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Environmental and economic trade-offs in conventional vs. additive manufacturing: A life cycle study of pump impeller production

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ABSTRACT

This study presents a comparative sustainability assessment of pump impeller production using conventional manufacturing (CM–sand casting) and additive manufacturing (AM), specifically Directed Energy Deposition (DED) by integrating life cycle assessment (LCA) and net present value–based life cycle costing (NPV-LCC) within a cradle-to-gate framework. Environmental impacts were evaluated using the Centrum voor Milieukunde Leiden (CML) method, while economic performance was analysed through time-dependent cost modelling, Monte Carlo uncertainty analysis, and scenario-based evaluation.

The results show that CM exhibits 46% higher abiotic depletion potential due to material losses and yield-related inefficiencies, whereas AM demonstrates 54% higher global warming potential than CM (33.7 vs. 15.5 kg CO_2 eq per impeller) because of its electricity-intensive manufacturing process. Electricity consumption contributes approximately 75% of the total environmental burden in AM. Economically, the NPV-LCC analysis indicates baseline lifecycle costs of approximately €175 per impeller for CM and €1265 per impeller for AM. Monte Carlo sensitivity analysis reveals that material cost and yield rate dominate CM cost variability ($\rho \approx 0.8$), while build duration (machine usage time) and energy consumption are the most influential drivers for AM ($\rho \approx 0.85$ and $\rho \approx 0.75$, respectively). Scenario analysis demonstrates that process efficiency improvements and increased utilization provide greater economic benefits for AM than renewable energy substitution alone. Overall, the findings indicate that AM functions as a complementary manufacturing route whose sustainability performance depends strongly on lifecycle-oriented process optimization strategies.

Abbreviations

Conventional manufacturing	CM	Additive manufacturing	AM
Life cycle assessment	LCA	Eutrophication	EP
Life cycle impact assessment	LCIA	Freshwater aquatic ecotoxicity	FAETP
Life cycle cost	LCC	Global warming (100)	GWP
Life cycle inventory	LCI	Human toxicity	HTP
Centrum voor Milieukunde Leiden	CML	Marine aquatic ecotoxicity	MAETP
Abiotic depletion (elements)	ADE	Ozone depletion potential	ODP
Abiotic depletion (fossil)	ADF	Photochemical oxidation	POCP
Acidification	AP	Terrestrial ecotoxicity	TETP
Greenhouse gases	GHG	Hazardous air pollutants	HAPs
Polychlorinated biphenyls	PCBs	Direct energy deposition	DED
Electron beam melting	EBM	Net Present Value	NPV
Laser powder bed fusion	L-PBF	Metal Additive Manufacturing	MAM

1. Introduction

Pumping systems are widely utilized across a broad spectrum of applications, including domestic, commercial, agricultural, municipal water/wastewater management, and various industrial sectors such as food processing, chemical, petrochemical, pharmaceutical, and mechanical engineering (Volk, 2013). Pumps used for fluid handling are

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susceptible to several physical and mechanical issues, including general and localized corrosion and cavitation (Liu et al., 2023; He et al., 2019). Under severe cavitation conditions, impellers can suffer from pitting or vane erosion, ultimately necessitating repair or replacement (Li et al., 2018). As a result, the manufacturing and replacement of impellers play a non-negligible role in the overall environmental and economic performance of pumping systems.

Traditionally, pump impellers have been manufactured using a variety of conventional manufacturing (CM) techniques, including casting, machining, welding, forging, and powder metallurgy (Ejiri, 2024). However, in recent years, additive manufacturing (AM) techniques, such as directed energy deposition (DED) and laser powder bed fusion (L-PBF), have emerged as promising alternatives for producing pump impellers (Adiaconitei et al., 2021). Owing to their thin, twisted blades, impellers are particularly challenging to machine using CM. AM offers a distinct advantage by fabricating components layer by layer, eliminating the need for cutting tools, fixturing, or multiple machining steps. This enables the efficient manufacturing of geometrically complex parts and supports mass customization (Frazier, 2014). Moreover, AM allows the deposition of multiple materials within a single build cycle, facilitating the development of hybrid material systems. It also enables the refurbishment of components that would otherwise be non-repairable, such as turbine blades, bearing seals, and shafts. Despite these benefits, it remains essential to assess the sustainability of AM compared to CM, particularly in terms of environmental and economic impacts.

In response to these emerging manufacturing possibilities, several studies have employed life cycle assessment (LCA) to evaluate the environmental performance of AM relative to CM. To investigate the sustainability of AM, Serres et al. (2011) conducted a LCA comparing DED with the CM. Their analysis revealed that while DED involves longer execution times and higher energy consumption, it achieves approximately a 70% reduction in resource consumption and human health damage compared to CM. Peng et al., 2017, 2018 performed a comparative LCA of multiple impeller manufacturing processes, including plunge milling, a hybrid approach combining laser cladding and plunge milling, and laser cladding forming (LCF). Their results showed that LCF exhibits the lowest overall environmental impact, primarily due to reduced material waste, lower energy demand from near-net-shape fabrication, and the elimination of extensive subtractive machining. Similarly, Jayawardane et al. (2022) assessed the environmental impacts of conventional CNC machining and Bound Metal Deposition (BMD)-based metal extrusion AM using LCA and reported that BMD exhibited a significantly higher environmental burden due to electricity-intensive deposition and post-processing operations.

More recently, sustainability-oriented studies have expanded beyond direct environmental comparison to include broader techno-economic and lifecycle considerations for Metal AM (MAM) systems. Ferreira et al. (2025) highlighted the importance of evaluating technical, environmental, and economic trade-offs during the early adoption stage of MAM. Lin et al. (2025) proposed rapid lifecycle assessment approaches for MAM products to support cleaner production decision-making, while Villafranca et al. (2026) emphasized that the sustainability performance of MAM strongly depends on process utilization, material efficiency, and system boundaries. These studies collectively demonstrate that AM sustainability assessment requires integrated environmental and economic evaluation frameworks capable of accounting for process complexity, resource flows, and operational variability.

Despite these advances, several important gaps remain. Existing studies largely rely on static cost models that do not account for capital amortization or the time value of money, limiting their ability to provide decision-relevant insights for capital-intensive technologies such as AM. Furthermore, uncertainty is rarely addressed systematically through Monte Carlo based sensitivity and correlation analysis, and most studies rely on deterministic assumptions or single-scenario comparisons. As a result, comparative evaluations of dominant cost drivers and lifecycle trade-offs between CM and AM remain limited.

Another important limitation in the existing literature is the lack of industrially oriented decision-support analysis. In practice, manufacturers selecting between CM and AM must consider factors such as production volume, machine utilization, tooling requirements, energy intensity, and post-processing operations. While CM remains economically advantageous for high-volume standardized components, AM is increasingly being explored for low-to-medium production volumes, spare parts, and geometrically complex components where design flexibility and reduced tooling can offset higher capital intensity. However, the conditions under which AM becomes environmentally and economically competitive remain insufficiently understood.

To address these gaps, the present study performs a comprehensive comparison of sand casting as a CM process and DED as an AM process for pump impeller production by integrating LCA with net present value-based life cycle costing (NPV-LCC). In contrast to prior studies by (Serres et al., 2011; Peng et al., 2017, 2018; Jayawardane et al., 2022) which primarily focused on environmental comparison or static cost evaluation, this work incorporates a time-dependent economic framework that explicitly accounts for capital amortization, utilization effects, and lifecycle cost dynamics. In addition, the study integrates Monte Carlo uncertainty analysis, comparative sensitivity evaluation, scenario-based modeling, and strategic trade-off assessment to identify dominant environmental and economic drivers and evaluate improvement pathways. By adopting a lifecycle and time-aware perspective, this work provides actionable guidance on when and under what conditions AM can complement CM, particularly for low-to-medium production volumes and geometrically complex components.

