The International Journal of Advanced Manufacturing Technology (2024) 134:3031–3050
https://doi.org/10.1007/s00170-024-14279-z

CRITICAL REVIEW

Current state and emerging trends in advanced manufacturing: smart systems

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Received: 25 June 2024 / Accepted: 12 August 2024 / Published online: 3 September 2024

Abstract
Advanced manufacturing is challenging engineering perceptions of how to innovate and compete. The need for manufacturers to rapidly respond to changing requirements and demands; obtain, store, and interpret large volumes of data and information; and positively impact society and our environment requires engineers to investigate and develop new ways of making products for flexible and competitive production. In addition to the associated operational, technological, and strategic advantages for industry, advanced manufacturing creates educational, workforce, and market opportunities. Thus, this literature review aims to investigate the current state and emerging trends in advanced manufacturing. Specifically, this study addresses advances in manufacturing from manufacturing systems perspective, concentrating on emerging trends in process sensing and monitoring, equipment control and automation, machine tools, sustainable manufacturing, and green supply chain management. This review finds myriad efforts have been undertaken by researchers in industry, academia, and government labs from around the world, which have supported the development and implementation of new process technologies to improve manufacturing systems extending from unit process and shop floor operations to facility and supply chain management activities. However, emerging global challenges remain in various domains including energy (e.g., resource scarcities and global warming), critical materials vulnerable to supply disruptions due to crisis and rapid changes in demand, and services (e.g., healthcare supply chains during COVID-19 pandemic). Thus, manufacturing industry must continue the innovative development of advanced materials, manufacturing processes, and systems that ensure cost efficient, rapidly flexible, high quality, and responsible production of goods and services.

Keywords Advanced manufacturing · Conventional processes · Additive manufacturing · Manufacturing systems · Smart manufacturing

1 Introduction

Advanced manufacturing represents a continuous transformation of manufacturing in terms of technologies, processes, skills, and strategies to satisfy the future needs of society as a result of growth in affluence and population [1]. National efforts in the USA [1, 2], Japan [3, 4], and other countries throughout Europe [5, 6] and across the globe highlight the importance of healthy and robust advanced manufacturing industries. Strategic support of advanced manufacturing

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aims to improve the competitive advantages and leadership of national manufacturing industries across global markets. In particular, advanced manufacturing technologies and a skilled workforce provide significant benefits for the production of industrial and consumer products by utilizing cutting-edge developments at the manufacturing process and systems levels [7, 8]. Considering the importance of advanced manufacturing to the global economy and society, the objective of this literature review is to summarize recent operational, technical, and strategic developments in advanced manufacturing systems. We then use this summary as a springboard to discuss open challenges and future trends in advanced manufacturing. This research presents emerging trends in manufacturing equipment and systems, as well as measurement, modeling, analysis, and decision making for manufacturing. To conclude the literature review, the challenges, future trends, and recommendations identified are discussed as well.

2 Emerging trends in smart manufacturing systems

The following sections discuss several emerging trends in advanced manufacturing—process sensing and monitoring, equipment control and automation, multi-axis and multi-tasking machine tools, and developments in model-based enterprise and sustainable manufacturing—followed by a discussion on how manufacturing policy is driving emerging supply chain management practices.

2.1 Process sensing and monitoring

Process monitoring is intended to improve the productivity of machining processes and to mitigate tool/workpiece failure [9]. This goal mandates the accurate prediction of tool condition and, accordingly, setting of process parameters, such as speed and feed, to attain optimal production conditions. In traditional monitoring practices, the prediction of tool condition is dependent on the skill of the operator, and always marked with uncertainty [10]. Sensor-based monitoring yields accurate and valuable information about tool conditions [11]. Essential elements of a sensor-based monitoring system are: (1) sensor or sensing elements, (2) signal processing algorithms, (3) feature generation, (4) feature selection/extraction, and (5) process knowledge modeling [12]. Table 1 lists types of sensors and associated algorithms for tool wear monitoring, which are detailed below.

2.1.1 Single sensors

During metal cutting, process variables such as acoustic emissions, vibrations, and forces are influenced by cutting tool conditions [13]. Information for some of these variables, e.g., acoustic emissions data, can be independently used for inferring the tool conditions. In prior research [10,

Table 1 Summary of recent process monitoring developments

Category	Sensor types	Application	Model	References
Single sensors	Acoustic emissions sensor	Estimation of grinding wheel wear in surface and creep-feed grinding	Support vector machine (SVM), Genetic clustering algorithm, C4.5 algorithm	[10, 14, 15]
	Dynamometer	Identification of chatter and estimation of tool wear in micro-milling	Index-based reasoner hidden Markov models (HMMs)	[16, 17]
	Current sensor	Induction motor rotor bar condition	Support vector machine (SVM)	[18]
	Accelerometer	Rotary system fault detection	Transformer-based classifier using Mahalanobis distance	[19]
	Power sensor	Machine state identification such as tool and cutting conditions	Unsupervised nonintrusive load monitoring (NILM)	[20]
Multiple sensors	Fusion of current and sound sensor	Tool wear monitoring in turning	Least squares version of support vector machines (LS-SVM)	[21]
	Dynamometer, load cell (force), strain gauge, and accelerometer	Estimation of tool wear in broaching	Least squares version of support vector machines (LS-SVM)	[22]
	Dynamometer, current, voltage, accelerometer, microphone, and acoustic emissions sensor	Estimation of tool wear for an industrial face milling center	Artificial neural network (ANN)	[23]
	Dynamometer, accelerometer, and microphone	Estimation of tool wear in drilling	Two-stage fuzzy logic scheme	[24]
	Accelerometer	Estimation of tool state in turning	Artificial neural network (ANN)	[25]
	Dynamometer, accelerometer, and microphone	Estimation of tool wear in milling	Random Forest (RF)	[26]

14, 15], acoustic emissions sensor data processed by artificial intelligence techniques (e.g., support vector machine (SVM) modeling and genetic clustering algorithms) are used for determining the grinding wheel condition. Other single sensors that have been used to monitor tool and rotor conditions include dynamometers, current and voltage sensors, and microphones (Table 1).

2.1.2 Multiple sensors

With the development in microelectronics and sensing technology, multiple types of sensors can be embedded to collect data. With the concept of multiple-sensor data fusion, the information collected by different sensors can be synthesized to estimate the status of cutting tools with improved accuracy [12]. Aliustaoglu et al. [24] used the fuzzy logic technique to fuse or combine information from force, vibration, and acoustic emission sensors to predict drilling tool wear. It was found that the estimated tool wear based on the fused data was more accurate compared to the results based on any individual sensors. The authors reported that tool wear estimates could be further improved by considering multiple sensor inputs and sensor fusion technique as part of the fusion model. In another study [21], current and acoustic emissions sensors were used for monitoring tool wear in a computer numerical control (CNC) lathe. The study demonstrated that with increased cutting speed and feed rate, the accuracy of tool wear estimates increased due to the improved signal to noise ratio in sensor data under these conditions.

