Defining Near-term to Long-term Research Opportunities to Advance Metrics, Models, and Methods for Smart and Sustainable Manufacturing

Arvind Shankar Raman[1], Karl R. Haapala[1]*, Kamyar Raoufi[1], Barbara S. Linke[2], William Z. Bernstein[3], and KC Morris[3]

[1] School of Mechanical, Industrial, and Manufacturing Engineering, Oregon State University, Corvallis, OR, US

[2] Department of Mechanical and Aerospace Engineering, University of California Davis, Davis, CA, US

[3] Systems Integration Division, Engineering Laboratory, NIST, Gaithersburg, MD, US

* Corresponding Author: Karl.Haapala@oregonstate.edu

ABSTRACT

Over the past century, research has focused on continuously improving the performance of manufacturing processes and systems – often measured in terms of cost, quality, productivity, and material and energy efficiency. With the advent of smart manufacturing technologies – better production equipment, sensing technologies, computational methods, and data analytics applied from the process to enterprise levels – the potential for sustainability performance improvement is tremendous. Sustainable manufacturing seeks the best balance of a variety of performance measures to satisfy and optimize the goals of all stakeholders. Accurate measures of performance are the foundation on which sustainability objectives can be pursued. Historically, operational and information technologies have undergone disparate development, with little convergence across the domains. To focus future research efforts in advanced manufacturing, the authors organized a one-day workshop, sponsored by the U.S. National Science Foundation (NSF), at the joint manufacturing research conferences of the American Society of Mechanical Engineers (ASME) and Society of Manufacturing Engineers (SME). Research needs were identified to help harmonize disparate manufacturing metrics, models, and methods from across conventional manufacturing, nanomanufacturing, and additive/hybrid manufacturing processes and systems. Experts from academia and government labs presented invited lightning talks to discuss their perspectives on current advanced manufacturing research challenges. Workshop participants also provided their perspectives in facilitated brainstorming breakouts and a reflection activity. The aim was to define advanced manufacturing research and educational needs for improving manufacturing process performance through improved sustainability metrics, modeling approaches, and decision support methods. In addition to these workshop outcomes, a review of the recent literature is presented, which identifies research opportunities across several advanced manufacturing domains. Recommendations for future research describe the short-, mid-, and long-term needs of the advanced manufacturing community for enabling smart and sustainable manufacturing.

Keywords: *Smart Manufacturing, Sustainable Manufacturing, Advanced Manufacturing, Future Research, Education Needs*

1. Introduction

Manufacturing has undergone rapid advancement in the past few decades, due to improvements in information technology, sensing methods and technologies, tooling and equipment, new and improved materials, and improved understanding of process characteristics through data analytics, all of which has enabled new manufacturing methods (e.g., cyber-manufacturing and distributed manufacturing) and manufacturing processes (e.g., additive manufacturing and hybrid manufacturing) (1). Integration of current-day manufacturing methods, processes, and equipment with sensors, controls, computational methods, new materials, data analytics, artificial intelligence, and communication technologies drive smart manufacturing (2), an emerging manufacturing concept that has seen a variety of definitions. The U.S. National Institute for Standards and Technology (NIST), states, “[Smart manufacturing systems are] fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs” (3). The U.S. Department of Energy (DOE) Clean Energy Smart Manufacturing Innovation Institute (CESMII) posits, “Smart Manufacturing (SM) enables all information about the manufacturing process to be available when it is needed, where it is needed, and in the form it is needed across the entire manufacturing value-chain to power smart decisions” (4). Such technological advances will enable a broad range of industries to lower costs, improve quality, increase productivity, improve material management, increase efficiency, reduce energy use, and improve worker health and safety, among other performance measures (2,5).

Further, continuously monitoring and improving upon these key performance indicators (KPIs) helps in improving the sustainability performance of smart manufacturing systems beyond that previously attainable with asynchronous, manual collection and interpretation of performance data. Sustainable manufacturing requires a balance of KPIs that span the three pillars of sustainability (economic, environmental, and social) based on stakeholder preferences (6). However, smart and sustainable manufacturing systems exhibit a complex nature, often due to varied, non-uniform manufacturing processes that make quantifying process metrics, ensuring data integrity, and establishing relationships between the systems and sub-systems extremely difficult (7,8). Through the evolution of manufacturing, new processes, materials, and supporting technologies have been developed based on industry needs. Complementary efforts were undertaken to quantify metrics, model systems and sub-systems, and develop methods of quantification for performance measures. These developments have been completed quite independently, however, and have had little to no convergence. To address this deficiency, NIST worked to (a) develop standard smart manufacturing measurement methods, (b) model and characterize smart manufacturing system complexity, (c) develop guidelines for methods, metrics, and tools that enable manufacturing stakeholders to assess and assure cybersecurity of smart manufacturing systems, and (d) develop methods and protocols for the integration of smart manufacturing systems (9). In addition, recently developed ASTM standards led by NIST researchers guide companies in evaluating and characterizing the sustainability performance of manufacturing processes in their facilities and supply chains (10,11).

To support research efforts in smart and sustainable manufacturing, the authors organized a one-day workshop, sponsored by the U.S. National Science Foundation (NSF), at the joint manufacturing research conferences of the American Society of Mechanical Engineers (ASME) Society of Manufacturing Engineers (SME) held at Texas A&M University in June 2018. The workshop invited participants from the industry, academia, and government labs to engage in presentations and discussions of recent developments within emerging areas of advanced manufacturing. It aimed to identify the basis for future research in smart and sustainable manufacturing to support performance metrics, characterization models, and analysis methods attendant with conventional manufacturing, nanomanufacturing, and additive/hybrid manufacturing, as well as for process-level and system-level characterization. This approach enabled the research team to gather perspectives from across various domains of manufacturing and to synthesize these findings to address common research needs for advancing smart and sustainable manufacturing with an emphasis on the role of standards in advancing the field. Workshop activities undertaken to generate and synthesize this information are described in Section 3. To supplement the findings from the workshop presented in Section 4, the research team conducted a literature review which identifies the current state of several key domains of manufacturing and their relevant challenges. Section 5 reports future research opportunities and expected outcomes in short- to long-term time ranges. Section 2 provides background information in support of the work reported herein.

2. Background

The objective of the study reported herein aims to focus future research efforts in advanced manufacturing, with an emphasis on smart and sustainable manufacturing processes and systems. A foundational assumption for smart manufacturing is that models of manufacturing processes provide a basis for computationally improving manufacturing operations. The principles on which these models are organized are emerging. ASTM subcommittee E60.13 on Sustainable Manufacturing (12) has published an initial set of standards to codify these principles, yet more research is needed to understand the fundamental modeling concepts—the abstractions—needed to enable model reuse and composition across the variety of manufacturing processes and systems.

To provide an initial foundation for this work, the findings from a prior workshop on Reusable Abstractions for Manufacturing Processes (RAMP), held in 2017, and the purpose of the 2018 RAMP workshop are next introduced. Both workshops were held in conjunction with a competition for modeling manufacturing processes using standard methods under development by

ASTM subcommittee E60.13. The competitions motivated application of the standards to several manufacturing processes and user experiences from which to generate meaningful feedback.

