Industry Review of Distributed Production in Discrete Manufacturing

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ABSTRACT

Distributed production paradigms have grown in discrete manufacturing as discrete products are increasingly made by global, distributed networks. Challenges faced by discrete manufacturing, such as increased globalization, market volatility, workforce shortages, and mass personalization have necessitated scalable solutions that improve the agility of production systems. These challenges have driven the need for better collaboration and coordination in production via improved integration of production systems across the product lifecycle. This paper describes key industry use cases to motivate the research and development needed for distributed production in discrete manufacturing. The technological challenges that have hindered distributed production in discrete manufacturing are presented as is a state-of-the-art review of the standards and technologies that have been developed to overcome these challenges. Based on this review, future research directions are described to address the needs of industry and achieve the goals of distributed production in discrete manufacturing.

Keywords

Distributed manufacturing systems; Discrete manufacturing; Smart manufacturing; Industry 4.0; Use cases

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Dedication

David Dornfeld made many contributions to the advanced manufacturing literature including work on the application of acoustic emissions sensing for monitoring and control of machining processes, the characterization of the mechanics of burr formation for de-burring and edge finishing applications, the development of methods and tools for sustainable manufacturing, and the development of standards and technologies to support smart manufacturing. Always recognizing the importance of addressing industry needs, Dave's research increasingly focused on topics central to distributed production in discrete manufacturing, such as his efforts to enable data interoperability on the manufacturing shop floor as one of the early contributors that co-led the development of MTConnect. This paper is dedicated by the authors to Dave in the hope that we too can highlight opportunities for researchers to help industry.

1 Introduction

Discrete manufacturing is the production of separate, distinct things such as automobiles, airplanes, biomedical devices, and electronics. These products are increasingly produced by global, distributed networks that are increasingly decentralized from Original Equipment Manufacturers (OEMs) [1, 2, 3, 4]. Distributed production paradigms have proliferated as OEMs have transformed to system integrators that assemble and integrate their products and manage their supply chains. The traditional tiered supply chain common in many sectors is a well-known example [1].

Several challenges have driven the observed trend. First, many countries suffer a shortage of skilled workers in manufacturing [5, 6, 7, 8]. Many younger workers lack interest in manufacturing even as industry's changing nature has created a gap between workforce skills and those required by employers. Manufacturers have looked to new tools and technology to augment and support workers to alleviate the skills gap. In fact, this is a goal of Smart Manufacturing and Industry 4.0 [9].

Other challenges have created a need for agile and flexible production operations including global competition, market and resource volatility, and mass personalization [1, 2, 3, 4, 10, 11]. Agility enables quick responses and minimized impact from events that would normally disrupt operations [12]. Distributed production has so far failed to address these challenges fully [1]. Industry needs technology-forward approaches to software, networking, and digital transformation to remain competitive globally. This problem is not unique to manufacturing, but manufacturing presents unique manifestations requiring further exploration.

An effective and scalable response to the challenges and needs that have been described is better collaboration and coordination in production via improved integration of production systems across the product lifecycle [1, 13]. Production systems designed for openness and interoperability reduce costs, improve productivity, ensure first-pass success, and augment existing workforce capabilities [1, 13, 14, 15]. As industry has pursued open, interoperable systems, open-standards-development activities have created a stronger technical foundation for distributed production. While that foundation will ultimately benefit all of industry, a handful of critical use cases have motivated most of this development.

The goal of this paper is to identify industry needs in the development of distributed production for discrete manufacturing. Section 2 describes the Distributed Manufacturing System (DMS) concept that has been developed in the literature. Key use cases are then described in Section 3 followed by a discussion of the major technological challenges that have

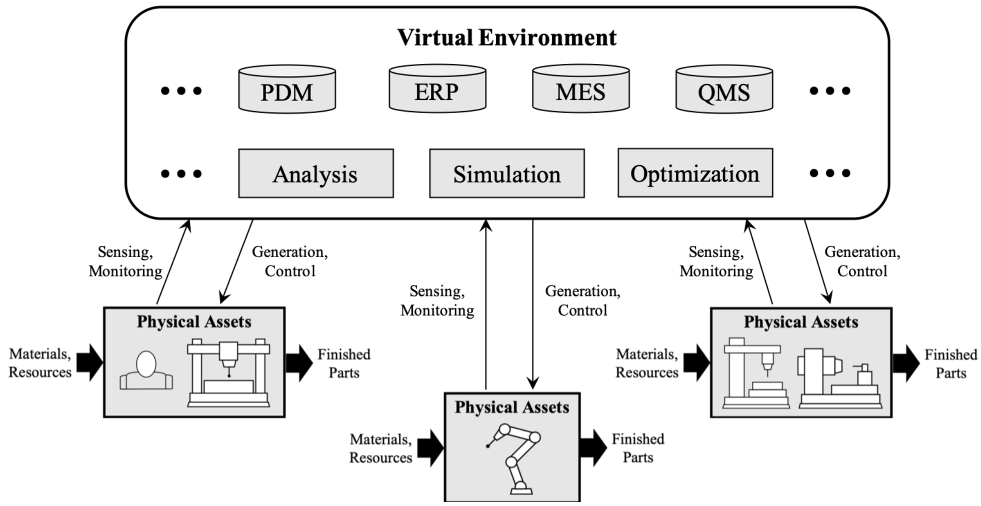

Fig. 1. Distributed production in discrete manufacturing where various virtual tools aim to use available assets that can provide process capabilities to address part requirements in some optimal sense given different constraints on the system (based on Hedberg et al. [1])

limited the implementation of DMS in Section 4. Section 5 reviews the state-of-the-art standards and technologies for DMS. Finally, Section 6 summarizes research directions to guide future work and address industry needs for DMS in discrete manufacturing.

2 Distributed Manufacturing Systems

Growing interest in distributed production led to the development of the DMS concept. The literature contains several definitions of DMS, such as Hedberg et al. [1] who define DMS as systems of heterogeneous components that have some means of semantic interoperability. By exchanging data such that all components understand the meaning of that data, these components can be coordinated and controlled. Similarly, Matt et al. [3] describe DMS as decentralized, distributed networks of small, flexible, and scalable manufacturing units developed in response to business trends, such as rising logistics costs, regionalism, democratized design, and mass customization. Srai et al. [4] extend this description by stating that DMS represent the changing nature of manufacturing operations from traditional, centralized, large-scale, and forecast-driven to decentralized, autonomous, and end-user driven. DMS may take multiple forms from large-scale operations managed across geographically-distributed facilities to individual, small-scale production lines or cells [1, 3].