2. Materials and methods

2.1. Materials

In the present study, steel is used to manufacture the pump impeller using both CM and AM methods. The inventory details for both manufacturing methods are provided in section 2.3.

2.2. Life cycle assessment methodology

A cradle-to-gate scope is adopted to develop the life cycle models and assess energy consumption and environmental impacts for both CM and AM processes. The LCA is conducted in accordance with the ISO 14040 and ISO 14044 standards (International Organization for Standardization, 2006a; International Organization for Standardization, 2006b). The goal of the study is to compare the environmental performance of CM and AM routes for impeller production, while the scope is defined by the selected system boundary, functional unit, and impact assessment method.

The LCA modeling for both CM and AM is performed using GaBi software (version 10), with inventory data sourced from the GaBi database (Sphera Solutions Inc, 2022). Life Cycle Impact Assessment (LCIA) is carried out using the Centrum voor Milieukunde Leiden (CML) methodology (Borgaonkar and McNamara, 2024a, 2024b). The functional unit is defined as the production of 11 kg of impeller (Verdi et al., 2022; Faludi et al., 2015). The system boundary considered for the LCA of CM and AM is illustrated in Fig. 1.

The system boundary adopted in this study is cradle-to-gate and includes raw material extraction, pre-manufacturing, manufacturing, and post-processing operations required to produce the final impeller (Fig. 1). For CM, the assessment includes material production, mold and core preparation, melting, casting, cooling, mold removal, and machining operations. For AM, the assessment includes powder production, powder preparation, substrate preparation, shielding gas supply, DED processing, support removal, and surface finishing. Transportation of materials between lifecycle stages, manufacturing equipment production, plant infrastructure, and facility construction were excluded due to their comparatively small contribution per

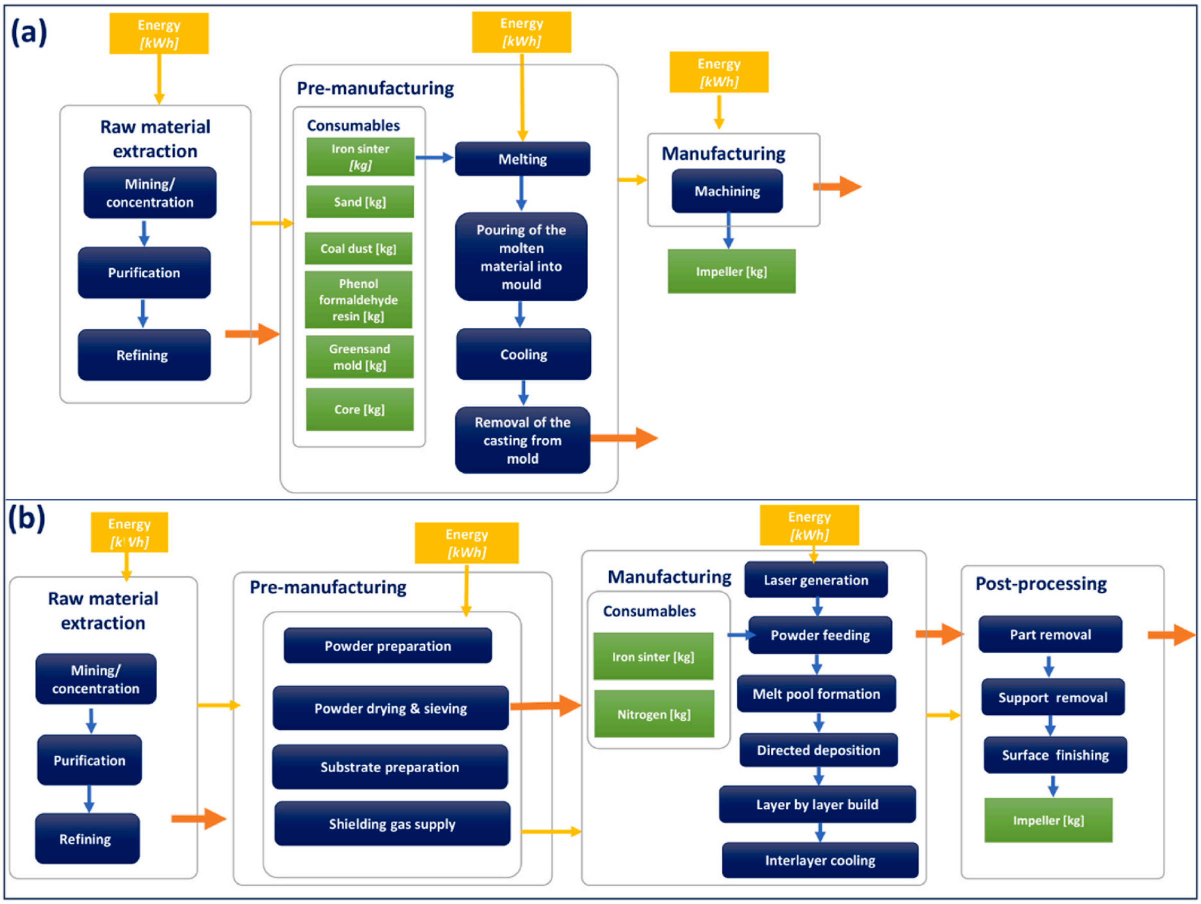

Fig. 1. Cradle-to-gate system boundaries and process flows for (a) conventional manufacturing (CM) using sand casting and (b) additive manufacturing (AM) using Directed Energy Deposition (DED).

functional unit and limited data availability. Recycling benefits associated with end-of-life material recovery, closed-loop scrap recycling, and long-term powder reuse cycles were not credited within the system boundary. Powder recovery and reuse were assumed only to the extent reflected in the inventory data, while residual powder losses were accounted for as waste. Heat treatment operations were not included because they were not reported as part of the manufacturing route considered in the source inventory datasets.

2.3. Life cycle inventory (LCI) for the production of the impeller

The Life Cycle Inventory (LCI) phase involves compiling and quantifying inputs such as energy and raw materials, along with outputs including air emissions, waterborne pollutants, solid waste, and other environmental releases associated with each stage of a product's life cycle (Rosenbaum et al., 2018).

2.3.1. Conventional manufacturing

In the present study, casting is considered a CM process. The raw materials required for manufacturing a steel impeller (11 kg) by casting, based on the research by Yilmaz et al. (2015), are listed in Table 1. The inventories needed for the pre-manufacturing and manufacturing stages of casting are presented in Table 1, which provides comprehensive material and energy flow information for iron casting operations. Although the use of a single literature source ensures internal consistency within the life cycle model, it may not fully capture variability arising from differences in foundry technologies, process efficiencies, raw material compositions, and regional operating conditions. Consequently, the results should be interpreted as representative of the manufacturing configuration reported in the source study rather than universally applicable to all casting facilities.

2.3.2. Additive manufacturing

The additive manufacturing route evaluated in this study is DED, and all inventory data, process assumptions, and environmental and economic analyses presented herein are based on this process.

