload using the Dashboard

5.1.2 Pilot Line

Figure 7 describes the detailed data communications and tasks in the Pilot Line. This current early stage involves three metal AM machines in three distributed shop floors, including an in-house developed EBM machine [57], an EOS M290 DMLS machine and an EOS M270 DMLS machine. These machines are equipped with different sensors or monitoring systems. For example, a backscatter electrons (BSE) detector is installed in the EBM machine to acquire electron optical (ELO) images of the printed layers; while the EOS M290 machine has a built-in process monitoring system called EOSTATE ExposureOT and MeltPool.

An Edge DT is developed for each machine in the local shop floor. During printing, the machine logs and sensor signals generated by the machines and sensors are transferred to the Edge DT through field bus, Ethernet, WiFi, etc. The operators in the shop floors utilise the local intelligence provided by the Edge DT to conduct various computationally intensive tasks as listed in Figure 7. The main tasks of the Cloud DT for the Pilot Line are also listed in Figure 7. The interactions between the Edge DTs in Pilot Line and the Dashboard will be demonstrated in a representative application scenario in Section 5.2.

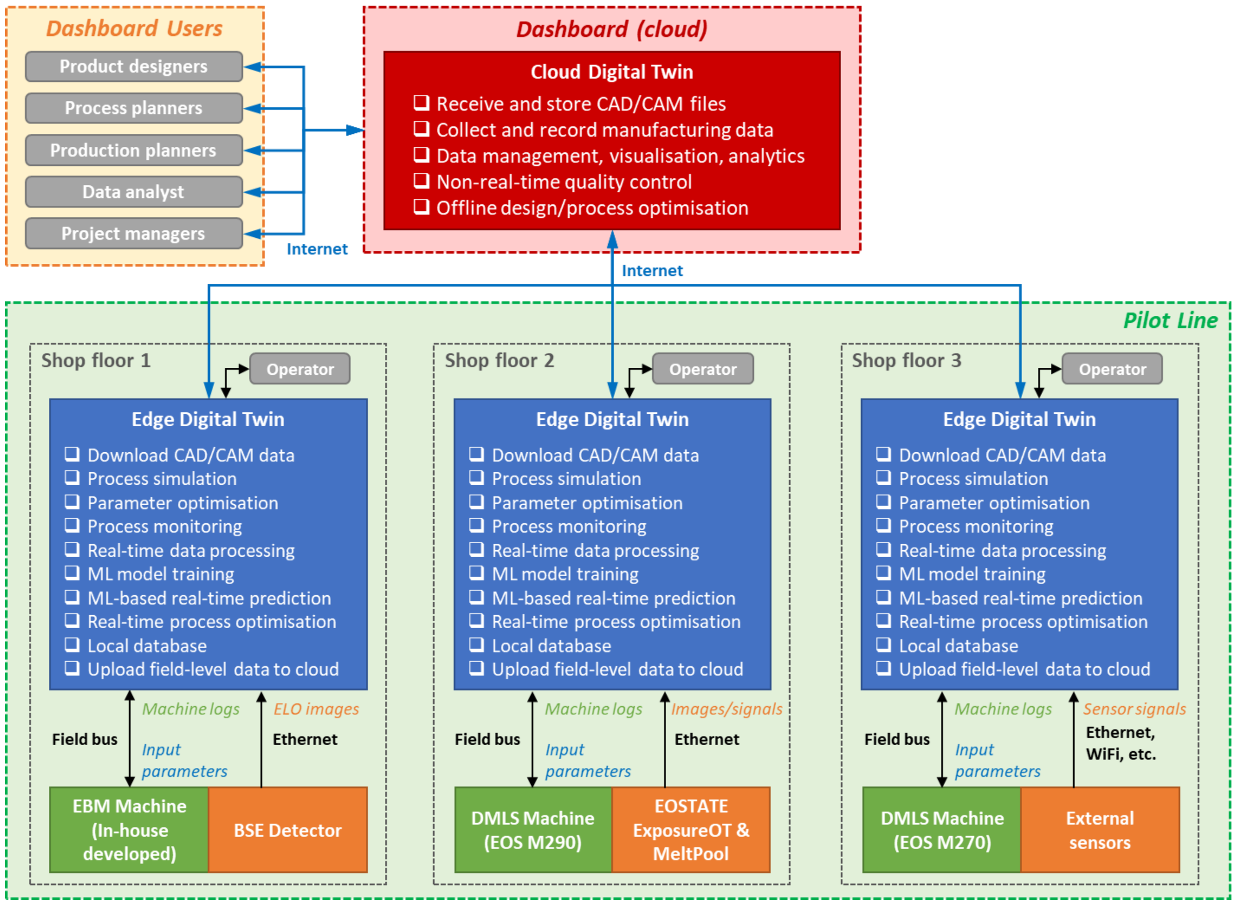

Figure 7. Detailed data communications and tasks in Pilot Line

5.1.3 Post AM

Figure 8 describes the detailed data communications and tasks in Post AM. The Post AM module comprises a post AM cell, an automated supply chain, a main Programmable Logic Controller (PLC) and an Edge DT. The post AM cell consists of a machine tool (for post machining), a furnace (for heat treatment), a robot arm and a laser scanner (for quality assurance). The automated supply chain consists of an Automated Guided Vehicle (AGV) and a robot. The main PLC is used to control all the devices via field bus such as EthernetIP or Profinet. ProfiSafe (a safety layer on top of the field bus) is implemented to ensure safe data communications among the devices. All the devices send handshakes to the PLC and the PLC responds with control commands of the next actions.

The Edge DT downloads all the post processing tasks from the Cloud DT and sends the process sequences and process parameters to the main PLC and the AGV to coordinate the post AM processes. The AGV is controlled via the AGV interface (HTTP REST API) embedded in the Edge DT. Ethernet TCP is used to send and receive process data between the Edge DT and the devices. During post processes, computational tasks such as process simulation and real-time data processing are conducted with the local intelligence of the Edge DT. The process events and process data are stored in the local database and transferred to the Cloud DT. The main tasks of the Edge DT and the Cloud DT are listed in Figure 8.

