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A flexible decision support tool for the green selection of additive over subtractive manufacturing approaches

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A R T I C L E I N F O

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A B S T R A C T

To reduce environmental impacts, energy- and resource-efficient manufacturing strategies must be continuously implemented on a global scale. The industrial sector is a major source of greenhouse gas emissions, and ongoing research into more sustainable practices is crucial. Since its birth, additive manufacturing has gained increasing importance, and it has often been claimed to be a green solution. Nevertheless, scholars have been questioning whether it is a truly sustainable alternative to traditional methods, and several comparative analyses have been released. Studies revealed a complex and ambivalent nature of additive technology; actually, the environmental sustainability domain of additive approaches is not well-defined because it depends on the case-specific nature of the developed comparative analyses. This leads to the lack of a generalizable framework and straightforward guidelines for selecting environmentally friendly manufacturing approaches. In the present paper, cumulative energy demand model simplification of additive and subtractive processes was conducted starting from complex and fully analytical formulations. A model, requiring 60 % less input data than full formulation, has been identified for developing a new decision support tool, relying just on the material embodied energy, specific energy consumption of additive process and geometrical characteristics of the component to be manufactured. This tool minimizes, therefore, the computational and data inventory effort. The designed tool has been tested on different materials, additive manufacturing processes and component geometries. Results revealed that the designed tool represents a generalizable framework easy to be implemented and useable for mapping the energy efficiency performance of different metal powder bed additive approaches.

Nomenclature

EBM	Electron Beam Melting;
SLM	Selective Laser Melting;
BJ	Binder Jetting;
WAAM	Wire Arc Additive Manufacturing;
LENS	Laser Engineering Net Shaping;
DMD	Direct Metal Deposition;
CLAD	Construction Laser Additive Directe;
CED	Cumulative Energy Demand;
GWP	Global Warming Potential;
α	input/output material ratio for powder production;
ε	input/output material ratio for workpiece production;
k	weight reduction factor due to topology optimization for AM;
r	end-of-life recyclability;
E^{AM} (MJ/part)	primary energy demand for producing one part by AM;
E^{CM} (MJ/part)	primary energy demand for producing one part by CM;

(continued on next column)

(*continued*)

E_A (MJ/kg)	energy demand for metal powder atomization;
E_E (MJ/kg)	embodied energy of the material, including the recycling benefit awarding;
E_F (MJ/kg)	energy demand for forming the workpiece;
E_V (MJ/kg)	energy demand for the primary production of the material;
E_R (MJ/kg)	energy demand for the secondary production of the material;
m_A (kg)	mass of the machining allowance to be removed by finishing process;
m_C (kg)	mass of the chips machined by means of CM;
m_P (kg)	mass of the part to be produced.
m_S (kg)	mass of the support structures for AM;
SEC^{AM} (MJ/kg)	specific (primary) energy consumption of AM machine;
SEC_i^{CM} (MJ/kg)	specific (primary) energy consumption of CM machine;
P_{stb}^{AM} (kW)	stand-by power of the AM machine;
t_{stb}^{AM} (h)	stand-by time of the AM machine;
P_{stb}^{CM} (kW)	stand-by power of the CM machine;

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(continued)

t_{stb}^{CM} (h)	stand-by time of the CM machine;
t_{tc} (h)	time necessary for tool change;
T_i (h)	tool life; with i = roughing or finishing
MRR_i	Material Removal Rate;
E_{tool_i} (MJ)	embodied energy of the cutting tool;
t_{Ci} (h)	cutting time;
E_{lub} (MJ/kg)	embodied energy of the cutting fluid;
q_l (kg/h)	consumption rate of the cutting fluid;
E_{gas} (MJ)	energy for inert gas consumption;
E_{HIP} (MJ/kg)	energy for Hot Isostatic Pressing;
E_{SEP} (MJ/kg)	energy for the part separation from the build plate and of supports;
E_{FM} (MJ/kg)	energy for finish machining;

1. Introduction

The industrial sector is a significant contributor to global electricity consumption and CO_2 emissions, largely due to its energy-intensive processes. In 2023, energy-intensive industries, including the production of iron, steel, and non-ferrous metals, accounted for nearly three-quarters of the sector's total energy use. Compared to 1990, emissions coming from them increased by about 54 %, and in 2022, these industries were directly responsible for emitting 9.0 Gt of CO_2, making up approximately 25 % of the global energy system CO_2 emissions (IEA, International Energy Agency: World Energy Outlook, 2024). This trend highlights the challenges in decarbonizing the sector, as it is a major source of greenhouse gas emissions. To align with the objectives set by the international community through the Kyoto Protocol and the Paris Agreement, energy- and resource-efficient strategies must be continuously implemented on a global scale to mitigate environmental impacts. At the core of the industrial sector are manufacturing processes, which place a significant demand on the environment (Nagarajan and Haapala, 2018), highlighting the need for ongoing research into more sustainable manufacturing practices.

Over the past four decades, Additive Manufacturing (AM) has evolved from being a rapid prototyping technology to a fully-fledged production process, now recognized as a disruptive technology with the potential to revolutionize or even replace conventional manufacturing pathways, but still with a long way to go, as both better mechanical properties and cost efficiency than conventional methods should be provided by its adoption (Kaushik et al., 2023). AM has gained popularity as an environmentally friendly solution, specifically because of some advantages (Sefene, 2022), including: (*i*) waste reduction, as AM processes, differently from traditional ones, do not require tooling, (*ii*)

Table 1
Environmental comparison between Additive Manufacturing and Conventional Machining processes.