Different assumptions were made based on published literature to collect and organize the inventory required for fabricating the part using AM. The atomization process for powder production is assumed to exhibit high material utilization, consistent with industrial AM practice where a significant fraction of unused powder can be recovered, sieved, and reused in subsequent builds. Nevertheless, a small proportion of powder losses is assumed due to handling, contamination, oxidation, and quality-control requirements, and these losses are included in the life cycle inventory (Walachowicz et al., 2017). Due to the limited availability of publicly accessible industrial inventory data for steel powder atomization, the electricity and nitrogen gas requirements for producing 1 kg of steel powder were assumed to be equivalent to those reported for titanium powder production, following the approach adopted by Paris et al. (2016). This assumption was considered acceptable because the dominant energy requirements in metal powder production are primarily associated with melting, gas atomization, and powder handling operations. It should be noted that the use of titanium powder production data as a proxy for steel powder atomization introduces additional uncertainty into the AM inventory model. Although this approach has been adopted in previous AM LCA studies (Paris et al., 2016), the availability of steel-specific industrial powder production datasets would improve the accuracy of future assessments. Generally,

Table 1
Life cycle inventory data for the pre-manufacturing and manufacturing stages of the conventional manufacturing (CM) route (sand casting), adapted from Yilmaz et al. (2015)

Pre-manufacturing (Sand casting)		
Input	Unit	Quantities
Sinter	kg	40
Electricity (Mold making)	kWh	6.85
Electricity (core preparation)	kWh	3.2
Sand	kg	180.8
Bentonite	kg	6.3
Coal Dust	kg	6.3
Water	kg	4.85
Phenol-formaldehyde resin	kg	2.6
Output	**Unit**	**Quantities**
Ductile steel	kg	21.73
Greensand Mold	kg	126.3
Core	kg	67.9
Manufacturing		
Input	Unit	Quantities
Ductile steel	kg	21.73
Electricity (melting)	kWh	2.2
Electricity (casting)	kWh	4.1
Greensand mold	kg	126.3
Core	kg	67.9
Output	**Unit**	**Quantities**
Impeller	kg	10.79
Slag	kg	1.3
Used sand	kg	180.8

Note: The casting and machining stages result in an overall material yield of approximately **49.7%**, calculated from the ratio of the final impeller mass (10.79 kg) to the ductile steel produced during pre-manufacturing (21.73 kg). The difference corresponds to material losses associated with gating systems, risers, slag generation, and subsequent machining operations.

the energy required to build a part is directly linked to the printing time, which depends on process control parameters such as laser power, laser speed, scanning pattern, hatch spacing, particle feed rate, and idle time (Thompson et al., 2015). In the present study, the build time required to print the impeller was estimated based on the process control parameters reported in the literature (Thompson et al., 2015). The inventory required for the pre-manufacturing and manufacturing stages of AM is presented in Table 2. The post-processing operations shown in Fig. 1, including part removal, support removal, and surface finishing, were considered within the AM system boundary. However, these operations were not modelled as separate unit processes in Table 2 because the available inventory data report them in aggregated form within the AM manufacturing/post-processing inventory. In particular, the source literature reports support separation/recycling and a finishing operation required to meet dimensional and surface quality requirements. Therefore, the electricity and material flows associated with AM post-processing are included in the overall manufacturing-stage inventory rather than reported as individual inventory rows.

Table 2
Life cycle inventory data for the pre-manufacturing and manufacturing stages of DED (Paris et al., 2016; Sun et al., 2016; Anderson et al., 2021).

Pre-manufacturing		
Input	Unit	Quantities
Electricity (atomization)	kWh	71.15
Nitrogen gas	kg	67.46
Sinter	kg	13.04
Output	**Unit**	**Quantities**
Metallic powders	kg	11.86
Manufacturing		
Input	**Unit**	**Quantities**
Electricity	kWh	39.53
Nitrogen gas	kg	61.33
Metallic powders	kg	11.86
Output	**Unit**	**Quantities**
Impeller	kg	10.78

2.4. Life cycle costing (LCC)

While conventional static Life Cycle Costing (LCC) provides a snapshot of manufacturing costs, it does not account for the time value of money or the temporal distribution of costs over the service life of production equipment. This limitation is particularly relevant for AM, which is characterized by high upfront capital investment and comparatively lower tooling requirements. Therefore, the present study extends the LCC analysis using a NPV-LCC-based framework to enable a fair, time-dependent economic comparison between AM and CM.

2.4.1. Static cost structure

LCC is employed to complement the LCA by linking environmental performance with economic evaluation. While both analyses focus on the cradle-to-gate manufacturing stage, their scopes differ in accordance with methodological conventions. The LCA excludes environmental impacts associated with capital equipment, whereas the LCC explicitly includes both capital expenditure (CAPEX) and operational expenditure (OPEX).

The static cost model is first used to identify and quantify the individual cost components contributing to the total manufacturing cost. This structure serves as the basis for the subsequent NPV-based LCC analysis.

The LCC framework accounts for capital investment, material procurement, labour, energy consumption, and process-specific operational costs. Capital investment costs for CM and AM are adopted from published literature and represent machine purchase and associated investment costs (Table 3).

The static cost structure was used to identify the principal cost components associated with each manufacturing route. For CM, the cost model includes fabrication, machining, tooling, setup, material, labour, energy, and overhead costs. For AM, the cost model comprises material, pre-processing, processing, and post-processing costs, including electricity and inert gas consumption. These cost elements form the basis of the subsequent NPV-LCC analysis and are summarized in Table 3. Detailed descriptions and formulations of these cost components are available in the studies by Mecheter et al. (2023) and related AM cost modelling literature (Anderson et al., 2021; Costabile et al., 2017).

Table 3
NPV-LCC input parameters and cost components for CM and AM.

Item	CM	AM	References
Capital Investment (€)	410000	1267202	Paris et al. (2016)
Machine lifetime (years)	15	10	(Ruffo et al., 2006; Baumers et al., 2013)
Discount rate (%)	8	8	ISO 15686-5 (2017)
Annual machine availability (h/year)	4000	4000	Baumers et al. (2017)
Utilization rate (%)	70	60	(Kellens et al., 2017; Mohammadkamal et al., 2025)
Annual production (parts/year)	560	218	Calculated
Electricity consumption (kWh/part)	16	111	Anderson et al. (2021)
Material cost (€/kg)	20	138	Mecheter et al. (2023)
Labour cost (€/h)	13	15	Mecheter et al. (2023)
Inert gas cost (€/L)	–	204	Anderson et al. (2021)
NPV-based cost per part (€)	175	1265	This study

These cost elements were subsequently incorporated into the NPV-based lifecycle costing framework described in Section 2.4.2.

2.4.2. Net present value (NPV)-Based LCC framework

To incorporate the time value of money, the static cost components were extended using a NPV-based LCC approach. In this framework, capital investment costs are allocated at the beginning of the system lifetime, while operational costs are incurred annually and discounted to their present value (Dutta et al., 2023).

The NPV-based lifecycle cost is calculated as:

$$NPV_{LCC} = C_0 + \sum_{t=1}^{N} \frac{C_t}{(1+r)^t} \tag{1}$$

where C_0: Initial capital investment (€), C_t: Annual operational cost (€ per year), r: Discount rate, and N: Equipment lifetime (years).

The total lifecycle cost per part is obtained by dividing the NPV-based total cost by the cumulative number of parts produced over the system lifetime.

The NPV-based LCC framework enables the assessment of AM's economic performance beyond upfront investment costs, highlighting the influence of machine utilization, production volume, and system lifetime (Shi et al., 2019).

The higher utilization rate assumed for CM (70%) compared to AM (60%) reflects the greater production stability and operational maturity of CM systems, whereas AM systems experience comparatively lower effective utilization due to build preparation, calibration, powder handling, and post-processing requirements (Baumers et al., 2017; Basak et al., 2022).

Fig. 2 illustrates the conceptual structure of the NPV-based lifecycle cost model, highlighting the relative contribution of annualized capital investment and operational expenditures for AM and CM.

2.5. Sensitivity and correlation analysis

To evaluate the robustness of the NPV-LCC results and to identify the key drivers influencing economic performance, a Monte Carlo simulation was conducted. This approach captures uncertainty by repeatedly sampling input parameters from predefined probability distributions and recalculating the total lifecycle cost. A total of 10,000 simulation iterations were performed for both CM and AM routes for pump impeller production.

