WORKSHOP REPORT

Challenges in Representing Manufacturing Processes
for Systematic Sustainability Assessments

Held June 21, 2018
Texas A&M University, College Station, TX

December 17, 2019

Workshop Organizers
Dr. Karl R. Haapala
Oregon State University

Dr. Barbara S. Linke
University of California Davis

Ms. Katherine C. Morris
U.S. NIST

Dr. William Z. Bernstein
U.S. NIST

Dr. Fu Zhao
Purdue University

TABLE OF CONTENTS

EXECUTIVE SUMMARY

A one-day workshop on *Challenges in Representing Manufacturing Processes for Systematic Sustainability Assessments* was held on June 21, 2018 at Texas A&M University, College Station, TX. The workshop was supported by the National Science Foundation (NSF) Nanomanufacturing Program (now the Advanced Manufacturing Program). The workshop was hosted in conjunction with the 13th Manufacturing Science and Engineering Conference (MSEC) of the American Society of Mechanical Engineers (ASME) and 46th North American Manufacturing Research Conference (NAMRC) of the Society of Manufacturing Engineers (SME). It was comprised of two-half day sessions and an evening poster session.

The workshop, as documented in this report, aimed to identify challenges and barriers related to various advanced manufacturing technologies. The workshop invited experts from academia and government labs to provide thought provoking perspective on persistent problems and issues in current manufacturing domains in the form of lightning talks. These talks acted as a foundation for breakout brainstorming discussions. The breakout discussions focused on gathering viewpoints from workshop participants on challenges related to metrics and indicators, models and algorithms, and tools and methods in various advanced manufacturing fields. As a follow-up to the breakout discussions, a notecard activity was conducted to gather participant perspectives on two questions: *What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?* and, *What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?*

In addition to the lightning talks, breakout session, and notecard activity, there were student presentations from the Reusable Abstractions of Manufacturing Processes (RAMP) competition. Another session involved a schema refinement activity organized by co-organizers from NIST. This activity focused on receiving inputs from the workshop participants on improving the current schema specified in the ASTM standard E3012-16 for manufacturing process characterization.

Through the various workshop activities, many ideas emerged as potential challenges and barriers within the advanced manufacturing research and educational domain. These ideas have been gathered as recommendations in this report. They reflect a range of potential opportunities for the manufacturing research and educational community to pursue. The recommendations outlined in this report are classified under the following major 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
e) Cross-cutting issues, including artificial intelligence, cybermanufacturing, sustainability, and education and workforce training for advanced manufacturing careers.

1 INTRODUCTION

The *Workshop on Challenges in Representing Manufacturing Processes for Systematic Sustainability Assessments*, supported by the U.S. National Science Foundation (NSF), was held in conjunction with the 2018 ASME Manufacturing Science and Engineering Conference (MSEC) of the American Society of Mechanical Engineers (ASME) and the 46th North American Manufacturing Research Conference (NAMRC) of the Society of Manufacturing Engineers (SME) on June 21, 2018 at Texas A&M University, College Station, TX. The workshop was comprised of two half-day sessions and an evening poster session to engage the research community in discussions around emerging topics in advanced manufacturing, nanomanufacturing, sustainable manufacturing, and engineering education. The workshop hosted 46 student participants from the National Institute of Standards and Technology (NIST) Reusable Abstractions for Manufacturing Processes (RAMP) Competition, including six teams of 23 student finalists. The undergraduate and graduate students had the opportunity to present posters reporting their research in manufacturing process development and sustainability performance assessment.

The day-long workshop aimed to (1) provide a venue for participants from industry, government labs, and academia to exhibit manufacturing process developments of their own interest; (2) identify educational and research challenges and requirements relevant to manufacturing process model development and validation; (3) familiarize the research community with developments in the recent standards from the ASTM E60 Subcommittee on Sustainable Manufacturing for modeling manufacturing processes; (4) identify candidate models to populate an extensible repository of reusable manufacturing process models; (5) gather inputs on best practices for sharing, reusing, extending, and composing models of conventional and advanced manufacturing processes for characterizing manufacturing systems; (6) develop a research roadmap that defines key research gaps and strategies for addressing them; and (7) enable participants to share their experiences in process model development for evaluation of sustainability performance.

Thus, the expected outcomes of the workshop were to help identify needs for education and research to support the characterization of unit manufacturing processes (UMPs, see Figure 1) for sustainability assessment, to define current limitations in associated education and research practices, and to prioritize the challenges to be pursued by the manufacturing research community to best meet industry needs in adopting and applying analytical methods for improving process and system performance. The outcomes of the workshop are described in detail in this report, and summarized in Section 8 with recommendations for overcoming identified barriers and challenges. These outcomes 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, digitalization of continuous and batch processes, fundamental models of manufacturing processes, and efficient process and system models for decision support in cloud manufacturing.

This report is organized into eight sections. The previous RAMP workshop held in 2017 as well as the theme and organization of the 2018 RAMP workshop are presented in Section 2; the NIST RAMP Competition and each of the RAMP Competition finalist submissions are described in Section 3; workshop lightning talks and full-length presentations are summarized in Section 4; and a process modeling schema refinement activity is described in Section 5.

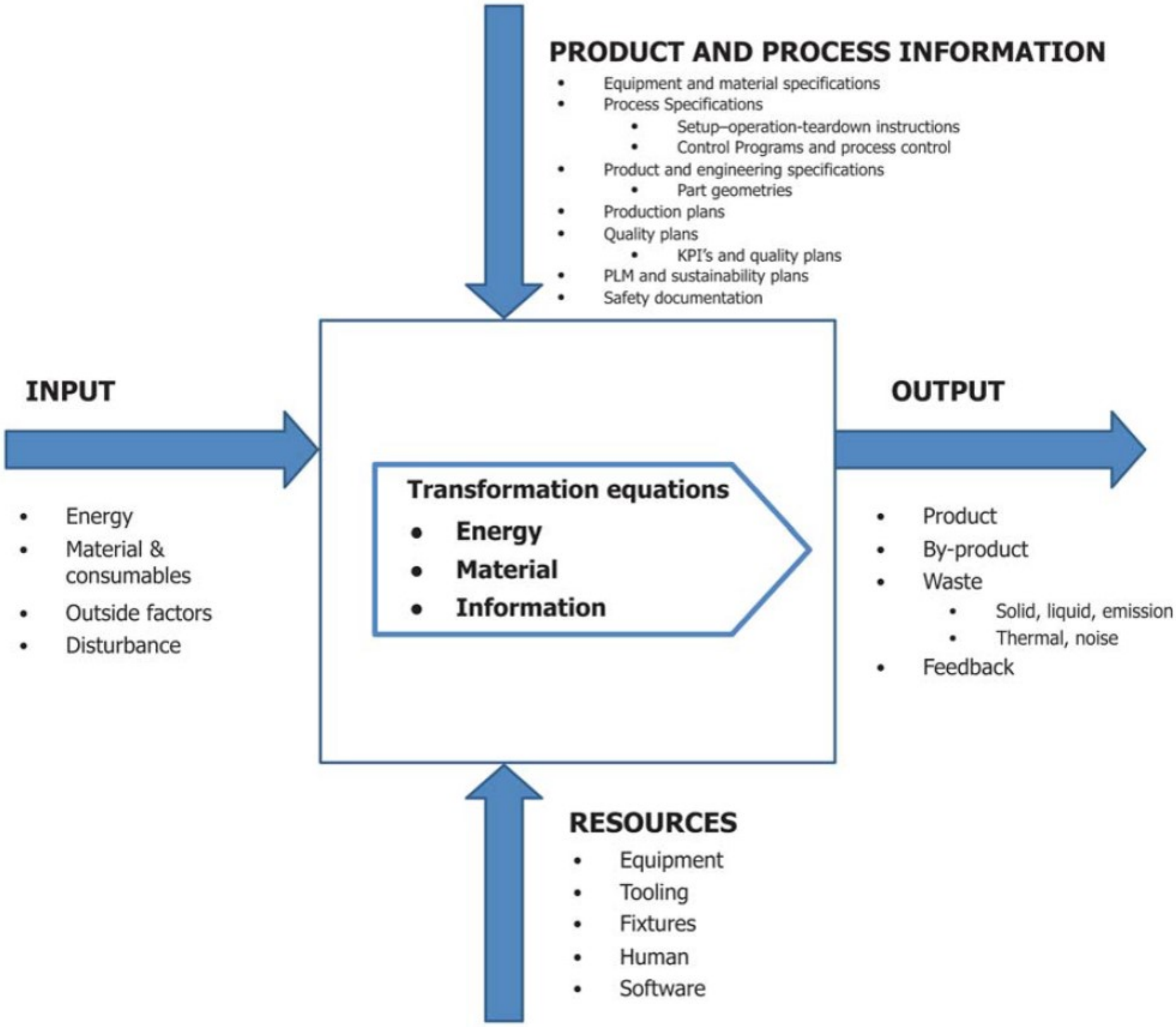

Figure 1. Unit manufacturing process (UMP) modeling underpins the RAMP concept [1].

Next, a brainstorming discussion and a break-out session to identify the barriers and opportunities in manufacturing process modeling are presented in Section 6; the process of selecting student travel awardees as well as the winners of the RAMP competition finalists and the poster competition is discussed in Section 7; and, finally, a summary of the workshop and future recommendations are presented in Section 8.

2 BACKGROUND

A workshop on *Formalizing Manufacturing Processes for Structured Sustainability Assessments*, supported by the U.S. National Science Foundation (NSF), was held in conjunction with the 2017 ASME Manufacturing Science and Engineering Conference (MSEC) of the American Society of Mechanical Engineers (ASME) and the 45th North American Manufacturing Research Conference (NAMRC) of the Society of Manufacturing Engineers (SME) on June 7, 2017. The workshop was announced by the National Institute of Standards and Technology (NIST) in partnership with ASTM International, NSF, and ASME. The objectives of the workshop were to:

a) Provide examples/cases of applications of unit process modeling, including those from industry, research, and educational settings and across manufacturing processes and scales.
b) Gather input on current challenges of process model development and validation, as well as challenges with model shareability, reusability, extensibility, and composability.

The workshop attracted several dozen participants from industry, academia, and government labs. The inaugural RAMP competition was held in conjunction with the workshop. An example of how one submission interpreted the ASTM standard to model grinding is shown in Figure 2. It is seen that transformation equations are at the core of the UMP model, which takes in information about material and energy inputs and provides output information about the part, wastes, and key metrics and indicators. Results from this workshop highlighted the need for an open repository of process models [2], and also identified emerging efforts including both standards and research, and outlined a vision for coalescing these efforts towards an open process model repository.

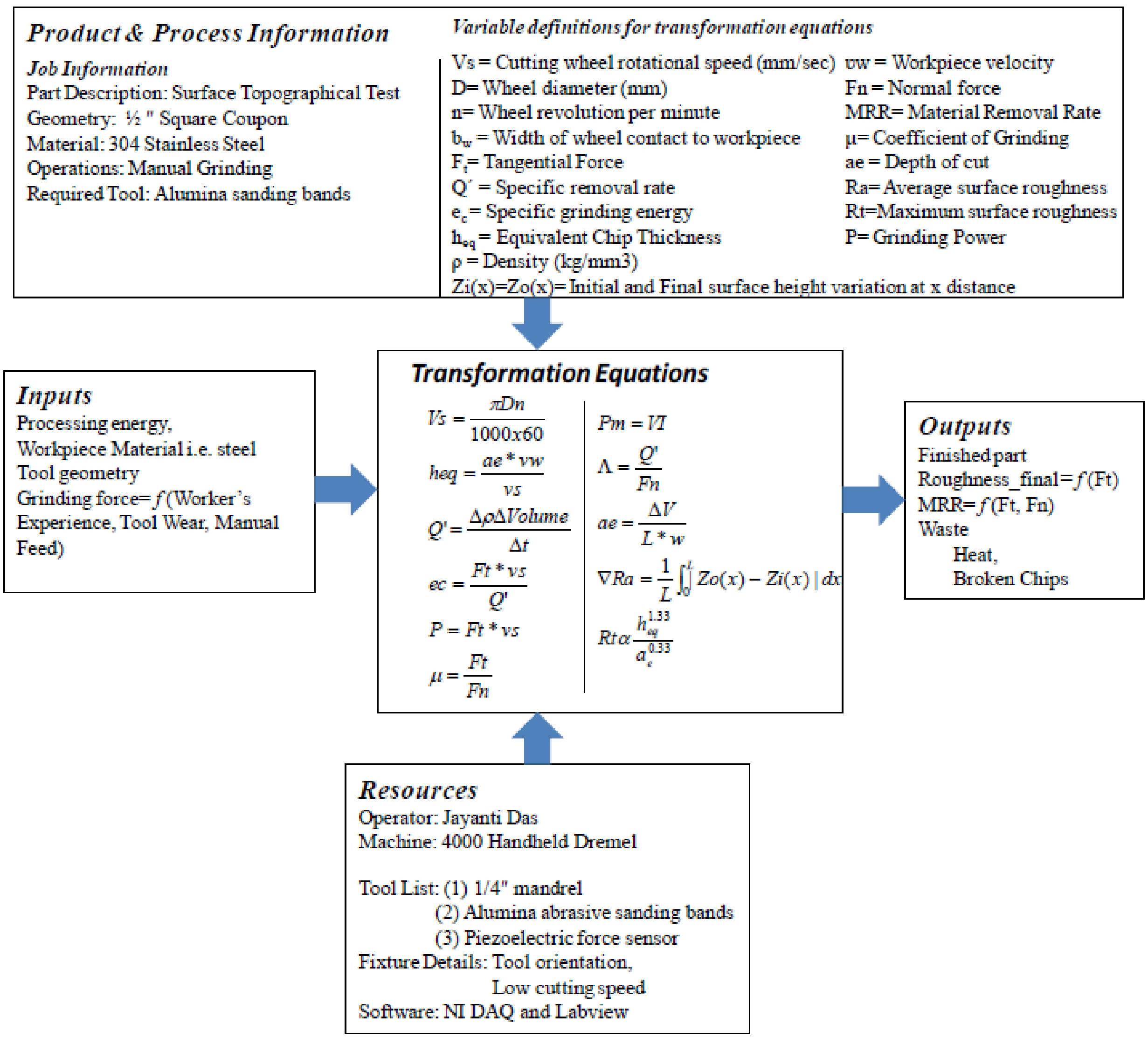

Figure 2. An example unit manufacturing process (UMP) model for the grinding process

In addition, lessons from the workshop led to proposed revisions of ASTM E3012-16 [3]. Experience through the workshop revealed a need for more rigorous definition of the concepts presented in the standard to support consistent application and implementation. In response to this need, Committee E60.13, the ASTM Subcommittee on Sustainable Manufacturing, is revising the E3012 standard with a more robust information model. The new information model will facilitate 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, a follow-on workshop in 2018 was planned to:

1. Provide a venue for participants from industry, government labs, and academia to exhibit manufacturing process developments of their own interest;
2. Identify educational and research challenges and requirements relevant to manufacturing process model development and validation;
3. Expose the research community to developments in the recent standards for modeling manufacturing processes being proposed to the ASTM E60.13 subcommittee;
4. Identify candidate models to populate an extensible repository of reusable manufacturing process models;
5. Gather inputs on best practices for sharing, reusing, extending, and composing models of conventional and advanced manufacturing processes for characterizing manufacturing systems;
6. Develop a roadmap that defines key research gaps and strategies for addressing system-level modeling; and
7. Enable sharing of model development experiences for evaluating sustainability performance.

