Strengthening the Sustainability of Additive Manufacturing through Data-Driven Approaches and Workforce Development

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The additive manufacturing (AM) industry is rapidly developing and expanding, thereby becoming an important and integral component of the digital revolution in manufacturing practices. While the engineering aspects of AM are under intensive research, there still remain many chances to strengthen the sustainability of additive manufacturing (SAM). Cognitively increasing the AM community’s attention to SAM is vital for developing the AM industry sustainably from the bottom up. The digital nature of AM provides new opportunities for acquiring, storing, and utilizing data to strengthen SAM through data-driven approaches. Herein, spotlight on SAM is shone upon and it is placed on a more concrete footing. The corresponding advances in data-driven methods that can strengthen SAM are featured, such as optimizing designs for AM, reducing material waste, and developing databases. How the AM workforce can be developed and grown as a collaboration between the industry, government, and academia to extensively harness the full potential of AM as well as mitigate its adversarial social impact is discussed. Finally, several critical digital techniques that have the potential to further strengthen SAM in the factory of the future, including hybrid manufacturing, Internet of Things, and machine learning and artificial intelligence, are highlighted.

1. Introduction

The current manufacturing practices are being profoundly transformed by digital manufacturing (DM), which constitutes a technological foundation of future manufacturing. DM is being widely implemented in the world’s leading industrial nations by combining advanced technologies in manufacturing, computer systems, networking, and management. An important component of the DM revolution is the rapid development of additive manufacturing (AM). When first commercialized in the 1980s, AM technology was considered suitable only for prototyping. Now, swiftly maturing AM technology greatly improves its compatibility with actual production methods beyond prototyping, leading to extensive exploration for potential applications in industries that require high-performance engineering materials, such as energy, aerospace, and defense. This remarkable growth is concretely exemplified by the financial projection of SmarTech Analysis, a provider of market research and industry analysis in the 3D printing/AM sector, where the market size of AM is expected to exceed 40 billion dollars by 2027 (Figure 1).

The rapid expansion of the AM industry is precipitating new challenges. Over the past decades, the AM community has exerted a lot of effort in tackling engineering issues in a wide range of additive processes and has made significant progress. Meanwhile, AM is frequently claimed, and just as frequently accepted, to have latent potential for dramatically improving materials efficiency, reducing life cycle impacts, and possessing enhanced engineering functionality compared with conventional manufacturing (CM). Nonetheless, in practice, researchers are beginning to realize that many of such potential benefits remain beyond reach. For example, a comparative study showed that AM could not be categorically stated to be more environmentally friendly than machining or vice versa. Therefore, in recent years, there is growing attention to Sustainability of Additive Manufacturing (SAM) from both the AM community and government agencies, such as the National Science Foundation (NSF) in the United States. Many research opportunities on SAM are identified, such as design optimization, material waste reduction, and workforce development. Although some successful methods, such as life-cycle assessment (LCA) methods, in promoting sustainability of CM can be also be applied to promote SAM, several AM-specific challenges must be addressed immediately, such as lack of data and standards in certain contexts.

The digital nature of AM creates new possibilities to enhance SAM. Being inherently digital in contrast with the analog origins of traditional manufacturing, AM allows for further development of data-driven approaches. In this article, we focus on data-driven approaches and workforce development towards SAM.
of CM, AM is naturally adaptable to cutting-edge technologies such as Internet of Things (IoT), cloud manufacturing, industrial 5G networks, machine learning (ML), and artificial intelligence (AI). These technologies are becoming the enablers of smart AM of the future. By harnessing these advanced digital technologies, AM processes are continuously and rapidly evolving toward being smarter (due to the data-driven methods coupled with networks and sensors) and more sustainable. By embedding design goals for environmental, economic, and social sustainability from the bottom up, smart and sustainable AM will play an important role in the factories of the future.

Therefore, we aim to shine a spotlight on SAM herein in the hope of igniting greater interest and awareness in this crucial issue. We will first define SAM and discuss why SAM is of critical importance for the healthy development of the AM industry. Then, we will focus on several data-/algorithm-driven methods that can promote SAM, including optimizing product designs for AM, reducing material waste, and developing databases. We will also discuss the workforce development in the AM industry to mitigate the social impact of AM as well as prepare the next generation of AM engineers with sustainability in mind. Finally, we discuss the outlook for AM in the factory of the future, with a focus on how digital techniques such as hybrid manufacturing, IoT, and ML/AI will benefit AM and SAM in the future.

