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Ex-ante life cycle assessment of directed energy deposition based additive manufacturing: A comparative gearbox production case study

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ABSTRACT

As new technologies emerge is necessary to assess if they can actually contribute to sustainable improvement of industrial processes. Life Cycle Assessment (LCA) is a valuable tool to determine environmental impacts and compare systems. However, this comparison raises challenges when they have different maturity. This paper performs ex-ante LCA of an additive manufacturing (AM) technology, based on a step-wise approach built with parametrized modelling, allowing fair comparison with its conventional counterpart, for the study case of a gearbox component. Results show that AM technology generates higher impacts than conventional manufacturing (CM) casting process, using baseline values. These impacts can be reduced by 94% with best operating performances from literature, with emissions from 4520 to 264 kg CO_2 eq./kg piece, and non-significant difference with CM (demonstrated by Monte Carlo sampling). A 58% weight reduction is necessary for the AM process to improves its environmental sustainability. This research provides eco-design recommendations supporting decision making for further development of new technology.

1. Introduction

The industrial sector represents a significant environmental pressure, with 22% of the total greenhouse gas emissions at European level (European Environment Agency [1] and 29% of the total energy consumption at worldwide level [2]. It is therefore necessary to improve the sustainability of industrial processes [3] and adopt new technologies to do so. The deployment of additive manufacturing (AM) can play an important role towards this transition [4,5,6].

The term “additive manufacturing” (AM) refers to the technique of creating components by mixing materials based on 3D model data, often layer by layer, in opposition to formative manufacturing and subtractive manufacturing, as defined by ASTM and ISO standards [7]. It can reduce resource, energy and waste, reconfigure supply chains and produce more efficient designs [8,9]. Combining such advanced technology with new performant materials such as Metal Matrix Composites (MMCs) can further reduce emissions [10]. MMCs, composed of metal and additional component(s) such as ceramics with high strength, wear resistance, fatigue or other specific properties [11], can represent a promising lightweight and sustainable alternative for the automotive industry [12].

To demonstrate the sustainability of these developing technologies, it is necessary to compare their environmental impact with conventional technologies, via the comprehensive Life Cycle Assessment (LCA) methodology [13]. Up to now, only a few studies performed such evaluation. Paris et al., [13] compared the environmental impacts of a Ti6AlV turbine made by a subtractive conventional manufacturing (CM) process with an AM technique called Electronic Beam Melting (EBM) with a not completely optimized geometry, based on primary process data. The results showed lower impacts for the AM technology, in particular in the case of complex shapes (high material removal). Ingarao et al., [14] created different geometry scenarios for aluminium alloys, using bibliography data, and showed that the AM technology is suitable in terms of sustainability when the weight is reduced by 50% and even more if the use phase is included in the scope. The benefits of AM process were also shown in [15] for Ti6Al4V components, using a partially parametrized model and data from literature, with a better

Abbreviations: AM, Additive Manufacturing;; MMCs, Metal Matrix Composites; LCA, Life Cycle Assessment; CM, Conventional Manufacturing; DED, Directed Energy Deposition.

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Nomenclature

BED	Break-even distance
$E_{Casting}$	Energy used in casting unit process
$E_{Cleaning1}$	Energy used in first cleaning unit process
$E_{Cleaning2}$	Energy used in second cleaning unit process
$E_{Computer}$	Energy used by the computer process
E_{DED}	Energy used during the printing process
$E_{Deburring}$	Energy used in deburring unit process
$E_{Finishing}$	Energy used in finishing unit process
E_{Fume}	Energy used in the fume extraction unit process
$E_{Machining}$	Energy used in machining unit process
E_{Mixing}	Energy used in the powder mixing unit process
$E_{Polishing}$	Energy used in the polishing unit process
E_{Sieved}	Energy used in the sieving unit process
$E_{Support\ plate}$	Energy used in the support plate manufacturing process
$E_{Thermal}$	Energy used in thermal treatment unit process
E_{Vacuum}	Energy used in the vacuum cleaner unit process
$m_{alloy,in}$	Mass of alloy introduced
$m_{alloy\ waste}$	Mass of wasted alloy
$m_{Brass\ wire}$	Mass of brass wire used in the support plate manufacturing
$m_{final,AM}$	Final mass of the product
$m_{final,CM}$	Final mass of the product
$m_{metal\ waste}$	Mass of wasted metal
$m_{sand,Cleaning1}$	Sand introduced in the first cleaning unit process
$m_{sand,Cleaning2}$	Sand introduced in the second cleaning unit process
$m_{sand,in}$	Total mass of sand introduced
$m_{sand\ waste}$	Mass of wasted sand
$m_{Support\ plate}$	Mass of the support plate
$m_{oil,Casting}$	Oil introduced in the casting unit process
$m_{oil,Finishing}$	Oil introduced in the finishing unit process
$m_{oil,in}$	Total mass of oil introduced
$m_{oil,Thermal}$	Oil introduced in the thermal treatment unit process
$m_{oil\ waste}$	Mass of wasted oil
$m_{oil,Machining}$	Oil introduced in the machining unit process
$m_{powder,in}$	Raw metallic powder introduced
$m_{powder,not\ used}$	Mass of powder not deposited
$m_{powder,sieved}$	Mass of sieved powder
$m_{powder,total}$	Total metallic powder fed into the system
$m_{powder,vacuum}$	Mass of vacuumed powder
$m_{powder\ waste}$	Mass of wasted powder
$m_{wastewater}$	Mass of wasted water
$m_{water,Casting}$	Water introduced in the casting unit process
$m_{water,Finishing}$	Water introduced in the finishing unit process
$m_{water,in}$	Total mass of water introduced
$m_{water,Machining}$	Water introduced in the machining unit process
$P_{Computer}$	Power of computer
P_{DED1}	Power of part one of the DED machine (laser)
P_{DED2}	Power of part two of the DED machine (robot arm)
P_{Fume}	Power of fume extraction system
$P_{Polishing}$	Power of polishing machine
P_{Sieved}	Power of sieving device
$P_{Supplort\ plate}$	Power of support plate manufacturing machine
P_{Vacuum}	Power of vacuum cleaner machine
$Q_{Blowing}$	Argon blowing flow
Q_{DED}	Argon printing time
r_{flow}	Metal powder flow rate
$r_{Recirculation}$	Argon recirculation rate
SD_{g95}	Standard deviation under a 95% interval confidence
$S.I.$	Sensitivity index
$t_{Blowing}$	Blowing argon flow time
t_{DED}	Printing time
$t_{Polishing}$	Polishing time
t_{Sieved}	Sieving time
$t_{Support\ plate}$	Support plate manufacturing time
t_{Vacuum}	Vacuum cleaner time
$V_{Ar,in}$	Volume of argon introduced
$V_{Ar,total}$	Total volume of argon used in the printing chamber
$Weight\ Decrease$	Break-even weight point
$\eta_{Casting}$	Efficiency of the casting unit process
$\eta_{Deburring}$	Efficiency of the deburring unit process
$\eta_{Deposition}$	Deposition efficiency
$\eta_{Finishing}$	Efficiency of the finishing unit process
$\eta_{Machining}$	Efficiency of the machining unit process
$\eta_{Polishing}$	Polishing efficiency
μg	Geometric mean
σg	Geometric standard deviation

energy efficiency thanks to the lower amount of input material used. A study by van Sice & Faludi, [16] used information to simulate various CM and AM techniques from a database and from literature review, respectively, to compare the manufacturing of steel, aluminium and titanium parts. The authors concluded that AM processes generated higher impacts when focusing only on the manufacturing process, while the further effects on mass reduction and design need to be considered to improve their sustainability. Landi et al., [17] analysed and compared the environmental impacts of an AM technology with a subtractive CM, using primary data obtained from direct measurements in the production process of spur gears made of steel alloy, obtaining advantages for the AM process, but pointing out that it is still an experimental technology with a lower maturity level than its counterpart. A comparative gate-to-gate LCA was carried out on a software-simulated AM process and a CM industrial method, by Swetha et al., [18], obtaining that an optimization on the component's topology it is necessary to obtain a more environmentally friendly process. Kokare et al. [19,20] compared 2 AM techniques (Wire arc additive manufacturing, WAAM, and Selective Laser Melting, SLM) with a conventional subtractive technique, for the production of a steel marine propeller, showing WAAM as the best favourable option.

