Towards an automated life cycle assessment system for additive manufacturing: influential parameters and framework design

Ahmed Z. Naser[1], Fantahun Defersha[1], Eujin Pei[2], Yaoyao Fiona Zhao[3], Sheng Yang[1*]

1. School of Engineering, University of Guelph, Guelph, ON N1G 2W1, Canada
2. Brunel Design School, Brunel University London, Kingston Lane, Uxbridge UB8 3PH, UK
3. Department of Mechanical Engineering, McGill University, Montreal, QC H3A 0G4, Canada

anaser@uoguelph.ca, fdefersh@uoguelph.ca, eujin.pei@brunel.ac.uk, yaoyao.zhao@mcgill.ca, syang19@uoguelph.ca

Corresponding Author

Abstract

Additive Manufacturing (AM) enables the building of parts layer-by-layer directly from 3D models. This technology has been considered to be a much cleaner production process as compared to other conventional production routes. This is because AM can contribute to significantly reduced material and energy consumption, supporting a shorter supply chain, and reducing the waste stream by supporting the repair of parts, etc. The majority of the current quantitative studies on the environmental assessment of AM are based on utilizing Life Cycle Assessment (LCA) approaches. Current studies on assessing the environmental performance of AM are based on a limited selection of design- or process-related parameters. These knowledge barriers may hinder the selection of the optimal design and process parameters for additively manufactured parts in the design and planning stages due to the iterative design-evaluation process. Therefore, an automated LCA tool is needed to support a sustainable AM process. In this paper, three main contributions are made. First, this paper identifies a comprehensive set of influential AM design and process parameters that may pose an impact on the environmental performance of AM. Second, the impact from each parameter is summarized. Third, an automated LCA framework that can be used to support assessment and optimization of both design and process parameters is proposed. The proposed framework is anticipated to take advantage of Machine Learning (ML) and opportunities for co-design to mitigate the challenges and limitations associated with the current LCA-based assessment tools.

Keywords: additive manufacturing; life cycle assessment; design for additive manufacturing; design and process parameters; product-process co-design; machine learning; data-driven predictive models

1. Introduction

Various manufacturers are currently competing to develop innovative ways to achieve sustainability in their designs and products [1]. Hence, environmental sustainability and cleaner production have become important for manufacturers and companies [2]. Over the last few years, Additive Manufacturing (AM) has seen improvements in terms of accuracy, better material properties, faster processing times, reduced cost and better reliability [3,4]. As such, AM is ushering in a new era for sustainable production [5]. AM stands out as a promising and innovative technology that has the potential to produce parts with green credentials [6–8]. The global ecosystem for AM is currently growing at 24% a year and is anticipated to reach US $35.0 billion by 2024. Today, one in a thousand products is produced using AM [9–11]. The significantly expanded product complexity and flexibility offered by AM and potential for sustainable production of using AM technology is seen to be an inevitable part of the modern manufacturing era [12]. In comparison to Conventional Manufacturing (CM), AM provides a great opportunity to achieve environmentally sustainable production [13]. This is mainly due to the potential of AM technology that can create complex shapes with less waste, optimizing material consumption, and reducing production times [14]. The main application of AM in comparison to CM lies in the design phase. The prototyping process is traditionally expensive. This is attributed to the need for molds, tools, as well as specialized workers. On the other hand, AM has great potential to address both design quality and cost efficiency to enable sustainable product design [15]. Other aspects of AM include the potential to use recycled materials, the ability to produce lightweight components, producing more durable products, eliminating or reducing hazardous materials, in addition to other value-added features for the consumer [16].

The potential of using AM to remanufacture, repair, and update tooling also shows an opportunity for significant reduction in emissions, cost and energy consumption [17]. The concept of having manufacturing systems on-site allows for the rapid production of customized products closer to customers which minimizes the complexity of supply chains and reduces the need for costly warehousing and packaging. This in turn reduces the amount of waste required for transport. Furthermore, this also reduces logistics and the fuel associated with delivering products to customers [18]. Studies have shown that material waste in AM can be reduced by 40% in comparison to CM, and 95%-98% of the leftover materials can be potentially recycled [19]. Other studies also show that AM has the capability to significantly reduce the environmental impact and energy per unit of gross domestic product [20–22]. AM has the potential to reduce the carbon footprint by reducing waste and optimizing designs [23]. Global carbon dioxide emissions have grown by 45% since 2000. In this regard, lightweight parts produced using AM is expected to play a major role in reducing energy consumption and carbon dioxide emission. Over the entire life cycle of an additively manufactured part, savings of 2.54-9.30 EJ and 130.5–525.5 Mt in terms of primary energy supply and carbon dioxide emissions are anticipated by 2025 [6]. The use of AM can support sustainable production in terms of high resource efficiency [12]. Although a number of studies have assessed the environmental impact of AM [27–29], the findings are limited in terms of how design- and process-related parameters can contribute to green production. Thus, this paper aims to introduce a framework for automating the environmental assessment process within the design stages to mitigate the challenges and limitations associated with current tools. To achieve this goal, LCA-based approaches used to assess the environmental performance of AM is first reviewed. Next, key parameters/strategies for production are identified. Finally, a framework for the environmental sustainability assessment in AM is proposed by coupling Machine Learning (ML) with co-design. Figure 1 provides an overview of the research framework.

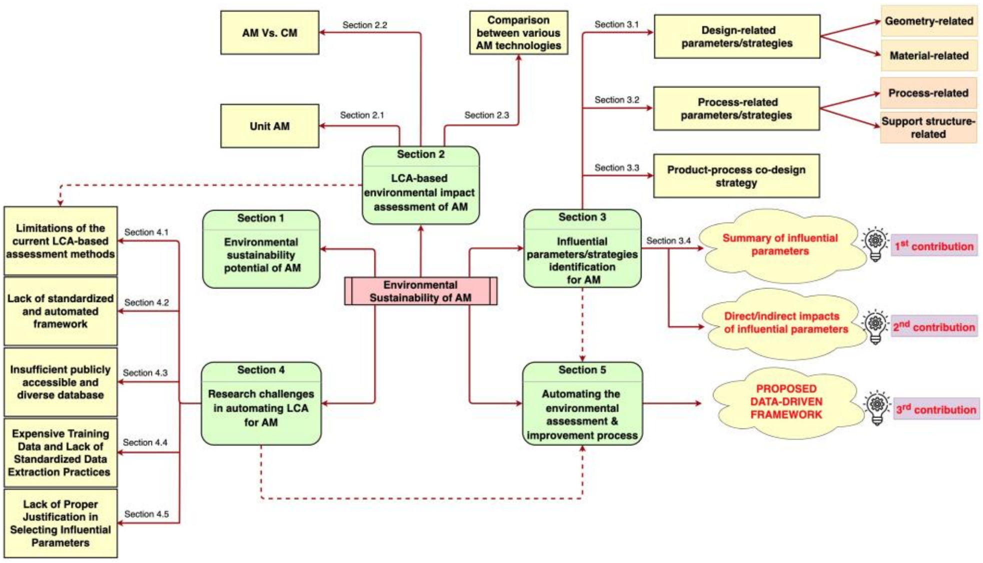

Figure 1. Overview of the research framework.