The first RAMP workshop also was supported by NSF and held in conjunction with the 13^{th} ASME Manufacturing Science and Engineering Conference (MSEC) and the 45^{th} SME North American Manufacturing Research Conference (NAMRC) on June 7, 2017 at the University of Southern California in Los Angeles, CA. The workshop was held in partnership also with NIST and ASTM International. The objectives of the workshop were to:

a) Familiarize the research community with standards from the ASTM E60.13 Subcommittee for modeling manufacturing processes, including the ASTM E3012 Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes (11);
b) Provide an opportunity for participants to put those standards into practice in modeling processes of their own interest, and to share experiences in applying the standards; and
c) Provide a source of candidate models to populate an extensible repository of reusable manufacturing process models being developed by NIST and its academic partners.

The workshop attracted several dozen participants from industry, academia, and government labs. The workshop highlighted the opportunities for an open repository of process models (13), and identified emerging efforts, including both standards development and academic and industrial research, to outline a vision for coalescing such efforts towards an open process model repository. Lessons from the workshop led to a new information model that facilitates more consistent characterization of physical artifacts in production systems, leading to better reusability of models and reproducibility of environmental analyses. Based on the 2017 workshop results and findings from ongoing research, the follow-on workshop held in 2018 and reported here was designed to:

a) identify needs for education and research to support the characterization of unit manufacturing processes (UMPs) for sustainability assessment;
b) define current limitations in associated education and research practices; and
c) prioritize the challenges to be pursued by the manufacturing research community to best meet industry needs in adopting and applying analytical methods for improving smart and sustainable manufacturing process and system performance.

The outcomes of the workshop are expected to benefit basic research programs within NSF, for example by leading to funded research and advancements in topic areas such as sustainability of nanomanufacturing processes and nano-products, digitization of continuous and batch processes, fundamental models of manufacturing processes, and efficient process and system models for decision support in cloud manufacturing. Academic researchers with foci in smart and sustainable manufacturing systems, manufacturing machines and equipment, materials engineering and processing, nanomanufacturing, and engineering education were particularly encouraged to attend; the workshop attracted participants with broad interests in teaching undergraduate and graduate students and conducting basic and applied research in analytical methods for sustainable manufacturing.

3. Overview of the 2018 RAMP Workshop

The second RAMP workshop was comprised of two half-day sessions and an evening poster session. The first half of the day was dedicated to presentations that introduced a variety of perspectives on manufacturing metrics and process modeling. The second half of the day was designed to engage the participants in defining relevant advanced manufacturing research challenges. In addition to participants from academia, industry, and government labs, the workshop hosted 46 undergraduate and graduate student participants, including 23 student finalists comprising six teams from the NIST-sponsored RAMP competition (14). The student participants presented posters reporting their research in manufacturing process modeling and sustainability performance assessment. Additional details of the sessions are described in the following sections.

3.1. Student Presentations and Expert Lightning talks

In the first session of the workshop, RAMP competition finalists presented their projects, summarized in Table 1. In the following session, experts from across the advanced manufacturing domain presented lightning talks to report ongoing research activities and their personal perspectives on the current and future research challenges and modeling needs for advanced manufacturing. These expert talks were not meant to be comprehensive, but provided context for participants in the afternoon session of the workshop to identify and discuss extant challenges across manufacturing research domains.

The talks in the second session started with Dr. Khershed Cooper of NSF presenting *Nanomanufacturing Research at NSF*. He discussed various NSF programs that address the growing demands and challenges of advanced manufacturing. He presented several specific approaches that have been pursued to address needs for scalability in nanomanufacturing under NSF funding. He also discussed avenues of NSF funding to support such work, including cyber-manufacturing and nanomanufacturing.

Table 1: Summary of RAMP Competition finalist presentations

Presentation Topic	Author(s)	Affiliation
A Production Line for Polylactide Business Card	Ian Garretson and Barbara Linke	University of California, Davis
Sustainability Analysis of Stereolithography using UMP Models	Timothy Simon[1], Yiran Yang[1], Wo Jae Lee[1], Jing Zhao[1], Lin Li[2], and Fu Zhao[1]	Purdue University[1], University of Illinois-Chicago[2]
Aggregating UMP Models to Enable Environmental Impact Characterization of Polymer-Based Hybrid Manufacturing	Sriram Manoharan and Dustin Harper	Oregon State University
UMP Model for Flexible Manufacturing System	Feng Ju, Daniel McCarville, Hashem Alshakhs, Weihao Huang, Xuefeng Dong, Hussain Alhader	Arizona State University
Data Driven UMP Model for Monitoring Specific Energy in Surface Grinding Process	Zhaoyan Fan and Sai Srinivas Desabathina	Oregon State University
Grinding Analysis and Model	Justin Canaperi, Yongxin Guo, John Park, Jun Yang, and Yuki Yoshinaga	Stony Brook University

Next, Dr. Ajay Malshe of the University of Arkansas outlined key drivers for standardization of nanomanufacturing in his talk titled *Standardization and Scale-up of Nanomanufacturing Processes*. He provided his perspective on the future of nanomanufacturing and described some of the limitations, specifically noting increasing stress levels in the research lab because of a dramatically changing invention-to-product life cycle. He also highlighted the missing link between research and industrial application, a need to account for the frequency of products changing hands, and the value of students being exposed to industry perspectives before contributing to lab research.

Mr. Kevin Lyons of NIST then presented *Standardization and Scale-up of Additive Manufacturing Processes*. He began by defining additive manufacturing processes and then providing his perspective on the key drivers for advancing additive manufacturing technology. He indicated that data handling and sharing, model development and adaptation, and design for additive manufacturing were key shortcomings to be addressed. He also introduced potential research opportunities in additive manufacturing, such as the need to integrate various process models while considering the inherent complexities, underlying assumptions, and constraints, the lack of a robust method to verify and validate process models for additive manufacturing, the need to develop an approach for capturing design rules for additive manufacturing, and the need to develop simulation testbeds for modelers to test their models against rigorous, highly-controlled additive manufacturing benchmark test data.

Moving away from the process-specific focus, Dr. Fazleena Badurdeen of the University of Kentucky next spoke about *Educating Engineers on Sustainable Manufacturing*. She presented several engineering education challenges, and emphasized that realizing sustainable manufacturing innovations requires developing an educated and skilled workforce. One research opportunity she noted was a need for a multi-disciplinary approach to address sustainable manufacturing challenges that incorporates convergent research and education. In order to achieve this vision, a continuous effort of collaboration between key stakeholders, such as universities, industry, and state and federal agencies is required. She introduced various NSF programs and other funding opportunities that could be used to facilitate such efforts to bolster sustainable manufacturing engineering education.

Dr. Barbara Linke of the University of California Davis next focused on *Modeling Manufacturing Processes*. She outlined the Unit Process Life Cycle Inventory (UPLCI) effort (15) to characterize a broad set of manufacturing processes. The UPLCI approach uses industrial information for each manufacturing process (machine) to estimate material inputs, energy use, and material losses for a particular product design. Linke also introduced a more involved approach for modeling process environmental performance metrics developed under the Cooperative Effort on Process Emissions in Manufacturing (CO2PE!) initiative (16). She discussed the challenges encountered during the creation of UPLCI, including data quality and availability, reduction of complexity while remaining generic, managing empirical models, dependence of materials and energy on machine setup, and an unclear vision of how to capture impacts of auxiliary processes. To improve dissemination, Linke encouraged researchers to report their UPLCI models in standard format as peer-reviewed journal articles in *Production Engineering - Research and Development*, where recent UPLCI studies have appeared for grinding and welding (17,18).