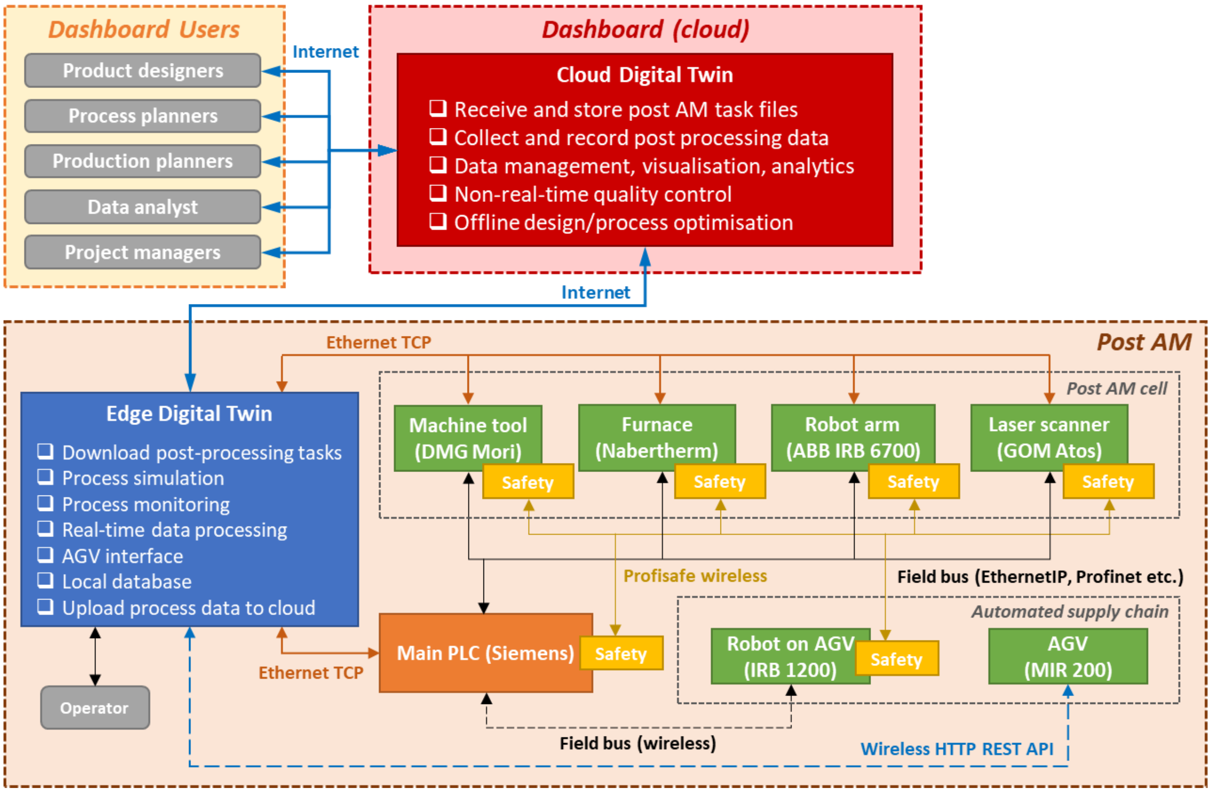

Figure 8. Detailed data communications and tasks in Post AM

A Virtual Reality (VR)-based DT application is developed for the Post AM shop floor as shown on the right of Figure 9. The application allows real-time field-level data to be communicated between the manufacturing facilities and their virtual models, and hence providing real-time post AM process monitoring functions. An Application Programming Interface (API) is developed in the MaterialCenter to allow data communication between the Dashboard and the DT application. Figure 9 shows the developed GUI in the Dashboard for post AM machine status monitoring. More advanced data analytics for the Post AM processes will be integrated in the Dashboard in the future.