2. LCA-Based Quantitative Environmental Impact Assessment of AM

There have been various approaches used to quantitively assess the environmental impact of AM. These include Life Cycle Assessment (LCA), Design for Environment (DfE), and Environmental Impact Scoring Systems (EISS) [23]. However, the most widely used methodology is LCA [12] that was developed by the Society of Environmental Toxicology and Chemistry (SETAC) and later was normalized by the United Nations Environment Program (UNEP) and SETAC under the standard ISO 14044 [31]. LCA is an internationally recognized methodology to systematically assess the environmental impact of various industrial activities, products and processes [32,33]. In comparison to other methodologies such as Carbon Assessment or DfE [34], LCA can quantify the environmental impact of a global system in a precise way and with diverse criteria [22,35,36]. According to ISO 14040 [37], LCA involves four phases. These phases are performed under the umbrella of the framework shown in Figure 2 [33]. In the first step, the scope and goal of the study along with the restrictions are defined. Based on that, the definition of a process or a product, as well as the system boundary is determined. The next step is the input or output inventory analysis (Life Cycle Inventory (LCI)). In this step, all inputs (e.g., energy, material, etc.) as well as the resulting outputs (e.g., emissions, wastes, etc.) are identified and quantified. The third step involves obtaining the outcome of the quantified inputs and outputs on the human health and ecosystem via Life Cycle Impact Assessment (LCIA) methods such as Impact 2002+, Eco-Indicator 99, ReCiPe, or CML. The final step is an interpretation of the system results to control the consequences [38]. A more accurate evaluation of the sustainability impact of manufacturing processes involves material, process and energy consumption as well as production waste and disposal as shown in Figure 2 [39].

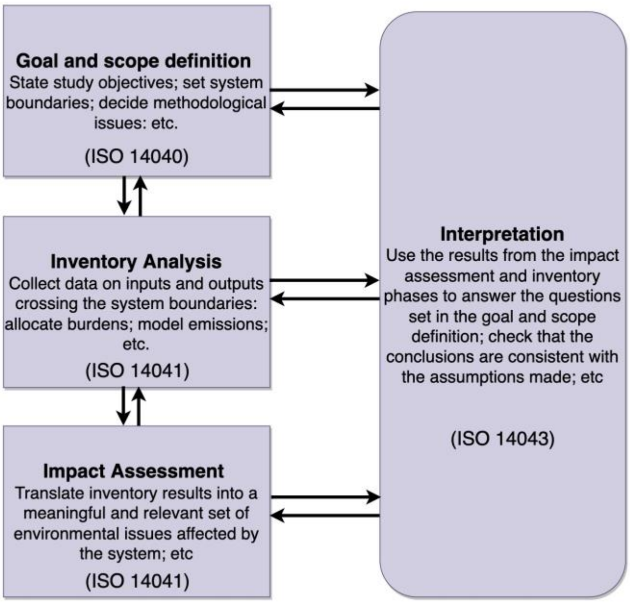

Figure 2. The conceptual framework of LCA [33].

Current quantitative studies on the environmental assessment of AM are based on utilizing the LCA methodology and its application to evaluate the environmental impact of AM. These studies can be categorized into studies of AM process modeling [31,40,41], studies comparing the environmental impact between two or more AM technologies [42–44], or between AM and CM [45–47]. Other studies compare the energy consumption between two or more AM technologies [48,49] or comparing the energy and/or material consumption between AM and CM [50,51]. Figure 3 depicts some of the major studies on the environmental sustainability assessment of AM and the sections below provide detail about each of the different categories.

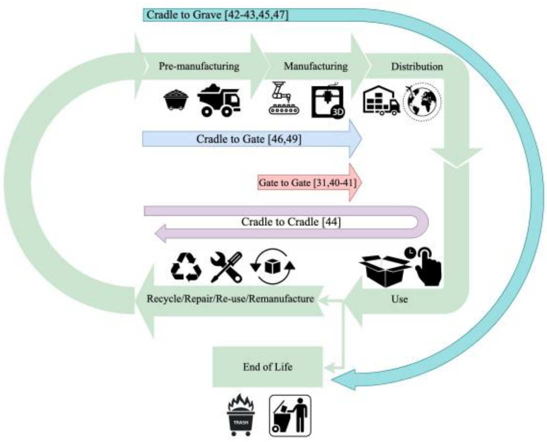

Figure 3. Scope of LCA in terms of environmental sustainability assessment of AM

2.1 Unit AM process modeling

Studies under this category investigate various materials, AM processes and environmental indicators such as energy use. Moreover, these studies differ whether embodied energy in machine and auxiliary tools, production of raw materials, and post-processing are included in the analysis. Studies of various AM processes include Selective Laser Sintering (SLS) [40,52], Selective Laser Melting (SLM) [53], Fused Deposition Modeling (Material Extrusion) [54], Binder Jetting [41,55], Direct Metal Laser Sintering (DMLS) [56], Stereolithography (SLA) [39], Direct Laser AM (DLAM) [31], Additive Laser Manufacturing (ALM) [57], Powder Bed Fusion [38], and Laser Sintering (LS) [20]. The majority of these studies agree that energy and material consumption are the main contributors to the environmental impact of AM. Other studies propose generalized assessment frameworks that can be applied to any AM process [58–60].

2.2 Comparison between various AM technologies

Studies under this category compare different types of AM techniques or processes. The scope of LCA considered include cradle to grave, cradle to gate, etc., and the resources used such as materials, energy, transportation, etc. that may vary. These studies were mainly based on comparing the energy consumption of metal SLM, DMLS, EBM, and polymeric LS and Material Extrusion [61], Fused Layer Modeling (FLM), and binder jetting [62] or metal wire-based and powder-based AM technologies [49]. Li et al. [43] compared the environmental impact of polymeric Material Extrusion, SLA, and Polyjet AM techniques and found that Material Extrusion parts exhibited the lowest environmental impact, whereas the environmental impact associated with parts fabricated via Polyjet was the highest. This might be attributed to the low energy consumption for Material Extrusion, the potential to produce lightweight Material Extrusion parts with an infill density of less than 100%, as well as the possibility to recycle Material Extrusion printed parts after disposal [43]. Kellens et al. [48] presented a comparison of the energy use of polymeric SLS and metallic EBM process. According to their study, the specific energy consumption (SEC) for SLS was in the range of 107 to 145 MJ/kg. It was observed that almost 50% of the environmental impact associated with SLS was due to the waste powder. For EBM, the most determinant factor of energy consumption per layer was the cross-sectional melting area. The reported SEC values ranged from 60 to 375 MJ/kg. In EBM, the majority of the energy was used in the operational mode [48]. Jackson et al. [49] developed a model to calculate the energy consumption for wire-based and powder-based AM technologies. The energy consumption to produce three sizes of steel tensile bars was measured. The study showed that throughout the deposition phase, the wire-based process required less energy, while the powder-based process required less energy during machining [49]. The energy use for Material Extrusion has also been investigated in many studies [28,50]. The reported SEC values significantly varied between 83.1 and 1247 MJ/kg. According to Yoon et al. [50], around 60% of the energy used for Material Extrusion is during the warm-up phase. Hence, SEC values can be significantly reduced if multiple parts are printed at once. Balogun et al. [54] reported that the setup, start up, warm up, as well as ready energy states consume around 64 % of the total energy for Material Extrusion processes [54].

2.3 Comparison between AM and CM

Studies have compared the environmental impact of AM and CM methods [45–47] and Priarone and Ingarao [45] compared the environmental impact of fabricating metal parts using CM and an integrated process using AM plus finish machining. Results showed that the combination of AM with finish machining is more eco-friendly taking into consideration the carbon dioxide gas emission and energy consumption [45]. Huang et al. [46] discussed the environmental advantages if a shift from CM to AM processes is to be implemented in the aerospace sector. Results showed that the fabrication approach via AM resulted in significant savings in primary energy use as compared to CM. Such savings ranged from around 2 GJ for brackets to around 70 MJ for seat buckles. Most of the energy savings were achieved due to a reduction in airplane fuel consumption as a result of lightweight AM parts [46]. The environmental impact associated with fabricating four aluminum parts utilizing three manufacturing processes including forming, machining and SLM were investigated by Ingarao et al. [47]. Their study examined the amount of material to be machined, and comparing this with the solid-to-cavity ratio. The study also found that even if there is a weight reduction of 50% using AM, subtractive manufacturing methods were preferable due to the high processing energy intensity for SLM required by the laser to melt aluminum powder layers. The study concluded that AM is more sustainable for aluminum alloy if used to produce a complex structure and thereby achieving a significant reduction in weight [47]. According to

Kellens et al. [66], AM can be beneficial from an environmental perspective in cases of very small batch production, part remanufacturing, and lightweight part designs [66]. Similar conclusions were also reported by Watson and Taminger [51]. According to Marshall et al. [64], a high degree of freedom can be achieved using AM, in which their study presented an example of aircraft bracket design comparing CM with EBM processes. The buy-to-fly ratio of the design using CM was 8:1 where the raw material was converted to chips in the CM route. In contrast when using AM, the buy-to-fly ratio was only 1.5 in which AM utilizes less material and substantial energy was also saved using AM due to having an optimized geometry [64]. To calculate whether AM has a higher or lower environmental impact when compared to CM depends mainly on the type of manufacturing method that AM is substituting. For instance, despite the lower environmental impact associated with injection molding, the process is only cost-effective for a higher volume production run due to the cost of the mold [27].