All of the definitions proposed for DMS have the following in common:

- Geographically dispersed or otherwise physically separated components
- Closely integrated components with high interoperability despite physical separation
- Physical and virtual (or cyber) components forming a so-called Cyber-Physical System (CPS)
- Decentralized control such that no one central entity may directly control all components
- A goal of matching part requirements to process capabilities given technical, business, or logistical constraints

DMS is therefore a federated system of physical and virtual assets integrated across the production lifecycle so that the best manufacturing decisions may be made in response to the current and anticipated state of the system. Figure 1 provides an overview of such a system where physical assets perform manufacturing tasks turning materials and resources into finished parts based on given requirements. Each asset can provide information about its state to the virtual environment via sensing and monitoring. This information can be combined with other information from production systems, such as Product Data Management (PDM), Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), Quality Management System (QMS), to determine the optimal control of the physical assets using analysis, simulation, optimization, or other modeling constructs.

Different solutions have been proposed to meet the industry needs implied by DMS. One solution is cloud manufacturing, which is the application of cloud computing to manufacturing [16]. In cloud manufacturing, a network of shared, configurable production assets (both virtual and physical) can rapidly provide services to an end-user on demand with little or no interaction between provider and user. Two other solutions are networked manufacturing, which focuses on connecting data flows between manufacturing systems [17, 18], and collaborative manufacturing, which focuses on enabling collaboration between different entities in manufacturing [19, 20]. However, these solutions are difficult to evaluate with respect to DMS without clear requirements and constraints based on industry use cases. Section 3 captures key motivating use cases for DMS.

3 Key Industry Use Cases

Three categories of industry use cases are relevant to the development of DMS for discrete manufacturing: (1) production optimization, (2) on-demand or pull production, and (3) workforce management.

3.1 Production Optimization

Figure 2 provides examples of production optimization use cases for DMS. Manufacturing assets may represent either suppliers (and all of their available equipment and resources) or equipment and/or systems within a manufacturer's facility.

Supplier certification and qualification is one important use case within the category of managing complex production systems. We have already discussed in Sections 1 and 2 how large OEMs typically manage large networks of suppliers. Similarly, a manufacturer may also choose to send work to one or more suppliers. These cases are denoted by (c) and (d) in Figure 2. In both cases, the supplier must often be certified and/or qualified to accept work so that the OEM can be assured that the finished part meets all of its requirements. An OEM can spend significant money and human capital to manage the certification of suppliers through surveys and audits. The process is also challenging for suppliers, since certification/qualification can be expensive, time-consuming, and difficult, particularly for industry sectors that produce complex parts or that may have substantial regulations, such as aerospace and automotive. The result is that many suppliers, especially Small- and Medium-sized Enterprises (SMEs), tend to specialize in one specific sector. This can limit a supplier's competitiveness and increase sensitivity to market volatility risk, especially in sectors with a history of downturns, such as oil and gas. Instead, a supplier may prefer to "plug and play" into different supply chains across multiple sectors to take advantage of available capacity and identify new business opportunities. Doing so requires the ability to effectively

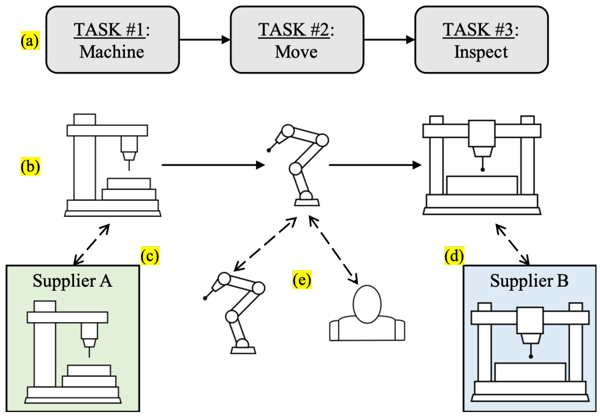

Fig. 2. Different options to manage manufacturing assets for the tasks denoted by (a), including (b) an in-house routing, (c)/(d) a qualified external supplier for one or more tasks, and (e) exchange of one asset for another asset; part tracking and traceability may be necessary, especially for highly-regulated industry sectors

and efficiently describe manufacturing capability so that manufacturing organizations may better market their services and OEMs can more easily validate that these capabilities meet their needs and requirements.

Equipment interchangeability (including human-in-the-loop systems) is another critical use case that focuses on managing manufacturing assets on the shop floor as denoted by (e) in Figure 2. Similarly to supplier certification and qualification, substituting one asset for another asset on the shop floor requires a good understanding of the capability of these assets as well as their current and anticipated capacity. Such information is essential to ensure that scheduling and routing activities best match the needs of the part. While this may be sufficient for manufacturers that operate like job shops where individual machine tools may be independently scheduled, further challenges arise for more automated production systems. Traditionally, automation is accomplished through rigid, hierarchical, bespoke systems integration and control solutions, such as Programmable Logic Controllers (PLCs). Low-cost, scalable automation solutions that enable choreography-based control are needed to provide the flexibility required for equipment interchangeability. Such approaches provide flexibility by allowing different manufacturing assets to collaborate on completing tasks by providing specific services and sharing data. More sophisticated and advanced choreography-based systems require an increased level of self-awareness and asset intelligence to find localized optimal solutions for selection and bidding on tasks and problem solving.

Part tracking and traceability is a use case that results when managing complex production systems. No matter the decision made within the operation of a production system, it is often critical to ensure that parts are tracked within the system to measure the current state and predict the future state of the system. Such information also enables the construction of the genealogy (or complete history) of a part. Part genealogy can help a manufacturer expose longer-term trends that may be used to improve manufacturing processes and part design. It can also support part traceability, which is very valuable for highly-regulated industry sectors such as aerospace and biomedical devices. Traceability has traditionally been limited to paper-based inspection and verification reports – often cumbersome, expensive, and prone to error – especially when required to maintain information for the life of these parts, which may be over 20-30 years. Digitizing the information and moving away from paper-based approaches to model-based approaches – i.e., the Model-Based Enterprise (MBE) – can dramatically ease the management of these traceability requirements and provide a complete record of all machine and environmental

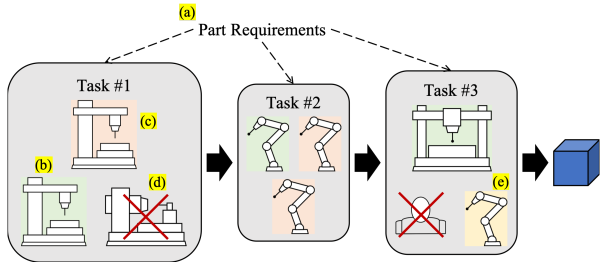

Fig. 3. Application of on-demand or pull production to address the part requirements denoted by (a) using available capable resources such as (b); other resources may be unavailable, such as (c), incapable, such as (d), or available for an added cost, such as (e)

conditions that occurred during the production of the product [15].