Most of these studies relied on both the collection of primary data and process simulation. Due to the low maturity of AM technologies, it is important to consider upscaling changes to get a fair comparison with mature CM technologies [21,22,23]. For this purpose, several frameworks with different scopes and definitions have emerge in recent times, as shown in the following references: (i) Wender et al. [23] introduced the idea of anticipatory LCA as a “forward-looking, non-predictive tool that increases model uncertainty through inclusion of prospective modelling tools and multiple social perspectives”; (ii) Arvidsson et al. [24] stated that “an LCA is prospective when the technology studied is in an early phase of development but the technology is modelled at a future, more-developed phase”; (iii) an ex-ante LCA “explores the future by assessing a range of possible scenarios that define the space in which the emerging technology may operate at future performance on full operational scale” as explained by Cucurachi et al. [25]. Despite the minor differences between the sources cited, as the anticipatory LCA included a socioeconomic perspective, and the prospective LCA can be performed on an already established technology, the term ex-ante has been adopted as the preferred one for this study. The use of this expression makes clearer than the assessment can be performed prior market introduction [26].

In order to apply an ex-ante LCA and facilitate the creation of exploratory scenarios, parametric modelling built by mathematical correlations to generate the material and energy balances and focused on the most influencing parameters, can be introduced. A parametric framework was applied by Yao & Huang [27] for the identification of research development priorities but this study only focuses on energy and cost assessment, without a comparative purpose. In literature, some parametrized LCA studies were used to evaluate and support the eco-design of emerging technologies in other sectors (e.g. [28,29]) based on process modelling, scenarios building with different parameters values and sensitivity analysis to identify the key parameters.

Furthermore, as deduced from the comprehensive review of AM process carried out by [20] certain AM technologies have not received much attention to date, because of their lower maturity level, and some process variable parameters have not yet been thoroughly investigated. For these reasons, future research must develop predictive environmental models.

The present paper builds an ex-ante LCA approach, based on parametric modelling, to evaluate, in this case, the environmental impacts of an AM emerging technology compared to a CM mature process, for the case study of a titanium gearbox component produced by a novel Directed Energy Deposition (DED) technique. The parametric methodological approach and further analyses (sensitivity, break-even point and uncertainty) are first described, since they could be used in other context studies, while the results for the specific case study are further analysed and discussed. The main objective of the present study is to develop a methodology that can be used as a predictive tool for the future impacts of emerging technologies, allowing fair comparison with more mature ones, and giving early-stage design recommendations. This is demonstrated by comparing a conventional casting technology with a DED AM technology, which use titanium matrix composite powder, that have not been found to date in literature. The results and methodology proposed in this study can help AM manufacturers to choose the most sustainable technology and to ensure that the parameters of new technologies are developed under an eco-design approach.

2. Methodology

To support the design of an AM technique with environmental criteria, a stepwise approach based on the standardized LCA methodology (ISO 14040/44, 2006) is followed.

As first step, a parametrized inventory model is built for the AM technique, expressing relationships between dependant parameters, using technology prototype data as baseline values for the independent variables. Then, scale-up scenarios are defined. To do so, the most influential parameters are identified via sensitivity analysis. Based on a literature review and expert knowledge, the best available values for the sensitive independent parameters that could be affected by the upscale of the technology are determined (e.g. best efficiency rates obtained by similar technologies). The literature values are used to model the best scenario of the AM technique. After that, the results analysis takes part, including several different techniques. Besides the contribution and sensitivity analyses identifying the key processes and parameters, the calculation of break-even point values is performed to determine the target value of a parameter that allows the AM technique to generate less environmental impacts than the conventional alternative. These outcomes can therefore support the eco-design of the technology by prioritizing efforts and defining design objectives. Finally, a comparative uncertainty analysis (based on Monte Carlo sampling) of the scenarios is applied to understand the robustness of the potential environmental benefits and trade-offs of the AM technique.

The modelling is done in SimaPro® 9.3 software, using parameters, scenarios and uncertainty analysis functions.

2.1. Study case

Two different technologies are assessed in this study, both capable to produce the same gearbox component. The first one is a conventional technology, already implemented in the market. It uses aluminium that goes first through casting, followed by different steps of refining such as deburring, sand cleaning and heat treatment, each of them with a different performance over the material quantity, using auxiliary materials as water, sand and oil. The second technology assessed is an AM technique called Directed Energy Deposition, where the powder material fed is fused by a laser, placed on a robotic arm, which deposits the material over a metallic plate to make the desired form, while is controlled by a computer with the 3D design. This operation takes place under a vacuum chamber filled with argon to avoid any oxygen reaction with the metal that can cause problems during the manufacturing process. The printing process is carried out on a titanium metal plate, which varies in shape and size depending on the part to be manufactured in each process. The powder material used is a Titanium Matrix Composite made from alpha-beta titanium alloy (Ti6Al4V) and titanium carbide (TiC) nanoparticles, produced in a High Energy Ball Milling process. This alloy provides high-quality properties: strength to weight ratio, corrosion resistance, biocompatibility, and low thermal expansion [30], and the TiC ceramic particles apport functionalities as its high melting point, elastic modulus, high hardness, low density, high flexure strength, good thermal conductivity, high resistance to corrosion and oxidation, and high thermal shock resistance [31]. A complete LCA study of the production route for this powder has been studied by Santiago-Herrera et al. [32].

2.2. Goal and scope of the LCA study

The main aim of this study is to evaluate and compare the environmental performance of two different technologies, capable to produce a gearbox component for automobiles: (i) a conventional manufacturing technology based on casting, and; (ii) an additive manufacturing one using the DED technique.

Figs. 1 and 2 represents the system boundaries for CM and AM processes, respectively. The systems boundaries are focused on the production phase of the gearbox component, including all the specific processes constituting the foreground data, and background data retrieved from databases. It also incorporates the use phase, in order to analyse potential benefits of the AM component depending on its potential weight savings. The use phase is modelled only for the calculation of the break-even point distance depending on the component mass reduction and associated fuel savings. End-of-Life is not included due to the lack of data at this stage of the project. Infrastructures components are also excluded from this study.

The function of the assessed systems is the production of one complete piece. Due to the uncertainties on final weight and properties of the manufactured piece at such development stage, the comparison is primarily done on a mass unit basis, which is a tangible unit which facilitates mass balance. The functional unit is there for the manufacturing of 1 kg of piece. The further sensitivity analysis will analyse the possible weight differences between AM and CM and the effects on impact results.

The geographical representativeness of the study is set under the European framework.

2.3. Life cycle inventory

Production data, obtained during the 2021–2022 period from two European industrial partners from the automotive sector, are used as a basis for the foreground inventory data. Background processes are modelled with ecoinvent v3.8 database and "APOS" system model (at the point of substitution), to adopt an attributional approach while extending the system boundaries to allocate co-products burdens [33].

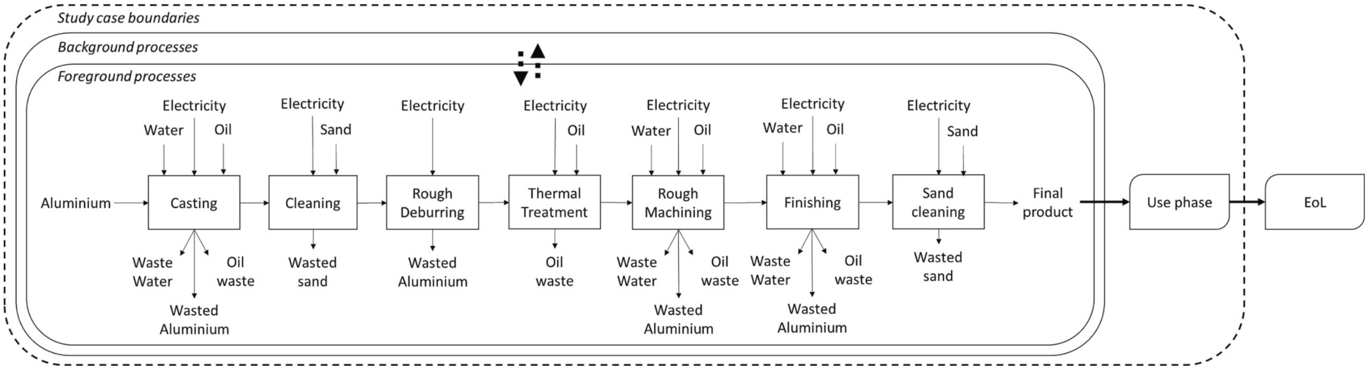

Fig. 1. Flow model and system boundaries of the conventional manufacturing technology.