Workshop participation was open to everyone with broad interests in teaching undergraduate and graduate students and conducting basic and applied research in analytical methods for sustainable manufacturing. Academic researchers with foci in advanced manufacturing, nanomanufacturing, and engineering education were particularly encouraged to attend. Participants in the NIST RAMP Competition were also encouraged to attend, since they had practical (application) knowledge based on their work completed to supply an entry to the challenge. Competitors from the NIST RAMP Competition were invited to present and receive feedback their work at the poster session (Session 3) from a panel of experts.

3 2018 WORKSHOP OUTCOMES

The 2018 workshop, titled *Challenges in Representing Manufacturing Processes for Systematic Sustainability Assessments*, supported by the NSF Nanomanufacturing program, was held in conjunction with the 2018 ASME MSEC and the 46th SME NAMRC conferences on June 21, 2018 at Texas A&M University, College Station, TX, and sponsored by ASME, ASTM International, NIST, NSF, and SME. Expected outcomes of the workshop were to identify needs for UMP characterization to support system-level sustainability assessment, to define limitations in associated engineering education and research practices, and to prioritize the challenges to be pursued by the advanced manufacturing research community to best meet industry needs in adopting and applying analytical methods for improving process and system performance.

The workshop was comprised of two half-day sessions and an evening poster session, and engaged the research community in discussions of emerging topics in advanced manufacturing, nanomanufacturing, sustainable manufacturing, and engineering education. The workshop hosted 46 student participants from the NIST RAMP Challenge competition [4], which included six teams of 23 student finalists. Also, there were two dozen participants from industry, academia, and government labs (Figure 3). As part of the workshop, undergraduate and graduate students were able to present their research in manufacturing process development, process modeling, and sustainability performance assessment in the morning session. After the student presentations, workshop organizers presented use cases of applications exploring unit process modeling and system composition, including those from industry, research, and educational settings, in the form of lightning talks.

Figure 3. The workshop hosted attendees from industry, academia, and government labs.

The afternoon session started with a schema refinement activity, which was organized by NIST. This activity focused on identifying improvements to the current XML (eXtended Markup Language) schema defined in the ASTM E3012-16 standard. Feedback was collected from the workshop participants who had implemented the schema. Following the schema refinement activity, a brainstorming session was conducted. Brainstorming focused on identifying challenges and barriers in six topical areas: advanced discrete manufacturing processes, nanomanufacturing at scale, additive manufacturing, process level sustainability assessment, system level sustainability assessment, and engineering education in advanced manufacturing. Identification of challenges and barriers were limited to metrics and indicators, models and algorithms, and tools and methods for each of the six topical areas. The workshop ended with an award ceremony for the RAMP competition and best posters presented at the workshop.

4 RAMP COMPETITION FINALIST TALKS

As noted above, the morning workshop session began with presentations from the NIST-hosted 2018 RAMP Challenge competition on modeling UMPs. The theme for the 2018 RAMP Challenge competition was *Tracking Resources and Flows through the System*. Competition finalists were invited to present their work during the workshop, and six finalist teams presented their RAMP submissions at the workshop. Brief synopses of their presentations are provided below.

4.1 A PRODUCTION LINE FOR POLYLACTIDE BUSINESS CARD HOLDERS

The RAMP Competition submission by Ian Garretson and Barbara Linke (*University of California, Davis*) along with Henning Voet, Björn Falk, and Robert Schmitt (*RWTH Aachen University)* focused on tracking resources and flows of a manufacturing system. As a case study, the research focused on a polyactide business card holder as the product to characterize the material flow. The methodology included composition of a set of UMPs to conduct a material flow analysis and minimize waste. Production of the case study product involved several manufacturing processes, including 3D printing, vibratory finishing, laser engraving, and packaging. Each manufacturing process was evaluated based energy consumption which also tracked flow of material, waste heat, and emissions. Physics-based models were developed for each manufacturing step. These models were validated using a real-time experimental setup. Extensions of the research will improve the UMP models to better represent the various process phases (e.g., start-up, travel, and processing) of manufacturing by comparing model results to in-process data.

4.2 SUSTAINABILITY ANALYSIS OF STEREOLITHOGRAPHY USING UMP MODELS

The RAMP Competition submission by Timothy Simon, Yiran Yang, Wo Jae Lee, Jing Zhao, Lin Li, and Fu Zhao (*Purdue University*) emphasized sustainability analysis of the stereolithography process. Stereolithography requires complex manufacturing equipment involving multiple sub-systems (e.g., computer, control board, projector, and motor) making it a challenge to model for sustainability characterization. Detailed models for each of the sub-systems were developed to calculate energy use and track material flow. Simplified sub-system models were composed to represent the stereolithography manufacturing system. The composed model and individual sub-system models were then validated using experiments. The complex models and simplified models improve sustainability characterization of stereolithography process and thus enable better design techniques like build strategy, part orientation, design alterations, and composability of stereolithography process to other manufacturing processes.

4.3 AGGREGATING UMP MODELS TO ENABLE ENVIRONMENTAL IMPACT CHARACTERIZATION OF POLYMER-BASED HYBRID MANUFACTURING

The RAMP competition submission by Sriram Manoharan and Dustin Harper (*Oregon State University*) was on characterizing a polymer-based hybrid manufacturing system. A hybrid manufacturing system is a combination of two or more manufacturing processes, tapping into the benefits of those manufacturing processes for efficient production. For this research, the case study hybrid system combined CNC milling (subtractive manufacturing) and fused filament fabrication (additive manufacturing). Thus, this approach focused on exploiting the benefits of both additive and subtractive manufacturing. UMP models of both systems were developed for sustainability characterization. A decision support tool was also developed for determining the optimal manufacturing sequence. The models were demonstrated using four parts of varying complexity to determine the energy efficiency of a hybrid manufacturing process compared to conventional manufacturing processes (milling).

4.4 UMP MODEL FOR FLEXIBLE MANUFACTURING SYSTEM

The RAMP Competition submission by Feng Ju, Daniel McCarville, Hashem Alshakhs, Weihao Huang, Xuefeng Dong, Hussain Alhader (*Arizona State University*) focused on sustainability characterization of a flexible manufacturing system. The research was conducted on a case study of LEGO car production. Material flow analysis was done to track flow of raw material; waste was the key performance indicator. The research focused on improving sustainability performance by determining emissions and cost of production. A UMP model was developed for the two robotic arms and 3D printer that processed parts. The UMP model focused on reducing idle time and cycle time of production and assembly, thereby improving the sustainability performance of the system. Model performance (goodness of fit) analysis was conducted to validate if results of the regression model of the samples could be extended to the population the samples had been chosen from.

4.5 DATA DRIVEN UMP MODEL FOR MONITORING SPECIFIC ENERGY IN SURFACE GRINDING PROCESS

The RAMP Competition submission by Zhaoyan Fan and Sai Srinivas Desabathina (Oregon State University) was to develop a data-driven UMP model to indirectly measure specific grinding energy in a surface grinding process. Their model was based on the multi-sensor fusion concept. Measurement of specific grinding energy is usually made using a single force sensor (dynamometer). Applicability of a dynamometer is limited by its cost. Their research focused on identifying multiple process variables that correlate with specific grinding energy and on developing a data-driven model using those variables as inputs to indirectly measure specific grinding energy. In this method, multiple low-cost sensors can be used. Raw sensorial data was processed in time and frequency domain to extract features. Features are fused together using data-driven modeling techniques such as artificial neural network to indirectly estimate specific grinding energy. Process variables that correlate well with the specific grinding energy are vibration, sound and energy consumption of the spindle motor and grinding machine. Experimental validation of this technique presented accuracy of this technique as 73%. The future work entails development of models using other data-driven modeling techniques such as support vector machines.

4.6 GRINDING ANALYSIS AND MODEL

The RAMP Competition submission of Justin Canaperi, Yongxin (Jack) Guo, John Park, Jun (Albert) Yang, and Yuki Yoshinaga (*Stony Brook University*) focused on developing a new aggregated model of cylindrical and surface grinding. The research focused on waste and production time reduction. Two models for the grinding methods were developed and validated using experiments. Based on the experiments conducted, an optimal working condition for both the manufacturing processes were proposed for better sustainability performance. This would eventually lead to efficient use of energy and materials within the process, thereby reducing waste and having lower environmental impacts.

5 WORKSHOP LIGHTNING TALKS

Following the presentations by the RAMP finalists, lightning talks were presented by experts from across the advanced manufacturing domain. These talks were intended to report an ongoing activity (or activities) within the domain and to allow the experts to present their perspective on the current and future challenges related to their research activities. These talks provided context for the discussions held later in the afternoon session to identify and discuss the extant challenges in advanced manufacturing research.

As described in greater detail below, lightning talks were presented by Dr. Khershed Cooper (nanomanufacturing research at NSF), Dr. Ajay Malshe (standardization and scaleup of nanomanufacturing processes), Mr. Kevin Lyons (standardization and scaleup of additive manufacturing processes), Dr. Fazleena Badurdeen (educating engineers on sustainable manufacturing), Dr. Barbara Linke (modeling manufacturing processes), Ms. KC Morris and Mr. Arvind Shankar Raman (an approach for modeling of manufacturing processes and manufacturing systems), and Dr. Alex Brodsky (reusable model repository for manufacturing systems).

5.1 ADVANCED AND NANOMANUFACTURING RESEARCH AT NSF

Dr. Khershed Cooper is a Program Director in the NSF Division of Civil, Mechanical & Manufacturing Innovation (CMMI) with responsibilities in Nanomanufacturing (now Advanced Manufacturing (AM)), the Network for Computational Nanotechnology (NCN), and Semiconductor Synthetic Biology for Information Processing and Storage Technologies (SemiSynBio). Dr. Cooper's lightning talk discussed various NSF programs that address the growing demands and challenges of advanced manufacturing. He also presented several specific approaches that have been pursued to address needs for scalability in nanomanufacturing under NSF funding.

Some NSF programs Dr. Cooper highlighted included Cybermanufacturing (CM), Manufacturing Machines and Equipment (MME), and Designing Materials to Revolutionize and Engineer our Future (DMREF). In his presentation, he noted that cybermanufacturing systems aims to "…create an interoperable, cross-process manufacturing service layer, built upon app-based infrastructure for manufacturing processes." MME often targets mass customization through on-demand fabrication of complex parts in small lots. Immediate scalability challenges being addressed by MME research are often associated with quality control. Maintaining quality control in additive manufacturing is a challenge due to large product variety and small batch sizes. Cooper noted that the purpose of the DMREF program is to *accelerate materials discovery and development*. The program has a cyclical approach that transitions from computation to experimentation, and then to application. For a list of the NSF programs discussed, see Appendix A. These programs often focus on improving methodologies and approaches to alleviate challenges associated with additive manufacturing and nanomanufacturing, as discussed next.

After discussing NSF programs that could be utilized to support advanced manufacturing research, Dr. Cooper presented the goals and challenges of Nanomanufacturing (NM). He defined nanomanufacturing as "…fabrication of nanoscale building-blocks (nanomaterials, nanostructures), their assembly into higher-order structures, and the integration of these into larger scale systems with manipulation and control of matter at the nanoscale." The main challenges that Cooper discussed were related to processes, metrics, precision, speed of production, scaling up unit processes to use, and integration and packaging. The goals for nanomanufacturing as outlined in his talk are to establish fundamental principles for nanoscale manufacturing processes that enable novel materials, structures, devices, and systems, and to achieve scalable pathways from nanomaterials and nanodevices to nanosystems and nano-enabled products. To accurately identify and assess challenges, desired outcomes need to be outlined. Processes, production methods, and product requirements are the principal contributors/determiners to successful manufacturing. Processes should be controllable, reproducible, repeatable, and reliable. Production methods should be scalable, affordable, safe, and have high yields and efficiency. Products should be of high quality, durable, and exhibit desired performance and functionality. With these factors in mind, the appropriate metrics to be evaluated can be determined, such as precision of placement, feature size, and density.

