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Foundations of information governance for smart manufacturing

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Abstract

The manufacturing systems of the future will be even more dependent on data than they are today. More and more data and information are being collected and communicated throughout product development lifecycles and across manufacturing value chains. To enable smarter manufacturing operations, new equipment often includes built-in data collection capabilities. Older equipment can be retrofitted inexpensively with sensors to collect a wide variety of data. Many manufacturers are in a quandary as to what to do with increasing quantities of data. Much hype currently surrounds the use of AI to process large data sets, but manufacturers struggle to understand how AI can be applied to improve manufacturing system performance. The gap lies in the lack of good information governance practices for manufacturing. This paper defines information governance in the manufacturing context as the set of principles that allow for consistent, repeatable, and trustworthy processing and use of data. The paper identifies three foundations for good information governance that are needed in the manufacturing environment—data quality, semantic context, and system context—and reviews the surrounding and evolving body of work. The work includes a broad base of standard methods that combines to create reusable information from raw data formats. An example from an additive manufacturing case study is used to show how those detailed specifications create the governance needed to build trust in the systems.

Keywords

Information governance, context awareness, Computer integrated manufacturing, system verification, part qualification, systems integration.

Introduction

Data and related technologies—sensors that collect data, networks for transmitting and sharing data, and computational techniques such as data analytics and artificial intelligence (AI)—are transforming the way manufacturers do business. These technologies when successfully combined and applied to manufacturing are often referred to as smart manufacturing. Many studies have shown that smart manufacturing can improve operations at the different levels in the factory.[1] At the device level, strategies for in situ monitoring have been shown to be effective. These strategies link sensing data to the part as it is being processed and identify deviations from historical processing runs, especially those deviations known to be associated with rejected parts,

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and/or models to predict future performance. Such insight allows for adjustments to the processing in response to the perceived performance. At the system level which addresses the network of individual manufacturing processes, data are aggregated such that machine performance can be monitored, compared and analyzed to identify problems such as bottlenecks in real-time. While performance dashboards are becoming mainstream[2][3][4], more advanced strategies for improving performance are emerging. For example, performance prediction through data synthesis can be used to anticipate problems in a system before they occur.[5] Other strategies use measurement of product quality to identify performance degradation before systems are out of tolerance, allowing for more proactively planned maintenance[6] and the potential for in situ adjustments[7][8]. Even manufacturing maintenance can be improved through the application of data analytics to identify previously unseen patterns supporting better failure prediction [9] and in the process improving overall system efficiency through better planning.[28]

The common elements in these advancements are the information processing and the computing capabilities that allow data to be processed and interpreted in ways that lead to actionable outcomes. The results have been demonstrated in both real world and research settings, but they are still not being applied ubiquitously. The problem lies in the details of turning data into useful and reliable information.[10][11] Data by itself is not enough to achieve the desired outcomes. Much human effort is still needed to curate, clean, and make use of data in meaningful ways.[6] Data needs to be not only accurate but well understood to derive meaningful insights. Often data needs to be linked or compared to other data sets. Knowledge of both data sets is needed to make the right connections for logical comparisons. The tasks of working with data require unique and very different skill sets than typical manufacturing operations. Hence a new job function emerges: data wrangler. Data wranglers are different from data scientists in that their sole purpose is to know how the different data sets are related and how to transform the data in ways that will be useful and reliable for engineering decision making. In practice this knowledge resides with an organization's manufacturing engineers or data specialists. Considering the explosive potential of data analytics and machine learning when applied to manufacturing data, the need for a strong framework to build quality into and provide context for data is apparent. Enhanced in quality and with context, data transforms into information. Ultimately that information is accessed in the context of a system. The rules—mechanisms and policies—for accessing information in the system complete the foundations for information governance.

A recent study from the Manufacturing Policy Institute (MPI) defines information governance for manufacturing as the "rules (formal and informal) concerning the collection, flow, and analysis of information, often in digital form. These rules are determined over time through collective action by governmental and nongovernmental organizations."[12] In this definition, the term "information governance" is used broadly, covering all data, information and knowledge in digital forms. This paper focuses on technical foundations and discusses the governance needs for the technical data belonging to manufacturing operations, in other words operational technology (OT) or the information that flows on the shop floor. The MPI report states that information governance practices for manufacturing are a critical and necessary component to broadly deploying smart manufacturing. Without strong and rigorous information governance many manufacturers will not be able to commit to the technology. Information governance is needed to reduce the risk of investing. In addition, many manufacturers work in regulated environments where they must not only demonstrate but also have outside parties certify tried and true processes, that can only be achieved through strong governance protocols. Such protocols are underpinned by information standards and best practices.

Beyond that, information governance serves three vital roles for manufacturers.
1) It can spur innovation. Curating data with context makes it more accessible for future, unforeseen needs. A promise of smart manufacturing is the rich opportunity for openness in the systems where multiple parties are able to provide innovative solutions, and manufacturers take control of their own data.[13] If this promise is to be fulfilled we must tackle the information governance problems in an open manner.

2) Solutions to two of the largest challenges for manufacturers today—workforce development and cybersecurity—require strong information governance. The practices established through information governance lay the foundations for training the next generation of manufacturers to accomplish repeatable and reliable operations. This is especially important as many in the current labor force are reaching retirement age. Much of the knowledge for today's operations is embodied in the experience of workforce members who are moving to retirement. Good governance will help to codify that for future generations. Cybersecurity also depends on strong information governance. Good practices for collecting and storing data are necessary for diagnosing, detecting, and remedying cybersecurity problems.

3) Information governance is necessary for responsiveness to policies and regulations of the future. Regulatory practices attempt to guide the behavior of manufacturers in directions that benefit or at least do no harm to society at large. Information governance can be useful in demonstrating progress towards such goals. For instance the recently established UN goals for sustainable development call for sustainable industrialization (Goal 9) and responsible consumption and production patterns (Goal 12).[14] Information governance is necessary to allow us to meaningfully measure progress towards these goals.

Information Governance Today

Information governance for smart manufacturing systems today is in its infancy. While many large service providers offer information governance guidance to their client base, other organizations, and too often individuals, are left to develop their own best practices. When individuals develop their own best practices, that supports the professionalism of those individuals but does little to serve the corporate interest where shared common practices provide efficiency and interoperability across an organization. Some efforts are emerging to standardize data governance practices within standards development organizations including the Object Management Group (OMG)[15], ASTM International [16] , and the Institute of Electrical and Electronics Engineers (IEEE)[17]. While not comprehensive frameworks, the efforts of other standards organization, including the International Organization for Standardization (ISO), International Electrotechnical Commission (IEC), Open Group, and American Society of Mechanical Engineers (ASME), contribute to information governance as well.

OMG, a consortium of software vendors and other interested parties, develops technology standards to support the integration of software systems across a range of industries. Their standards span a horizontal axis consisting of standards that are common across a broad range of domains and several vertical axes that dive into the specific areas for given industries. OMG is the managing organization for the Industrial Internet Consortium (IIC)[18] and, hence, has a focus on the standards needs for manufacturing integration. OMG has established a Data Governance Working Group. The group works on four technical standards including Data Residency, Data Provenance and Pedigree (formed June 2016), Tagging and Labeling, and an Information Exchange Framework that integrates the others. These standards will contribute to a strong governance foundation.