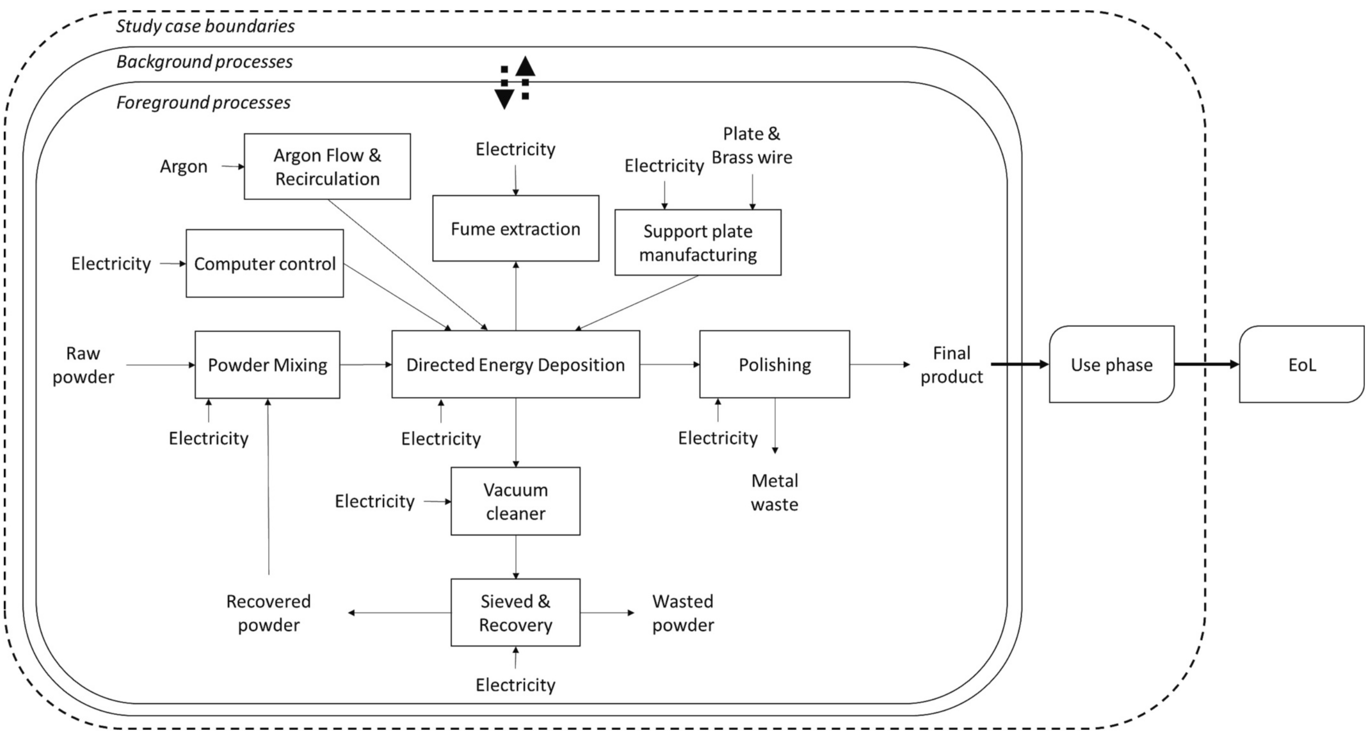

Fig. 2. Flow model and system boundaries of the additive manufacturing technology.

The different chosen datasets are shown on Supplementary Material, Table S1&S2.

The following sub-sections detail the development of the parametrised model for the determination of foreground data, the definition of parameters values and their uncertainty, and the construction of different scenarios.

2.3.1. Development of the parametrised model

The aim of the parametrised model is to determine the foreground inventory flows based on the energy and mass balance, and their common relationships. A list of variables is included in Table 1 for a better understanding and following-up of the model. The independent parameters are fixed with numerical values, while dependent parameters are calculated according to the independent ones (see Table 2).

For the CM case, fixed parameters are set for the specific energy consumption data per kg of product since their characterization is based on mature technology data, although the values are still subject to uncertainties. Regarding the input of alloy as raw material, the losses during casting, deburring, machining and finishing are considered. The efficiencies of these processes (in %) are used to calculate the necessary amount of input alloy for the functional unit, i.e., 1 kg of final product. Regarding water, oil and sand flows, the input flows are set with primary data and no losses are assumed during the processes.

Regarding the AM technology, the specific energy consumption is more uncertain. For each step, the latter (e.g. $E_{Support\ plate}$) is derived from the machine power (e.g. $P_{Supplort\ plate}$) and the processing time (e.g. $t_{Support\ plate}$). The processing times are mostly independent, while the printing step depends on the mass of input power ($m_{powder,total}$). The printing time t_{DED}, in straight relation with the Directed Energy Deposition process, is calculated from the ratio between $m_{powder,total}$ and the flow rate r_{Flow}, and influences the energy consumption of other processes. For instance, it affects the mixing step, since the powders are mixed and introduced during the entire printing process. It also affects polishing, the vacuuming and sieving of the undeposited powders, as it is stressed by a mathematical expression indicated by manufacturers. Argon is used for the blowing and the printing steps. The total volume of argon used in the chamber $V_{Ar,total}$ is the product of the argon flow and the processing time for these two steps ($Q_{Blowing}$ (1200 L/h) and $t_{Blowing}$, Q_{DED} (900 L/h) and t_{DED}, respectively). The argon recirculation rate

Table 1
List of variables.

Variable	Description	Unit
Conventional manufacturing		
$E_{Casting}$	Energy used in casting unit process	kWh
$E_{Cleaning1}$	Energy used in first cleaning unit process	kWh
$E_{Deburring}$	Energy used in deburring unit process	kWh
$E_{Thermal}$	Energy used in thermal treatment unit process	kWh
$E_{Machining}$	Energy used in machining unit process	kWh
$E_{Finishing}$	Energy used in finishing unit process	kWh
$E_{Cleaning2}$	Energy used in second cleaning unit process	kWh
$m_{alloy,in}$	Mass of alloy introduced	kg
$m_{sand,in}$	Total mass of sand introduced	kg
$m_{oil,in}$	Total mass of oil introduced	kg
$m_{water,in}$	Total mass of water introduced	kg
$m_{alloy\ waste}$	Mass of wasted alloy	kg
$m_{sand\ waste}$	Mass of wasted sand	kg
$m_{oil\ waste}$	Mass of wasted oil	kg
$m_{wastewater}$	Mass of wasted water	kg
$m_{water,Casting}$	Water introduced in the casting unit process	kg
$m_{oil,Casting}$	Oil introduced in the casting unit process	kg
$\eta_{Casting}$	Efficiency of the casting unit process	%
$m_{sand,Cleaning1}$	Sand introduced in the first cleaning unit process	kg
$\eta_{Deburring}$	Efficiency of the deburring unit process	%
$m_{oil,Thermal}$	Oil introduced in the thermal treatment unit process	kg
$m_{water,Machining}$	Water introduced in the machining unit process	kg
$m_{oil,Machining}$	Oil introduced in the machining unit process	kg
$\eta_{Machining}$	Efficiency of the machining unit process	%
$m_{water,Finishing}$	Water introduced in the finishing unit process	kg
$m_{oil,Finishing}$	Oil introduced in the finishing unit process	kg
$\eta_{Finishing}$	Efficiency of the finishing unit process	%
$m_{sand,Cleaning2}$	Sand introduced in the second cleaning unit process	kg
$m_{final,CM}$	Final mass of the product	kg
Additive manufacturing		
E_{Mixing}	Energy used in the powder mixing unit process	kWh
E_{DED}	Energy used during the printing process	kWh
$E_{Polishing}$	Energy used in the polishing unit process	kWh
E_{Vacuum}	Energy used in the vacuum cleaner unit process	kWh
E_{Sieved}	Energy used in the sieving unit process	kWh
$E_{Computer}$	Energy used by the computer process	kWh
E_{Fume}	Energy used in the fume extraction unit process	kWh
$E_{Support\ plate}$	Energy used in the support plate manufacturing process	kWh
t_{DED}	Printing time	kW
r_{flow}	Metal powder flow rate	%
P_{DED1}	Power of part one of the DED machine (laser)	kW
P_{DED2}	Power of part two of the DED machine (robot arm)	kW
$P_{Polishing}$	Power of polishing machine	kW
$t_{Polishing}$	Polishing time	h
P_{Vacuum}	Power of vacuum cleaner machine	kW
t_{Vacuum}	Vacuum cleaner time	h
P_{Sieved}	Power of sieving device	kW
t_{Sieved}	Sieving time	h
$P_{Computer}$	Power of computer	kW
P_{Fume}	Power of fume extraction system	kW
$P_{Supplort\ plate}$	Power of support plate manufacturing machine	kW
$t_{Support\ plate}$	Support plate manufacturing time	h
$m_{powder,total}$	Total metallic powder fed into the system	kg
$m_{powder,in}$	Raw metallic powder introduced	kg
$m_{powder,not\ used}$	Mass of powder not deposited	kg
$m_{powder,vacuum}$	Mass of vacuumed powder	kg
$m_{powder,sieved}$	Mass of sieved powder	kg
$m_{Support\ plate}$	Mass of the support plate	kg
$m_{Brass\ wire}$	Mass of brass wire used in the support plate manufacturing	kg
$V_{Ar,total}$	Total volume of argon used in the printing chamber	L
$V_{Ar,in}$	Volume of argon introduced	L
$m_{final,AM}$	Final mass of the product	kg
$\eta_{Polishing}$	Polishing efficiency	%
$\eta_{Deposition}$	Deposition efficiency	%
$Q_{Blowing}$	Argon blowing flow	L/h
$t_{Blowing}$	Blowing argon flow time	h
Q_{DED}	Argon printing time	L/h
$r_{Recirculation}$	Argon recirculation rate	%
$m_{powder\ waste}$	Mass of wasted powder	kg
$m_{metal\ waste}$	Mass of wasted metal	kg
$\eta_{Polishing}$	Polishing efficiency	%