3.2 On-Demand or Pull Production

Another category of DMS use cases centers on the demands placed on such systems. In Section 2, we discussed how DMS represents a change from forecast-driven to end-user-driven operations [4]. In other words, this trend can be viewed as a transition from push to pull or on-demand production where the manufacture of a part occurs once it has been requested by the end-user rather than some predicted demand. Other similar and related concepts include Flexible Manufacturing Systems (FMS) [21, 22], Reconfigurable Manufacturing System (RMS) [22], and mass personalization, or lot-size-one, or batch-of-one production [10]. Figure 3 provides some examples of the types of decisions made in response to a demand for a part.

Maintenance, Repair, and Overhaul (MRO) and Sustainment is a critical use case, especially for those products with long service lives. A typical example of MRO/Sustainment is when a need arises for a new part or repair of an existing part to service a product in the field. Typically, an end-user may keep spare parts on hand, which can be expensive. Instead, the end-user may prefer to use manufacturing assets available at the site of service or more capable manufacturing assets that exist elsewhere to produce replacement parts as needed. The final decision for the sourcing of this part or repair service then must consider the requirements of the task, the capability and availability of each potential manufacturing asset, and the costs associated with lead times, consumables (e.g., materials, tooling, workholding), and shipping. There may be other relevant constraints as well: e.g., it may only be possible to produce or repair sensitive parts for an aircraft engine or defense system at a limited number of suppliers. This type of use case has been especially motivating for the development of flexible unitized manufacturing capabilities since these may be geographically positioned to support the sustainment needs of a large network of products for an organization. For example, additive manufacturing may provide the capability needed for this use case, but issues remain with verifying and validating additive manufacturing processes. Another consideration beyond manufacturing assets is the communication of part requirements. It can be challenging to obtain all useful information to recreate a part that was originally designed years before the MRO activity. Even when the location of this information is known, it may exist in a format that lacks sufficient interoperability with modern systems, which further complicates these tasks.

Dynamic scheduling and routing is one use case that has arguably always had interest among the manufacturing community. The goal here is to respond quickly to changing demands or potential disruptions on manufacturing operations (e.g., due to maintenance, workforce issues, or upstream production delays). This use case also requires an interoperable means of communicating part requirements across a variety of different systems, each tasked with producing all or a portion of a part. Many of the same considerations with the equipment interchangeability use case are important here as well, especially the need for a standard definition of manufacturing capability so the right assets may be used to respond dynamically to different events as they occur, as well as a standard interface for these assets to communicate through so that they may "plug and play" with different tasks as needed. Furthermore, dynamic scheduling and routing require sufficient interoperability between lower-level shop-floor systems (e.g., machine tools) and higher-level control systems (e.g., MES, ERP) so these systems have insight into the state of all relevant assets and may provide instructions to them. The form of this interoperability should capture relevant information on the part and the processes used to produce it so that each system using this data for analysis and decision making has enough context to do so.

Manufacturing as a Service (MaaS) is a similar use case to dynamic scheduling and routing as these systems are DMS that leverage the excess capacity of assets that are either wholly owned or distributed across a geographically-dispersed network of suppliers. The successful operation of these systems depends on sufficient interoperability between production systems so that: (1) a clear understanding of part requirements may be communicated, (2) insight on the current state of all relevant assets may be gleaned, and (3) all part- and process-related information (including work instructions) may be shared across all control levels. There are also needs for additional capabilities, such as automated quoting. Quoting in many contract manufacturing environments tends to be a manual process requiring cognitive input from a human planner. While this can be challenging when all assets are wholly controlled – e.g., it can be difficult, if not impossible, to determine if an inaccurate quote was generated because of issues with the quote, design, process, operator, or material – it becomes much more complicated when manufacturing assets are distributed across a network of different suppliers who may provide little insight into their operations. Developing successful means to evaluate and generate quotes automatically would be extremely beneficial for MaaS as well as all contract manufacturing operations.

3.3 Workforce Management

A final category of DMS use cases focuses on opportunities to improve workforce management. Section 1 described some of the labor challenges that have motivated further research into DMS, Smart Manufacturing, Industry 4.0, and related concepts [5, 6, 7, 8]. Figure 4 provides two general examples of how these technological solutions may support the larger issues of managing the manufacturing workforce. Once manufacturing requirements are defined for DMS, the same information may be used for matching workforce capabilities and identifying workforce gaps.

Worker matching is one example use case shown in Figure 4(a). Here, we see three workers with different skill sets and capabilities. Each worker is matched based on their ability to operate each of the manufacturing assets successfully. While this should obviously be the goal of any manufacturing organization, it can be difficult to determine the capabilities of workers accurately. More importantly, this information may be lacking when one worker is unable to work and a replacement must be identified to prevent further disruption to operations. Addressing these needs requires similar considerations as the

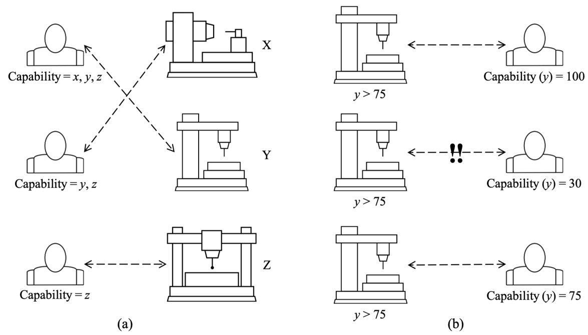

Fig. 4. Two examples of workforce management: (a) matching workers using their skill set(s) or capabilities, and (b) leveraging and understanding their capabilities to identify training opportunities (denoted in red)

use cases presented in Sections 3.1 and 3.2. Specifically, a standard definition of capability that can be easily and effectively measured and communicated to planners and planning systems, as well as models or other means of more easily integrating workers into manufacturing operations.

Worker training is another use case shown in Figure 4(b). In this use case, many of the same considerations as with worker matching can be used to identify opportunities to provide additional training to workers. Such training may be useful to improve the capability of the worker on his/her task, thereby improving the overall efficiency and/or effectiveness of operations. In addition, these approaches could be used to identify opportunities for valuable cross-training so that operations are more resilient to any unexpected workforce issues that may arise (e.g., illness or separation).

4 Current Technological Challenges

Building on the use cases described in Section 3, there are a variety of challenges that have hindered the development of DMS despite the obvious need for appropriate technological solutions. While industry has been clear about the types of solutions that they seek, there have been three types of challenges facing industry: (1) system complexity and disconnectedness, (2) lack of interoperable models, and (3) lack of contextual interoperability. Understanding these challenges is critical to have the context needed to evaluate the current state of the art and identify future research directions.