3. Influential Parameters and Strategies for AM

From the literature, various AM parameters have been found to pose a significant influence on the environmental performance of AM. To identify such parameters, an extensive search using academic databases such as Web of Science and Google Scholar was used to locate publications from 2001-2023. Search keywords include “sustainability or environment” AND “additive manufacturing or 3D printing” in which over 1060 articles were found. By filtering out unrelated conference papers and review articles, only 650 journal articles appeared. The articles were then focused on only those that examined the relationship between process or design parameters and the environmental impact. The number of articles was reduced to 153 publications. Studies examining the impact of influential AM parameters/strategies on the environment can be categorized into three major categories. In the first category, studies investigated the impact of using design-related approaches and design parameters. In the second category, studies examined the effect of process-related parameters; and the last category included studies that explored the combined effects of AM design and process parameters via the product-process and co-design concept. The following sections provide a discussion of each category in detail.

3.1 Design-Related Parameters and Strategies

Studies under this category focused on examining the impact of geometry-related, and material-related parameters and approaches on the environmental sustainability of AM. Nine geometry-related parameters and strategies such as the part orientation, height, surface area, cross-sectional area, base area, weight, volume, shape complexity, and the number of parts; and five material-related parameters/strategies such as the material density, shrinkage rate, CO2 emissions, biodegradability, recyclability were found to pose an influential impact on the environmental performance of the process. Figure 4 provides the number of articles investigating the environmental impact of each of these design parameters and strategies.

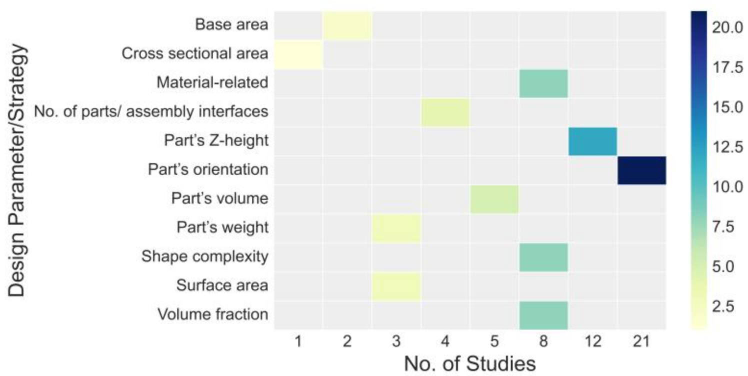

Figure 4. Publications showing AM design parameters and strategies.

3.1.1 Geometry-related Parameters/Strategies

One of the most widely studied geometry-related parameters for AM is part orientation. Optimal orientation is dependent on the nature of the support structures, the complexity of the part, as well as downstream post-processing requirements [29]. Orienting the part in an optimum direction can significantly reduce energy consumption and material waste [69], as well as CO2 emissions [70]. Another geometry-related parameter associated with the part orientation that has an impact of the environmental performance of AM is the height of the part in the z-direction. The height of the part determines the number of required layers whereby the number of layers is consequent to the build height and the layer thickness; as well as the total layer preparation time fraction that equates to the time spent on the moving of the build plate and the re-positioning of the machine nozzle [40,71]. Reducing the height of the part will result in a shorter fabrication time and consequently lower the electrical energy consumption [72]. The part surface, cross-sectional and base areas have been found to affect the environmental sustainability of AM. The surface area poses an impact on the total length of border scanning while the base area exhibits a direct impact on the support volume of the base and this has a correlation with the average area of the cross sections that influences the total time spent on moving the nozzle [29]. Therefore, the part surface, cross-sectional, and base areas have a significant influence on the print time and energy consumption [73,74]. The weight of the part and its volume are two other geometry-related influential parameters. Lighter components can result in significant energy and materials savings, as well as reducing CO2 emissions [46]. According to Zhang et al. [71], the volume has an impact on the environmental sustainability of AM due to its effect on the total interior scanning length of the geometry. Parts with larger volumes tend to result in higher energy consumption and carbon footprint [54]. One design strategy to achieve lighter AM parts with lower volumes is to use Topology Optimization (TO). TO is a mathematical model that spatially optimizes material distribution within a defined domain, by fulfilling previously defined constraints and minimizing a predefined cost function. The three main elements in TO are the assigned constraints, design variables, and cost function [75,76]. TO does not only optimize the boundary shape of a part but also modifies its topology. Therefore, in comparison to shape and size optimization methods, TO can offer a better solution for specific requirements [41]. Utilizing TO in AM can lead to improvements in sustainability, shorter fabrication time, lower material and energy consumption, lower CO2 emissions, thereby producing cost-effective designs. TO has been used for enhancing individual parts and assemblies for weight reduction [77–79]. Leary et al [78] have combined the concept of TO that could produce AM parts without support material. Figure 5 shows an example of using TO without support structures that could potentially reduce fabrication time and support material consumption without sacrificing its functionality [78].

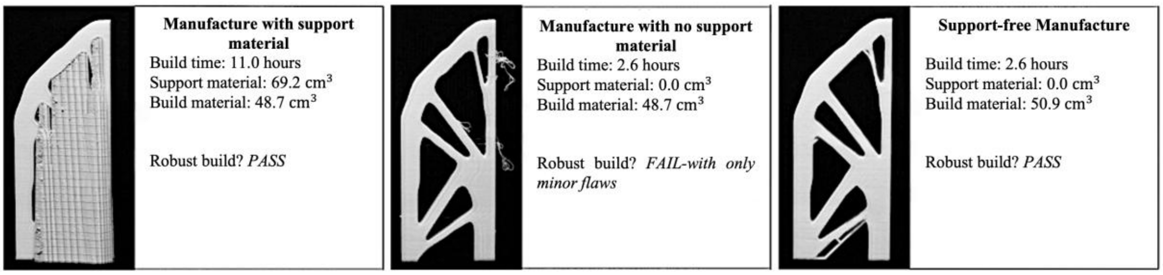

Figure 5. Using Topology Optimization (TO) for producing parts without support structures [78].

Ryan-Johnson et al [80] examined the integration of TO with bioinspired designs to aid designers in finding optimal solutions in the material functional environment. They were able to successfully develop an approach that could integrate TO into bioinspired designs, and considering AM processing conditions to ensure its mechanical performance. Using the Material Extrusion process, three lightweight material structure designs including spiderweb, turtle shell and maze were used to demonstrate the proposed approach and use of Finite Element Analysis (FEA) and environmental impact assessment were carried out. Figure 6 depicts the FEA analysis for the three structures at 30% remaining mass for different force values. Significant reduction in print time, energy, and gas emissions were achieved after integrating TO with bioinspired design structures [80]. Similarly, Yi et al. [44] optimized a holder block using TO to ensure ecological benefits by using multiple design mechanisms using SLM and Material Extrusion. Eight various design solutions with different layer thicknesses and printing speeds were proposed in the study and TO was found to be an efficient tool that could reduce energy consumption and CO2 emissions [44].