$r_{Recirculation}$ is applied to calculate the necessary input of argon $V_{Ar,in}$. The necessary input of raw powder ($m_{powder,in}$) depends on the polishing and deposition efficiencies, based on the final product weight, $m_{final,AM}$. To obtain the total mass, $m_{powder,total}$, it is necessary to add a maximum of 5% coming from the recovering process ($m_{powder,recovered}$), to not downgrade the quality of the printed piece. This corresponds to the quantity of powder not deposited but aspirated by the vacuum cleaner process ($m_{powder,vacuum}$) which is sieved later, at a 92.5% efficiency, obtaining $m_{powder,sieved}$ that can be used to feed the system again. All these calculations are presented in Table 2.

2.3.2. Definition of parameters values

This sub-section explores the determination of independent parameters, both for baseline scenarios and for scaled-up scenarios in the AM case.

Baseline values were obtained with the help of two different industrial manufacturers, representing data collected during the 2021–2022 period. These baseline values, for both technologies are included in Tables 3&4.

For additive manufacturing, the parameters include the fixed mass data (for support plate and brass wire), flow rates of the powder, recirculation and efficiency rates, the power of the different used machines and the time for specific processes (blowing and on support plate). The time of deposition process (t_{DED}) is derived from the total mass of powder ($m_{powder,total}$) and the powder feeding rate (r_{flow}): $t_{DED} = m_{powder,total} / r_{flow}$.

As mentioned in the Introduction section, the technologies of this study cannot be totally comparable under the LCA framework as they are not at the same level of maturity. However, some aspects of the AM technology are expected to be improved in the future with the optimization of the process performance. For this purpose, a set of the previously build-up parameters were selected, as they were the most likely to be improved in a forthcoming developed scenario and can vary more substantially the final outcome results, as can be seen in the sensitivity analysis results section:

- "r_{Flow}": is the flow rate, which express the quantity of powder fed into the system that can be possible processed, within a set of time, measured in kg/h.
- "$\eta_{Deposition}$": measuring the powder utilization efficiency by the laser melting process (in %).
- "$r_{Recirculation}$": the argon recirculation rate inside the vacuum chamber where the 3D printing process takes part (in %).
- "$\eta_{Polishing}$": as the successfully reduced surface roughness to obtain a final component (%).

A comprehensive literature review on the state-of-the-art for the assessed AM technique (Directed Energy Deposition), using the same or similar alloy (Titanium grade 5), was performed to understand the range for these parameters, support the creation of prospective scenarios and prioritize efforts for future improvements.

The retrieved information (Table 5) shows possible scenarios where r_{Flow} could be up to 3.6 kg/h, $\eta_{Deposition}$ to 90%, $\eta_{Polishing}$ rises up to a 95%, and a highest point of 98% for the $r_{Recirculation}$ is achieved. Therefore, a final scenario with these values was set for the AM technology as the most promising scenario in a higher mature level with an optimistic development process.

Table 2
List of model parameters and their determination.

Flow type	Parameter	Fixed	Definition
Conventional manufacturing			
Energy consumption	$E_{Casting}$	X	
	$E_{Cleaning1}$	X	
	$E_{Deburring}$	X	
	$E_{Thermal}$	X	
	$E_{Machining}$	X	
	$E_{Finishing}$	X	
	$E_{Cleaning2}$	X	
Materials inputs	$m_{alloy,in}$		$m_{alloy,in} = (((m_{final,CM}/\eta_{Finishing})/\eta_{Deburring})/\eta_{Machining})/\eta_{Casting}$
	$m_{sand,in}$	X	
	$m_{oil,in}$	X	
	$m_{water,in}$	X	
Waste amount	$m_{alloy\ waste}$		$m_{alloy\ waste} = m_{alloy,in} - m_{final,CM}$
	$m_{sand\ waste}$		$m_{sand\ waste} = m_{sand,in}$
	$m_{oil\ waste}$		$m_{oil\ waste} = m_{oil,in}$
	$m_{wastewater}$		$m_{wastewater} = m_{water,in}$
Additive manufacturing			
Energy consumption	E_{Mixing}		$E_{Mixing} = P_{Mixing} \times t_{DED}$ with $t_{DED} = m_{powder,total}/r_{flow}$
	E_{DED}		$E_{DED} = (P_{DED1} + P_{DED2}) \times t_{DED}$
	$E_{Polishing}$		$E_{Polishing} = P_{Polishing} \times t_{Polishing}$ with $t_{Polishing} = (t_{DED}/9.5) \times 4$
	E_{Vacuum}		$E_{Vacuum} = P_{Vacuum} \times t_{Vacuum}$ with $t_{Vacuum} = (t_{DED}/9.5)$
	E_{Sieved}		$E_{Sieved} = P_{Sieved} \times t_{Sieved}$ with $t_{Sieved} = (t_{DED}/9.5)$
	$E_{Computer}$		$E_{Computer} = P_{Computer} \times t_{DED}$
	E_{Fume}		$E_{Fume} = P_{Fume} \times t_{DED}$
	$E_{Support\ plate}$		$E_{Support\ plate} = P_{Supplort\ plate} \times t_{Support\ plate}$
Materials inputs	$m_{powder,total}$		$m_{powder,total} = (m_{final,AM}/\eta_{Polishing})/\eta_{Deposition}$
	$m_{powder,in}$		$m_{powder,in} = m_{powder,total} \times 0.95$
	$m_{powder,not\ used}$		$m_{powder,not\ used} = m_{powder,total} \times (1- \eta_{Deposition}) = m_{powder,vacuum}$
	$m_{powder,vacuum}$		
	$m_{powder,sieved}$	X	$m_{powder,sieved} = m_{powder,vacuum} \times 0.925$
	$m_{Support\ plate}$		
	$V_{Ar,total}$		$V_{Ar,total} = (Q_{Blowing} \times t_{Blowing} + Q_{DED} \times t_{DED})$
	$V_{Ar,in}$		$V_{Ar,in} = V_{Ar,total} - (r_{Recirculation} \times V_{Ar,total})$
Waste amount	$m_{powder\ waste}$		$m_{powder\ wasted} = m_{powder,vacuum} \times 0.075$
	$m_{metal\ waste}$		$m_{metal\ waste} = (m_{final,AM}/\eta_{Polishing}) \times (1 - \eta_{Polishing})$

a Fixed parameter are marked with and "X".
b Sand, oil and water inputs are introduced in different quantities at each stage of the process, so they are named differently, as presented in Table 2.
c Waste amounts are different in each stage of the process as in relation with each material input.