4.1 System Complexity and Disconnectedness

The complexity of modern production systems has grown tremendously especially given trends towards globalization and digitalization [1, 2, 3, 4, 9]. As manufacturing systems have evolved to become data driven, it has become evident that today's Smart Manufacturing implementations are hampered by the complexity of connecting and configuring heterogeneous systems, including machine tools, PLCs, devices, and sensors on the shop floor [1, 9, 13]. Further complexity has been added by the fact that these systems that generate on-site process data and information (e.g., machine controller data) are disconnected from higher-level decision-making systems, such as MES and ERP software [1]. This has been due largely to a lack of standardized communication models to define protocols for horizontally and vertically integrated manufacturing systems.

To explore these issues of system complexity and disconnectedness, we can consider the International Society of Au-

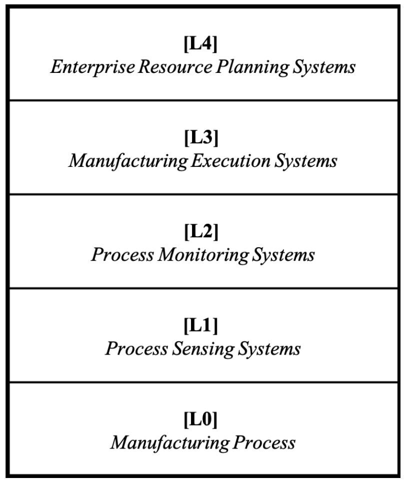

Fig. 5. ISA-95 hierarchy showing the different control levels within the scope of the standard (based on [24])

tomation (ISA)-95 (Enterprise-Control System Integration) standard, which has been standardized through the American National Standards Institute (ANSI) as ANSI/ISA-95 and the International Organization for Standardization (ISO) as ISO 62264 [23]). The goal of ISA-95 is to enable the development of interfaces between the control levels shown in Figure 5 [24]. These interfaces may be used in discrete, batch, and continuous manufacturing for the vertical integration of information across a production enterprise to improve different activities, such as maintenance and production operations. While ISA-95 has been valuable in providing common terminology and hierarchy models, there remains no meaningful implementation of the standard as envisioned. The challenge again has been the inherent complexity of connecting heterogeneous production systems that were never designed to work outside of their silos. One may even argue that by defining these control levels, ISA-95 has helped perpetuate these silos.

An important element of the DMS vision (and by extension Smart Manufacturing and Industry 4.0) is that such systems can operate in a flexible, decentralized manner by communicating, reconfiguring, and describing themselves to form on-demand manufacturing segments for production down to unit one [1, 2, 3, 4]. In this way, a manufacturing system can attain a degree of self-awareness by knowing its components, how they connect to each other, and how to adapt to different uncertainties to optimize production. The key to achieving this vision is overcoming the challenges highlighted by ISA-95 through the seamless exchange of information and communications between various systems in the production enterprise. Today's DMS do not incorporate such flexibility by strongly correlating acquired data with on-the-fly decision making.

The major technological challenge is the integration of heterogeneous data sources and information to realize a consistent end-to-end view of a design through its manufacture and subsequent life [13, 25]. This type of integration has been referred to as the "digital thread," which provides an infrastructure to support the use of product lifecycle data for various data-driven applications, such as the digital twin. Realizing a digital twin requires simultaneous advancements from the digital thread in representing the different viewpoints of a design as it moves through its lifecycle (e.g., the manufacturing process plan and the various CAE models to predict its performance, operational behavior, or maintenance) as well as the production systems used to fabricate the physical object. However, current MES and ERP systems are paper-based or relatively inflexible software systems that do not adapt to manufacturing bottlenecks, such as unplanned downtime, increased setup time, or poor resource utilization. Computer-Aided Design (CAD) representations have not been able to scale to include the geometric complexity enabled by additive manufacturing, and Computer-Aided Manufacturing (CAM) systems have not anticipated the growth of novel manufacturing processes, such as hybrid additive and subtractive manufacturing. A true digital twin needs access to enough information content such that a stakeholder can extract the context they need for their viewpoint (e.g., as-designed, as-manufactured, as-planned). Information exchange across all data and models associated with a product may not be possible with one standard that encompasses multiple viewpoints, but may be enabled by the use of sophisticated algorithms that transform between viewpoints. Such a pipeline of connected, interoperable workflows for manufacturing is missing.

4.2 Lack of Interoperable Models

Research developments that have come from the Industrial Internet of Things (IIoT) and analytics communities have not improved the agility of manufacturing systems. Much of the challenge has been due to the assumption that observations in manufacturing (e.g., sensing and monitoring) can enable systemic change without addressing deficiencies at the beginning of design and engineering processes. Agility requires models with a common structure and interface that enable efficient and effective mapping of information across domain boundaries. Instead, the models that are usually leveraged may be only present in the mind of the designer or engineer. The ephemeral nature of this information makes the decision-making and control process brittle and dependent on single agents to deliver the desired outcome. For example, inferring design intent can be challenging using drawings and notes without the context provided by other pieces of information, such as the initial set of constraints and requirements that informed the specifications and features selected by designer.

The lack of interoperable models can also be observed when considering that many DMS use cases require production operations to be adapted dynamically based on currently available assets and the capabilities of these assets. Such adaptation may require a different decomposition of parts for the assembly due to limitations or enhancements of the target machines. On the other hand, a requirement previously realized through one manufacturing process may be satisfied using an alternative manufacturing process, which could remove the need for a lengthy sourcing process. For example, the need for a near-net forging process may be satisfied using an additive manufacturing process available sooner and proximate to the demand. Part models must be improved to ensure sufficient interoperability to make these types of decisions.

The agility described in many of the use cases in Section 3 also implies small-batch and on-demand inventory. An agile process requires a verifiable correct outcome and continually controlled process from the first article until the last. Otherwise, the cost of scrap and wasted time may exceed the margin, which can financially disincentivize such approaches. For example, suppliers that have participated in MaaS networks have found that the costs associated with re-engineering and process development have minimized the motivation to participate in such networks. Conversely, leveraging additive manufacturing processes for similar purposes can be more profitable for high-mix, low-volume production where quality may be less critical since there is no or little additional cost when adding parts to an existing build. The main difference between traditional additive and subtractive workflows is the level of automation provided by the more model-based approach of “slicing” and planning common in additive manufacturing.

4.3 Lack of Contextual Interoperability

Sections 4.1 and 4.2 highlight the growing challenge that must be overcome for meaningful implementations of DMSs: the growing number of data and models being generated across production systems cannot be leveraged effectively to drive improved decision making and control because these systems (and the domains they represent) are inherently siloed. While each silo may have a suite of standards and technologies well designed and suited for the specific domain, the observation that all decisions made in one stage of the product lifecycle become constraints on subsequent phases shows the value of taking a broader lifecycle or systems perspective in all aspects of production [26, 27]. This is a fundamental aspect of the DMS paradigm: the integration of data and information across production systems (and thus domains) throughout the lifecycle. Historically, such integration has been accomplished using human capital, but such reliance has become inefficient, ineffective, and costly, especially given the workforce challenges described in Section 3.3. These difficulties increase when we consider that even singular organizations often use several standards and technologies because of mergers, acquisitions, and differences in legacy policies.