ASTM standards from the E60.13 subcommittee on Sustainable Manufacturing provide guidance for modeling manufacturing processes and collecting data for process improvement. In addition, ASTM's F42 committee on Additive Manufacturing Technologies recently established the subcommittee on Data and will produce standards in the areas of data specification, data packaging, and others that will contribute to a governance framework. The standards from this activity will provide a platform for certifying products resulting from additive manufacturing processes.

IEEE has also initiated a standards activity for Big Data Governance and Metadata Management (BDGMM) which is broader than manufacturing but very relevant to manufacturing data. The effort is a joint activity between IEEE's research and standards activities. This work is in the early stages. An initial white paper is in development to identify the standards requirements, existing base standards, and standards gaps.

Information governance is difficult because it engages all aspects of an organization. According to Gartner, information governance encompasses "processes, roles and policies, standards and metrics."[19] This paper does not attempt to address the social aspects of governance teams, roles, and policies supporting business processes—other very important aspect of governance—but rather the technical foundations on which such teams can build standards and metrics. Earley [20] addresses these broader items in a framework for metrics-driven information governance that explores methods for introducing and retaining information governance efforts in an organization by showing their value.

Information governance for manufacturing operations will incorporate the evolving principles developed within standards organizations such as those mentioned above. Foundations of good information governance are discussed here in the unique perspective of manufacturing operations with respect to

- Reliability in data,
- Semantic context for data, and
- Interactions within and between systems.

These foundations will provide the rigor necessary to build policies and procedures that can be consistently and repeatably applied to create trustworthy system performance. While much of the work needed to build these foundations is still in the research phase, the efforts reviewed below provide a good starting point for these discussions. To better elaborate the good information governance foundations, an example of a new technique for improving an additive manufacturing process is presented first.

Additive Manufacturing Data Landscape and Analytics Scenarios

Additive manufacturing (AM) processes build parts layer-by-layer directly from 3D models. Additive manufacturing was originally developed as a rapid prototyping technique and, as such, the expectations for part quality were limited.[21] Over time, however, the process has proven capable of producing production quality parts. Compared to traditional manufacturing processes where objects are shaped or cut out of blocks of solid materials with well understood material properties, AM enables the fabrication of complex heterogenous parts, but the material properties of AM parts are not as well characterized. The advantages of AM make it an attractive alternative for high-value, low-volume production. However, the information governance necessary to support consistent and repeatable AM processing is lagging the pace at which the process technology is maturing.

Barriers to the turnkey deployment of the technology include low part repeatability, lack of effective design, engineering and qualification tools, as well as limited material choices.[12] Fundamental issues exist with the understanding and control of the dynamic and stochastic nature of AM processes. Numerous factors, including the product design, process settings, feedstock material properties, and machine performance, contribute to the final part quality and hence need to be understood and reliably controlled. Figure 1 shows an AM ecosystem, which illustrates data flows in an AM build process. It captures both an AM part development lifecycle and its related value chain activities. In the figure, an initial part design is transformed into an AM design which incorporates AM process-specific requirements for material and build rules. The part is then built layer by layer, post processed as needed, and finally tested. Each of these steps produces and uses data. The engineering decisions from these activities are primary factors affecting final product performance, e.g., choices for part shape design, build orientation and support structure design, process parameters and post-process procedures and settings. Value chain activities that determine feedstock material quality and machine operating quality could introduce problems directly leading to build failures.

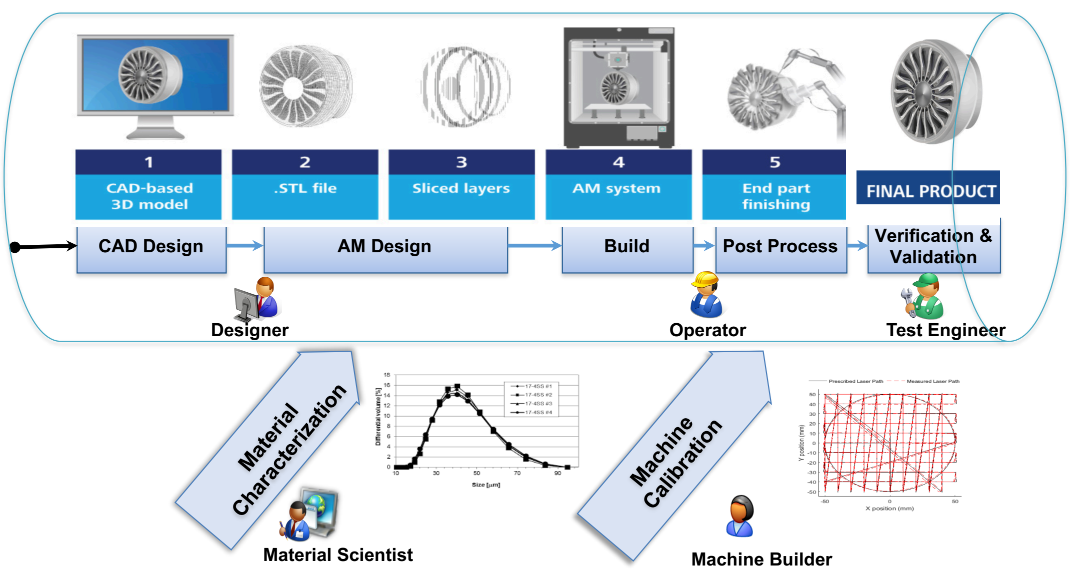

FIG 1. An AM Ecosystem in which data drives the creation of a part.

AM data originates from a range of sources. Many ongoing efforts attempt to define physics-based principles in the form of models of AM processes and quantify the effects of the factors mentioned above on AM part quality. While some researchers work on understanding AM processes using physics-based models and simulations, others diligently experiment in research labs or conduct field studies in production environment and disseminate information to derive process-structure-property (PSP) relationships directly from data.[22] In these experiments and studies, various material characterization methods, in-situ sensing and ex-situ non-destructive evaluation (NDE) techniques are used extensively to qualify the feedstock, monitor the stability of AM process signatures and inspect the structure and properties of the final products, respectively.

AM qualification efforts require and generate large quantities of data. A typical, in-situ sensing and NDE for a single build can produce several terabytes of data. Figure 2 illustrates an estimate of thousands of terabytes of data generated from a qualification procedure for an aircraft system with AM-built components. [23] Different aspects of the additive build process are tested at each level starting at the base with evaluation of the material. The amount of data produced is estimated at 3000 TB for qualification for an additively built aircraft component. Note the length of time and large variation in cost estimates as well.

