Proceedings of the 2018 Manufacturing Science and Engineering Conference
MSEC 2018
June 18-22, 2018, College Station, TX, USA

MSEC2018-6550

A STANDARDS AND TECHNOLOGY ROADMAP FOR SCALABLE DISTRIBUTED MANUFACTURING SYSTEMS

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ABSTRACT

The increasing decentralization of manufacturing has contributed to the growing interest in scalable distributed manufacturing systems (DMSs). The emerging body of work from smart manufacturing, Industrie 4.0, Industrial Internet of Things (IIoT), and cyber-physical systems can enable the continued development of scalable DMS, particularly through the digital thread. However, significant challenges exist in understanding how to apply the digital thread most appropriately for scalable DMS. This paper describes these major challenges and provides a standards and technology roadmap developed from the digital thread viewpoint and consensus-built industrial standards to realize scalable DMS. The goal of this roadmap is to guide research that enables manufacturers to take advantage of opportunities provided by scalable DMS, including improved agility, flexibility, traceability, dynamic decision making, and utilization of manufacturing resources.

1 Introduction

Several trends have contributed towards the growing decentralization of manufacturing systems. For example, with the growth of global production networks original equipment manufacturers (OEMs) have increasingly become system integrators rather than just manufacturers. There is also a growing desire to design and manufacture products closer to the end user, which requires customer involvement in the product development process and enables more individualized products [1]. Furthermore, both small and large manufacturers have identified opportunities to leverage external capacity to provide flexibility. For example, small-to-medium manufacturers often have excess capacity that can be monetized by providing services to OEMs that need resources to meet planned or unplanned production changes. These trends have contributed to a growing interest in distributed and federated systems, which we will call distributed manufacturing systems (DMSs).

DMSs are manufacturing systems composed of heterogeneous components that have a means of semantic interoperability that enables the coordination and control of activities. Figure 1 provides a schematic representation of a DMS. There are a variety of examples of DMSs, including tiered supply chains common in the aerospace and automotive sectors, traditional job shops that may use equipment of different capability and vintage from a variety of vendors, and emerging organizations focused on providing manufacturing services on-demand. While the scale of each of these examples may be substantially different, they are architecturally similar at a meaningful level of abstraction, which enables the scalability of DMSs. Scalable DMSs can provide useful capabilities to manufacturers, including agility, flexibility, traceability, dynamic decision making, and ultimately improved utilization of manufacturing resources.

The growing body of work from smart manufacturing, Industrie 4.0 (I4.0), Industrial Internet of Things (IIoT), and cyber-physical systems (CPSs) can support the continued development of scalable DMSs. These concepts all promise to link the various phases, viewpoints, and systems of the product lifecycle, which allows manufacturers to deliver higher-quality products to mar-

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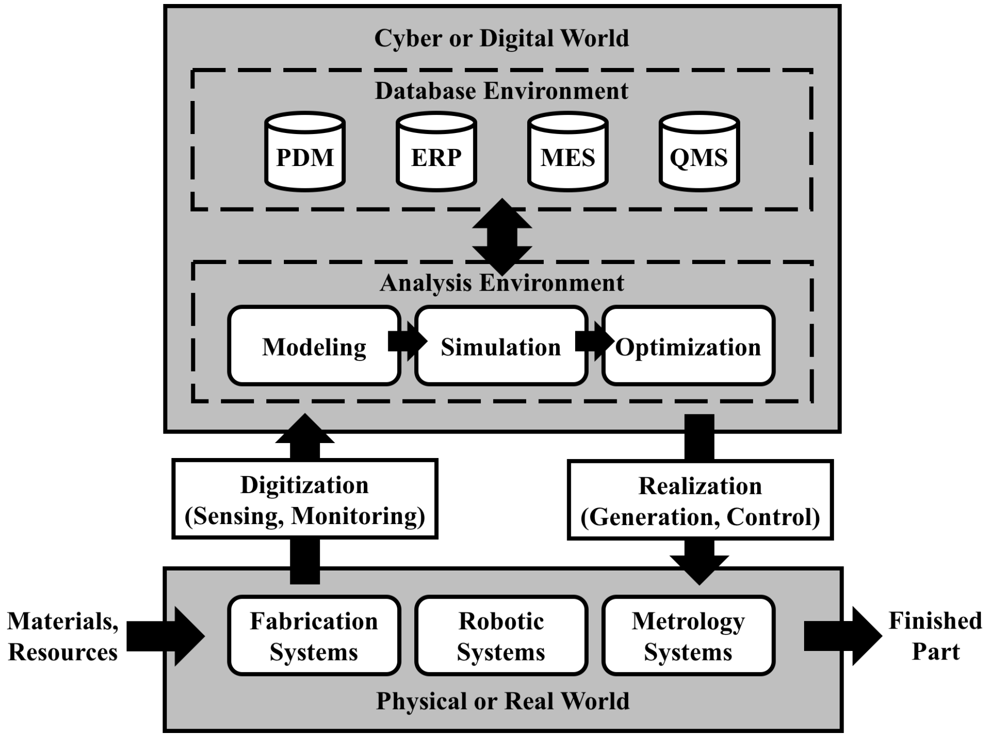