Mr. Arvind Shankar Raman of Oregon State University next presented the talk titled, *Approach for Modeling of Manufacturing Processes and Manufacturing Systems*. He discussed the motivations for companies to pursue sustainable manufacturing practices, including social responsibility, investor demands, government regulations, international standards, and customer consciousness. However, he noted a considerable number of challenges; for example, analysis applications for sustainability assessments are often deficient in supporting integrated system-, process-, and machine-level manufacturing decisions. Data collection and reporting within and across supply chains remain a large challenge for manufacturers. Prior manufacturing process modeling efforts (e.g., UPLCI and CO2PE!) have focused on developing information models that are problem-specific, making them extremely limited in their extensibility. In addition, such approaches require technical understanding of the manufacturing processes, which makes them difficult to adopt and apply within different product designs and production settings. Shankar

Raman presented an information modeling framework for reusing and extending existing models of manufacturing processes for sustainability characterization (19).

To close out the lightning talks, Dr. Alex Brodsky of George Mason University, in his presentation titled *Reusable Model Repository for Manufacturing Systems*, introduced a web-based system, called Factory Optima, being developed in his lab for composition and analysis of manufacturing service networks based on a reusable model repository (20). This architecture aims to overcome the limitations of current decision-making tools and models for smart manufacturing. Most analysis and optimizations tools are currently developed from scratch, which leads to high cost, long-duration development, and restricted extensibility. Factory Optima is a high-level system architecture based around a reusable model repository and the Unity Decision Guidance Management System. Brodsky described this software framework and system for composition, optimization, and trade-off analysis of manufacturing and contract service networks. The work is unique in its ability to perform tasks on arbitrary service networks without manually crafting optimization models.

The expert lightning talks laid the foundation for the interactive afternoon sessions of the workshop. Three exercises were conducted to engage workshop participants: a schema refinement activity, brainstorming on process modeling challenges and opportunities, and a reflective activity to contemplate the lessons of the day.

3.2. Schema refinement activity

Researchers from NIST led the activity to gather feedback from 2018 RAMP Competition participants and others to support extending and strengthening of the schema standardized in the ASTM E3012-16 standard (recently superseded by ASTM E3012-19). One of the key goals of ASTM E3012-16 is to characterize and record UMP models in a consistent manner to promote model reuse and sharing. The schema provided in the standard did not explicitly support reuse, which was made apparent from the NIST-hosted RAMP Competition in 2017, where use of the standard was a requirement for process model development. The submissions rarely conformed to the standard. NIST designed a formal implementation schema (21) for the 2018 RAMP Competition to ensure that the standard was followed more closely by process modelers. NIST also proposed revisions to the standard that are captured in the new schema, including the inclusion of more specific elements within the product and process information element as well as other elements and attributes to promote model traceability.

The proposed revisions to the standard were reviewed and explained in a 15-minute presentation. Participants were then asked to navigate to the online tool, IdeaBoardz (22), on their personal devices (e.g., mobile phones, laptops, or tablets) and to respond under six categories of feedback: keep doing, start doing, stop doing, less of, more of, and action items. Participants were asked to anonymously post concepts, ideas, and suggestions related to each category. The online tool allowed for “up-votes,” wherein workshop participants could show their agreement with ideas posted by other participants. Once concepts were posted to the board, participants volunteered to provide a verbal explanation of their ideas, which led to a discussion and clarification of key ideas.

Based on the number of votes, it was evident that participants desired more modeling examples, specifically those that would be industry-relevant (19 total votes). There was also a considerable need for better definitions and documentations for the elements and attributes within the schema (7 total votes). With proper tools and frameworks, participants suggested that there would be fewer barriers to the use of UMP information models. Based on comments received, a critical future direction would be to demonstrate the use of the revised schema in industrial settings. In particular, validating the approach at scale would garner more interest and use of the standard. Validation could be facilitated by the generation of models (or adaptation of manufacturing process models) undertaken by the advanced manufacturing research community.

3.3. Brainstorming activity and results

Parallel brainstorming discussions that focused on the six lightning talk topic areas were each facilitated by a subject matter expert. The session was guided by Dr. Karl Haapala, of Oregon State University, and focused on advancing discrete manufacturing processes, nanomanufacturing at scale, additive manufacturing at scale, process-level sustainability assessment, system-level sustainability assessment, and manufacturing engineering education. The brainstorming session involved 26 participants from academia and three from government labs. Each of the groups discussed challenges and opportunities related to metrics and indicators, models and algorithms, and tools and methods for each topic area. Participants first distributed themselves among the topic areas and then advanced through facilitated discussion rounds to brainstorm ideas related to the topics in a timed manner. The structure of this session allowed for a continuous flow of perspectives and ideas that were guided toward identifying challenges and approaches to overcoming them for each topic. Results of the activity were synthesized and provided in Table 2 (metrics/indicators), Table 3 (models/algorithms), and Table 4 (methods/tools) for each topic area.

Table 2. Results for metrics and indicators from the brainstorming activity

Topic	Metrics and Indicators
Discrete manufacturing	• Identified challenges, including product customization, standardization, and bolstering the flexibility of processes • Identified connecting process level controls and system level metrics as a key barrier
Nanomanufacturing at scale	• Identified key metrics and indicators which include (depending on the process) fluid type, electron beam power, scan rate, beam diameter, material removal rate, structural resolution, feature size, tolerances, nanoparticle medium, roll-to-roll speed, printing speed, ink spread, sintering conductivity, circuit device design, and reactor design • Identified a key barrier as control over process parameters to achieve defined dimensional tolerances, which is difficult due to the extreme sensitivity of nanomanufacturing processes
Additive manufacturing at scale	• Identified metrics included temperature, layer thickness, material uniformity, material density, extrusion rates, feed rates, internal geometries, product dimensional constraints, melt pool geometry, build time, profile, accuracy, surface finish, and repeatability, including preventative maintenance, post-processing operations, and control of multi-axis equipment • Noted a need for developing and implementing methods of non-destructive inspection for measuring features (internal and external). In addition, current indicators of process variables are deficient in their ability to control the melt pool within desired operating ranges of existing additive manufacturing processes
Process-level sustainability assessment	• Identified metrics and indicators at the process level, which broadly include cost, productivity, quality, energy, resources, waste, environmental impacts, personal health, and safety • Noted a difficulty in identifying and quantifying metrics at the process level, which requires sophisticated models for accurate characterization
System-level sustainability assessment	• Identified metrics included lead time, resource availability, material stability, and system reliability • Indicated importance of considering interactions of multiple manufacturing processes for accurate metric quantification and assessment, requiring integration of models across engineering domains and information-sharing across industries
Manufacturing engineering education	• Noted that an identifiable increase in confidence within manufacturing classes is a key indicator for education in advanced manufacturing • Identified the lack of sustainability topics in undergraduate studies is a weakness of advanced manufacturing education • Found metrics for engineering education in advanced manufacturing difficult to define

3.4. Reflection activity and results

The final stage of the afternoon workshop session involved an individual activity that allowed participants to reflect on what they had heard and to offer their own insights. As such, the workshop organizers posed two questions: (1) *What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?* and (2) *What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?*