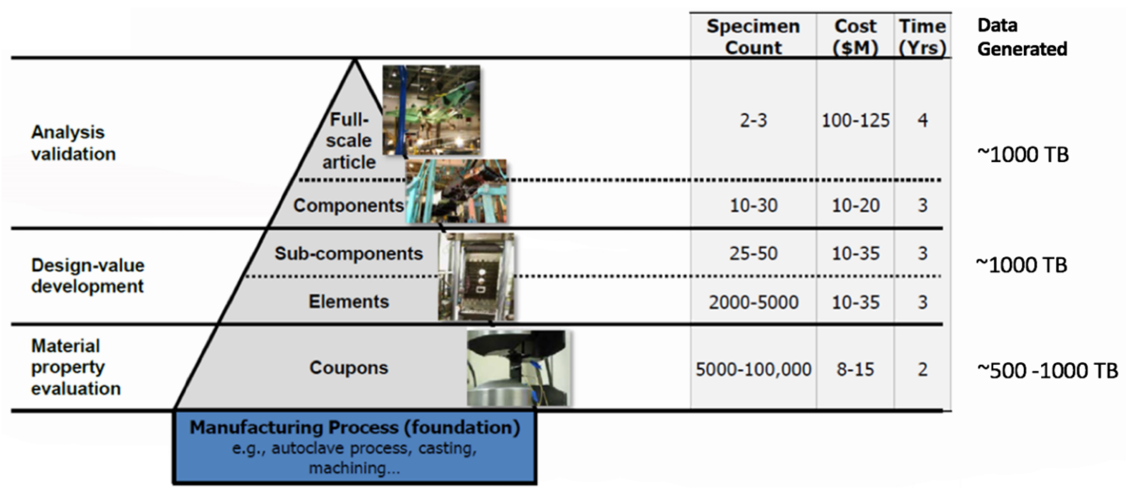

FIG 2. Building block test structure to qualify the production of an aircraft component (adapted from [23]).

Besides large quantities, AM data sets are also characterized by high velocity, variety and low veracity. High-speed melt-pool monitoring cameras can capture 20,000 frames per second, with a typical image sized around 20 KB. For in-situ monitoring using acoustic emission or photodiode, 100 MHz sampling rate is often applied to acquire 8 bit or 12 bits data. With multiple in-situ monitoring systems deployed, gigabytes of data can be generated during an AM building process every second. Data generated through the AM product lifecycle and value chains can vary from 1D time series data, 2D images, 3D models as well as unstructured texts and inspection results. Since most data is collected from sensors and measurement devices, quantitative errors and missing samples are inherent and can lead to either data accuracy problems and/or completeness problems. In addition, sensing and other measurement technologies are often subject to random noise. Extracting high quality data through the noise is necessary for veracity.

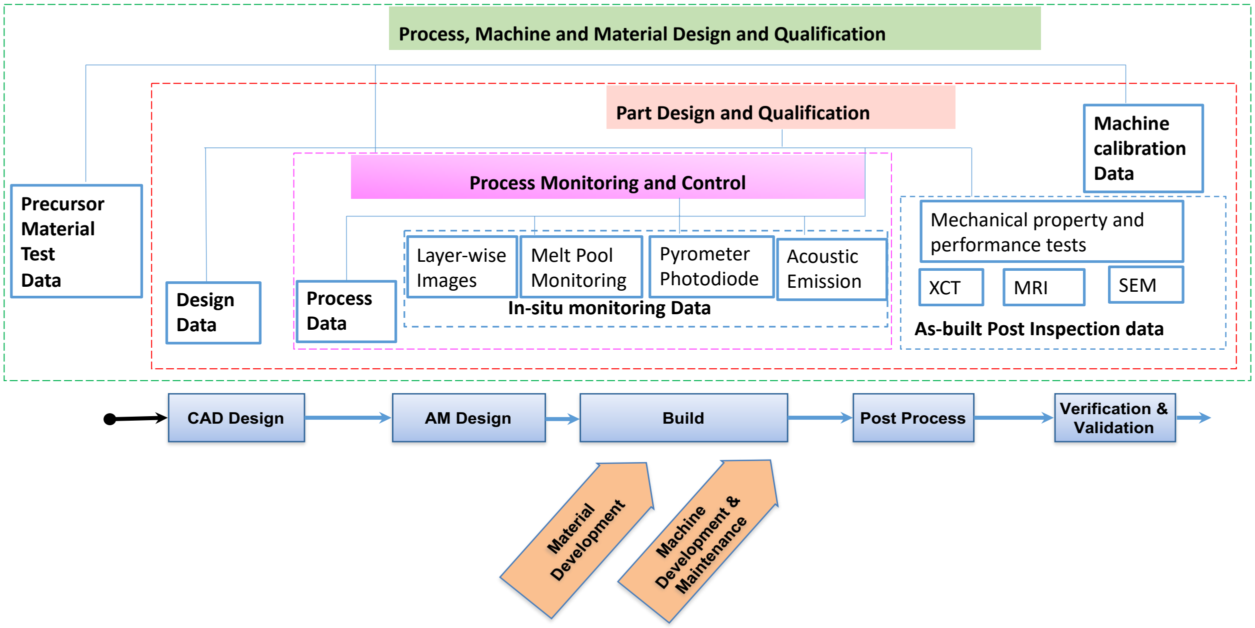

FIG 3. Data produced and analyses performed in an AM build scenario.

Figure 3 illustrates detail of the various data flows that go into part verification and validation for an AM build. At the bottom of the figure is the sequential flow of the overall process as shown in Figure 1. In Figure 3 three scenarios for applying data analytics with increasing complexity emerge to qualify the use of AM as a production technology as illustrated by three boxes:

- Process Understanding, Monitoring and Control: fuses process data with multiple in-situ sensing techniques to provide monitoring and control of an AM build.
- Part Design and Qualification: fuses in-situ data with geometric data from the CAD model and post-process inspection data to qualify a part
- Process, Machine and Material Design and Qualification: uses historical performance from hundreds of qualified builds to qualify a process, a machine, or a material independently from the part design.

The Process Understanding Monitoring and Control box in the figure shows that prediction of part quality is initially formulated on in-situ monitoring data such as melt-pool monitors, acoustic signals, and layer-wise inspections. The Part Design and Qualification box illustrates a data-intensive part certification approach that combines these predictions with geometric models (i.e. CAD) of the original design and the processing instructions with post-processing inspection tests results of sample productions for a probability-based qualification. Finally, the historical data that produced products qualified using the Part Design and Qualification methods results in a build history data set. Researchers are attempting to use this historical data to qualify the process, machine and material designs for production of subsequent parts which may have different geometric properties. If successful, this approach will be particularly impactful for additive manufacturing where each build may be based on a unique geometric model. In this case the material, machine, and processes can be qualified independently and/or in combination, circumventing the more traditional sequential approach to qualification that is illustrated at the bottom of the figure.

Machine learning techniques are widely used for both in-situ data analysis and correlation of the NDE results with the in-situ measurements. Yang et al apply various meta-modeling approaches to approximate the impact of process parameters on single track melt-pool width.[24][25] Figure 4 shows the latest result of applying convolutional neural network (CNN) on classifying melt-pool size. The two figures contrast (a) Actual melt-pool types with (b) CNN classified melt-pool types, illustrating the accuracy of the predictions. Blue indicates "Small", green "Normal", yellow "Large" melt-pools. The research team classified the melt-pools relative to each based on the measurement distributions; the classification technique itself is labor intensive and an area of active research. The physical properties of the final part reflect the formation of the melt-pools. The experimental melt-pool measurements can be used to correlate the melt-pool variability to properties of the physical part. Once trained the melt-pool classifications can be accelerated using the CNN. The CNN classifier supports a 10-fold improvement of computation speed over a traditional image processing-based method, enabling real-time melt-pool feedback control to maintain AM process stability.