2. Sustainability of AM

Although various principles of sustainability are widely adopted in manufacturing, to date, the understanding of sustainability in manufacturing is still fairly subjective. It is generally accepted that sustainability has three distinct dimensions: environmental (ecological), economic, and social. A recent literature review defined 18 subcategories of sustainable performance of AM and specified 68 further subcategories, as well as corresponding sustainability performance indicators based on product life cycle studies. For example, under the ENERGY subcategory in the environmental dimension, there are three further subcategories, corresponding to three indicators including energy consumption, energy efficiency, and renewable energy. Figure 2 shows the three dimensions of SAM and the definition of the 18 subcategories. The 68 further subcategorical indicators with detailed explanation and their quantifications are omitted in Figure 2 and can be found in the literature review. While readers are referred to the original review for a more thorough case study, we provide a simple example of using such indicators to compare

![Figure 1. Recorded and projected total AM market size for 2014–2027. Generated using publicly available data on SmarTech’s website published in 2019.](image1)

![Figure 2. The three dimensions of SAM and the 18 subcategories of sustainability performance defined in the recent literature review. 68 further subcategories and indicators with detailed explanations can be found in this review.](image2)
powder bed fusion (PBF) versus directed energy deposition for better sustainability (see Example 1 in Appendix A1). We remark on the fact that such exhaustive lists of sustainability performance indicators for AM are only recently starting to be proposed and summarized, and the proposed indicators still need further validation in actual manufacturing practices. This recency further highlights the current lack of thorough studies on SAM.

There is no doubt that the sustainability of today's technology is essential for future generations to meet their own needs. However, historically, during the advent of numerically controlled machining and mass production, there was a 50-year gap before serious attention was given to sustainability.[14] Currently, research on the sustainability of AM is being urgently expeditied but the documented knowledge is still scarce. Therefore, careful and thorough studies on AM sustainability must be conducted in a tight lockstep as the industry develops further.

AM is claimed to be promising for reducing manufacturing processes that are energy and resource intensive.[4] For example, parts with complex geometries, structures, and compositions can be fabricated with relative ease using AM compared with conventional subtractive manufacturing. Meanwhile, AM has the potential for improving materials efficiency. For example, powder materials used in many AM processes are usually highly reusable and recyclable. The improved materials efficiency and thus reduced material waste may help with reducing the carbon footprint.[14] Also, AM can enable decentralized production and, hence, can be closer to the point of consumption. Therefore, the corresponding supply chain may be compressed and become simpler. In turn, shortening and simplifying supply chains may result in lower environmental impact while being easier to manage. Overall, AM is generally accepted as a green technology for small-to-medium batch production with better time and cost efficiency compared with CM processes.

However, one must be careful with these seemingly obvious benefits that AM might introduce. Following are examples found in literature where AM is not a perfectly "green" technology.

1) Due to the principle of economies of scale, the incremental cost of conventional mass production is almost always lower than one-off AM production.[16] 2) Once the entire operating procedure is considered, including stages of equipment warm-up/cool-down, AM may not be turn out to be superior to CM processes in terms of energy consumption.[17] 3) Desktop 3D printing devices equipped with the fused deposition modeling (FDM) technique are responsible for the emission of toxic gaseous substances called volatile organic compounds (VOCs) and ultrafine particles (UFP) that are several tens of nanometers in diameter. As these devices are common in offices, classrooms, and libraries, such air pollution poses potential health risks to the general occupants and indoor workers.[18] 4) The introduction of AM can sometimes result in more complex supply chains due to its secondary processes and additional supplier requirements.[19] 5) AM usually needs additional support structures for overhanging parts, but these structures waste material, time, and energy.[20] 6) Being a disruptive technology,[21] AM is responsible for both the creation of some jobs and the disappearance of others. Thus, its net effect on the job market is still debatable.[22]

These examples have strong implications for the "green" credentials of AM: AM may not be as cost effective as CM and it may not be that superior to CM processes in terms of energy consumption. Also, just like CM, AM may also produce diverse unexpected chemical pollution. In addition, due to the actual impact that AM has on supply chains, it may not be ideal to simply assume that AM will end up with shorter and simpler supply chains. Case-by-case analysis of AM’s impact on supply chains must be done before the introduction of AM.[19] Furthermore, it is true that AM reduces waste through waste recycling. Nevertheless, there is still significant room for waste reduction. The social dimension of SAM is nontrivial as well. Many new jobs are created around AM technology, such as software development, consultancy activities, and product design.[22] However, the impact on the flipside is real, such as job losses of currently untrained or redundant workers. Preventing these negative outcomes will require support from both the public and private sectors for current workers. Therefore, an underdeveloped understanding of SAM combined with the rapid development of the AM industry may lead to unexpected issues in the future.