Table 3. Results for models and algorithms from the brainstorming activity

Topic	Models and Algorithms
Discrete manufacturing	• Noted that complexities in model composition and optimization are barriers to developing flexible models and algorithms, requiring support of related products with complementary models across multiple enterprises • Indicated that scheduling intricacies are a challenge for modeling flexible discrete product manufacturing systems • Noted that modeling dynamic processes and processes that are interdisciplinary (involving various engineering technologies) can be extremely difficult
Nanomanufacturing at scale	• Noted current modeling methods include modeling of nano-scale fluid dynamics, roll-to-roll modeling, circuit modeling, molecular dynamics, and density functional theory • Indicated a lack of models or algorithms for metrics and indicators of interest such as electron beam power, scan rate, beam diameter, structural resolution, feature size, nanoparticle medium, printing speed, ink spread, and sintering conductivity
Additive manufacturing at scale	• Indicated some of the existing modeling challenges include support structure optimization, design features (form, fit, and function), and model fidelity • Expressed a need for representing key performance indicators (KPIs) as a function of control parameters • Noted that cloud-based process design is needed, perhaps combining parameterized product design methods with new process design approaches
Process-level sustainability assessment	• Indicated limited availability of models and algorithms that enable the assessment of process-level sustainability metrics • Noted that exploration of physics-based and empirical models, predictive models, optimization methods, process planning, and sensor data collection and storage for data-driven models should be studied as disparate means to assess and improve process-level sustainability
System-level sustainability assessment	• Noted a need to develop models for risk assessment and evaluating system dynamics • Indicated models that describe manufacturing processes accurately have an important role in robust system-level sustainability assessment

Topic	Models and Algorithms
Manufacturing engineering education	• Identified the need for models to apply sustainability concepts in real life, as well as the need for models that are easy-to-apply with existing software solutions and sustainability assessment methods • Indicated a need to incorporate design methodologies, especially Design for X concepts, into manufacturing engineering curricula

Participants recorded their answers to the two questions on individual notecards. The answers received were varied, but could be grouped into the following categories:

a) Connection between academia, industry, and government

b) Manufacturing engineering education improvement and workforce development

c) Development, verification, and validation of manufacturing process models

d) Development of advanced manufacturing technologies and novel materials

e) Scalability improvements and standardization for advanced manufacturing

f) Integration of advanced manufacturing with cross-functional engineering domains

The categorization of responses to the open-ended first question are indicated in Fig. 1. More than one quarter (27%) of the participants reported that *manufacturing engineering education improvement and workforce development* efforts are most needed to advance manufacturing research or education. Individual responses indicated that participants perceived a lack of industry-relevant curricula in advanced manufacturing engineering education or a lack of adoption of basic engineering education in manufacturing industry. Key ideas shared by workshop participants included improving education, providing hands-on experience, promoting manufacturing education to inspire younger generation, and developing online resources for manufacturing education.

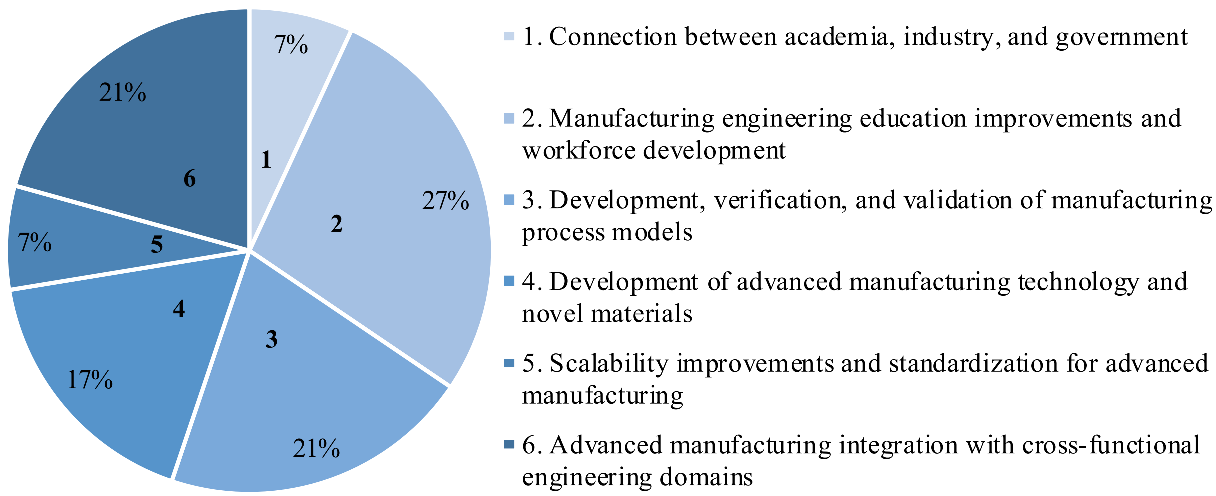

Fig. 1. Summary of responses to Question 1: ***What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?***

The third category (*process model development, verification, and validation*) and the last category (*integrating manufacturing with cross-functional engineering domains*), scored high as well; 21% of respondents identified these areas as having the most pressing need. In particular, participants noted that process models with validated datasets, methods, and algorithms were needed. These responses may have been due to the workshop discussions tailored toward addressing a need for models to fill current characterization gaps and engineering education needs. Respondents indicated that fields of engineering such as design (*connecting design and manufacturing*) and computer science (*artificial intelligence, machine learning, and improvements in analytical tools*) play a critical role in advancing manufacturing industry and enabling smart manufacturing.

Table 4. Results for methods and tools from the brainstorming activity

Topic	Methods and Tools
Discrete manufacturing	• Identified a need to classify problems of existing manufacturing processes to advance the understanding and optimize the performance of discrete manufacturing processes using machine learning

Topic	Methods and Tools
	• Expressed a need to develop software for interpreting and linking disparate process models
Nanomanufacturing at scale	• Noted that common tools include mathematical solvers, computational fluid dynamics software, finite element analysis software, and finite volume methods, as well as analytical tools (e.g., scanning electron microscopes and transmission electron microscopes) • Noted that key barriers include the precision and accuracy of current metrological methods/tools and limited ability to control motion components with extreme precision
Additive manufacturing at scale	• Indicated a need for tools that aid selection of the process type, build orientation, and material, in addition to tools that support metrology, in-process monitoring, quality measurement, and verification and validation • Noted a need to develop/improve tools that perform cross-validation, and provide sustainability decision support, cost modeling, and product design optimization
Process-level sustainability assessment	• Indicated a need for tools that support teaching of sustainability assessment at the process level through adaptable, easy-to-use, open source methods of quantification • Identified skills training, societal influence, and social behaviors as approaches to communicate the importance of considering sustainability factors
System-level sustainability assessment	• Indicated current challenges include how to collect, sort, and validate data for system-level assessment • Noted a need to develop tools that establish and define process relationships between models for systemic assessments
Manufacturing engineering education	• Noted that manufacturing techniques that can be taught using in-house demonstrations would be highly beneficial for students to develop a physical understanding of processes • Indicated that basic technical knowledge should be included in physics-based classes, and taught using case studies in an interactive manner (e.g., labs associated with reading materials)

For the second question, the responses were coded using the same six categories (Fig. 2). More than one-third of the participants felt that the key next step was related to *manufacturing engineering education improvement and workforce development*. In particular, workshop participants noted needs in providing internship opportunities for students, developing online educational tools on advanced manufacturing, promoting engineering at all levels of education, enabling education research, recruiting people for advanced manufacturing careers, and combining industry practice with traditional educational methods.