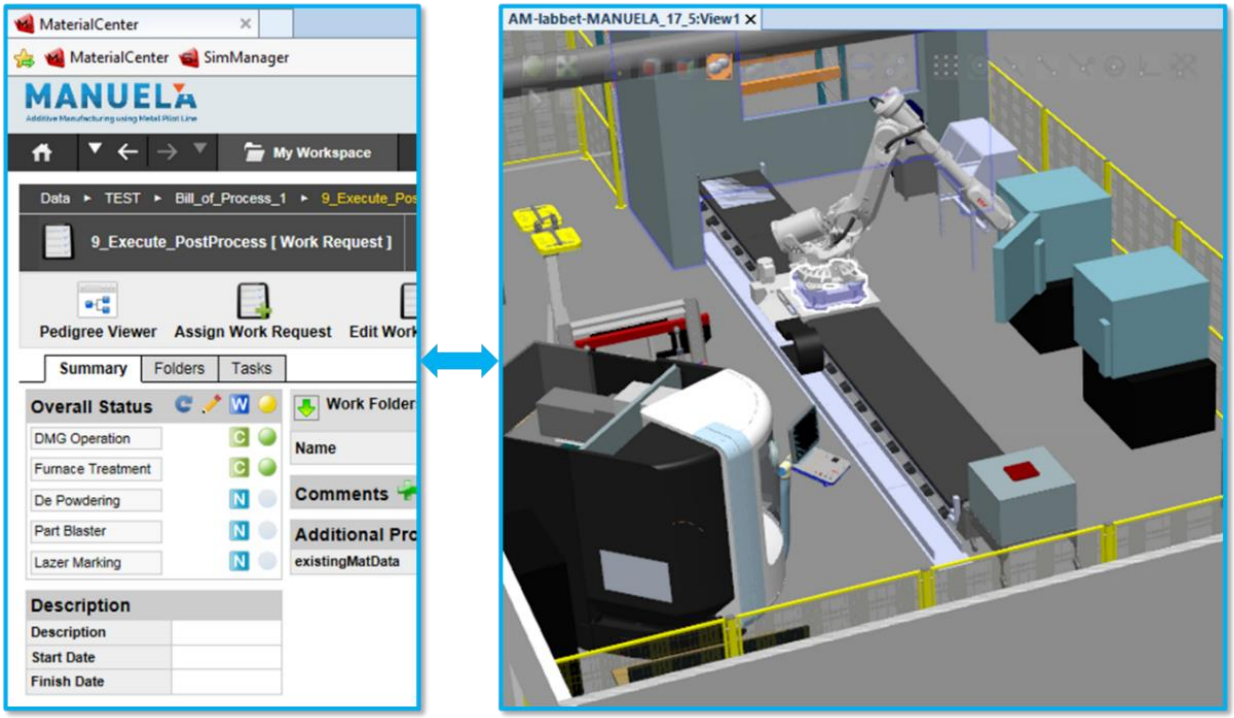

Figure 9. Interaction between Dashboard and Edge DT in Post AM

5.1.4 Quality Measurement

Figure 10 describes the detailed data communications and tasks in Quality Measurement. The Quality Measurement module comprises product quality measurement and analysis devices, including an X-ray Computed Tomography (CT) scanner, a tactile Coordinate Measurement Machine (CMM), their control PCs and an Edge DT. The CT scanner take cross-sectional images of the product and send the radiographs to the control PC for image analysis and 3D reconstruction; while the tactile CMM measures the dimensional accuracy of the product and send the tactile probe data to the control PC for data processing.

The Edge DT retrieves the measurement tasks and the related product design files from the Cloud DT via the Internet. All the measurement results are sent to the Edge DT and processed into product quality data and measurement reports corresponding to the data items in the metal AM product data model. Then the product quality data and measurement reports are uploaded to the Cloud DT to be stored and shared with the Dashboard Users.