Source	AM process	CM process	Material	Environmental Metric	Findings
Morrow et al. (2007)	DMD	Milling	H13 tool steel	Energy consumption	SCR is a key metric: simple molds are more sustainable to produce via CM while more complex molds are better to produce via AM process.
Serres et al. (2011)	CLAD	CNC milling	Ti6Al4V	LCA metrics	AM reduces environmental impact by ~70 % due to lower material waste.
Doran et al. (2016)	DED	Milling	Aluminum alloy	GHG emissions	Milling has lower emissions for low material removal, while DED is preferable only above 85 % material removal.
Paris et al. (2016)	EBM	CNC Milling	Ti6Al4V	LCA metrics	EBM outperforms machining for parts with high geometrical complexity, such as the aeronautical turbines.
Tang et al. (2016)	BJ	CNC Milling	Bronze infiltrated stainless steel	Energy consumption and ReciPe midpoint categories	AM process can save energy and reduce environmental impact, especially if optimized design freedom is considered, due to its better material and energy efficiency
Mami et al. (2017)	SLM	Machining	Titanium	LCA metrics	In manufacturing an aircraft doorstop, 3D printing provides an impact reduction of 20 % compared to machining.
Priarone et al. (2017)	EBM	Turning	Ti6Al4V	CED and CO_2 emissions	Considering 3 geometries the Solid-to-cavity ratio is a key in determining the most sustainable process.
Bekker and Verlinden (2018)	WAAM	CNC Milling	Stainless Steel 308L	ReCiPe endpoints categories	Environmental impact scales linearly with material consumption.
Kamps et al. (2018)	SLM	Milling	Steel	Embedded energy (MJ/part)	SLM is ideal for small-batch lightweight gear production, while Milling remains more efficient for larger volumes and non-optimized designs.
Le and Paris (2018)	EBM	CNC milling	Titanium	LCA metrics	EBM is more sustainable than CNC milling for smaller build heights and near full build configurations
Liu et al. (2018)	LENS	Milling	AISI 4140	LCA metrics	Milling is more sustainable than LENS in 5/6 impact categories.
Jiang et al. (2019)	LENS	CNC milling	AISI 4140	Emergy	LENS is more sustainable; CM has over 4 times the impact of AM considering the reliance on non-renewable resources.
Campatelli et al. (2020)	WAAM	Milling	EN S23 5JR Steel	CED	For thin-walled structure, WAAM saves 34 % energy compared to machining due to higher material efficiency.
Ingarao and Priarone (2020)	EBM	Turning	Ti6Al4V	CED	EBM is sustainable only for SCR values lower than 0.3.
Priarone et al. (2020)	WAAM	Milling	Titanium – ER706 s steel – AA2319	CED	WAAM is more energy efficient for its better material efficiency
Lyons et al. (2021)	EBM	Milling	Ti6Al4V	Energy consumption and CO_2 emissions	For producing a specific knee implant, EBM is more sustainable due to lower material waste.
Lunetto et al. (2021)	EBM	CM	Ti6Al4V	CED and CO_2 emissions	Break-even surfaces for CO2 emissions and energy demand depend on SCR and deposition rate.
Pagone et al. (2022)	WAAM	Machining	Steel	Energy consumption and CO_2 equivalent emissions	In a disk drive repair, WAAM material efficiency significantly influences the overall environmental impact of manufacturing
Kokare et al. (2023a)	WAAM And SLM	Milling	ER70 steel	CED	WAAM is energy-efficient only when material savings outweigh environmental costs of wire feedstock production
Liao et al. (2023)	SLM	Machining and casting	AlSi10	CED and GWP	Powder based AM benefits are sensitive to part design and machine settings; thus, break-even points vary with material and complexity.
Reis et al. (2023)	WAAM	CNC milling	ER70 steel	LCA metrics	WAAM is more sustainable due to its better material efficiency
Tran et al. (2023)	SLM	Turning	Stainless steel	Energy consumption per mass of material (MJ/kg)	AM reduces energy use and transport costs, making it a more sustainable alternative to CM for specific geometries.

high geometry freedom, enabling product customization by simply modifying CAD files, (*iii*) ability to produce complex components in a single step, eliminating the need for subsequent assembly, (*iv*) topology optimization, which is about the design of complex geometries to keep the volume to a minimum, thus enabling weight reduction, which is a great benefit especially for automotive (Zhao et al., 2023) and aviation (Gisario et al., 2019) applications, (*v*) in absence of economies of scale, AM allows for the production of a limited number parts without increasing unit costs.

The growing adoption of additive technology as a greener solution has led scholars to question whether it is a truly sustainable alternative to traditional methods. Specifically, since in 2007 the first environmental comparison of AM and conventional manufacturing was published, several comparative analyses have been developed. The main released research studies concerning comparative analyses conducted between AM and Conventional Machining (CM) processes applied to metals are reported in Table 1. It is worth noting that this table does not include comparative analyses between AM and mass conserving approaches; this choice was driven by the awareness that conventional mass conserving approaches (i.e., casting, forging, etc.), taking advantage of their batch size dependent nature, have proved to be the best solution only in mass production environments (Ingarao et al., 2018). Consequently, in comparative analyses between AM and mass-conserving methods, production volume is a key consideration. For instance, Binder Jetting (BJ) has been found to be more sustainable than Metal Injection Molding for production volumes below 1000 units (Raoufi et al., 2022). Instead, it is fair to compare AM and subtractive approaches, as neither of them takes advantage of the economy of scale phenomenon. From what reported in Table 1 it is possible to note that, apart from Direct Energy Deposition (DED) processes, which are mainly used for repair purposes, the powder-based processes (namely, EBM, SLM and BJ) are more environmentally friendly only under specific circumstances.

The increasing interest in this topic has led to the publication of review articles exploring the application of Life Cycle Assessment (LCA) to AM processes (Kokare et al., 2023a), aiding in defining the contexts and parameters in which AM demonstrates better environmental performance compared to CM. Jung et al. (2023) emphasized the complex and ambivalent nature of AM sustainability, highlighting environmental hidden aspects that must be considered. These include: (*i*) the high energy intensity associated with the production of metal and polymer powders, which serve as the material feedstock for AM processes, (*ii*) the slow production rate, requiring AM machines to operate for extended periods – ranging from hours to days – that results in significant electricity consumption and corresponding emissions, (*iii*) the extensive post-processing requirements, such as the removal of support structures, surface smoothing and extra steps like heat treatment (e.g., Hot Isostatic Pressing HIP), leading to additional environmental burdens. Thus, when assessing the environmental performance of AM, it is crucial to carefully account for a wide range of factors of influence if the goal is to achieve sustainable production. Consequently, a significant area of uncertainty regarding the environmental dimensions of AM, as sketched out by Kellens et al. (2017a), still remains relevant today.