FIGURE 1. Cyber-physical representation of a scalable distributed manufacturing system (DMS)

ket in ways that are faster, cheaper, and more sustainable. Linking each portion of the lifecycle requires a means to integrate information and the structure of that information, which is the digital thread [2]. The digital thread is an integrated information flow that connects all of the phases of the product lifecycle using an accepted authoritative data source (e.g., technical data package [3], three-dimensional (3D) computer-aided design (CAD) model) [2, 4, 5]. The digital thread provides the infrastructure needed to link heterogeneous systems to support decision making, knowledge generation, and control.

Both distributed and federated systems can be integrated using the digital thread, but manufacturers require a standards and technology roadmap to understand how to apply the digital thread most appropriately for scalable DMSs. One example of research in this area is the digital surrogate, which is an application of the digital thread to the manufacturing shop-floor environment where integrated information flows are leveraged to digitize production systems and apply modeling and simulation to enable dynamic control (i.e., the Digitization and Realization boxes in Figure 1). The digital surrogate has also been called the digital twin [6, 7, 8, 9]. The term “twin” implies a one-to-one match between a digital model and a physical asset, but one must consider that models are simply representation of things. Thus, models have an inherent uncertainty that must be attributed to them, which is why digital surrogate is a more precise term. The lack of understanding about this inherent uncertainty further motivates the need for a standards and technology roadmap. The goal of this paper is to describe such a roadmap to guide the research needed to realize scalable DMSs.

2 Challenges Hindering Scalable Manufacturing Systems

ISA-95 [10] is an enterprise-control system integration framework, which is intended to help organizations integrate business processes, manufacturing operations, control, and low-level processes. Figure 2 presents the scope and hierarchy of the ISA-95 framework. The framework is broken into five levels – level four is the highest level, which is focused on business planning and logistics. Level four is where systems such as enterprise-resource planning (ERP) are deployed. Level three deals with manufacturing operations management and is where a manufacturing-execution system (MES) is utilized. Level two and level one deal with control, where level two focuses on monitoring and level one focusing on sensing. The lowest level is level zero, which deals with the individual physical processes of manufacturing (e.g., milling, turning).

ISA-95 provides a sound foundation for describing the different types of systems and functions that exist in a manufacturing system. Part three [12] of ISA-95 standardizes several activity models of manufacturing operations. These activity mod-