Ongoing research funded by NSF strives to address the nanomanufacturing challenges mentioned above. Core nanomanufacturing research aims to enable and improve large-scale or customized manufacturing of nanomaterials and nanostructures. The Scalable Nanomanufacturing for Integrated Systems (SNM-IS) program studies and formulates fundamental principles of scalable or customized manufacturing as well as process integration for nanotechnology-based systems towards the eventual manufacturing of useful nanotechnology products in areas such as medicine, electronics and fuel cells. Another area of research in nanomanufacturing at NSF includes materials and structures, which encompasses 0D to 3D structures and material systems. Nanomanufacturing process-related research includes chemical, lithography, assembly, and 3D nanomanufacturing. Additionally, research investigates environmental, chemical, structural, and sensing and biomedical applications.

Improving the scalability of nanomanufacturing will continue to pose dynamic challenges as technological advancements are made. These challenges are related to throughput, quality, and yield, among others. To identify solutions to these challenges, Cooper posited that an awareness of current methods of scalability is necessary. He discussed some of the scale-up methods being used and highlighted some of their respective limitations. Continuous roll-to-roll processing (top-down or bottom-up), for example, is a currently used method that requires further advancement due to its unrealized potential for high throughput and wide applicability. Current areas of research in roll-to-roll processing include imprint embossing and patterning, use of alternative conducting layers, nanoporous membranes, and functional hybrid films. Existing research gaps include in-line inspection and testing equipment, design and simulation tools, and high performance inks for applications such as organic light-emitting diode displays (flexible electronics). Another scale-up approach that has great potential in advanced nanomanufacturing is large-area 3D nanofabrication. One such implementation of this technique is using a focused ion beam (FIB) process, which works similar to scanning electron microscopy, using a beam of ions instead of electrons, as the name suggests. This technique is limited by its slow rate of slicing and alteration of samples, however, and requires further research and development to achieve higher throughput. Additional examples of scale-up approaches that have been explored are vibration-assisted convection deposition, roll-to-roll nanopatterning, micellular electrospraying of nanocomposites, and 3D printing of biomimetic scaffolds.

In closing, Dr. Cooper presented a model that described the integral role of machine learning in optimizing manufacturing processes by using predictive analysis based on large inputs of data derived from various parameters of individual processes. For example, raw materials serve as an input for an additive manufacturing system. This input has a measurable influence over certain parameters of the manufacture process, for example, part quality. Large volumes of data collected of this input in conjunction with other inputs can serve as training for a machine learning model, which assists in the predictive analysis of outputs of the manufacturing process. With a well-trained model, determination of whether or not a part will have defects, may be observed *in situ*. These inputs are fed into what is referred to as a machine learning node. Outputs are tuned from the machine learning node and fed back in for additive manufacturing process optimization.

5.2 NANOMANUFACTURING: ESTABLISHING AN EFFICIENT MANUFACTURING PLATFORM

Dr. Ajay Malshe is a Professor of Mechanical Engineering at the University of Arkansas, and has research interests and expertise in nanomanufacturing, surface engineering for advanced machining, micro-electro-mechanical systems (MEMS), micro-systems packaging, and high-density micro-electronic packaging. Dr. Malshe began his presentation by discussing some of the drivers for standardization.

The three main drivers for standardization he outlined are efficiency, yield, and a diverse operating environment. He emphasized the importance of having a business and industrial perspective of standardization, by keeping factors such as return of investment (ROI) and productive yield in mind. Efficiency is important to businesses, and therefore should be thoroughly considered in developing nanomanufacturing methods. He also discussed the importance of considering a diverse operating environment. As materials and systems continue to improve, demand will continually change. Appropriate adaptations need to be implemented as nanomanufacturing technology develops to effectively react to diverse operating environments.

Dr. Malshe next discussed the future of nanomanufacturing; specifically discussing where he anticipates future research efforts to focus. He introduced three waves of nanomanufacturing: 1) nanoparticle-based production; 2) nanoscale template-based production; and 3) true self-assembly for production. Nanoparticle based production is broken into two main categories: Top-down and bottom-up approaches. The top-down approach is analogous to sculpting a statue out of marble, where the sculptor starts with a large base of material, and etches away unwanted material to reach a specific final shape. On the other hand, bottom-up nanoparticle production is analogous to building a house, brick by brick. Instead of bricks, the construction of a product is atom by atom. Top-down approaches are the predominant method, as bottom–up approaches have not yet been refined to the point of being commercially available to manufacturers. This lack of refinement creates a potential for future research endeavors pursuing process improvement of bottom-up approaches. Bottom-up approaches utilize the concept of molecular self-assembly inherent in supramolecular chemistry. Molecular self-assembly is the organization and construction of systems without the influence of an outside force [5]. This method has obvious benefits, such as the placement of nanoparticles, which is one of the most difficult steps of nanofabrication. However, Dr. Malshe warned of the disadvantages associated with use of the term *self-assembly*, as it describes a utopia-based process. He pointed out the fact that processes involving self-assembly have inherent limitations that may or may not be able to be overcome.

Dr. Malshe proceeded to discuss two eminent objectives in nanomanufacturing. Objective 1 is based on the three Rs: Repeatability, Reliability, and Reproducibility. Regarding these aspects, he emphasized the need to account for the fact that less technically able individuals may drive some downstream operations. In addition to this possibility, he also made the point that industries are interested only in large-scale (100-200%) efficiency changes. Researchers in nanomanufacturing may lack the perspective of industry when considering these three Rs. Research initiatives in nanomanufacturing will need to focus on the needs and applicability to industry. Malshe introduced Objective 2, which involves the three Ps: Product, Productivity, and Producibility. Products should be scalable and minimize waste. Thus, the conclusion logically arises that research advancing the scalability of products and waste minimization should be a major focus for academia. Second, the perception of products is a reality, according to Dr. Malshe, and he advised that the customer's attitude toward the product should be considered. These considerations can be achieved by marketing the product in a way that induces positive perception.

Dr. Malshe presented some of the current limitations of nanomanufacturing through the lens of an industry perspective. One limitation he discussed was the increasing stress levels in the research lab because of a dramatically changing *invention-to-product* life cycle. Additional limitations are due to the complex solutions required in nanomanufacturing. He described a need to account for the frequency of products changing hands and recommended gaining industry exposure before contributing to lab research to gain perspective. As Dr. Malshe sees it, research ideas start on the industry shop floor. He sees a missing link between research and industrial application. To mitigate this gap, researchers should identify market pulls. The overall vision Dr. Malshe described is the need for *manufacturing science and engineering research to support the development of 3Rs and 3Ps for sustainable nano-manufactured products with ROI.*

5.3 SYSTEMS INTEGRATION FOR ADDITIVE MANUFACTURING – SUPPORTING INFRASTRUCTURE FOR PROCESS CHARACTERIZATION

Mr. Kevin Lyons is a senior research engineer in the Systems Integration Division at NIST with research interests in design and manufacturing processes for sustainable manufacturing, assembly, additive manufacturing, simulation and modeling, and nanomanufacturing. He presented on additive manufacturing and began by giving an overview of the process. Additive manufacturing begins with computer-aided design of the product to be fabricated, which is followed by additive manufacturing process design, build, post processing, and verification and validation. Lyons then discussed three main research topics: Industry drivers, research challenges, and scientific and engineering approaches for additive manufacturing.

Regarding industry drivers, Lyons stated that limited connectivity exists between additive manufacturing lifecycle activities and supply chain activities. He identified a disconnect between the various additive manufacturing software tools, in addition to a limited process understanding and knowledge for design decision support [6]. The management and representation of additive manufacturing models and knowledge are isolated in industry. Data is generated individually and becomes costly through additive manufacturing lifecycle activities with limited coordination among industry partners. Additionally, because of the heterogenous nature of additive manufacturing process models, it is difficult to combine them. Lyons identified a strong need for higher levels of collaboration in data collection methods and processes in industry.

One of the predominant related research challenges Lyons posed is the collection and curation of additive manufacturing data. Mass data collection methods are rapidly improving; hence, the capabilities of data management must be improved to be able to best utilize the data. Further, the diversity of additive manufacturing operating environments gives rise to several important questions: How do researchers integrate across the various process models while considering the inherent complexities, underlying assumptions, and constraints? How should these models be coordinated (collected and shared) and maintained? Process models and information must not only be made available, but must be beneficial to users across the additive manufacturing community. Arguably, the most important question is: How are these models validated?

As a new process domain, these questions are at the forefront of the additive manufacturing research. Solutions will require innovative thinking and advanced organization. There will need to be methods in place, for example, to facilitate knowledge management and finding the best fitting model for different applications. Lyons advocated for a means of combining process models for system-level views, which will require the development of new tools to accomplish manufacturing process model composability. These process models will be comprised of data-driven, physics-based, and hybrid models, and underpin decision support and decision making tools.

In addition to process data management, model development and adaptation, and decision support, methods of accurately determining and verifying quality are paramount. Lyons introduced the Additive Manufacturing Benchmark Test (AM-Bench) as an approach to develop an effective means of quality control. AM-Bench is "a continuing series of highly controlled benchmark tests for additive manufacturing, with modeling challenge problems and a corresponding conference series" [7]. The primary goal of AM-Bench is to "allow modelers to test their simulations against rigorous, highly controlled additive manufacturing benchmark test data" [4]. AM-Bench has a growing breadth of benchmarks, including a wide range of additive processes and materials, e.g., for metals, polymers, ceramics, and composites. Metals, such as steels, nickel-based super alloys, and titanium alloys, and associated processes, such as powder bed fusion, binder jet, and direct energy deposition, are within the scope of AM-Bench. AM-Bench is based on a cyclical two-year plan. Although the breadth of AM-Bench is extending, the growing scope of additive manufacturing methods and materials poses a major challenge to developing benchmark tests.

Lyons also discussed Design for Additive Manufacturing (DfAM), which is an approach to characterize performance and other lifecycle considerations using design methods or tools for additive manufacturing optimization. He discussed several drivers of DfAM, such as providing manufacturers an approach to capture design rules for additive manufacturing processes while using formal representations. Additionally, DfAM provides the architecture to derive design rules in a computer-interpretable way to allow the effective exchange of additive manufacturing information; an ontology is being used to develop a better understanding [8]. The DfAM ontology establishes relationships between design features and design parameters which were linked to manufacturing processes and material parameters. These relationships provided a method of choosing the desired set of manufacturing process parameters and materials for the production.

5.4 CHALLENGES TO EDUCATION ENGINEERS ABOUT SUSTAINABLE MANUFACTURING

Dr. Fazleena Badurdeen, is a Professor of Mechanical Engineering at the University of Kentucky with research interests in modeling and analysis of manufacturing systems and supply chains for the development of tools and techniques to enable value creation through sustainable manufacturing. She presented on challenges to educating engineering students about sustainable manufacturing.

Badurdeen began with an introduction to sustainable manufacturing, outlining the need to demonstrate reduced negative environmental impact, to offer improved energy and resource efficiency, to provide operational safety, and to offer improved personal health, all at the product, process, and systems levels. She introduced a 6R approach for sustainable manufacturing, which includes reduce, recycle, reuse, recover, redesign, and remanufacture. Throughout the lifecycle of a product, these 6Rs are continually implemented, such as redesign activities during the manufacturing stage [9]. She continued by describing product-process-system integration for sustainable manufacturing. Product innovation incorporates sustainable materials, advanced product design, design for reuse and remanufacturing, effective product disassembly/recovery, modular and reconfigurable design, and design for improved performance. Process innovation includes sustainable processes, advanced process technologies, integrated processes, and improved process performance. System innovation capitalizes on sustainable systems, enterprise level system integration, and supply chain integration. The three components, i.e., product, process, and system integration, are all drivers of sustainable manufacturing.

According to Badurdeen, *realizing sustainable manufacturing innovations requires developing an educated and skilled workforce.* This idea falls directly in line with the United Nation's Sustainable Development Goal Number 4: *Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all* [10]. She introduced a lifecycle approach to recruit, reeducate, and retrain at all levels for building the workforce pipeline [11]. Additionally, she emphasized a need for a multi-disciplinary approach to address sustainable manufacturing challenges that incorporates convergent research and education. As the NSF describes, *convergence research is a means of solving vexing research problems, particularly complex problems focusing on societal needs. It entails integrating knowledge, methods, and expertise from different disciplines and forming novel frameworks to catalyze scientific discovery and innovation* [12]. To achieve this, Badurdeen stated that a continuous effort of collaboration between key stakeholders, such as universities, industry, and state/federal agencies is required.

Badurdeen noted various programs and opportunities that facilitate efforts to bolster sustainable manufacturing education. For example, the NSF Education and Human Resources (EHR) Directorate sponsors programs such as the Research on Learning in Formal and Informal Settings (DRL), as well as programs in the Division of Undergraduate Education (DUE). These programs promote activities that strengthen STEM education and intend to prepare future STEM leaders for a rapidly developing work environment. Appendices A & B summarize these and other programs.

5.5 UNIT PROCESS LIFE CYCLE INVENTORY (UPLCI)

Dr. Barbara Linke, an Associate Professor of Mechanical Engineering at the University of California-Davis, has research interests in sustainable manufacturing, abrasive machining technologies, and smart and data-driven manufacturing. Dr. Linke presented on the Unit Process Life Cycle Inventory (UPLCI) effort to characterize a broad set of manufacturing processes.

A UPLCI uses industrial information for a single manufacturing process (a machine) to estimate material inputs, energy use, material loss, and dependency on product design. Several UPLCIs are integrated together to evaluate a sequence of manufacturing processes (a production line) leading to a completed part or product [13]. UPLCI is a multi-institutional effort by Katholieke Universiteit Leuven, Northeastern University, Oregon State University, Purdue University, University of California-Davis, University of Michigan, University of Virginia, University of Wisconsin, and Wichita State University. UPLCIs follow a clear template, are easy to follow, and have breadth to allow different metals, plastics, and designs. Each takes about one month of development time, suitable for graduate class project or part of thesis. Moreover, the *Production Engineering - Research and Development* journal, sponsored by the The German Academic Society for

Production Engineering (Wissenschaftliche Gesellschaft für Produktionstechnik, WGP) and published by Springer, will publish peer-reviewed UPLCI.