It should be noted that some of the comparative analyses summarized in Table 1 represent an initial step toward the development of Decision Support Tools (DSTs) incorporating factors such as shape complexity and weight reduction. Paris et al. (2016) proposed a DST for identifying the most environmentally friendly solution between Electron Beam Melting and conventional machining for titanium based part manufacturing. In this paper the authors investigate the effects of varying the shape complexity on the comparative analysis. Similarly, Tran et al. (2023) introduced a tool to assess the environmental impact of SLM compared to turning with varying the shape complexity. Ingarao and Priarone (2020) used also this approach by developing a DST that accounts for both the Solid-to-Cavity Ratio (SCR) and weight reduction factor aiming to support the selection of the most energy-efficient manufacturing route. Despite their contributions, these DSTs present two main limitations: they are designed on a specific additive technology (i.e., EBM, SLM) and the results are valid only for the used material. Moreover, these approaches are based on complex analytical models, which may limit their general applicability and ease of use in broader industrial contexts.

Summing up, existing work is focused on specific case studies and scenarios. Results of main comparative analyses might offer qualitative guidelines based on their findings, but their case-specific nature cannot be overlooked. Environmental benefits of AM are not universally assured. Rather, they depend on factors such as the component's geometric shape, the material and the process employed. Therefore, the sustainability domain of manufacturing approaches remains limited by the assumptions made in these studies, as none of them adopts a holistic approach, resulting in the lack of a generalizable framework for selecting environmentally friendly manufacturing approaches.

The present study was conducted with the objective of addressing this gap by developing a general Decision Support Tool (DST), providing quantitative guidelines from an energy efficiency perspective, as the reduction of energy consumption is one of the strategies used to achieve sustainable manufacturing systems (Diaz and Ocampo-Martinez, 2019). The main idea is to ensure ease of set up, thus creating a tool relying on a minimal number of variables, minimizing the computational and data inventory effort.

To this aim, a comprehensive framework for mapping the sustainability performance of various Powder Bed Fusion (PBF) processes across a range of metallic materials is here presented. Specifically, the designed DST can be easily adapted to different materials, product geometries and AM processes, overcoming the main limitations of the already presented comparative analyses. The development of such a holistic tool for assessing the sustainability of AM processes can support sustainable manufacturing globally, guiding the selection of the most energy-efficient manufacturing route and consequently contributing to the increasingly stringent international environmental goals.

The paper is structured as follows. Section 2 presents the methodology adopted in this study, detailing the simplification process of cumulative energy demand models and the case study upon which the analysis and the subsequent DST are based. Section 3 provides a detailed life cycle inventory for each stage within the system boundaries, describing the relevant processes. Section 4 reports and discusses the results obtained from comparative analyses conducted under the proposed simplified models, highlighting their accuracy and effectiveness with additional sensitivity analyses. Section 5 focuses on the development of the DST, while Section 6 validates its applicability through case studies drawn from existing literature. Finally, Section 7 summarizes the key conclusions and outlines potential directions for future research.

2. Materials & methods

To address the complexity associated with extensive primary energy models, a first attempt towards simplifying process modeling was recently proposed in literature (Ingarao et al., 2024) and made up the starting point for this study. A comparative analysis between AM and CM was conducted considering seven models, where Model I, inspired by previous research (Priarone and Ingarao, 2017), was considered as the full model, thus the baseline for benchmarking. The remaining six were derived from Model I through the stepwise exclusion of some factors, in order to simplify the processes' modeling while maintaining an adequate level of accuracy. The objective was to identify simplified models that can reliably estimate the energy requirements of AM and CM processes in comparative analyses, enabling a more straightforward approach for selecting the most sustainable manufacturing route.

Comparison was made with Cumulative (primary) Energy Demand (CED) method, since CED represents an important environmental metric directly related to carbon emissions (Rejeski et al., 2018) and it's often used for impact assessment.

The outcomes of that research reveal that simplified models, when low computational effort is required, can provide reliable results. However, this result is constrained to some limitations: (1) the full model, indicated as Model I, was itself a simplified version and, also, it does not take into account some energy contributions (i.e., stand-by phases, finishing, consumables, etc.); (2) the analysis was conducted exclusively on titanium alloy Ti-6Al-4V, with specific inventory data; (3) only 1 a.m. process (the Electron Beam Melting) was considered with a Specific Energy Consumption (SEC) value.

To overcome these limits, the approach discussed in the following lines was employed. Firstly, new full analytical formulations are here proposed; they have been modified in accordance with the formulation suggested by (Ingarao and Priarone, 2020) and visible in Eqs. (1) and (2) for AM and CM approaches, respectively. From now on, the formulations referred to as Model I represent the benchmark to evaluate the accuracy of simplified models on.

$$E^{AM} = \overbrace{(k^*m_P + m_A + m_S)^*\alpha^*(E_E + E_A)}^{E_{material+premanufacturing}} + \overbrace{(k^*m_P + m_A + m_S)^*SEC^{AM}}^{E_{deposition}} + \frac{3.6}{\eta}^*\overbrace{\left(P^{AM}_{stb}{}^*t^{AM}_{stb}\right)}^{E^{AM}_{idle}} + E_{gas} + E_{HIP} + E_{SEP} + E_{FM}; \tag{1}$$

$$E^{CM} = \overbrace{(m_P + m_C)^*\varepsilon^*(E_E + E_F)}^{E_{material+premanufacturing}} + \overbrace{\sum_{i=1}^{n}\overbrace{\left(SEC_i^{CM}{}^*m_{c_i}\right)}^{E_{cutting}} + \frac{3.6}{\eta}^*\left(\overbrace{\left(P^{CM}_{stb}{}^*t^{CM}_{stb}\right)}^{E^{CM}_{idle}} + \sum_{i=1}^{n}\overbrace{\left(P^{CM}_{stb}{}^*t_{tc}{}^*\frac{t_{c_i}}{T_i}\right)}^{E_{toolChange}}\right)}^{E_{machining}} + \sum_{i=1}^{n}\overbrace{\left(E_{tool_i}{}^*\frac{t_{c_i}}{T_i}\right)}^{E_{CuttingTool}} + \overbrace{E_{lub}{}^*q_l{}^*t_c}^{E_{CuttingFluid}} \tag{2}$$

