ASM Handbook, Volume 24A, *Additive Manufacturing Design and Applications*
M. Seifi, D. Bourell, W. Frazier, H. Kuhn, editors
https://doi.org/10.31399/asm.hb.v24A.a0006965

Additive Manufacturing Data Integration and Recommended Practice

Yan Lu, Milica Perisic, and Albert Jones, National Institute of Standards and Technology (NIST)

ADDITIVE MANUFACTURING (AM) creates parts layer by layer directly from three-dimensional computer-aided design data. Building in layers allows the fabrication of complex geometric shapes as well as functionally graded materials (Ref 1). Despite the part-quality and process-control challenges (Ref 2), the AM process has proven capable of producing production-quality parts, and its applications have evolved from rapid prototyping to industrial commercialization (Ref 3). According to *Wohlers Report 2021* (Ref 4), AM has already been commercialized as a routine production technology in aerospace, automotive, medical, and consumer products sectors.

While continuous improvements in AM are being made, the push toward successful industrialization depends on the ability to solve many remaining issues that include limited material choices quality consistency, and scalability (Ref 2). Collectively, recent advances in materials science, process monitoring and control, and nondestructive evaluation techniques are offering a means to address those issues (Ref 5–7). Large amounts of different data types are generated from the emerging AM technologies, and AM materials-development processes are being used as inputs to data-driven analytics that can sustain these advances. In addition, connecting AM machines and activities with existing manufacturing systems, including both machines and management applications, is likely to increase production throughput and address known scalability issues (Ref 8, 9).

As of this writing (2022), the industrialization of AM has not reached its scale. One of the more pressing problems is the lack of system and data integration. The AM systems are commonly siloed, and manufacturing executive systems are seldom set up for AM-based production. The big data generated from AM in-process monitoring and nondestructive evaluation are commonly acquired manually and scattered around the shop floor. The AM engineering data are still seldom reused across departments. Even though both AM machine builders and industrial automation software providers are creating partnerships to push the development of AM integration and data-management solutions (Ref 8–11), the applications are not reported, and standard practices have not been established and shared. Challenges in AM data integration stem from the complexity of the tasks, including:

- The wide scope of integration across product, machine, and material domains
- The variety of data types
- The unstructured high volume and high velocity of the data

This article discusses systematic ways to address the aforementioned challenges by exploring various AM-specific data-integration scenarios that can improve the current AM ecosystem. A reference framework that captures the heterogenous AM data sources and existing data-integration mechanisms are used (Ref 12). General data-integration practices—based on existing manufacturing data and lab information system integration experiences—are recommended to automate AM data flow, operations, and development.

Projecting forward, AM data standards will play a key role in AM data integration. ASTM International Committee F42.08 focuses on AM data interoperability standards. New AM standards are arriving in the areas of data registration, data fusion, and data security. With the advancements of AM data standards and by leveraging existing, more general data standards and other manufacturing-domain information standards, the commercialization of the AM industrialization process is expected to accelerate.

The Additive Manufacturing Ecosystem

The AM processes create part geometries and material properties simultaneously. Consequently, the quality of AM parts depends on a multitude of factors related to feedstock material properties, machine performance, and build process parameters. Like traditional manufacturing, AM development includes product development, machine life-cycle management, and production control and operation. Unlike traditional manufacturing, AM depends more on material development and uses advanced data analytics and artificial intelligence technologies extensively.

Figure 1 shows a totally integrated AM ecosystem, which captures all AM activities along the part, material, and machine axes that intersect at the production center. Implementing the broad scope and multidisciplinary nature of the AM ecosystem requires solutions to expanded data-integration problems. In Fig. 1, the part axis comprises life-cycle activities that constitute a rapid transformation process from part design to qualified part. Each of these activities produces and uses data that ultimately affect the final part's performance. Similarly, the activities in the material axis determine the AM raw quality of the material and the machine axis defines the AM machine performance, both of which can introduce problems, directly leading to build failures. The three life-cycle axes come into play during the production phase.

Along each life cycle in the AM ecosystem, the digital data from upstream activities must be integrated naturally into the downstream activities to form a digital thread. In the production phase where the three life cycles meet, data from all three digital threads must be integrated and used as inputs to the production activities, such as process control and production management.

In addition, data also flow across each life cycle (shown in red in Fig. 1) to support AM part qualification and engineering/control decisions. These flows result in the need to fuse and integrate data residing in different sources and to provide users with a unified view of the combined data. Therefore, easy access to all the data from the three threads is key to enabling AM production control and understanding product quality. The following sections present AM data-integration scenarios based on the life cycles to support the part, material, and machine development and the production functions.

Additive Manufacturing Part Life Cycle

Additive manufacturing part development includes seven major activities. The initial specific activity results in customer specifications, which are used as inputs to the part-design and the process-selection activities. The second activity creates an AM-process-specific design, which can include build orientation, lattice selection, and support structures. During process planning, parameters such as build layout, layer thickness, scan path, and so on are decided. The output of this activity is a machine-specific job file that includes the selected process parameters. The production activity covers the AM build process, which is followed by the postprocess activity. The last activity is AM inspection and certification, which ensures that an AM component meets specifications.

