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ORIGINAL ARTICLE

Intelligent manufacturing paradigms: linking design optimization and sustainability in large-area additive manufacturing

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Abstract
The next generation of computer-aided intelligent manufacturing systems must enable the exploration and exploitation of cause-and-effect relationships across multiple disciplines. This capability strengthens human decision-making and supports sustainability-by-design in digital design-to-manufacturing workflows. To enhance system intelligence, seamless integration is needed between material systems, design methods, manufacturing processes, and sustainability metrics. This study presents a case study on large-scale mold manufacturing using large area additive manufacturing. A multidisciplinary design optimization (MDO) framework combines parametric and generative design strategies with manufacturing process planning, material selection, and environmental impact analysis. The study examines the trade-offs between structural integrity, production efficiency, and ecological impact, focusing on two different short fiber-reinforced polymer materials. Empirical and model-driven analyses methods reveal a direct correlation between mass reduction and improved sustainability. While carbon fiber reinforcement offers better structural performance, it also increases the carbon and water footprints by approximately 400% and 100%, respectively, compared to glass fiber alternatives. The case study on wind turbine rotor blade mold manufacturing highlights how parametric and generative design approaches can produce both structurally sound and sustainable solutions. Future research should focus on improving the algorithmic transparency of commercial software, increased flexibility to add manufacturability constraints, and potentially including sustainability models to enhance the intelligence in design-to-manufacturing workflows. This study highlights the potential of intelligent manufacturing systems to drive cleaner, more efficient, and sustainable production processes.

Keywords Intelligent manufacturing · Sustainability-by-design · Digital manufacturing · Additive manufacturing

1 Introduction

Sustainability has emerged as a pivotal global concern, highlighting the need to balance environmental preservation, economic growth, and social well-being. According to the United Nations, sustainability is defined as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" [1]. Achieving this balance requires informed decisions based on reliable, science-driven metrics. Consequently, a variety of sustainability indicators, such as carbon footprint (CFP) and water footprint (WFP), have been developed to guide policymakers, industries, and other stakeholders in pursuing more sustainable pathways. Within the broader landscape of sustainability metrics, the National Institute of Standards and Technology categorizes environmental indicators according to their impacts on emissions, resource consumption, pollution, and habitat conservation [2]. Life cycle assessment (LCA) has thus become one of the most widely adopted methodologies for evaluating environmental impacts in manufacturing, offering a systematic means of quantifying factors like energy use, waste generation, and greenhouse gas emissions [3]. Dong et al. [4] provide a comprehensive review of sustainability indicators by examining their applications in various decision-making contexts, organizing them under the Drivers-Pressures-States-Impacts-Responses framework. They further propose strategies for selecting and implementing suitable indicator systems. Therefore, selecting indicators that reflect the complexity of sustainability is key to helping decision-makers navigate trade-offs