In the AM energy formulation presented in Eq. (1), the E_{gas} factor was not included in the original formulation, as the considered AM process operated under vacuum. In this study, when considering Selective Laser Melting, gas consumption is included. E_{FM} is computed as the $E_{machining}$ detailed in Eq. (2) considering only finishing operations with a 1-mm thickness of allowance to be removed. In both formulations, energy contributions coming from productive and non-productive phases are taken into account, as the term E_{idle}, related to the stand-by state of the machine, is considered for AM and CM. For machining operations, roughing and finishing are differentiated to enable more accurate modeling. This differentiation is reflected in the term $E_{cutting}$ in Eq. (2), which aggregates the energy of each needed operation *i*, where *i* can represent roughing (*r*) or finishing (*f*). In contrast, this differentiation is missing in the simplified models, since a single-step machining operation is assumed. Additionally, in Model I, the impact of cutting tools and consumables – such as cutting fluid or inert gas – is included to provide a comprehensive baseline. All these elements were not included in the Model I used in the reference study, and it is important to emphasize that in none of the simplified models are present. On the other hand, there are factors – such as the embodied energy of the material, the mass of the part, the machining process scraps and the deposition energy – which are included in every model, as they significantly contribute to the energy consumption (Ingarao et al., 2024) and their influence cannot be neglected. The factor 3.6/ η is used to adjust electric energy demand values. This factor is essential when values (e.g., coming from literature) are electricity values provided in kWh and must be converted into primary energy (MJ) including the transmission losses. Energy values, indeed, were always traced back to the same level, that, in this study, is the primary energy. It is worth noting that the Model I, here used as benchmark, is a complete model allowing to include all the factors contributing to cumulative energy demand in component manufacturing flow (see Fig. 1). Such kind of model formulations are accepted by the scientific community when comparative analyses are presented, and the authors have already proved their effectiveness (Priarone and Ingarao, 2017; Ingarao and Priarone, 2020).

To provide a comprehensive view of the models employed in this study and their differences, Table 2 is built, including analytical formulations of each model used to quantify and compare AM and CM approaches, highlighting the factors that are included or excluded in each case. The logic behind the stepwise exclusion lays in the willingness to remove pieces of information that are equivalent in terms of information at the industrial level. Therefore, considering the generic process flow (Fig. 1), each process step is characterized by equivalent factors (energy or scrap type) that vary depending on the selected manufacturing approach. The aim is, therefore, to remove the same factors from both sides, i.e., the AM process (on the right) and the CM process (on the left). As shown in Table 2, there are certain factors that remain present in all models due to their significant influence. Specifically, it has been observed that the impact of machining is almost entirely determined by the process scrap produced (m_c) while for AM, the deposition energy is mandatory, as revealed in the breakdown analysis already developed by some of the authors (Priarone et al., 2017; Ingarao et al., 2018).

To address the other two limitations characterizing the previous study (Ingarao et al., 2024), the comparison was conducted on three metallic materials: titanium alloy Ti-6Al-4V, stainless steel 316L and aluminum alloy AlSi10Mg. These two latter were specifically selected due to their distinct characteristics compared to titanium. Stainless steel features a low embodied energy, which favors machining by minimizing material-related environmental impacts. In contrast, aluminum alloy is characterized by a high atomization energy, making the processing stage particularly significant in its environmental footprint. Additionally, they are relevant across different sectors such as: medical, with the use also of magnetic materials (Kaushik and Garg, 2024); aerospace and automotive, since applying lightweight construction principles has become today a top priority to meet regulatory pressures to comply with fuel efficiency and recycling standards (Tisza and Czinege, 2018).

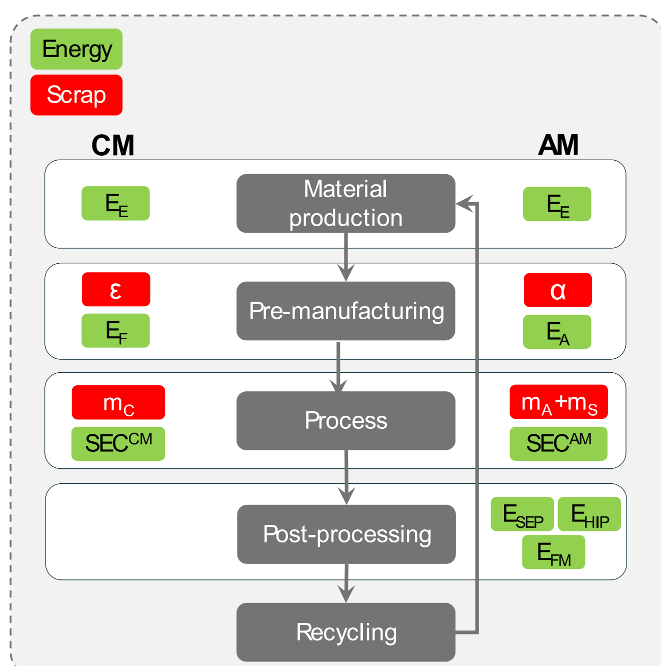

Fig. 1. Process flow with the main contributing factors (energy and scrap) for each stage of AM and CM approaches.

Table 2
Analytical formulation of the models with included factors (I = included; N.I. = not included).