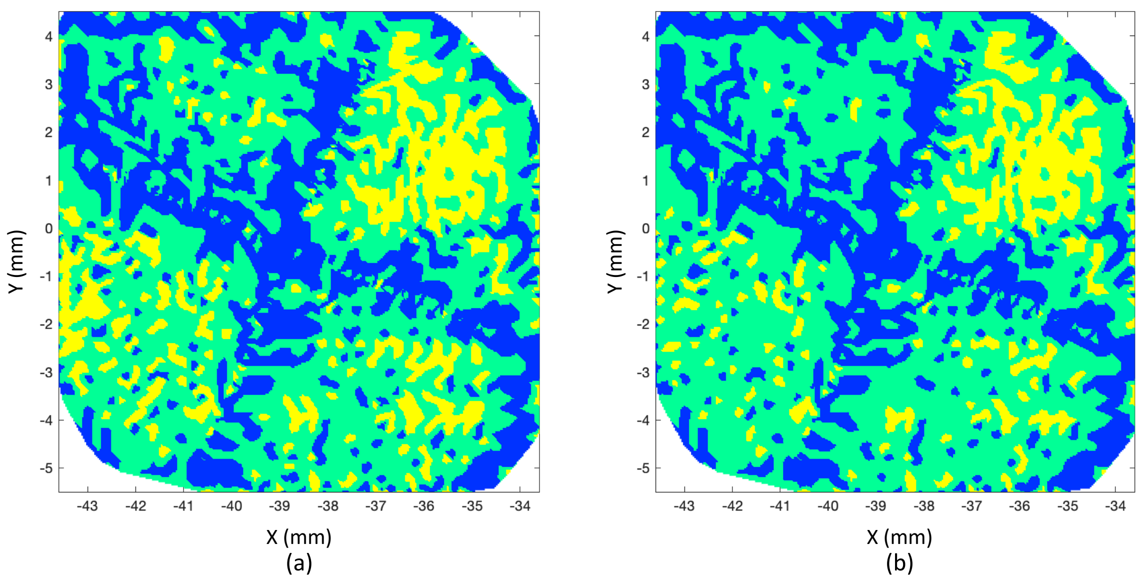

FIG 4. Machine learning applied for fast melt-pool characterization. Figure (a) shows the actual melt pool types and (b) is the CNN classified melt pool types.

The primary research challenge for AM is to control the process well enough to provide the reliability necessary to take it mainstream. The expectation is that experimentation and metrology, correlated with definitions of the fundamental physics of the process, can achieve that control. Of the many fundamental challenges that exist in pursuit that goal, governing the information, is a significant and complex one. The heterogeneity of data sources including the various sensors, cameras, and post-inspection NDE tests require a wide variety of computer and domain expertise to process the range of data. An effective data residency mechanism is needed to meet the various needs of AM stakeholders who may be dispersed both physically and across the lifecycle in the development of a part. Data residency addresses the location and access rights for data and associated metadata in a distributed environment.[26] Data across various AM lifecycle activities and value chain stakeholders needs to be validated and linked before they can be used for fusion and analysis. To support effective data exchange between entities, AM data generated from sensors and tests needs to be described, registered, and tracked, including all related information such as configuration and calibration data, ownership, data formats, authorized users, and even anonymization requirements. Standardized interfaces are lacking to support data sharing and discovery. AM data analytics can be implemented in-device, with edge computing (e.g., controller) or in the cloud depending on the real-time requirements and the computation capability of these computing platforms. Overall, at the heart of all this is a fundamental need to control the information environment in addition to the physical environment

Three Pillars of Information Governance

The three foundations for good information governance serve the fundamental roles to

- Support data quality and information reliability,
- Provide semantic context for data analysis and decision making, and
- Provide system context to enable integration, validation, and verification.

Significant work is needed in each of these directions to extend these foundations into pillars of support. Information governance is more than a technical solution. It is a social order enforced through shared understanding and agreed upon rules of behavior that over time and with experience are woven into the fabric of work and work processes. Our institutions including standards bodies, educational organizations, and regulatory frameworks serve to sanctify the rules of governance as they evolve. Here we describe some beginnings of the journey towards information governance for smart manufacturing.

PILLAR 1: DATA QUALITY AND INFORMATION RELIABILITY

Data quality and reliable information lead to good decisions that generate business value, while poor data fouls up operations and decision making.[27] Data quality can be evaluated in terms of accuracy, completeness, consistency and validity. Helu et al [28] defined a framework with a generalized data-driven decision-making process as shown in FIG 5. Each step in this process involves data operations of various kinds and each step is subject to a unique set of errors. The large number of points at which errors may be introduced is one reason that data-driven analyses are still very much human-driven activities. Good principles of data governance will reduce the opportunity for errors to start with and will provide a basis for testing to find those that are introduced.

To understand data-driven decision-making processes, consider the following scenario from additive manufacturing. An approach to controlling an additive manufacturing process is to use images of the melt-pool to predict the quality of the resulting parts by evaluating the process stability and material continuity. However, the images themselves cannot be analyzed without accurate context. For example, camera parameters and physical configurations, as well as the corresponding scan settings must be considered in the analysis. Given suitable data sets, defects may be correlated to qualities of melt-pools and then predicted in subsequent productions by analyzing melt-pools in situ. Ultimately, real time control may be developed driven by the in-situ monitoring of melt-pools.

This scenario represents a data-driven decision-making process in which the goal is to control the quality of the part by determining the quality of the melt-pools in situ. The first step in the decision-making process is to determine the scope of data that will be needed for the analysis. In the example, experiments may be conducted to determine a threshold for melt-pool stability based on size. Given this performance threshold, scope definition would involve what factors are considered in the evaluative process and which are not. In the example, an image of the melt-pool will be the basis for the decision so the scope of the data set is all images of the melt-pools; however, depending on the quality being sought, higher resolution images, and more data, may be needed for more accuracy in interpretation. The accuracy/speed trade-off will inform data identification and should be part of the scope definition. The scope definition is followed by an action plan including

- Data identification where the specific data is identified along with the contextual meta-data;
- Collection methods including measurement instruments (e.g. camera) and settings and reporting procedures and data formats,
- Transmission protocols for retrieving data for use in the analysis: this can include networking choices, e.g. wireless vs wired or edge vs cloud computing architectures.
- Analysis methods that include techniques specific to the particular data types, such as image processing
- Methods for sharing the analysis including both data and the results, and
- Procedures for retrieving the analysis for future use which may include archiving protocols.

As more experiential data is available, the process is repeated and refined. Furthermore, good governance principles may allow the reuse of the processing data in things such as failure traceability and subsequent process improvements. Anticipation of future analysis such as failure traceability can inform data collection and archiving.