Material Life Cycle

In the material life cycle, specifications for a new material are first generated based on the customer's requirements for the AM part. The AM material life cycle continues with the development phase. Here, feedstock materials are developed to meet the requirements of the AM system, and AM material is developed by combining feedstock material with process parameters and postprocessing treatments to meet the requirements of the final part. Feedstock material development must also include scaleup to meet the needs for large-scale production. Both feedstock materials and final AM part materials must go through strict qualification or certification processes. For example, for metal powders, the certification process includes chemical tests for material grade conformance, particle size distribution, and microstructure characterization, among others. Also, as-built material tests are often required, using one or multiple AM systems and predefined process settings. The AM feedstock is often reused to increase feedstock efficiency by reducing waste. However, before reuse, the feedstock material must be recertified (Ref 13).

Machine Life Cycle

As previously mentioned, an AM machine can fabricate free-form parts with complex geometries and structures. The commissioning activity involves installing and testing the AM machine. If successful, the operating and maintenance activities, typically the longest activities in this life cycle, will repeat until the AM machine is retired. (Information about the design and setup can be used to refurbish a retired AM machine.) When a machine reaches end of life, decommissioning activities, which

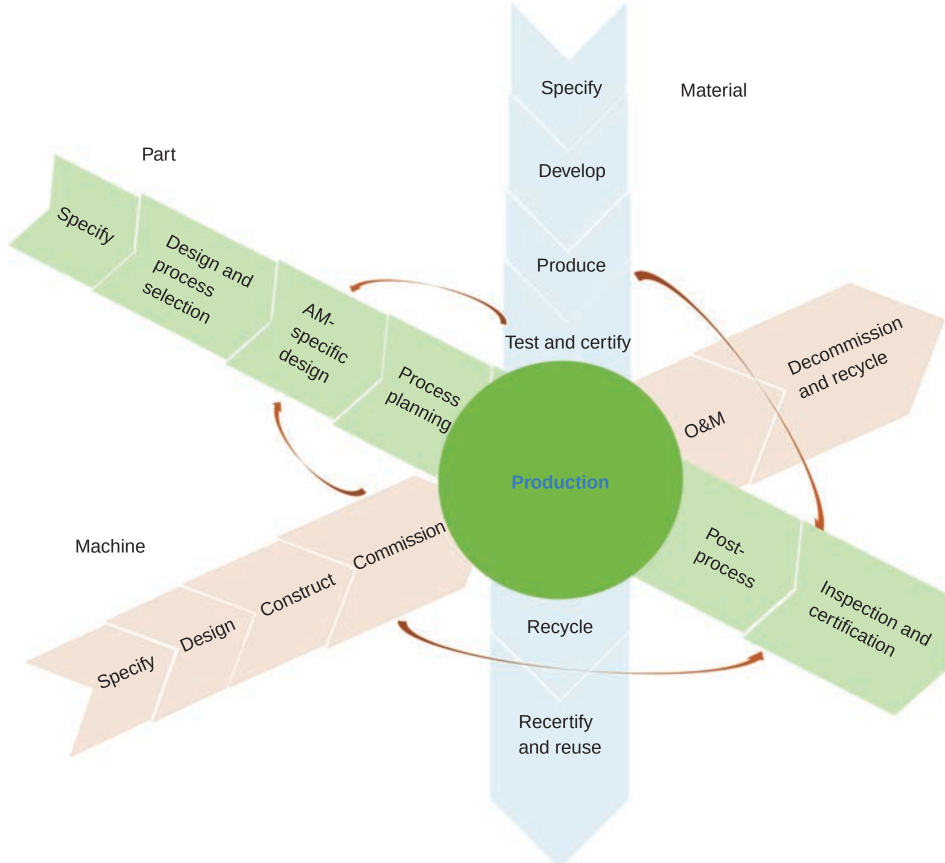

Fig. 1 Part, material, and machine life cycles in the additive manufacturing (AM) ecosystem. O&M, operation and management. Adapted from Ref 7

involve disconnecting, disassembling, and disposing of an AM system, are required. When possible, the recycled functional components can be reused.

Additive Manufacturing Production Hierarchy

The AM production phase shown in Fig. 1 can be described as a hierarchical system (Ref 13). Additive manufacturing production involves a vertical function integration of process monitoring and control, job dispatch and machine monitoring, operation management, and production planning (Fig. 2). In a smart operation, autonomous and intelligent machine behaviors—including self-awareness, reasoning and planning, and self-correction—are key, but information resulting from these behaviors must flow up and down the hierarchy. The data integration across the manufacturing production hierarchy is vital and critical for AM industrialization. Data integration during production allows access to field and plant data for making quick decisions and optimizing production throughput and quality, for accurate measures of energy and material use, and for improved shop floor safety and enhanced manufacturing sustainability.