MOD	Analytical formulation	Material production energy (E_E)	Pre-manufacturing scrap (ε and α)	Pre-manufacturing energy (E_E and E_A)	AM process scrap ($m_A + m_S$)	CM process scrap (m_c)	AM process energy (SEC^{AM})	CM process energy (SEC^{CM})	AM Finishing energy (E_{FM})	Part separation energy (E_{SEP})	Hipping energy (E_{HIP})
I:	$\mathbf{E^{AM}} = (k^*m_P + m_A + m_S)^*\alpha^*(E_E + E_A) + (k^*m_p + m_A + m_S)^*SEC^{AM} + \frac{3.6}{\eta}^*E_{idle}^{AM} + E_{gas} + E_{HIP} + E_{SEP} + E_{FM}$; $\mathbf{E^{CM}} = (m_P + m_c)^*\varepsilon^*(E_E + E_F) + \sum_{i=1}^{n} (SEC_i^{CM} * m_{c_i}) + \frac{3.6}{\eta}^*(E_{idle}^{CM} + E_{toolchange} + \sum_{i=1}^{n} E_{cuttingtool_i}) + E_{cuttingfluid}$;	I	I	I	I	I	I	I	I	I	I
II:	$\mathbf{E^{AM}} = (k^*m_P)^*(E_E) + (k^*m_P)^*SEC^{AM}$; $\mathbf{E^{CM}} = (m_P + m_c)^*(E_E)$;	I	N.I.	N.I.	N.I.	I	I	N.I.	N.I.	N.I.	N.I.
III:	$\mathbf{E^{AM}} = (k^*m_P + m_A + m_S)^*(E_E) + (k^*m_P + m_A + m_S)^*SEC^{AM}$; $\mathbf{E^{CM}} = (m_P + m_C)^*(E_E)$;	I	N.I.	N.I.	I	I	I	N.I.	N.I.	N.I.	N.I.
IV:	$\mathbf{E^{AM}} = (k^*m_P)^*\alpha^*(E_E + E_A) + (k^*m_P)^*SEC^{AM}$; $\mathbf{E^{CM}} = (m_P + m_C)^*\varepsilon^*(E_E + E_F)$;	I	I	I	N.I.	I	I	N.I.	N.I.	N.I.	N.I.
V:	$\mathbf{E^{AM}} = (k^*m_P + m_A + m_S)^*\alpha^*(E_E + E_A) + (k^*m_P + m_A + m_S)^*SEC^{AM}$; $\mathbf{E^{CM}} = (m_P + m_C)^*\varepsilon^*(E_E + E_F)$;	I	I	I	I	I	I	N.I.	N.I.	N.I.	N.I.
VI:	$\mathbf{E^{AM}} = (k^*m_P + m_A + m_S)^*\alpha^*(E_E + E_A) + (k^*m_p + m_A + m_S)^*SEC^{AM} + m_A{}^*SEC^{CM}$; $\mathbf{E^{CM}} = (m_P + m_C)^*\varepsilon^*(E_E + E_F) + m_C{}^*SEC^{CM}$;	I	I	I	I	I	I	I	I	N.I.	N.I.
VII:	$\mathbf{E^{AM}} = (k^*m_P + m_A + m_S)^*\alpha^*(E_E + E_A) + (k^*m_P + m_A + m_S)^*SEC^{AM} + m_A{}^*SEC^{CM} + E_{SEP}$; $\mathbf{E^{CM}} = (m_P + m_C)^*\varepsilon^*(E_E + E_F) + m_C{}^*SEC^{CM}$;	I	I	I	I	I	I	I	I	I	N.I.

The present research is focused on Powder Bed Fusion (PBF) additive processes compared to conventional machining processes. As indicated by market and literature trends (Pusateri et al., 2024), PBF has become one of the most widely adopted and investigated technologies, along with Direct Energy Deposition (DED) processes. Two distinct AM processes were analyzed based on energy source variations within PBF: Selective Laser Melting (SLM) for stainless steel and aluminum alloy, and Electron Beam Melting (EBM) for titanium. These two processes are considered among the most industrially relevant for metals applications (Herzog et al., 2016) and have gained increasing importance over the years, standing for more than 50 % of AM explored technologies in literature (Jemghili et al., 2021).

The comparative energy requirements for each model were evaluated by summing the energy contributions from each stage, and the models' performances were subsequently assessed using the Root Mean Square Error (RMSE) as a statistical measure of accuracy. To increase the robustness and generalizability of the findings, sensitivity analyses were performed.

2.1. Case study definition

The environmental impact of a single metal component was analyzed and used as basis for the manufacturing approaches comparison. The component to be manufactured is an axisymmetric rotational part (Fig. 2) inspired by Watson and Taminger (2018) and used also in Ingarao et al. (2024). To account for a wide range of shape complexity, energy models were applied by varying the part's inner radius (R_i) from 2 to 25 mm. The measure of complexity used is the Solid to Cavity Ratio (SCR), defined by Morrow et al. (2007) as the ratio of the mass of the final part to the theoretical mass that would be contained within the volume circumscribed by the part itself, therefore the lower its value the more complex the part is. It has already been proved that geometrical complexity is a factor of influence when comparing AM and CM. Especially, SCR has an inverse relationship with AM environmental performances (Ingarao et al., 2018). When geometrical complexity increases, AM results to be preferable in a sustainable choice perspective, thanks to the lower amount of scrap and therefore to the reduced material impact. As a matter of fact, SCR is a factor of influence in this study when the new DST is developed.

This case study is not intended to be restrictive; all quantities used in the analyses are expressed per kilogram of deposited mass. Such an assumption allows analyzing even a complete AM component redesign. Furthermore, in AM processes, energy consumption per layer is influenced by the cross-sectional melting area of the layer rather than by geometric complexity (Baumers et al., 2017). This supports the applicability of the proposed approach, as it focuses on fundamental process characteristics and not on specific design features.

2.2. System boundaries

A cradle-to-gate + End of Life (EoL) system boundary was adopted. The focus is therefore on material and production phases, even if it is acknowledged that incorporating the use phase within the system boundaries could expand the applicability domain of AM as energy-efficient choice. Recycling was selected as EoL scenario, and its benefits were included in the material energy with the substitution approach (as detailed in subsection 3.1). Boundaries range from raw material's extraction to its subsequent recycling. Impacts related to material production, pre-manufacturing, manufacturing, post-processing, and recycling were evaluated. Premanufacturing stage – related to the processes to turn ingots into necessary input –includes atomization for AM and hot extrusion for CM. With regard to the manufacturing stage, energies for processing (i.e., depositing for AM and cutting for CM) but also stand-by phases and tool changes were considered when full energy formulation was applied. All additively manufactured parts require a finishing process with a 1 mm allowance to make the surface smoother and ensure a

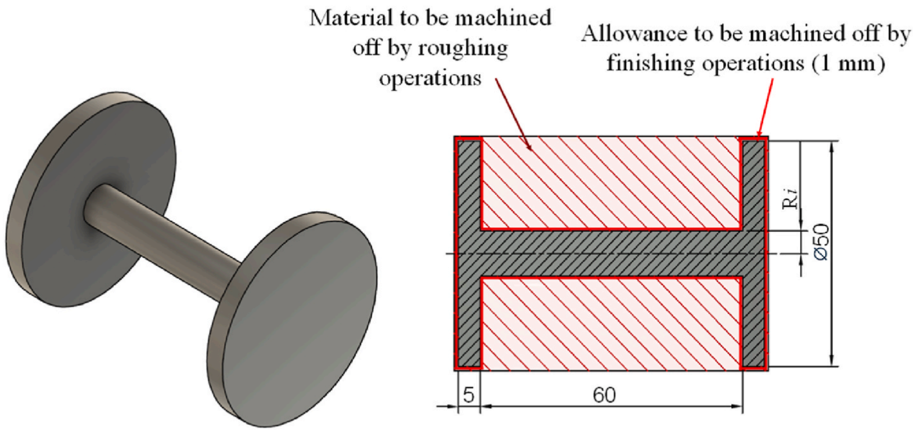

Fig. 2. Analyzed case study (measures in mm).