In each step of this scenario errors may be introduced. The decision-making framework provides a way of categorizing those errors to isolate barriers to implementing data-driven process improvements and proposes a strategy for capturing the knowledge needed to reduce those problems in the future. The approach borrows from cybersecurity practices for collecting and publishing common weaknesses.[29]

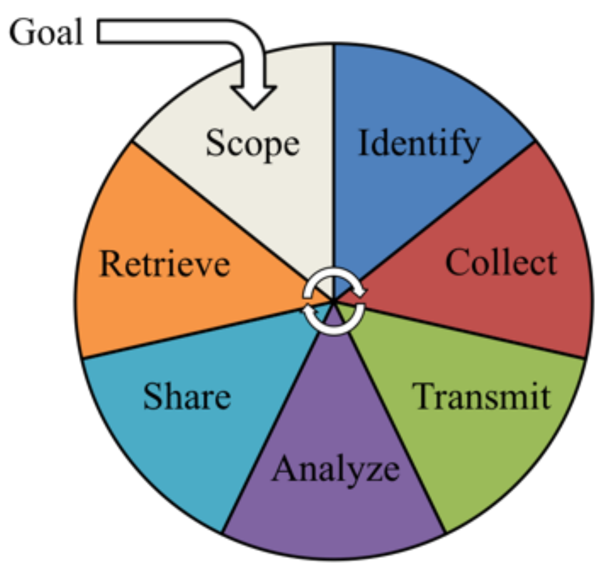

FIG 5. The data-driven decision-making process provides a framework for identifying, classifying, and addressing errors in implementing smart manufacturing.

Today's systems are being developed more rapidly than their errors, or weaknesses in the cybersecurity vernacular, can be identified. The result is weaknesses in deployed systems often only become apparent based on experiences in the field. In the AM example, fault analysis may show that the melt-pools mistakenly had been judged as good quality when the shutter speed of the camera was insufficient introducing blurs in the image. This error may be spread as a common practice with little insight into the implications; however, once uncovered the ability to pinpoint the error in terms of the framework will help to prevent its reoccurrence. Alternatively, the collection or transmission of the measurement data could have resulted in misreported data due to a problem in a reporting format—a very different and avoidable weakness once it is identified. Through pooling experiences from the field, weaknesses can be identified, prioritized, and their existence and solutions can be made known to the community at large. Without an understanding of the collective experience, these problems may go undetected leaving many systems at risk. The deployment of smart manufacturing technology can benefit from the shared experience of practitioners and is a necessary component for developing trust in these systems. The quality of manufactured goods relies on being able to detect errors in production. Sometimes those errors are not apparent immediately. Detecting errors is often a matter of knowing what to look for.

Helu et al[28] propose to use the steps in the data-driven decision making process to identify problem spots and begin the process of classifying those with the goal of identifying the most pervasive and detrimental. Once identified, solutions can be shared, initiating the process of governing the technology. Appropriate standards, best practices, guidelines, and regulations can be identified or developed to control for and prevent known errors. For example, ISO 8000 Parts 130[30] and 140[31], [32] specify requirements for representation and exchange of information related to data accuracy and completeness. The data-driven decision-making framework can be used to identify opportunities to apply these standards.

An assumption underlying the data-driven decision-making process is that, not only will the data be used to make a decision, but also the data that drives the process maybe valuable beyond the initial use, hence the circular nature of the process. Initially the data may be reused in refining the scope of the original study, perhaps adjusting the camera shutter speed as suggested in the example above; however, the data may also prove useful in unanticipated ways explaining the need for adding context to the data. The addition of context is categorized in the share and retrieve functions of the data-driven decision-making process and is the focus of the two remaining pillars.

PILLAR 2: SEMANTIC CONTEXT OF DATA

A primary challenge in data governance is providing metadata to capture the context and meaning of the data. According to the Merriam-Webster dictionary metadata is "data that provides information about other data." The Dublin Core Metadata [33] is a good example of a standardized set of metadata. It defines a small set of vocabulary terms that can be used to describe digital resources. Semantic context can be judged by the availability and quality of its metadata using metrics such as availability of descriptions [34], use of metadata standards and/or best practices, and rate of mismatch between the data and its metadata.

In smart manufacturing, data coming from equipment and sensors at different points in time need to be combined with data from other sources to provide context. For example, consider the heat map in FIG 4a. The colors in the map represent an interpretation of data that comes from sensors. The sensors do not output blue, green, and yellow, but rather raw data. In the in-situ AM process monitoring scenario, the melt-pool images are used to evaluate the process stability and material continuity. However, the images themselves cannot be analyzed without the context, for example, camera parameters, configurations, as well as the corresponding scan settings. The meta-information provides the context to analyze the in-situ generated data for defect detection and part failure traceability analysis. Using this context, the raw data can be understood to be processed into clusters. Assigning meaning to the raw data and then to those clusters is typically a manual step, referred to as "labeling the data." In the case of the melt-pool images, the labels are "small", "normal", and "large", and are represented visually through the colors. Research into automation to support labeling strategies is ongoing.[35][36]

Another example involves melt-pool image registration that is used to detect material discontinuity. Using this technique an image is registered against the previous image in the sequence to characterize changes of melt-pool location, size and direction. While melt-pool location or size change might be introduced in a problematic scanning process, alternatively the direction change of a melt-pool could be caused by the turning of the laser beam when it reaches the end of the row. In this situation, the melt-pool measurement must be aligned to the laser scanner position measurement. Only after the melt-pool direction change is normalized over the scan position command, can the data set be used for material discontinuity detection. The need to normalize data is a human-directed activity that requires knowledge of the context in which data was collected. More generally, human expertise is relied on to associate appropriate context with data. It is hard to know in advance what data will be important and hence the reliance on human cognition to make the associations. Experience from NIST work with melt-pools revealed that the angle of the camera can skew the data making it necessary to rely on human insights to correlate data from different trials. One can envision that with proper conventions, based on more extensive experience, more and richer context can be supplied in a computer processible form making these interpretations automatable.

Bernstein et al [37] defined a vision for a repository of models for manufacturing processes, which serves as a contextual reference for data collected from manufacturing processes. In this work a model of a manufacturing process is a formal representation of the physical transformations and associated performance metrics for a given process. Such models can be collected into a repository for reuse to study the performance of specific manufacturing processes. The form of the models follows ASTM's definitions for manufacturing process representation.[38][39] The representation form is rich enough to identify metrics of interest relative to the process and provides a basis for translating collected data into those metrics.
In a collaborative visioning activity with the manufacturing research community at the joint ASME and SME conference on manufacturing in 2017, researchers identified key components of the software infrastructure for such a repository.[40] The components and existing building blocks for their construction were summarized in the concept map shown in FIG 6. The vision defines four primary functional areas needed to support such a repository, shown starting clockwise from the upper left corner:

- manufacturing domain models,

- supporting software and information science infrastructure,
- supporting systems integration technologies, and
- processes for governance and validation of data and other artifacts.