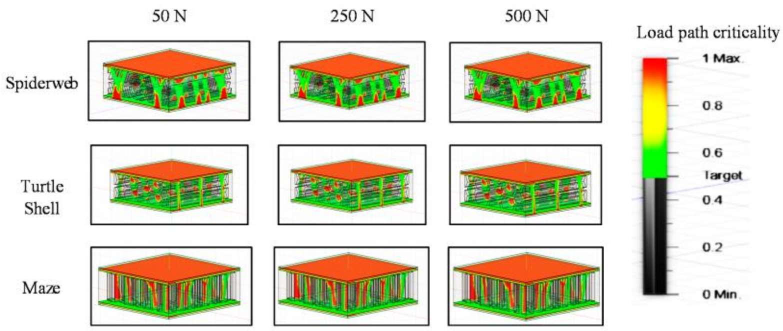

Figure 6. Using and TO for structures under various loads [80].

Another design strategy to achieve lightweight AM parts is to use cellular structures. These porous structures distribute materials in specific locations that improve mechanical and thermal performance in various aspects. Cellular structures can be either stochastic or non-stochastic (Figure 7(A)). The former can have open or closed cell structures while the latter consists of repeating lattice structures. These structures can withstand a high amount of load and large deformation at low densities [81,82]. In addition to Figure 7 (A), Figure 7 (B), other forms of cellular structures include cubic, diamond, kelvin, and kagome. Cellular structures combine functional materials with high performance, high heat transfer capacity, good thermal insulation, low thermal conductivity, high strength-to-weight ratios, etc. Cellular structures have been utilized in different fields, including aerospace, automotive, and biomedical fields [16]. Studies have utilized lattice structures to reduce the weight of additively manufactured parts [83,84]. According to Hao et al. [13], improving the sustainability of AM can be achieved by using cellular structures to reduce the mass and weight of parts. This approach can reduce the amount of material, yet providing high performance for medical, aerospace and other engineering products [13]. Zhang et al. [73] believe such bio-inspired designs can be applied to AM applications to reduce material while still fulfilling the desired function. In their study, they developed a conceptual model for a sustainable bioinspired design of AM products using SLS to fabricate titanium parts with diamond, honeycomb, and bone structures. Results of the study showed that the bone structure exhibited the least environmental impact and lowest cost due to shorter processing time [73].

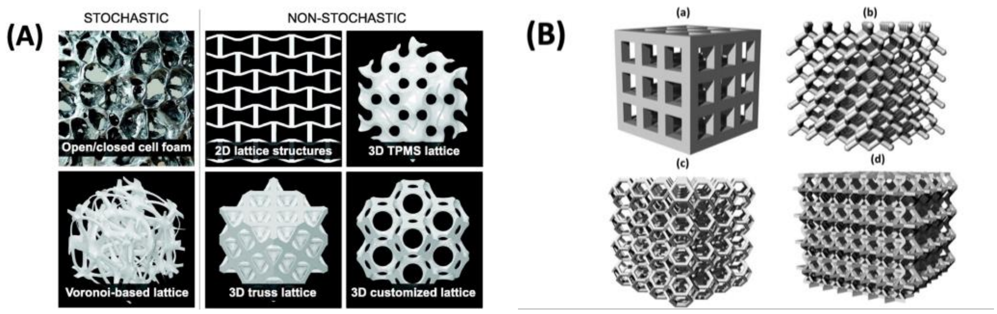

Figure 7 (A) stochastic Vs. non-stochastic cellular structures [82], and (B) various forms of cellular structures, (a) cubic, (b) diamond, (c) kelvin, and (d) Kagome [85].

Other studies investigated the effect of different shapes or the geometric complexity based on fabrication time and energy consumption [54,74,86,87]. Balogun et al. [54] used an experimental case study to evaluate the carbon footprint and energy consumption of the Material Extrusion process. Results showed that print time is related to part complexity and the volume. Longer print times can result from parts with larger volumes and more complex parts. This can lead to higher energy consumption and a higher carbon footprint [54]. Baumers and co-authors [74] studied the impact of variations in terms of shape complexity on the energy consumption of using EBM. They used a Spies ratio to measure the level of complexity which is calculated by dividing a part’s mass over the mass of a correctly aligned bounding primitive, which is typically a cylinder or a cuboid, made from the same material. The results of the investigation suggested that there could be a need for a better understanding regarding the relationship between shape complexity and process energy consumption. The study concluded that the process energy consumption is not determined by shape complexity but rather due to the cross-sectional area and hence by the overall mass. Reducing the volume of material may lower the energy consumption in the EBM process [74]. Pradel et al [86] studied the effect of shape complexity on the energy consumption and printing time of Material Extrusion printed parts. They used a case study in which different shape complexities of a load cell holder were created. Four design types of the load cell holders were created and their material consumption and build time were compared. It was found that parts with the largest thickness and greatest height resulted in a production time that was up to three times more [86]. Pradel et al. [87] also investigated the effect of shape complexity on the building time of Material Extrusion and Material Jetting, looking at the layer area (the area of the layer in which the material has been deposited), the component size (the overall dimensions of the minimum bounding box of the layer), and the increase in perimeter. The results showed that these three factors had a profound impact on the build time for Material Extrusion. On the other hand, the size was the only factor that exhibited a significant effect in Material Jetting. The authors suggest minimizing the layer area, component size, and perimeter length to reduce the build time for Material Extrusion. The authors also found that minimizing the component size, avoiding empty spaces, and using design spaces efficiently can reduce the build time for Material Jetting [87]. These findings demonstrate that shape complexity can have a significant impact on the environmental performance of AM.

The number of parts required in a product is another significant parameter that influences the environmental impact of the AM process. Part Consolidation (PC) is an important design strategy to reduce the number of parts and simplify the product's structure. PC can contribute to lower-cost products with lower weight and improved performance. Moreover, the design for assembly in AM also contributes to reducing the complexity of product structures with minimal buildup and assembly time. PC is a potential substitute for manual assembly due to its ability to combine multiple parts in one without the need for assembly operations. PC is considered one of the major motivations behind utilizing AM technologies [88,89]. The main advantages of PC include the reduction of part assembly requirements and complexity of production management, and the elimination of tedious assembly operations and assembly tools [16]. Therefore, investigating the sustainability potential of PC is of great importance. Yang et al. [90] have evaluated the environmental impact of two design approaches using a developed LCA-based model. The first design approach consists of Assembly Design (AD) via CM plus assembly operations, while the second approach was PC via AM plus machining. The study used a throttle pedal assembly as a case study to assess its environmental impact throughout the lifespan of a vehicle using the two design approaches. The two design approaches of the throttle pedal as well as the throttle pedal before and after consolidation are shown in Figure 8. The study concluded that the PC approach could lead to a greener design when the consolidated part's lifespan is prolonged by over 200% or when the weight savings for AD exceeds 30% [90].

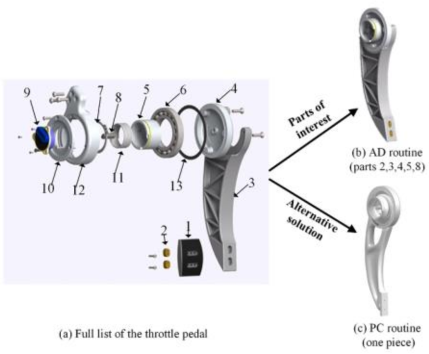

Figure 8. Original design of throttle pedal vs. integrated approach with AM by Yang et al. [90].