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across environmental, economic, and social dimensions. By providing essential goods and services, and accounting for nearly one-quarter of all jobs worldwide, manufacturing plays a pivotal role in the global economy [5, 6]. Nonetheless, the manufacturing sector also contributes substantially to escalating the pressures on the environment. Underscoring its profound impact, Schipper [7] reports that manufacturing is responsible for 84% of energy-related CO_2 emissions within the industry and accounts for 90% of industry-wide energy consumption. Industrial activities, particularly within manufacturing, often demand large inputs of renewable and non-renewable resources (e.g., metals, fossil oil-derived materials, and water) and require substantial energy use. These processes generate solid, liquid, and gaseous waste streams that can damage the environment if not properly managed. Against this backdrop, sustainable manufacturing has emerged as a crucial strategy for aligning production processes with broader sustainability goals. The U.S. Department of Commerce defines sustainable manufacturing as "the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers, and are economically sound." This definition emphasizes the importance of balancing economic viability with environmental stewardship and social responsibility across all stages of the manufacturing life cycle [8]. Over the past decades, several studies have been published on sustainable manufacturing. Ding et al. [9] propose a sustainable design concept for active remanufacturing using a modular approach based on parameter flow and clustering to quantify module division. Integrating sustainability with product life cycles, they structure design into modules by component association. Jamil et al. [10] present a sustainability-focused manufacturing framework supported by an overall performance index that integrates machinability and sustainability metrics. The study evaluates factors such as operator health, shop floor environment, air quality, chip removal, and surface quality. A case study assesses green and hybrid lubri-cooling technologies in machining, highlighting their role in reducing cutting fluid, tool wear, energy use, and carbon emissions. The research aims to promote these technologies in engineering and establish practical sustainability guidelines by reviewing their benefits, implementation, and challenges for sustainable manufacturing systems. As industries seek innovative solutions for sustainable manufacturing, additive manufacturing (AM) has emerged as a key technology, offering benefits such as design flexibility, on-demand production, reduced material waste, and less environmental effects [11, 12]. Additive manufacturing (AM) (a.k.a. 3D printing), provides unique benefits, such as design flexibility, on-demand production, and reduced material waste [13, 14]. Bikas et al. [15] critically evaluate modelling approaches, key advantages, and technical challenges. Despite the numerous advantages of additive manufacturing (AM), one of its primary limitations lies in restricted build volume [15, 16], which can hinder the production of large components or assembly-scale parts. In response, large area additive manufacturing (LAAM), also commonly referred to as big area additive manufacturing (BAAM) or large scale additive manufacturing (LSAM), overcomes the size limitations and slow throughput of conventional polymer-based AM processes [17]. By utilizing high-throughput deposition systems and pellet-based feedstocks, often reinforced with carbon or glass fibers, LAAM can notably reduce energy intensity per manufactured part [18, 19]. Early studies, including those by Gutowski et al. [17] and the U.S. Electric Power Research Institute [20], highlighted LAAM's potential for enhanced process rate and lower electricity consumption. Post et al. investigated the cost associated with traditional fused deposition modeling (FDM) and LAAM for the composite tooling industry. This comparative study indicated that LAAM can reduce manufacturing costs by a factor of 17 and manufacturing time by a factor of 50 [21]. However, many of these investigations relied on limited or extrapolated data, leaving a knowledge gap regarding how operational parameters, material formulations, and part geometries affect overall sustainability. A recent work [22] has begun to fill this gap by collecting real-time electricity usage measurements over two months of industrial-scale LAAM operations, encompassing fifteen printing jobs with fiber-reinforced polymer pellets. The objectives of this paper are: (i) To integrate different engineering tools and form a fully automated multi-disciplinary optimization framework, capable of assisting engineers and decision-makers in designing and manufacturing technically and ecologically optimal products, while comparing different design strategies, (i.e., parametric design, which involves rule-based modeling with adjustable parameters, and generative design, which uses algorithm-driven exploration to automatically generate design alternatives based on predefined objectives and constraints.). (iii) To investigate the trade-offs between material selection, structural performance, and environmental impact in LAAM-produced lightweight designs. Specifically, assessing the sustainability implications of using carbon fiber (CF) versus glass fiber (GF) reinforced materials, considering their carbon footprint (CFP) and water footprint (WFP) in fully integrated design-to-manufacturing workflows.

2 Materials and methods

2.1 Multi-disciplinary optimization framework and sustainability-by-design

This research employs a multi-disciplinary design optimization (MDO) framework to balance ecological, economic,

and engineering objectives. As shown in Fig. 1a, the framework comprises four disciplines: material (D1), design and simulation (D2), manufacturing (D3), and sustainability (D4). ModeFRONTIER [23] is used to integrate these disciplines, with a Python script coordinating data exchange among different software tools, such as SOLIDWORKS and AbaqusCAE for design and simulation, and ORNL Slicer 2 for build preparation and manufacturing.

A Non-dominated Sorting Genetic Algorithm II (NSGA-II) guides the multi-objective optimization, leveraging both model-driven (e.g., finite element analyses) and data-driven (e.g., empirical) surrogates to account for material properties, geometric parameters, process conditions, and performance constraints. To embed environmental considerations early in the process, we adopt Sustainability-by-Design principles, which refer to the strategic integration of environmental sustainability metrics, such as energy consumption, carbon footprint (CFP), and water footprint (WFP), during the early design stages to reduce long-term ecological impact [24]. These indicators reflect a cradle-to-gate scope, covering raw material preparation, feedstock transportation, and the manufacturing process itself. Figure 1b indicates the manufacturing process mapping, and the system boundaries considered in this research. By integrating the sustainability discipline (D4) within the broader MDO framework, each design iteration is evaluated for environmental impact alongside mechanical performance. This approach empowers design engineers to make informed decisions on geometry, material choices, and process parameters, yielding a product solution that optimizes across all relevant criteria while reducing the overall ecological footprint.