Wu et al. [26] monitored cutting force, vibration, and acoustic emissions using a dynamometer, three accelerometers, and an acoustic emission sensor. The authors implemented a random forest (RF) algorithm on a scalable cloud computing system. By implementing RFs in parallel on the cloud, the processing speed was significantly increased with a high prediction accuracy of tool wear in milling. Nasir and Sassani [27] reviewed the opportunities and challenges presented by machining and tool monitoring through deep learning techniques. Opportunities highlighted were the ability to handle large data sets, handling high-dimensional data, optimal sensor fusion, and hybrid intelligent models. Some of the challenges highlighted included model selection and process uncertainty. Serin et al. [28] reviewed and summarized the various tool monitoring techniques and provided the underlying theory of recent deep learning techniques that have emerged in tool monitoring such as kernel filters and neural networks. Areas of opportunities the authors highlighted include the use of support vector machine (SVM) in tool monitoring since this algorithm has the potential to broaden its training over time with various cutting conditions. The authors also highlighted transfer learning (TL) since it can also reduce the task of collecting and labeling large amounts of data. TL can adapt knowledge for one task and apply it to another, thus reducing the collection of data and training of a new algorithm.

2.2 Equipment control and automation

The growth in cyber-physical systems (CPS) research has been driven by recent breakthroughs in sensor and sensor network technologies with simultaneous improvements in distributed computing and advanced algorithms. These trends have important impacts on manufacturing processes by expanding the capabilities of machining operations, improving reliability, and reducing waste to improve sustainability, leading to the creation of a distinct area termed cyber-physical production systems (CPPS) [29]. The following sections provide an overview of recent work in this area.

2.2.1 Advances in motion command algorithms for positioning systems

The software-based tools used in machine tools to control metalworking operations are improving as a result of the development of myriad iterative machine learning techniques [30]. These data-driven methods have critical advantages over conventional techniques for monitoring workpieces with improved tolerances due to iterative motion control and positioning systems [31]. One important application of these algorithms is in additive manufacturing where the repeatability of metal part production is difficult to achieve [32]. Conventional additive manufacturing operations function in x, y, and z axes, but advanced controllers can enable material addition along multiple axes (via rotating platforms) and in non-uniform material layer thicknesses, which could address some of the primary drawbacks of existing additive manufacturing methods.

2.2.2 Supervisory systems and factory automation

At the manufacturing enterprise level, the growth of cyber-physical systems stands to revolutionize the ways in which manufacturing systems operate by leveraging advances in the Internet of Things (IoT) [33]. In particular, advances in the way humans interact with these complex systems-of-systems are important to reduce the impact of human error. Situational awareness, which is the broad study of human perception and comprehension within a manufacturing environment, stands to greatly enhance the capability of manufacturing workers [34]. The benefits of these developments will vary based on the size of the manufacturing facility and resources available to invest in the hardware and software required, but as domain-specific languages and frameworks emerge, adoption will be more widespread [35]. Moreover, machine tool controllers provide important advantages in predictive maintenance, e.g., predicting tool wear [30]. Large-scale data sets can now be processed across a broad range of operating conditions, workpiece materials, tools, and other factors to predict tool condition, unexpected failures, and unexploited life enabling real-time cost-based maintenance decisions [36]. As an example, non-parametric techniques are used to carry out time-series analysis of machine tool vibration and workpiece surface roughness to estimate tool health and forecasting [37].

2.3 Machine tool development

With continuously changing market requirements, e.g., the need for products with more complex geometries at higher precision and lower cost, machine tools have been subject to evolutionary, ground-breaking improvements and satisfying multiple criteria, including productivity, accuracy, longevity, serviceability, energy consumption, and environmental, health, and safety (EHS) considerations [38]. As a result of these capability improvements, multi-functional machine tools have emerged as a pathway for efficiency and productivity by integrating multiple operations (e.g., milling, turning, and additive processes). Conventionally, parts are machined to the intended geometry, dimensions, and surface quality by a series of processes, which necessitates a variety of machine tools. Multi-functional machine tools have been investigated from two directions: multi-tasking machine tools and hybrid machine tools, which are discussed next. More recently, research has begun investigating machine tools as integral components to cyber-physical and digital systems [39, 40], which are discussed in the following sections.

2.3.1 Multi-tasking machine tools

Multi-tasking machine tools are able to execute simple and complex turning, milling, drilling, boring, reaming, and tapping operations [41–44]. These machines have been built with intelligence such that operator intervention is eliminated for operations including workpiece set-up changes and tool changes. Multi-tasking machines often have two main spindles and plural tool posts, while multi-axis machine tools are developed based on milling machine tool architectures. The five-axis machine tool is the most common type of multi-axis machine tool. With the development of multi-axis control and multi-tasking functionality, multi-tasking machine tools can also be multi-axis machine tools. Figure 1 shows the evolution of machine tools from two-axis lathes developed four decades ago to the recently developed multi-functional machine tools. Recently, the demand for simultaneous five-axis and multi-tasking machine tools has increased for making large-scale and complex products, such as ship propellers and crank shafts, aerospace components,

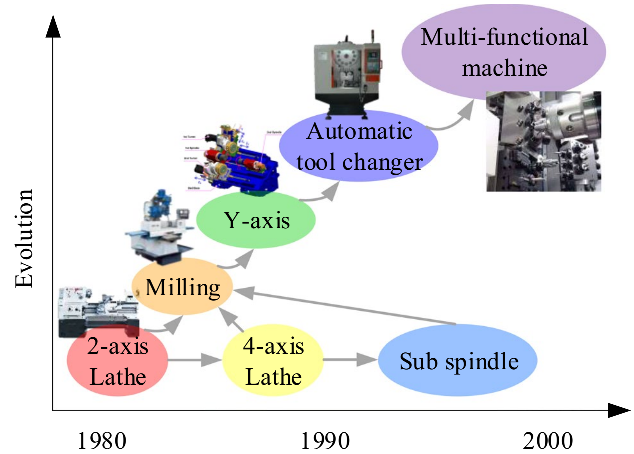

Fig. 1 The evolution of machine tools [41]

and large spiral bevel gears [43–45]. The need for making parts with complex geometries with high accuracy in a single setup can be met by using a single multi-axis or multi-tasking machine tool. These multi-function machine tools reduce or eliminate workpiece clamping and handling processes, which improves production efficiency, simplifies production management and planning, and improves transparency throughout the production of a single part. Multi-axis and multi-tasking machine tools have many advantages, but due to their complex structure, achieving successful machining operations can be difficult. Researchers have investigated computer-aided manufacturing systems to minimize associated programming time and labor needs [42, 46]. While displacement errors are a challenge, up to 75% of the overall geometrical errors of machined workpieces are due to the effects of temperature [47, 48]. In particular, the aerospace industry requires complex parts using high performance alloys with superior thermal and mechanical properties, which decrease machinability and productivity [49]. Another drawback of the multi-axis and multi-tasking machine tools is self-interference [42].