To explore the implications of the lack of integration between domains along the product lifecycle, we can consider how current design methodologies constrain manufacturing processes when creating the design of a part. An assembly presupposes the capabilities of manufacturing assets, including equipment and available tooling, and process planning often decomposes the part features given the assets currently available without considering what future manufacturing assets and capabilities may be available. No effective means exist to communicate design intent either, which can present additional challenges for process planners, operators, and other manufacturing decision makers trying to ensure that the finished part meets the initial part requirements. Without an understanding of the context motivating different decisions, it is impossible to evaluate the space of possible design solutions given a set of manufacturing assets to determine the most effective solution from a cost and delivery perspective. The same is true for feedback from manufacturing to improve design decisions. This lack of context prevents the sharing of knowledge from domain experts.

As the previous example highlights, a greater degree of interoperability is needed than semantic interoperability, which has been the focus of much of the current literature. Figure 6 describes the degree of interoperability that may exist between two or more systems using conceptual interoperability [28, 29]. Semantic interoperability implies that these systems are able to share the meaning of data they generate whereas contextual (or pragmatic) interoperability implies that these systems also understand the methods and procedures they each use. So, contextual interoperability provides integration across different domains to communicate the context needed to understand why certain decisions were made or why certain events occur. As an example, semantic interoperability allows a system to understand that an observed feedrate is low while contextual interoperability enables the system to understand if a low feedrate is due to the material being machined, some fault or failure in the machine, or some operator error.

The need for contextual interoperability with DMS is clear given the volume and dynamic nature of data anticipated from such systems as well as security and privacy concerns. The complexity of each lifecycle domain and the number of systems involved challenge the use of a single standard, format, or model to provide the entirety of information needed for sufficient content to enable cross-domain analysis. Instead, systems would interrogate data and information integrated

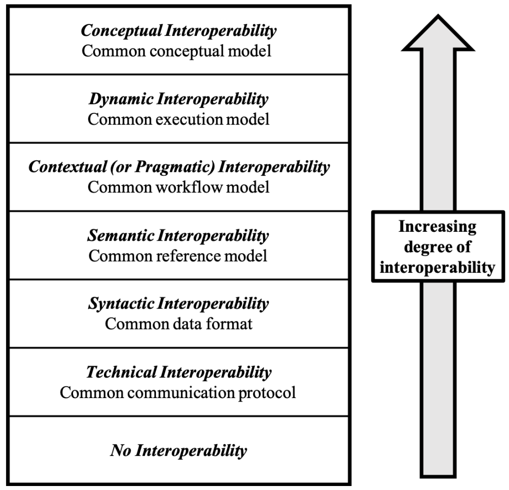

Fig. 6. Degree of interoperability between two systems based on the LCIM (based on [28, 29])

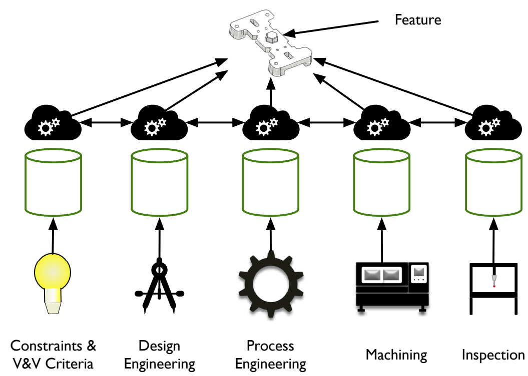

Fig. 7. Implied DMS information exchange from different domains across the lifecycle focused on the viewpoint of a feature of part

across the lifecycle rather than get data for specific analysis. Figure 7 shows such an approach for sharing the perspective of different domains on the viewpoint of a part feature. This level of interoperability minimizes or even eliminates the movement of data, which provides security and privacy and is a requirement for security-based cloud implementations. To summarize, contextual interoperability provides several benefits, such as: (1) reduced data transfer when a full model is not required or is too large to communicate effectively; (2) secure analysis where the underlying geometry or requirements may be restricted; and (3) inter-connectivity of otherwise unrelated data sources to enable increased feedback from other portions of the lifecycle.

There are several challenges to achieve contextual interoperability. For example, the data collected from manufacturing assets, such as machine tools, consists of streamed observations of machine control states and sensor data. This data is specific to each manufacturing asset and may be mapped to a standardized information models to enable semantic interoperability. Considering that the entire product lifecycle may have several similar sources of data, the amount of data and information that needs to be managed may be in the terabyte range for a single product. More significantly, this information may need to be communicated across vendor and possibly organizational boundaries, which presents additional complexity. Standards may help address these challenges so that domains can enrich provided data with the additional context needed to enable DMS. There are several diverse standards development efforts to use ontologies to enable greater interoperability between systems. The Industrial Ontologies Foundry (IOF) is one example in the industrial domain [30].

4.4 General Technologies Needed

Based on the discussion presented in Sections 3 and 4, we can identify the general technologies needed to realize the DMS paradigm. These technologies include solutions to:

- Define part requirements and features
- Measure the capability of manufacturing assets
- Assess production constraints
- Match part requirements to process capabilities
- Manage data and information in production systems
- Assess the outcome of manufacturing processes
- Predict costs and time to delivery
- Assess manufacturability, verifiability, and maintainability of parts
- Assess the availability of manufacturing capacity

5 State-of-the-Art Technologies for DMS

There has been a tremendous amount of research in the literature within each of the technology areas identified in Section 4.4. To constrain the scope of a discussion of the state-of-the-art technologies in DMS, we focus on those areas where recent industry interest has motivated new research developments and efforts. The discussion that follows is not meant to be exhaustive. Instead, it has been structured to provide the reader with a the general scope of relevant research activities.

5.1 Defining Part Requirements and Features

Using models to communicate design information to production planning and manufacturing is an effective way of separating concerns between design and manufacturing. Such separation is important because designs may live longer than the technologies used for their production, and new production and materials technologies can lead to more effective realization of existing designs. The current state-of-the-art for information exchange between CAD models and manufacturing processes has been through the use of feature-based models [31] that encapsulate engineering significance about portions of the part geometry (i.e., features) to provide an additional layer of information for downstream production-planning applications. For example, industrial CAM systems typically rely on feature recognition as a fundamental technology to assist engineers in creating effective process plans to manufacture a shape that closely approximates the nominal CAD design. While the geometric definition of features, such as shoulders, slots, or holes, can be very effective in process planning, such definitions are also used by cutting tool manufacturers to design specialized tools that can optimize machining performance for specific features. In addition, the language of Geometric Dimensioning and Tolerancing (GD&T) predicated upon classifying features of size and based on decades of industrial practice is now known to have fundamental connections with special subgroups of continuous symmetry groups [32]. Thus, feature-based CAD/CAM is a principled, but very specialized, example of how information models can be effectively communicated between design and production systems by capturing manufacturing requirements within the design representation. Standards for GD&T and part representation (e.g., ISO 10303-242 or the Standard for the Exchange of Product Model Data (STEP) AP 242 [33]) include explicit definition of features to be managed between design and manufacturing.