3.1.2 Material-related Parameters/Strategies

Due to their ease of use, availability and versatility, polymers and composites are among the most widely used materials in the AM industry. Photopolymer resins, thermoplastic polymers, alumina powders, ceramics, as well as concrete have been used in AM. Furthermore, different metals and alloys such as titanium alloys, stainless steel, nickel-based alloys, as well as some aluminum alloys can be processed via AM. Materials fabricated by AM have been applied in different new areas including, polymers (e.g., advanced composite parts and toys) [93], metals, ceramic, and polymers (e.g., heat exchangers, aerospace, biomedical, electronics, automotive) [93,94], ceramic, concrete, and soil (e.g., buildings and large biomedical structures) [95]. Many studies in the literature have investigated the effect of material's density [96,97], the use of bio-based and biodegradable materials [98,99], the development of 3D filaments from wastes [100], and recycling 3D filaments [99,101,102] on the energy consumption and/or the environmental impact of the AM process. Baumers and co-authors [96] presented a comparative assessment of the consumption of electricity in two main metallic AM processes, namely EBM (titanium) and SLM (stainless steel). The 3D printers were monitored during the entire print time to measure the total energy consumption. The energy in phases prior to the actual print such as the energy required for vacuum drawing or bed heating was also recorded and included in the analysis. Results showed that EBM consumed less energy due to the lower density of titanium and the higher layer thickness [96]. Mohammad et al [97] provided a detailed cradle-to-gate LCA to evaluate the environmental impact of conventional concrete construction, 3D concrete prints without any reinforcement, 3D concrete prints with reinforcement elements, and 3D lightweight printable concrete material without reinforcement. Results showed that additively manufactured concrete was able to substantially lower the environmental impact in terms of acidification potential, eutrophication potential, global warming potential, fossil fuel depletion, and smog formation potential in comparison to conventional construction. A reduction of the environmental impact criteria was achieved when lightweight concrete was used [97]. According to Pakkanen et al. [99], improving the sustainability of AM process can be achieved by recycling additively manufactured parts and waste at the end of their life cycle as well as by substituting oil-based feedstock with bio-based and biodegradable plastics such as Polylactic acid (PLA), Polyhydroxyalkanoates (PHAs), Polyvinyl alcohol (PVA), High Impact Polystyrene (HIPS), and Polyethylene terephthalate (PET) [99]. Kumar and Czekanski [101] were able to use discarded Polyamide PA12 powders from the SLS process to develop Material Extrusion filaments after mixing the waste with tungsten carbide. Results showed that the incorporation of tungsten carbide resulted in increased melt flow index, glass transition temperature and improved strength of the composite filament.

3.2 Process-related Parameters/Strategies

Studies under this category investigated the effect of process parameters and/or support structures on the environmental performance of AM. Fourteen process-related parameters (layer thickness, laser power, printing/scanning speed, deposition speed, powder feed rate, nozzle temperature, infill density, batch size, printing path, printing resolution, powder flow rate, raster width, raster angle, and air gap) and six support related parameters/approaches (support's height, volume, filling strategy, optimized structure, and reusability) were found to pose an impact on the environmental sustainability of AM process. The total number of articles associated with investigating the environmental impact of each of these process parameters/strategies is shown in Figure 11.

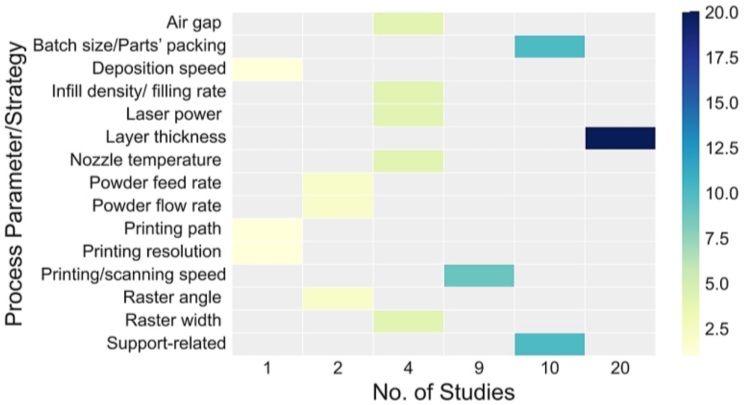

Figure 11. Number of publications related to sustainability and the AM process parameters

3.2.1 Process-related Parameters

Various studies investigated the effect of layer thickness [103,104], laser power [104–106], printing/scanning speed [104,106], powder feed rate [104–106], nozzle temperature [20,107,108], infill density

[109,110], and batch size/nesting efficiency [61,111] on the energy consumption and environmental impact of the AM process. The environmental impact of layer thickness have been widely investigated in the literature. According to McAlister and Wood [27], layer thickness has a significant impact on the printing time and energy consumption. Therefore, it is recommended to use the largest layer thickness that can achieve an acceptable surface finish and geometric tolerance. Reducing layer thickness can result in significant energy and material savings [29,44].

Laser power is another influential process parameter that if properly optimized can yield significant energy savings. Liu et al. [104] have developed an empirical model to characterize the relationship between process parameters and energy efficiency for Metal Laser Direct Deposition (MLDD). MLDD can be divided into four types of subprocesses based on its forming characteristics, namely Single-track Single-layer Deposition (SSD) process, Single-track Multi-layer Stacking (SMS) process, Multi-track Single-layer Lapping (MSL) process, and Multi-track Multi-layer Accumulation (MMA) process. The study showed that the laser power exhibited a significant effect on the energy efficiency in the SSD process, while the scanning speed and powder feed rate demonstrated little effect on the energy efficiency. Increasing laser power led to improvement in energy efficiency. Moreover, in the SSD process, the energy efficiency was mainly affected by the cross-sectional area of the deposited layer. This is attributed to the effect of process parameters on the effective utilization of laser energy which eventually altered the cross-sectional area of the deposited layer. In the SMS process, the energy efficiency was exponentially related to the number of deposited layers. When optimal process parameters were used, improvements in energy efficiency up to 50.3% for MSL and 5.7% for SMS were reported [104]. Printing/scanning speed has been also found to affect the environmental sustainability of AM. Printing parts at high speed while maintaining the print's quality can result in lower environmental impact [44] and energy consumption [107,112]. Mohammad et al. [97] reported a lack of significant impact between the building speed and the resulting environmental impact of AM processes using concrete. Similarly, Liu et al. [104] reported a negligible impact of printing speed on the energy efficiency in the SSD process. Increasing the powder feed rate that increases the deposition volume may result in lower energy consumption [105], yet this effect was found to be less pronounced in the SSD process [104]. Liu et al. [105] investigated the impact of the laser power, printing/scanning speed, and powder feed rate on the energy consumption during the laser deposition process. Results showed that the powder feed rate is inversely proportional to the energy consumption while the scanning speed and laser power are proportional to the energy consumption. Increasing the scanning speed resulted in a reduction in the fabrication time which caused a reduction in the unit energy consumption [105]. Vinod et al [106] investigated the energy consumption associated with use of Inconel-625 via laser-based metal deposition process. Results showed that decreasing the energy consumption and deposition time can be achieved by increasing the laser power, scanning speed and powder flow rate [106]. Another process-related parameter that influences the environmental sustainability of AM process is the nozzle temperature. High nozzle temperature results in more energy consumption in terms of more thermal energy needed to melt the printing filaments [112]. Baumers et al [20] evaluated the energy consumption of the LS process using a power monitoring approach. Results showed that the energy efficiency of the process can be enhanced by reducing the time-dependent energy consumption [20]. An experimental study was conducted by Sreenivasan et al. [108] to assess the energy consumption in SLS and found that one-quarter of the energy was consumed by feed and build piston stepper motors, 16% of the energy was consumed by the laser system, while 40% was consumed by the powder feed and part bed heaters. The authors recommend using better thermal management and high-efficiency lasers to eliminate the need to heat the powder and thus reduce the amount of energy consumption [108]. Simon et al. [107] found that temperature regulation and printing bed heating are big energy consumers of the Material Extrusion process. Nonetheless, Tian et al. [112] reported little evidence that the nozzle temperature poses a major impact of the energy consumption during the preheating phase for Material Extrusion. The infill pattern is also a significant AM process parameter that allows for faster printing with semi-hollow structures. The infill pattern uses lattices to maintain a level of strength in the part. Sustainability ranking for different infill patterns (e.g., honeycomb, gyroid, star, spherical, etc.) in Material Extrusion was compared. The Gyroid infill pattern reported the best sustainability ranking [109]. Podroužek et al [110] were able to develop bioinspired infill patterns for structural applications using AM. They employed numerical TO that could optimize the outer shape of the structure. Figure 12 depicts a transition from a classical column to (organic) branching structures. FEA was repetitively used to remove the least utilized material with respect to stress [110].