The inner circle in the figure shows foundations already in place to support the different functionality, while the outer circles show areas where more research and development are needed. Emerging research and standards in the four areas will progress the vision of a repository of manufacturing process models suitable for providing context to manufacturing data. In terms of information governance, important to note is that this figure is a consensus view of a group of manufacturing researchers. While far from sufficient, consensus on such a vision, including the vernacular used to describe it, is a step towards a model of governance. Similar visions are now starting to emerge within standards development communities as described above; however, those typically stop short of specifying research needs as shown in the outer layers of this figure.

The Industrial Ontology Foundry, shown in the upper right of the figure, is an effort focused specifically on developing a consensus set of formal definitions for basic terminology used in the manufacturing domain.[41] If adopted widely, these definitions will also be an important component of a governance model. The definitions will serve in much the same way that the definitions for units of measure currently serve the scientific community. They provide a common basis for understanding data by providing context to the measurements. From these definitions, more specific domain models may be derived, particularly in the area of modeling manufacturing processes.

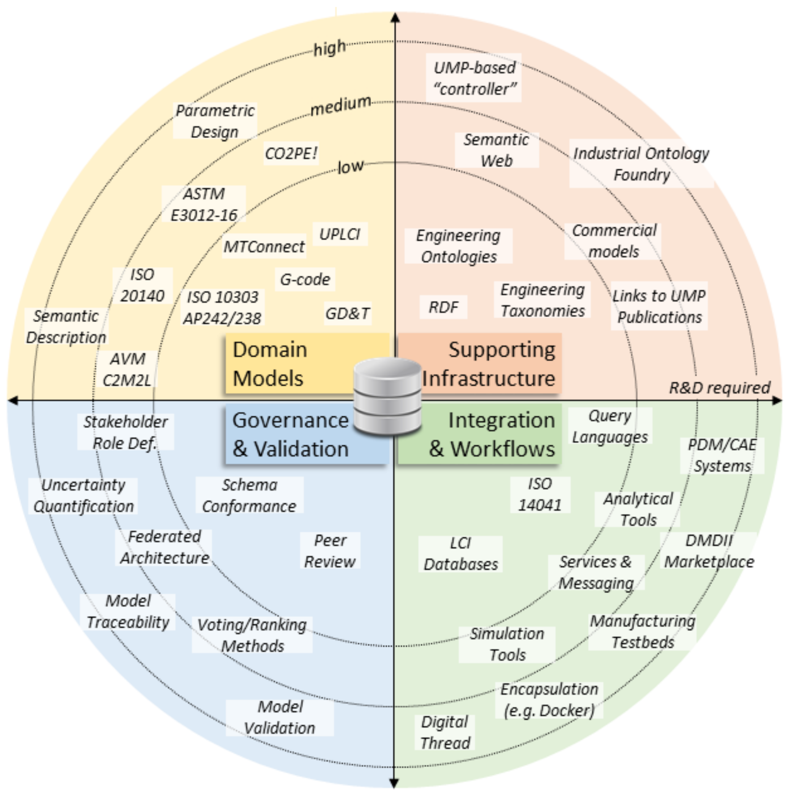

FIG 6. Research roadmap towards a repository of manufacturing process models.

In working towards this vision and using the experienced gained in modeling process models using the ASTM standard, we found that providing structured metadata through association with other technical data standards strengthened the modeling of the manufacturing processes, resulting in more understandable and more reusable models. As a result, the ASTM E3012 standard was updated in 2020 to directly reference metadata standards including XML[4], UML[5], XML Schema[6], MathML[7], and PMML[8]. Reference to these metadata standards forces more rigor in manufacturing process models. Other items in the research roadmap will be adopted as they mature,

PILLAR 3: SYSTEM CONTEXT OF DATA

The first two pillars of governance address data in terms of its quality and clarity for the purpose. The third pillar addresses the structures surrounding data to place it within a system context. The system context adds a new dimension to the complexity of creating and using interoperable data. While data that informs the performance of a manufacturing system may be accurate and well understood with good data quality and clear semantic context, the use of that data in unintended ways can lead to unanticipated behaviors. Metrics for evaluating the specification of system context for data include the use of best practices for system definition and testing including establishing boundary conditions on the applicability and use of data.

All data is created within a system context and its use outside of that context must be carefully controlled so as to not be misused. For instance, performance data does not necessarily generalize beyond the particular machine on which it was generated, such as to the type of machine. The methods in the ASTM E60.13 standards provide grounding for modeling manufacturing systems. Research is on-going as to how to extend those methods for integration into a system context[42] and to support reusable performance models of manufacturing system.[43] Manufacturing processes performance is often characterized through the definition of Key Performance Indicators (KPI). Effective KPI definition requires an intimate understanding of the system and data sources available to describe the system, hence the ASTM E3096 standard calls for a collaborative process involving multiple stakeholders for identifying these characteristics.[44] Likewise, in the additive manufacturing area, an approach involving the definition of Key Characteristics (KC) is being defined to correlate system performance data with characteristics of the system or end product and are still in a research stage.[23]

Interoperable system integration is governed by interface standards and system specification methods. Interface standards may be formally sanctioned through a standards-setting body or de facto through a common practice such as a widely adopted data file format, canonical message model, or application programming interface (API). These interfaces represent system boundaries

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4 eXtensible Markup Language (XML) 1.0 Recommendation, World Wide Web Consortium (W3C); accessible via http://www.w3.org/TR/xml.
5 Unified Modeling Language (UML) 2.5.1, Object Management Group; accessible via https://www.omg.org/spec/UML/.
6 W3C XML Schema Definition Language (XSD) 1.1, World Wide Web Consortium (W3C); accessible via http://www.w3.org/XML/Schema.
7 Mathematics Markup Language (MathML), World Wide Web Consortium (W3C); accessible via https://www.w3.org/Math/.
8 Predictive Model Markup Language (PMML) 4.3, Data Mining Group; accessible via http://dmg.org/pmml/v4-3/GeneralStructure.html.

that often divide spheres of responsibility. The standards that define the boundaries can become the basis for testing and validation, defining a level of reliability for the system. Standards enable manufacturing automation to support smart manufacturing whether that be the embedding of in situ performance monitoring or the automated control of the shop floor to enable mass customization. The range of data and information standards available is leading to broader automation of manufacturing systems, but the range of standards also can overwhelm a system or manufacturing engineer in planning their implementation strategy.

Many organizations have evolved to fill the role of 3rd party system integrators and assist in establishing the systems, process, and procedures to help manufacturers utilize their data. Off-the-shelf Manufacturing Execution Systems (MES), and Enterprise Resource Planning (ERP) are built around their capabilities to manage parts of this complexity and data in specific functional areas.[45] However, value can often be found by using data in cross-functional ways. In addition, as manufacturers throughout and including the lowest tiers of the supply chains embark in the digitalization of manufacturing the need to interact across integration system providers grows. Furthermore, the ability to recreate not only the data but also the context of the analytics is growing. For some time, customers have been asking their suppliers for not only design specifications but also the data that represents the designs.[46] In additive manufacturing, where the analytics are intimately involved in the design, it is not meaningful to compartmentalize data and analytics. In summary, four factors motivate the need for more open information management capabilities:

- sharing data across system boundaries within an organization,
- interacting with multiple partners in a supply chain,
- archiving the digital version of the product, and
- qualifying production processes.