quality comparable to that of CM-manufactured parts. Additionally, separation of the part from the build plate and of supports (assumed to be 20 % of the mass of the part) was carried out on all AM parts through the Electrical Discharge Machine (EDM). A post-heat treatment (e.g., Hot Isostatic Pressing, HIP) was also applied for the titanium part, as further detailed below.

3. Life cycle inventory (LCI)

The main LCI data necessary for models' application are listed in Tables 3 and 4 for each material.

For the sake of clarity, in this section, variables necessary for the impact assessment are discussed at each life cycle stage. Only in sub-section 3.2 processes are discussed separately since different manufacturing processes differ in terms of resources and energy used due to different machines. It is worth remembering that, since the focus is on primary energy consumption, all the energy values must be traced back to the same level.

3.1. Material production and premanufacturing

In order to be useable for the manufacturing phase, materials must be first produced – so extracted from ores – and then pre-processed. Since recycling is chosen as EoL strategy, it is taken into account when calculating the material production energy. The so-called "substitution method" (Hammond et al., 2011) was applied and the embodied energy for material production is calculated according to Eq. (3). With this method, environmental credits for recycling are allocated to the EoL stage, considering the future recyclability (r) of the material.

$$E_E = E_V - \overbrace{r^*(E_V - E_R)}^{credits} \tag{3}$$

Where:

- E_V (MJ/kg): energy demand for the primary production of the material;
- r: end-of-life recyclability;
- E_R (MJ/kg): energy demand for the secondary production of the material.

Regarding the premanufacturing stage, it involves two possible routes: (*i*) atomization for the AM process, as the material input must be in powder form; (*ii*) hot extrusion for the CM process to create the initial workpiece. Both pre-processes are characterized by energy values, respectively E_A and E_F (listed in Table 3), and input/output factors, because of material losses, with values $\alpha = 1.05$ (Paris et al., 2016) and $\varepsilon = 1.12$ (Ingarao and Priarone, 2020).

Table 3
Materials Eco-properties inventory data.

Eco-properties	Titanium alloy (Ingarao and Priarone, 2020)	Stainless Steel (Priarone and Ingarao, 2017)	Aluminum alloy (Ingarao et al., 2020)
E_V (MJ/kg)	685	84.5	199
E_R (MJ/kg)	87	12	33.9
r	0.8	0.9	0.95
E_E (MJ/kg)	206.6	19.3	42.16
E_F (MJ/kg)	29.1	8.2	5.3
E_A (MJ/kg)	70	2.9	8.1

3.2. Manufacturing

In this section, LCI is performed under three processes: EBM, SLM and Machining. Using different materials implies the application of different machines, characterized by different electrical energy consumptions.

3.2.1. Electron Beam Melting (EBM)

When the titanium alloy component is considered, EBM is chosen as AM process, due to its prevalent use in processing titanium alloys. For this process, the ARCAM A1 machine (Baumers et al., 2017) is employed, with its operational parameters and specifications fully integrated into the model. The machine is assumed to work at full capacity, involving a stand-by phase to account for setup activities. Data used for the analysis are primarily sourced from (Ingarao and Priarone, 2020) and reference therein; all the used values are listed in Table 4. Although a minimal amount of helium (1 l/h) can be consumed during the process to maintain an inert environment ("near vacuum"), as reported by Baumers et al. (2017), the process is assumed to operate under vacuum, allowing the exclusion of E_{gas} factor from Model I. As a matter of fact, gas consumption in EBM is significantly lower than in Laser-PBF processes and therefore is negligible.

3.2.2. Selective Laser Melting (SLM)

Different from EBM, Selective Laser Melting needs the use of inert gases (generally Argon) to create a protective atmosphere in the process chamber and avoid metal oxidation during printing. The machine selected for this process is Renishaw AM250, which is reported to have an argon consumption of 208 l/build (Faludi et al., 2017) and, given that it does not require continuous flooding of argon during the build process, its impact is lower than that of SLM 280 machine, which is reported to consume a higher quantity of gas (Kellens et al., 2017b). Gas consumption indeed depends on the building chamber dimension, which in

Table 4
Manufacturing processes inventory data.

	Titanium alloy		Stainless Steel		Aluminum alloy	
AM machine	ARCAM A1		Renishaw AM250			
SEC^{AM} (MJ/kg)	176.8	Baumers et al. (2017)	244.1	Priarone and Ingarao (2017)	1385.3	Ingarao et al. (2018)
P^{AM}_{stb} (kW)	1.09	Baumers et al. (2017)	0.43	Kellens et al. (2017b)	0.43	Kellens et al. (2017b)
t^{AM}_{stb} (h/job)	0.3	Laureijs et al. (2017)	0.3	Laureijs et al. (2017)	0.3	Laureijs et al. (2017)
CM machine	Colchester Tornado A50					
P^{CM}_{stb} (kW)	1.75	Li and Kara (2011)	1.75	Li and Kara (2011)	1.75	Li and Kara (2011)
t^{CM}_{stb} (h)	0.17	Ingarao and Priarone (2020)	0.17	Ingarao and Priarone (2020)	0.17	Ingarao and Priarone (2020)
MRR_r (cm^3/s)	0.5	Ingarao and Priarone (2020)	0.4	Priarone et al. (2020)	1.5	Ingarao et al. (2018)
MRR_f (cm^3/s)	0.1	Ingarao and Priarone (2020)	0.05	Priarone et al. (2020)	0.15	Ingarao et al. (2018)
t_{tc} (h)	0.03	Ingarao and Priarone (2020)	0.03	Ingarao and Priarone (2020)	0.03	Ingarao and Priarone (2020)
T_r (h)	0.17	Ingarao and Priarone (2020)	0.5	Priarone et al. (2019)	0.17	Ingarao et al. (2016)
T_f (h)	0.5	Ingarao and Priarone (2020)	0.75	Priarone et al. (2019)	0.7	Ingarao et al. (2016)

Renishaw AM250 is smaller than SLM 280. It was possible to select this machine based on the available working volume, considering the dimensions of the part to be manufactured. The impact of gas (E_{gas}) was therefore assessed by multiplying the quantity of consumed argon by its cumulative energy demand (CED), which is reported to be 40.6 MJ/kg (Liao et al., 2023). The stand-by time is assumed to be the same used for titanium alloy, while the stand-by power, depending on the machine, is different, and it's indicated in Table 4.