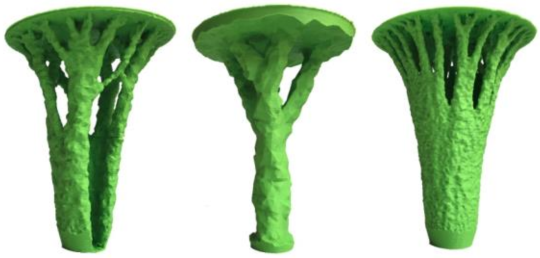

Figure 12. The transition from a classical column to organic branching structures [110].

Another influential process-related parameter is the batch size. Baumers et al. [61] found that the 3D printers' utilization capacities had an effect on energy savings in terms of specific energy consumption per kg of material deposited, ranging from extreme (-97.79 % for LS) to small (-3.17 % for Material Extrusion). Considering LS and EBM technologies, which include extensive energy consumption for warm-up, cool-down, and atmosphere generation, utilization of the printer's full capacity can lead to far greater energy efficiency in comparison to a single-part mode of production. Results showed that Material Extrusion technology did not take advantage of full capacity utilization. This is attributed to the absence of the printer's warm-up and cool-down phases. Figure 13 shows the energy consumption for single build vs. full build for the various AM technologies [61].

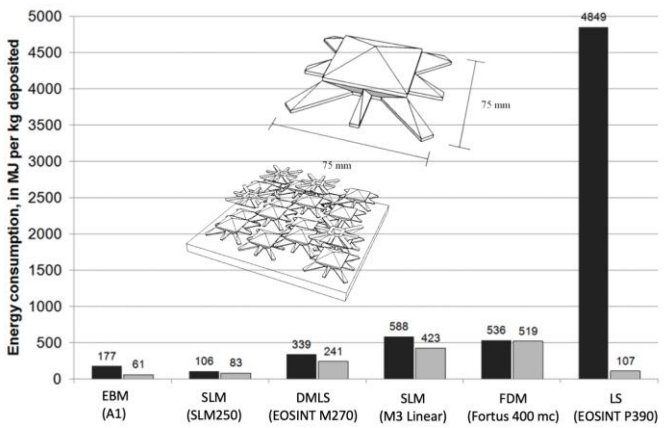

Figure 13. Energy consumption for single vs. full build for different AM technologies [61].

3.2.2 Support Structures-related Parameters/Strategies

The use of support structures is crucial in AM. Typically, supports are cellular or hollow structures that can be removed after the process is complete and support structures in AM present a significant waste in terms of energy, material and time dedicated to their construction and removal [113]. Many studies investigated the effect of the support's height [28,71], volume [114,115], filling strategy [29], optimized [113,114,116], and reusable [117] support structures on the consumption of energy, material, and environmental impact of AM processes. Lowering the height and volume of support structures yields significant reductions in printing time, energy, and materials consumption [28,73]. Further, reducing the volume of supports can maximize the printer's space and increase the number of parts printed together [115]. Mani et al. [28] reported that the height of a support, the printing time and energy consumption for Thermojet and SLS processes are less pronounced. Furthermore, using sparse support structures may lead to improvements in the environmental performance of AM in terms of lower material and energy consumption [29]. Optimizing the structures of supports and developing reusable support structures have shown benefits. Lantada et al [116] investigated the idea of bioinspired support structures such as tree-like and fractal geometries. Compared to the traditional support structure, the novel support as shown in Figure 14 resulted in around 50% of material savings. Reduction in cost values ranged from about 10% to around 40% [116]. Strano et al. [113], presented a new method for the design of support structures that optimizes the orientation of the part and the support cellular structure for metallic AM processes. This two-step optimization algorithm is based on pure mathematical 3D implicit functions for the creation and design of cellular support structures including graded supports. This study included an evaluation of the support optimization for a complex shape geometry. Results showed that the proposed method can yield substantial savings in terms of materials (45% savings in the material in this case) and can be used to improve the sustainability and efficiency of metallic AM processes [113]. Fahad et al [117] presented novel support material compositions consisting of Methylcellulose and propylene glycol or butylene glycol for Material Jetting. According to their study, these gels allow for the easier removal of the supports due to their softness. Furthermore, their low melting points (about 500°C) provide the advantage of reusability [117].

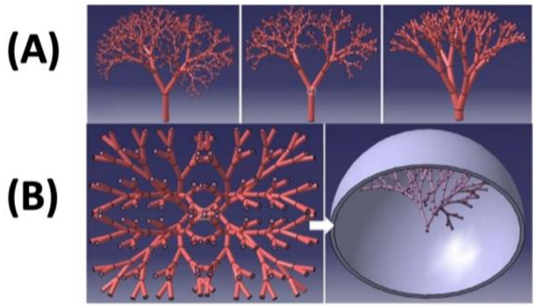

Figure 14 (A) Novel tree-like supports (B) a half sphere supported by the tree-like structure [116].

3.3 Product-Process Co-design Strategy

The third category of studies investigate the impact of influential AM parameters/strategies on the environment based on co-design. Kellens et al. [40] investigated the effect of nesting, the ratio between the useful AM part volume and the volume of the total build container, the optimal layer thickness selection and environmental impact of the SLS process. Results showed that energy reduction could be achieved by minimizing the building height that can be achieved by optimizing the part's orientation and thus increasing the nesting efficiency of builds with multiple products. Higher nesting efficiencies in addition to a higher recycling powder rate can also lead to less powder being wasted [40]. Yang and Liu [121] illustrated the possibility of improving the sustainability impact associated with CAD designs and process parameters in AM. Their proposed framework is shown in Figure 15.

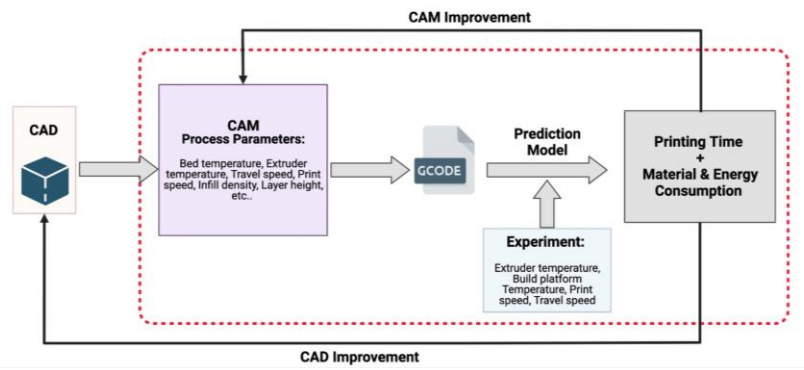

Figure 15. A framework used to improve AM's sustainability by optimizing the design and process parameters [121].