Fig. 2 Additive manufacturing (AM) production hierarchy, the core of the AM ecosystem

Cross-Life-Cycle Additive Manufacturing Data Integration

Design for Additive Manufacturing

Design for AM is a process to design for manufacturability using AM machines (Ref 14). Different from traditional manufacturing, this additive design process empowers engineers to create more complex parts by taking advantage of the free-form printing process while considering the specific capability limitations of AM machines, for example, minimum thin-wall width. This design process takes information not only from product requirements but also from AM processes and AM machines.

Additive Manufacturing Part Qualification

Part qualification represents the broadest data-integration scenario in AM. It facilitates validation that an AM-built component is meeting design intent. The qualification process has four aspects: supplier qualification, machine/process qualification, part qualification, and lot acceptance (Ref 15). This indicates that to qualify an AM part, information from all the digital threads in the AM ecosystem are needed; consequently, totally integrated AM data are demanded.

Additive Manufacturing Data Are Big Data

The AM ecosystem consists of a wide range of data sources, including both managed systems and unmanaged, distributed raw sources. As of this writing (2022), the different types of unstructured AM data—generated from and used in AM ecosystem activities—are often termed "big data," which can vary from one-dimensional time-series data to two-dimensional images to three-dimensional (3D) models to unstructured texts and to inspection results. Consequently, across the entire life cycles shown in Fig. 1, volumes of data are produced. For example, during the fabrication and inspection of a single AM part, several terabytes of data can be collected.

Aside from the volume, AM data sets are also characterized by high velocity but low veracity. For example, high-speed, melt-pool-monitoring cameras alone can capture 20,000 frames per second, with a typical image size of approximately 20 kB. With multiple, in situ monitoring sensors deployed, gigabytes of AM process and part data can be generated every second. Quantitative errors and missing samples can lead to either data-accuracy problems and/or data-completeness problems. Representative AM data sources are described in the following sections.

Material Databases

Material databases store material data according to type, physical characteristics, mechanical properties, and standard classifications. They can be stand-alone commercial products or individual modular software components. Some users build their own proprietary and customized database systems; others use open-source, material-database, software systems. Both software systems provide the functions for database access and integration. The content of the material database systems can be based on various databanks, for example, MIL-HDBK-17F produced by the Air Force Materials Laboratory and maintained by the Composite Materials Handbook-17 organization (Ref 16). There are multiple online material databases that are accessible by everyone from everywhere:

- ASM International: https://www.asminternational.org/materials-resources/online-databases
- MatWeb: https://www.matweb.com
- Matmatch: https://matmatch.com
- MATDAT: https://www.matdat.com

Note that these databases typically have limited software-integration interfaces.

Lab Information-Management Systems

Lab information-management systems (LIMS) are designed for managing workflow and data created in research and development labs, especially across the material-development process and life cycle. The data include those related to lab instruments, samples, experiment pedigree, analytics tools, and reports. The LIMS play a critical role in AM material and process development by collecting, sharing, analyzing, and archiving scientific data.

Asset-Management Systems

In addition to AM machines, additive manufacturers often have several different types of assets to monitor and maintain them. Asset-management systems act as a data hub for storing any information related to those manufacturing assets, including AM machines, sensors, postprocessing equipment, and Internet of Things (IoT) devices. This information can include the age of the asset, acquisition date, location, functionality, and operational life cycle. Information is usually available to track the asset's health condition, calibration results, and maintenance data. These asset data are extremely useful for AM process control and part defect diagnosis.

Enterprise Resource Planning

Enterprise resource planning (ERP) is a type of software that organizations use to manage day-to-day, enterprise-level activities. The ERP-related activities include master planning, accounting, procurement, and supply chain operations. By collecting the shared, transactional data of an organization from multiple sources, ERP systems eliminate data duplication and provide data integrity with a single source of truth. The ERP systems are designed around a single defined data structure (model) that typically has a common underlying database.

Product Life-Cycle Management

Product life-cycle management (PLM) software manages all the information associated with every step of a product or service life cycle across global supply chains. This information includes the data from items, parts, products, documents, requirements, engineering change orders, and quality workflows. The PLM builds a coherent data structure frequently used as part of various digital threads. Standards, such as the standard for exchange of product model data, are key to enable product life-cycle data integration.

Manufacturing Execution System

Manufacturing execution system (MES) software manages, monitors, and synchronizes the execution of real-time manufacturing processes. The ISA 95 provides standard models of MES functions (Ref 17). The MES coordinates the transformation of raw material to finished goods by executing work orders based on the production schedules and integrating ERP and PLM systems. The MES integration also mandates machine connectivity for process monitoring, provides feedback on process performance, and supports component and material-level traceability, genealogy, and integration with process history, where required. These capabilities extend from product/process design release and work order release through completion of the manufacturing process.

Aside from conventional MES software vendors for traditional manufacturing, a smaller group of specialized niche players whose sole expertise is additive MES is emerging on the market. Even though the pool is smaller, their workflows and features can be quite unique (Ref 18).