The definition of a product model in design can be specified recursively at multiple levels of detail. Starting from the broadest view of the product as a system of interacting functional components, these models do not include the internal details or implementation of a component but instead focus on its interfaces (inputs and outputs) to other components in the assembly. Modeling languages, e.g., Modelica, or platforms, e.g., Simulink, are very effective in capturing the behavior of a system model defined this way, but they fundamentally assume that a collection of interacting parts in an assembly can be defined as a lumped-parameter system. Mathematically, this definition requires approximating the partial differential equations that model the continuum of a part's behavior into a differential algebraic system of equations that can be simulated. In practice, this approach is quite successful as evidenced by the use of Modelica and Simulink in defense and industrial applications. Capturing a part's functional requirements in lumped-parameter, system-modeling languages is almost always done at the expense of losing geometric detail and treating integral properties, such as mass, stiffness, or moment of inertia, as the defining parameters to simulate performance. Manufacturing information is lost at these higher levels of abstraction, so while it may be possible to design such a system model for optimized functional performance, it is not clear whether a physical realization of such a system model may be feasible due to manufacturing limitations. Evaluating the functionality and physical realization of a design at the assembly and system levels is very challenging due to a lack of standardized interoperability between CAD, CAM, Computer-Aided Engineering (CAE), and lumped parameter system models, which forces explicit (and thus expensive) evaluation of every design option (see Figure 8).

Current CAD technology assumes a set of manufacturing processes as a precondition to the design, but there has been increasing interest in reasoning over the range of possible design solutions using time and cost-based optimization. Such interest has focused on generative design approaches, which is an iterative design exploration process centered on design requirements and constraints [34]. Much of this technology has been applied to additive manufacturing since there are fewer constraints due to existing legacy solutions compared to traditional substractive processes. When applied to additive manufactured parts, generative design tools can explore the solution space of designs with human curation of the result for aesthetics and inference focused on customer needs. Further application of generative design approaches requires improved modeling of requirements.

5.2 Measuring Capability of Manufacturing Assets

Capability in the context of manufacturing represents the value that can be provided by a manufacturing asset (i.e., "an item, thing, or entity that has potential value" [35]) and is a fundamental aspect of decision making in production. For

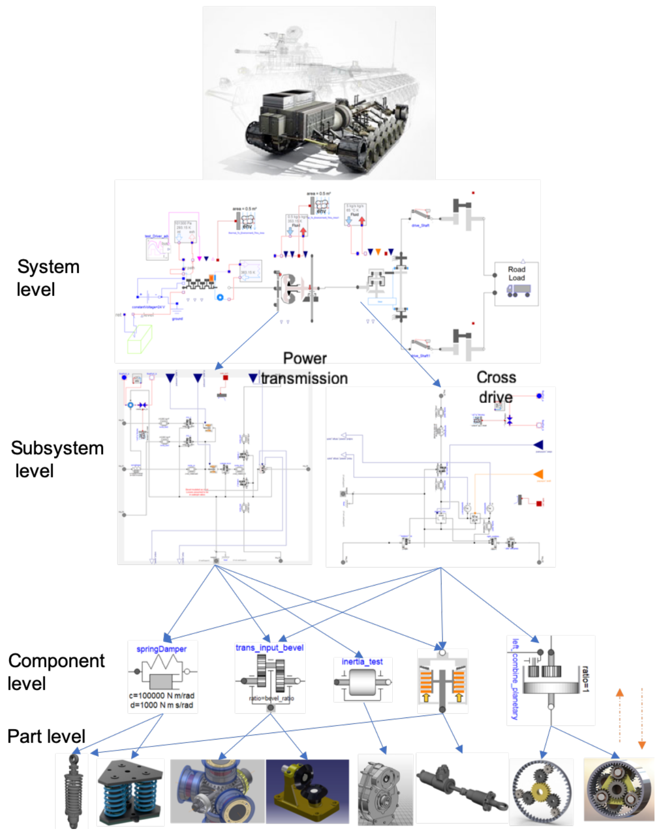

Fig. 8. Specifying a product model at multiple levels of detail using Modelica and CAD. A Modelica system model consists of several subsystems and components each of which can be instantiated using multiple CAD assembly options. The lack of standardized interoperability to capture manufacturing and functional requirements across CAD and Modelica forces explicit evaluation of every design option.

example, scheduling and routing decisions are made based on the assumed or measured capability of an asset: e.g., "can this asset produce my part?" Similarly, managing and optimizing the operations of a supply chain requires knowledge of the capability of a supplier, i.e., the value that a supplier can provide to a customer based on experience, skill, and assets [36]. Thus, capabilities enable an asset to express what it can do and what it may require to provide this value. This information can be reasoned against and used to compose larger manufacturing systems that can address a set of part requirements.

Much of the literature on manufacturing capability has been driven by research to support supplier discovery and general supply chain management. For example, Ameri and Thornhill [36] developed a formal thesaurus to capture manufacturing concepts that can be used to represent and describe the manufacturing capability of a supplier. The resulting tool, called *ManuTerms*, contains over 2000 manufacturing concepts that enable capability modeling. This work was extended through the Capability Modeling for Digital Factories (CaMDiF) project funded by the Digital Manufacturing and Design Innovation Institute (DMDII) (now MxD). The goal of the CaMDiF project was to improve supply-chain decision making, such as sourcing and capability and capacity adjustment, by developing an ontology to enable the representation of manufacturing capabilities for SMEs [37]. This ontology could be used to create so-called "digital factories," which are digital representations of a physical production facility that can be used to assess the capability, capacity, and quality of a manufacturing supplier.