2.2 Case study description: wind turbine rotor blade mold

LAAM offers new opportunities for fabricating wind turbine rotor blade molds by enabling near-net-shape production of large composite tooling. Traditionally, rotor blades are produced from fiberglass-reinforced resin using vacuum infusion or fiber placement, requiring a specialized mold to form and cure the composite structure, see Fig. 1c. Previous work demonstrated how LAAM could serve as a low-cost approach for mold fabrication, focusing on key material properties such as operating temperatures and pressures, coefficient of thermal expansion (CTE), thermal conductivity, surface finish, and system integration [25]. Table 1 presents the MDO problem formulation for a wind turbine blade mold produced by LAAM. In this study, we automated a parametric model that integrates over 2000 CAD variants of the wind turbine rotor blade mold interfaced with CAE and CAM. We used two design optimization strategies to investigate how design choices and material types affect the technical performance and environmental sustainability of LAAM for large-scale composite tooling. Since full-scale turbine blades can exceed 15 ms, surpassing typical LAAM build volumes, a representative segment of the mold is optimized as the final product.

2.2.1 Materials (D1):

Material characteristics represent a key factor in product development, influencing attributes such as mass, durability, manufacturing time, and environmental sustainability. As illustrated in Fig. 1a, the material discipline indirectly drives

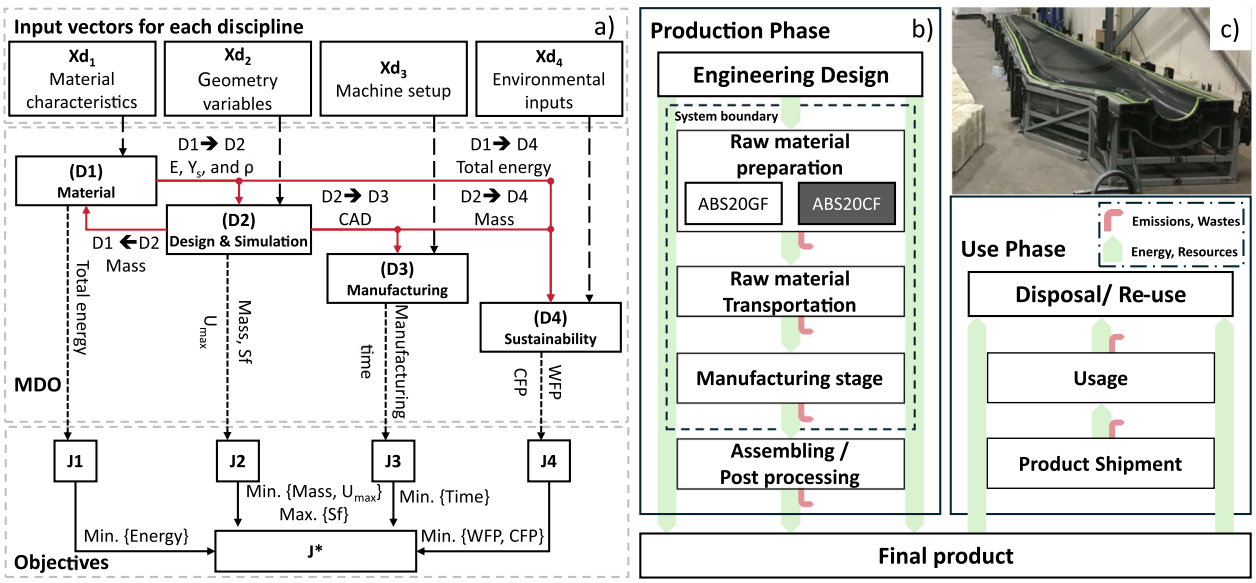

Fig. 1 **a** MDO problem formulation execution flow, **b** manufacturing process chain mapping, and **c** case study