Historian

Historian is a database software service for short-term, long-term, and permanent monitoring. It is an important component for both supervisory control and data-acquisition (SCADA) systems and manufacturing operation-management systems. The SCADA systems allow industrial organizations to monitor, gather, and process real-time data and to control industrial processes both locally and remotely with human-machine interface software. Trended manufacturing process data and events are stored in Historians that allow for easier data analysis in both real-time and offline.

Data Lake

A data lake is a place to store several different types of data, as well as a method for organizing large volumes of highly diverse data from distributed sources. The data lake is mainly designed to handle unstructured data in the most cost-effective manner possible.

The term *unstructured data* refers to data characterized by not having any structure, apart from that record or file level (Ref 13). These data can be textual or nontextual and human or machine generated. Unstructured data can also be anything from design files, which include engineering documents and images, to machine data such as log files and sensor data.

Another large group of AM data is referred to as semistructured. These data are largely unstructured but use internal tags and markings that separate and differentiate various data elements, thereby placing them into pairings and hierarchies. Common examples include emails, HyperText Markup Language (HTML), comma-separated values (CSV), Extensible Markup Language (XML) and JavaScript Object Notation (JSON) documents, and electronic data interchange (EDI) and Resource Description Framework (RDF) files. Each example has metadata that enable their correct interpretation.

Distributed Additive Manufacturing Data Storage

The data sources described previously are generally either stored in centralized structured query language databases or managed by commercially available manufacturing information systems (Ref 19–21). However, in AM, most data are distributed in local personal computers or servers. Data from feedstock characterizations, for example, are typically manually ingested into .csv files and stored in lab computers. Computer tomography data, exported from an x-ray computed tomography scan of an as-built part, are transferred to a shared server through mobile hard-disk drives. Mechanical test data are captured in figures and plots and stored in third-party lab computers. Hundreds of gigabytes of high-speed melt pool images, captured during an AM process, are typically stored on a local hard-disk drive and transferred manually for more permanent storage.

Streaming Additive Manufacturing Data Sources

Data streaming is the process of transmitting data continuously into data-processing or data-visualization software. A data stream consists of a series of data elements ordered in time. In traditional manufacturing, measurement and control data can be streamed from fabrication equipment or workstations continuously. Additive manufacturing systems have sensors measuring process variables such as the oxygen concentration, laser power, position of the build platform, and chamber and build platform temperatures. There are also camera-type systems that collect images of the powder bed and melt pools during fabrication. With embedded real-time data analytics in the AM systems, process anomalies can be detected when measurements or observations deviate from expected or predicted values. When either occurs, the build processes could be paused or stopped.

Additive Manufacturing Data-Integration Framework

Data in the AM ecosystem can be located anywhere across AM value chains and in different types of data repositories (managed or unmanaged). Integrating such disparate types and sizes of that data and across such a wide scope is challenging. Figure 3 shows an example of a three-level, big-data-integration framework that covers data sources, integration mechanisms, and management technologies. The lowest level deals with raw data cleaning and contextualization and curating them into managed data systems. The middle level combines data residing in different managed sources for business analytics. The top level facilitates information exchange between different software applications.

Lower-Level Data Integration

Manual Data Ingestion

In AM facilities or labs, data (especially metadata) are commonly collected and ingested manually. For example, in a Hall flow test for metal powders, multiple measurements of the elapsed time for 50 g of powder discharged through a funnel are measured and recorded. Information on the powder sample pedigree, specialized equipment, measurement, and test results must be recorded. Each lab uses its own data-element definitions and records the associated measurements in customized, proprietary Excel (Microsoft) spreadsheets.

IoT Data Acquisition

IoT data streams can only be acquired by computer systems through communication protocols. Traditional manufacturing field devices, such as programmable logic controllers, process instruments, actuators, and intelligent input/outputs, are connected using industrial field-bus standards such as Profibus, Controller Area Network (CAN), and Modbus. Collectively, these standards enable computer-integrated manufacturing. Today (2022), MTConnect and Open Process OPC UA are two emerging standards at the forefront of harmonizing data exchange across shop floors, especially for alarms and events. At the same time, more and more standardized, session-layer protocols are being adopted as part of integrating more modern manufacturing devices, such as Message Queuing Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), and Data Distribution Service (DDS).

However, the protocols previously mentioned do not support a high data rate by nature, and they are normally limited to lower payload sizes. For high-speed camera data, for example, AM melt pool images sampled at 10 kHz, specialized protocols are employed for data acquisition, such as Camera Link. Note that real-time processing or streaming this type of high-velocity data can be extremely challenging.