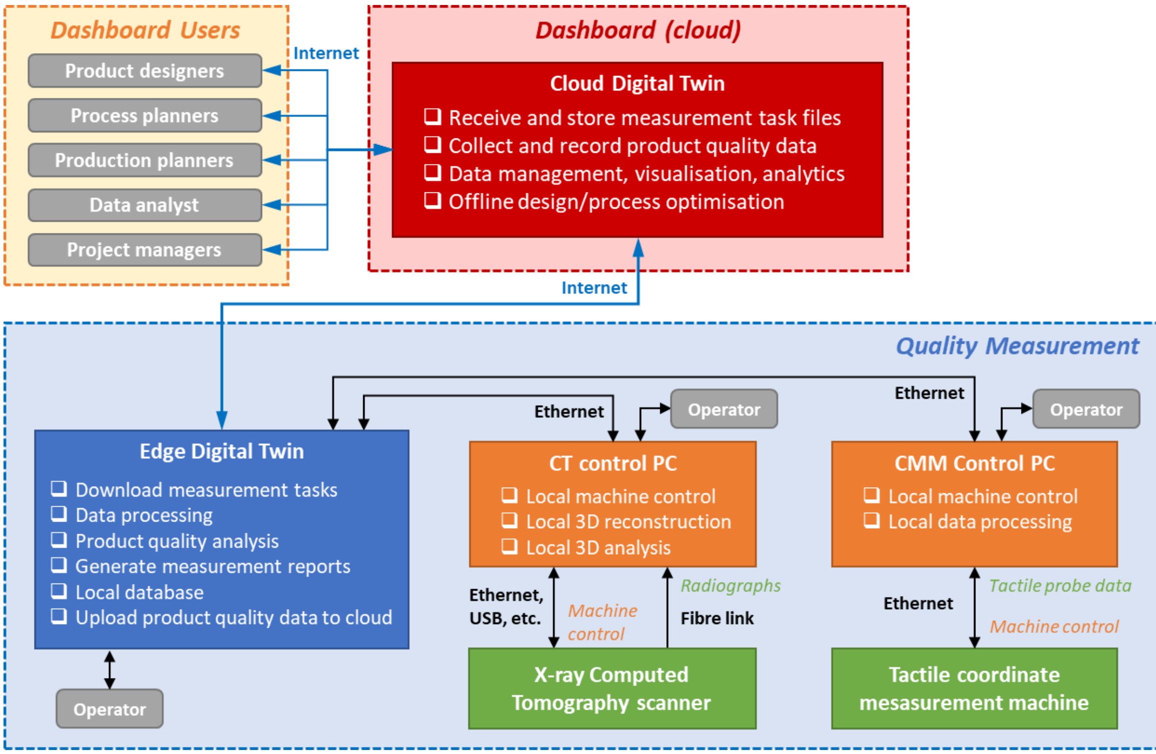

Figure 10. Detailed data communications and tasks in Quality Measurement

5.2 Representative application scenario: cloud-based and deep learning-enabled layer defect analysis

The implementation of DT-enabled collaborative data management in MANUELA enables various possibilities for advanced cloud-based metal AM data analytics, thus improving the metal AM process performance and product quality. This sub-section briefly introduces a representative application scenario, i.e. cloud-based and deep learning-enabled metal AM layer defect analysis, to demonstrate the great advantages and potential of the proposed approach.

The overview of the application scenario is described in Figure 11. First, the product designers and process planners upload the design and process parameters of the product to the cloud database through the Dashboard GUI. Then the operator in the shop floor retrieves the process parameters from the Dashboard to configure the machine and conduct the experiment. The experiment is conducted on the in-house developed EBM machine mentioned in Section 5.1.2. Ti-6Al-4V ELI (grade 23) powders are utilised to build eight cuboid samples with different scan speeds. During the metal AM process, the BSE detector installed in the building chamber of the EBM machine generates the ELO images of each printed layer. The raw ELO images are processed with image processing techniques in the Edge DT and then uploaded to the cloud database in the Dashboard. Figure 12 shows a snapshot of the cloud database in the Dashboard that contains the product lifecycle data uploaded by different users.

Data analysts download the processed ELO images from the Dashboard and use them as the training data to train a Convolutional Neural Network (CNN) model. The training data includes over 16,000 ELO images that are labelled into three categories: 1) good, 2) porous and 3) bulging, corresponding to three types of layer defects appeared during the metal AM process. Since the development of CNN model is not the focus of this application, we applied the transfer learning technique to train the AlexNet [58] with the ELO images and achieved 95.0% test accuracy. The trained CNN model is finally integrated into the Dashboard as an embedded data analytics function that is accessible for different users through the Internet.