We are of the sentiment that AM still has not been sufficiently examined from a sustainability perspective. The current state of SAM was analyzed in several recent reviews.[4,12,24,25] In most of these reviews, the authors called for more attention on SAM. However, according to a recent literature review, the portion of research publications on the theme of AM sustainability is no more than 10%, whereas the AM community pays overwhelmingly more attention to practical issues, such as improving mechanical properties, characterizing microstructures and properties, and refining structural imperfections of AM products.[26] While these techniques and studies are under rapid development and will most likely make the most impact on the future directions of AM, insufficient consideration of sustainability may well become the Achilles’ heel of AM in the time to come. Therefore, early engagements to stimulate discussions of SAM are sorely needed. As digital techniques are key enablers of AM, in the following sections, we will focus on some of the data and algorithm-enabled smart techniques that have the potential for strengthening SAM and the workforce development needed to harness such techniques and mitigate the adversarial social impact of AM.

3. Design Optimization for Sustainability

Design optimization is a process in which design variables such as part dimensions, geometries, material properties are varied iteratively to optimize an objective function subject to performance constraints.[27] The design freedom and the high-level local process control of AM provided a new technology roadmap for design, resulting in the framework of Design for Additive Manufacturing (DfAM). DfAM is a class of methods and tools used in the design stage of AM, aiming to optimize product designs that are subjected to the specific capabilities of AM technologies. As design decisions can significantly alter the extent of energy and material consumption, considerations of sustainability should be directly incorporated in DfAM, especially in terms of environmental sustainability.

Many DfAM methods aim to improve the material properties of the final products. For example, by leveraging the AM-enabled design freedom, complex cellular structures with extraordinary mechanical properties can be designed and manufactured.[28] A recent study showed that AM components consisting of an
open cellular foam can have 40% higher strength than a fully dense solid component.

Further research efforts aim to optimize the design of cellular structures, such as the theory and method for optimizing the variable-density hexagonal cellular structures. While improving the material properties, these techniques can lessen material usage, simplify the manufacturing process, and reduce energy consumption. However, sustainability is not inherently considered as a design objective to optimize and therefore relegated to be a potentially suboptimal, albeit positive, side effect.

A possible way to overcome this deficiency is to implement eodesign. Ecodesign is a concept that actively introduces sustainability considerations into design optimization. To incorporate eodesign into DFAM, LCA is commonly and intimately integrated into the design stage. According to the International Organization for Standardization (ISO), LCA is the “compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle.” In practice, LCA is data intensive. To carry out LCA for a certain product, process, or service, a thorough data inventory which characterizes the resource usage across the industry value chain is needed to drive the analysis.

Although LCA was originally developed for energy analysis only, modern LCA is evolving into a more comprehensive tool that considers all three dimensions of sustainability—namely, the environmental, economic, and social impacts. LCA is widely used in studies of CM but such studies are limited for AM. A recent study claimed that the design methods and guidelines for CM processes are not suitable for AM and proposed a general model-based framework that closely integrates design optimization techniques and LCA to effectively reduce AM product environmental impact. The framework is shown in Figure 3. In each round of optimization, the functional descriptions of a design are inputs to the framework. These inputs are fed into energy and material consumption models to estimate the energy and material consumption. Then, the framework optimizes the product design using the environmental impact estimation based on the energy and material consumption as a feedback signal. At the end of the optimization, an improved product design with respect to the environmental performance is generated. The design freedom of AM enhances such design optimization processes by removing manufacturing constraints that primarily exist in CM.

However, a major challenge still remains. LCA-driven design optimization methods usually rely on predictive models that take extensive effort to develop. Developing such models requires interdisciplinary knowledge that can include materials engineering, energy, physics, and chemistry, manufacturing, and mechanical engineering. This complex assimilation makes it challenging to construct effective models for estimating the energy and environmental impact of AM from a life cycle perspective. Therefore, efficiently and effectively acquiring and utilizing AM process data may help with developing such models.