Data Migration

Data migration is the process of migrating data from one or more input sources into a target system. In AM, legacy data are often migrated for the purposes of querying and analysis. Data from heterogeneous sources are extracted first, then cleaned and reorganized based on the target-system data format or structure. Finally, the newly structured data

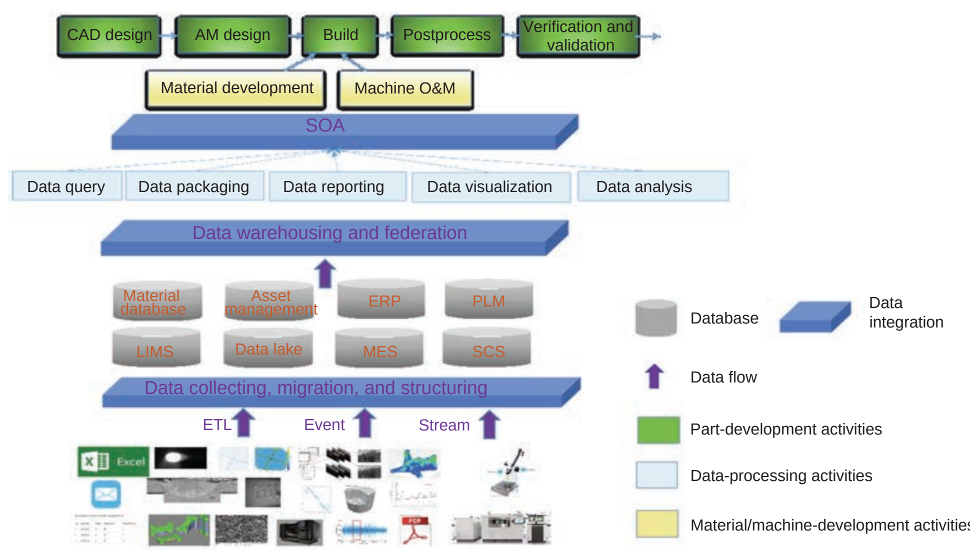

Fig. 3 Multilevel data integration for the additive manufacturing (AM) ecosystem. CAD, computer-aided design; O&M, operation and management; SOA, service-oriented architecture; ERP, enterprise resource planning; PLM, product life-cycle management; LIMS, lab information-management system; MES, manufacturing execution system; SCS, supply chain structures; ETL, extract, transform, and load. Source: Ref 12

are loaded into the target data-management system, such as a material database, LIMS, PLM, ERP, or data lake. The process is also referred to as ETL (extract, transform, and load).

Data Modeling

At the lower levels of integration data modeling is a critical step to curate raw data and integrate legacy data sources into managed data systems. *Data modeling* refers to the description of the organization of data in the management information system of an enterprise (Ref 22). Data modeling provides the definition, structure, and format of the data, whether logical or physical (Ref 23). General practice for enterprise data modeling can be found in Ref 24. Standard, neutral data models and data schema enable simple data integration.

Higher-Level Data Integration

Lower-level data integration contextualizes raw data and structures the data and metadata into information. The resulting organized data are managed by various information systems within an enterprise (Fig. 3). To support the totally integrated AM ecosystem, these individual information systems must be further integrated. This is referred to as high-level data integration; there are two types of integration techniques: data warehousing and data federation.

Data Warehousing

Data warehousing establishes data stores from various data sources to support different business analytics and reporting needs. The ETL tools previously mentioned are the key components of a data-warehousing software product. When using such a product, individual—but related—data are extracted from each individual source, cleaned, and then merged to form integrated data stores. These type of data stores contain no duplication or redundancy of information. Data-warehousing software is a key means to create the integrated data needed to support enterprise-wide decision making. Today (2022), these products are moving from local data centers to cloud-based data warehouses.

Data Federation

When data integration goes beyond the boundary of an enterprise, data federation is needed. Data federation is a process that allows multiple databases to function as virtually one. Without copying data and duplicating data using another storage system, data federation establishes a virtual data repository that provides a unified interface for a range of sources based on a common data model. Figure 4 shows an example of a common AM data model developed at the National Institute of Standards and Technology (NIST) (Ref 25). This common model provides a single source of data for front-end applications. A data-federation system includes metadata repositories, data abstraction, read and write access to source data systems, and advanced security. Data federation is a technique to create a collaborative data-management system for data sharing within the AM ecosystem. This data sharing enables, facilitates, and accelerates AM development and deployment.