Paul and Anand [123,124] were able to develop parametric correlations between the part's orientation, its geometry, the thickness of the slice, and the laser energy. The overall energy required to manufacture a product was calculated for SLS [123] and metal AM technologies [124]. Results suggest that slice thickness is inversely proportional to the total laser energy for building the part. This is because the large number of slices associated with thinner slices leads to a greater total area of sintering. Moreover, the effect of the part's orientation on laser energy is dependent upon the part's geometry. For a cylinder, the lowest laser energy occurs when the cylinder axis and build vector are parallel. Results show that the parts' slice thickness exhibited a greater effect on the laser energy in comparison to the part's orientation [123]. Verma and Rai [122] propose the optimisation for both part and layer levels enabling AM processes to be more sustainable. At a part level, the material waste was reduced, along with improvements towards surface quality by optimally orienting the part along the build direction. Results reported a reduction of material waste in terms of support structures of up to 67.26 %. Parts printed with maximum layer thickness were faster to build, and required less processing energy. Nonetheless, these parts required additional post-processing due to being more prone to errors. Using a slice level optimizer, the part slices were optimized to provide an optimal laser scan movement of each slice while minimizing the slice energy consumption. Results showed a strong correlation between the laser processing energy and printing time. The developed approach resulted less material waste [122].

3.4 Summary of Influential Design- and Process-related Parameters/Strategies Along with their Environmental Impact

Figure 16 summarizes the various concepts towards AM's environmental sustainability. Other studies [112,126–130] have argued that it would be impractical to assess the environmental impact associated with the AM process without considering the final quality of the part. This argument is supported by the fact that parts with poor quality tend to "indirectly" increase energy consumption, environmental impact and waste due to failed prints, shorter life cycle and re-fabrication of parts. Quality-related parameters, such as the part's surface finish and dimensional accuracy were found to be important. According to Nancharaiah et al. [129], poor surface quality can account for more energy consumption and materials waste. Maintaining an appropriate surface finish may cause an increase in the process energy consumption yet will minimize the post-processing time. Similarly, parts with poor thickness deviation and average out-of-tolerance tend to increase the energy consumption, environmental impact and waste associated with failed prints [27,112]. Although this review did not explicitly focus on analyzing AM's environmental sustainability with regards to quality parameters, it investigated the environmental impact that design and process parameters pose on the quality of additively manufactured parts.

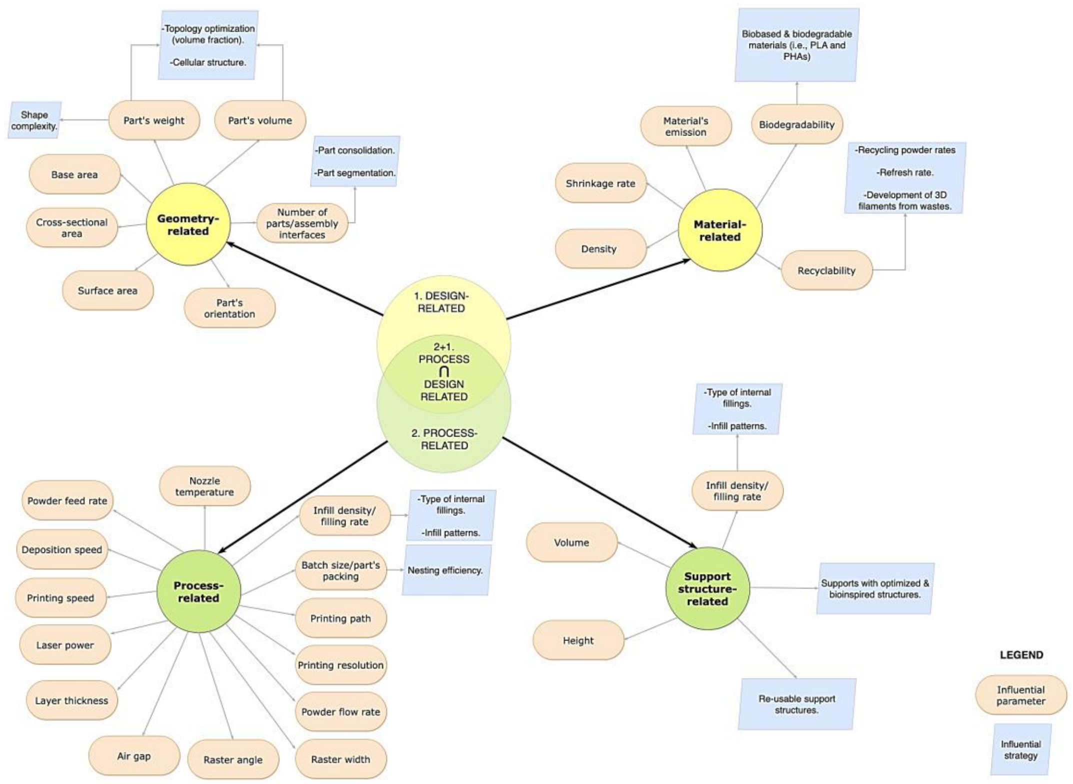

Figure 16. Summary of AM's environmental sustainability influential parameters/strategies

4. A Discussion - Research Challenges in Automating LCA for AM

LCA is widely accepted as an efficient tool that can be used for assessing, improving, and designing environmentally benign industrial processes for a wide range of products and services [131]. However, utilizing LCA tools is considered a challenge by many firms and designers. This is attributed to the fact that LCA can be expensive to perform and require judgment on environmental priorities and detailed extensive knowledge to carry out the analysis [132]. Interpreting LCA results may require experience that could make people hesitant to rely on it [133]. Another challenge of LCA is the requirement for data collection for process and life cycle inventories [134]. LCA is a data-intensive methodology that demands access to detailed information and may delay investment decisions [135,136]. Such data-intensive procedures can be inefficient in the early process design stages where a lot of required background and foreground inventory data are still missing [134]. There is a growing research about use of Machine Learning (ML) that can estimate LCA data [137]. A number of studies in the literature have investigated the feasibility of coupling LCA with ML [138,139]. One goal of such studies was to develop digitized alternative methods to support decision-making during the planning and designing stages. Such studies have also aimed at providing sustainability improvement guidance through "ahead of detailed design" assessments and critical parameters identification. When integrated with LCA, ML has been proven to be efficient in assessing the environmental impact of buildings [138,140–142] as well as estimating the life cycle impact of materials [143]. Moreover, ML methods have been successfully employed to estimate unit process data [144], greenhouse gas emissions [145], carbon emissions [146], LCA metrics of bio-based and biorefinery processes [134], as well as characterization factors [137]. Nonetheless, there is still a knowledge gap regarding the feasibility of ML algorithms to assess and predict the environmental impact of the AM process. This is mainly attributed to the absence of a standardized framework for automating LCA for AM. Thus, efforts are needed to be put together towards developing a general framework that with proper modifications can be applied to various AM technologies.

One of the main challenges of automating LCA for AM is the lack of publicly available datasets for AM. Some specific fields have established large datasets for training purposes, such as MNIST [147] for optical character recognition, and ImageNet [148] for image recognition. As a result, ML tools have great potential in these areas. On the other hand, this is not the case for AM. Although some platforms (i.e., additive manufacturing materials databases, IEEEDataPort, DOE Data Explorer, and DATA.GOV) offer some AM-related datasets, they are very limited to specific AM technologies and design/process features. Further, maintaining the reproducibility of research is a fundamental principle. Reproducibility entails obtaining consistent results when replicating a study using the same input data, methodology, codes and experimental conditions. With the increasing number of ML studies conducted in AM applications, the lack of shared datasets has become a significant challenge to reproducibility. To date, there is still no well-known or commonly used dataset in AM research. The current databases are not suitable for AM and are typically intended for managing internal data within an organization. There is no straightforward approach that would allow users to share and access AM data publicly. Additionally, some AM processes are not fully mature or standardized, which presents difficulties in constructing a general database or dataset for AM. To cater to the needs of AM, it is necessary to develop a database that is specifically designed for this purpose. This database should be user-friendly, easily accessible, and well-organized to ensure that the required data can be easily located and utilized. This would allow for the collection of data from various studies in an efficient way. Data sharing would also encourage collaboration among researchers [149,150]. Additionally, combining multiple small datasets could result in a larger, and more diverse dataset that would benefit all AM researchers [149,150].