2.3.2 Hybrid machine tools

Hybrid machine tools can be considered as machining equipment that implement other manufacturing process functions, beyond conventional cutting operations. Hybrid machine tools, which are different from multi-tasking machine tools, have been defined as integrated manufacturing processes with different forms of energy or forms of energy sources [50], such as additive or subtractive machine tools combined with laser-based machining. The commonly used manufacturing processes, such as mechanical machining (MM), electrochemical (ECM), electric discharge machining (EDM), additive manufacturing, laser cutting, forming, and laser heating have been at least partially integrated. Three or more processes can be integrated into a single hybrid machine tool. Possible hybrids of typical manufacturing processes are shown in Table 2. Hybrid machine tools can be categorized into three types, i.e., subtractive manufacturing (SM), forming manufacturing (FM), and additive manufacturing (AM).

SM-based hybrid machine tools generally aim to realize higher performance, in terms of material removal rate, surface integrity, and tool wear [51]. Zhu et al. [52] established an experimental bench that combines grinding and ECM to machine precision small holes in hard-to-machine materials. Similarly, the combination of EDM and MM is also able to machine hard and brittle materials [51]. Combining laser cutting and other machining processes, such as MM [53], EDM, and ECM, is usually adopted to reduce tool wear and production time, as well as to increase surface quality. Moreover, laser heating and ultrasonic vibration have been explored as auxiliary processes for improving machining performance. Laser-assisted mechanical machining (LAMM), which can reduce material hardness, was presented over 20 years ago [54] and was used to machine high-strength materials in recent years [55]. Kumar et al. [56] studied a laser-assisted micro-grinding process for a hard silicon nitride ceramic. Assisted by the laser, the machining force of the grinding process was reduced by up to 40%. Researchers have also investigated ultrasonic-assisted cutting. For example, Zhong et al. [57] proposed an ultrasonic vibration rig of a CNC machine tool for the turning of aluminum-based metal matrix composite workpieces. They demonstrated that ultrasonic vibration improved the surface roughness of the workpiece under given combinations of speed, feed, depth of cut, and vibration frequency.

FM-based hybrid machine tools, which combine traditional forming and laser treatment processes can be of benefit for sheet metal forming. In particular, the heat energy provided by lasers is effective for changing the microstructure and mechanical properties of the irradiated workpieces. Using a laser to heat the material near the drawing edge before the operation can reduce the drawing force and forming steps as well as to obtain deeper features [58, 59]. Duflou et al. [60] utilized a laser to heat the underside of the sheet for increasing formability in the single point incremental forming (SPIF) process. Biermann et al. [61] found that using a laser for heating the workpiece in front of the forming tool is effective to assist the forming process. Modeling of the laser-assisted SPIF process was investigated to predict the bending angle of workpieces [62]. Additive-incremental forming hybrid manufacturing can result in the development of a rapid prototyping technique that exploits the peculiarities of both the utilized processes [63]. Additive manufacturing-based hybrid machine tools address some of the challenges of additive processes capable of making metal parts with complex geometries, but tend to exhibit poor surface quality, low dimensional accuracy, and long production time [64]. For improving accuracy and surface quality and saving companies time and costs, the integration of additive manufacturing with traditional machining technologies has been widely practiced in research areas and industries, such as the HYBRID HSTM 1000 [65] system from France and the INTEGREX i-400 AM [66] from Japan. Additive manufacturing-based hybrid manufacturing processes are usually called hybrid additive and subtractive manufacturing (HASM) processes. HASM processes generally use an additive manufacturing process to build a near-net shape, which is subsequently machined to its final shape with desired accuracy using an SM process [51, 67].

Manogharan et al. [68] investigated the HASM process, and presented that the key to a successful rapid high precision hybrid process is developing a process that does not inhibit future developments and makes use of existing additive and subtractive processes. Du et al. [69] developed a process technology to take advantage of selective laser melting (SLM) and precision milling. Additive manufacturing-based hybrid tools are generally developed based on multi-axis 3D printing mechanisms. A disadvantage of traditional 3D printers is that the product can only be printed along flat layers. With the development of robotic technology, 3D printers employing an industrial robot with more than three degrees of freedom (DOF), can realize multi-plane motion [70]. Li et al. [71] developed a novel HASM platform that

Table 2 Possible hybrids of typical manufacturing processes

	MM	ECM	EDM	Additive manufacturing	Laser cutting	Forming	Laser heating
MM		■	■	■	■	■	■
ECM	■		■		■		■
EDM	■	■			■		
Additive manufacturing	■					■	
Laser cutting	■	■	■				
Forming	■			■			■
Laser heating	■	■				■	

combines fused deposition modeling (FDM) and a 6-DOF machine tool to overcome limitations of typical additive processes. Manogharan et al. [72] analyzed the economics of HASM processes and presented a composite model to determine the unit cost of producing mechanical parts. Le et al. [64, 73] proposed a direct material reuse strategy to recover end-of-life (EoL) parts using a HASM process. Their methodology starts with investigating the feasibility of applying metal-based additive processes for printing new features onto an EoL part. Next, a manufacturing process plan for additive and machining operations is determined. By considering the relationships of the added and removed features as well as manufacturing precedence constraints, the setups are designed. Their approach could reduce energy and resource consumption for a selected part.

2.4 Model-based enterprise

A model-based enterprise integrates technical and business processes through the definition of a common product model through which the data from different life cycle phases can be coordinated and various modeling and simulation efforts can be integrated [74, 75]. This will reduce cost and time for development, production, and support. Within a model-based enterprise, data is created once and reused downstream. However, acquiring the right data to build and improve the models and provide the data to stakeholders throughout the life cycle is challenging. The idea of a digital thread has been investigated to support the collection and transmission of data throughout a product's life cycle. This section will provide an overview of digital threads and their support of model-based enterprises.

2.4.1 Digital system model, digital thread, digital twin

The digital thread, originating from the aerospace industry, was initially described as a technique supporting the systems engineering process for digital management through Computer Aided Design (CAD), manufacturing, assembly, and delivery [76]. The definition has since expanded beyond the design and manufacturing stage to include other data throughout a product's life cycle. Many threads, when woven together, make up a "digital tapestry," as described in Bullen [77]. The terms *digital system model* and *digital twin* are associated with a digital thread. Definitions of digital system model (adapted from Kraft [76]), digital thread (adapted from the working draft of ISO/AWI 23247–5 [78], and digital twin (adapted from ISO and National Academies [79, 80] are listed below.