Thirty-one UPLCIs have been created, with categories including: heat treatment, surface finishing, joining, auxiliary, material conversing, and material reducing. Two are now available through the journal indicated above. The general procedure for UPLCI development uses rules of engineering and industrial practice to estimate LCI energy and mass loss. First, when calculating LCI energy, the direct, incremental energy to accomplish the unit process task is considered. Additionally, fixed energy from auxiliary systems active during idling times of equipment are analyzed. Second, LCI mass loss calculations consider basic materials (e.g., metal loss from a drilled hole), auxiliary chemicals (e.g., cutting fluid), and unit process malfunctioning.

Linke described how the UPLCI focuses on the various machine energy levels during operation. The unit process is decomposed into physics-driven equations that describe energy consumption. Process energy consumption states of the candidate unit process are defined, such as basic operating power, idle power, and grinding power, as well as associated times, for a grinding operation. These process parameters are annotated in the form of a capital letter followed by subscript descriptive of the nomenclature. P_{basic}, for example, is the variable name for the basic operating power of the candidate machine.

Linke followed up her discussion of UPLCI by introducing an in-depth approach for process inventory development under the Cooperative Effort on Process Emissions in Manufacturing (CO2PE!) initiative. The first objective of the CO2PE! initiative is to "[s]tudy the environmental footprint of manufacturing processes with energy consumption/CO_2 emission as first priority" [14]. This methodology for evaluating discrete part manufacturing consists of three studies: energy study, consumables study, and emissions study. The energy study is comprised of a power study (evaluating power consumption) and time study (performing operational mode identification and scenario determination). The consumables study identifies the process materials used (e.g., compressed air, lubricants, and tooling) and evaluates the consumption of these consumables during processing. The emissions study involves identification and determination of emissions produced during the process.

Linke concluded by discussing challenges encountered during the creation of UPLCI, including data quality and availability, reduction of complexity while remaining generic, managing empirical models, materials and energy-dependence based on machine setup, and an unclear vision of whether auxiliary processes are to be included or not. As UPLCI researchers and practitioners continue to address these problems, the demand for inventorying models will increase. Development of about 70 UPLCIs for a range of manufacturing processes is needed, which could be completed in support of a thesis or for a graduate class project.

5.6 TOWARDS A STANDARDS-BASED METHODOLOGY FOR EXTENDING MANUFACTURING PROCESS MODELS FOR SUSTAINABILITY ASSESSMENT

Ms. KC Morris, a Group Leader in the Information Modeling and Testing Group at NIST, and **Mr. Arvind Shankar Raman**, a Graduate Research Assistant at Oregon State University, presented a standards-based methodology for extending manufacturing process models for sustainably assessment. Morris has research interests in smart and sustainable manufacturing, and techniques for design, testing, and evaluation of systems and standards. Shankar Raman has research interests in advanced manufacturing with a focus on standardized information modeling of manufacturing processes and manufacturing systems, enabling sustainability characterization.

Morris and Shankar Raman discussed the motivation for companies to pursue sustainable manufacturing practices, considering factors such as social responsibility, investor demands, government regulations, international standards, and customer consciousness. However, they noted a considerable number of challenges exist. For instance, most manufacturing assessment tools are focused on the economic and environmental aspects of sustainability, while little attention has been paid toward the social dimension. As manufacturing processes advance and the demand for high technology products increases, the need for effective assessment tools for engineers and other decision makers will also increase across a wide range of processes, materials, and products.

In particular, analysis applications are often deficient in supporting integrated system-, process-, and machine-level manufacturing decisions. Data collection and reporting within and across supply chains remains a large challenge for manufacturers. As mentioned previously, efforts have been made to characterize manufacturing processes, including the UPLCI and CO2PE! initiatives. However, these methods are focused on developing information models that are distinct and specific, making them extremely limited in their extensibility. In other words, without a deep, technical understanding of the manufacturing process, these methods can be difficult to adopt and apply to different product designs and production settings. Additionally, to build up a process library, process models must be developed from the ground up, based on empirical data or by developing a physical understanding of the process. These approaches require time and resources often not available within manufacturing companies, especially in small and medium-sized businesses. Thus, the question to address becomes: How can researchers develop methodologies that allow industry to collect, analyze, and disseminate data-driven conclusions about sustainability factors linked to unique manufacturing processes?

Shankar Raman discussed the idea of model extensibility, which is the reuse and abstraction of an already existing model, e.g., a template model of a process, by adding new information layers to the prior model of the process. These layers could either constitute auxiliary systems, such as exhaust gas pressure control systems, monitoring equipment, and electric boosting systems, or may constitute a higher-order variant of the manufacturing process considered [15]. A template model is the most basic machine form for any manufacturing process or similar manufacturing processes that has multiple alternatives of machine types. The template model can then be expanded to accommodate models for similar machine configurations or higher complexity machine configurations depending on the specificity of the manufacturing process in application. An example would be a manual drill. A model developed for the manual drill is defined as the template model. As all drills of similar type or variations such as electric hand drill or a drill press can be instantiated by making alterations to the template model. From an object-oriented programming standpoint, template models may be defined as abstraction models. The method could also be applied for removing layers from a detailed information model for abstracting the model (to form a new template model). For the purposes of the research, addition of layers has been previously considered [16]. Shankar Raman and Morris suggested this research could lay as the foundation for the advanced manufacturing community to characterize data exchange between multiple manufacturing processes for characterizing sustainability performance of a manufacturing system.

5.7 TOWARD FACTORY OPTIMA: A WEB-BASED SYSTEM FOR COMPOSITION AND ANALYSIS OF MANUFACTURING SERVICE NETWORKS BASED ON A REUSABLE MODEL REPOSITORY

Dr. Alex Brodsky, a Professor of Computer Science at George Mason University, has research interests in Decision Support, Guidance, and Optimization (DSGO) systems, and their application to manufacturing, supply chains, energy, and sustainability. Brodsky presented a web-based system, called Factory Optima, for composition and analysis of manufacturing service networks based on a reusable model repository [17].

Brodsky's previous work, which serves as the foundation for the work he presented, was involved architectural design for rapid, software solution development for descriptive, diagnostic, predictive, and prescriptive analytics of dynamic production processes. The proposition of this architecture was in response to the limitations of decision-making tools and models that enable smart manufacturing. One such limitation is the fact that most analysis and optimizations tools are currently developed from scratch, which leads to high cost, long-duration development, and restricted extensibility. Additionally, there are numerous computational tools designed to model individual activities, which require the use of specialized, low-level mathematical abstractions. This operating environment fosters the development of various tools that model the same manufacturing knowledge. This previous proposition for an architecture that addresses these limitations was unique in the way that the middleware layer was based on reusable, modular, and an extensible knowledge basis. However, this architecture lacked systematic design of the UMP and was based on linear functions as opposed to real-world process models which are physics-based and typically non-linear. Additionally, the original architecture did not take into consideration the composability of UMP models into a hierarchy of service networks. In his presentation, Brodsky discussed work toward addressing these deficiencies.

A manufacturing service network used in this context is defined as *network of service-oriented components that are linked together to produce products or product service systems (PSS) to meet some demand*. The various components of a service network include a vendor, contract manufacturer, internal manufacturer, and production line. The vendor describes *an organization that provides a finished product*. The contract manufacturer describes *an organization that provides a manufacturing service, e.g. precision welding, mold-making, and precision machining*. The internal manufacturer describes *an internal activity "controlled" by the original equipment manufacturer (OEM) of the PSS*. The production line describes *a chain of Internal Manufacturer activities. It is assumed that a production line is also "controlled" by the OEM*. Brodsky explained how these terms can describe decision paths to the realization of a PSS based on demand. Each of these components, he explained, can be characterized using a performance model (PM) where the parameters can be adjusted to find optimal settings for the network. Having each activity in the service network allows for the possibility of posing questions that, if answered, can facilitate achieving specific objectives.

Factory Optima is a high-level system architecture based around a reusable model repository and the Unity Decision Guidance Management System (Unity DGMS). The architecture consists of upper tools, middle tools, and lower tools. Upper tools entail a web interface connected to the Unity server. Unity DGMS *automatically generates low-level mathematical programming optimization models from simulation-like performance models* [18]. The middle tools communicate with the DGMS middleware, which consists of Unity DGMS, a model repository and model description and discovery services. Lower level tools are connected via Unity tool management, and contain statistical machine learning, mathematical programming and constraint programming solvers, data manipulation, and analysis.

The proposition, as Brodsky describes, is a software framework and system for composition, optimization, and trade-off analysis of manufacturing and contract service networks. This work is unique in its ability to perform tasks on arbitrary service networks without manually crafting optimization models. Brodsky discussed the goal of a web-based end-user facing graphical user interface (GUI), as opposed to the closed-network ATOM IDE, a framework that enables cross-platform (MacOS, Windows, and Linus) desktop applications, which is currently being used. Additionally, the intention is to use an industrial case study to further develop the architecture. Future work also includes stochastic optimization based deterministic approximations, and model calibration and training.

6 SCHEMA REFINEMENT ACTIVITY

The schema refinement activity was focused on garnering feedback from RAMP 2018 participants regarding the revision of the ASTM E3012-16. This revision is mainly focused on extending and strengthening the schema presented in ASTM E3012-16. One of the key goals of ASTM E3012-16 is to characterize and record UMP models in a consistent manner to promote re-use and sharing of the UMP models. The current schema provided in the standard does not explicitly support this activity. This was apparent when NIST hosted a modelling challenge in 2017 with ASTM E3012-16 as a requirement. The submissions rarely conformed to ASTM E3012-16. In response, NIST designed a more detailed schema for the second version of the competition, RAMP 2018, to ensure that the standard is followed more closely by process modelers. NIST also proposed some additional 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 traceability of the models. This session was conducted by Dr. Bill Bernstein and Dr. David Lechevalier.

The activity lasted for about one hour and there were about 40 participants. To begin, all 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 [19], on their personal devices (e.g., mobile phones, laptops, tablets). The activity proctors prepared a board with six sections: *keep doing*, *start doing*, *stop doing*, *less of*, *more of*, and *action items*. These labels abide by the Star Fish Retrospective method [20], a well-known organizational management tool to garner feedback regarding a process. Participants were asked to anonymously post concepts, ideas, and suggestions related to each category. The online tool also allowed for up-votes, wherein workshop participants could show their agreement with ideas posted to the boards. Once concepts were posted to the board, participants volunteered to provide a verbal explanation of their ideas.

From the activity, based on the number of votes, two concepts highly outweighed the others. RAMP 2018 participants want more examples of models, specifically industry-relevant ones (19 total votes). Also, there is a considerable need for better definitions and documentations for the elements and attributes within the schema (7 total votes). Another key takeaway is that with proper tools and frameworks, there would be fewer barriers to the use of UMP information models. NIST provided a free open-source tool, the UMP Builder [21], for RAMP participants to use to construct and visualize their models. Improvements to the UMP Builder and the development of additional tools will help users. One example of a new feature that would provide value is the ability to link to master data, describing validated database entries that can be reused and extended. Based on comments received, a critical future direction would be to demonstrate the use of the revised schema in an industrial setting. Validating the approach at scale would garner more interest and use of the standard. This validation could be facilitated by the generation of models (or adaptation of manufacturing process models) undertaken by advanced manufacturing researchers.

7 BRAINSTORMING DISCUSSIONS AND REFLECTION ACTIVITY

Parallel brainstorming discussions were facilitated by six subject matter experts (the workshop presenters introduced above and I.S. Jawahir, a Professor of Mechanical Engineering at the University of Kentucky). Discussions were guided by Karl Haapala, an Associate Professor of Manufacturing Engineering at Oregon State University, and focused on six categories introduced in Section 7.1. Scribes captured the ideas generated during three timed sessions. These ideas are summarized in Section 7.2.

Each group discussed challenges and opportunities related to metrics and indicators, models and algorithms, and tools and methods. Participants first distributed themselves among the six topic areas and then advanced through facilitated discussion rounds to brainstorm ideas related to the topic in a timed manner. The structure of this breakout session allowed for a continuous flow of perspectives and ideas that were guided toward identifying challenges and approaches to overcoming them for each topic.

The final stage of this afternoon workshop session involved an individual reflection activity, which posed two questions: *What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?* and *What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?* Participants recorded their individual responses to these questions on notecards, as described in Section 7.4.

7.1 BRAINSTORMING SESSION METHODOLOGY

The parallel brainstorming sessions were led by workshop organizers; each coordinating a guided brainstorming station. There were six stations: *Advanced Discrete Manufacturing Processes*, *Nanomanufacturing at Scale*, *Additive Manufacturing*, *Process Level Sustainability Assessment*, *System Level Sustainability Assessment*, and *Engineering Education in Advanced Manufacturing*. Additionally, each organizer was supplemented with a scribe to capture collaborative notes and ideas developed during the timed session. The talking points of each group were broken down into *Metrics and Indicators*, *Models and Algorithms*, and *Tools and Methods*. Any other topics brought up were recorded as well. Participants distributed themselves among the six groups and had 12 minutes per facilitated discussion round to brainstorm, whereby there were four minutes were allotted for each subtopic. There was a total of three rounds, allowing for participants to have exposure to, and the opportunity to contribute to, several topics of interest presented.

7.2 BRAINSTORMING SESSION RESULTS

The parallel brainstorming session results are reported in terms of three subtopic lines (i.e., metrics and indicators, models and algorithms, and tools and methods). Discussions revolved around challenges, barriers and solutions to overcome the identified barriers.

a) Topic 1: Advancing discrete manufacturing processes

Metrics and Indicators: Challenges include product customization, standardization, and bolstering the flexibility of processes. One key barrier is to connect process level controls and system level metrics. Modeling interdisciplinary/dynamic processes can be extremely difficult.