Key cost, process, and economic parameters were selected from Table 3, including material input per impeller (kg), energy consumption (kWh), yield rate (%), machine usage time (hours), labour cost rate (€/hour), and material cost (€/kg). In addition, parameters specific to the NPV-based LCC framework, namely the discount rate (%), machine utilization rate (%), and equipment lifetime (years), were incorporated to account for uncertainties associated with time-dependent cost modelling.

All parameters were assumed to follow uniform probability distributions within defined variation ranges. Uniform distributions were selected because detailed statistical datasets describing the probability behavior of the selected process and economic parameters were not available, and only plausible upper and lower bounds could be established from published literature and engineering assumptions. Under such conditions, uniform distributions are commonly adopted in preliminary LCA and LCC uncertainty analyses, as they avoid introducing artificial bias toward central values while treating all values within the specified range as equally probable (Borgonovo and Plischke, 2016; Kim et al., 2022). Process and cost parameters were varied by ±10% around their nominal values, consistent with similar LCC and AM cost studies reported in the literature (Borgonovo and Plischke, 2016; Kim et al., 2022). Economic parameters were assigned wider uncertainty ranges to reflect their inherently higher variability and forecasting uncertainty: the discount rate by ±20%, the machine utilization rate by ±15%, and the machine lifetime by ±20%. For each iteration, the NPV-LCC was recalculated using the sampled input values.

In addition to the sensitivity analysis, the Pearson correlation coefficient was computed to quantify the linear relationship between individual input parameters and the total NPV-LCC. This correlation analysis enables the identification of the most influential parameters driving cost variability for both CM and AM, thereby supporting robust interpretation of the economic performance and highlighting key levers for cost optimization. This analysis also provides insight into how improvements in machine utilization, system lifetime, and process efficiency could enhance the long-term economic competitiveness of AM.

3. Results and discussion

3.1. Life cycle impact assessment (LCIA)

The impact values summarized in Table 4 and illustrated in Fig. 3 represent output results generated using GaBi LCA software following the life cycle impact assessment (LCIA) of the modelled CM and AM manufacturing systems. The LCIA results were normalized to the system exhibiting the highest impact within each respective impact category. To improve transparency regarding inventory variability, uncertainty ranges associated with the major environmental inventory inputs are provided in Supplementary Table S1.

In the case of CM, the environmental impact arises from waste sinter material, electrical energy consumption, and raw materials such as sand,

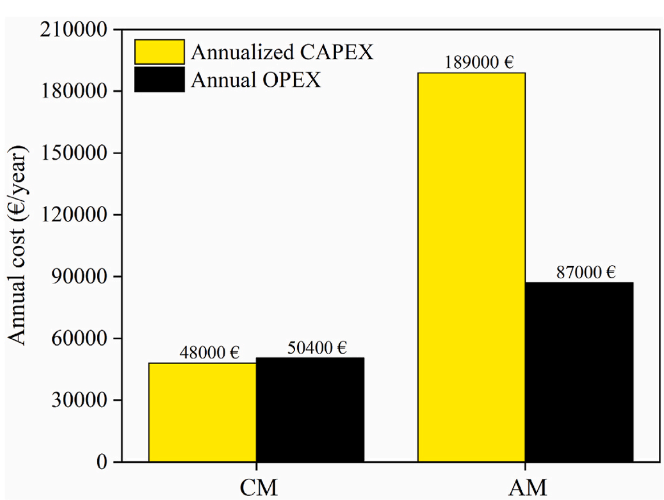

Fig. 2. NPV-based lifecycle cost breakdown for CM and AM, showing annualized CAPEX and OPEX represented as absolute annualized euro values (€/year).

Table 4
LCIA results for an 11 kg pump impeller manufactured using CM and AM processes.

Impact category	Unit	CM	AM
Abiotic depletion elements (ADE)	kg Sb eq	0.0000574	0.00000852
Abiotic depletion fossil (ADF)	MJ	253	393
Acidification (AP)	kg SO_2 eq	0.0512	0.066
Eutrophication (EP)	kg Phosphate eq	0.00819	0.00952
Freshwater aquatic ecotoxicity (FAETP)	kg DCB eq	0.0455	0.0722
Global warming (GWP)	kg CO_2 eq	15.5	33.7
Human toxicity (HTP)	kg DCB eq	0.661	1.71
Marine aquatic ecotoxicity (MAETP)	kg DCB eq	1130	4530
Ozone depletion potential (ODP)	kg R11 eq	3.97E-10	6.85E-10
Photochemical oxidation (PCOP)	kg Ethene eq	0.00277	0.00488
Terrestrial ecotoxicity (TETP)	kg DCB eq	0.0247	0.0296

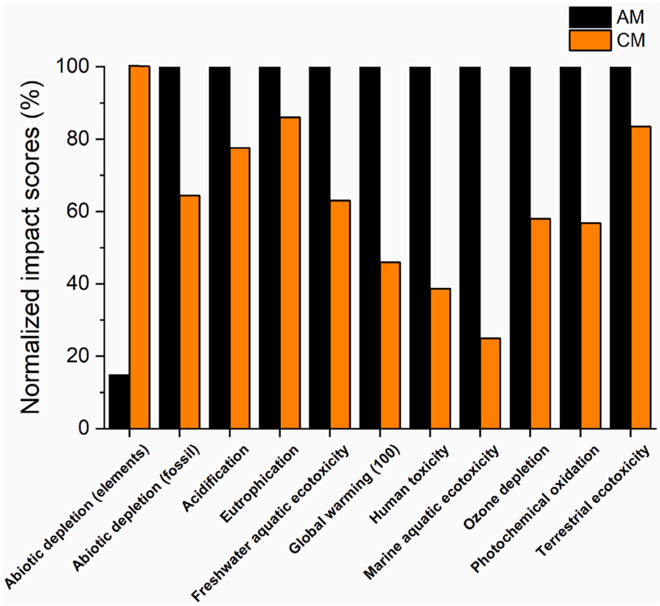

Fig. 3. Normalized environmental impacts of pump impeller production using CM and AM based on the CML methodology.

coal dust, and chemicals (e.g., resins and binders) used in mold and core preparation. Based on the life cycle inventory presented in Table 1 and the aggregated LCIA results, the raw sinter material generates 27% of the solid waste at the end of the manufacturing stage, accounting for approximately 25% of the overall normalized environmental impact. Electricity consumption during both the pre-manufacturing and manufacturing stages accounts for 22% of the cumulative normalized impact. The use of raw materials for mold and core preparation, including sand and coal dust, contributes 12%, while phenol–formaldehyde resin and bentonite contribute 21% and 11%, respectively, to the summed normalized CML impact score.

The sinter material is melted to produce the impeller. During the melting process, polluting gases such as carbon monoxide, nitrogen oxides, and organic compounds are released into the atmosphere, contributing to air pollution (Mitterpach et al., 2017). Additionally, during the melting process, impurities in the sintered material release airborne metal oxides, polychlorinated biphenyls (PCBs), and dioxins/furans (Lv et al., 2011). The combustion of raw materials, including sand, coal dust, resins, and binders triggered by molten metal during manufacturing, generates particulate matter such as soot, which leads to the release of hazardous air pollutants (HAPs). Sand, used in mold and core preparation, results in the largest volume of solid waste, which is typically sent to landfills and contributes to soil pollution (Zhu et al., 2023).

Compared to AM, CM exhibits significantly higher Abiotic Depletion Elements (ADE), primarily due to the consumption of sand, coal dust, phenol–formaldehyde resin, and bentonite during mold and core preparation. The ADE metric is a measure of the depletion of natural resources, including fossil fuels, minerals, metals, clay, and peat (Mancini et al., 2015).