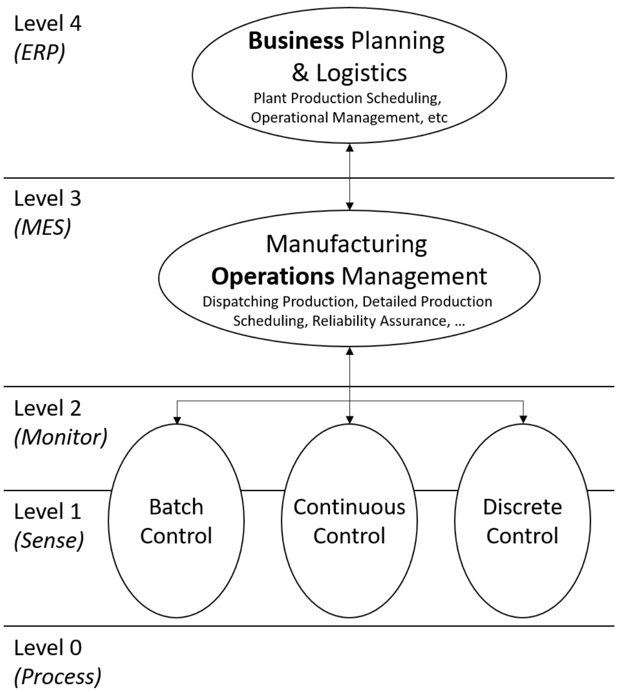

FIGURE 2. Scope and hierarchy of the ISA 95 enterprise-control system integration framework (based on [11])

els provide concise guidance to organizations for the purposes of integrating the various systems encountered within each level. However, in practice, it is difficult to integrate vertically across the levels of ISA-95 [13, 14, 15, 16]. Further, the framework implies single monolithic MES and ERP systems. If this is true, are monolithic integrations capable of being scaled or distributed? This is a question that must be answered before the full benefits of a framework like ISA-95 could be achieved to enable a scalable DMS.

ISA-95 was developed by the process industry. The framework was not purpose built for discrete manufacturing. Enabling scalable DMSs requires both vertical integrations within domains and horizontal integrations between domains. Horizontal integration requires connecting heterogeneous information and systems, which implies the need for semantic mediation. Thus, are the information models (or behaviors, methods, interfaces, services) described with sufficient precision to enable translation of data (e.g., syntactic integration) and/or semantic interoperability? The answer is, not completely.

Each phase of the product lifecycle has different viewpoints and concerns, which lead to different levels of abstraction in modeling and simulation [17, 18, 19]. The various viewpoints lead to information models and systems being developed for a specific purpose, which results in different information models across phases of the lifecycle to look at the same data in different ways. A "fit for purpose" approach to modeling is recommended because it enables "expert systems" that support the user (i.e., human), in a specific function and role, to make decisions in a contextual way.

Conversely, purpose-built models are not scalable. Data requires context when related to decisions [20]. Data alone is not sufficient for decision making because the decision maker must understand the scope and type of the problem the decision is intended to solve. As the scope of the problem changes, the models must also change. Thus, connecting of heterogeneous information and systems to enable scalable DMSs introduces a paradox to the steadfast approach of purpose-driven modeling. A trade-off of how purpose-built to make a model versus how scalable to make a model must be considered with the shift towards scalable DMSs.

Scalable DMSs require an effective and efficient forward and backward communication backbone. This requires integrating domains in multiple directions while providing scalable contextual models. Overcoming these challenges to a scalable DMS is not easy, but we believe a standards-based approach, using the digital thread, provides the best opportunity for maximizing the successful deployment of scalable DMSs.

3 Defining Use Case for Research

Addressing the challenges and barriers to scalable manufacturing systems described in Section 2 requires defining an appropriate use case reflective of industrial practice, but manageable in the context of research. The use case we propose is a flexible machining cell composed of a numerical control (NC) machine tool, coordinate-measurement system (CMS), robot, in-process metrology system (e.g., cutting-tool metrology), and material-handling system (e.g., automated-guide vehicle); see Figure 3. Such a cell would act as an on-demand, pull manufacturing system that autonomously produces finished parts from stock material and resources using the following sample workflow:

1. Humans set the initial work plans
2. Autonomous systems execute the work
3. Control systems study the execution of the work while all systems communicate with each other
4. Autonomous systems self-adjust the work plans and act based on inputs from the control system and other systems