Models and Algorithms: The complexities in model composition and optimization pose barriers to developing flexible models and algorithms. Participants identified a need to support related product categories with similar models across multiple enterprises. Additionally, transient analysis is required for developing robust models of complex systems, especially non-steady state manufacturing elements. Scheduling intricacies pose a challenge for modeling flexible discrete systems.

Tools and Methods: Participants noted that robots, which are widely used in discrete product manufacturing, can be extensively integrated to achieve process improvements. It was also established that machine learning classifications of problems is increasingly important in advancing the understanding and optimizing the performance of discrete manufacturing processes.

b) Topic 2: Nanomanufacturing at scale

Metrics and Indicators: Participants identified some of the key metrics and indicators that need to be considered for nanomanufacturing as follows: fluid type, electron beam power, scan rate, beam diameter, material removal rate, structural resolution, feature size, tolerances, nanoparticle (e.g., silver) medium, roll-to-roll speed, printing speed, ink spread, sintering conductivity, circuit device design, and reactor design. One key barrier of nanomanufacturing, due the extreme sensitivity of the processes, is controlling process parameters to achieve defined dimensional tolerances.

Models and Algorithms: To model the metrics and indicators identified in the above, participants noted existing models and algorithms. Some of the current modeling categories include fluidic modeling, roll-to-roll modeling, circuit modeling, molecular dynamics, and density functional theory (DFT). Participants indicated that models or algorithms for other metrics and indicators of interest currently do not exist.

Tools and Methods: Participants indicated that common tools for modeling and analyzing nanomanufacturing processes include MATLAB software, scanning electron microscopes (SEM), transmission electron microscopes (TEM), computational fluid dynamics (CFD), finite element method (FEM), and finite volume method (FVM). The UMP Builder [21] was also noted as a potential enabler of process analysis. Key advancements in tools have been achieved by using machine learning (for prediction), image processing, and fuzzy logic, with advancements in computing technology and an increase in usage of artificial intelligence techniques. Key barriers of nanomanufacturing include needs for the improvement of metrological methods for precision and accuracy. Additionally, the ability to control motion components with extreme precision would improve the quality of the processes and products.

c) Topic 3: Additive manufacturing at scale

Metrics and Indicators: The participants identified several basic metrics for additive manufacturing, including temperatures, layer thickness, material uniformity, material density, extrusion rates, feed rates, internal geometries, product dimensional constraints, melt pool geometry, and build time. Quality-oriented indicators identified included surface profile, accuracy, surface finish, and repeatability. In addition, it was noted that a variety of factors can influence final part quality, including preventative maintenance, post-processing operations, and control of multi-axis equipment. However, improved methods of non-destructive inspection must be developed and implemented for measuring additively manufactured features, especially internal geometries. Current indicators of process variables are deficient in their ability to control the melt pool within desired operating ranges of existing additive manufacturing processes.

Models and Algorithms: Some of the challenges identified were limitations to support structure optimization, design features, and fidelity of current models. A need exists for topology optimization and an expression of key performance indicators (KPIs) as a function of control parameters. Participants posited cloud-based process design is needed, perhaps also combining parameterized product design with process design.

Tools and Methods: The participants desired tools and methods which are able to provide information on selection of the process type, build orientation, and material. Also, tools should be able to support metrology, in-process monitoring, quality measurement, and verification and validation. Further, cross-validation tools, sustainability decision support methods, cost models, and product design optimization methods require development and/or improvement.

d) Topic 4: Process level sustainability assessment

Metrics and Indicators: The participants indicated that metrics and indicators for sustainability at the process level include cost, productivity, quality, energy, resources, waste, environmental impacts, personal health, safety, and public policy measures - each essentially addressing at least one the three pillars of sustainability. These metrics can be difficult to identify and quantify at the process level. Safety and public policy, for example, consider societal impacts, legislative and administrative issues, and ethics, which are difficult indicators to effectively assess.

Models and Algorithms: One of the key challenges identified by the participants is the limited availability of models and algorithms that enable the assessment of process-level sustainability metrics. Physics- and empirical-based methods were discussed, as well as predictive and optimization methods. In addition, participants identified process planning, sensors, and data-driven models as disparate means to assess and improve process-level sustainability.

Tools and Methods: One topic that emerged as a necessary element of effective sustainability assessment was education. A strong need for bolstering education, e.g., through adaptable, easy-to-use, open source tools, was identified to address the growing demands and urgency for improved awareness, ability, and accuracy for sustainability assessment at the process level. Beyond education, skills training, societal influence, and behaviors were identified as approaches to communicate the importance of considering sustainability factors at the process level.

e) **Topic 5: System level sustainability assessment**

Metrics and Indicators: At the system level, lead time and resource availability appear to be the most relevant indicators, in addition to material stability and system reliability. Further, it is important to consider the interactions of multiple manufacturing processes involved at a system level, as one process feeds into the next; the connections between process models needs to be seamless to ensure more accurate metric quantification and assessment.

Models and Algorithms: It is important that models for risk assessment and for evaluating system dynamics are developed. In particular, models that accurately describe manufacturing processes were found to have an important role in robust system-level sustainability assessment. It was noted that game theory can be applied iteratively to identify critical issues. Discussions also raised the point that network models should be developed, in addition to unit manufacturing process models.

Tools and Methods: Current challenges for modeling sustainability at the system level include how to collect and sort data. Methods for defining interactions of processes within the system would be helpful. Obtaining a system-level view is essential for the task of sustainability assessment. Participants identified the potential for application of machine learning in predictive modeling of systems level sustainability. Discussions also raised the idea of diagnostic problem identification through degradation classification.

f) **Topic 6: Manufacturing engineering education**

Metrics and Indicators: An indicator for education in advanced manufacturing is an identifiable increase in confidence in manufacturing classes. Participants suggested that introducing students to advanced manufacturing at young ages (such as through the use of cartoons) would help increase their interests in advanced manufacturing-related careers. A current indicator of weak advanced manufacturing education is the lack of sustainability studies in undergraduate studies. In general, however, metrics for engineering education in advanced manufacturing were found hard to define.

Models and Algorithms: Some models and algorithms associated with engineering education in advanced manufacturing include the applicability of sustainability concepts in real life, easy-to-apply solutions and methods, and circular design. Additional models taught are design for X (DfX), e.g., design for manufacturing (DFM) and design for end of life (EOL), including considerations of cost, feasibility, and material use. It was suggested that a robust advanced manufacturing curriculum should include instruction on systems engineering models.

Tools and Methods: The tools and methods for bolstering engineering education for advanced manufacturing largely include learning in groups and sharing knowledge. It was noted that manufacturing techniques that can be taught using in-house demonstrations would be highly beneficial. Basic technical skills to be taught include physics-based classes, which participants suggested being taught in conjunction with case studies and interactive in nature (i.e., labs associated with the material). To provoke students' thinking about sustainability earlier, the group recommended tracking sustainability in real life and relating sustainability impacts to cost in industry. Hands-on exposure to learning the impacts of manufacturing and relating them to sustainability performance can be achieved through visits to manufacturing facilities, for example.

7.3 NOTECARD ACTIVITY- INDIVIDUAL REFLECTION

The final activity allowed participants to reflect on what they had heard and to offer their insights. As such, the organizers posed two questions: *What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?* and, *what do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?* Participants wrote down their answers to these questions on individual notecards.

7.4 RESULTS FROM INDIVIDUAL REFLECTION

As an open-ended first question (*What do you see as the most pressing need for advanced manufacturing research or advanced manufacturing education?*), the answers received were quite varied, but can be grouped into the following categories (percent responses so classified):

1. Linkages between academic and industrial research (24%)
2. Development of process models (20%)
3. Improvements in manufacturing education (20%)
4. Advancements in technology and methods of scalability (16%)
5. Encouragement of an interest in manufacturing (12%)
6. Validation of models (8%)

Based on these results, it can be noted that nearly a quarter of the participants reported that stronger collaboration between research and industry was the most pressing need. These responses seem to indicate participants may perceive a lack of industry-relevant, applied research in advanced manufacturing research or a lack of adoption of basic research in manufacturing industry. The second category, related to process model development, scored high as well, likely in response to the workshop discussions tailored toward addressing a need for more models to fill current characterization gaps. Somewhat surprisingly, however, validation of said models was noted as the lowest category, even though model validation was consistently presented as one of the more pressing areas of need throughout the workshop. This gap may be a result of coding of responses from overlapping categories; for example, some responses were more related to industry and academic research collaboration, but referred also to the need for validation.

For the second question (*What do you see as the key next step to be taken to address a pressing research or educational challenge in advanced manufacturing?*), the responses were coded using the same six categories, but the number of responses appeared in a slightly different order:

1. Improvements in manufacturing education (39%)
2. Linkages between academic and industrial research (17%)
3. Development of process models (13%)
4. Encouragement of an interest in manufacturing (13%)
5. Advancements in technology and methods of scalability (9%)
6. Validation of models (9%).

As demonstrated here, when posed with questions about the future of advanced manufacturing, more than one third of participants regarded education as the pivotal next step in its progression. This perspective, in addition to "encouraging an interest in manufacturing" category together assumed a majority of responses (52%). There was consensus that strengthening the advanced manufacturing community in both numbers and ability is crucial to addressing the pressing needs of advanced manufacturing research and education posed during the workshop.

8 STUDENT TRAVEL AWARDS AND POSTER COMPETITION

As part of the RAMP Workshop proposal, funds for a student travel award were budgeted for 14 students. A questionnaire was disseminated through e-mail to potential student participants and also posted on the RAMP Workshop webpage [22]. The students were identified through various sources including prior RAMP Competition attendees, students who had submitted for the 2019 RAMP Competition, and through mailing lists available to the workshop organizers. Based on the responses to the questionnaire, a total of 19 student travel awards were offered to potential participants. Full travel award of $800 each was offered to 15 students and four students received half travel awards of $400 each as these students had already received the NSF travel award for attending the ASME MSEC conference. As one of the required criteria for the participants to receive the travel award students had to present a technical poster at the conference related to the theme of the RAMP Workshop. Each poster was judged by a panel of judges to recognize outstanding student work. The poster judging sheet used is attached in Appendix C.

The poster competition had four poster awards: Best Undergraduate Poster, Best Graduate Poster, Best Poster, and Judge's Choice Awards. The poster awards were presented at the end of the RAMP Workshop. The Best Undergraduate Poster was awarded to Dustin Harper and Sriram Manoharan for their poster titled "Aggregating Unit Process Models to Enable Environmental Impact Characterization of Polymer-Based Hybrid Manufacturing"; the Best Graduate Poster was awarded to Destiny Garcia for her poster titled "Technical and Environmental Aspects of Quality Assurance"; the Best Poster Award was awarded to Hua-Wei Ko, Patrick Bazzoli, Adam Nisbett, Douglas Bristow, Yujie Chen, Shiv Kapoor, and Placid Ferreira for their poster titled "Machine-Tool Error Observer Design with Application to Thermal Error Tracking"; and the Judge's Choice Award was awarded to Rishi Malhan, Ariyan Kabir, Brual Shah, Timotei Centea, and Satyandra Gupta for their poster titled "Hybrid Cells for Multi-Layer Prepreg Composite Sheet Layup."

9 SUMMARY AND FUTURE RESEARCH OPPORTUNITIES

The outcomes of the workshop are expected to benefit research programs, for example, by leading to funding for basic and applied research in topic areas such as 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 (cyber) manufacturing. Based on the foregoing, the following research directions emerged:

a) Machine learning methods can support fundamental understanding of a variety of discrete manufacturing processes, e.g., nanomanufacturing, and system-level sustainable manufacturing analysis and optimization.
b) Bridging the gap between process-level controls and system-level metrics can enable deeper insight for discrete and bulk product manufacturing. A mapping of product categories that have similar models and can be used across multiple enterprises is also needed.
c) Transient analysis of complex manufacturing systems can lead to robust manufacturing process models.
d) 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.
e) Scalability in nanomanufacturing needs to lead to reduced defects and defectives, improved metrology, and measurement of moving parts and assemblies.

f) Scalability of additive manufacturing requires material, geometry, and support structure optimization methods.
g) Additive manufacturing key performance indicators must be connected as a function of process controls.
h) In additive manufacturing, 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.
i) Societal influences of sustainable manufacturing, e.g., stakeholder behavior, must be better understood.
j) Engineering education approaches are needed to address the growing urgency for accurate sustainability assessment at the process and system levels.
k) Systemic sustainable manufacturing requires insight from risk assessment and system dynamics methods.
l) Robust methods to characterize interactions of processes, activities, and decisions across the system are needed to advance systemic sustainable manufacturing.
m) Diagnostic problem identification can be aided through degradation classification of physical assets.
n) Developing and sharing metrics for improving the effectiveness of learning in advanced manufacturing should be a focus of engineering education research.

For identification of more specific research opportunities, these research directions have been categorized into five topical areas within the advanced manufacturing domain: conventional manufacturing, nanomanufacturing, additive/hybrid manufacturing, process and system characterization, and cross-cutting issues (e.g., AI, cybermanufacturing, sustainability, and education/workforce training). Detailed summaries of future opportunities identified within each topic area are provided in Appendix D. In identifying these opportunities, the workshop organizers focused on defining the state of current research in each area. They then described the research challenges that have been raised in prior research to capture the key needs/gaps that need to be addressed by the advanced manufacturing community. Finally, they identified the expected outcomes of successful research undertaken in each area.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation (NSF) under Grant No. 1831141. The authors wish to thank the NSF for their generous support of this research. The authors also extend a warm thank you to the invited speakers, competitors, and supporters of the 2018 workshop. Special thanks go to Mr. Dustin Harper and Mr. Arvind Shankar Raman of Oregon State University for their assistance in the preparation of this report.

REFERENCES

[1] National Institute of Standards and Technology (NIST), U.S. Department of Commerce (DoC), “Unit Manufacturing Process Curation System.” [Online]. Available: https://umpbuilder.nist.gov/. [Accessed: 19-Dec-2019].
[2] W. Z. Bernstein *et al.*, “Research directions for an open unit manufacturing process repository: A collaborative vision,” *Manufacturing Letters*, vol. 15, pp. 71–75, Jan. 2018.
[3] ASTM, “Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes (ASTM E3012-16).” ASTM International, Conshohocken, PA, Mar-2016.