Table 3
Conventional Manufacturing technology data of parameters, values and uncertainty factors.

Conventional manufacturing								
Parameters	Unit	Baseline values	Basic uncertainty	Pedigree Matrix				
				Reliability	Completeness	Temporal correlation	Geographical correlation	Further technological correlation
$E_{Casting}$	kWh	243	0.0006	1	4	1	1	1
$m_{water,Casting}$	kg	1.43	0.0006	1	4	1	1	1
$m_{oil,Casting}$	kg	0.071	0.0006	1	4	1	1	1
$\eta_{Casting}$	%	0.8	0.0006	1	4	1	1	1
$m_{sand,Cleaning1}$	kg	0.071	0.0006	1	4	1	1	1
$E_{Cleaning1}$	kWh	0.14	0.0006	1	4	1	1	1
$E_{Deburring}$	kWh	0.071	0.0006	1	4	1	1	1
$\eta_{Deburring}$	%	0.975	0.0006	1	4	1	1	1
$E_{Thermal}$	kWh	0.71	0.0006	1	4	1	1	1
$m_{oil,Thermal}$	kg	0.071	0.0006	1	4	1	1	1
$E_{Machining}$	kWh	0.5	0.0006	1	4	1	1	1
$m_{water,Machining}$	kg	0.71	0.0006	1	4	1	1	1
$m_{oil,Machining}$	kg	0.035	0.0006	1	4	1	1	1
$\eta_{Machining}$	%	0.84	0.0006	1	4	1	1	1
$E_{Finishing}$	kWh	0.57	0.0006	1	4	1	1	1
$m_{water,Finishing}$	kg	1.43	0.0006	1	4	1	1	1
$m_{oil,Finishing}$	kg	0.035	0.0006	1	4	1	1	1
$\eta_{Finishing}$	%	0.85	0.0006	1	4	1	1	1
$E_{Cleaning2}$	kWh	0.14	0.0006	1	4	1	1	1
$m_{sand,Cleaning2}$	kg	0.071	0.0006	1	4	1	1	1

2.3.3. Uncertainty characterization

The uncertainty of a system expresses the lack of confidence in the representativeness of the true value of a parameter [34]. Despite it is a necessary step to determine the reliability of the results and it is recommended by ISO standards, it is still not widespread among LCA studies [35].

Due to the lack of statistical data, the ecoinvent database guideline from Weidema et al. [36] was used to generate the uncertainty distribution of parameters. Here, two different kinds of uncertainty are presented: basic uncertainty, which reflect the intrinsic variability, and the additional uncertainty, due to the use of imperfect data.

The lognormal is the common distribution in the ecoinvent database, because it allows multiplicative effects and is a skewed distribution without negative values. The geometric mean (μ_g) and the geometric standard deviation (σ_g) define the distribution, with the latter determining the uncertainty [34].

The aforementioned guideline provides the values of both uncertainty types, expressed as the square of the geometric standard deviation. For the basic uncertainty, ecoinvent defines default values depending on the type of flow, which are here the same for all parameters (process mass and energy flows). The pedigree matrix was used for the additional uncertainty, where an uncertainty value is assigned for five different quality indicators ("reliability", "completeness", "temporal correlation", "geographic correlation", and "further technological correlation") with a score between 1 and 5. The selection is based on the reliability of the data sources, being slightly higher for the assessed variable parameters. These applied uncertainty factors are included in Tables 3 and 4, for both technologies assessed.

These different values can be add up expressing the dispersion around the mean, based on the standard deviation under a 95% interval confidence (SD_{g95}), which is the square of the geometric standard deviation, and an accurate indicator of the distribution's spread [34], as can be seen in Eq.1:

$$SD_{g95} \cong \sigma_g^2 = exp^{\sqrt{[ln(U_1)]^2+[ln(U_2)]^2+[ln(U_3)]^2+[ln(U_4)]^2+[ln(U_5)]^2+[ln(U_b)]^2}} \quad (1)$$

where U_1 = uncertainty factor of reliability, U_2 = uncertainty factor of completeness, U_3 = uncertainty factor of temporal correlation, U_4 = uncertainty factor of geographic correlation, U_5 = uncertainty factor of further technological correlation, and U_b = basic uncertainty factor.

In addition, the uncertainty included in the datasets of the background processes is also considered.

2.4. Life cycle impact assessment

The evaluation of environmental impacts is done in SimaPro® 9.3 with the EF 3.0 method. The latter is based on the Environmental Footprint (EF) initiative, launched by the European Commission to create a harmonised EU methodology to communicate environmental performance of products or organisations [55]. This method consists of 16 midpoint impact categories, extracted from [56]: Climate change (kg CO_2 eq.), Ozone depletion (kg CFC11 eq.), Ionising radiation (kBq U-235 eq.), Photochemical ozone formation (kg NMVOC eq.), Particulate matter (disease incidence), Human toxicity, non-cancer (CTUh), Human toxicity, cancer (CTUh), Acidification mol (H+ eq.), Eutrophication, freshwater (kg P eq.), Eutrophication, marine (kg N eq.), Eutrophication, terrestrial (mol N eq.), Ecotoxicity, freshwater (CTUe), Land use (Pt), Water use (m^3 deprived), Resource use, fossils (MJ) Resource use, minerals and metals (kg Sb eq.).

In order to obtain a single score of the environmental impacts to facilitate the comparison of technologies, two steps are necessary: normalization, to convert the impacts in a common unit scale, expressing the total impact occurring in a reference region for a certain impact category within a reference year, based on [57]; and weighting, to consider the relevance and reliability of indicators, based on [58].

2.4.1. Calculation of sensitivity index

One-at-a-time variations were performed for the independent parameters, on their uncertainty range. The sensitivity index (S.I.) is calculated for each parameter, as the ratio between the percentage of change in the output's impact category (ΔIC) over the percentage change of the variable increased value (ΔVI), as shown in Eq.2:

$$S.I. = \frac{\Delta IC}{\Delta VI} \quad (2)$$

The higher the S.I., the more sensitive are the results to the parameter.

2.4.2. Break-even point

Since the AM technology is supposed to produce lighter pieces, the mass reduction factor required to obtain environmental benefits compared to the conventional technology, is calculated. This factor,

Table 4
Additive Manufacturing technology data of parameters, values and uncertainty factors.

Additive manufacturing								
Parameters	Unit	Baseline values	Basic uncertainty	Pedigree Matrix				
				Reliability	Completeness	Temporal correlation	Geographical correlation	Further technological correlation
$t_{Support\ plate}$	h	4.50	0.0006	2	4	1	1	2
$P_{SupportPlate}$	kW	17.7	0.0006	2	4	1	1	2
P_{Mixing}	kW	0.22	0.0006	1	4	1	1	1
P_{DED1}	kW	0.58	0.0006	1	4	1	1	1
P_{DED2}	kW	0.68	0.0006	1	4	1	1	1
$P_{Computer}$	kW	0.16	0.0006	1	4	1	1	1
P_{Vacuum}	kW	1.2	0.0006	1	4	1	1	1
P_{Sieved}	kW	0.2	0.0006	1	4	1	1	1
$P_{Polishing}$	kW	0.2	0.0006	2	4	1	1	2
P_{Fume}	kW	0.02	0.0006	1	4	1	1	1
$m_{Supplort\ plate}$	kg	1.8	0.0006	2	4	1	1	2
$m_{Brass\ wire}$	kg	4	0.0006	2	4	1	1	2
r_{Flow}*	kg/h	0.525	0.0006	4	4	2	3	3
$\eta_{Deposition}$*	%	0.43	0.0006	4	4	2	3	3
$\eta_{Polishing}$*	%	0.65	0.0006	4	4	2	3	3
$t_{Blowing}$	h	1.5	0.0006	1	4	1	1	1
$r_{Recirculation}$*	%	0.724	0.0006	4	4	2	3	3

Note: Parameters with * are the ones affected by the upscale approach, with changes in their baseline values.

Table 5
Overview of the literature review for the parametric variables prospective data.