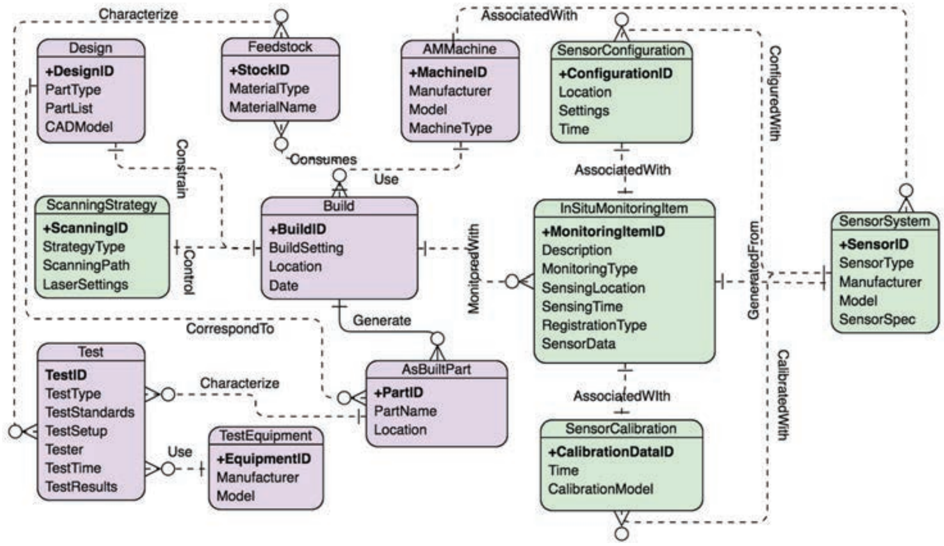

Fig. 4 National Institute of Standards and Technology additive manufacturing common data model. Source: Ref 19

Data Flow for Application Integration

Additive manufacturing development relies on a workflow of various business analytics functions. Smart manufacturing systems allow data to flow in and out of these functions based on a service-oriented architecture (Ref 26) or application programing interface (API).

Enterprise Bus

Enterprise bus (ESB) is a common implementation pattern for service-oriented architectures. The ESB can route messages between enterprise applications and provide commodity services. These services include event handling, data transformation and mapping, message and event queuing and sequencing, security or exception handling, protocol conversion, and enforcing the proper quality of communication service.

Canonical Data Model

The canonical data model (CDM) is a data model that covers all data from connected enterprise systems. The CDM models all the data from individual data sources so that there are always unambiguous translations from the CDM to the individual data models and vice versa. Open Application Group Integration Specification is a good example that defines a canonical model for enterprise application integration.

REST Application Programing Interface

Application programing interface (API) is a software intermediary that allows two applications to communicate through a predefined set of definitions and protocols (Ref 27). The API allows an organization to share resources while maintaining security, control, and authentication. Today (2022), applications usually use REST API, also known as RESTful API, a set of architectural constraints. Developers can implement RESTful API by following several criteria for an API to be considered RESTful (Ref 28). By using REST API, users do not need to understand every application in a system to use its functions. These functions can be exposed through APIs, and data can be easily exchanged between them.

Recommended Additive Manufacturing Data-Integration Practice

After identifying AM-specific application scenarios and their associated data-integration requirements, AM data architects and engineers can proceed to plan and execute those scenarios using existing data-integration techniques and tools. Figure 5 presents a workflow that can facilitate two such scenarios: process monitoring and control for real-time applications and long-term data archiving for offline applications.

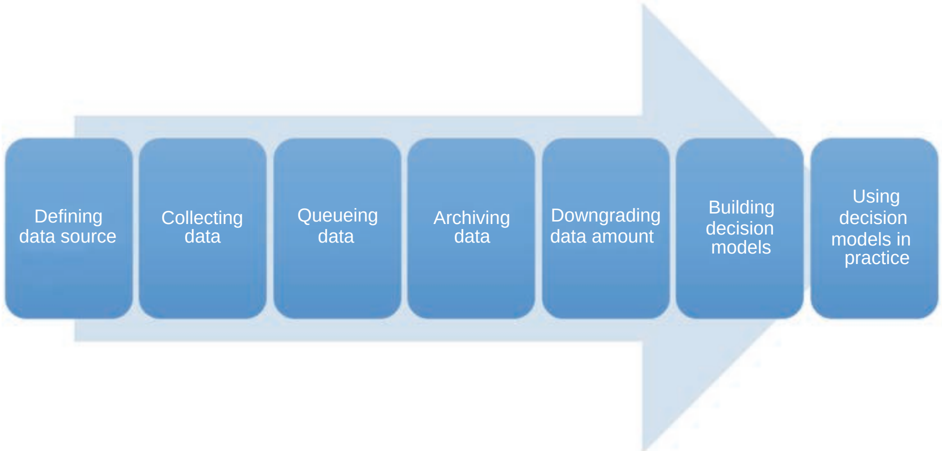

Fig. 5 Example of a big-data-integration workflow

The workflow consists of seven steps listed in the following sections (Ref 29). These steps can be applied for both data streaming and batch-data processing. In the former case, the seven steps run in consecutive, discrete periods, to be scheduled or manually triggered. In the latter case, however, those steps run continuously.

Step 1: Defining a Data Source

Recall that the AM ecosystem integrates the data from three external life cycles within the AM production hierarchy. Within each life cycle, there are numerous and varied data sources and their associated life-cycle activities and integration methods. Defining each varied data source is required, and its definition is based on answers to questions about the chosen data-integration methods. Questions can include: What are the data that must be integrated? What are their structures? What type of data source can provide both, and how do we integrate them? The AM data architects and engineers typically provide answers to these questions based on specific needs and use cases. These answers define the capabilities that a potential data source must have to become a viable part of the solution to AM data-integration problems. The first answer is the data types themselves. Example data types include images, videos, and 3D models. A coordinate system is another example of a first answer that can be used to interpret the position and size of any measurement data. The second answer includes any data source, or device, that has the capabilities to provide one of the named data types. Each such data source has a data-source description, which provides the information attributes about the defined, physical data source. The metadata associated with each device, such as device model and device type, are also needed.