4. Material Waste Reduction

As AM is not waste free, as discussed in Section 2, material waste reduction not only closely relates to the environmental dimension of SAM, but also impacts the economic dimension, because it affects the cost of the equipment, material, storage, etc. In many AM processes, support structures are a significant source of waste, which is still a challenging issue to resolve. Techniques such as topology optimization (TO) during the design stage may help with this problem. In powder-bed AM specifically, material powders are usually recycled, but the limited recyclability of material powders will eventually render the powders unusable and generate material waste. Furthermore, the shortage of data characterizing the waste inhibits AM waste reduction, but the considerable knowledge and experience in waste reduction from other manufacturing processes can serve as inspirations for AM.

4.1. Optimization of support structures

Due to the inability to support some of the stresses in the manufacturing process, one typical source of waste specific to AM is support structures. These additional structures not only introduce material waste, but also contribute to time and energy waste. Thus, it is important to minimize the support structures to reduce waste.

Optimizing the geometry and topology of the support structure is a potential solution, and as an application of DFAM, it is closely related to Section 3. A recent study applied a genetic algorithm to prune a supporting lattice structure without impairing its supporting functionality. Another method is to design self-supporting parts that eliminate the need for support during AM. Explicit TO was used in a recent work to generate self-supporting designs by optimizing a set of explicit geometry parameters. Such TO-enabled methods can also benefit from recent advances in combining TO with machine learning to reduce the inner/outer support structures. For example, a recent study proposed a data-driven TO method for AM based on microstructure libraries that contain different microstructures and corresponding mechanical properties and multiresponse latent-variable Gaussian process. Furthermore, when developing TO-enabled methods, it is important to include the true capabilities of AM as constraints, such as the minimum feature size and maximum overhang angle that are manufacturable. To this end, data-driven AM constraints derived from experimental data can be helpful, as shown in a recent study.

While numerous methods come under the umbrella of TO, there are other ways of reducing the supports. In a recent work, the printable threshold overhang angle and the longest printable bridge length in an extrusion-based AM process are used for better process planning toward minimizing waste. More related studies can be found in recent reviews.

4.2. Powder Recycling and Upcycling

Material powders are usually reused and recycled in powder-bed AM. For metal powders, the reusability can be more than 95% of the waste. However, recycled powders exhibit different or even degraded characteristics compared with virgin powders, which will eventually result in material waste due to incompatibility with AM process parameters. A recent study showed that in an electron-beam melting process, recycled Ti–6Al–4V powders have at least 35% higher oxygen content than virgin powders, which will potentially impair the quality of AM parts. While
the powders degrade and become unusable at the end of life, manufacturers must still dispose of these waste powders properly. A recent review summarized and discussed the studies of powder degradation in metal AM. Among several potential solutions, the review claims that currently, the only financially feasible way to reduce powder waste may be to return end-of-life powders to the original supplier for upcycling, using advanced technology such as plasma spheroidizing. However, more studies are needed to improve our understanding of material powder degradation, as well as to develop new methods for recycling unusable powders. Knowledge and data on powder recycling and upcycling provide deep insight into the corresponding AM processes from a life-cycle perspective. Therefore, they have the potential for benefiting LCA-driven design optimization, as discussed in Section 3, and should be collected and organized carefully.

4.3. Experience from Other Processes

Limited data and information are available to accurately characterize the waste generated by AM processes. Nevertheless, data-informed material waste management practices in a broad

Figure 3. A general framework of sustainable design optimization enabled by LCA for AM as proposed in recent studies. [7,37]
spectrum of manufacturing processes can be found in industrial practices. Concepts and techniques such as reduction, reuse, recycle (3 R), green manufacturing, and LCA are widely adopted in these practices. These concepts and expertise that were successful in other processes can inspire similar developments in waste-reducing technologies for AM, although adaptations are needed. For example, unlike CM processes, AM generally produces minimal wastewater, AM does not follow the traditional assembly principles and has different forms of assembly lines, and AM produces waste that has different forms from CM, such as metal and polymer powders and support structures.

5. Databases that Need to be Developed

While AM is celebrated as a revolution in manufacturing, Professor Neil Gershenfeld critiqued that “the revolution is not additive versus subtractive manufacturing; it is the ability to turn data into things and things into data.” The essence of AM is not the additive manner of fabrication, but the digital transformation of fabrication, along with other numerically controlled machining technology. While the fabrication becomes digital, the design, the manufacturing logistics, and the management are all being digitized simultaneously. With these developments, a massive amount of data is generated during almost every step of an AM process. To handle, manage, and extract knowledge from such big data for sustainability considerations, the current manufacturing framework must incorporate database infrastructure. For example, a recent study proposed a framework for sustainable and smart AM that is driven by big data. This framework includes perception and acquisition, storage and preprocessing, mining and decision-making, and application services of big data to support sustainable and smart AM. Clearly, data play a central role in this framework. The combination of AM, sustainable manufacturing, and data-driven methods constitutes data-driven SAM, as shown in Figure 4. From current literature, we identified design feature databases and the life cycle inventory (LCI) databases as two of the most fundamental infrastructure for enhancing AM’s sustainability.