Reference	Technology & Material	Maturity level	Variable parameters	Values
[37]	Directed Energy Deposition and Ti-6Al-4 V	Lab-scale	r_{Flow}	0.81 kg/h
[38]	Directed Energy Deposition and Ti-6Al-4 V	Full scale	r_{Flow}	1.8 and 3.6 kg/h
[39]	Directed Energy Deposition and Ti-6Al-4 V	Lab-scale	r_{Flow}	0.72 kg/h
[40]	Directed Energy Deposition and Ti-6Al-4 V	Prototype	r_{Flow}	0.36–0.96 kg/h
[41]	Directed Energy Deposition and Ti-6Al-4 V	Industrial scale	r_{Flow}	2.52 kg/h
[42]	Directed Energy Deposition and Ti-6Al-4 V	Lab-scale	$\eta_{Deposition}$	60% - 84.3%
[43]	Directed Energy Deposition and Ti-6Al-4 V	Full scale	$\eta_{Deposition}$	65% - 90%
[44]	Directed Energy Deposition and Ti-6Al-4 V	Lab-scale	$\eta_{Deposition}$	70% - 90%
[45]	Laser polishing on Electron Beam Melted Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	75%
[46]	Laser polishing on Selective Laser Melting Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	85%
[47]	Laser polishing on Selective Laser Melting Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	76%.
[48]	Laser polishing on Additive Manufacturing Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	80%
[49]	Laser polishing on Electron Beam Melted Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	75.1% - 91.6%
[50]	Laser polishing on Selective Laser Melting Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	95%
[51]	Laser polishing on Electron Beam Melted Ti6Al4V component	Lab-scale	$\eta_{Polishing}$	80
[52]	Gas recycling loop	Prototype	$r_{Recirculation}$	85%
[53]	Recycling system for Gas Atomization process	Full scale	$r_{Recirculation}$	97.8%
[54]	Gas Recycling in Inductively Coupled Plasma Optical Emission Spectrometry	Prototype	$r_{Recirculation}$	90%

expressed as a percentage, corresponds to the relative difference between the impact of CM technology (I_{CM}) and the one of AM technology (I_{AM}) (see Eq. 3). This break-even point is calculated at single score level using the best-case AM scenario.

$$\text{Weight Decrease} \geq \frac{I_{CM} - I_{AM}}{I_{AM}} \tag{3}$$

In order to propagate the input uncertainty, explained in section 2.2.2.3, into output uncertainty, the Monte Carlo sampling method was applied. This method makes a large number of calculations which provides a probabilistic range to understand the uncertainty of the impacts results [59]. A sampling with 10,000 simulations was applied in this study. Monte Carlo simulation, from SimaPro, includes the 95% interval confidence by default, which is also the one typically chosen for a variety of different field investigations (Röhrig et al., 2009). A discernibility analysis was performed to consider the common uncertain parameters and determine the number of simulations when one technology has a higher impact that its counterpart.

Table 6
Single score factors for AM (additive manufacturing) best scenario and reduction percentage as compare with baseline values.

Impact category	Unit	Baseline values	Best scenario	Impact reduction
Total	**mPt**	**533**	**31.2**	**−94%**
Climate change	mPt	117	6.87	−94%
Ozone depletion	mPt	0.36	0.03	−91%
Ionising radiation	mPt	29.6	0.93	−96%
Photochemical ozone formation	mPt	12.6	1.01	−92%
Particulate matter	mPt	14.8	2.21	−85%
Human toxicity, non-cancer	mPt	3.74	0.35	−90%
Human toxicity, cancer	mPt	2.39	0.45	−81%
Acidification	mPt	27.8	1.82	−93%
Eutrophication, freshwater	mPt	77.4	3.47	−95%
Eutrophication, marine	mPt	6.66	0.41	−93%
Eutrophication, terrestrial	mPt	8.04	0.54	−93%
Ecotoxicity, freshwater	mPt	30.5	2.77	−90%
Land use	mPt	1.69	0.11	−93%
Water use	mPt	60.5	1.56	−97%
Resource use, fossils	mPt	121	5.35	−95%
Resource use, minerals and metals	mPt	17.8	3.33	−81%

Table 7
Relation between km covered by the AM (additive manufacturing) piece and the weight reduction to equal CM (conventional manufacturing) impact.

Thousands of kilometres covered	Weight reduction
7717	0%
4417	25%
1117	50%
787	52.5%
457	55%
325	56%
259	56.5%
193	57%
127	57.5%
61	58%
0	58.46%

2.4.3. *Use phase modelling*

As final step, it was decided to assess the operational step of the final component, to find the Break Even Distance (BED) when the new technology could start to be feasible. For this, the calculation presented in Salonitis et al. [60] was modified by changing energy burdens with single score impact, as shown in Eq. 4:

$$BED = \frac{\Delta Ip}{(\delta F_s \times I_{FC} \times \Delta m)} \times 10^4 \tag{4}$$

where ΔIp: Impact difference between both technologies for a given weight (e.g. in mPts/kg);

δF_s: Fuel savings per weight reduction (constant factor of 0.2 L/km·kg);

I_{FC}: Impact of fuel consumption (e.g. in mPts/L fuel);

Δm: Product weight difference between both technologies (in kg).

Finally, to find a reasonable distance where the new technology could be less environmental impactful, different AM component weights will be tested.

3. Results

The outcomes of the study reflect the comparative analysis between both technologies, using the step-wise methodology presented. The impacts are shown in the weighting single-score, in mPts, to facilitate its interpretation, but more specific data with unnormalized impact factors can be found in the Supplementary Material, Tables S3, S4&S5.

3.1. Baseline comparative and contribution analysis of each technology

Firstly, the processes were assessed in their baseline values, to compare both at current state, as presented in Fig. 3. The single score of CM is almost 13 mPts, mainly due to energy use (79% of contribution), while more than 530 mPts are obtained for the AM technology (93% of impacts are due to Argon use). Besides energy, the environmental profile of CM process is also influenced by the raw material input of aluminium alloy (19% in single score, with the highest contribution on Particulate matter and Human toxicity cancer, with more than 50% contribution). Regarding AM process, the other process flows have mostly a contribution lower than 10% regardless of the impact category, except for the titanium materials on particulate matter (16%) and human toxicity, cancer. The most impacted categories for the single score are Climate change and Use of fossil resources, for both technologies. These data are detailed on Supplementary Material, Tables S6&S7.

3.2. Sensitivity, scenario and break-even point analysis

The sensitivity analysis (one-at-a-time variations) was performed for the AM scenario using the data range from literature. The analysis of the four key parameters (r_{Flow}, $\eta_{Deposition}$, $r_{Recirculation}$, $\eta_{Polishing}$) highlighted a negative relationship, i.e. the higher the parameter, the lower the impacts (see Figs. S1-S4 in Supplementary Material). Each parameter has a different scale of variations, from +35% compared to the baseline value for $r_{Recirculation}$ to +585% for r_{Flow}. The highest impact variation was observed for $r_{Recirculation}$ (−86% with highest value), leading to a sensitivity index of −2.45, while it is between −0.52 for $\eta_{Polishing}$, −0.36 for $\eta_{Deposition}$ and − 0.11 in the case of r_{Flow} parameter. The same trends are observed for all environmental indicators. This outcome means that the recirculation of argon is the most affecting impacting variable of the process and should be optimized in priority to improve the environmental performances of the AM process.

A final best-case scenario is built with the best available data from the state-of-the-art review, obtaining a 94% scoring reduction compared to the baseline value on the single score, with a variation of 81% to 97% reduction depending on the indicator, as it is shown in Table 6.