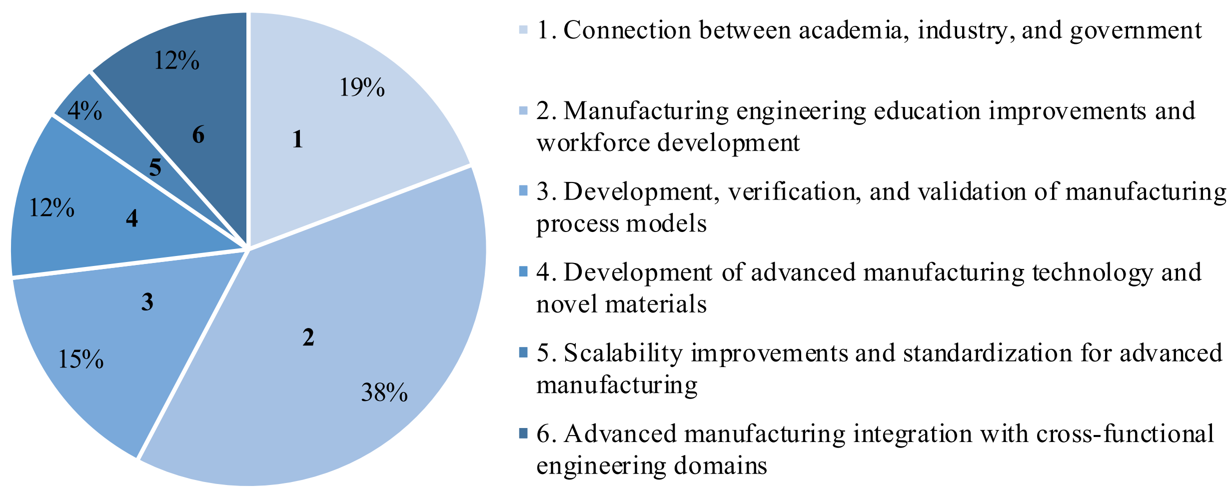

Fig. 2. Summary of responses to Question 2: ***What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?***

A significant fraction of participants (19%) reported key next steps related to *connection between academia, industry, and government*, noting that academic research, government policies, and industry adoption need to work hand-in-hand for advancing manufacturing. Some of the key points mentioned by participants were needs for better communication between academia and industry, in addition to implementing policy changes for encouraging more sustainable practices, using industry-driven research to create value, and bridging the gap between people and technology through defined guidelines for practitioners.

4. Summary of Workshop Findings

The workshop activities identified potential directions for basic and applied research related to sustainability of nanomanufacturing processes and nano-products, digitization of continuous and batch processes, development of physics-based models of manufacturing processes, and efficient process and system models for cloud- and cyber-manufacturing. In particular, the following research directions emerged:

a) Machine learning methods can support understanding of a variety of discrete manufacturing processes, e.g., nanomanufacturing, as well as system-level sustainable manufacturing analysis and optimization.

b) Metrics and indicators for nanomanufacturing are plentiful and span process parameters, material properties, and part characteristics. They should be unified/harmonized to enable technology comparisons.

c) Scalability in nanomanufacturing needs to lead to reduced defects, improved metrology methods and tools, and measurement of moving parts and assemblies.

d) Scalability of additive manufacturing requires optimization methods for new material development, part geometry generation, and support structure design.

e) Additive manufacturing key performance indicators must be connected as a function of process controls.

f) Integration of in-situ and out-of-process metrology, sustainability decision tools, model selection tools, cost models, and product design optimization tools, are all areas of research need, especially in emerging domains, e.g., additive manufacturing.

g) Transient analysis of complex manufacturing systems can lead to robust manufacturing process models.

h) Bridging the gap between process-level controls and system-level metrics can enable deeper insight for discrete and bulk product manufacturing.

i) Systemic sustainable manufacturing requires insight from risk assessment and system dynamics methods to capture the emergent behaviors of interconnected, complex systems.

j) Societal influences of sustainable manufacturing, e.g., stakeholder behavior, must be better understood to enhance development and adoption of new materials, processes, and products.

k) Robust methods to characterize interactions of physical processes, human activities, and decisions across systems are needed to advance systemic sustainable manufacturing.

l) Problem identification and diagnostics can be aided through classification of physical asset degradation.

m) Innovative engineering education approaches are needed to address the growing urgency for accurate and meaningful sustainability assessment at the process and system levels. Engineering students often need a more physical connection to the process, while technical students require more fundamental knowledge and skills for advanced manufacturing.

n) Developing and sharing knowledge (e.g., learning metrics, models, and approaches) for improving the effectiveness of learning in advanced manufacturing should be a focus of engineering education research.

o) Standards can support the reusability and replicability of research into advanced manufacturing processes.

5. A Review of Future Research Opportunities

Based on these workshop findings, the authors synthesized the research directions that emerged into five advanced manufacturing topics: conventional manufacturing, nanomanufacturing, additive/hybrid manufacturing, process and system characterization, and workforce education and training. These categories follow key NSF areas of research interest. Next, a review of the recent literature was undertaken with a goal of identifying future research opportunities in each of these domains. We focused on first defining the state of current research in each topic area by reviewing recent NSF advanced manufacturing projects and related literature from the manufacturing research community. Based on this work, we present short-, mid-, long-term research challenges raised to help define key gaps to be addressed by the advanced manufacturing community. Finally, we identify expected outcomes of successful research undertaken in each area. We caution that these findings are limited (specific technology development may not have broad consensus); the community should expand areas of research opportunity through continued discourse.

5.1. Conventional Manufacturing

Conventional manufacturing commonly includes established processes, categorized as primary shaping, deformation, material removal, coating, heat treatment, and joining processes (23). While the physical phenomena of each of these processes have not been completely characterized, a majority of recent phenomenological research has been directed at additive manufacturing, as discussed in Section 5.3. In addition, in the U.S., welding process research has been well-supported by the NSF. The emphasis has been on solid-state welding processes, which occur below the melting temperature of the components to be joined. These research efforts include advancements in friction stir welding (e.g., defect detection and prevention (24,25), joining dissimilar metals (26,27), and effects of temperature and force control (28,29)); hybrid ultrasonic resistance welding (30–32); magnetic pulse welding and friction stir blind riveting (33–35); and impact welding (36). Fewer research efforts have tackled fusion welding processes, such as vibration-assisted laser keyhole welding (37).

Recent research in material removal operations have explored specific challenging phenomena, such as those attendant with ultra-precision machining of ceramics (38–40); machining-induced distortion in milling (41,42); through-tool minimum quantity lubrication drilling (43); and atomized dielectric-based electro discharge machining (44). Research in this domain is also directed at improving machine tools, such as software-supported improvement of speed and accuracy of vibration-prone machines (45–47); at metrology, such as measurements of part features using freeform optics (48–50), measurement of dynamic moving parts in manufacturing tools (51), and manufacturing of optics used in metrology (52); and at non-destructive evaluation of composites (53). Table 5 identifies the relevant potential research opportunities and expected outcomes in the short-, mid-, and long-term ranges.