To reduce the overall environmental impact of waste sinter material, recycling and reusing it as an input in the CM process is recommended. Moreover, alternative materials should be considered to replace conventional resins and binders in mold and core preparation. Inorganic binders, such as sodium silicate, represent a promising alternative to traditional organic chemical binders used in casting (Yilmaz et al., 2015). Additionally, solid waste from used sand can be mitigated by recovering and reusing it within the casting process (Joseph et al., 2017).

AM is generally considered a cleaner manufacturing process than CM, particularly casting, as it does not involve the use of sand, coal dust, or chemical binders such as resins. This omission helps to significantly reduce the generation of solid waste. AM also demonstrates higher material efficiency, making it a superior alternative to the CM process in this regard (Ford and Despeisse, 2016). However, one major concern associated with AM is its extensive energy consumption, which results in a higher overall environmental impact.

The present findings differ from those reported by Peng et al. (2017), who observed lower overall environmental impacts for LCF compared to conventional impeller manufacturing routes. This discrepancy is likely attributable to differences in AM technology, process energy intensity, and system boundaries. In the present study, DED exhibited substantially higher electricity consumption and longer build durations, which strongly influenced impact categories such as global warming potential and marine aquatic ecotoxicity. In contrast, Peng et al. (2017) considered process configurations with reduced subtractive machining requirements and different operational assumptions, leading to lower overall environmental burdens. In addition, differences in functional units, inventory assumptions, and system boundaries contribute to the variation in reported environmental impacts across studies.

With the exception of ADE, AM exhibits greater environmental impact than CM across several key impact categories, including Abiotic Depletion of Fossil Fuels (ADF), Acidification Potential (AP), Eutrophication Potential (EP), Freshwater Aquatic Ecotoxicity Potential (FAETP), Global Warming Potential (GWP), Human Toxicity Potential (HTP), Marine Aquatic Ecotoxicity Potential (MAETP), Ozone Depletion Potential (ODP), Photochemical Oxidant Formation Potential (PCOP), and Terrestrial Ecotoxicity Potential (TETP). Within AM, the environmental impact is predominantly driven by electricity consumption, contributing approximately 75% across the assessed CML midpoint impact categories. A detailed contribution analysis of the major inventory flows to the aggregated AM environmental impacts is provided in Supplementary Table S2.

The present findings are consistent with those of Jayawardane et al. (2022), who reported higher environmental burdens for AM compared with CM. While the direction of the trend is similar, the magnitude differs because the present study compares DED with sand casting rather than CNC machining. Casting involves material losses and mold-related impacts that are not present in machining, thereby influencing the relative differences observed between manufacturing routes. Serres et al. (2011) reported approximately 70% lower resource consumption for DED compared with machining. Such reductions are not observed in the present study because the comparison baseline is sand casting rather than machining, and because the environmental burden associated with electricity-intensive powder production and DED processing offsets the material-efficiency benefits of AM.

The pre-manufacturing stage of AM, primarily the atomization of metal powders, accounts for 86% of the environmental impact associated with electricity use (Seifi et al., 2016). The remaining 14% occurs during the manufacturing stage, including the operation of laser systems and stepper motors, work surface preheating, and auxiliary equipment such as computers, fans, lighting, and post-processing systems (Sreenivasan et al., 2010). In addition, the use of inert nitrogen gas during both pre-manufacturing and manufacturing stages contributes 20% to the total environmental impact (Paris et al., 2016). Nitrogen plays a critical role in purging the process chamber of atmospheric gases and by-products, thereby facilitating powder atomization and improving the overall performance of the AM process (Graf et al., 2018). Of this impact, 53% is attributed to nitrogen use during the pre-manufacturing stage, while 47% occurs during the manufacturing stage.

The substantially higher MAETP observed for AM is primarily associated with upstream electricity generation and metal powder production processes, particularly emissions related to mining, refining, and atomization activities. In the CML methodology, MAETP is highly sensitive to trace heavy metal and industrial emissions linked to energy-intensive upstream operations, which become amplified due to the high electricity demand and powder-processing requirements of DED-based manufacturing.

Waste metal powder generated during the process contributes approximately 5% to the total environmental impact. This contribution represents residual powder losses after accounting for the recovery and reuse of unused powder assumed in the baseline inventory. This contribution can be mitigated by recycling and reusing unused powder as feedstock in subsequent AM builds (Moghimian et al., 2021). In DED systems, unused powder can be collected, sieved, and requalified for reuse in subsequent builds, thereby reducing the demand for virgin feedstock and lowering the environmental burden associated with powder production. However, powder reuse must be carefully managed because repeated thermal exposure, contamination, and oxidation can alter powder characteristics and potentially affect process stability and part quality (Jandaghi and Moverare, 2024; Warner et al., 2024).

To improve the sustainability of AM, emphasis should be placed on optimizing process parameters and building strategies to reduce energy consumption per part. Adjusting laser power, scan speed, layer thickness, and hatch spacing can significantly reduce build time and electricity consumption without compromising part performance (Borgaonkar et al., 2026). Moreover, higher build utilization, optimized part nesting, and reduced support structures enable more efficient use of energy and materials, thereby improving the overall environmental performance of AM.

3.2. LCC analysis

Fig. 2 presents the NPV-based LCC breakdown for CM and AM, illustrating the contribution of annualized capital investment and discounted operational costs over the system lifetime. When evaluated using a static cost model, AM exhibits substantially higher total costs than CM, primarily due to its higher upfront capital investment, elevated material prices, and higher electricity consumption. However, the NPV-based LCC framework provides a more realistic economic comparison by accounting for cost distribution over time and machine utilization.

The NPV results indicate that while AM remains more capital-intensive than CM, the cost disparity is significantly influenced by machine utilization, production volume, and system lifetime. In the NPV framework, the high initial investment associated with AM is amortized over the equipment lifetime, reducing its impact on the cost per part at higher utilization rates. In contrast, CM benefits from lower initial investment but exhibits comparatively higher proportional operational costs related to labour, tooling, and setup, particularly at lower production volumes.

These findings are consistent with previous studies reporting that CM is generally more cost-effective for high-volume production of low-to-medium complexity components, whereas AM becomes increasingly competitive for low-volume, batch-size, and customized production of geometrically complex parts (Jayawardane et al., 2022; Faludi et al., 2015). The NPV-based analysis further highlights that improvements in AM process efficiency, such as increased build rates, higher packing density, and reduced post-processing requirements, can substantially improve its economic performance by lowering discounted operational costs.

Moreover, the sensitivity and correlation analysis demonstrate that machine utilization rate, material cost, and energy consumption are the dominant contributors to cost variability in AM. This indicates that strategies to increase build-chamber utilization, enhance powder reuse efficiency, and optimize process parameters can significantly reduce the NPV-based cost per part. For CM, labour costs and tooling-related expenses exerted a stronger influence on total lifecycle cost, reflecting its greater reliance on manual operations and tool-intensive processes.

The NPV-based LCC results suggest that although AM currently exhibits higher lifecycle costs under baseline assumptions, its economic competitiveness improves markedly under conditions of higher utilization, longer machine lifetimes, and optimized process performance. When considered alongside its demonstrated advantages in design flexibility, reduced tooling requirements, and potential environmental benefits, AM emerges as a viable and economically promising manufacturing route for applications requiring customization, complexity, and shorter production runs.

3.3. Monte Carlo sensitivity analysis

Figs. 4 and 5 present the results of the Monte Carlo simulation conducted using the NPV-based LCC framework for CM and AM, respectively. Monte Carlo methods are widely used in manufacturing cost analysis to evaluate uncertainty propagation and model robustness under stochastic input conditions (Budiono et al., 2014; Offermann et al., 2015).