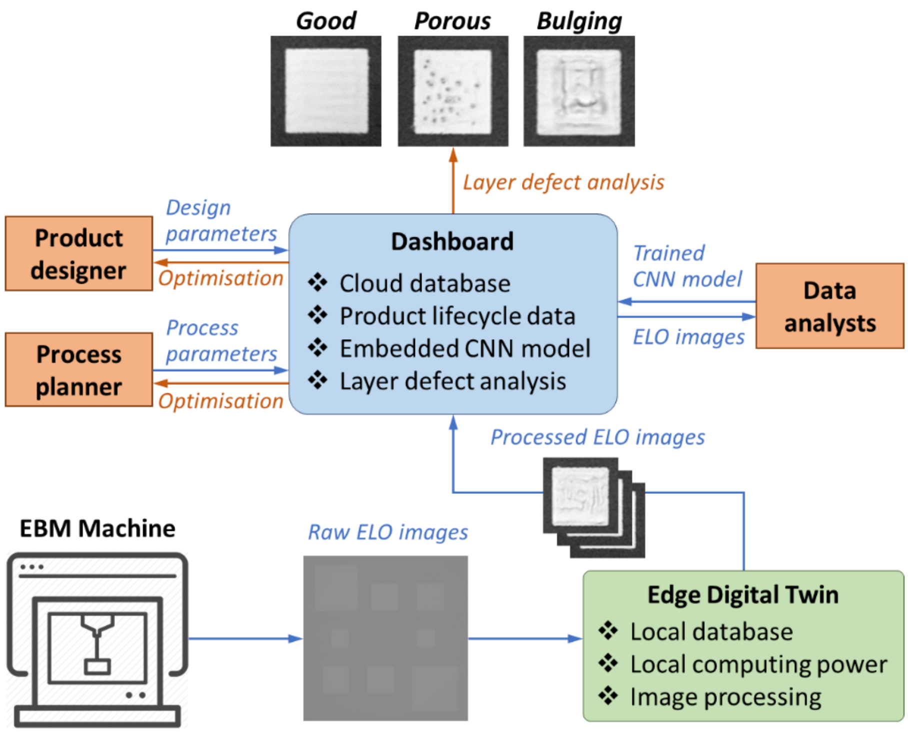

Figure 11. Overview of the cloud-based and deep learning-enabled metal AM layer defect analysis