Table 1 MDO problem formulation

Find Engineering design subsystem level variables: tlen, numt, shellth, tth, and sth Satisfy	Bounds
Inequality constraint: $Sf \geq 0$ $U_{max} \leq 5$ [mm] Goals (objective functions): (J1) Min E [Mj]: Embodied energy (J2.1) Min U_{max} [mm], m [kg]: Def. and Mass (J2.2) Max Sf: Safety factor (J3) Min Mt [h]: Manufacturing time (J4.1) Min CFP [kg CO_2e]: Carbon FP (J4.2) Min WFP [m^3]: Water FP	Material subsystem D1 (Xd1): ABS 20GF, ABS 20CF Manufacturing subsystem D2 (Xd2): Layer Height = 3.81 [mm] Nozzle Diameter = 7.62 [mm] Print Speed = 279.4 [mm/s] Bounding Box = 1365×960×960 [mm^3] Product-design D3 (Xd3): Parametric design: $50 \leq$ tlen [mm] ≤ 200 (Cont.[1]) $2 \leq$ numt ≤ 20 (Dis.[2], step=1) $10 \leq$ shellth [mm] ≤ 25 (Cont.) $10 \leq$ tth [mm] ≤ 25 (Cont.) $10 \leq$ sth [mm] ≤ 30 (Cont.)
System-level optimisation objective (J*): An optimal set of feasible and non-dominated solutions for: Scenario #1: Min. [m, CFP, WFP]; Max. [Sf]; while [$Sf \geq 0$, $U_{max} \leq 5$]; Mat. [ABS 20GF] Scenario #2: Min. [m, CFP, WFP]; Max. [Sf]; while [$Sf \geq 0$, $U_{max} \leq 5$]; Mat. [ABS 20CF]	

[1]Continuous variable
[2]Discrete variable

the optimization process by providing critical input parameters to the other disciplines (design and simulation, and sustainability). Table 2 shows material properties employed in this study, obtained from Ansys Granta EduPack [26]. In the present study, two short fiber-reinforced polymer materials are selected to investigate the impact of material choice on the final product, namely, acrylonitrile butadiene with 20% glass fiber (GF) and acrylonitrile butadiene with 20% carbon fiber (CF). These materials offer distinct mechanical properties and thermal behavior, which affect manufacturing performance (e.g., process parameters, processing time, and energy usage) and final product structural behavior (e.g., durability and integrity). As a result, selecting between both material options will affect achievable mechanical properties at the cost of material embodied energy, which is the total amount of energy consumed throughout the life cycle of a material or product, from raw material extraction to final manufacturing [24] (J1).

2.2.2 Design & simulation (D2):

The mold segment design parameters are illustrated in Fig. 2. As previously mentioned, this study concentrates on optimizing a representative segment of the mold, with a bounding box of 1365 mm × 960 mm × 1750 mm. Two design approaches are explored in this research (i.e., parametric optimization and generative design). First, a parameter-based design optimization problem is defined. The mold design incorporates hollow sections reinforced by internal walls. The parametric design factors include the shell thickness of the wind turbine face profile (shellth), the thickness of the mold walls (wallth), the number of support beams (tnum), the thickness of each column beam (sth), and the distance between column beams (tlen). The next phase involves generating metrics for structural stability. To achieve this, a static linear elastoplastic Finite Element Analysis (FEA) was conducted using the material properties from Table 2. As illustrated in Fig. 2, each

Table 2 Mechanical and environmental material properties

Material	General	Elastic phase			Plastic phase		Environmental		
	Density [g/cm3]	Young's Modul [MPa]	Poisson's ratio	Tensile Strength [MPa]	Yield stress [MPa]	Plastic Strain	Climate change [kg CO_2/kg]	Water usage [l/kg]	Embodied energy [MJ/kg]
ABS 20GF	1.2	5564	0.37	81	80.54 80.94	0.0 0.1	3.58- 3.95	190- 210	85.3–94
ABS 20CF	1.13	13081	0.34	106.5	106.44 106.75	0.0 0.1	16.2- 17.8	529- 585	262–289

Obtained from [26]