5.1. Designing Feature Databases

In industrial practice, design engineers still lack sufficient experience and knowledge of DiAM due to its novelty, and the management and sharing of AM design knowledge is not fully developed. Design feature databases are useful for product designers to access and build on top of aggregated AM knowledge, thereby avoiding costly and time-consuming reinvention iterations. In an early effort, developers used an AM-enabled feature taxonomy to develop an AM feature database. With this database, designers can either consult or search via keywords and access information of the features that fit their requirements. However, this database contains mostly conceptual information and is therefore less effective for experienced professional designers. A recent work made new progress in this direction by parameterizing the features to enable future reuse and modification. The database in this work was integrated into the computer-aided design environment to enable direct feature import and modification in the embodiment and a detailed design phase. When tested by an experienced designer, the database provided additional design solutions and reduced design iterations.

As such database construction is its infancy, we believe that relevant sustainability information should be included in design feature databases for designers’ reference. Such information can include material efficiency, energy consumption, and waste and pollution associated with different design features. This information might be scarce now, but it is vitally important to collect and share this information broadly so as to bolster the community’s burgeoning attention to AM sustainability. Also, as AM technology is evolving rapidly and new features are being generated, these databases need constant curation, maintenance, and updates. Moreover, as AM equipment is becoming widely available, the user interface of these databases needs to be more intelligent and easy to use to increase their benefit in society holistically. For example, developers may implement recommendation algorithms into the user interface to support smart design.

5.2. Life Cycle Inventory Databases

LCA is an important tool for sustainability analysis in each phase of manufacturing. LCA is also especially helpful for ecodesign, as mentioned in Section 3, and material waste reduction, as mentioned in Section 4. However, LCA is inordinately data intensive and it requires an LCI to conduct life cycle impact assessments (LCIAs). LCI contains the quantification of inputs and outputs of a system, such as its material and energy flows. International joint efforts to harmonize and update LCI data as well as various LCIA methods for different economic sectors exist. For example, the Ecoinvent database, which is already relatively mature, covers products such as metals, packaging materials, and waste recycling. However, compared to materials production, data of manufacturing processes for discrete parts manufacturing are inadequately documented in this database. In general, process-dependent data of innovative processes such as AM are insufficient. Therefore, gathering life cycle data is especially important to inform LCA for AM.

In CM, cooperation initiatives, such as the Cooperative Effort on Process Emissions in Manufacturing (CO2PE), conducted...
systematic analysis and generation of manufacturing unit process LCI data.[39,62-64] In AM, effective information flow management across a product’s life cycle and the corresponding manufacturing systems is currently insufficient,[3] hindering life cycle data collection and integration. The lack of data may result in spurious assumptions being used in predictive models for LCAs[40] and other data-driven analyses, thereby significantly impairing the quality of the assessments. Nonetheless, with smart devices, meters, and sensors being readily deployed across the entire manufacturing cycle of AM, we can expect a tremendous increase in the quantity of material and energy consumption data[10] of different AM processes. Also, it was suggested in a review[46] that methods of CO2PE! may serve as an overarching model to the AM community for assessing the material and energy consumption of AM processes. In the longer term, the AM community needs to collaborate on developing a standardized LCI database across different AM technologies,[4] requiring an immense amount of effort in aggregating multidisciplinary knowledge.

6. Developing the AM Workforce

Although AM technologies offer impressive capabilities, there remains a pressing need for relevant workforce skills in industrial operation and management of AM. [3] The dearth of AM-specific design skills is identified as one of the most commonly discussed barriers to realizing the full benefits of AM. Such skills can be remarkably diverse, including but not limited to intimate familiarity with modeling software, deep understanding of AM’s design flexibility and constraints compared with CM, broad knowledge regarding properties of different AM equipment,[65] and ample awareness of the life-cycle impacts of AM. Furthermore, other skillsets in machine operation and process planning, supply chain management, and research and development must also be updated along with the crossover to AM. Such a sweeping undertaking will necessitate concerted collective effort from the public sector, academia, and industries for the continued development of a well-trained AM workforce for better perfusion of AM technology in current industrial manufacturing. In this section, we show that developing the AM workforce is essential to the social dimension of SAM as it involves training/education and social equity and fairness. Also, it can be anticipated that a well-developed workforce with SAM in mind will benefit SAM in general in the future.