- **Digital system model:** A digital representation of a system that integrates authoritative data, information, algorithms, and systems engineering to define aspects for specific activities throughout the system life cycle.
- **Digital thread:** The connected communication framework of contextualized life cycle data. The communication is supported by information modeling standards and technologies and enables data traceability.
- **Digital twin:** A fit for purpose digital representation with synchronization between an observable element and its digital representation, has predictive capability, and informs decision-making.

The expanded digital thread systems perspective aligns with the need for life cycle considerations in sustainable manufacturing systems. Methods and approaches that connect the product and manufacturing process life cycle stages contribute to the goal and definition of sustainable manufacturing. An indication of this alignment is found in Hedburg et al. [81], which proposes a concept to address unstructured datasets, multiple data repositories, and domain-specific schema for life cycle stages. The research concept proposed the system to share and utilize data across the life cycle. It would respond to industry's major challenge of linking product life cycle data resulting from the unique contexts in which data is used for a specific product life cycle stage (e.g., design vs. use). While this concept did not address sustainability, its principles can be applied to support sustainable manufacturing. A digital thread may connect design tools, sensors, machines, models, companies, and more to one another [77]. It allows for communication and data sharing across multiple entities. This idea builds on smart manufacturing, Industry 4.0, and other emerging technologies to share data that can improve processes and entities beyond the originating individual. These connections can have great benefits in efficiency and optimization. These technological benefits can include lower costs and reduced cycle times, and also a number of environmental benefits, e.g., improved energy efficiency and higher resource efficiency [82, 83].

Process and system models are a digital twin of the manufacturing processes or systems, that may contain sustainability-related information, and traverse a digital thread. While much knowledge is captured across this digital thread from design through production and inspection, manufacturing organizations have not fully realized smart manufacturing through model-based enterprises for improving quality and sustainability performance [81]. Much work is still needed to attain sustainability goals through model-based enterprises. Cloud technologies enable digital model-based enterprises by moving data storage and computing away from desktops and local servers to distributed data centers across the Internet, and exhibit *elasticity*, or the ability to adapt to changes; *economy*, or the reduction in cost due to renting server space; and *virtualization*, or the ability for multiple users to store data on a single server [84]. Elasticity enables nearly continuous optimization to improve energy and resource efficiency. Storage space rental, along with the ability for multiple users to store data on the same physical equipment, allow for the reduction in physical server space (only the space required is paid for). Using cloud-based technologies, a faster response to changes in computing requirements can be provided in addition to reduced waste in data storage.

Maintenance can account for as much as 60–70% of production life cycle total cost [85], and replacing worn-out components may be up to 70% of the total maintenance cost [86]. The use of cloud-based augmented reality can promote preventive maintenance practices, reducing cost, time, and resources used in maintenance [87]. Mourtzis et al. [87] proposed a Cloud-Based Augmented Reality Remote Maintenance Shop-Floor Monitoring Product-Service System (CARM^2-PSS) approach that consists of a wireless sensor network that can pull data in real time, preprocess the data, and then determine the machine status and the machining time. This information is used to provide augmented reality service instructions. Manufacturing process monitoring allows for better control of process parameters. For example, part quality often presents challenges in the implementation of additive manufacturing of metallic parts due to a variety of factors, including a poor understanding of the complex physical phenomena that take place during the process [88]. Other defects include part geometric errors caused by poor process control. Real-time monitoring can increase the availability of process knowledge and the ability to improve quality by modifying process parameters [89–91].

2.4.2 Data collection and transmission

As the semantic framework in the digital system model, the digital thread supports the interplay (sharing) of data and information [76]. Here, the digital thread is involved in data collection and transmission, and the digital system model includes data certification, traceability, authenticity, and cybersecurity. Hedberg et al. [92] identified three standards for creating a manufacturing digital thread: (1) MTConnect [93], (2) ISO 10303 the Standard for the Exchange of Product Model Data (STEP) [94], and (3) the ISO 23952:2020 the Quality information framework (QIF) [95]. MTConnect is an open protocol standard based on Extensible Markup Language (XML) [96] for data integration that facilitates communication within a manufacturing system [97]. Near-real time data is supported by MTConnect. Bengtsson et al. [98] utilized MTConnect to collect production data from a Boeing shop floor along with discrete event simulation to investigate sustainable machining using Life Cycle Assessment (LCA). The STEP standard enables defining and sharing product manufacturing information (e.g., geometric dimensions, tolerances, and part specifications), kinematics, and tessellations [81, 99]. For example, STEP contains information that can support assembly/disassembly analysis during the design stage [100, 101]. Lastly, QIF enables the exchange of metrology data using information models and integrates the product definition into the quality information [81].

The Smart Manufacturing System (SMS) testbed, developed and operated at NIST [102], exhibited many of the digital thread concepts. Lu et al. [103] stated an SMS maximizes a manufacturer's competitiveness "by using advanced technologies that promote rapid flow and widespread use of digital information within and between manufacturing systems." The SMS testbed demonstrated the integration between product designs and fabrication/inspection data. Data was collected using the MTConnect standard. Technical data packages, query-able data, and a real-time stream of data were provided [104]. Challenges identified by the testbed include cybersecurity concerns in the form of data losses and cyber-attacks [102]. A challenge of data transmission is the issue of data interoperability. Throughout the life cycle, there are many data standards and data formats, which can make it difficult to transfer and read data from other parts of the product life cycle. MTConnect, STEP, and QIF are three standards that can provide an interoperable digital thread throughout design, manufacturing, and inspection. To address data interoperability concerns within manufacturing, Monnier et al. [105] provided a review of the data formats that can be found within the manufacturing stage of the product life cycle data (design, manufacturing, and inspection) and a description of the different mapping techniques across these standards with the associated tradeoffs. AM has its own challenges in data interoperability due to how new the field is. To address this, Li et al. [106] outlined the need for a common data model within AM to make AM data FAIR (Findable, Accessible, Interoperable, and Reusable) and described the design philosophy around the current effort to develop an AM common data model.

Collection and transmission of critical data (e.g., process parameters) is currently an area of research in additive manufacturing receiving intense scrutiny to achieve component quality certification. Additively produced components require continuous monitoring during production to ensure sufficient quality throughout all layers of a component, which requires research into both sensor technology and monitoring algorithms. Tapia and Elwany [88] reviewed several types of sensors used in additive manufacturing, e.g., pyrometers, photodiodes, digital cameras, thermocouples, and displacement sensors. They concluded that additional studies are required to fully understand monitoring and control in metal additive manufacturing and that there is a lack of statistical models and algorithms developed based on the monitored data. They found that research is limited to simple geometries and, thus, potential effects of complex geometries is unknown. To increase the usability of

AM data, Lu et al. [107] describe how metadata needs to be collected and accessible. The authors surveyed common AM data-collection methods, including in the lab and in the field, as well as in-process monitoring and post-process part inspection. The focus was to identify acquisition-related metadata to improve data usability. Data fusion has been a challenge in AM due to the increasingly available data from the monitoring of AM processes. Feng et al. [108] presented a data registration method to align data acquired from AM as a first step towards addressing data fusion. The authors provided a common reference and coordinate system as well as effective ways to transform between coordinate systems.