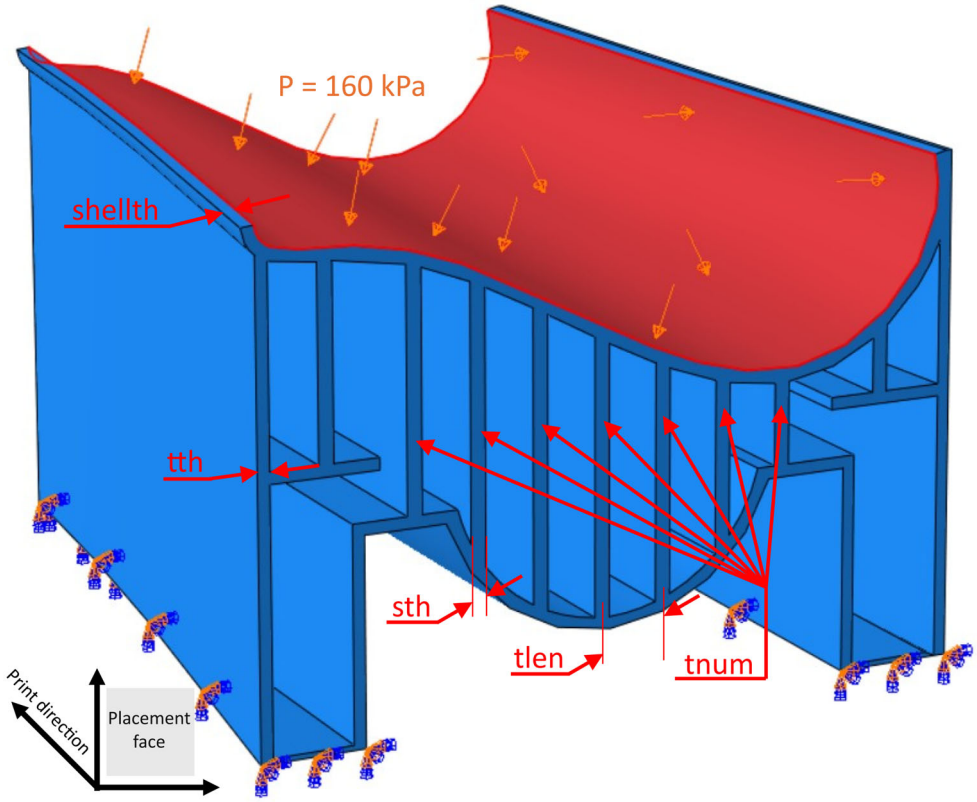

Fig. 2 CAD, CAE, and CAM for the mold. CAD model highlighting geometry inputs, location of loads and boundary conditions, part placement, and printing direction in the AM process

design variant was subjected to a 160 kPa pressure load, reflecting the conditions typically encountered during the fiber placement process. From this simulation, the safety factor (Sf) and maximum deformation (U_{max}) were determined, while the mass (m) of each design was extracted directly from the CAD model. To compare different design strategies, i.e., parametric design and generative design, a generative design process is conducted in Fusion360 using the same boundary conditions and loads [27]. The generative design process is limited to maximize the stiffness while complying with a safety factor limit of 3, a mass target of 300 kg, and a maximum deformation limit of 5 mm. As a result, minimizing objective function (J2.1) and maximizing (J2.2) will lead to lighter designs with increased safety factor.

2.2.3 Manufacturing (D3):

In this study, the dataset created by Chen et al. [22] was used to estimate the total energy consumption in LAAM. This dataset provides detailed electricity consumption measurements from printing jobs conducted in an industrial setting, including the total energy consumption for jobs with unique designs, varying masses, and two different fiber-reinforced polymer materials. To estimate the impact of geometrical variation in manufacturing time (mt), we use the open access ORNL Slicer2 [28]. Figure 2 illustrates the print direction to ensure manufacturability. For comparative purposes, a standard slicer configuration was applied to every design. However, the layer height was set to 3.81 mm, the nozzle diameter to 7.62 mm, and the printing speed to 279.6 mm/s (see Table 1) based on typical processing parameters. The disciplinary optimization objective (J3) aims at minimizing Mt that increase together with volume or mass of the final design.

2.2.4 Environmental sustainability (D4):

Sustainability is built upon three pillars, namely economic, environmental, and social aspects. From the perspective of the economic pillar, the adoption of AM processes has similar limitations in performance metrics such as small part sizes, low production rates, and expensive feedstocks. Utilizing pellets-based feedstock in LAAM has improved the economic perspective by increasing deposition speed and decreasing the material cost. Additionally, the use of carbon fiber-reinforced polymer eliminates the need for a heated chamber, which leads to reducing machine power requirement and hence energy consumption [21]. The cost structure of additive manufacturing (AM) can be broadly divided into four main components: preprocessing, material usage, processing, and post-processing [29]. Among these, post-