Many standards facilitate sharing data across system boundaries within the manufacturing enterprise. Every standards development organization (SDO) has an overview of their set of standards, most device providers support one or more interfaces to their system, any given manufacturing installation will involve a plethora of standards and interfaces including interfaces to things such as sensors that may be self-configured. No guidebook covers all the standards.

To provide some guidance, Lu, et al[47][48] documented a standards landscape and ecosystem (the NIST Smart Manufacturing Ecosystem) that identifies a set of standards that manufacturers may consider when integrating smart manufacturing systems within their own facilities. In this rapidly evolving field, the landscape is not exhaustive, but rather it provides a conceptual overview. Other conceptual frameworks exist, in particular the Reference Architecture Model for Industrie 4.0 (RAMI) [49] which focuses on smart device and software development for industrial internet of things. The NIST Smart Manufacturing Ecosystem is unique in that it emphasizes manufacturing applications providing a manufacturing planning perspective, rather than a software development perspective. Both the ecosystem model and the RAMI model were used to inform the formation of a joint working group between IEC and ISO.[50]

The standards landscape illustrated in FIG 7 shows three dimensions that manufacturers will want to consider in their own installations: production, product, and business. These three dimensions have evolved independently over time. The widespread digitization of manufacturing brings the dimensions together on the factory floor, represented in the figure as the manufacturing pyramid. The blue ovals in the figure represent areas where existing standards are fairly-well established to integrate along a single dimension. Smart manufacturing enables more integration across the dimensions by using cloud-based service and data integration capabilities. Some examples are shown by the red arrows connecting between the dimensions and life cycle phases in the diagram and include the following:

- Data drawn from the business dimension representing supply chain capabilities can be available for product design, called Design for Supply Chain Management (DFSCM) in the figure.
- Production data can be used for continuous product design improvement (CPI), e.g., features requiring an extraordinary amount of energy or time in fabrication should be modified to improve efficiency, reduce cost, and reduce the environmental impact.
- Continuous Commissioning (CCX) engages ongoing monitoring, diagnosis, prognosis of production equipment and can be used to develop more sophisticated maintenance strategies and improve production system performance.
- Performance data collected on manufacturing and assembly processes can be correlated with design features and used to inform design decisions leading to Design for Manufacturing and Assembly (DFMA).
- Fast Innovation Cycles form when data related to the use a product is analyzed to improve the product.

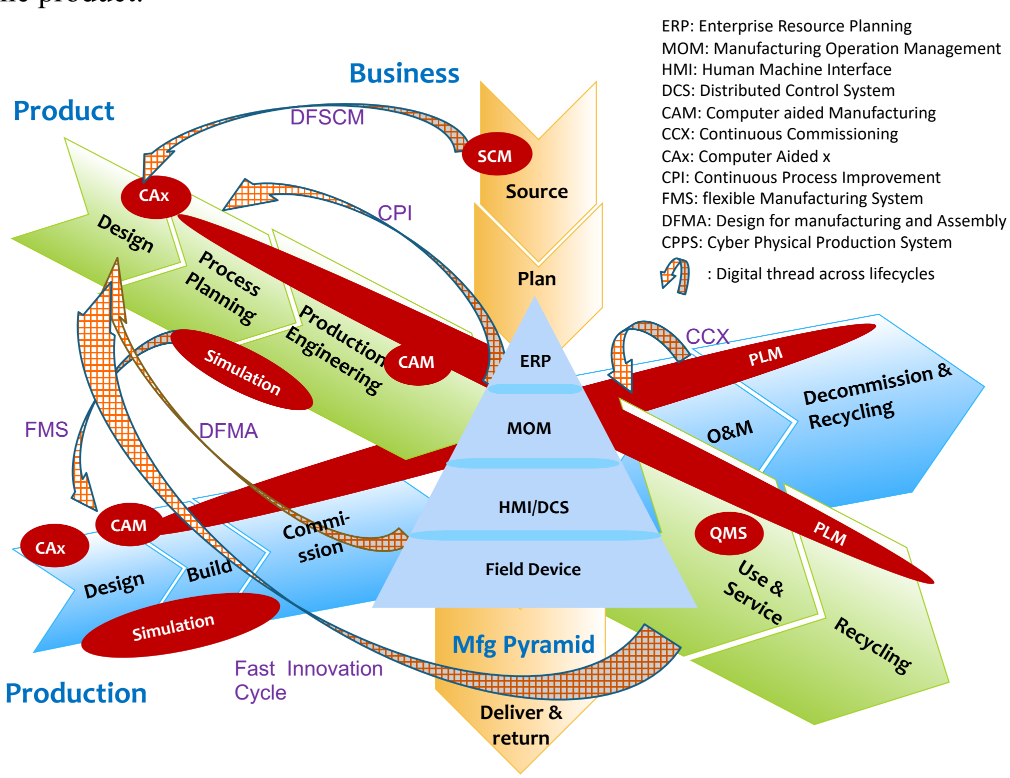

FIG 7. Eco-system of smart manufacturing system standards showing the three dimensions of manufacturing applications: Product, Production System, and Business.

Digital interactions across a manufacturing supply chain become even more complex while at the same time become more achievable with smart manufacturing. Customers are able to request and receive critical information, such as purchase orders, available inventory, or capacity estimations from their supply-chain helping them plan for production. For more focused engineering activities like product designs and manufacturing specifications, small manufacturers may struggle to try to support customers that work with different competing software platforms.[51] Often, OEMs will maintain separate stove pipes of installed software in order to interact with their different suppliers or even other parts of their own organizations, especially as organizations merge. The result is increasing pressure for standards-based solutions that are testable and verifiable. In this environment, concerns around protection of privacy within the supply network emerge as suppliers do not want their capacity capabilities or trade secrets exposed to their competitors.

At the heart of the new look of the supply chain is the digital delivery of information. Some information is made available through the automation of processes that were previously done on paper, rapidly accelerating response times for queries. Other information must be provided digitally to be meaningful. The vision of a Model Based Enterprise (MBE) is based on the digital delivery of product designs including descriptions of production requirements and explicit linkages, i.e., the digital thread, into the broader enterprise information. [52] The decade long evolution towards the vision has resulted in some success and growing expectation that more challenges to the vision can be conquered.

The concept of a technical data package is used for digital delivery of information. Technical data packages are intended to allow the recipient to recreate the engineering or manufacturing processes that the data describes. In many cases the expectation is that the data sets can be used in the future to create replacement parts. Furthermore, the data packages can be used as a record of the verification and validation of system components.