2.5 Sustainable manufacturing

Sustainable manufacturing has been defined as, “[t]he creation of goods or services using a system of processes that simultaneously addresses economic, environmental, and social aspects in an attempt to improve the positive or reduce the negative impacts of production by means of responsible and conscious actions” [109]. Environmental and economic metrics for sustainable manufacturing often focus on material and energy inputs and wastes and other outputs for a given manufacturing process or system. This focus is driven by the scope of evaluation for sustainable manufacturing systems (Fig. 2), which suggests a circular path of materials and products and includes design, manufacturing, distribution, use, and value recovery.

In this system, material and product flows alone will not fully support sustainable manufacturing. Rather, material and product flows must be supported by information flows between stages in the context of the digital systems model, digital thread, digital twin, and model-based definition/enterprise [76, 103]. Major initiatives in the USA and abroad, e.g., Industry 4.0, the National Institute of Standards and Technology (NIST) Smart Manufacturing programs, the Smart Manufacturing Leadership Coalition (SMLC), and the Clean Energy Smart Manufacturing Innovation Institute (CESMII), sponsored by the US Department of Energy, are pursuing efforts to predict and reduce energy use, waste, cost, and cycle times within the manufacturing phase of the life cycle, among other sustainability performance measures, which are seen as key benefits of implementing a digital thread [82, 83, 102]. This section describes three approaches to addressing sustainable manufacturing challenges.

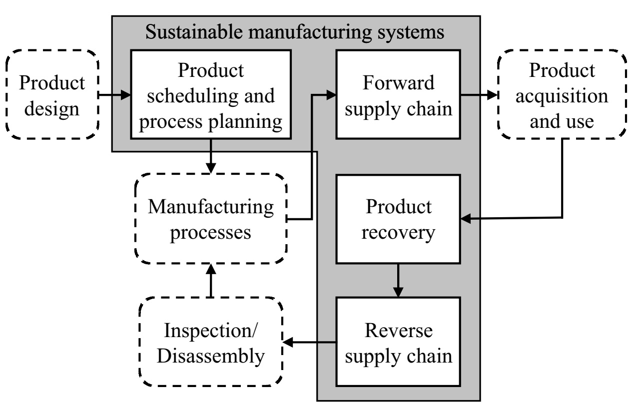

Fig. 2 Sustainable manufacturing system elements for material flow. Similar routing of information and data is possible with a digital thread [110]

2.5.1 Unit manufacturing processes (UMPs)

Mani et al. [111] recognized a need for a standard science and information base to measure manufacturing sustainability impacts. Five elements were determined as necessary and sufficient elements for sustainability performance: (1) unit manufacturing processes (UMPs) and operations, (2) inputs and outputs, (3) operation rules, (4) operation resources, and (5) dataflow among operations. A standard representation of a generic UMP model is defined in the ASTM E3012-22 standard and is shown below in Fig. 3 [112, 113]. Importantly, UMP models document sustainable manufacturing related aspects, such as energy/material inputs, wastes, product life cycle management (PLM) and sustainability plans, and human resources. ASTM E3012-22 models interface with ASTM E2986-22 [114] to guide UMP boundary determination.

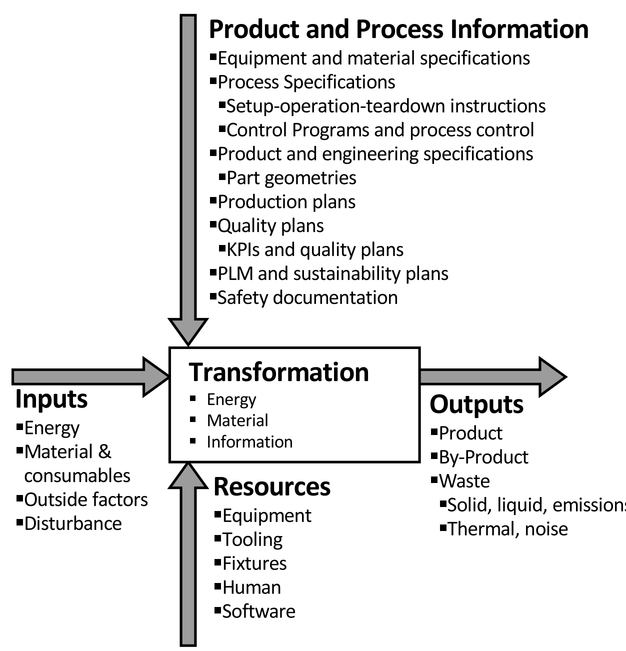

Fig. 3 Schematic of NIST-developed UMP model to capture inputs, outputs, resources, and information for a process under consideration [113]

Information about the manufacturing process parameters is contained in the model as are transformation equations that define how energy, material, and information are converted from model inputs to outputs. Rickli et al. [115] showed there is the capacity for networks of UMPs to be modeled by describing the potential for connecting UMP models as part of modeling an additive metal deposition process. Bernstein et al. [116] demonstrated the potential for informing a LCA through the data generated from the development and application of UMP models. More research is required for these applications. However, a repository of standardized UMP models will promote consistency among performance assessments, allow for data-driven analysis activities, and provide reference material that will assist industry in modeling and improving their operations [117, 118].

2.5.2 Measurements, metrics, and characterization for sustainable manufacturing

Recognizing the importance of measuring sustainability practices to quantify improvements, it is necessary to clarify the differences between measurements, metrics, and indicators. Sustainability indicators help manufacturers evaluate their performance from the triple bottom line perspective, i.e., environment, economic, and social, perspectives. Such indicators can also be used in ways that directly relate to manufacturing metrics, such as energy use, material consumption, and productivity. Feng and Joung [119] identified several key characteristics of indicators, i.e., they must be measurable, relevant, understandable, reliable/usable, data accessible, and flexible. They described the sustainability measurement process as "a sequence of operations, with the necessary instruments and tools and having the objective of determining the value of an indicator." Sustainability metrics are simply "a set of measurements, corresponding to standard indicators that are used to evaluate sustainability performance" [119].