processing has been identified as the most significant cost driver in large-area additive manufacturing (LAAM), as highlighted by Post et al. [21]. While economic considerations are important in evaluating additive manufacturing systems, this study primarily focuses on the environmental aspects of sustainability, particularly energy consumption, carbon footprint (CFP), and water footprint (WFP), covering both blue and grey water. This scope spans raw material production, transportation, and manufacturing processes, using energy consumption and product mass to build regression models for total impact assessment. Raw material production impacts are sourced from Ansys Granta EduPack. For transportation, a 500 km trip in a EURO4, 7.5–16-ton truck is assumed, yielding 2.5×10^{-4} kg CO_2/(kg · km) of emissions and 0.236–0.402 $l/(kg{\cdot}km)$ of water use [30]. Although these assumptions may limit the model's generality, Fig. 3b and c indicate that transportation impact is low compared to raw material production. For the manufacturing phase, electric energy usage is converted to primary energy with a factor of 0.38, alongside a grid carbon intensity of 0.3 kg CO_2/kwh [31] and a water footprint of 1.308 l/TJ [32]. Material efficiency is set between 90 and 98% [26]. Finally, total embodied energy for raw material production, transportation, and manufacturing is calculated and modelled. Optimization objectives in this study are centered around minimizing environmental impacts (i.e., CFP and WFP) and mass while maximizing the structural integrity of the final product (i.e., Sf). To ensure durability and prevent failure in operation, Sf and U_{max} are constrained to be greater than 0 and less than 5 mm respectively. Minimizing the objective functions (J4.1) and (J4.2) lead to more environmentally sustainable designs.

3 Results and discussion

Figure 3a shows the linear regression model used to estimate the total energy consumed as a function mass produced for both materials [22]. The error metrics include R-squared error (R2) and Root Mean Squared Error (RSME), for GF and CF, indicating high predictive accuracy. Figure 3b and c outline the total embodied energy as a function of mass for both materials. This figure supports the minimal effect of energy used for raw material transportation and manufacturing process in comparison to raw material production process, emphasizing on the need for lighter designs to achieve reduced environmental impact.

Figure 4 shows the results of the MDO problem. Figure 4a illustrates an exemplary result for a part designed using the parametric design process. This figure outlines the maximum displacement in the part as well as its location. Figure 4b shows an exemplary generative design solution. Both results show mass and safety factor along with their respective structural and environmental implications.

Figure 4c and d demonstrate the linear relationship between environmental impacts, namely CFP and WFP, and material mass processed by LAAM for both materials. The uncertainties include geographical variations in material sourcing, differences in manufacturing practices, and other process variabilities. Notably, WFP is subject to a higher degree of uncertainty than CFP. Meanwhile, Fig. 4e and f illustrate 3D scatter plots of feasible and non-dominated solutions for ABS 20GF and ABS 20CF, respectively, showing the trade-offs among maximum displacement (U_{max}), manufacturing time, and part mass. Each point represents a viable design solution, enabling visual comparison across key performance metrics. Specifically, lowering U_{max} (to achieve a stiffer product) generally leads to increased manufacturing time and mass, reflecting the typical compromise between structural performance and production efficiency. Additionally, these plots visually reinforce the correlation between mass and environmental indicators such as carbon footprint (CFP) and water footprint (WFP), where increased mass directly translates to higher CO_2 emissions and water consumption. Comparing the results for ABS 20GF and ABS 20CF, it is evident that while ABS 20CF parts demonstrate superior structural integrity (i.e., higher safety factor and lower U_{max}) and reduced mass, these benefits come at a substantial environmental cost. In particular, CFP and WFP for ABS 20CF are approximately 400% and 100% higher, respectively, than for equivalent ABS 20GF parts.

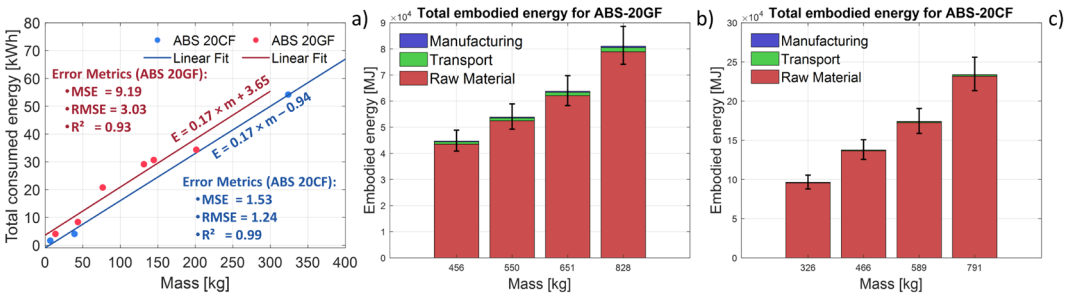

Fig. 3 **a** Linear regression models for estimating total manufacturing energy, **b** total embodied energy for ABS 20GF, and **c** total embodied energy for ABS 20CF