At present, cost is a barrier to establish a cohesive data collection system capable of hosting and providing training data for various AM research and practices. Generative models are a set of techniques that could be employed to increase the size of a dataset through a process known as data augmentation. An example of such a technique is the use of an autoencoder that has the ability to generate new data. The autoencoder involves the use of an encoder to transform inputs into an internal representation, and a decoder to generate new outputs that closely resemble the inputs based on this representation [150]. To date, there is no standardized practice for extracting data for design and process parameters in AM. Some design (i.e., volume, surface area, weight, etc.) and process (layer thickness, infill density, printing speed, support volume, etc.) data can be manually extracted using slicing software. However, this can be expensive and time-consuming. Therefore, it is essential to develop standardized data extraction algorithms for AM parts and processes that are capable of utilizing computational power to extract AM parameters with a commonly acceptable degree of error. Another challenge that hinders the utilization of ML tools in AM is the lack of knowledge in selecting influential features.

Some AM design and processing parameters may demonstrate a significant impact on the environmental performance of AM whereas other parameters may exhibit a smaller effect. For a small dataset, having too many input features can lead to inefficiencies. Thus, it is vital to ensure that the ML algorithm can operate on a good set of features. Feature selection can be done using established statistical tools to perform quantitative analysis such as correlation analysis as a means to determine the strength of a relationship between two variables. Another approach for feature selection is feature combination which applies dimensionality reduction on input features to produce a new powerful feature. Another approach under the umbrella of feature selection is the scatter matrix. A scatter matrix can be thought of as an estimation of the covariance matrix when such covariance is costly to compute or cannot be computed. This approach consists of plotting scatter plots to visualize the relationship between two input features and spot their correlation. Therefore, automating the feature extraction process could provide an opportunity for future research [150]. One potential solution to overcome the aforementioned challenges is to develop automated tools to assess and improve the environmental performance of AM. Figure 17 depicts the proposed framework to support data-driven predictive sustainability assessment and optimization in AM.

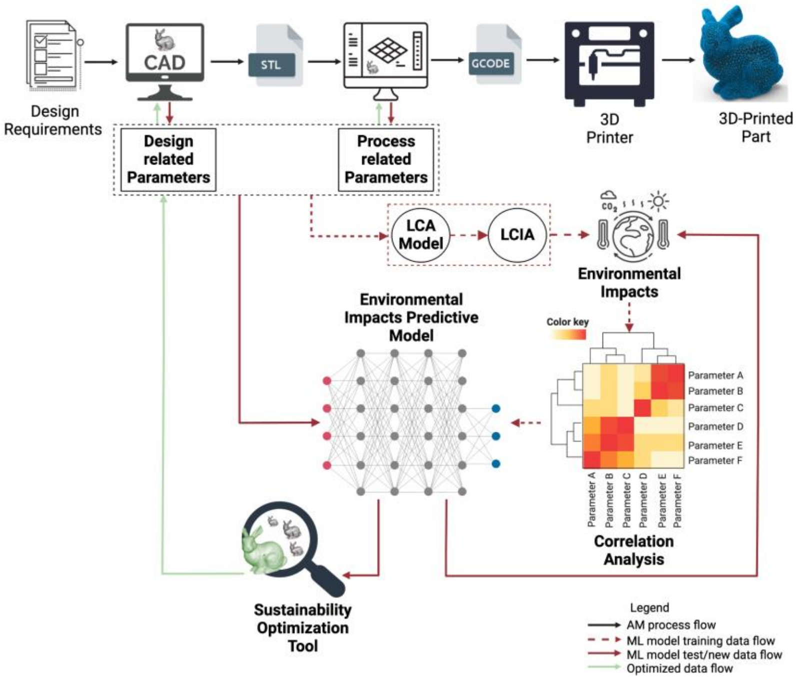

Figure 17. Proposed framework for automating LCA within the AM process

The framework consists of three main workflows: the general AM process, the environmental impact prediction process, and the sustainability optimization process. The AM general process starts with design requirements and then the design requirements are mapped to specific design features in the form of a Computer-Aided Design (CAD) file. To be acceptable for printing, the CAD file is converted to a Stereolithography (STL) file which contains the geometric information of the part. The next step involves selecting process parameters and slicing the STL file. The 3D printer will then execute the print job according to the G-Code. The first step in the environmental impact prediction process involves deciding on the AM's environmental sustainability influential design and process-related parameters to be used for the data-driven model. The choice of such a set of influential parameters is dependent on the AM technology. From current studies, it has been observed that the most extensively researched design parameter is the orientation of the part, while the layer thickness is the most widely studied process parameter. Conversely, certain parameters, such as the base area, cross-sectional area, and air gap, have not received as much attention. This could be because their impact on the environment is minimal, or because they require more comprehensive studies to fully understand their influence on AM's environmental performance. Thus, to develop an influential set of parameters for Material Extrusion as an example, practitioners might use five design parameters (part volume, weight, z-height, surface area, and material type/density) and seven process parameters (layer thickness, printing/scanning speed, nozzle and platform temperatures, infill density, support height, and volume). These parameters can then be instantiated using parts with various shape complexities (topology optimized parts and parts with various cellular structures). The values for these parameters can be then be extracted using a 3D CAD slicing software, or programmed to use data extraction algorithms. Next, a comprehensive set of sustainability impact indicators is to be established via LCA. Depending on LCA results and interpretation, a key parameters is to be derived by considering only those parameters that exhibit the most significant impact on the environmental sustainability of AM. This can be done using correlation analysis and dimensionality reduction that can avoid feeding the data-driven predictive model with redundant variables. The next step involves normalization, training, and building the environmental impact predictive model. The last step in the prediction process involves evaluating the performance of various ML models. Since the environmental impact categories are continuous variables, a simple regression prediction model might be a good idea to start with and consider as a baseline model. The performance of various advanced supervised learning regression models (i.e., deep neural network, extreme gradient boosting (XGBoost), and random forest regressor, etc.) can then be compared relative to the baseline model. The last part of the proposed framework includes the sustainability optimization process. In this process, optimization tools are to be utilized to find optimum AM design and process parameters that minimize sustainability impact indicators. The optimization tool will also act as a feedback loop to support early design stage modifications.

5. Conclusions

This paper has discussed the various environmental sustainability potentials for AM. It has categorized the different LCA-based approaches by which the environmental impact of AM is assessed according to unit AM process modeling, comparison between various AM technologies, and comparison between AM and CM approaches. Furthermore, studies examining the impact of influential AM parameters and strategies on the environment were divided into three major categories investigating the impact of design-related parameters/approaches, examining the effect of process-related parameters and/or support structures, and exploring the integrated impact of AM design and process parameters via product-process co-design. The direct and indirect impact of these parameters and strategies on the environment were reviewed and summarized to help understand the environmental impact of the parameters selection and to develop best environmental sustainability practices. This study also discussed the various limitations associated with the current environmental impact assessment tools. It has highlighted various challenges hindering the adoption of automated LCA for AM. As recent studies have shown that the adoption of ML algorithms in the manufacturing field has become an urgent need, it is proposed that this new framework to support data-driven predictive sustainability assessment in AM could be viable. The proposed framework takes advantage of the integrated effect of ML with the product process co-design concept to mitigate the challenges and limitations associated with the current assessment tools. Both simplified and detailed qualitative and quantitative LCA methods should be further improved to provide a flexible set of tools for a wide range of applications and decision-makers. More research including comparative and deep-dive single case studies is still required to ensure that AM does not become a missed opportunity for enhancing manufacturing sustainably.

Declaration of Interest

Each of the authors confirms that this manuscript has not been previously published and is not currently under consideration by any other journal. To the best of our knowledge, none of the above-suggested persons have any conflict of interest, financial or otherwise.

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