Over the years, a number of indicators have been proposed for sustainability performance measurement. The Organization of Economic Co-operation and Development (OECD) published a Sustainable Manufacturing Toolkit [120] that uses 18 indicators for sustainable manufacturing under three categories, i.e., inputs, operations, and products. The NIST Sustainable Manufacturing Indicator Repository defined metrics under five dimensions of sustainability, i.e., environmental stewardship, economic growth, social well-being, technological advancement, and performance management [121]. Cohen et al. [122] compiled a database of 557 sustainability indicators in 2014, indicating the growth in sustainability management during the previous decade. On reviewing several sustainability performance tools for evaluation and decision-making in practice, Feng and Joung [119] noted that manufacturers require a standardized framework to evaluate their own sustainability practices and to minimize their reliance on external stakeholders. They proposed the development of a sustainability management infrastructure comprising a sustainability indicator repository, measurement methods, guidelines, and performance analysis. Building on previous work, Joung et al. [123], reviewed eleven sets of publicly available sustainability indicators and identified those that were related to manufacturing, providing manufacturers a common repository of sustainability indicators.

With regard to the development and use of sustainability metrics, Feng et al. [124] highlighted the fact that developed metrics can be applied to assess sustainability across the product life cycle and can also be used at an organizational level for decision-making. De Silva et al. [125] developed a scoring method to put the idea of sustainability evaluation in practice in the context of electronics products. Lu et al. [126] presented a framework for the development of product and process metrics and explored how both sets of metrics interact with each other to support sustainable manufacturing. More recently, Faulkner and Badurdeen [127] used sustainability metrics to develop a methodology that could lead to Sustainable Value Stream Mapping, building on a technique used in lean manufacturing. Shuaib et al. [128] proposed the development of a Product Sustainability Index (Prod SI), a metrics system that helps assess sustainability at the product level. Huang and Badurdeen [129] extended this work to the enterprise level through the development of the framework for the Enterprise Sustainability Index, En SI. Meanwhile, Calik and Badurdeen [130] developed the first known scale to measure sustainable innovation performance. However, this scale requires validation using industry data. Lucato et al. [131] developed a conceptual framework to evaluate the sustainability performance of a manufacturing process from the triple bottom line perspective. Unlike previously proposed frameworks, their approach integrates all three pillars of sustainability, environmental, social, and economic, into a single measurement variable.

One major challenge in developing absolute measures for sustainability is the lack of well-defined approaches to characterize sustainability performance for manufacturing [132]. Through the characterization of sustainability performance, manufacturers can better position themselves in improving productivity. In the recent past, LCA tools that use life cycle inventory (LCI) databases have been developed and used in measuring impacts. LCAs require a lot of data that can be sparse and may not align with the actual manufacturing processes, which makes performing an LCA difficult and prone to inaccuracies [133]. To aid in metric characterization, Kellens et al. [134, 135] developed a two-level screening and in-depth approach based on the LCA methodology to combine the unit process life cycle inventory (UPLCI) effort in the USA and the CO2PE! initiative in Europe. This UMP modeling methodology has been used to generate process models for evaluating the environmental impacts of various UMPs such as grinding [136], drilling [137], metal injection molding [138–140], high speed laser directed energy deposition [141], laser powder bed fusion [142], stereolithography [143], gas metal arc welding [144] polymer injection molding [145], and fused deposition modeling [146].

To improve the communication of sustainability performance across integrated supply chains, especially in sharing relevant data and information, Garretson et al. [109] focused on better defining the terminology associated with sustainability related practices. Vinodh and Joy [147] used structural equation modeling (SEM) to model sustainable manufacturing system enablers and outcomes. The benefit of SEM is the use of actual empirical data from industry as opposed to theoretical data. Further, as a means of characterizing the performance of sustainable manufacturing, Shao et al. [148] proposed the sustainable process analysis framework (SPAF), Zhang et al. [149] developed a product sustainability index (ProdSI) based on a five-level hierarchical framework, and Ordouei et al. [150] introduced the concept of analytical hierarchy process (AHP) and the implementation of sustainability indices from the triple-bottom line perspective. Kluczek [151] developed a multi-criteria approach for the assessment of sustainability of manufacturing processes.

Using AHP, activities in the manufacturing processes are assigned rankings in terms of sustainability objectives, allowing a less technical approach to evaluating sustainability. Zhang et al. [152] integrated systems thinking methods as an initial step to defining a unified theoretical framework for assessing sustainability. Duflou et al. [153] emphasized the variety of considerations that go into reducing environmental impact, focusing on energy and resource efficiency. They characterized analysis and system optimization challenges and opportunities at each level of the manufacturing system (i.e., the unit-process through supply chain levels). Loglisci et al. [154] proposed a set of indicators for sustainable manufacturing evaluation focusing on conditions of human work and the environment. Similarly, Sutherland et al. [155] explored ways of integrating social impacts into LCA. Shokravi and Kurnia [156] proposed a conceptual method of measuring sustainability performance of industrial networks quantitatively using aleatory and epistemic uncertainties considering economic, environmental, and social aspects. In the past, the main challenges in characterizing sustainability performance have included a lack of harmonized nomenclature and standards, lack of structured information, and limited decision models. Sustainability metrics existed at company, regional, and national levels [157]. However, standards have started to emerge to provide guidance to small and medium-sized manufacturers, as outlined in Escoto et al. [158]. These include quality management standards (ISO 9000 series), environmental management standards (ISO 14000 series), and sustainable production standards (ISO 20140 & ASTM E60.13 series). Continued work is required to develop standards, unify nomenclature, and build decision models addressing the lack of definite information.

2.5.3 Data visualization of sustainability assessment

Advancing digital thread technologies for sustainable manufacturing involves research opportunities in data visualization [159]. In particular, the complex interplay of economic, environmental, and social metrics for sustainable manufacturing increase the difficulty of communicating the metrics and their implications to people from machine operators to engineering and business decision makers, consumers and policy makers [160]. Innovative data visualization methods can enhance communication of such complex information and the importance of considering sustainability performance indicators in manufacturing, to different audiences. Effective visualization of sustainability performance analysis results should lead to awareness and a subsequent need to take action (e.g., apply the results in making a decision). While one intended audience for a visualization of results may need detailed information (e.g., experimental design or analysis methodology), another audience may only be interested in the results of the analysis. Consequently, to develop analysis methods, software tools, and other solutions, the needs of various audiences should be considered. Raoufi et al. [159] introduced two questions to be taken into account in presenting sustainability analysis results: (1) *What does the user hope to accomplish*? and (2) *What barriers do users face in achieving their objective(s)*? While the answers to these questions are specific to the system(s) under study, they clarify the decision to be made, its magnitude, and its frame of reference. Given this focus, decision makers will be able to arrive at a conclusion without need to interpret extraneous information. Educating decision makers about sustainability analysis methods related to their industry was seen as a key to helping them better understand the goal(s) of conducting such assessments.

While visualization of sustainability assessment results can inform decision makers of the attendant uncertainties [161–164], few studies have investigated the impact of quantitative uncertainty visualization on different audiences [161]. The inherent uncertainties in LCA and the volume of data required across the product life cycle increase the complexity and the challenges for visualization of the results [165, 166]. Tabular data and bar charts are the typical formats for reporting LCA results, which do not support rapid and intuitive visual analysis of the uncertainties and, in fact, may cause a false sense of certainty for some audiences [159]. Ramanujan et al. [166] reiterated this point in their work to identify opportunities for future research in product LCA to support effective sustainable design decision making. They concluded that visualization frameworks are needed to integrate life cycle data with visual representations of the results and to address the attendant complexities and uncertainties in an easy-to-understand way.