FIG 8 illustrates sources of information for the typical components of a technical data package.[53] The data package includes not only data but also the context in which that data is used. The package will have a structured format specifying what is to be included; the structure may itself be based on a standard but at a minimum would be based on detailed guidance agreed on between the sender and receiver. Application specific guidance may be provided for given types of data packages, e.g., all CAD data or all production data. The detailed package will describe

- data and the semantic references for the data set, e.g. what standards and version of standards the data set is based on;
- when, how, and by whom the data was collected, e.g., experimental vs. generated data;
- any software pipelines created for the data set;
- validation tests performed on the data and the results;
- optionally, functional partitions of data to facilitate comprehension of data subsets; and
- business rules surrounding the production or intended use of the data and perhaps cryptographic information.

The first five bullets above related to data quality and semantic context. The last, business rules surrounding the intended use of data, is key to establishing appropriate reuse of data within a system. Defining this system context best involves engagement with multiple stakeholders to bring a diversity of perspectives.

For additive manufacturing, technical data packages are especially complex. Work is currently underway to develop consensus and standards around them.[48], [49] The traditional approach to system validation that has worked well for some time no longer suffices for the complexity of today's systems, which are systems of systems. The system components can change frequently introducing opportunities for error. The data-driven nature of the systems, where machines are learning from and responding to changes, also introduces variability in control previously not found. For example, additive manufacturing machines qualified for producing test coupons using defined sets of machine process parameters are not guaranteed to produce quality parts, since the part performance also heavily depends on its shape. Certain types of features tend to deform more than others since the scan path introduces residual stress. Likewise, the materials can also vary in their characteristics impacting the AM builds. This type of variability is not acceptable in manufacturing systems where performance requirements are such that parts be certified to ensure quality for critical uses, such as aircraft, medical, nuclear and space applications.[56] A new paradigm for validating performance and verifying system reliability is needed for smart manufacturing systems. This new paradigm will be at the crux of a smart manufacturing information governance model.

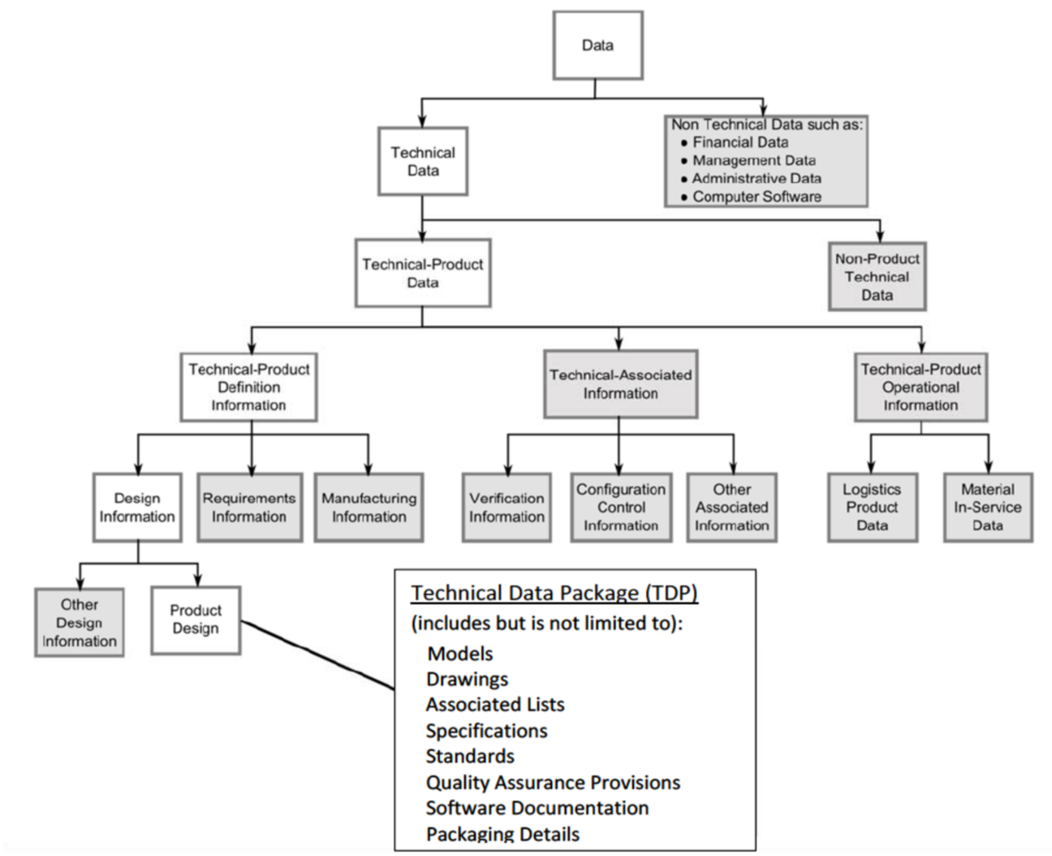

FIG 8. Composition of Department of Defense (DoD) Technical Data Package through relationships to sources.[53]

Summary

The problem of information governance is both social and technical. The convergence of the two results in an even broader range of conflicts to be resolved. While the technical conflicts on the surface may appear resolvable, they are laden with the legacy of the past and the many directions that the present is taking. A focus on developing consensus around fundamental building blocks for manufacturing information governance is an investment that will have a high return for all. The time to reach consensus on technical foundations is before groups have strong investments along their own paths. We need to get the technology right to make room for all the players to participate in the systems of tomorrow while maintaining the reliability of those systems.

This paper identifies foundational categories of information standards that will be needed to form a system of governance and progress research towards reproducible results that can be reliably applied across systems. It includes an overview of standards activities in this area and many research efforts that support the foundations presented, particularly those from the Smart Manufacturing Systems programs at the National Institute of Standards and Technology (NIST). Much of the described work are results from the past five years of effort in understanding the measurement science underlying these systems. Measurement science refers to the system of methods, techniques, and standards that support the conveyance of information for the purpose of reproducing results. This system forms the basis for shared understanding of the world around us.

The paper will be useful for researchers and practitioners alike in framing their questions, problems, and solutions and establishing the solid basis for communication when working through these challenges to conceive of the next generation of systems. The example of information challenges for additive manufacturing are given to illustrate the concepts. The additive context presents new challenges for information governance beyond traditional manufacturing technology. In additive systems, data feedback loops are necessary to control the production process even more than in traditional systems, making it even more imperative that information governance is carefully and thoroughly applied. Many open research questions still exist into what these new approaches will look like. For instance, the correlation of data to characterization models of manufacturing system performance, material variability, and product quality will form the basis for more verifiable systems; however, producing these characterization models in a rigorous and systematic way and following sound scientific principles needs much research and consensus building to achieve reproducible and reliable results.[57] Similarly, considerations of cybersecurity and lifecycle management of information need to be factored into information governance models across each of the foundational pillars. Both of these areas span data quality, semantic context, and system context considerations. The framework can help clarify these considerations through the decomposition of concerns and is a direction of future work.

Good governance is born of community. Efforts such as those described here help to establish pre-competitive consensus and shared visions to provide the social foundations for good governance. In these environments, industry partners can come together to work through solutions that will serve their common interests as well as those of society. Not only is it important for good solutions to be developed, they must also be adopted through vetting and consensus building. As has been discussed professional societies, standards bodies, and consortia serve as forums for doing this hard and important work.[48]

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