3.3.1. Conventional manufacturing (CM)

Fig. 4(a) shows the probability distribution of the NPV-based LCC for CM. The histogram exhibits a near-normal distribution centered around the mean value, indicating that the CM cost model is stable and exhibits predictable behavior under parameter uncertainty. Such bell-shaped distributions are characteristic of mature manufacturing processes with well-established cost structures (Ruffo et al., 2006; ISO 15686-5, 2017).

The tornado chart in Fig. 4(b) presents the Pearson correlation coefficients between selected input parameters and the NPV-based LCC. Material cost emerges as the dominant contributor to cost variability ($\rho \approx 0.8$), underscoring the critical influence of raw material pricing and consumption in casting based manufacturing systems. This finding is consistent with previous studies reporting that material costs account for a substantial share of total cost variability in CM processes (Baumers et al., 2017; Iraola-Arregui et al., 2023).

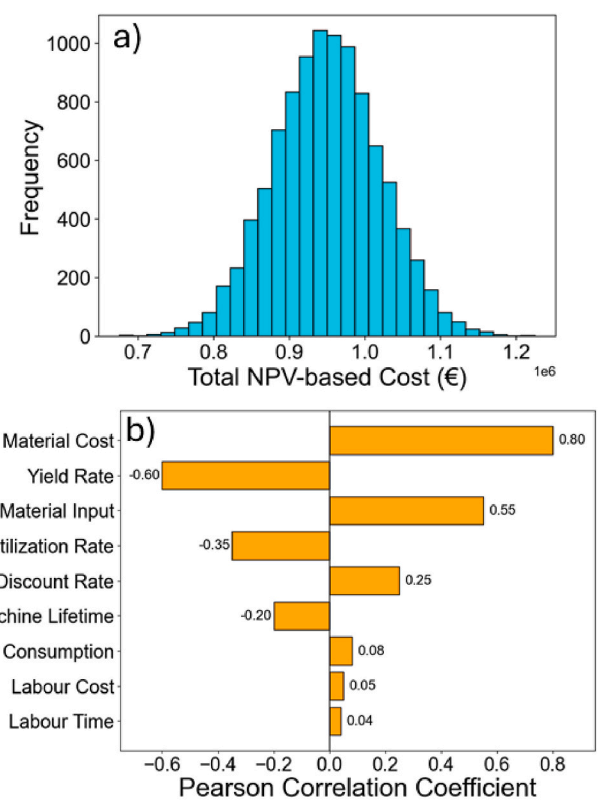

Fig. 4. a) Probability distribution of NPV-based lifecycle cost for CM obtained from Monte Carlo simulation; b) Tornado chart showing Pearson correlation coefficients between input parameters and the NPV-based lifecycle cost.

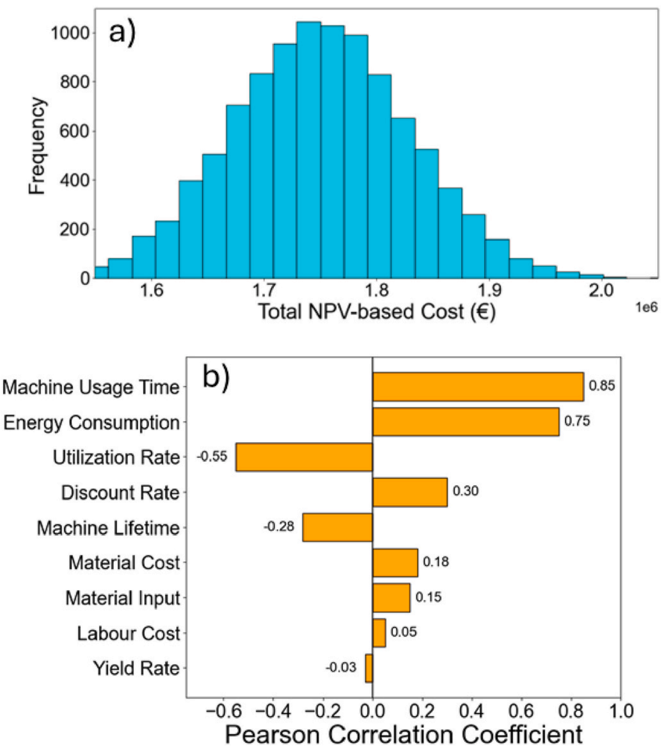

Fig. 5. a) Probability distribution of NPV-based lifecycle cost for AM obtained from Monte Carlo simulation; b) Tornado chart showing Pearson correlation coefficients between input parameters and the NPV-based lifecycle cost.

The yield rate shows a strong negative correlation with lifecycle cost, highlighting its role as a key lever for economic efficiency. Improvements in yield reduce scrap rates, material losses, and energy consumption per functional unit, thereby lowering overall lifecycle cost. Similar conclusions have been reported for casting and machining operations in high volume production environments (Baumers et al., 2017).

Other parameters, including labour cost rate, machine usage time, and energy consumption, exhibit comparatively lower correlations, indicating that cost reduction strategies for CM should primarily focus on material efficiency and yield optimization, rather than marginal reductions in labour or processing time (Kellens et al., 2017).

3.3.2. Additive manufacturing (AM)

Fig. 5(a) illustrates the distribution of the NPV-based LCC for the AM process. Compared to CM, the distribution exhibits a broader spread and slight right skewness, reflecting the higher uncertainty associated with capital-intensive and time-dependent manufacturing technologies. This behavior arises from compounded uncertainties in build duration, machine utilization, energy consumption, and discounting effects, which strongly influence the discounted lifecycle cost of AM systems (Baumers et al., 2017; Wang et al., 2024).

The sensitivity analysis in Fig. 5(b) identifies machine usage time as the most influential parameter affecting the NPV-based AM cost ($\rho \approx 0.85$), followed by energy consumption ($\rho \approx 0.75$). These results are consistent with previous techno-economic and life cycle studies, which have shown that build time and energy intensity are among the dominant factors governing the economic performance of MAM systems, including DED and other laser-based AM technologies (Wang et al., 2024; Lu and Shi, 2022).

In contrast to CM, material input and material cost exhibit lower correlations, reflecting AM's inherent material efficiency and near-net-shape capability. High buy-to-fly ratios and reduced material waste diminish the relative importance of raw material price fluctuations, particularly for high-value alloys used in aerospace and medical applications (Kadir et al., 2020).

Labour cost rate and yield rate show limited influence on AM lifecycle cost variability, owing to the high degree of automation and process control in industrial AM systems. This reduced dependence on manual operations has been widely recognized as a key economic advantage of AM for high-mix, low-volume production scenarios (Mellor et al., 2014).

Overall, the NPV-based sensitivity analysis highlights that time-dependent parameters, particularly machine utilization, build duration, and energy consumption, dominate the economic performance of AM. Consequently, strategies such as process parameter optimization, increased build-chamber utilization, parallel processing, and predictive maintenance offer substantial potential for improving the long-term economic viability of AM (Huang et al., 2015; Hazoary et al., 2025).

3.4. Comparative analysis of cost sensitivities

The comparative sensitivity and correlation analysis, conducted within the NPV-based life cycle costing framework, highlights the fundamentally different cost structures and optimization levers governing CM and AM. By accounting for the time value of money and cost distribution over the equipment lifetime, the analysis provides a more realistic interpretation of how process and economic parameters influence lifecycle cost variability.

In CM, variability in the NPV-based LCC is primarily driven by material cost and yield rate, with material cost exhibiting a strong positive correlation and yield rate showing a pronounced negative correlation. This indicates that reductions in raw material price volatility and improvements in process yield directly lower both OPEX and discounted lifecycle cost. Such behavior is consistent with studies on subtractive and casting-based manufacturing, where material losses and yield inefficiencies substantially inflate production costs, particularly in material-intensive sectors such as aerospace and heavy machinery (Musca et al., 2016; Petrovic et al., 2011). The limited influence of time dependent parameters in CM reflects its relatively low capital intensity and shorter processing times per part.