The objective of the proposed research is to develop a reference implementation for a flexible machining cell that will scale to larger production systems. The research would leverage and extend the lifecycle information framework and technology proposed by Hedberg et al. [21]. The framework consists of three layers: (1) linked product-lifecycle data, (2) data certification and

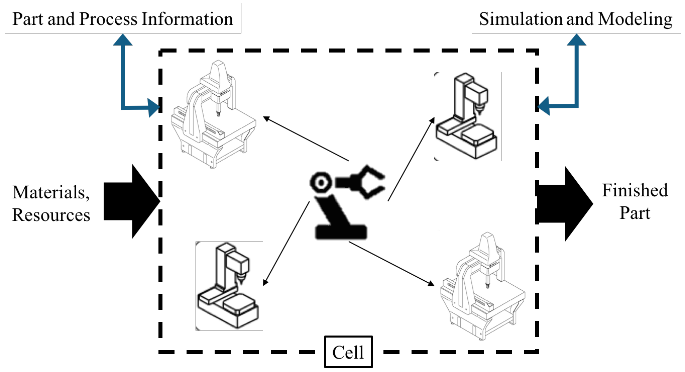

FIGURE 3. Representation of flexible machining cell for on-demand, pull production

traceability, and (3) data-driven applications. The framework and technology supports both vertical (i.e., intra-phase) and horizontal (i.e., inter-phase) integration in the product lifecycle.

The proposed research would enable all decisions (e.g., process parameters, schedule, routing) to be made based on the measured and predicted status or capability of the physical components of the manufacturing system as well as additional part and process information (e.g., product and manufacturing information (PMI), order and delivery schedules, process constraints and specifications) from production management and control databases (e.g., product-data management (PDM), ERP, MESs, and quality-management systems (QMSs)). Data and information would be shared across the manufacturing system based on consensus-built industry standards, including Standard for the Exchange of Product Model Data Application Protocol 242 (STEP AP242) [22], MTConnect [23], and Quality Information Framework (QIF) [24]. Such a manufacturing system would represent a CPS paradigm for manufacturing where control of the physical elements would be determined using modeling, simulation, and optimization that occurs in a cyber or digital environment (see Figure 1).

To achieve the goals of the proposed research, the cell must be composed of industry-standard equipment and must process parts designed to reflect authentic production components. Ideally, the development of such a cell would be supported through collaborations between academia, government, and industry partners to ensure that all stakeholder needs are recognized and satisfied. A longer-term goal of this work is to deploy several of these cells with industry partners to verify and validate the implementation and its scalability.

4 Proposed Standards and Technology Roadmap

Distributed decision making is an important component to successfully enabling a scalable DMS. Flexibility and agility is added to the manufacturing system by decoupling the decision directives from the specification requirements – allowing the manufacturing system to focus on managing itself for how best to schedule and make product. This idea moves manufacturing systems towards logistics systems where the manufacturing systems acts as an agent in a larger supply chain [25, 26, 27]. However, several areas of research must be expanded and integrated to support the shift towards scalable DMSs. We identify four immediate areas of need: (1) cyber-infrastructure integration, (2) physical-infrastructure integration, (3) modeling and simulation, and (4) analytics and data science for manufacturing. Successful extension of these four areas of research, coupled with emerging IIoT concepts, provides opportunities to integrate cyber and physical systems in meaningful ways to support the realization of a scalable DMS as depicted in Figure 1.

4.1 Cyber-infrastructure integration

The Digital Thread for Smart Manufacturing project[1] at National Institute of Standards and Technology (NIST) defined the conceptual framework [21], described in Section 3, for lifecycle information management and integration of emerging and existing technologies that support data curation, discovery, and reuse in manufacturing. The project provided a standardized infrastructure to richly represent lifecycle data and place it into the appropriate context to generate useful knowledge. The framework leverages and promulgates existing data standards such as STEP AP242, MTConnect, and QIF.