The public sector is taking the lead in developing the AM workforce with government agencies actively proposing new ventures and avenues to do so. Drawing some examples from the context in the United States, in a 2016 workshop organized by the US NSF,[86] representatives from academia, industry, and the public sector conceptualized multiple important educational themes and offered many educational recommendations, such as narrowing the gap between rapid advances and interest in AM and the current shortage of knowledgeable AM industrial workforce. These themes and recommendations can serve as general guidelines for educational institutes. Also, America Makes,[67] a national-level institute in the United States, is participating in developing the AM workforce by promoting numerous webinars, seminars, and training related to AM. Moreover, in AM workforce development, the lack of standards in certain contexts often results in less efficient ad hoc training. For example, in AM polymeric parts, cellular and lattice structures are widely used, introducing significant anisotropy and discontinuity at different scales and directions. Such anisotropy and discontinuity make many standards for mechanical testing inapplicable and require further regulatory developments.[68] As a result, the testing of parts fabricated with such structures usually does not refer to any testing standards and does not even use the specimens defined in the standards.[68] National Institute of Standards and Technology (NIST) is actively involved in developing AM standards with other government agencies.[69] Though still under constant and active development, standardized AM technologies will eventually minimize ad hoc training.

Academia should also prepare for this upcoming trend and explore ways of effectively educating the next generation of AM engineers. A study conducted in Politecnico di Torino Master’s degree program evidenced that early exposure of future designers to AM tools is very important for future AM product designers so as to “think additive” when designing.[70] This encompasses being able to redesign the existing assembly to maximize the advantages in AM.[70] This is consistent with a recent study that emphasized the need for cultivating DfAM early in the students’ learning process to motivate effective learning.[71] The results of these studies imply that to meet the growing need for a skilled AM workforce, universities and other educational institutions urgently have to provide both practical and conceptual courses focusing on AM, particularly in the early stages, to engineering students who are interested in the AM industry. Simultaneously, to ensure that these forthcoming AM engineers have sustainability considerations in mind, basic concepts of SAM should also be a critical core of their curricula.

Industry, government, and academia will also need to work together to address potential social issues within current manufacturing workers stemming from the inescapable shift to AM in the manufacturing sector. For instance, the AM digital transformation will result in ever-increasing automation of manual tasks, which may induce the anxiety of job losses among current workers. Such anxiety is not groundless. For example, using parts consolidation as an application of the DfAM philosophy, engineers are able to redesign a multicomponent assembly into a single component, thereby reducing the material consumption, while improving the reliability of the part.[72] The generalization of such applications will eventually diminish many labor-intensive jobs, such as assembling individual components that constitute an entire product. Thus, for workers experiencing such potential impact, relevant technical training is a humanitarian requirement and sustainability effort. Such training may not only preserve but even elevate the quality of the lives of many manufacturing workers, thus reducing the AM’s adversarial social impact and improving AM sustainability. The private sector must shoulder part of the responsibility to upgrade the existing workforce via technical training. The public sector has to enact policies to support workers with new skillsets and opportunities that are transferable to related careers in AM.[73] As the study on the social impact of AM is still in its infancy, academic communities should pay more attention to it through socially directed research.[22,74] Therefore, harnessing and integrating academic research with governmental and industrial practices
will lead to greater sophistication in our current understanding of the social impact of AM.

7. AM in Factories of the Future

Rapid adaptation to versatile external demands and realization of higher degree of sustainability are two characteristics of the factory of the future.[75] With respect to these requirements, new trends are emerging in AM philosophy. First, AM is increasingly integrated with CM through computer control systems to form hybrid manufacturing systems. Second, using information technology and cloud computing, the IoT is enabling data-driven methods by generating large amounts of data that facilitate cloud AM. Third, machine learning models are trained for decision-making in AM, such as TO, materials design, and anomaly detection. Ultimately, thoroughly integrating these technologies and other developments will transform AM technology in present factories into smarter and more sustainable forms.