2.6 Supply chain management

The role of the supply chain management (SCM) is to provide the right product to the right customers at competitive costs, time, quality, and quantities. In the short-term, SCM principles help reduce cycle times and inventory, thereby contributing towards greater productivity. The overarching objective of sustainable SCM is to develop the means for long-term environmental, social, and economic value for all stakeholders. This section first provides a brief introduction to green SCM, and then investigates SCM from a sustainability perspective.

2.6.1 Green supply chain management

A supply chain is a network that consists of the stakeholders (e.g., suppliers, manufacturers, distributors, wholesalers, retailers, and customers) involved directly or indirectly in the development, production, and delivery of products and/or services to customers. These activities take place both through upstream and downstream flows and distribution of information and finances [167]. It is known that environmental, social, and economic impacts exist across the supply chain. With this awareness, business and government leaders have been striving to address SCM from the triple bottom line perspective.

According to the UN, supply chain sustainability or green supply chain management (GSCM) is "the management of environmental, social, and economic impacts and the encouragement of good governance practices throughout the life cycles of goods and services" [168]. Managing a supply chain is a complex process given that the network comprises numerous sub-systems, activities, relationships, and operations. The *green* component of GSCM integrates a set of sustainability principles in the procurement, manufacturing, distribution, and reverse-logistics stages [169]. Effective implementations of SCM result in accurate demand forecasts, increased customer service and responsiveness, better supply chain communications as well as reduced risk, production cycle time, and duplication [170]. With an increasing foothold, a greater number of governments, firms, and supply chain partners are collaborating to tackle problems related to minimizing waste, energy, and pollution, while working on increasing goodwill and maintaining profits [171, 172].

Collaborations between various stakeholders are especially beneficial, since they promote mutual learning with respect to increasing supply chain sustainability performance. According to a study by Flammer [173], it has been observed that companies who incorporate sustainability practices have experienced significant increases in stock prices. Thus, firms have realized that sustainability is a business strategy related not just to environmentally friendly practices, but also to corporate social responsibility. Such firms have gained a competitive advantage in the market, including greater customer approval. In short, to achieve long-lasting competitive advantages, firms need to approach sustainability from the triple bottom line perspective, taking into account economic, environmental, and social aspects [174].

One key SCM activity is the coordination and efficient flow of raw materials and components from suppliers to manufacturing units during production of a given product. Studies carried out by Rao and Sarkis [175, 176] emphasized the need for effective collaboration with suppliers through implementing green design, increasing awareness of supply chain impacts, and helping suppliers develop their own GSCM programs. Chin et al. [170] found that environmental collaboration between practitioners and suppliers in designing green products facilitates the connection between GSCM and industrial sustainability performance. Similarly, Singh and Dyer [177] reported that the establishment of long-term collaborative relationships characterized by strong interorganizational interactions facilitates the pursuit of GSCM initiatives.

2.6.2 GSCM initiatives

Supply chain managers may encounter a number of green initiatives. Prior research has attempted to define the most important factors in developing a sustainable supply chain [178]. Masoumik et al. [179] highlighted the lack of research demonstrating how external and internal drivers can interactively affect business managers' decisions in selecting strategies for implementation of GSCM. While some studies use AHP, they found that the decision factors included in these models are more relevant to operational levels rather than strategic levels of management. They proposed a conceptual model based on application of the natural-resource-based view (NRBV) and institutional theory. The model comprised a literature review and used analytic network process (ANP) modeling to structure the decision framework, where ANP is a more generalized form of AHP. Pimenta and Ball [180] recognized that the scope of GSCM is extremely broad, ranging from green purchasing to integrated life cycle management. Their study focused mainly on upstream supply chain management activities because it is at this stage that the main diffusion of environmental sustainability practices takes place. Similarly, Lee et al. [181] developed a research model relating GSCM practice and business performance through three organizational variables as moderators, i.e., employee satisfaction, operational efficiency, and relational efficiency. To test the proposed hypotheses relating GSCM practice implementation and business performance, SEM was used (e.g., [182]). They found that the GSCM practice implementation improves the operational efficiency and the relational efficiency, which eventually enhances the business performance.

While GSCM initiatives can help promote supply chain sustainability, the implementation of GSCM strategies must be performed with prudence. Laosirihongthong et al. [183], for example, reported that pursuing a low-cost strategy may negatively impact an organization's ability to invest in GSCM. The purpose of their study was to examine the deployment of proactive and reactive practices in the implementation of GSCM. The study found that the threat of legislation and regulation (reactive practices), including the applicability of Waste Electrical and Electronic Equipment (WEEE) directive in August 2005, Kyoto Protocol's Clean Development Mechanism (CDM) in 2008–2012, Climate Change Act (in the UK) in 2008, American Clean Energy Bill (USA) in 2009, and Restriction of Hazardous Substance (RoHS) directive in July 2006, were a consideration that compelled companies to enhance their environmental, economic, and intangible performance. Among proactive practices reported, i.e., green purchasing practices, eco-design practices, and reverse logistics practices, the last were less common and did not have a significant impact on GSCM performance. In addition, while corporate social responsibility encourages reduction of negative social impacts (and increasing social benefits) across supply chains, a review on supply chain network design by Eskandarpour et al. [184] found that a large body of work focuses on the environmental and economic aspects of sustainability. In fact, there has been little consideration of social aspects in the context of sustainable manufacturing, especially in terms of quantitative studies. The authors observed that most research with regard to modeling techniques concentrates on the development of deterministic MILP (mixed integer linear programming) models as opposed to stochastic models. These deterministic models are solved using standard modeling tools and solvers.

3 Challenges, future trends, and recommendations

This review considered recent research in support of advanced manufacturing systems. Emerging trends include process sensing and monitoring, equipment control and automation, multi-axis and multi-tasking machine tools, model-based enterprises, and sustainable manufacturing. These trends are each summarized below, and relevant opportunities for future research are highlighted.

3.1 Process sensing and monitoring

Process sensing and monitoring provides valuable information about tool and workpiece conditions, which helps in reducing the failure and, consequently, improves machining productivity. Sensor-based monitoring is conducted through single sensors or multiple sensors. For single sensors, miniaturization of the sensor package and embedding the sensor within the cutting tool is a key to accessing parameters with high signal-to-noise ratios [185]. Multiple sensors can help improve the sensing accuracy by fusing the data from individual sensors [186, 187]. Data-based algorithms, such as the Artificial Neural Network, Support Vector Machine, and Random Forest [188] approaches, that rely on historical data have been identified as powerful solutions to fusing multiple streams of sensor data for most applications. To better understand the correlations among sensor data and target phenomena being monitored, physical models, especially for complicated machining process such as grinding, are still highly demanded.