Needs for cyber-infrastructure integration should include a focus on further extending the digital thread – particularly integrating the elements of the cyber-world depicted in the top portion of Figure 1 while supporting information flow on all the arrows. This area of focus would build upon previous work in the areas of dynamic knowledge-base management, decision support, requirements management, and architectures [16, 21, 28, 29, 30]. Research components for extending the previous work on reference architectures should include the use of agents and on-demand micro-services [31, 32, 33].

Furthering linked-data and semantic web concepts for manufacturing, including the use of handles [34], is required for realizing the goal of autonomous knowledge generation and decision diagnostics. Semantic web for manufacturing would be enabled by standardizing the interfaces between functions, roles, and phases of the product lifecycle. Standard interfaces could be achieved by continuing to identify normalized elements to support a minimum information model [35, 36]. However, gaps [37] in integrating product design, manufacturing, and quality data must be resolved to successfully link the phases of the product lifecycle using standard interfaces.

In addition, authentication, authorization, and traceability cannot be ignored. Hedberg et al. [38] proposed using X.509 Public Key Infrastructure (X.509-PKI) [39] for embedding trace-

[1] https://www.nist.gov/programs-projects/digital-thread-smart-manufacturing

ability metadata into artifacts. The embedded metadata would assist functions of the lifecycle in determining what data is, how the data can be used, and who did what to the data. This could all be done in support of trustworthiness. Additional work is required to determine a metadata schema that enables trusted exchange of artifacts throughout the product lifecycle. Emerging technologies, such as blockchain and distributed ledgers, could also support trustworthiness requirements.

4.2 Physical-infrastructure integration

The Prognostics, Health Management, and Control (PHMC) project[2] at NIST delivered methods, protocols, and tools for robust sensing, diagnostics, prognostics, and control that enable manufacturers to respond to planned, new, and un-planned performance changes towards the goal of enhancing the efficiency of smart manufacturing systems. The project promoted advanced sensing, prognostics and health management, and control from ISA-95 manufacturing levels zero through three. The resulting impact is improved decision-making support and greater automation with a focus on vendor-neutral approaches and plug-and-play solutions.

In addition, NIST provides the public with real manufacturing data of a contract manufacturer through the Smart Manufacturing Systems (SMS) Test Bed. The SMS Test Bed is comprised of a computer-aided technologies (CAx) lab containing several computer-aided technology tools, a manufacturing lab mimicking the configuration of a contract-manufacturing shop, and data publication web services. The goal of the SMS Test Bed is to extend existing production-focused concepts by designing and developing an architecture [30] for a test bed that enables smart manufacturing research and development across the product lifecycle [40].

Needs for physical-infrastructure integration should include focusing on leveraging the reference architecture from the SMS Test Bed [30] while coupling the work from the PHMC project with part-process methods and an integration of fabrication systems, robotic systems, and metrology systems. This focus would address the the physical-world depicted in the bottom portion of Figure 1 and would define standard interfaces for the inputs from realization and outputs to digitization.

Sensing, monitoring, and control methods would be further studied to provide a full integration of ISA-95 from level zero to level four. This would require support from the cyber-infrastructure integration work to support connecting and contextualizing the representation of ERP and MES systems. Further, methods to control physical machines (e.g., fabrication, robots, metrology) requires an innovative shift towards model-based control.

Manufacturing has reached the fundamental limits of what its tools and processes can manage. For example, G-code was developed at a point when hardware and computing power was a limiting factor and the programming approach was not intended for accessing the machine controller directly [41]. However, computing power today far exceeds the capabilities of G-code for programing machine tools. Hardware and computing are no longer the limiting factors – G-code has become the functional limits of what a machine tool can achieve. Model-based control systems are feasible now because of the advancement in computing power. Fabrication systems would benefit significantly by enabling a controller to interact directly with a part and process model [42].