[4] NIST, "RAMP: Reusable Abstractions of Manufacturing Processes," *National Institute of Standards and Technology*, 23-Mar-2018. [Online]. Available: https://www.nist.gov/news-events/events/2018/01/ramp-reusable-abstractions-manufacturing-processes. [Accessed: 30-Aug-2019].

[5] Y. Dahman, "Self-Assembling Nanostructures**By Yaser Dahman, Gregory Caruso, Astrid Eleosida, and Syed Tabish Hasnain.," in *Nanotechnology and Functional Materials for Engineers*, Elsevier, 2017, pp. 207–228.

[6] Y. Lu, P. Witherell, F. Lopez, and I. Assouroko, "Digital Solutions for Integrated and Collaborative Additive Manufacturing," in *Volume 1B: 36th Computers and Information in Engineering Conference*, Charlotte, North Carolina, USA, 2016, p. V01BT02A033.

[7] P. Hernandez, "Additive Manufacturing Benchmark Test Series (AM-Bench)," *NIST*, 06-Jun-2017. [Online]. Available: https://www.nist.gov/ambench. [Accessed: 20-Sep-2018].

[8] S. Kim, D. W. Rosen, P. Witherell, and H. Ko, "A Design for Additive Manufacturing Ontology to Support Manufacturability Analysis," in *Volume 2A: 44th Design Automation Conference*, Quebec City, Quebec, Canada, 2018, p. V02AT03A036.

[9] I. S. Jawahir and R. Bradley, "Technological Elements of Circular Economy and the Principles of 6R-Based Closed-loop Material Flow in Sustainable Manufacturing," *Procedia CIRP*, vol. 40, pp. 103–108, 2016.

[10] "Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all — SDG Indicators." [Online]. Available: https://unstats.un.org/sdgs/report/2017/goal-04/. [Accessed: 19-Nov-2018].

[11] F. Badurdeen and I. S. Jawahir, "Strategies for Value Creation Through Sustainable Manufacturing," *Procedia Manufacturing*, vol. 8, pp. 20–27, 2017.

[12] "What is Convergence? | NSF - National Science Foundation," *Convergence Research at NSF*. [Online]. Available: https://www.nsf.gov/od/oia/convergence/index.jsp. [Accessed: 31-May-2019].

[13] M. R. Overcash and J. Twomey, "Unit Process Life Cycle Inventory (UPLCI) – A Structured Framework to Complete Product Life Cycle Studies," in *Leveraging Technology for a Sustainable World*, D. A. Dornfeld and B. S. Linke, Eds. Springer Berlin Heidelberg, 2012, pp. 1–4.

[14] CO2PE!, "CO2PE! (Cooperative Effort on Process Emissions in Manufacturing)," 2015. [Online]. Available: http://www.co2pe.org/?Methodology.

[15] M. P. Brundage, D. Lechevalier, and K. Morris, "Towards Standards-Based Generation of Reusable Life Cycle Inventory Data Models for Manufacturing Processes," *JMSE*, Nov. 2018.

[16] A. Shankar Raman, K. R. Haapala, and K. C. Morris, "Towards a Standards-Based Methodology for Extending Manufacturing Process Models for Sustainability Assessment," in *ASME 2018 13th International Manufacturing Science and Engineering Conference*, College Station, Texas, 2018, p. V001T05A024.

[17] A. Brodsky, M. Krishnamoorthy, M. O. Nachawati, W. Z. Bernstein, and D. A. Menasce, "Manufacturing and contract service networks: Composition, optimization and tradeoff analysis based on a reusable repository of performance models," in *2017 IEEE International Conference on Big Data (Big Data)*, Boston, MA, 2017, pp. 1716–1725.

[18] A. Brodsky, M. O. Nachawati, M. Krishnamoorthy, W. Z. Bernstein, and D. A. Menascé, "Factory optima: a web-based system for composition and analysis of manufacturing service networks based on a reusable model repository," *International Journal of Computer Integrated Manufacturing*, vol. 32, no. 3, pp. 206–224, Mar. 2019.

[19] A. Agrawal, A. Nayak, A. Maiti, C. Doshi, D. Doshi, and D. Mohan, “IdeaBoardz - Brainstorm, Retrospect, Collaborate,” 2009. [Online]. Available: http://www.ideaboardz.com/. [Accessed: 20-Sep-2018].
[20] L. Gonçalves, *Getting value out of agile retrospectives: a toolbox of retrospective exercises*. 2014.
[21] W. Z. Bernstein, D. Lechevalier, and D. Libes, “UMP Builder: Capturing and Exchanging Manufacturing Models for Sustainability,” in *Volume 1: Additive Manufacturing; Bio and Sustainable Manufacturing*, College Station, Texas, USA, 2018, p. V001T05A022.
[22] “2018 Ramp Workshop (Rreusable Abstractions of Manufacturing Processes) | Industrial Sustainability Laboratory | Oregon State University,” May-2018. [Online]. Available: http://research.engr.oregonstate.edu/isl/feature-story/2018-ramp-workshop-reusable-abstractions-manufacturing-processes. [Accessed: 29-Mar-2019].
[23] M. P. Groover, *Fundamentals of Modern Manufacturing*. New York: Wiley, 2015.
[24] NSF, “Understanding How Aluminum Moves Around a Friction Stir Welding Tool in order to Prevent Welding Defects (NSF Award #1826104),” 2018. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1720701. [Accessed: 22-Jul-2019].
[25] A. Shrivastava, C. Dingler, M. Zinn, and F. E. Pfefferkorn, “Physics-based interpretation of tool-workpiece interface temperature signals for detection of defect formation during friction stir welding,” *Manufacturing Letters*, vol. 5, pp. 7–11, Aug. 2015.
[26] NSF, “Joining of Dissimilar Materials through a Novel Hybrid Friction Stir Resistance Spot Welding Process (NSF Award #1537582),” 2015. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1720701. [Accessed: 22-Jul-2019].
[27] X. Fei, X. Jin, Y. Ye, T. Xiu, and H. Yang, “Effect of pre-hole offset on the property of the joint during laser-assisted friction stir welding of dissimilar metals steel and aluminum alloys,” *Materials Science and Engineering: A*, vol. 653, pp. 43–52, Jan. 2016.
[28] A. Fehrenbacher, N. A. Duffie, N. J. Ferrier, F. E. Pfefferkorn, and M. R. Zinn, “Effects of tool–workpiece interface temperature on weld quality and quality improvements through temperature control in friction stir welding,” *The International Journal of Advanced Manufacturing Technology*, vol. 71, no. 1–4, pp. 165–179, Mar. 2014.
[29] A. Fehrenbacher, C. B. Smith, N. A. Duffie, N. J. Ferrier, F. E. Pfefferkorn, and M. R. Zinn, “Combined Temperature and Force Control for Robotic Friction Stir Welding,” *Journal of Manufacturing Science and Engineering*, vol. 136, no. 2, p. 021007, Jan. 2014.
[30] NSF, “An Innovative Hybrid Ultrasonic Resistance Welding Process for Joining Advanced Lightweight and Dissimilar Materials (NSF Award#1853632),” 2019. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1853632&HistoricalAwards=false. [Accessed: 11-Aug-2019].
[31] J. Yang and B. Cao, “Investigation of resistance heat assisted ultrasonic welding of 6061 aluminum alloys to pure copper,” *Materials & Design*, vol. 74, pp. 19–24, Jun. 2015.
[32] H. Liu, Y. Hu, S. Du, and H. Zhao, “Microstructure characterization and mechanism of acoustoplastic effect in friction stir welding assisted by ultrasonic vibrations on the bottom surface of workpieces,” *Journal of Manufacturing Processes*, vol. 42, pp. 159–166, Jun. 2019.
[33] NSF, “CAREER: Surface Interactions in Dissimilar Material Joining (NSF Award #1651024),” 2016. [Online]. Available:

https://www.nsf.gov/awardsearch/showAward?AWD_ID=1720701. [Accessed: 22-Jul-2019].

[34] W.-M. Wang, H. Ali Khan, J. Li, S. F. Miller, and A. Zachary Trimble, "Classification of Failure Modes in Friction Stir Blind Riveted Lap-Shear Joints With Dissimilar Materials," *Journal of Manufacturing Science and Engineering*, vol. 139, no. 2, p. 021005, Sep. 2016.

[35] H. A. Khan, W.-M. Wang, K. Wang, S. Li, S. Miller, and J. Li, "Investigation of mechanical behavior of dissimilar material FSBR joints exposed to a marine environment," *Journal of Manufacturing Processes*, vol. 37, pp. 376–385, Jan. 2019.

[36] T. Lee, S. Zhang, A. Vivek, B. Kinsey, and G. Daehn, "Flyer Thickness Effect in the Impact Welding of Aluminum to Steel," *Journal of Manufacturing Science and Engineering*, vol. 140, no. 12, p. 121002 (7 pages), Sep. 2018.

[37] NSF, "CAREER: Vibration-Assisted Laser Keyhole Welding to Improve Joint Properties (Award #1752218)," 2018. [Online]. Available: https://nsf.gov/awardsearch/showAward?AWD_ID=1752218&HistoricalAwards=false. [Accessed: 26-Aug-2019].

[38] NSF, "CAREER: Material Removal Mechanism of Ceramic Materials in Ultra-Precision Machining (NSF Award #1844821)," 2019. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1844821&HistoricalAwards=false. [Accessed: 11-Aug-2019].

[39] Y. Mizumoto, P. Maas, Y. Kakinuma, and S. Min, "Investigation of the cutting mechanisms and the anisotropic ductility of monocrystalline sapphire," *CIRP Annals*, vol. 66, no. 1, pp. 89–92, 2017.

[40] H.-S. Yoon, S. B. Kwon, A. Nagaraj, S. Lee, and S. Min, "Study of stress intensity factor on the anisotropic machining behavior of single crystal sapphire," *CIRP Annals*, vol. 67, no. 1, pp. 125–128, 2018.

[41] D. Weber, B. Kirsch, C. R. D'Elia, B. Linke, M. Hill, and J. C. Aurich, "Concept to Analyze Residual Stresses in Milled Thin Walled Monolithic Aluminum Components and Their Effect on Part Distorsion," in *Proceedings of the WGP Annual Congress 2019*, Hamburg, Germany, 2019.

[42] C. R. Chighizola, C. R. D'Elia, and M. R. Hill, "Intermethod Comparison and Evaluation of Near Surface Residual Stress in Aluminum Parts Subject to Various Milling Parameters," in *Proceedings of the Annual Conference and Exposition on Experimental and Applied Mechanics*, Reno, NV, 2019, p. Extended Abstract.

[43] J. Raval, W. N. P. Hung, and B. L. Tai, "Multiphase flow distribution in MQL drilling using optical intensity distribution based approach," in *Proceedings of the ASME Manufacturing Science and Engineering Conference*, Erie, PA, 2019.

[44] S. S. Mujumdar, S. G. Kapoor, and D. Curreli, "Experimental Investigation of Atomized Dielectric-based MicroEDM Plasma Characteristics," in *Proceedings of the 2017 World Congress on Micro and Nano Manufacturing*, Kaohsiung, Taiwan, 2017.

[45] NSF, "Boosting the Speed and Accuracy of Vibration-Prone Manufacturing Machines at Low Cost through Software (NSF Award #1825133)," 2018. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1825133&HistoricalAwards=false. [Accessed: 11-Aug-2019].

[46] X. Dong and C. E. Okwudire, "Semi-active joint for ultra-precision positioning using sliding/rolling bearings," *CIRP Annals*, vol. 68, no. 1, pp. 385–388, 2019.

[47] M. Duan, D. Yoon, and C. E. Okwudire, “A limited-preview filtered B-spline approach to tracking control – With application to vibration-induced error compensation of a 3D printer,” *Mechatronics*, vol. 56, pp. 287–296, Dec. 2018.
[48] NSF, “CAREER: Breaking the Freeform Optics Metrology Barrier with Synthetic Wavelength Interferometry (NSF Award #1851739),” 2018. [Online]. Available: https://nsf.gov/awardsearch/showAward?AWD_ID=1851739&HistoricalAwards=false. [Accessed: 11-Aug-2019].
[49] H. Villarraga-Gómez, C. Lee, and S. T. Smith, “Dimensional metrology with X-ray CT: A comparison with CMM measurements on internal features and compliant structures,” *Precision Engineering*, vol. 51, pp. 291–307, Jan. 2018.
[50] C. Wang, F. Zhong, and J. D. Ellis, “Two-dimensional straightness measurement based on optical knife-edge sensing,” *Review of Scientific Instruments*, vol. 88, no. 9, p. 095109, Sep. 2017.
[51] C. Lee, A. Zolfaghari, G. H. Kim, and S. Jeon, “An optical measurement technique for dynamic stiffness and damping of precision spindle system,” *Measurement*, vol. 131, pp. 61–68, Jan. 2019.
[52] J. D. Ellis *et al.*, “Manufacturing of Gradient Index Lenses for Ophthalmic Applications,” in *Optical Design and Fabrication 2017 (Freeform, IODC, OFT)*, Denver, Colorado, 2017, p. OW1B.3.
[53] M. D. Crall, S. G. Laney, and M. W. Keller, “Multimodal Damage Detection in Self-Sensing Fiber Reinforced Composites,” *Advanced Functional Materials*, vol. 29, no. 12, p. 1806634, 2019.
[54] S. C. Feng, W. Z. Bernstein, T. Hedberg, and A. Barnard Feeney, “Toward Knowledge Management for Smart Manufacturing,” *Journal of Computing and Information Science in Engineering*, vol. 17, no. 3, p. 031016, Jul. 2017.
[55] S. Jeschke, C. Brecher, H. Song, and D. B. Rawat, *Industrial Internet of Things: Cybermanufacturing Systems*. Springer, 2016.
[56] H. Yao, Y. Ren, and Y. Liu, “FEA-Net: A Deep Convolutional Neural Network With Physics Prior For Efficient Data Driven PDE Learning,” in *AIAA Scitech 2019 Forum*, San Diego, California, 2019.
[57] B. Esmaeilian, S. Behdad, and B. Wang, “The evolution and future of manufacturing: A review,” *Journal of Manufacturing Systems*, vol. 39, pp. 79–100, Apr. 2016.
[58] K. Cooper and R. F. Wachter, “Nanomanufacturing: path to implementing nanotechnology,” *International Journal of Nanomanufacturing*, vol. 9, no. 5/6, p. 540, 2013.
[59] L. Li *et al.*, “Laser nano-manufacturing – State of the art and challenges,” *CIRP Annals*, vol. 60, no. 2, pp. 735–755, 2011.
[60] J. A. Liddle and G. M. Gallatin, “Nanomanufacturing: A Perspective,” *ACS Nano*, vol. 10, no. 3, pp. 2995–3014, Mar. 2016.
[61] K. Cooper, “Scalable Nanomanufacturing—A Review,” *Micromachines*, vol. 8, no. 1, p. 20, Jan. 2017.
[62] A. A. Busnaina, J. Mead, J. Isaacs, and S. Somu, “Nanomanufacturing and sustainability: opportunities and challenges,” in *Nanotechnology for Sustainable Development*, Springer, Cham, 2013, pp. 331–336.
[63] S. Dimov, E. Brousseau, R. Minev, and S. Bigot, “Micro- and nano-manufacturing: Challenges and opportunities,” *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 226, no. 1, pp. 3–15, Jan. 2012.