3.2 Equipment control and automation

The recent research in the area of equipment control and automation has focused on two key areas: (1) advances in motion command algorithms for positioning systems and (2) supervisory systems and factory automation. In the former research area, development of iterative motion control and positioning systems improved the quality (tolerances and repeatability) of parts produced using machining, metal-based additive manufacturing, and other processes. However, further research is needed for developing advanced controllers in multi-material, multi-scale additive manufacturing processes. Moreover, to improve real-time control, analytical and data-driven models are needed to address the high computational challenges of simulation and physics-based finite element analysis. In the latter research area, advances in the Internet of Things (IoT) improved manufacturing systems operations. However, further studies are needed to investigate the hardware and software required for integrating data analytics with IoT and other distributed processing techniques. Moreover, collecting data and applying data analytics across all phases of the product life cycle needs further investigation.

3.3 Machine tool development

Recent industrial initiatives, such as Industry 4.0 and Factories of the Future, have placed demands on the development of machine tools for more intelligent and more autonomous manufacturing systems. Moreover, increasing energy costs and environmental problems have pushed research forward on the sustainable operation of machine tools with considerations of higher speeds, efficiency, and reliability, and lower emissions. Unified management of machine tool programs and standardization of process approval mechanisms utilizing cloud platforms can reduce the risk of errors caused by human factors and avoid security risks caused by transmission media. Unified management and standardization can also ensure the consistency of programs and drawings without repeated programming, which improves operator performance and machine tool efficiency. Such platforms can also improve safety and quality, and reduce scrap rates, maintenance costs, and operational risks. In a related manner, process control, health monitoring, and energy management based on CPS, digital twins, and other advanced approaches need to be applied in multi-functional machine tools, for better performing and cleaner processes. It is increasingly a trend to provide users with customized multi-functional machine tools and system solutions based on the IoT and cloud service platforms. Future research on remanufacturing of machine tools should be a focus of materials, energy, and value recovery; strategies include remanufacturing-oriented design and residual life prediction of critical components.

3.4 Model-based enterprise (MBE)

Connectedness and aggregation of disparate data sources are key characteristics of digital manufacturing and the digital thread that can significantly alter data availability for sustainability performance assessment. While research into the digital manufacturing enterprise has been prevalent, research leveraging the digital thread specifically for sustainability evaluation is less common. The review conducted herein and reflection on recent research have identified several research recommendations related to the digital thread for sustainable manufacturing. First, manufacturing case studies must be undertaken and reported to better demonstrate the capabilities and benefits of linking digital manufacturing information with life cycle methods and tools, such as the integration NIST UMP models and Brightway2 discussed in Sect. 2.5.1.

3.5 Sustainable manufacturing

The degree to which a manufactured product or process is environmentally impactful can be quantified using any one of a number of different frameworks — most based on life cycle accounting principles [189]. While these frameworks vary in flexibility and customizability (e.g., [190–192]), a comparatively small number of metrics appear regularly in the life cycle literature for sustainable manufacturing: energy use, greenhouse gas (GHG) emissions, water use, and a few others. More recently, specialized ways of characterizing the performance of a manufacturing system are gaining acceptance. The focus on GHG emissions in recent years had led to formalized carbon auditing schemes that are now widespread in industry [193]. GHG accounting protocols typically bin firm's activities into three tiers [194]: Tier 1 represent all the direct emissions from the operations of a firm, Tier 2 captures the emissions from energy that a firm uses, and Tier 3 accounts for all the upstream emissions that come from suppliers. As many companies make commitments to decarbonize over the coming decades, this kind of carbon accounting will be applied more broadly to manufacturing operations. For those seeking a broader evaluation of sustainability, the United Nations released sustainable development goals in 2015 [195] that take a comprehensive and quantifiable approach to measuring sustainability. Recent work has sought to apply these development goals to sustainable manufacturing by thinking beyond individual technical decisions at the plant level and focusing on directed technical change and the way that firms operate to achieve sustainability goals [196].

Data visualization is another area that will advance technologies for sustainable manufacturing. Promising efforts are being made around investigating visual communication of sustainability assessment results. However, there is still a need to investigate the types, means, and content for sustainability performance visualization that align with industry experience. The effective visual representation of quantitative information, including uncertainty, for sustainability performance is still preliminary. In addition to developing pedagogical approaches for educating and training decision makers (e.g., [197–212]), a related area identified from academic and industrial perspectives is the need to define user interface/user experience (UI/UX) factors and visualization formats enabling or preventing decision makers in interpreting sustainability performance data and information.

3.6 Supply chain management

Supply chain management (SCM) enables stakeholders to provide products and/or services to customers. Green SCM (GSCM) integrates sustainability principles with different stages of an SCM and develops long-term values from triple bottom line perspective for all the stakeholders. However, its implementation is challenging due to the limited amount of data available in supporting green supply chain decision making. Few studies have been carried out using SEM and regression analyses to address this issue. However, further research is needed in this area. Moreover, given the strong support of industry and academic researchers for implementing GSCM initiatives, a challenge lies in the ability to strategically implement initiatives that are most effective for different manufacturing enterprises. Several models and approaches implementing GSCM have been conceptualized and future research would require these concepts to be validated through the development of robust manufacturing enterprise and product supply chain models. As approaches and tools for economic and environmental analysis of industry continue to mature, future research must focus on how to adequately evaluate the broad social impacts of manufacturing activities. These activities occur across the whole product life cycle and directly impact workers, communities, and global society in profound and often unpredictable ways.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Kamyar Raoufi, John W. Sutherland, Fu Zhao, Andres F. Clarens, Jeremy L. Rickli, Zhaoyan Fan, Haihong Huang, Yue Wang, Wo Jae Lee, Nehika Mathur, Matthew J. Triebe, Sai Srinivas Desabathina, and Karl R. Haapala. The first draft of the manuscript was compiled by Kamyar Raoufi and Karl R. Haapala and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding We gratefully acknowledge the broad-based support received over the course of this research. In particular, this material is based upon a work supported by the U.S. National Science Foundation under Grant Nos. DUE-1432774 and DUE-1935708 at Oregon State University and CBET-1512217, CBET-1605472, and IGERT-1144843, as well as the Wabash Heartland Innovation Network (WHIN), at Purdue University. We also wish to express appreciation to the National Natural Science Foundation of China (Grant No. U20A20295) for its support of this work.

Declarations

Competing interests The authors declare no competing interests.

Disclaimer Certain commercial systems are identified in this paper. Such identification does not imply recommendation or endorsement by NIST. Nor does it imply that the products identified are necessarily the best available for the purpose.

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