Step 2: Collecting Data

After defining each selected data source (device type), it is necessary to determine how each source will collect and communicate its data. For static and discrete data sources, importing/exporting functions can be used. For streaming and continuous data sources, data are generated during a predetermined time interval, defined either when an important event occurs or when a specific condition is satisfied. Independent of the device or mechanism that creates the data, there are two main approaches when it comes to collecting that data from the device: push or pull. In the first approach, data are pushed from the device at their own frequency. In the second approach, when the device cannot push its data, the device stores that data until its recipient must launch an application that will pull the data from the device. In either case, it is important to define a standard for exchanging the data. Recommended best practice is to define a standard for representing the location of both data and metadata. These standards result in messages to the receiving system that is hosting the application.

Step 3: Queueing Data

Processing and parsing these messages require system resources. To prevent system overload, a message queue can be helpful. In that way, data will be temporarily stored in the queue until it is processed and then stored in the system. (Multiple queues may be necessary.) For example, the first queue stores raw, unprocessed data waiting to be processed. The second queue temporarily holds that processed data while it is waiting to be stored in the system. Two examples of common multimessage-queue technologies are Apache Kafka and IBM MQ. From this point, data will be archived for both real-time analysis and long-term archiving.

Step 4: Archiving Data

Developing a stable and tenable archiving system depends on which persistent-storage technology is selected. Regardless of the choice, AM image data and its associated metadata should be defined and stored separately. It is common to use file systems as an image-storage mechanism. Another convenient way to handle images and other binary objects is to shift responsibility to cloud-based storage centers. Storage-as-a-service provides features to easily scale computational resources and provide access permissions. It also offers a user interface, command-line tools, and an API for several programming languages.

The decision of what type of storage to use depends on the target use case. If there are no technical or financial obstacles, uploading images to an external cloud-managed storage system is a recommended choice, because images are easier to maintain, and space limitations are not a factor. On the other hand, if image data are private and should be kept in local systems, then cloud storage is not a recommended option; a file system storage may be a better fit in this case. However, this option requires more resources and skills to set up and later administrate. A file system does allow for more freedom to customize and adjust the solution to specific target use cases.

In addition to storing images, metadata should be stored. Unlike the actual data, the most common way to store the metadata is a relational database-management system (RDBMS). The main advantage of an RDBMS is that most engineers know this technology, and the commercial DBMS tools have integrations with many external tools. Also, because metadata in AM production processes do not often change, document databases could be used, such as NIST's Additive Manufacturing Materials Database (AMMD).

Step 5: Downgrading Data Amount

To achieve sustainability, the system must be capable of managing different data sizes and saving only the data necessary for future use cases. Several policies must be defined, including deleting old data, aggregating data, removing duplicates, and reducing data quality (if needed).

Step 6: Building Decision Models

Data are being collected and processed for one reason: to gain value from it. Machine learning-based predictive models need a solid history of the labeled data as input to make future predictions. Rule-based expert systems are built using if-then rules, which are defined by the experts in the specified area. A common practice is to combine both approaches to build reliable, prediction-based decision-making systems.

Step 7: Using Decision Models in Practice

There are several options on how decision-making models can be used in practice. In AM, for example, if a model can predict a critical event in the machine, an alert can be sent to the staff in charge of handling that issue. If the model reports an in-process monitoring anomaly, it can be used to change the process parameters or stop the build.