In contrast, the sensitivity profile of AM shifts markedly toward machine usage time, utilization rate, and energy consumption as the dominant contributors to NPV-based cost variability. This reflects the time and energy-intensive nature of layer-by-layer fabrication processes, where prolonged build durations and lower machine utilization significantly amplify discounted operational costs over the system's lifetime. Prior techno-economic and life cycle studies have similarly demonstrated that the economic performance of AM systems is strongly governed by build throughput, machine utilization, and energy efficiency rather than static material costs (Kadir et al., 2020; Baumers et al., 2016).

Material cost and material input exhibit comparatively lower influence on AM lifecycle cost variability, underscoring AM's inherent material efficiency and near-net-shape capability. High buy-to-fly ratios and reduced waste diminish the impact of raw material price fluctuations, a trend widely reported in assessments of AM for aerospace and biomedical applications (Petrovic et al., 2011). Furthermore, labour cost and yield rate show limited sensitivity in AM, reflecting the high degree of automation and process precision, which reduce dependence on manual operations and post-processing activities (Mellor et al., 2014). In contrast, these parameters remain moderately relevant in CM due to greater reliance on human intervention and process variability.

Overall, the NPV-based comparative analysis demonstrates that cost mitigation strategies must be technology-specific and time-aware. For CM, economic improvements are best achieved through enhanced material efficiency and yield control. For AM, the greatest gains arise from increasing machine utilization, reducing build time, and lowering energy intensity, thereby decreasing discounted operational costs over the equipment lifetime. These findings reinforce the need for context specific optimization strategies and support broader efforts in sustainability-oriented process design and techno-economic modelling (Jayawardane et al., 2023).

To facilitate interpretation of the sensitivity analysis results, Table 5 summarizes the relative effectiveness of key optimization levers for CM and AM. The table highlights the fundamentally different cost structures of the two manufacturing routes and identifies the most impactful strategies for improving lifecycle economic performance.

3.5. Scenario analysis and trade-off assessment

To further investigate the economic implications of alternative operational strategies, a scenario-based analysis was conducted within the NPV-based LCC framework. Three scenarios were considered for both CM and AM: (i) baseline process performance, (ii) renewable energy substitution affecting electricity-related operating costs, and (iii) process efficiency improvements targeting reduced machine usage time. The analysis was evaluated for an illustrative production scenario of 500 impellers, with cost components decomposed into material, labour, energy, and capital investment, as shown in Fig. 6.

It should be noted that, under an NPV-LCC framework, the scenario analysis does not represent a simple comparison of batch-level total costs. Instead, it illustrates how changes in OPEX influence the discounted lifecycle cost and equivalent annual cost, while capital investment remains largely invariant across scenarios.

In the baseline scenario, AM exhibits a substantially higher NPV-based LCC than CM, reflecting its higher capital intensity and the elevated cost of metal powder feedstock. This observation is consistent with previous techno-economic studies that identify capital investment and machine utilization as the dominant cost drivers in AM systems (Baumers et al., 2017; Huang et al., 2015). Although AM benefits from superior material efficiency and near-net-shape production, these advantages are insufficient to offset the impact of high upfront investment and prolonged machine usage time under baseline operating conditions.

The renewable energy scenario demonstrates a reduction in electricity-related operating costs for both manufacturing routes; however, the overall impact on the NPV-based LCC of AM remains limited. This is because electricity costs constitute a relatively small fraction of the total discounted cost when compared to capital amortization and time-dependent operating expenses. Consequently, while renewable energy integration offers clear environmental benefits, its influence on the economic competitiveness of AM is secondary within the evaluated lifecycle framework (Sun et al., 2021; Kellens et al., 2012).

In contrast, the process efficiency scenario characterized by reduced machine usage time produces a more pronounced effect on the NPV-based cost of AM. Shorter build durations directly enhance machine utilization and reduce discounted operational costs over the system lifetime, leading to meaningful reductions in equivalent annual cost. This highlights the importance of throughput-oriented improvements, such as optimized process parameters, increased packing density, and reduced idle time, as primary levers for improving the economic performance of AM.

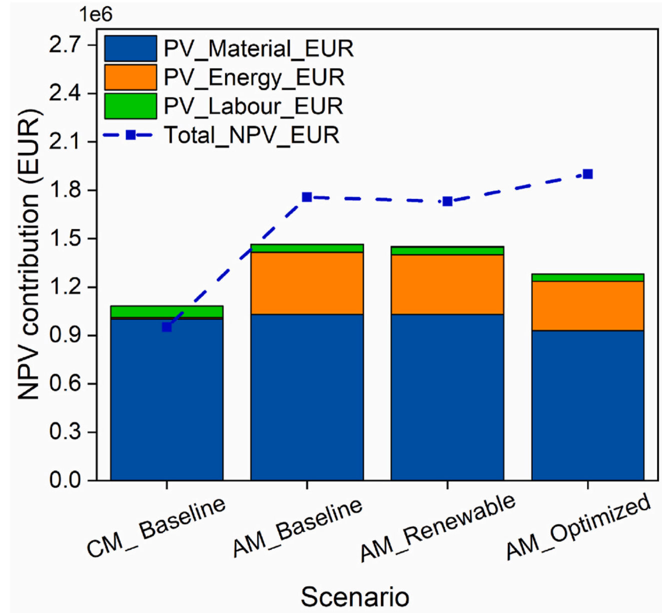

Fig. 6. Scenario-based NPV-LCC comparison of CM and AM, illustrating PV material, energy, and labour cost contributions together with total NPV for baseline, renewable energy, and process optimization scenarios. *Inert gas costs were included in the NPV-LCC calculations but are omitted from the graphical representation because their contribution is negligible relative to the other cost components.*

For CM, the scenario analysis reinforces that material efficiency and yield improvement remain the most effective cost mitigation strategies. High material waste associated with casting and machining operations increases both raw material expenditure and the embodied energy of unused material, thereby inflating lifecycle cost and environmental burden (Sun et al., 2021). In comparison, energy-related improvements yield comparatively smaller economic benefits for CM, reflecting its lower sensitivity to electricity consumption relative to material usage.

Overall, the scenario and trade-off assessment demonstrate that economic optimization strategies must be interpreted through a time-dependent lens. While static batch-level comparisons may overstate the apparent cost disadvantage of AM, the NPV-based framework reveals that improvements in machine efficiency and utilization offer the greatest potential for narrowing the cost gap between AM and CM. These findings support the adoption of context-specific, lifecycle-oriented optimization strategies and reinforce the need to align economic and environmental objectives in sustainable manufacturing system design (Sun et al., 2021; Kellens et al., 2012).

Table 5
Comparative assessment of cost optimization levers for CM and AM based on Monte Carlo sensitivity analysis.

Optimization lever	CM effectiveness	AM effectiveness	Supporting parameter (ρ)	Implication
Material cost reduction	High	Low	CM: Material cost ≈ 0.80; AM: Material cost ≈ 0.18	More effective for CM due to higher material consumption and lower yield
Yield improvement	High	Low	CM: Yield rate ≈ -0.60; AM: Yield rate ≈ -0.03	Yield optimization significantly reduces CM lifecycle cost
Machine utilization improvement	Low	High	CM: Utilization ≈ -0.35; AM: Utilization ≈ -0.55	Increased utilization substantially improves AM cost competitiveness
Build time /machine usage reduction	Low	High	AM: Machine usage time ≈ 0.85	Dominant economic lever for AM
Energy consumption reduction	Low	High	CM: Energy ≈ 0.08; AM: Energy ≈ 0.75	Energy efficiency has much greater influence on AM
Labour cost reduction	Medium	Low	CM: Labour cost ≈ 0.05; AM: Labour cost ≈ 0.05	Limited influence in both systems, slightly more relevant for CM

3.6. Strategic interventions and trade-offs

3.6.1. Material recycling and yield improvement in CM

For CM, the NPV-based sensitivity analysis identified material cost and yield rate as the dominant contributors to lifecycle cost variability. Consequently, strategic interventions aimed at material efficiency and yield improvement offer the most effective pathway for reducing both discounted lifecycle cost and environmental burden. Closed-loop recycling of metal chips, improved gating and feeding system design, and enhanced near-net-shape casting techniques can significantly reduce raw material demand and scrap generation. Although recycling may introduce additional energy requirements for remelting and handling, the net effect is typically positive when evaluated over the system lifecycle, particularly for material-intensive production environments (Mawson and Hughes, 2019; Papetti et al., 2019). Such strategies directly lower the present value of material-related costs and remain economically robust under both static and NPV-LCC frameworks.