The detailed single score comparison of the best-case AM scenario with CM is shown in Fig. 4. Argon use remains with a significant contribution but to a lesser extent (30.5% of single score impact), followed by the production of the titanium support plate (28%) and the titanium powder (21%), as shown in Fig. 4. These three flows remain the main sources of all impact types, with some variations depending on the indicator. For example, argon has the highest impact on ionising radiation and water use (60% and 74%, respectively), the support plate on carcinogenic impacts, particulate matter, ozone depletion (50%, 49% and 42%, respectively) and the titanium powder on particulate matter and human toxicity, cancer (35%). The only indicator for which these flows have a minor effect is the use of mineral and metallic resources, for which brass contributes to 57% of the production impacts (mainly due to tellurium extraction for the production of copper cathode used for brass manufacturing). The consumption of electricity never dominates the impact, but has a non-negligible contribution, between 5% and 24% depending on the indicator. Once the best values for the four key

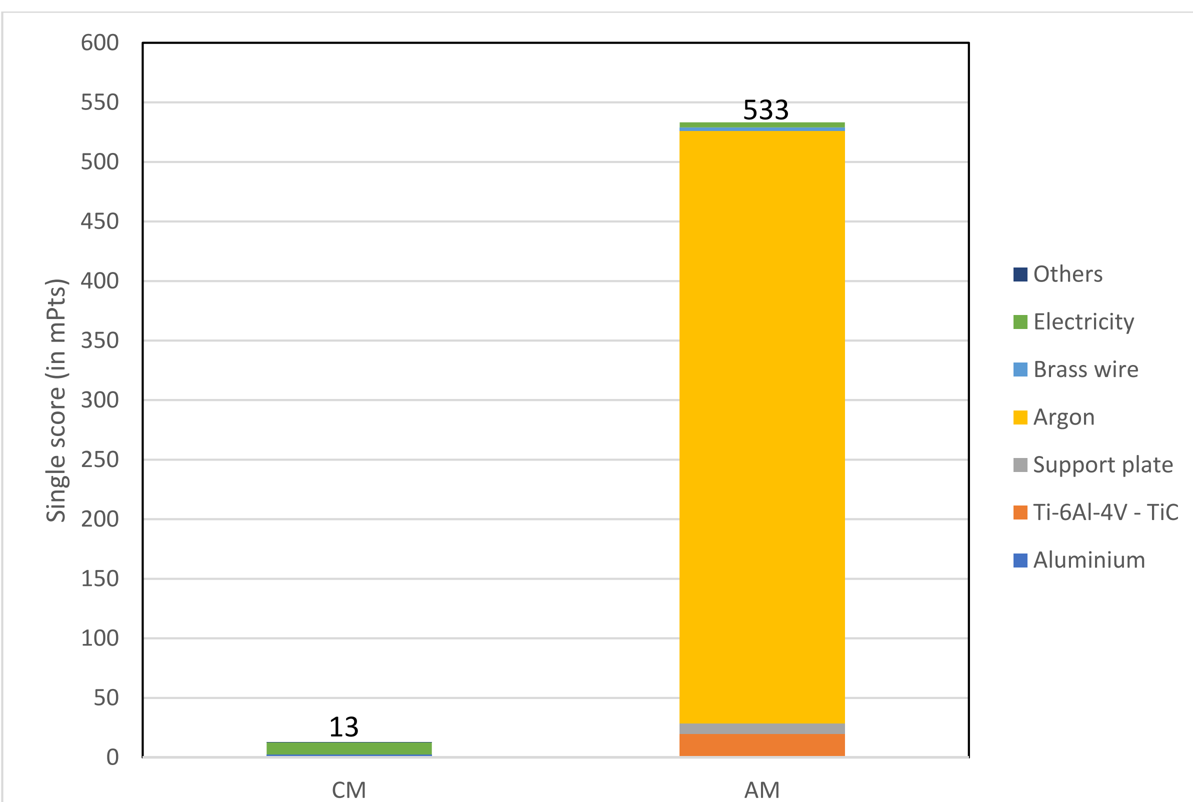

Fig. 3. Single score factors for CM (conventional manufacturing) and AM (additive manufacturing) at baseline values.

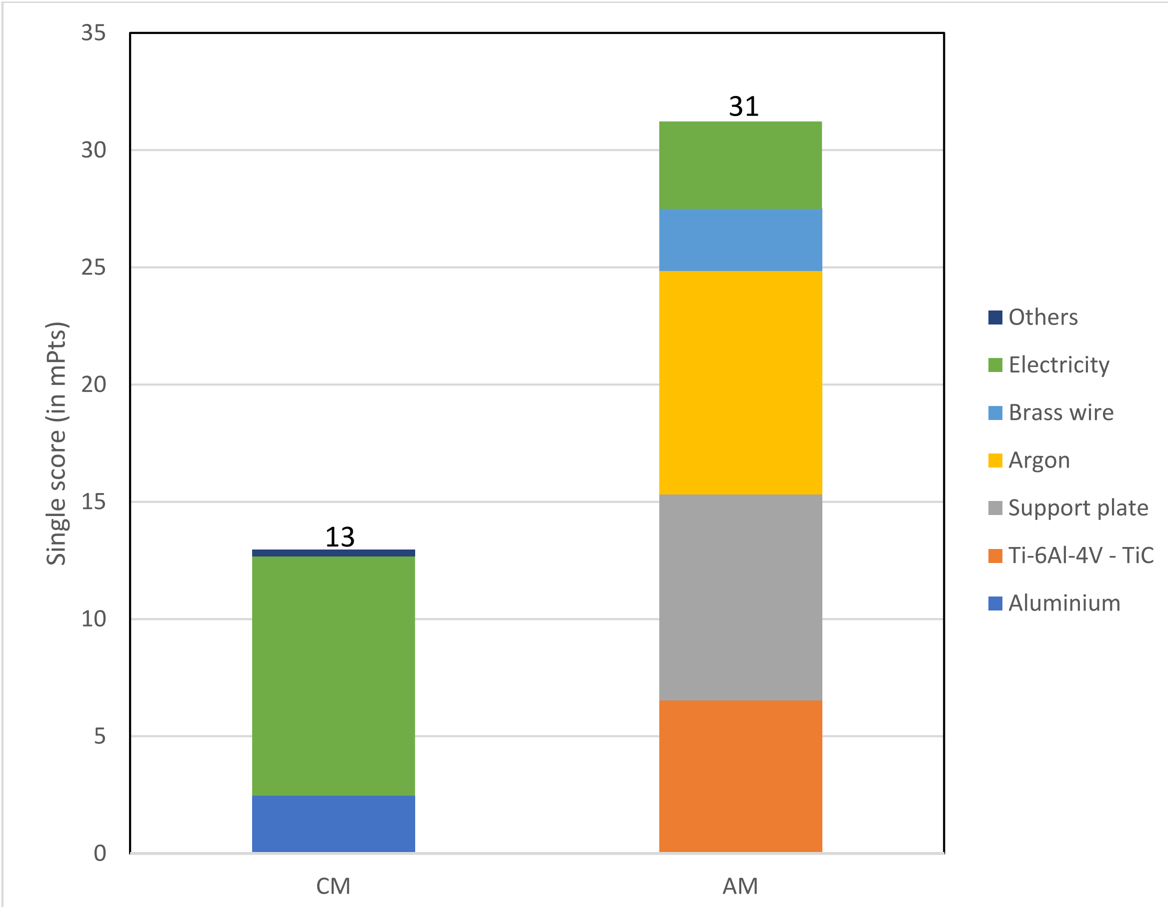

Fig. 4. Single score factors for CM (conventional manufacturing) and AM (additive manufacturing) at best scenario values.

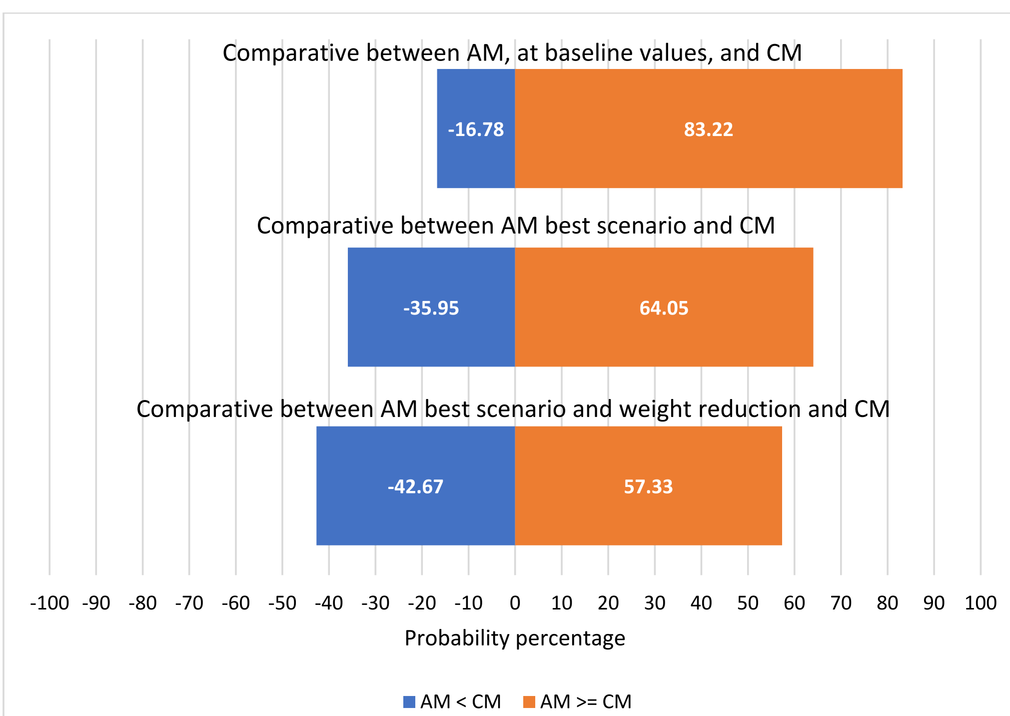

Fig. 5. Discernibility analysis between different scenarios for CM (conventional manufacturing) and AM (additive manufacturing) comparative.