The research direction we propose for physical-infrastructure integration would enable a model-based transformation of manufacturing control. Models, coupled with sensing and monitoring, would be used to *plan* processes, execute (*do*) those processes, *study* the execution, and take *action* to ensure effective and efficient performance of the manufacturing system. Applying the Deming-Shewhart Plan-Do-Study-Act cycle [43] to our proposed approach of scalable DMSs would ensure the system is achieving its goals and that all decisions are determined based on measured physical components of the system and part and process information.

4.3 Modeling and simulation

Two related projects at NIST are focused on increasing access to and availability of analytical capabilities to support smart manufacturing [16]. The Systems Analysis Integration for Smart Manufacturing Operations (SAISMO) project[3] has developed methods and protocols to facilitate analysis of smart manufacturing operations by enabling efficient integration of smart manufacturing systems models and engineering analysis models. The Modeling Methodology for Manufacturing System Analysis project[4] has developed new ways of applying analytical and empirical methods using domain-specific modeling methodologies tailored for smart manufacturing.

Modeling and simulation research addresses the needs of the analysis environment of Figure 1. Grand challenges in modeling and simulation for manufacturing systems have been addressed in [44, 45]. An overarching challenge is time and expertise required to develop useful models and simulations of manufacturing systems and populate (or update) them with information gathered from the system.

System models developed using the Systems Modeling Language (SysML) [46] provide a 'single source of truth' for organizing and integrating heterogeneous models and information gathered from multiple engineering disciplines involved in sys-

[2]https://www.nist.gov/programs-projects/prognostics-health-management-and-control-phmc

[3]https://www.nist.gov/programs-projects/systems-analysis-integration-smart-manufacturing-operations

[4]https://www.nist.gov/programs-projects/modeling-methodology-smart-manufacturing

tem design and operation. Formal system models convey unambiguous, shared meaning of manufacturing concepts that extends beyond common information models. Model-based systems engineering (MBSE) methods integrate concerns from multiple engineering disciplines to support the design, operation, and maintenance of product and production systems [17, 47], including the many viewpoints and abstractions used to construct analysis models [18, 48].

One area of intense focus is the formalization of part and process models and linking those models to shop floor data collection. Part models capture details about what should be produced (e.g., CAD models) and how well the resulting object was actually produced (e.g., QIF information). Process models describe both what needs to be done to produce a part (capabilities) and capture options for sequencing the execution of those capabilities (process steps). These models capture execution information, including duration and machines that executed each step. They may provide a common representation of manufacturing capabilities, both required by parts and provided by machines. Incorporating semantic meaning with raw data enables consistent interpretation across applications using that data. This information informs many operational decisions, such as scheduling, enabling these decisions to be made dynamically using real-time feedback from the shop floor.

Enabling dynamic decision making, such as scheduling, in smart manufacturing environments requires access to robust decision-support, often provided by simulation and optimization tools. Integrating simulation and optimization tools with sources of system information can be enabled by system models that describe standard interfaces to analysis tools [49].

The research direction we propose for addressing the analysis environment requirements for smart manufacturing systems focuses on modeling and simulation challenges. Standard reference models containing reusable domain-specific part, process, and resource definitions provide a semantic foundation for integrating simulation and optimization models, methods, and tools with shop floor decision-support.

4.4 Analytics and data science for manufacturing

The Data Analytics for Smart Manufacturing project[5] at NIST developed standards, software tools, methodologies, and guidelines to enable small-and-medium enterprises to apply data analytics services to improve decision-making and performance in smart manufacturing systems. The project studied four key areas: information standards, measurement methods, integration framework, and a data analytics testbed. The project proposed two new models to extend Predictive Model Markup Language (PMML) – Gaussian process regression and Bayesian networks. In addition, the project supporting the development of the American Society of Mechanical Engineers (ASME) subcommittee for verification and validation of computational modeling for advanced manufacturing[6].

Needs for analytics and data science in manufacturing should include a focus on extending the information standards, measurements methods, and integration framework further into predictive and prescriptive analytics. The goal would be to further mature manufacturing models for predictive analytics, domain-specific languages for performing predictive analytics, standard interfaces for data analytics tools, and further study of uncertainty quantification. Then, models could be developed to move beyond predictive analytics toward prescribing what needs to be done based on an ability to predict the future and understand the interactions of the various operation and materials on the systems. Enhancing analytics and data science in manufacturing would support decisions in and interactions with each component represented in Figure 1.