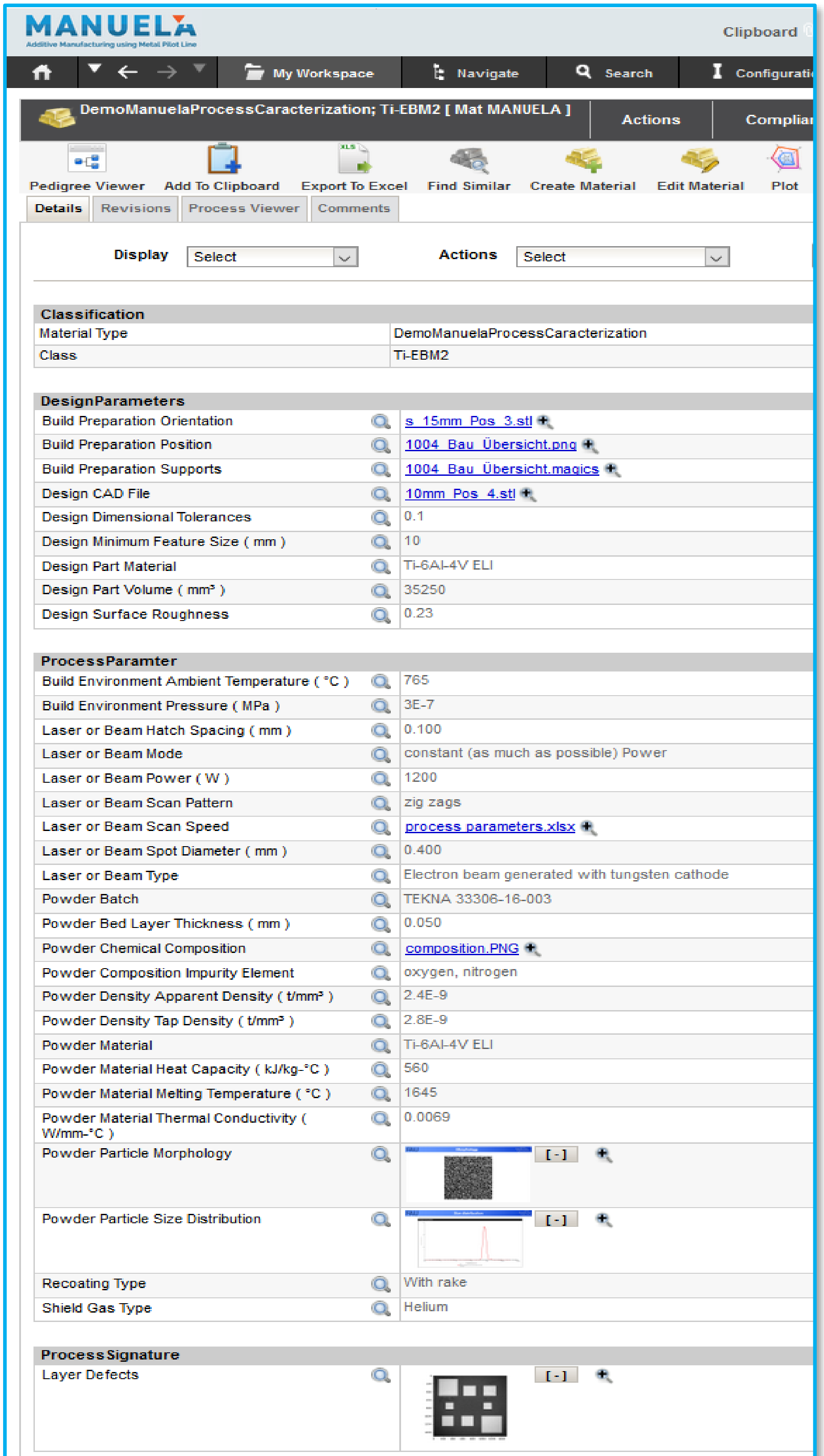

Figure 12. Snapshot of the uploaded product lifecycle data in the Dashboard

The developed application enables both off-line product quality optimisation and on-line layer defect detection. On the one hand, product designers and process planners can effectively correlate the layer defect analysis results with specific product design features and process parameters (part geometry, laser power, layer thickness, scan pattern, etc.), and hence perform design and process optimisations to improve the product quality. On the other hand, during metal AM building process, the ELO image can be uploaded to the Dashboard once it has been generated and processed locally, then the embedded CNN model can detect the layer defects on-line.

The on-line layer defect detection function has been developed by integrating the CNN model into the Dashboard's backend. Figure 13 illustrates the designed GUIs and procedures of the on-line layer defect detection in the Dashboard. Briefly, it includes four steps as follows:

- Step 1: Import ELO images to the Dashboard.
- Step 2: Launch the embedded deep learning-enabled layer defect detection function.
- Step 3: Display runtime status of the data analytics function and generate the prediction results as a .csv file.
- Step 4: Import the predicted defect result as a child object of the ELO image in the database.

This application allows distributed users to monitor the layer quality during the metal AM building process. The early identification of layer defects not only protects the recoating system from being damaged, but also reduces production costs in terms of material waste and production time.