With the trend towards smart, automated, and cyber-integrated manufacturing, the need for realistic digital representations of conventional manufacturing processes is also gaining importance (7,54). Though much insight can be gained through purely data-driven models, a hybrid approach, wherein physical knowledge is also leveraged, is preferred (55). Emerging electronic, biomedical, and aerospace products are driving applications of new smart technologies, providing challenging material combinations, tolerances, and lot sizes for conventional manufacturing.

Table 5. Research opportunities for conventional manufacturing processes

	Research Opportunity	Expected Outcome
1-3 years	• Develop physical process models, in particular for new and hybrid processes • Develop transient analysis models of complex systems, especially non-steady state manufacturing elements	• Optimized digital twins of processes • Robust models with easier transferability and scalability
4-5 years	• Develop robust and process-representative machine learning algorithms • Develop scheduling models for flexible discrete systems • Develop models and controls for integrating robots into manufacturing processes, and model interactions between robots and processes • Develop models of metrology processes to allow smart manufacturing control	• Optimized performance of discrete manufacturing through improved process understanding • Process and process chain improvements

5+ years	• Develop models for product categories across multiple enterprises, in particular the connection of physical process models across factories	• Higher competitiveness of various industry sectors

5.2. Nanomanufacturing

Nanomanufacturing has been used in producing materials and products in almost all major industry sectors, such as electronics, automobile, aerospace, biomedical, energy, and food, among others (56). Nanomanufacturing is the production of nanoscale features (surface and sub-surface), materials (nanoparticles), parts (3D nanostructures, nanotubes, and nanowires), devices, and systems (57). Scalable nanomanufacturing involves the high volume manufacturing of nanomaterials and nanostructures, assembly into parts, devices and sub-systems, and integration into a complete system. Nanomanufacturing generally has a minimum of one lateral dimension in the range of 1-100 nm (58).

Nanomanufacturing has been broadly classified into three categories: top-down (producing nanoscale features using physical processes that remove material from a larger mass), bottom-up (building up nanoscale features from an atomic or molecular scale using chemical synthesis and self-assembly), and hybrid (a combination of top-down and bottom-up) approaches (59). Due to the application of nanomanufacturing in a variety of industry sectors, research of novel nanomanufacturing technologies focuses on scaling up from lab-scale to large volume production, lowering tooling and equipment cost, improving quality and reliability, increasing yields, reducing wastes, developing materials compatible for new techniques, and multi-material production (60–62).

Since nanomanufacturing relies on many fields of engineering for materials development, equipment and tool development, optical characterization of nanoscale features, and sensing and instrumentation, these fields need to work cohesively to advance new nanomanufacturing technologies. Current tools to characterize surface and sub-surface level topographical information are time-consuming (63), which is a bottleneck in high-volume manufacturing. Unlike discrete manufacturing processes, each nanoscale process is unique due to its complexity in controlling process variables, measurement, sensing, and material homogeneity at the nanoscale (60). These variations result in products of varying quality, introduce large failures, and decrease the relative reliability of resulting products.

Mechanical components in nanomanufacturing devices and equipment are subjected to multiple failure patterns due to system complexities such as, multiple sub-systems, complex underlying physical phenomena, and rapid degradation of tool components (64,65). Extensive research is often needed to troubleshoot equipment failures, occupying valuable human resources. Educating engineers in nanomanufacturing processes is a key to overcoming many of these barriers (64). In particular, educational materials for design for manufacturing and assembly (DFMA) and failure modes and effects analysis (FMEA) should be developed for nanomanufacturing process technologies. Another key area of emerging nanomanufacturing research is self-assembly of nano-components to form nanoscale systems. Robust self-assembly methods are needed, for example, in order for nanoscale components developed though bottom-up approaches to have a hierarchically-ordered structure with high quality (66–68).

It should be noted, nanomanufacturing technologies require large amounts of in-process manufacturing data to support robust process modeling. To overcome this challenge, statistical tools and machine learning methods could be applied for real-time process control to achieve desired quality levels. Researchers would thus be able to correlate process parameters that are crucial to performance improvement, while developing scientific understanding of the underlying physical phenomena. Such knowledge would facilitate development of hybrid (combination of physics-based and data-driven) models of nanomanufacturing processes (69).

Table 6 identifies the potential research opportunities and expected outcomes for nanomanufacturing in the short-, mid-, and long-term ranges.

Table 6. Research opportunities for nanomanufacturing processes

	Research Opportunity	Expected Outcome
1-3 years	• Improve control of in-process parameters (e.g., melt pool temperature, flow rates, and power levels) to achieve desired feature tolerances • Reduce scan speeds to improve upon current metrology methods, which take a long time to scan and require frequent calibration • Develop an initial repository that contains design for manufacturing methods for varied nanomanufacturing processes	• Increased product quality • Reduced cost for metrology and quality inspection • Improved process selection and design
4-5 years	• Integrate more precise control in current optical methods employed in fabrication and metrology to overcome inconsistencies in part quality due to power, beam diameter, and machine precision • Improve optimization and control of real-time process parameters, e.g., via artificial intelligence methods, to improve efficiencies, and reduce costs, environmental impacts, and wastes	• Products with higher quality and reduced defects • Efficient, high-throughput metrology • Reduced cost of nano-products through high-volume production

5+ years	• Develop standard guidelines for establishing performance metrics, analytical models, and evaluation methods for nanomanufacturing	• Better understanding of process and system factors to be prioritized for efficient manufacturing and high quality products

5.3. Additive Manufacturing

Additive manufacturing is a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies (70). Additive manufacturing is at a turning-point due to its increasing application in manufacturing a wide range of products in various industrial sectors (71). Industry sectors where innovations can be seen include food and consumer products, medicine and medical products, automotive, aviation, architecture, and construction (72,73). Competitive advantages of additive manufacturing processes include their adaptability to the geometric complexity of shape-optimized components, suitability for production of customized or tailored products, flexibility for just-it-time production approaches, and ability to reduce the need for part transportation and storage (56,74). Moreover, design for additive manufacturing approaches have enabled industry to generate lightweight product designs, reduce assembly errors, and improve sustainability performance of manufacturing by reducing waste and energy.

These advantages of additive manufacturing processes are attendant with their own inherent disadvantages. While conventional manufacturing processes are capable of making thousands to millions of identical parts at low cost, for example, current additive manufacturing process technologies are better suited for high-value, low-volume production applications (71) due to their relatively high capital investment needed to achieve high production volumes (75). Thus, the cost of products made using additive manufacturing is typically much higher than those made using conventional mass production methods. Current additive manufacturing equipment also imposes limitations on product size and part quality, and requires more highly skilled labor.

To address these challenges, new additive manufacturing capabilities have been investigated, including multi-material, multiscale, multiform, and multifunctional printing (76–78). Nano-positioning in micro-scale additive manufacturing (79,80) has also gained attention from researchers. Process modeling (81), precision improvement (82), and cost reduction (83) are the other areas in micro-scale additive manufacturing that have been investigated recently. In addition to micro-scale, some researchers have focused on developing new materials for nano-scale additive manufacturing(84).

An extant challenge is the limited set of materials available for industrial additive manufacturing use. These materials generally have limited mechanical and thermal properties, which restricts their broader application (75). Moreover, the sustainability performance of many materials in additive manufacturing is not well-understood (85). It has been suggested that developing lower cost biocompatible materials can help improve economic and environmental aspects of sustainability (86). In addition to material-related issues, the effect of different equipment and process technologies on various materials are poorly understood, often resulting in poor surface finish and tolerances, warping, and layer misalignment (87). Table 7 identifies the potential research opportunities and expected outcomes for additive manufacturing in the short-, mid-, and long-term ranges.