parameters could be reached, the further improvement of all process flows is thus important. These conclusions are valid for 1 kg of gearbox piece; however, the AM process normally leads to weight reduction. Using Eq.3 and the total impact in mPts, the weight reduction needed in the AM components to be at least equal to its counterpart's impact is 58% for the best-case scenario. More detailed data can be found in Supplementary Material, Table S8.

3.3. Uncertainty results

Fig. 5 shows the discernibility analysis results at single score level for the comparison of CM with AM process, using baseline values, best scenario, with or without weight reduction of 58%. Using the best scenarios, the probability of AM to be less impactful than CM is almost 36% and 43% when weight reduction is considered. These values place them in "about as likely as not" term of the likelihood scale, as used by the IPPC in their Assessment Reports [61], meaning that the probabilistic occurrence is about even. This outcome means that even with the investigated best operating conditions and a 58% weight reduction, the AM technology cannot bring significant environmental benefits, when considering only the production phase. More information about the distribution of uncertainty results from the discernibility analysis is included in Supplementary Material, Tables S9, S10&S11.

3.4. Use phase results

Table 7 is built showing the covered kilometres necessary to equal the CM impact in relation with the weight reduction, as explained in the calculation for Eq. 4. The calculation is based on the best-case AM scenario and at single score level. The results suggest that if the gearbox piece is installed in a car, at least 56% weight reduction is required. Indeed, this is the minimum weight to obtain a quite reasonable range of kilometres, aligned with the standard vehicle lifetime (commonly between 150,000 and 320,000 km) [62]. This value is slightly lower than the 58% reduction calculated when considering the production phase only. The fuel savings benefits during the gearbox component use are marginal. This is a logical finding, considering the small contribution of the gearbox to the total vehicle weight.

4. Discussion

The findings of this LCA are aligned with those in other studies. For instance, the requirement of mass reduction and design inclusion to reduce impacts from AM compared to a CM technique was also addressed by [16]. Also, the results from [14] shown that AM is only more sustainable when considering a 50% weight reduction and including the use phase benefits.

The stepwise approach presented in this document can be replicated for similar and different applications within industry field, following the procedure presented in the Methodology section. For this purpose, would be necessary to consider some limitations of the study that could have slightly influenced the results mentioned throughout the paper. Highest extent of produced impacts come from the chosen variables under study, specially from the argon used, as it is shown in the sensitivity analysis. Regarding this issue, no works disclosing quantity and impacts from argon used in DED technology for similar materials were found to date, but some other publications in AM field can help for comparison matters. For instance, while comparing the manufacture of a steel gear (less than 10 g) between traditional manufacturing and a directed energy deposition method, Liu et al. [63] obtained more negative emissions from the latter. They demonstrate a lesser consumption and subsequent environmental impacts from argon than in the present study since the printed item is small and made of steel, therefore the inert printing atmosphere is not as critical as in the titanium case. In a work by [64] performed an LCA on WAMM technique, showing that 48% of impacts comes from the argon gas continuously used in the process. Most of the works that deal with argon utilization are focused on powder metallurgy and gas atomization process to produce diverse material. [65] shown that argon lead the impacts in the gas atomization process, as is continuously consumed, and has the highest sensitivity among inputs, recommending measures for its reduction. Also [66] probe that argon is the main environmental impact in the gas atomization process. However, other inputs with relative importance in the outcome were not profoundly assessed. For instance, energy consumption (representing 12% of the single score for the best AM scenario modelled) may change and evolve different in the future, and these variations were only included as uncertainty factor but not with scaled-up values. Regarding this, the results obtained in this study align with those in other works, as in the review performed by [67], where authors found that machining and conventional techniques have a significant higher energy consumption during manufacturing phase than AM technologies. Furthermore, some studies have shown that cryogenic machining of titanium alloys is more sustainable and cost-effective than regular techniques [68], which could be applied in the support plate cutting phase of the present case study, reducing the final outcomes. In regards of the system eco-design, further research could include the 6R approach (reduce, reuse, recycle, recovery, redesign and remanufacture) for the circular evaluation of the system under study, using similar approaches as the ones developed by [69] and [70]. This work only focuses on the key parameters for AM because have more importance in the final outcome, according to the contribution and sensitivity analysis, and considering that their values variation is greater, as shown in the literature review. Along with this, the selection of certain datasets can have an influence in the final outcomes. The database used is the latest available version of ecoinvent during the first half of 2022, and as the process is established in Europe, most of the datasets used are related to the European territory, but for some of them a global average was chosen. In addition, some materials were not found in the database, such as the titanium alloy and the titanium carbide, and are specifically modelled based in other available datasets and literature, as detailed in Supplementary Material, Tables S1&S2. It is also worth mentioning that the datasets used have included an average transport impact, as logistics were not disclosed by the manufacturers involved. Thus, the proposed variables and background system should be subject to review and update, by enhancing the quality of data.

5. Conclusion

This paper followed a stepwise methodology to compare the environmental impacts of emerging technologies with conventional technologies, and to support their eco-design. It was applied to compare an AM technology (Directed Energy Deposition) with a CM casting process, for the production of a gearbox. The outcomes of the study show that the AM technology can only be competitive with the optimization and upscaling of the process design, reducing 94% of climate change impacts with emissions from 4520 to 264 kg CO2 eq./kg piece, and with a significant weight reduction of the produced component, leading to additional fuel reduction savings during the use phase. In this point, it would be important to further investigate that a reduced weight component can still meet quality and warranty standards.

In addition, considering the AM technology still emits double than the CM process (31 mPts versus 13 mPts), and even including a possible weight reduction, the uncertainty depicted within the study shows, in the discernibility analysis, just a 43% probability of the AM to be more sustainable than its counterpart.

The main influencing parameter was found to be the argon recirculation rate. This parameter, as well as the flow rate, deposition and polishing efficiency could be significantly improved based on information from similar technologies. These results can support process developers and manufacturers on the eco-design of the technology and the improvement of the process.

Most studies performed in the AM field do not consider the potential upscaling effects, as it has been developed in this work. The use of an ex-ante evaluation based on realistic future scenarios can better support decisions and the technology development trajectory.

The early-stage assessment of emerging technologies is decisive to be able to consider environmental criteria for design choices, while the latter cannot be changed once a higher maturity is achieved. Such ex-ante LCA studies can rely on several approaches, such as hotspot, sensitivity or scenario analysis to prioritize the development strategies and make greener choices, while dealing with the large uncertainties of the modelling for such low technological readiness level. This study could show the applicability of these methods for the specific case of Directed Energy Deposition.

Further research might explore the need for a standardized approach, which allow more reliable comparability between different studies, and the integration with other calculation methods and techniques, such as big data analysis, machine learning and process simulation tools to further consolidate the LCA modelling.

CRediT authorship contribution statement

Mario Santiago-Herrera: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Elorri Igos:** Conceptualization, Supervision, Validation, Writing – original draft, Writing – review & editing. **J.M. Alegre:** Supervision, Writing – review & editing. **Sonia Martel-Martín:** Funding acquisition, Supervision, Validation, Writing – review & editing. **Rocío Barros:** Funding acquisition, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.susmat.2023.e00819.

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