3.6.2. Energy sourcing as a cross-cutting environmental strategy

The integration of renewable energy sources represents a cross-cutting environmental strategy applicable to both CM and AM rather than a technology-specific economic lever. Within the NPV-LCC framework, reductions in electricity-related operating costs were shown to exert a relatively modest influence on total discounted lifecycle cost, particularly for capital-intensive AM systems (Fig. 6). Nevertheless, the substitution of grid electricity with low-carbon energy sources can substantially reduce greenhouse gas emissions and support compliance with sustainability targets and regulatory requirements (Hazoary et al., 2025; Sun et al., 2021). Given that electricity consumption accounts for approximately 75% of the environmental burden of AM, the use of 100% renewable electricity has the potential to reduce the global warming impact of AM by a similar order of magnitude, although the exact reduction would depend on the specific electricity mix and upstream emissions associated with the renewable energy source. Therefore, while renewable energy integration plays a secondary role in economic optimization, it remains a critical component of environmental performance enhancement for both manufacturing routes.

3.6.3. Capital utilization and throughput optimization in AM

In contrast to CM, the economic performance of AM is primarily determined by capital utilization, machine utilization time, and throughput, as highlighted by the NPV-based sensitivity analysis. Strategies such as optimized build orientation, increased batch sizes through part nesting, reduced idle time, and improved scheduling can distribute the high capital investment of AM systems over a larger number of functional parts, thereby reducing the discounted cost per unit. These interventions directly address the dominant time-dependent cost drivers identified in the NPV-LCC analysis. However, higher packing density and batch complexity may introduce additional challenges in support structure removal, post-processing, and quality assurance, necessitating careful process planning and trade-off evaluation (Baumers et al., 2017; Allwood et al., 2011).

3.6.4. Integrated perspective and decision-making implications

The combined NPV-based economic analysis and environmental assessment underscore the importance of context-specific, time-aware decision-making when selecting between CM and AM. For high-volume, cost-sensitive production, CM remains economically favourable, particularly when supported by yield-optimization and material-recycling strategies. Conversely, AM becomes increasingly attractive for applications requiring geometric complexity, production flexibility, and material efficiency, provided that throughput and machine utilization are optimized. Importantly, the results demonstrate that economic competitiveness cannot be inferred solely from static cost comparisons. Instead, lifecycle-oriented frameworks that integrate capital amortization, operational efficiency, material circularity, and environmental performance are essential for informed selection of a manufacturing strategy.

4. Conclusions

This study presented a comprehensive comparative assessment of Conventional Manufacturing (CM) using sand casting and Additive Manufacturing (AM) using Directed Energy Deposition (DED) for pump impeller production by integrating Life Cycle Assessment (LCA), Net Present Value–based Life Cycle Costing (NPV-LCC), Monte Carlo sensitivity and uncertainty analysis, scenario-based evaluation, and strategic trade-off assessment. By adopting a time-dependent economic framework, the study provides a more realistic and decision-relevant comparison between capital-intensive AM systems and conventional manufacturing routes.

From an environmental perspective, CM exhibits higher impacts primarily associated with solid waste generation, particularly sand waste, resin use, and yield-related inefficiencies. In contrast, AM demonstrates superior material efficiency and reduced solid waste generation due to its near-net-shape capability, but exhibits higher impacts across most environmental categories because of its electricity-intensive nature. Economically, the NPV-based LCC results indicate that AM incurs substantially higher lifecycle costs than CM under baseline conditions due to higher capital investment, machine usage time, and energy consumption.

The present findings are consistent with Baumers et al. (2017), who demonstrated that capacity utilization is one of the most influential factors affecting the economic performance of additive manufacturing systems. Similarly, the NPV-LCC results presented here identify machine utilization and build duration as dominant cost drivers governing the competitiveness of AM.

Key quantitative findings include: (i) a Global Warming Potential (GWP) of 33.7 kg CO_2 eq for AM compared with 15.5 kg CO_2 eq for CM, representing a 117% increase; (ii) a Marine Aquatic Ecotoxicity Potential (MAETP) of 4530 kg DCB eq for AM compared with 1130 kg DCB eq for CM, corresponding to a 301% increase; (iii) baseline NPV-LCC values of approximately €1265 per impeller for AM and €175 per impeller for CM; and (iv) dominant cost drivers identified through Monte Carlo analysis, with material cost and yield rate governing CM cost variability ($\rho \approx 0.8$), while machine usage time and energy consumption dominate AM cost variability ($\rho \approx 0.85$ and $\rho \approx 0.75$, respectively). Scenario analysis further demonstrated that throughput-oriented improvements, such as increased machine utilization and reduced build time, provide substantially greater economic benefits for AM than renewable energy substitution alone.

The trade-off assessment confirms that CM remains more cost-effective for high-volume, standardized production, whereas AM emerges as a competitive and strategically valuable option for low-volume, high-complexity, and customization-driven applications. These findings suggest that additive manufacturing should be considered a context-dependent complement to conventional manufacturing rather than a universal replacement.

Several limitations should be acknowledged. The study adopts a cradle-to-gate system boundary and therefore excludes transportation, use-phase, and end-of-life impacts. Consequently, potential differences in use-phase energy consumption arising from variations in surface finish, dimensional accuracy, and hydraulic performance between CM and AM impellers were not considered. The analysis also focuses on a single component geometry (pump impeller) and a single AM technology (DED), which may limit the generalizability of the findings to other products and AM processes. Furthermore, the inventory and cost models rely primarily on secondary literature data and techno-economic assumptions rather than experimental measurements. In particular, the use of titanium powder production data as a proxy for steel powder atomization introduces additional uncertainty into the AM inventory model. The environmental assessment was conducted using a single electricity mix and therefore does not capture regional variations in electricity generation. Although uncertainty associated with key economic parameters was evaluated through Monte Carlo analysis, additional uncertainty remains due to variability in industrial operating conditions, inventory datasets, and future market conditions. Therefore, the results should be interpreted as representative of the investigated manufacturing routes and assumptions rather than universally applicable to all manufacturing contexts.

Future research should extend the framework to cradle-to-grave assessments incorporating product use and end-of-life stages, apply the methodology to additional Metal AM technologies such as laser powder bed fusion (L-PBF) and electron beam melting (EBM), evaluate hybrid and multi-material manufacturing configurations, and examine the influence of regional electricity mixes on environmental and economic performance.

CRediT authorship contribution statement

Avinash Borgaonkar: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Greg McNamara:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. **David Kinahan:** Formal analysis, Investigation, Supervision, Writing – original draft. **Dermot Brabazon:** Formal analysis, Investigation, Supervision, Validation, Writing – review & editing. **Abdollah Saboori:** Formal analysis, Supervision, Visualization, Writing – review & editing. **Luca Iuliano:** Formal analysis, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cesys.2026.100477.

Data availability

No data was used for the research described in the article.

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