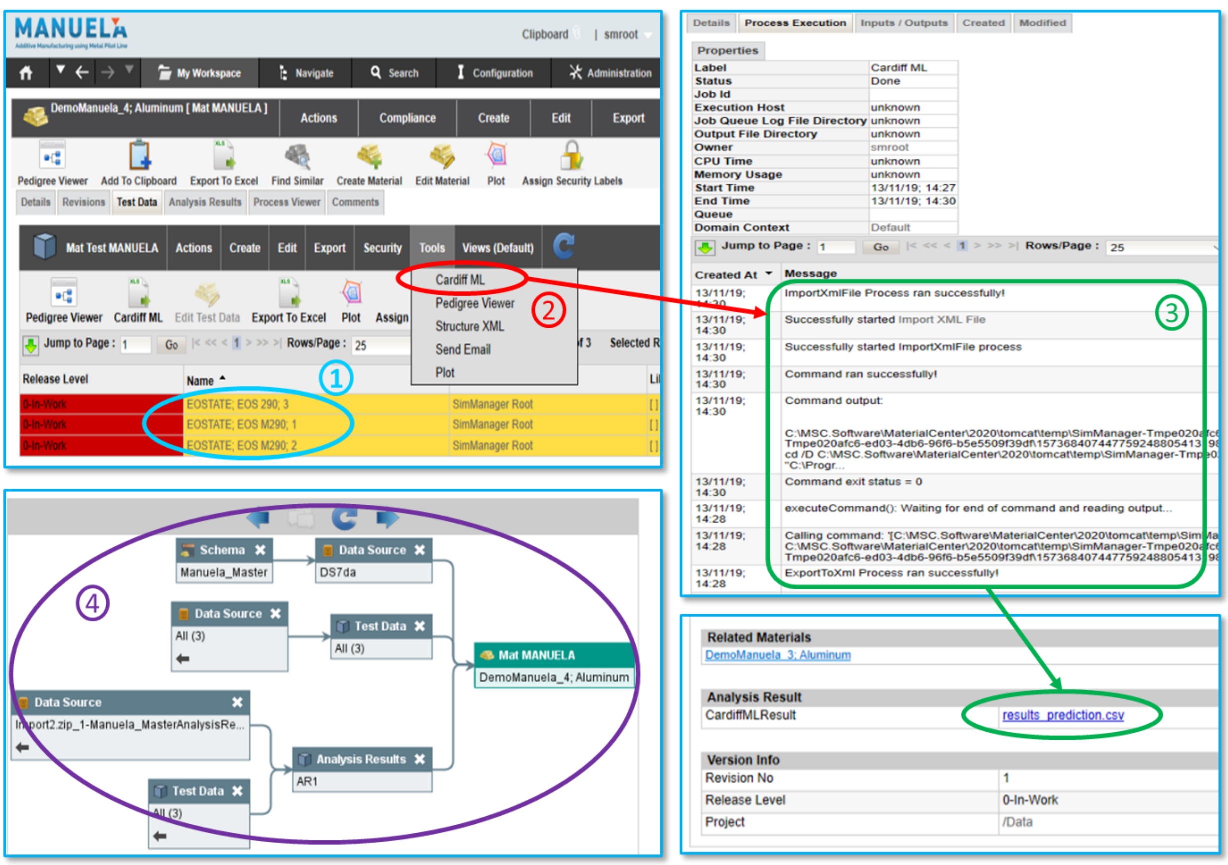

Figure 13. Procedures of the on-line layer defect detection in the Dashboard

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6. Conclusions and future work

Metal AM has been attracting a continuously increasing attention due to its great advantages compared to traditional subtractive manufacturing in terms of higher design flexibility, shorter development time, lower tooling cost, and fewer production wastes. However, the lack of process robustness, stability and repeatability caused by the unsolved complex relationships between material properties, product design, process parameters, process signatures, post AM processes and product quality has significantly impeded its broad acceptance in the industry. To enable efficient implementation of advanced data analytics, this paper proposes a novel DT-enabled collaborative data management approach for metal AM systems. The main contributions of this work are summarised as follows:

- Proposed a novel DT-enabled collaborative data management framework for metal AM systems, where a Cloud DT communicates with distributed Edge DTs in different product lifecycle stages.
- Proposed a metal AM product data model that contains a comprehensive list of specific product lifecycle data that has influence on the product quality.
- Practically implemented the DT-enabled collaborative data management in a distributed metal AM system. Early development of the data management system has demonstrated efficient data communications between the distributed shop floors and the cloud-based data management system.
- Developed a representative application scenario of cloud-based and deep learning-enabled metal AM layer defect analysis, which enables both off-line product design and process optimisation and on-line layer defect detection.

The proposed DT-enabled collaborative data management has shown great potential in enhancing fundamental understanding of metal AM processes, developing simulation and prediction models, reducing development times and costs, and improving product quality and production efficiency.

Moreover, the proposed DT-enabled conceptual framework is not limited to the application of metal AM systems. It can be treated as a generic reference framework for developing collaborative data management for other types of manufacturing systems. In those cases, domain-specific product data models need to be developed by identifying the specific product quality-related manufacturing data in each lifecycle stage. Efficient data communications between field-level manufacturing devices, the Edge DTs and the Cloud DT need to be established with consideration of the specific manufacturing facilities involved. Other product lifecycle stages that have not been considered in this work such as product usage stage and end-of-life treatment stage could also be included to enable various types of PLM services.

Our future work will focus on the development and implementation of machine learning-enabled advanced data analytics in the DT-enabled collaborative data management system in MANUELA. Recent advancements of machine learning will be studied and applied for metal AM process monitoring, control and optimisation. Various types of machine learning-enabled closed-loop metal AM applications based on the DT-enabled collaborative data management system will be developed to improve the metal AM product quality and production efficiency.

Acknowledgements

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Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

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