7.1. Hybridization of Manufacturing Technologies

While AM is being hyped as a revolution in manufacturing, it will definitively not replace CM as both manufacturing techniques possess unique advantages and limitations. Rather than replacing CM, AM is expected to actively complement, contribute to, and revolutionize traditional manufacturing activities in a symbiotic relationship. Some AM processes can be combined effectively with CM, resulting in a hybrid additive and subtractive manufacturing system that can be controlled through an integrated computer system.[76–79]

While being highly flexible and material efficient, AM “suffers from poor surface finish, long cycle time, and poor accuracy.”[78] However, these drawbacks can be very efficaciously alleviated by the ability of conventional machining to refine the final product. Thus, the hybridization of AM and conventional computer numerical control machining is highly relevant in the context of future manufacturing. Integrating AM and CM in the same machine tool system removes the need for the inefficient and error-prone transfer and setup of parts, while saving large amounts of valuable shop floor space.[78] Therefore, such hybridization can potentially improve the economic sustainability of AM by increasing the profitability of capital investment. Furthermore, as CM will still be an important component in such hybridized systems, hybridizing AM with CM inherently presents opportunities for the current CM workforce to translate hard and soft skillsets into an industrial setting with AM. The integration of blown powder laser DED into a single horizontal or vertical machining center is under intensive study and some of these hybrid systems are already commercialized.[78] Moreover, hybrid manufacturing enables many fabrication techniques at the micro- and nanoscale. Advances in this research direction can be found in this review.[80]

7.2. Implementation of IoT

IoT is anticipated to be progressively integrated with AM processes in factories of the future. In the context of manufacturing, IoT is an emerging production environment setting in which machines, products, production lines, and many other physical objects in the production process are interconnected, interacting with each other by exchanging information flows.[81]

IoT enables real-time monitoring of material supply and usage, machine availability, fabrication process, and energy consumption. Thus, it is a major source of manufacturing process data, which will improve material/energy consumption modeling. For instance, a recent study proposed a framework for AM energy consumption modeling using IoT.[82] In this framework, the physical objects in the AM systems are monitored by various sensors and components, and raw data are streamed from these sensors, in real-time or offline mode, to data integration and preprocessing facilities for data processing and selection. Numerous data-driven methods such as machine learning and data mining can be implemented to extract information and knowledge from the curated data. The extracted information and knowledge is used to build energy consumption models that can be used in techniques that improve sustainability, such as for ecodesign discussed in Section 3, and other important applications.

IoT also facilitates the application of the emerging cloud manufacturing paradigm. In cloud manufacturing, suppliers connect their manufacturing resources to the cloud platform, and customers explore the options on this platform and make suitable orders.[83] By fully harnessing the cloud manufacturing paradigm, sustainability can be realized through collaborative design, automation, waste valorization, and process resilience.[84] In a recently proposed cloud-based AM platform,[85] IoT uses the Internet to connect printers, sensors, and other hardware to the cloud. Thereafter, a cybertwin of each printer is created in the cloud such that the cybertwin and the physical printer form a cyber–physical 3D printer. Through this platform, the customers can access and control the printing process and mass customization becomes possible. A schematic model of an IoT-enabled cloud AM system is shown in Figure 5.

Figure 5. IoT-enabled cloud AM system. The cybertwin and the physical printer form a cyber–physical 3D printer.
Future industrial IoT will become wireless, device dense, and require high reliability and low latency in large quantity of information flow. The fifth-generation technology standard for broadband cellular networks (5G) is promising in this context, because its target reliability is up to 99.999% and latency down to 1 ms,[86] although the current actual performance is lower outside the lab. With the advances in 5G and even 6G, we can expect significant improvements in current IoT technology.

7.3. Integration of ML/AI

ML and AI will greatly benefit AM in the future. AM is a multi-stage process involving intensive decision-making, especially in the stages of design, process planning, and production monitoring. Data-driven ML and AI agents can automate a large portion of decision-making work in the future factories with equivalent or even better capability than human experts.[87,88] ML has been used in various studies to optimize AM product design. For example, TO is being tackled by advanced machine learning techniques. A universal machine learning framework for TO using deep neural networks was proposed in a recent work.[89] Numerous printable composite design studies were conducted using ML, with a focus on optimizing the layout of the constituent materials.[90–92] During the fabrication process, image processing methods and ML algorithms can detect part anomalies.[93–95] Furthermore, ML classifiers can help to develop a printability checker which automatically decides if a 3D object is printable.[96] ML algorithms can also real-time detect malicious design “STL” files by identifying abnormal defects in the design to counter cyberattacks for future manufacturing systems.[97] ML-enabled computer vision can be integrated with sensors in an IoT to enable self-diagnosis and automatically monitor part quality.[85] This is especially relevant in the factory of the future where IoT and cloud manufacturing are implemented. Many other applications of AI for AM can be found in this survey.[98]

In summary, ML intelligent agents will reduce the workforce required in a wide range of aspects of AM, especially those that require intensive decision-making. Therefore, ML techniques will eventually help to scale up AM production and achieve higher resource utilization efficiency in the future.