More recent research on manufacturing capability modeling has focused on the use of these models to support process

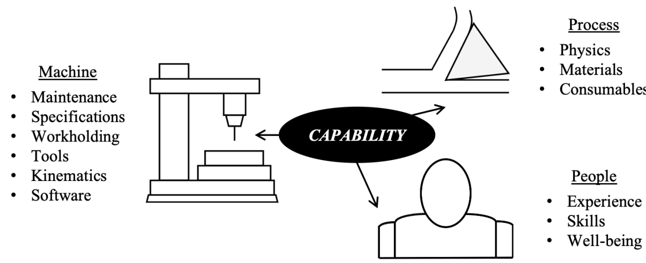

Fig. 9. Different factors related to the machine, process, or people that influence the capability of a manufacturing asset

planning, dynamic scheduling and routing, and maintenance activities. Palo Alto Research Center (PARC)'s recent work [38] is an early example of software that rapidly generates a process plan and a manufacturing time/cost estimation given a CAD file and capability information for available machines and tools. A similar, well-known example is the Instant Foundary Adaptive through Bits (iFAB) project that was part of the Defense Advanced Research Projects Agency (DARPA) Adaptive Vehicle Make (AVM) program. The iFAB project focused on the development of flexible, reconfigurable manufacturing systems that could be used to make a variety of military vehicles [39]. Both examples require a library of capability models for each asset that may be used to identify and predict the availability of machines able to address a set of part requirements. A similar set of information can support maintenance planning, specifically prognostics and health management strategies. Maintenance in these approaches is defined as the restoration of a machine's capability to perform necessary tasks. Thus, maintenance should be performed when the capability of an asset decreases or is predicted to decrease below an acceptable level.

No matter the manufacturing asset of interest, three types of factors influence manufacturing capability as shown in Figure 9. Machine factors (e.g., the specifications of the machine or the available workholding and tooling) often dominate the consideration of manufacturing capability. However, process (e.g., the materials and consumables involved in the process) and human (e.g., the skill and experience of an operator) factors also significantly affect the capability of a manufacturing asset. Human factors in particular are often overlooked in much of the manufacturing literature despite the importance of "affordances," which are the actions that an operator considers possible based on the operators capabilities, goals, and past experiences [40]. One example of recent research on this topic is Kim et al. [41] who develop a formal modeling approach to represent human participation in dynamic manufacturing systems. Other important considerations for manufacturing capability that are gaining interest in the literature include modeling the dynamic nature of capability and the varying levels of abstraction needed to model the capability of manufacturing assets at different control levels (e.g., process versus supply chain level). Manufacturing standards development organizations, including MTConnect and the Open Applications Group (OAGi), have also started to enhance standards to support capability modeling.

5.3 Matching Requirements to Capabilities

Early efforts towards matching part requirements to process capabilities can be seen in the automated process planning and Computer-Aided Process Planning (CAPP) literature. The goal of much of this research was to generate process plans based on a CAD file and representation of available manufacturing assets [42]. For example, Hayes and Wright [43] provide an early example of automated process planning applied to machining where an expert system is used to create toolpaths based on part features. Other examples are described by Alting and Zhang [44] who provide one of the early seminal reviews of the state-of-the-art in CAPP. More recently, Al-wswasi et al. [45] and Li et al. [46] provide a more updated survey of the advances in CAPP. Each of these reviews has shown how CAPP has been traditionally focused at the process level with a particular emphasis on machining. Critically, industry has been unable to adopt this research broadly towards fully automated solutions because these approaches rely on features rather than part requirements [42]. Essentially, these approaches pre-define operations for a given set of recognized features, which limits the applicability of these approaches for DMS, particularly in regards to the agility that is expected of these systems.

Cloud manufacturing has broadened the approach of automated process planning and CAPP. Xu [16] discusses the need to orchestrate the services that can be provided by manufacturing assets with specific capabilities towards addressing manufacturing needs. Liu et al. [47] discuss how these ideas have been extended to scheduling and manufacturing operations management. Much of this work has been focused on agent-oriented, service-based architectures and mechanisms to perform matching without defining the parts and processes to be matched. For example, Leo Kumar [48] provide a review of the use of expert systems to perform matching in process planning and scheduling. In this way, the ability to match part requirements to process capabilities is inherently dependent on the state of the art provided in Sections 5.1 and 5.2.

A critical area of research for matching part requirements to process capabilities is in identifying the right approach to decision making and control. Figure 10 describes two control paradigms: orchestration and choreography. Orchestration-based control has been the traditional means of systems integration in manufacturing. For example, a PLC manages different tasks that the system must perform by providing instructions to components of the system. Alternatively, choreography-based control requires that each component has the ability to control and inform other components of its own actions, which enables the components of a system to collaborate with other to accomplish a task. The distributed decision making implied by choreography-based control is an important aspect of DMS [1]. The challenge is in finding the right balance between both control paradigms, i.e., choreography-based control is easy to scale but does not guarantee an optimal solution without a clearly defined "market" to inform decision making. Early efforts to demonstrate choreography-based control have been primarily in lab environments. For example, the Emerging Technology Center at the 2018 International Manufacturing Technology Show (IMTS) demonstrated a standards-based approach to choreography [49], but as with other examples, no real industrial implementation exists yet. Hedberg et al. [1] state that identifying the right control approach for distributed decision making would achieve the vision of moving manufacturing systems towards logistics (i.e., a manufacturing system becomes an agent in a larger supply chain) as described by Duffie [50], Maturana and Norrie [51], and Shen and Norrie [52].

Moving forward, the primary role of smart manufacturing operations management should be the determination and execution of the optimal match between part requirements and process capabilities rather than the management of contractual obligations between OEMs and suppliers. This role should span from processes on the shop floor to the supply chain, and it should be inclusive of the traditional logistics processes. Different industry groups have started to develop solutions to achieve this vision. Examples include the modeling of part and process information in MTConnect, the DMDII-funded CaMDiF [37] and Standards-based Platform for Enterprise Communincation Enabling Optimal Production and Self-

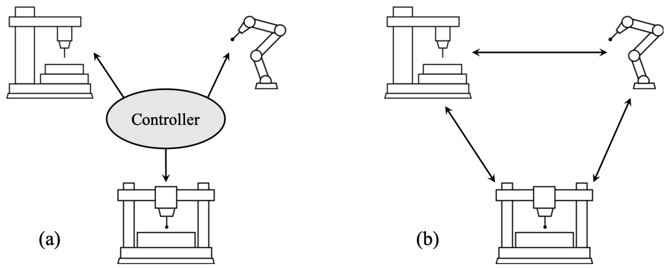

Fig. 10. Two approaches to control: (a) orchestration-based control where a controller (e.g., PLC) provides commands to each component, and (b) choreography-based control where each component coordinates its actions by sharing information with other components

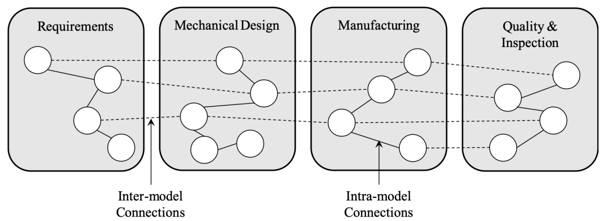

Fig. 11. Example of a subset of the digital thread in production where artifacts in a lifecycle repository may be connected to each other (intra-model connections) or to artifacts in different lifecycle repositories (inter-model connections) [55]

Awareness (SPEC-OPS) [53] projects, the PARC uFab project [42], the DARPA AVM program [39], and some scheduling products on the market, such as OptaPlanner and nMetric.