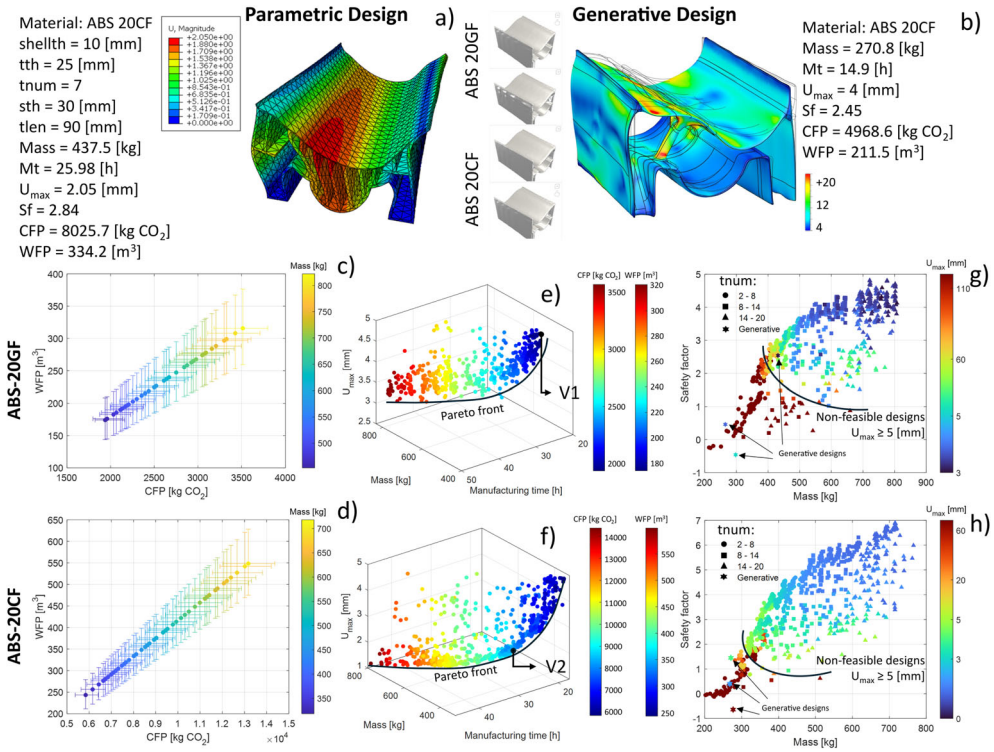

Fig. 4 Results of MDO problem. **a** An example of CAE model highlighting U_{max} and its location; **b** results of generative design process; **c** and **d** comparison of WFP and CFP along with their error for GF and CF, respectively; **e** and **f** 5-D scatter plots of feasible parametric designs for ABS 20GF (**e**) and ABS 20CF (**f**), showing trade-offs between maximum displacement, safety factor, mass, manufacturing time, and environmental impacts (CFP and WFP); and **g** and **h** parametric and generative designs for both materials

To better understand these trade-offs, we compare representative design variants from each material class, highlighting the contrasts in performance and environmental impact. The following table (Table 3) provides a detailed comparison of these variants, illustrating the key metrics and differences in performance and environmental considerations across the material classes. For example, design variants V1 (GF) and V2 (CF), described in Fig. 4e and f, have approximately the same mass (i.e., 453.25 kg for V1 and 453.30 kg for V2). However, they exhibit very different performance in terms of structural integrity (i.e., Sf = 2.33 and U_{max} = 4.97 mm for V1, and Sf = 3.8 and U_{max} = 2.01 mm for V2). On the other hand, the CFP and WFP for V1 are 1940 $kgCO_2e$ and 174.15 m^3, respectively, which are significantly lower than those for V2 (i.e., CFP = 8320 $kgCO_2e$ and WFP = 346.26 m^3). Additionally, while the lightest feasible design made of ABS 20GF has a mass of 453.06 kg, an Sf of 2.31, and a U_{max} of 4.99 mm, the lightest feasible design made of ABS 20CF has a lower mass of 318.58 kg, an Sf of 2.23, and the same maximum displacement of 4.99 mm. However, the CFP and WFP for the ABS 20GF part are 1940 $kgCO_2e$ and 174.08 m^3, respectively, which remain significantly lower than those for the ABS 20CF part (i.e., CFP = 5840 $kgCO_2e$ and WFP = 243.35 m^3). Figure 4g and h present the trade-off between Sf, Mass, and U_{max} for all the design variants including few generative design solutions. The parametric design process shows that the number of supports (tnum) is the most significant design variable. The figures also display the front of non-feasible solutions with $U_{max} \leq 5$ mm. The preliminary comparison between design approaches shows the little control of outcomes using generative designs. In principle, the generative solutions could provide better per-