The study of analytics and data science in manufacturing must include both data analytics [50, 51] and visual analytics [52]. This would leverage our proposed modeling and semantics work to enable effective decision making by both machines and humans. Further, leveraging the traceability, security, verification, validation, and data provenance methods from our proposed cyber-infrastructure integration work, and combining it with enhanced uncertainty quantification, would enable effective research in applying machine learning and artificial intelligence concepts to decision making in scalable DMSs.

Significant time is spent searching for data and developing knowledge across the product lifecycle. Leveraging trustworthy artificial intelligence would achieve autonomous decision support, requirements management, and knowledge management across distributed and/or federated systems. This would free up time for labor to focus solely on the activities that require human participation.

5 Summary

The digitalization of manufacturing systems is in full swing thanks to international pursuits in smart manufacturing, I4.0, IIoT, and CPSs. However, work remains in fully realizing the digital thread in support of scalable DMS. Shifting the design specification paradigm from primarily paper-based two-dimensional (2D) drawings to 3D model-based definitions could reduce manufacturing and inspection cycle time by up to 75% on average [2]. Further, managing digital-data streams through models while improving the transmission of digital information, enhancing sensing and monitoring, advancing the use of data analytics, and efficiently communicating information to decision makers to help determine and implement required actions would save United States manufacturers $57.4 billion annually [53].

[5] https://www.nist.gov/programs-projects/data-analytics-smart-manufacturing-systems

[6] https://cstools.asme.org/csconnect/CommitteePages.cfm?Committee=101978604

The annual savings could be significantly higher as the figures do not account for reinvestment of savings and other value gains as a result of more manufacturing-system availability and potential positive cash flow.

More importantly, deploying scalable DMS makes the overall system(s) more agile. Engineers would be able to do more with less. Decisions are made today based on a limited set of knowledge and/or selection options. Increasing the agility of manufacturing systems would enable designers and engineers to create on an unprecedented scale since they will now have tools to rapidly test ideas and create new products that will meet customer requirements much better than they do today.

However, barriers to innovation increase the cost of smart manufacturing research and development (R&D) and small-to-medium manufacturers face the highest burden to adopting smart-manufacturing technologies [1]. Therefore, standards must play a key role in the advancement of paradigm-setting technologies. Industry requires standards that support both vertical integrations of manufacturing systems and horizontal integrations of the manufacturing domain with design and other phases of the product lifecycle.

NIST researchers expect the development of a flexible machining cell with industrial partners will illuminate the challenges that must be addressed to enable growth of smart manufacturing and the digital thread in industry. For example, one area identified is the need for standardized interfaces between physical components of manufacturing systems that allow these components to coordinate their activities. Another need is modeling and simulation approaches that can capture the complex interactions in manufacturing systems as well as the lack of observability of certain process and system data. Through this effort, NIST hopes to contribute to the enhancement of standards and technologies where appropriate.

The primary goal of the effort proposed in this paper would be the development of a reference implementation of a flexible, on-demand, pull manufacturing system that may be used by industry to leverage the digital thread within production systems. The digital thread enables the collection, transmission, and sharing of data and information between heterogeneous product-lifecycle systems, which are typically silo-ed between different functions and organizations [21]. Such integration allows industry to use data and information to reduce costs, improve productivity, ensure first-pass success, and augment existing capabilities in the workforce [40]. Our proposal also addresses evolving industry challenges due to the increasingly distributed nature of modern manufacturing activities and the growing complexity of manufacturing systems and networks.

Acknowledgments

The authors wish to thank Allison Barnard Feeney (NIST), Michael Brundage (NIST), Vijay Srinivasan (NIST), William Sobel (Vimana), and the peer-reviewers for their comments and input to this paper.

Disclaimers

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