[64] S. Morita, F. J. Giessibl, E. Meyer, and R. Wiesendanger, Eds., *Noncontact Atomic Force Microscopy*. Cham: Springer International Publishing, 2015.
[65] S. Bukkapatnam, S. Kamarthi, Q. Huang, A. Zeid, and R. Komanduri, "Nanomanufacturing systems: opportunities for industrial engineers," *IIE Transactions*, vol. 44, no. 7, pp. 492–495, Jul. 2012.
[66] G. L. Hornyak, J. J. Moore, H. F. Tibbals, and J. Dutta, *Fundamentals of Nanotechnology*. Hoboken: CRC Press, 2008.
[67] Y. Chen *et al.*, "Light-enabled reversible self-assembly and tunable optical properties of stable hairy nanoparticles," *Proceedings of the National Academy of Sciences*, vol. 115, no. 7, pp. E1391–E1400, Feb. 2018.
[68] Y. Chen *et al.*, "Hairy Uniform Permanently Ligated Hollow Nanoparticles with Precise Dimension Control and Tunable Optical Properties," *Journal of the American Chemical Society*, vol. 139, no. 37, pp. 12956–12967, Sep. 2017.
[69] X. Li *et al.*, "Convenient and Robust Route to Photoswitchable Hierarchical Liquid Crystal Polymer Stripes via Flow-Enabled Self-Assembly," *ACS Applied Materials & Interfaces*, vol. 10, no. 5, pp. 4961–4970, Feb. 2018.
[70] NSF, "Network for Computational Nanotechnology - Hierarchical nanoMFG Node (NSF Award #1720701)," 2017. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1720701. [Accessed: 22-Jul-2019].
[71] ASTM, "Standard Terminology for Additive Manufacturing Technologies (Designation: F2792–12a)." ASTM International, Conshohocken, PA, 2012.
[72] S. A. M. Tofail, E. P. Koumoulos, A. Bandyopadhyay, S. Bose, L. O'Donoghue, and C. Charitidis, "Additive manufacturing: scientific and technological challenges, market uptake and opportunities," *Materials Today*, vol. 21, no. 1, pp. 22–37, Jan. 2018.
[73] Y. Huang, M. C. Leu, J. Mazumder, and A. Donmez, "Additive manufacturing: Current state, future potential, gaps and needs, and recommendations," *Journal of Manufacturing Science and Engineering*, vol. 137, no. 1, p. 014001, 2015.
[74] I. Gibson, D. Rosen, and B. Stucker, *Additive Manufacturing Technologies: 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing*, 2nd ed. New York: Springer-Verlag, 2014.
[75] H. P. Nagarajan, H. A. Malshe, K. R. Haapala, and Y. Pan, "Environmental Performance Evaluation of a Fast Mask Image Projection Stereolithography Process through Time and Energy Modeling," *Journal of Manufacturing Science and Engineering*, 2016.
[76] L. Chen, Y. He, Y. Yang, S. Niu, and H. Ren, "The research status and development trend of additive manufacturing technology," *Int J Adv Manuf Technol*, vol. 89, no. 9, pp. 3651–3660, Apr. 2017.
[77] Y.-S. Leung, T.-H. Kwok, X. Li, Y. Yang, C. C. L. Wang, and Y. Chen, "Challenges and Status on Design and Computation for Emerging Additive Manufacturing Technologies," *J. Comput. Inf. Sci. Eng*, vol. 19, no. 2, p. 021013, Jun. 2019.
[78] NSF, "CAREER: Mask Video Projection Based Additive Manufacturing at the Micro-scale over Large Areas (NSF Award #1151191)," 2014. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1431785. [Accessed: 19-Jul-2019].
[79] NSF, "Additive Manufacturing of Controlled Anisotropic Materials via Electrically Assisted Nanocomposite Fabrication (NSF Award #1663663)," 2017. [Online]. Available:

https://www.nsf.gov/awardsearch/showAward?AWD_ID=1663663. [Accessed: 19-Jul-2019].

[80] NSF, "Collaborative Research: Towards a Fundamental Understanding of a Simple, Effective and Robust Approach for Mitigating Friction in Nanopositioning Stages (NSF Award: CMMI 1855354)," 2019. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1855354&HistoricalAwards=false. [Accessed: 02-Sep-2019].

[81] NSF, "Vibration Assisted Nanopositioning: An Enabler of Low-cost, High-throughput Nanotech Processes (NSF Award #1562297)," 2016. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1855354&HistoricalAwards=false. [Accessed: 02-Sep-2019].

[82] NSF, "CAREER: Pushing the Boundaries: Advancing the Science of Micro-Additive Manufacturing (NSF Award: CMMI 1351469)," 2014. [Online]. Available: https://www.nsf.gov/awardsearch/showAward?AWD_ID=1855354&HistoricalAwards=false. [Accessed: 02-Sep-2019].

[83] NSF, "Collaborative Research: A Novel Control Strategy for 3D Printing of Micro-Scale Devices (NSF Award #1434693)," 2014. [Online]. Available: https://nsf.gov/awardsearch/showAward?AWD_ID=1851739&HistoricalAwards=false. [Accessed: 11-Aug-2019].

[84] NSF, "High Fidelity Additive Manufacturing at the Micro-scale (NSF Award #1334204)," 2013. [Online]. Available: https://nsf.gov/awardsearch/showAward?AWD_ID=1851739&HistoricalAwards=false. [Accessed: 11-Aug-2019].

[85] NSF, "SNM: Manufacturing Autonomy for Directed Evolution of Materials (MADE-Materials) for Robust, Scalable Nanomanufacturing (NSF Award #1727894)," 2017. [Online]. Available: https://nsf.gov/awardsearch/showAward?AWD_ID=1851739&HistoricalAwards=false. [Accessed: 11-Aug-2019].

[86] D. Rejeski, F. Zhao, and Y. Huang, "Research needs and recommendations on environmental implications of additive manufacturing," *Additive Manufacturing*, vol. 19, pp. 21–28, Jan. 2018.

[87] T. D. Ngo, A. Kashani, G. Imbalzano, K. T. Q. Nguyen, and D. Hui, "Additive manufacturing (3D printing): A review of materials, methods, applications and challenges," *Composites Part B: Engineering*, vol. 143, pp. 172–196, Jun. 2018.

[88] O. Abdulhameed, A. Al-Ahmari, W. Ameen, and S. H. Mian, "Additive manufacturing: Challenges, trends, and applications," *Advances in Mechanical Engineering*, vol. 11, no. 2, Feb. 2019.

[89] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *Journal of Manufacturing Systems*, vol. 48, pp. 157–169, Jul. 2018.

[90] M. M. Smullin, K. R. Haapala, M. Mani, and K. C. Morris, "Using Industry Focus Groups and Literature Review to Identify Challenges in Sustainable Assessment Theory and Practice," presented at the ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2016.

[91] J. Lee, B. Bagheri, and H.-A. Kao, "A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, Jan. 2015.

[92] M. Mani, J. Madan, J. H. Lee, K. W. Lyons, and S. K. Gupta, “Sustainability Characterization for Manufacturing Processes,” *International Journal of Production Research*, vol. 52, no. 20, pp. 1–18, Feb. 2014.
[93] W. Z. Bernstein, M. Mani, K. W. Lyons, K. C. Morris, and B. Johansson, “An Open Web-Based Repository for Capturing Manufacturing Process Information,” in *Volume 4: 21st Design for Manufacturing and the Life Cycle Conference; 10th International Conference on Micro- and Nanosystems*, Charlotte, North Carolina, USA, 2016.
[94] S. Choi, K. Jung, B. Kulvatunyou, and K. Morris, “An analysis of technologies and standards for designing smart manufacturing systems,” *J. RES. NATL. INST. STAN.*, vol. 121, p. 422, Sep. 2016.
[95] M. Hankel and B. Rexroth, “The reference architectural model industrie 4.0 (rami 4.0),” *ZVEI, April*, 2015.
[96] D. Ouelhadj and S. Petrovic, “A Survey of Dynamic Scheduling in Manufacturing Systems,” *J Sched*, vol. 12, no. 4, pp. 417–431, 2009.
[97] ASME, “Verification, Validation and Uncertainty Quantification (VVUQ),” *Verification, Validation and Uncertainty Quantification (VVUQ)*, 2019. [Online]. Available: https://www.asme.org/codes-standards/publications-information/verification-validation-uncertainty. [Accessed: 06-Sep-2019].
[98] G. Seliger, M. M. K. Khraisheh, and I. S. Jawahir, *Advances in Sustainable Manufacturing*. Springer Science & Business Media, 2011.
[99] C. Cunliff, “An Innovation Agenda for Deep Decarbonization: Bridging Gaps in the Federal Energy RD&D Portfolio,” *INFORMATION TECHNOLOGY*, p. 62, 2018.
[100] Center for Climate and Energy Solutions, “Decarbonizing U.S. Industry,” *Center for Climate and Energy Solutions*, 26-Jun-2018. [Online]. Available: https://www.c2es.org/document/decarbonizing-u-s-industry/. [Accessed: 23-Aug-2019].
[101] ISO 14000, “ISO 14000 family – Environmental management,” *ISO*, 23-Aug-2019. [Online]. Available: http://www.iso.org/cms/render/live/en/sites/isoorg/home/standards/popular-standards/iso-14000-environmental-manageme.html. [Accessed: 23-Aug-2019].
[102] M. Mani, J. Larborn, B. Johansson, K. W. Lyons, and K. C. Morris, “Standard Representations for Sustainability Characterization of Industrial Processes,” *J. Manuf. Sci. Eng*, vol. 138, no. 10, p. 101008 (7 pages), Oct. 2016.
[103] M. Mani, K. Morris, K. W. Lyons, and W. Z. Bernstein, “Reusable Models of Manufacturing Processes for Discrete, Batch, and Continuous Production - ProQuest,” *Journal of the Washington Academy of Sciences*, vol. 104, no. 4, pp. 21–30, Winter 2018.
[104] D. Choi, “Standards in Public Policy and Education,” *ASTM Standardization News*, pp. 20–22, Oct-2013.
[105] D. Ramanujan, N. Zhou, and K. Ramani, “Integrating environmental sustainability in undergraduate mechanical engineering courses using guided discovery instruction,” *Journal of Cleaner Production*, vol. 207, pp. 190–203, 2019.
[106] R. Reber, E. A. Canning, and J. M. Harackiewicz, “Personalized Education to Increase Interest,” *Curr Dir Psychol Sci*, vol. 27, no. 6, pp. 449–454, Dec. 2018.
[107] M. P. Brundage *et al.*, “Analyzing environmental sustainability methods for use earlier in the product lifecycle,” *Journal of Cleaner Production*, vol. 187, pp. 877–892, Jun. 2018.
[108] V. Kumar *et al.*, “Infusing Sustainability Principles into Manufacturing/Mechanical Engineering Curricula,” *Journal of Manufacturing Systems*, vol. 24, no. 3, pp. 215–225, 2005.

[109] Y. Lu, K. C. Morris, and S. Frechette, "Current Standards Landscape for Smart Manufacturing Systems," National Institute of Standards and Technology, NIST IR 8107, Feb. 2016.

[110] L. Rebouillat *et al.*, "Understanding Sustainability Data through Unit Manufacturing Process Representations: A Case Study on Stone Production," *Procedia CIRP*, vol. 57, pp. 686–691, 2016.

[111] Sacks R. and Barak R., "Teaching Building Information Modeling as an Integral Part of Freshman Year Civil Engineering Education," *Journal of Professional Issues in Engineering Education and Practice*, vol. 136, no. 1, pp. 30–38, Jan. 2010.

[112] Sacks R. and Pikas E., "Building Information Modeling Education for Construction Engineering and Management. I: Industry Requirements, State of the Art, and Gap Analysis," *Journal of Construction Engineering and Management*, vol. 139, no. 11, p. 04013016, Nov. 2013.

[113] J. Irizarry, P. Meadati, W. S. Barham, and A. Akhnoukh, "Exploring Applications of Building Information Modeling for Enhancing Visualization and Information Access in Engineering and Construction Education Environments," *International Journal of Construction Education and Research*, vol. 8, no. 2, pp. 119–145, Apr. 2012.