Table 3 Summary of optimization results for selected design variants using ABS 20GF and ABS 20CF

Design variant	Material	Mass [kg]	Sf	U_{max} [mm]	CFP [$kgCO_2e$]	WFP [m^3]
V1 (Feasible)	ABS 20GF	453.25	2.33	4.97	1940	174.15
V2 (Feasible)	ABS 20CF	453.30	3.80	2.01	8320	346.26
Lightest Feasible	ABS 20GF	453.06	2.31	4.99	1940	174.08
Lightest Feasible	ABS 20CF	318.58	2.23	4.99	5840	243.35

formance in structural integrity and mass (emissions and WFP accordingly). However, the design-to-manufacturing workflow becomes challenging as these designs do not lead to manufacturable results and require design refinements.

To improve the manufacturability of generative designs, additional constraints, such as feature size limitations, part orientation restrictions, design obstacles, and initial design shapes, can be integrated into the process. These constraints guide the design toward more manufacturable solutions. By applying them, the search space for generative design is narrowed, resulting in practical solutions that remain innovative yet feasible for production.

While the presented case study focuses on wind turbine rotor blade mold manufacturing, the proposed MDO framework and associated methodology are broadly generalizable. The workflow, combining parametric and generative design, material selection, sustainability assessment, and manufacturing constraints, can be readily adapted to other manufacturing methods and applications such as aerospace, marine, or automotive composite molds. The observed correlations between part mass and environmental indicators (CFP, WFP), as well as the trade-offs between structural performance and sustainability, are not unique to the wind energy sector. Rather, they reflect fundamental relationships in additive manufacturing of short fiber-reinforced thermoplastics. Therefore, this study serves as a template for applying intelligent design-to-manufacturing frameworks in a wide range of industrial contexts, where sustainability-by-design and performance-driven decision-making are critical.

4 Conclusion

This study presented a multidisciplinary design optimization (MDO) formulation to address ecological, economic, and engineering challenges through a case study focused on large area additive manufacturing (LAAM). By integrating four key disciplines, materials, design and simulation, manufacturing, and sustainability, into a unified workflow, we demonstrated how early-stage design decisions can be guided to balance structural performance, production efficiency, and environmental impact.

Empirical and model-based analyses revealed a direct correlation between reduced mass and improved environmental sustainability, highlighting the critical role of lightweight design. For instance, carbon fiber (CF)-reinforced materials outperformed glass fiber (GF) in structural integrity; however, this came at a significant ecological cost, with CFP and WFP values approximately 400% and 100% higher, respectively, than those of GF-based alternatives. This emphasizes the inherent trade-offs between material selection, mechanical performance, and environmental impact. The wind turbine blade mold case study demonstrated how tuning geometric parameters, process planning, and material choices can yield designs that are both structurally viable and more sustainable. The two design strategies employed, parametric and generative design, each offered unique advantages. Parametric design allowed structured control and better incorporation of manufacturability constraints, while generative design leveraged computational power to explore broader solution spaces.

Looking ahead, hybrid approaches that merge parametric control with generative exploration may offer an optimal pathway toward manufacturable, high-performance, and sustainable designs. Further research should focus on improving the transparency of commercial algorithms, expanding the integration of manufacturability constraints, and embedding economic and environmental sustainability models into digital workflows.

In conclusion, the proposed methodology and case study offer a transferable framework for balancing technical and ecological requirements in other complex manufacturing contexts. However, the absence of physical prototyping or experimental validation represents a limitation of this work, due to resource constraints and the representative, not full-scale, nature of the mold studied. Addressing this limitation could be a direction for future work. Overall, this holistic approach supports the integration of sustainability-by-design into digital design-to-manufacturing pipelines, paving the way for cleaner, more efficient, and more responsible production systems.

Author contribution • Amirmohammad Daareyni: conceptualized the study, developed the methods, and wrote the original draft of the manuscript.
• Emanuele Pagone: contributed to the development of the methods and reviewed and edited the manuscript.
• Samniroshan Thayapararajah: supported the development of the methods and participated in the review and editing of the manuscript.
• Hossein Mokhtarian: assisted with the development of the methods and contributed to writing the original draft.
• Guido Tosello: supported the methods development and critically reviewed the manuscript.
• Iñigo Flores Ituarte: contributed to the methods development and critically reviewed the manuscript.

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Declarations

Conflict of interest The authors declare no competing interests.

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