8. Conclusion

With the rapid expansion of the global AM industry, the sustainability aspects of AM are currently under the radar compared with intensive research and developments in AM’s engineering aspects. Compared with CM, AM has been classified as a “green” technology that has the potential for improving the efficiency of material usage and lowering energy consumption. However, evidence from previous literature showed that AM might still have nontrivial adversarial impacts in the environmental, economic, and social dimensions; hence, AM-related sustainability issues strongly deserve broader research and in-depth study. In recent years, the AM community has started expediting the study of SAM, but the relevant research still constitutes only a tiny fraction of the overall AM literature. The awareness of SAM need to be raised to ensure that the burgeoning AM industry develops in a sustainable manner as early as possible. We discussed the adoption of concepts from ecodesign to incorporate sustainability considerations in the AM design stage. In ecodesign, LCA gives information about the environmental impact of a design, and such information as feedback signal can help in the iterative AM design optimization. Also, AM is not 100% material efficient and there is still room for waste reduction. We introduced methods, such as TO, that can help to reduce the support structures. Powder recycling and upcycling can help reduce waste caused by powder degradation in AM, and experiences from other manufacturing processes can inspire the development of strategies to reduce AM waste. To leverage the advances in data-driven methods to improve SAM, we proposed that the AM community needs to develop databases, such as design feature databases with sustainability data embedded and LCI databases for different AM processes to support accurate LCA. All these technological advances and interdisciplinary integration in AM will create a very strong demand for skilled workforce in the AM industry, and skills for other manufacturing processes may not fit perfectly in the AM setting. Government, academia, and industry are working concertedly to develop the AM workforce and educate the next-generation AM engineers. While these efforts are expected to extend in the near future, it is also important to properly and adequately support the livelihood of the workers that may be adversely affected by the advent of AM at the same time. Finally, for faster adaptation to versatile external demands and higher degree of sustainability in factories of the future, efficient and smart technologies are being integrated with AM. Hybridization of AM and other manufacturing processes enables more efficient fabrication. IoT technology implemented in AM processes can generate large quantities of process data which have the potential for closing the data gap in data-driven methods. It also enables cloud AM to improve resource efficiency and support mass customization. Also, intelligent agents based on ML/AI will get more intimately involved in decision-making processes in AM, thereby lessening the massive workload, while maintaining the capability of human experts. By shining the spotlight on SAM herein, we hope to spark greater interest and keener awareness in the crucial issue of SAM, thereby paving the road toward greater considerations of SAM from the bottom up for smarter AM.

Appendix A1: Example 1: Sustainability of PBF Versus Directed Energy Deposition

Suppose we are decision makers and are concerned with comparing the sustainability of PBF versus direct energy deposition (DED) using the sustainability indicators proposed in the study by Taddese et al.[12] The nature of the decision-making problem may vary in different situations. For instance, a worker in a laboratory setting and another worker in an industrial setting may have different sustainability goals in mind. Assume that after analyzing the sustainability goals carefully based on our knowledge and judgment, we model the problem as a five-level hierarchy using four subcriteria and nine further sub-criteria in Scheme 1 through the analytic hierarchical process that is similar to the case study in the study by Taddese et al.[12] The importance of the criteria is to be determined by pairwise comparisons against the intended goal. The two alternatives, PBF and DED, are to be compared pairwise against each of the criteria. For example, to compare the material consumption, we need to account for the fact that
in PBF, complete layers of powder must be distributed over the entire substrate no matter the size of the desired AM component. Similarly in DED, certain amounts of powder are dispersed into the chamber which are not utilized. To compare energy consumption, we need the power requirement and build time (DED is typically much faster) of the two technologies. To quantify the comparison, one may follow the definitions of the sustainability indicators in the study by Taddese et al. Through such analysis, priorities of the nodes in the hierarchy can be determined to facilitate decision-making. While illustrating how sustainability considerations come into play, this example also highlights the importance of collecting the data associated with AM technologies throughout the product life cycle: a reasonable decision can be extremely hard to make without sufficient data.

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Conflict of Interest
The authors declare no conflict of interest.

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Scheme 1. A five-level hierarchy produced by an analytic hierarchical process to study the sustainability of PBF versus DED.

(References omitted for brevity)
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