3.2.3. Machining

Considering the geometrical shape of the selected case study, turning has been identified as the most appropriate CM process. In Model I, roughing and finishing phases are distinguished, corresponding into different Material Removal Rate (MRR). For the SEC calculation, the model proposed by Kara and Li (2011) has been used and is detailed as follows:

$$SEC_i^{CM} = C_0 + \frac{C_1}{MRR_i} \tag{4}$$

Where C_0 and C_1 are the machine specific coefficients, respectively set to 1.494 and 2.191, based on the Colchester Tornado A50 (Kara and Li, 2011) machine selected for turning operations across the three materials.

Since SEC varies according to the MRR of the material being processed, MRR values are specifically differentiated between roughing and finishing operations, as detailed in Table 4. It is worth remarking that this differentiation applies exclusively to the full model (Model I). In the simplified models, a single average SEC value, standing for a one-step machining process, was used. For consumables modeling, the same approach used for titanium alloy was applied for stainless steel and aluminum alloy. Across the three materials, standard carbide cutting inserts, with E_{tool} of 5.5 MJ/insert (Ingarao et al., 2016), were used. Inserts' tool life (T) varies depending on the material to be processed, as indicated in Table 4. Additionally, the consumption rate of cutting fluid q_l is set to 0.48 kg/h (Laureijs et al., 2017), with an embodied energy E_{lub} = 1.37 MJ/kg (Kellens et al., 2017b).

3.3. Postprocessing

Based on the functional requirements and the desired quality of the final part, AM processes may require one or more post-processing operations to achieve specified mechanical properties and surface quality, which often fall below those obtained through CM. Commonly employed post-processing steps include thermal treatment (e.g., Hot Isostatic Pressing – HIP) and finishing operations (machining, abrasive processes, shot peening, etc.) (Malakizadi et al., 2022).

In this research, AM post-processes included are:

(1) Removal of the part from the build plate and of support structures generated during printing: this step, typically inherent in PBF process, is performed using EDM with a specific energy consumption of 37 MJ/kg (Ingarao and Priarone, 2020).
(2) Hot Isostatic Pressing (HIP): used to reduce surface and subsurface defects, enhancing density and integrity (Malakizadi et al., 2022), with a specific energy consumption of 122 MJ/kg (Ingarao and Priarone, 2020). HIP was applied only to titanium alloy, due to lack of data for other materials.
(3) Finishing operations are often needed as feature resolution/the quality surface of the AM approaches might be poor, in this study machining was considered: a 1-mm thick allowance to be removed in order to achieve a smooth surface.

Additional post-processing techniques, including stress relief, that may also be applied, were here neglected, due to the usual lack of residual stresses on EBM components(Laureijs et al., 2017). This decision aligns with common practice where stress-relief treatments are more relevant for components with stringent mechanical property requirements, such as those used in the aeronautical industry, differently from those used in general industrial machinery (Gonçalves et al., 2023). Furthermore, from the literature review on comparative studies, it turned out that, in most of the cases, only finishing operations are considered, with HIP included only occasionally.

4. Model simplification and sensitivity analysis results

The results of comparative analyses conducted under the seven models are presented and analyzed in this section. They are discussed considering two different light-weighting scenarios: (1) AM- and CM-manufactured components are identical, thus k, the weight reduction factor, is equal to 1 (section 4.1); (2) the AM-manufactured component achieves a weight reduction due to its redesign, so k < 1 (section 4.2).

Before presenting the results, it is important to highlight that, for titanium alloy, a first evaluation indicated that the impact of HIP could not be disregarded. The error performance of the simplified models was significantly high, as only Model I included the E_{HIP}. Consequently, it was decided to incorporate the E_{HIP} value into the SEC of the EBM process, as it is multiplied by the same quantity (specifically, the mass of the powder to be deposited). Therefore, SEC^{EBM} was increased by 122 MJ/kg, reaching a value of 298.8 MJ/kg.

4.1. Scenario $k = 1$

When topology optimization is neglected, the k value is always equal to 1; consequently, SCR remains the only factor of influence for the outcomes. A graphical representation appears showing the Delta Energy (ΔE), calculated as $E^{AM} - E^{CM}$, by varying the SCR value. When $\Delta E = 0$, meaning that the AM approach equals the CM one, a Break-Even Point (BEP) is identified, and it represents the level of complexity at which the two approaches demand the same amount of primary energy. This is precisely the DST for the 1st scenario (Ingarao et al., 2020), indeed, for SCR exceeding the BEP, CM approach proves to be the most energy-efficient option (since $\Delta E > 0$), otherwise AM becomes the optimal choice. From Fig. 3 it can be seen that a curve for each model is achieved, and the three materials have different applicability domains for AM processes. Titanium alloy is the only material with real BEP, while for stainless steel and aluminum alloy BEP are not present. This is mainly due to the combination of SEC^{AM}-E_E values for the materials considered. For stainless steel and aluminum alloy, E_E is significantly lower than SEC^{AM}, indicating that the environmental impact of machining chips is limited, thus favoring CM as the preferred option. In contrast, titanium alloy exhibits a greater impact on primary material production, making AM more advantageous.