Table 7. Future research opportunities for additive manufacturing

Research Opportunity	Expected Outcome

1-3 years	• Develop automated geometric decomposition methods for efficient part buildup and assembly • Develop geometric dimensioning and tolerancing models for *a priori*, predictive analytics • Develop models to characterize product and process information (and/or performance) based on 3D model and 2D slice data	• Improved product quality by predicting warping and distortion • Better data sharing, storing, access, and modifying
4-5 years	• Develop new equipment and controls to reduce capital investment • Develop new materials and compatible deposition mechanisms to enable multi-material and multiscale additive manufacturing • Develop multifunctional processes to enable production of tailored alloys and microstructures	• Mass production of identical parts at low cost • Broad potential applications using new materials and equipment
5+ years	• Develop precision control strategies reduce cycle time while maintaining desired quality	• Rapid manufacturing of products with multiscale complex geometries

5.4. Process and System Characterization

Characterizing manufacturing processes at an in-depth level of detail and understanding manufacturing systems have traditionally been considered mutually exclusive activities. Entire disciplines and research communities have been built around each one in isolation. Engineering teams to address each perspective reside in many organizations. As a result, the tools to support these activities do not easily relate to one another (88). For example, manufacturing execution system (MES) and enterprise resource planning (ERP) software have been designed to singularly address the performance of manufacturing systems at different levels of control, while tools to assess manufacturing processes are often developed in an *ad hoc* manner within individual companies (89).

With the emergence of industrial internet of things (IIoT) and related smart manufacturing concepts (90), there has been a recent uptick in solutions to bridge the moat between these two domains. Realizing semantic interoperability across MES and ERP software is a current focus area in the manufacturing research, industry, and standards communities for characterizing manufacturing processes for sustainability assessment (91), developing repositories of manufacturing process information (13,92), and analyzing manufacturing processes for designing smart manufacturing systems (93). For example, Industrie 4.0, a German effort to develop a common framework that facilitates vertical integration across the traditional ISA-95 perspective, has gained much attention across the rest of the world (94). For manufacturers to remain competitive, react amid unforeseen disruptions, and become more environmentally efficient, a perspective that bridges these two traditionally separated domains is necessary. Table 8 identifies the potential research opportunities and expected outcomes for process and system characterization in the short-, mid-, and long-term ranges.

It is clearly beneficial to link perspectives related to manufacturing processes and manufacturing systems. Benefits include more accurate prediction in critical system objectives, e.g., cycle time, throughput, and cost estimation. However, there are significant challenges that must be overcome to realize these benefits. One challenge is the computational cost of simulating detailed, process-level models residing in large networks of manufacturing activities (95). For example, in traditional operations management problems, process-level metrics, such as cycle time and energy consumption, are simplified, e.g., assumed to be fixed, in order to deal with the complexity on the systems level.

Table 8. Research opportunities in process and system characterization

	Research Opportunity	Expected Outcome
1-3 years	• Construct guidelines for training data for data-driven models	• Public manufacturing process datasets and models
	• Develop methods for integrating between data contexts based on different standard	• Usability of the current smart and sustainable manufacturing standards

	information modeling paradigms (e.g., SysML, E3012, and Modelica) • Tightly integrate physical systems with analytical applications • Understand computational complexity of process-level and systems-level analyses	• New guidelines for standards integration (e.g., CCOM and E3012, MTConnect and OPC-UA) • Better communication across engineering domains
4-5 years	• Devise methods for consistent predictive models for process-level optimization • Define standards for linking process-level simulation to systems-level optimization • Develop methods for real-time monitoring and control from sensor data • Improve sensor development/deployment for higher quality data	• Better manufacturing analysis tools • High quality systems-level analysis • Better adaptability to changes at the process level • Near real-time trade-off analysis for assessing sustainability performance • Better public datasets for education, training, and process improvement
5+ years	• Improve scalability, flexibility, and adaptability of process-level to systems-level approaches • Define model verification, validation, and uncertainty quantification (V&V) • Develop standards to port process-level to systems-level thinking in an automated manner • Integrate broad-based security methods with data flow for robust, trusted process and system analysis and optimization	• Clear understanding of limits of paired process-to-systems approaches and standards that link the two perspectives • Clear guidelines for characterizing uncertainty of models • Pilot studies that demonstrate potential to educators, researchers, and practitioners • Tools for secure and private data transfer (e.g., blockchain for manufacturing) • Improved standards for process model and manufacturing data security

Other process and system characterization challenges include the following:

a) Validation modeling and uncertainty quantification methods across different abstraction levels (e.g., machines, processes, and systems) are not standardized [1].

b) Even if process-level models are available, e.g., in a repository, appropriateness of their reuse for a specific instance is not well-understood (92). Bridging the existing standards at

[1] ASME's Verification, Validation, and Uncertainty Quantification (VVUQ) initiative is an emerging standard area that provides guidance to develop, analyze, and enhance the credibility of computational models and simulations (96)

the various levels is another open research question, e.g., relating MTConnect to the E3012 standard.

c) To produce "what-if" scenario exploration in complex supply chain networks, relating disparate databases to one another is particularly challenging.

d) Privacy and security associated with sharing data across and between distributed manufacturing enterprises remains a primary concern of many manufacturing companies and an area of very rapid evolution. Applying best practices and known methods for incorporating levels of traceability, e.g., blockchain or digital signatures, is essential for enterprises to feel comfortable in sharing data. Articulating manufacturing needs is important to influencing ongoing development in these areas

5.5. Workforce Education and Training

Beyond traditional engineering and technical curricula, the current and future manufacturing workforce needs to be educated in advanced manufacturing and provided with the skills that will enable decision making in smarter, more sustainable industrial environments. Process and system modeling are primary mechanisms to continuously improving broad-based manufacturing performance (72,97). As noted above, manufacturing processes account for the most intensive energy use and waste production in many manufacturing facilities (98,99), yet are often overlooked because their solutions are complex and varied.

While process improvement based on Plan-Do-Check-Act cycles are well-established, technical standards for applying the practice routinely for improving individual manufacturing processes remain under development and deployment. ISO 14001 (100) provides guidelines for companies to establish environmental management systems that address waste and energy management, but stops short of offering guidance on improvements for individual processes. Engraining standards such as those from ASTM E60.13 (101,102) into widespread practice, first through standards education program development (103), will spur industry adoption of sustainability improvement practices (104). These standard practices can be extended with a focus on individual manufacturing processes to enable more replicable and repeatable evaluation. In addition, techniques for applying foundational yet interdisciplinary (cross-cutting) technologies that promise revolutionary impacts to manufacturing performance need to be integrated into manufacturing education. These technologies include sensing technology, computational skills, artificial intelligence (AI), machine learning, data analytics, ontological definition, cognitive computing, augmented and virtual reality, and quantum computing, among others. Process modeling may serve as a platform for such integrations.