[114] PCAST, "Report to the President: Accelerating U.S. Advanced Manufacturing," President's Council of Advisors on Science and Technology, Executive Office of the President, Washington, D.C., USA, Oct. 2014.

[115] J. B. Zimmerman and J. Vanegas, "Using Sustainability Education to Enable the Increase of Diversity in Science, Engineering and Technology-Related Disciplines," *The International Journal of Engineering Education*, vol. 23, no. 2, pp. 242–253, 2007.

[116] L. Klotz, G. Potvin, A. Godwin, J. Cribbs, Z. Hazari, and N. Barclay, "Sustainability as a Route to Broadening Participation in Engineering," *Journal of Engineering Education*, vol. 103, no. 1, pp. 137–153, 2014.

[117] C. J. Clark II and R. S. Gragg III, "Evaluation of Initial Environmental Engineering Sustainability Course at a Minority Serving Institution," *Sustainability: The Journal of Record*, vol. 4, no. 6, pp. 297–302, Dec. 2011.

[118] M. McCormick, A. R. Bielefeldt, C. W. Swan, and K. G. Paterson, "Assessing students' motivation to engage in sustainable engineering," *International Journal of Sustainability in Higher Education*, vol. 16, no. 2, pp. 136–154, 2015.

[119] M. Thürer, I. Tomašević, M. Stevenson, T. Qu, and D. Huisingh, "A systematic review of the literature on integrating sustainability into engineering curricula," *Journal of Cleaner Production*, vol. 181, pp. 608–617, Apr. 2018.

[120] K. Raoufi *et al.*, "A Cyberlearning Platform for Enhancing Undergraduate Engineering Education in Sustainable Product Design," *Journal of Cleaner Production*, vol. 211, pp. 730–741, Feb. 2019.

[121] B. Ferster, *Teaching Machines: Learning from the Intersection of Education and Technology*. JHU Press, 2014.

[122] F. Oprescu, C. Jones, and M. Katsikitis, "I PLAY AT WORK—ten principles for transforming work processes through gamification," *Front Psychol*, vol. 5, Jan. 2014.

[123] A. P. Markopoulos, A. Fragkou, P. D. Kasidiaris, and J. P. Davim, "Gamification in engineering education and professional training," *International Journal of Mechanical Engineering Education*, vol. 43, no. 2, pp. 118–131, Apr. 2015.

[124] O. Korn and A. Schmidt, “Gamification of Business Processes: Re-designing Work in Production and Service Industry,” *Procedia Manufacturing*, vol. 3, pp. 3424–3431, Jan. 2015.
[125] E. Paravizo, O. C. Chaim, D. Braatz, B. Muschard, and H. Rozenfeld, “Exploring Gamification to Support Manufacturing Education on Industry 4.0 as an Enabler for Innovation and Sustainability,” *Procedia Manufacturing*, vol. 21, pp. 438–445, Jan. 2018.
[126] M. Despeisse, “Teaching Sustainability Leadership in Manufacturing: A Reflection on the Educational Benefits of the Board Game Factory Heroes,” *Procedia CIRP*, vol. 69, pp. 621–626, Jan. 2018.
[127] J. Wise, “4 Other Times Plane Automation Software Went Haywire,” *Popular Mechanics*, 18-Mar-2019. [Online]. Available: https://www.popularmechanics.com/flight/airlines/a26854898/plane-automation-crashes-incidents/. [Accessed: 01-Dec-2019].
[128] N. Oliver, T. Calvard, and K. Potočnik, “The Tragic Crash of Flight AF447 Shows the Unlikely but Catastrophic Consequences of Automation,” *Harvard Business Review*, 15-Sep-2017.
[129] P. Oborski, “Man-machine interactions in advanced manufacturing systems,” *Int J Adv Manuf Technol*, vol. 23, no. 3, pp. 227–232, Feb. 2004.
[130] D. Gorecky, M. Schmitt, M. Loskyll, and D. Zühlke, “Human-machine-interaction in the industry 4.0 era,” in *2014 12th IEEE International Conference on Industrial Informatics (INDIN)*, 2014, pp. 289–294.

APPENDICES

Appendix A: NSF Programs Suitable for Advanced Manufacturing Researchers

Name	Description
Division of Civil, Mechanical and Manufacturing Innovation (CMMI)	CMMI funds potentially transformative research to enable advances in: 1) Manufacturing and building technologies across size scales from nanometers to kilometers, with emphases on efficiency, economy, and minimal environmental footprint; 2) Efficient, economical and sustainable transformation and use of engineering materials; 3) Resilient and sustainable civil infrastructure and distributed infrastructure networks; 4) Advances in the creation of models, analyses, and algorithms that link data with decisions related to manufacturing and service enterprises; and 5) Design, control, and optimization methods applied at levels ranging from component to enterprise systems. (www.nsf.gov/eng/cmmi/about.jsp)
Advanced Manufacturing (AM) Program	This program supports the fundamental research needed to revitalize American manufacturing to grow the national prosperity/workforce, and reshape our strategic industries. The AM program accelerates advances in manufacturing technologies with emphasis on multidisciplinary research that fundamentally alters and transforms manufacturing capabilities, methods and practices. (PD 19-088Y)
Critical Aspects of Sustainability (CAS) Program	This program seeks to support basic research through core disciplinary programs aimed at improving the sustainability of resources for future generations while maintaining or improving current products in order to offer technologically-advanced, economically competitive, environmentally-benign and useful materials to a global society. (PD 19-9102)
Directorate for Education and Human Resources (EHR)	EHR supports excellence in U.S. STEM education at all levels, in all settings for the development of a diverse and well-prepared workforce of scientists, technicians, engineers, mathematicians and educators and a well-informed citizenry (www.nsf.gov/ehr/about.jsp).
Division of Graduate Education (DGE)	DGE provides funding to support graduate students and the development of novel, innovative programs to prepare tomorrow's leaders in STEM (Science, Technology, Engineering, and Mathematics) fields. (www.nsf.gov/div/index.jsp?div=DGE)
Division of Undergraduate Education (DUE)	DUE's programs are intended to strengthen STEM education at two- and four-year colleges and universities by improving curricula, instruction, laboratories,

Name	Description
	infrastructure, assessment, diversity of students and faculty, and collaborations. (www.nsf.gov/div/index.jsp?div=DUE)
Division of Human Resource Development (HRD)	HRD programs support and promote activities that seek to strengthen STEM education for underserved communities, broaden their participation in the workforce, and add to our knowledge base about programs of inclusion. (www.nsf.gov/div/index.jsp?div=HRD)

Appendix B: Other Funding Sources for Advanced Manufacturing Researchers

Manufacturing USA Institutes	Manufacturing USA® is a network of 14 manufacturing institutes. Each institute is a unique public-private partnership, jointly funded by government and private industry, focused on a different advanced manufacturing technology area but working toward the same high-level goal: to secure America's future through manufacturing innovation, education, and collaboration. (www.manufacturingusa.com)
ONR Manufacturing Engineering Education Program (MEEP)	The National Defense Authorization Act (NDAA) for Fiscal Year 2017 established the "Manufacturing Engineering Education Program," (MEEP) (10 U.S.C. § 2196) which authorizes the Defense Department to support industry-relevant, manufacturing-focused, engineering training at U.S. institutions of higher education, industry, nonprofit institutions, and consortia of such institutions or industry. The Defense Department will administer this new program through the Office of Naval Research (ONR). (www.doncio.navy.mil/chips/ArticleDetails.aspx?ID=10927)
NIST Manufacturing Extension Partnership (MEP) program	NIST MEP advocates Notice of Funding Opportunities (NOFO) for projects designed to enhance the productivity, technical performance and global competitiveness of U.S. Manufacturers. NOFOs are implemented through the MEP National Network consisting of; Centers located in all 50 states and Puerto Rico, 558 service locations, more than 1,200 Center field staff and over 2,300 service providers. These opportunities help encourage the creation and adaption of improved technologies and provide resources to develop new products that respond to changing market needs. (www.nist.gov/mep)

Appendix C: RAMP Workshop Poster Judging Form

Authors: **Evaluator:** [Code letter]

Poster Title: **Category:**

Workshop Relevance	**Absent**	**Poor**	**Fair**	**Good**	**Excellent**
Relevance to RAMP theme: “Tracking Resources and Flows through the System”	0	4	6	8	10

Total Points: ________

Scientific Relevance	**Absent**	**Poor**	**Fair**	**Good**	**Excellent**
Clarity of the problem under study	0	4	6	8	10
Novelty of the scientific approach relative to prior work	0	4	6	8	10
Potential for extensions into future research	0	4	6	8	10
Significance of the work in terms of the academic field/discipline	0	4	6	8	10
Significance of the work in terms of industry/society	0	4	6	8	10

Total Points: ________

Poster Quality	**Absent**	**Poor**	**Fair**	**Good**	**Excellent**
Quality of figures, tables, and other images	0	4	6	8	10
Support of figures, tables, and other images to the work presented	0	4	6	8	10
Poster readability (text style, size, organization, etc.)	0	4	6	8	10
Writing quality (understandability, grammatical errors, etc.)	0	4	6	8	10

Total Points: ________

Final Score (sum total points): ________

Should this poster be considered for either of these awards?

Circle One

1) RAMP Best Poster Award (Undergraduate and Graduate Awards) **Yes, consider.** **No, don’t consider.**

This award recognizes the poster that best exemplifies the RAMP workshop theme.

Circle One

2) Judge’s Choice Poster Award **Yes, consider.** **No, don’t consider.**

This award recognizes the poster that the judge’s deem to be of highest technical and presentation quality. It does not necessarily need to follow the RAMP workshop theme.

Comments (Make additional comments on back if needed):

Appendix D: Opportunities for Future Research and Potential Impacts

Based on the workshop findings, the research directions that emerged can be synthesized 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). Below, 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); thus the community should expand areas of research opportunity through continued discourse.

D.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]. With the trend towards smart, automated, and cyber-integrated manufacturing, the need for realistic digital representations of conventional manufacturing processes is also gaining importance [54], [55]. Though much insight can be gained through purely data-driven models, a hybrid approach, wherein physical knowledge is also leveraged, is preferred [56]. 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 D.1 identifies relevant potential research opportunities and expected outcomes for conventional manufacturing in the short-, mid-, and long-term ranges.

Table D.1. 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

D.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 [57]. Nanomanufacturing is the production of nanoscale features (surface and sub-surface), materials (nanoparticles), parts (3D nanostructures, nanotubes, and nanowires), devices, and systems [58]. 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 [59].

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 [60]. Due to the application of nanomanufacturing in a variety of industry sectors, research of novel nano-manufacturing 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 [61]–[63].

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 [64], 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 [61]. 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 [65], [66]. 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 [65]. 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 [67]–[69].

Table D.2 identifies relevant potential research opportunities and expected outcomes for nano-manufacturing in the short-, mid-, and long-term ranges.

Table D.2. 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

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 [70].

D.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 [71]. Additive manufacturing is at a turning-point due to its increasing application in manufacturing a wide range of products in various industrial sectors [72]. Industry sectors where innovations can be seen include food and consumer products, medicine and medical products, automotive, aviation, architecture, and construction [73], [74]. 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 [57], [75].

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 [72] due to their relatively high capital investment needed to achieve high production volumes [76]. 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 [77]–[79]. Nano-positioning in micro-scale additive manufacturing [80], [81] has also gained attention from researchers. Process modeling [82], precision improvement [83], and cost reduction [84] 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[85]. 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 [76]. Moreover, the sustainability performance of many materials in additive manufacturing is not well-understood [86]. It has been suggested that developing lower cost biocompatible materials can help improve economic and environmental aspects of sustainability [87]. 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 [88].

Table D.3 identifies relevant potential research opportunities and expected outcomes for additive manufacturing in the short-, mid-, and long-term ranges.

Table D.3. 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

D.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 [89]. 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 [90].

With the emergence of industrial internet of things (IIoT) and related smart manufacturing concepts [91], 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 [92], developing repositories of manufacturing process information [2], [93], and analyzing manufacturing processes for designing smart manufacturing systems [94]. 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 [95]. 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.

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 [96]. 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 D.4 identifies relevant potential research opportunities and expected outcomes for process and system characterization in the short-, mid-, and long-term ranges.

Table D.4. Research opportunities in process and system characterization

	Research Opportunity	Expected Outcome
1-3 years	• Construct guidelines for training data for data-driven models • Develop methods for integrating between data contexts based on different standard 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	• Public manufacturing process datasets and models • Usability of the current smart and sustainable manufacturing standards • 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 [93]. Bridging the existing standards at 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

D.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 [73], [98]. As noted above, manufacturing processes account for the most intensive energy use and waste production in many manufacturing facilities [99], [100], 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 [101] 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 [102], [103] into widespread practice, first through standards education program development [104], will spur industry adoption of sustainability improvement practices [105]. 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

[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 [97]

education and training experiences to inspire the next generation to pursue manufacturing careers [106]. 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 [107], [108]. Standard practices for instilling manufacturing process modeling are lacking [90], and how such standards can by systemically employed in cyber-human systems must be better understood [109]. Early work has been done in this area, but more is needed to characterize manufacturing processes for sustainability [102], [110], for representing manufacturing processes using information modeling [102], [110], for reusing such information models variations of manufacturing processes [16], [103]. 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 [111]–[113].

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 [114]. Integrating sustainability concepts into engineering curricula has been shown to improve student perceptions, in particular for students underrepresented in engineering [115], [116], as well as motivating students to pursue careers in sustainability [117], [118] and increase student interest in the job opportunities in manufacturing [119], [120]. 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 [121]. Further, the more mundane aspects of manufacturing [122]–[124] and manufacturing education can be improved through the application of gamification techniques [125], [126]. 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 [127], [128]. 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 [129], [130].

Table D.5 identifies relevant potential research opportunities and expected outcomes for educational and training issues in the short-, mid-, and long-term ranges.

Table D.5. 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