REFERENCES

1. S.A.M. Tofail, E.P. Koumoulos, A. Bandyopadhyay, S. Bose, L. O'Donoghue, and C. Charitidis, Additive Manufacturing: Scientific and Technological Challenges, Market Uptake and Opportunities, *Mater. Today*, Vol 21 (No. 1), 2018, p 22–37
2. W. Frazier, Metal Additive Manufacturing: A Review, *J. Mater. Eng. Perform.*, Vol 23, 2014, p 1917–1928
3. "Department of Defense Additive Manufacturing Strategy," Jan 2021, https://www.cto.mil/wp-content/uploads/2021/01/dod-additive-manufacturing-strategy.pdf, accessed on May 31, 2022
4. 3D Printing and Additive Manufacturing State of the Industry, *Wohlers Report 2021*, Wohlers Associates, https://wohlerssassociates.com/2021report.htm
5. S.K. Everton, M. Hirsch, P. Stravroulakis, R.K. Leach, and A.T. Clare, Review of In-Situ Process Monitoring and In-Situ Metrology for Metal Additive Manufacturing, *Mater. Des.*, Vol 95, 2016, p 431–445
6. P. Charalampous, I. Kostavelis, and D. Tzovaras, Non-Destructive Quality Control Methods in Additive Manufacturing: A Survey, *Rapid Prototyp. J.*, Vol 26 (No. 4), 2020, p 777–790, https://doi.org/10.1108/RPJ-08-2019-0224
7. P. Fino and A. Aversa, *Materials Development by Additive Manufacturing Techniques*, MDPI Books, March 2021, https://doi.org/10.3390/books978-3-03943-033-8
8. "NextGenAM—The Future, Here Today: Industrial 3D Printing. Fully Automated," EOS, https://www.eos.info/en/innovations/digital-manufacturing-production/next-gen-am-industry-40, accessed Sept 1, 2022
9. "Strategic Partnerships for Advanced Additive Manufacturing," Siemens, https://new.siemens.com/us/en/company/press/siemens-stories/usa/strategic-partnerships-additive-manufacturing.html, accessed Sept 1, 2022
10. L. Scime, A. Singh, and V. Paquit, A Scalable Digital Platform for the Use of Digital Twins in Additive Manufacturing, *Manuf. Lett.*, Vol 31, 2022
11. "Additive Manufacturing Data and Process Management," Siemens, https://www.plm.automation.siemens.com/global/en/products/collaboration/additive-manufacturing-data-process-management.html, accessed Sept 1, 2022
12. H. Yang et al., Six-Sigma Quality Management of Additive Manufacturing, *Proc. IEEE*, Vol 109 (No. 4), April 2021, p 347–376, doi: 10.1109/JPROC.2020.3034519
13. "Information Technology—Big Data—Overview and Vocabulary," ISO/IEC 20546:2019, International Organization for Standardization/International Electrotechnical Commission, 2019, https://www.iso.org/standard/68305.html
14. M.K. Thompson, G. Moroni, T. Vaneker, G. Fadel, R.I. Campbell, I. Gibson, A. Bernard, J. Schulz, P. Graf, B. Ahuja, and F. Martina, Design for Additive Manufacturing: Trends, Opportunities, Considerations, and Constraints, *CIRP Ann.*, Vol 65 (No. 2), 2016, p 737–760
15. "Specification for Fabrication of Metal Components Using Additive Manufacturing," AWS D20.1/D20.1M:2019, American Welding Society, 2019
16. *Composite Materials Handbook-17*, https://www.cmh17.org/
17. "Enterprise-Control System Integration," ISA 95, International Society of Automation, https://www.isa.org/standards-and-publications/isa-standards/isa-standards-committees/isa95, accessed Sept 1, 2022
18. "Opportunities in Additive Manufacturing Software Market," SmarTech Analysis, June 20, 2020
19. N. Bicocchi, G. Cabri, F. Mandreoli, and M. Mecella, Dynamic Digital Factories for Agile Supply Chains: An Architectural Approach, *J. Ind. Inf. Integr.*, Vol 15, 2019, p 111–121
20. V.F. de Oliveira, M.A.O. Pessoa, F. Junqueira, and P.E. Miyagi, SQL and NoSQL Databases in the Context of Industry 4.0, *Machines*, Vol 10, 2022, p 20
21. A. Bonci, M. Pirani, and S. Longhi, A Database-Centric Framework for the Modeling, Simulation, and Control of Cyber-Physical Systems in the Factory of the Future, *J. Intell. Syst.*, Vol 27 (No. 4), 2018, p 659–679
22. "Information Technology—Vocabulary," ISO/IEC 2382:2015, International Organization for Standardization/International Electrotechnical Commission, 2015, https://www.iso.org/standard/63598.html
23. "Industrial Automation Systems and Integration—Integration of Industrial Data for Exchange, Access and Sharing—Part 1: Architecture Overview and Description," ISO/TS 18876-1:2003, International Organization for Standardization, https://www.iso.org/standard/33701.html
24. *DAMA-DMBOK—Data Management Body of Knowledge*, 2nd ed., DAMA International, 2017
25. Y. Lu, B. Kulvatunyou, A. Jones, and N. Ivezic, "AM Big Data Registration and Exchange Based on OAGIS Message Models," Int. Conf. on Additive Manufacturing, Nov 16–29, 2020
26. Y. Lu, F. Riddick, N. Ivezic, et al., The Paradigm Shift in Smart Manufacturing System Architecture, *Advances in Production Management Systems. Initiatives for a Sustainable World, APMS 2016, IFIP Advances in Information and Communication Technology*, Vol 488, Springer, Cham, 2016, https://doi.org/10.1007/978-3-319-51133-7_90
27. J. Ofoeda, R. Boateng, and J. Effah, Application Programming Interface (API) Research: A Review of the Past to Inform the Future, *Int. J. Enterpr. Inf. Syst. (IJEIS)*, Vol 15 (No. 3), 2019, p 76–95
28. M. Masse, *REST API Design Rulebook: Designing Consistent RESTful Web Service Interfaces*, O'Reilly Media, Inc., 2011
29. M. Perišić, D. Milenković, Y. Lu, A. Jones, N. Ivezić, and B. Kulvatunyou, "A Data Integration Framework for Additive Manufacturing Big Data Management," Int. Solid Freeform Fabrication Symposium (Austin, TX), 2021