5.4 Managing Data and Information from Production

Research on the infrastructure needed to manage data and information in production systems has increasingly fallen within the scope of topics such as "digital thread" and MBE. As stated in Section 4.1, the digital thread refers to the integration of production systems across the product lifecycle using an authoritative data source [13, 25, 54]. Figure 11 provides an example of the digital thread in production. The U.S. Air Force originally proposed the digital thread concept to incorporate MBE into its development processes so that product lifecycle data may be more easily leveraged to improve decision making [25, 54]. In this way, the digital thread seeks to provide a means of overcoming many of the technological challenges described in Section 4 so that a variety of data-driven applications, such as the digital twin, may be used to achieve savings and improvement in production activities [55]. While initial estimates of achieving the digital thread have been relatively large [54], these estimates highlight the lack of interoperability in production systems used by industry [55]. The state of the art contains many standards and technology advancements, though, that have started to address these costs in meaningful ways.

Early research on the management of production data has focused primarily on safely and efficiently collecting data from production systems. Much of this work has centered on cybersecurity-related challenges [56] and best practices for managing heterogeneous data sources in manufacturing [57]. These efforts have generated resources – such as the National Institute of Standards and Technology (NIST) Special Publication 800-82 Guide to Industrial Control System Security [58], the NIST Cybersecurity Framework Manufacturing Profile [59], and the NIST Smart Manufacturing Systems Test Bed [60] – that have helped acclimate industry to using data from their production systems. Further connectivity efforts have focused on the need for scalable pipeline architectures to support the increasing number of connected devices and systems providing data throughout the product lifecycle.

The growing use of data by industry has motivated improved interoperability so that the data collected could be used with different applications without the need for translation. For example, OPC Unified Architecture (OPC-UA), standardized by the International Electrotechnical Commission (IEC) as IEC 62541, has become a well-established standard to enable syntactic interoperability (i.e., common data format, see Figure 6) between manufacturing systems [61]. Similarly, MTConnect, standardized through ANSI as ANSI/MTC1.4-2018, has become a well-established standard to enable semantic interoperability (i.e., common reference model, including vocabulary and information model, see Figure 6) so that applications can be developed to interpret data from manufacturing equipment consistently [62]. These and other standards are now being extended to support the integration infrastructure needed for the distributed decision making and choreography-based control described in Section 5.3, such as the standards-based choreography demonstration at the Emerging Technology Center at the 2018 IMTS, which developed an Ethernet-based interface rather than use a PLC [49]. Other technologies are needed, though, to enable the contextual interoperability described in Section 4.3 that is required for causal models that support decision making and control.

Recent research efforts have started to address the need for contextual interoperability by applying linked-data concepts from the Semantic Web to connect data from different production domains [55]. One approach has been to develop a so-called "common information model" that links information common to domain-specific elements of models across different lifecycle phases [63]. Graph-based approaches have also gained interest to generate these types of common information models [55]. Lower-level integration between specific domains has also been explored in the literature. For example, Lynn et al. [64] develop an architecture to integrate CAM and Computer-Numerical Control (CNC), which enables the intelligence in CAM to control the machining process directly. Other efforts have developed standards-based approaches to align planning and execution data [65] as well as design, planning, and execution data [66] by mapping the processes used to generate the data in each lifecycle phase. All of this research shows how a common understanding of workflow can allow for greater interoperability between systems.

Standards development organizations have also started to address the need for contextual interoperability through harmonization efforts between different domain standards. For example, efforts have been on-going to harmonize the Quality Information Framework (QIF) for exchanging metrology information, standardized through ANSI as ANSI QIF 3.0 [67], with MTConnect [62] and STEP AP 242 [33] so that inspection data may be linked with manufacturing and design data, respectively. The American Society of Mechanical Engineers (ASME) recognized the importance of standards to enable the digital thread and MBE and established the ASME MBE Standards Committee, which has released a recommendation report to guide their standards development efforts [68]. Whether through standards or other technology, it is critical that the digital thread and MBE support the generation of context for each of the different viewpoints in production to ensure the quality of the application or use of data [69]. Supporting multiple viewpoints also provides the benefit of often unexplored, innovative solution spaces that can improve decision making and processes throughout the product lifecycle [66, 70].

6 Summary and Future Research Directions

One of our main goals in this paper has been to identify industry needs in the development of DMS for discrete manufacturing. We defined the DMS concept in Section 2 and how industry would like to leverage it by presenting key use cases for DMS in Section 3. Section 4 described the three types of challenges that have limited the development of DMS in industry, and Section 5 presented an overview of some of the state-of-the-art standards and technologies to address these challenges. Based on this review, we can identify several critical areas for the further development of DMS in industry, including:

- Fully traceable requirements starting from customer needs that enable abstraction to create appropriate context for each viewpoint across the product lifecycle
- Design representations that focus on part requirements and appropriate constraints
- Standardized models of manufacturing capability at appropriate levels of abstraction to support multiple viewpoints in production
- Scalable data pipeline architectures to support data collection across large networks of manufacturing assets
- Collated and/or synthesized information models that enable interoperability across the production control levels described by ISA-95
- Standard interfaces and common information models to enable integration across the product lifecycle and establish the digital thread
- Design of markets and new architectures and control paradigms that balance orchestration and choreography to improve the resiliency of production systems and enable matching between part requirements and process capabilities
- Harmonized representations of constraints to support analysis of manufacturability, verifiability, maintainability, cost, lead time, and other relevant factors that affect production decisions

As the research and industrial communities address these needs, it will be important to ensure that the collective set of solutions for DMS provide an open platform based on standards. Such a platform should focus on interfaces between domains to preserve the experience and collected knowledge of each domain while enabling the sharing of this knowledge across all domains. This approach to interoperability would breakdown the existing silos that have challenged the further development of DMS while democratizing innovation and ensuring equal access for all participants so that these solutions may be adopted by all organizations including SMEs. In this way, the community can collectively achieve the vision of DMS by leveraging the technology advancements inherent to Smart Manufacturing and Industry 4.0 to effect a sea change that dramatically improves production. This is a large goal that will require extensive collaboration across many domains. It is our hope that this work can help guide these efforts to strengthen and benefit industry.

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Disclaimer

The dedication of this paper to David Dornfeld is made by the authors and does not imply recommendation or endorsement by NIST. Certain commercial systems are identified in this paper. Such identification also does not imply recommendation or endorsement by NIST. Nor does it imply that the products identified are necessarily the best available for the purpose.

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