The challenges of workforce education and training are diverse, and include establishing practices in process and system modeling, sustainable thinking, life cycle assessment, and continuous improvement at all levels of the manufacturing enterprise as well as a need for personalized education and training experiences to inspire the next generation to pursue manufacturing careers (105). Such efforts need to be undertaken at all educational levels. Often, the sustainability-related trade-offs of our decisions are unknown, either due to a lack of information at the time the decisions are made, a lack of metrics by which the factors can be quantified (i.e., the externalities), or lack of visibility of the trade-offs to the decision maker (106,107). Standard practices for instilling manufacturing process modeling are lacking (89), and how such standards can by systemically employed in cyber-human systems must be better understood (9). Early work has been done in this area, but more is needed to characterize manufacturing processes for sustainability (101,108), for representing manufacturing processes using information modeling (101,108), for reusing such information models variations of manufacturing processes (19,102). What distinguishes these concepts from more traditional curricula is the heavy reliance on information to guide decision making. Information modeling and capture have traditionally not been part of manufacturing engineering curricula. The field of structural engineering has seen a similar transformation and several researchers have reported on educational aspects of this transformation (109–111).

While industry is in need of skilled workers in smart and sustainable manufacturing to enable the development, implementation, and continuous improvement of advanced manufacturing processes, interests in manufacturing careers has decreased due to the poor image young people have of industry (1). Integrating sustainability concepts into engineering curricula has been shown to improve student perceptions, in particular for students underrepresented in engineering (112,113), as well as motivating students to pursue careers in sustainability (114,115) and increase student interest in the job opportunities in manufacturing (116,117). A concerted effort is needed to synthesize existing resources through convergent research that raises the conscientiousness of sustainability objectives in the profession, develops the data and methods needed to inform effective decision making, and provides insight and intuition to externalities, while also focusing the educational objectives of the advanced manufacturing community. For instance, a key gap in existing science and engineering education is the lack of an appropriate learning environment for students to address technical solutions that consider the three aspects of sustainability (118). Further, the more mundane aspects of manufacturing (119–121) and manufacturing education can be improved through the application of gamification techniques (122,123). With a deep understanding of the principles of manufacturing processes themselves, in some cases these techniques may be applied to improve the performance of those processes.

Another fundamental distinction of future manufacturing systems is the interplay between the virtual and the physical worlds. This distinction is manifest throughout the discipline. AR and VR technologies are being applied in manufacturing training systems where significant training can take place without any physical engagement. Similarly, like the 3D product design models that came before it, the concept of the “digital twin” has emerged to describe the virtual model of operational systems that allow for monitoring and prognosis based on real-time data. What’s more, the use of robotics throughout manufacturing systems will require sophisticated human machine collaborations. The next generation of manufacturing engineers will need to shift seamlessly and accurately between the virtual and actual world in a way that has not been previously practiced, opening up a new area of research exploration. Automation of systems means seeding control of those systems, yet human expertise and knowledge is necessary to maintain control though all types of failure modes. The aviation industry has witnessed some highly-visible unexpected consequences from the introduction of automated navigation into the cockpit in terms of pilot preparedness in emergency situations resulting in loss of human life (124,125). Avoiding similar catastrophes in the manufacturing setting will take study and work towards implementing fail-safe solutions. Initial approaches to the problem have explored the form of interactions between humans and machines with the goal of identifying and optimizing those task for which a person’s unique skills are best suited by providing access to data on demand to improve their decision making capabilities (126,127).

Table 9 identifies the potential research opportunities and expected outcomes for educational and training issues in the short-, mid-, and long-term ranges.

Table 9. Research opportunities in workforce education and training

	Research Opportunity	Expected Outcome
1-3 years	• Use the design of products, processes, and systems as a basis to capture K-12 students' imaginations and interests • Use web-based learning, augmented reality, and virtual reality technologies to promote advanced manufacturing technical skills • Create resources and tools for teaching process and information modeling in technical and engineering education programs • Integrate sustainable manufacturing and life cycle thinking into K-12 curricula	• Motivated young people toward engineering and making for the social good • More engagement in engineering and manufacturing for a more productive society and more sustainable industry • Better trained students, technicians, and engineers to support advanced manufacturing
4-5 years	• Innovate current online and virtual media to teach K-12 and undergraduate students about advanced manufacturing and build their confidence through learning by doing • Understand what is required of intuitive user interfaces to improve operational choices, including gamification • Integrate life cycle thinking and design for X methods in engineering education	• Prevention of unintended consequence through proactive planning and informed decision making • Expanded knowledge and engineering intuition surrounding sustainability objectives • Effective learning tools and methods
5+ years	• Make estimation of impacts available to designers and other decision makers, e.g., real-time analytics using cyber-technology • Develop frameworks for integration of real-time data into design decision making • Create tools that enable users to find relevant existing information and research, and perform trade-off assessment • Develop systemic approaches and methods for teaching smart and sustainable manufacturing	• Ease of impact assessment for manufacturing processes and product life cycles • Integration of life cycle costs into design and manufacturing planning • Facilitated exploration of impacts of production systems on society in the presence or absence of life cycle thinking

6. SUMMARY

Over the past several decades, manufacturing industry has seen rapid development in sensing technologies, process equipment, and materials, among other areas, aided by the emergence of data and information technologies. These advancements have enabled new manufacturing methods (e.g., cyber-manufacturing and distributed manufacturing) and processes (e.g., additive manufacturing and hybrid manufacturing), but often experienced little or no convergence during their development, which has inhibited more systemic development and growth.

The foregoing presented the findings from a workshop organized within the manufacturing research community that aimed to identify challenges and barriers attendant with smart and sustainable manufacturing. The workshop activities (i.e., student presentations, expert talks, schema refinement feedback, and brainstorming and reflection) aided in defining challenges related to metrics and indicators, models and algorithms, and tools and methods across several advanced manufacturing fields. The ideas gathered from workshop participants reflect a range of potential opportunities for the manufacturing research and educational community to pursue.

To supplement workshop findings, a review of recent literature was completed under the following themes: (a) conventional manufacturing processes and systems; (b) nanomanufacturing processes and systems; (c) additive/hybrid manufacturing processes and systems; (d) process and system characterization methods; and (e) workforce education and training for advanced manufacturing industry. Existing challenges and barriers, potential research opportunities, and expected outcomes were presented from the short- to long-term range for each topic area. This study arrived at the following findings:

a) Improvements in sensing, controls, metrology, and processes have been reported across the various manufacturing technology domains;

b) There is a need for well-developed models, algorithms, and methods that can be utilized to improve process- and system-level performance for specific manufacturing applications;

c) Artificial intelligence (e.g., reasoning and machine learning) and other emerging technologies can have a great impact in process- and system-level improvements across manufacturing domains; and

d) Improved manufacturing education could inspire future generations into manufacturing engineering and research careers (e.g., through new hands-on, virtual, and off-site methods).

These findings can help stimulate future manufacturing research and benefit stakeholders across academia, government, and industry for advancing smart and sustainable manufacturing, as discussed in greater detail in Section 5. The fundamental and applied research opportunities identified under these themes can be undertaken by existing and emerging consortia (e.g., NSF Industry-University Collaborative Research Centers, Manufacturing USA, and EU Factories of the Future programs), as well as through conventional university, industry, and government agency funding mechanisms that are addressing emergent manufacturing challenges. It will be crucial that research solutions derive actionable implementation pathways for industrial organizations and educational institutions at all levels and scales in order to achieve the vision of academic, industry, and governmental leaders and policy makers for a smarter, more sustainable future.

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