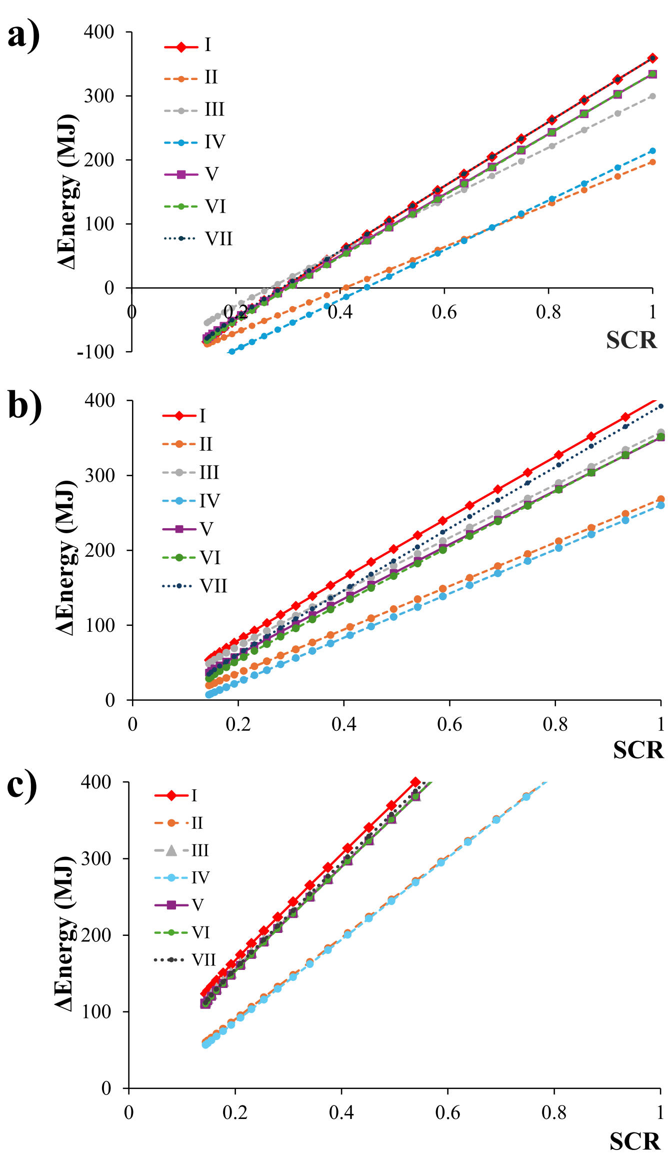

Fig. 3. Models result for Scenario 1 (when AM and CM parts are identical) for a) titanium alloy, b) stainless steel, c) aluminum alloy.

A quantification of the accuracy provided by the different models considering different materials is reported in Table 5 through the RMSE, which measures the average difference between a statistical model's predicted values and the actual values. This results in a measure of the distance of the curve of the simplified models from the benchmark (Model I) curve. When high RMSE values are observed, models exhibit poor performance. Therefore, it is evident that models II and IV are always the worst performers. Model II, the simplest configuration, accounts solely for the embodied energy for material production, the deposition energy, and the mass of chips. Model IV, on the other hand, deviates even more: in estimating the energy required for AM it considers only the mass of the final part, excluding the mass of the allowance and supports. This omission highlights the crucial role of these additional masses in determining the total energy consumption.

Model VII is the closest to Model I and is the best performer across all three materials: for titanium, it achieves a notably low RMSE, as it differs from Model I only by excluding E_{FM}, while considering stainless steel and aluminum alloy, Model I involves also E_{GAS} (associated to SLM process), which explains the increased RMSE observed in Model VII for these materials. The remaining models show good performance, especially Model III, when stainless steel and aluminum alloy are considered, outperforms, indicating that it can be used if a low computational effort is required.

4.2. Scenario $k < 1$

When the weight reduction obtainable by topology optimization enabled by AM process is included, results of comparative analyses depend also on k*, which is the critical weight reduction that makes AM equal to CM from the energy perspective. In this case, DSTs are represented by two-dimensional plots where curves show the trend of k* as a function of SCR. These curves define a region: specifically, if a given combination of k and SCR falls below the curve, the AM process proves to be more energy-efficient and is therefore to be preferred. An example, relative to Stainless steel, is provided in Fig. 4. Also in this case, RMSE values reflect the level of accuracy of simplified models and are presented in Table 6. It is worth noting that, since the DST for this scenario is based on k and SCR values, the RMSE differs from what reported in Table 4 for scenario 1, as it is in terms of SCR.

Values are significantly lower than those achieved with k = 1, but they are in line with them. Indeed, Model II and IV are still the worst performers, while the other models have good performances and the differences between RMSEs are minimal.

The results achieved in both scenarios confirmed what was already assessed in the research representing the starting point of this study: simplified models work properly, even changing material. In particular, it can be assessed that Models III and V, among the proposed simplified models, still deliver satisfactory results if the benchmark is a more

Table 5
Error performance indicator for Scenario 1 with varying material.

	RMSE (MJ)		
MOD	Titanium alloy	Stainless Steel	Aluminum alloy
I	/	/	/
II	81.2	76.67	119.70
III	27.5	21.35	16.61
IV	85.4	86.22	121.62
V	11.6	29.28	17.85
VI	12.1	32.76	18.14
VII	2.3	13.64	11.60

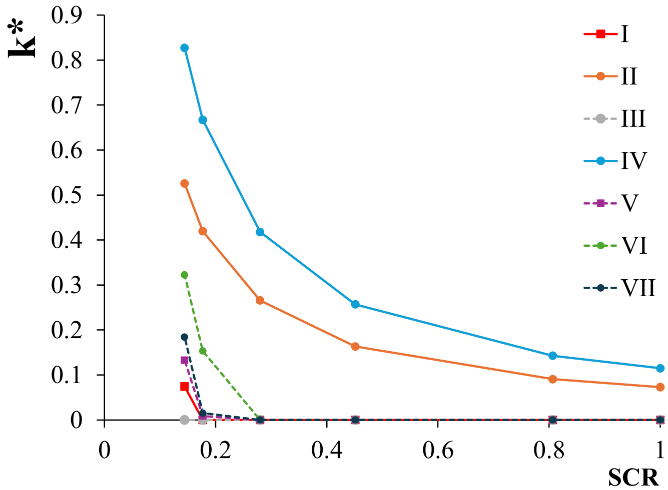

Fig. 4. Models result for Scenario 2 (when mass reduction is allowed for AM parts) for stainless steel.

Table 6
Error performance measure for Scenario 2 with varying material.

MOD	RMSE (SCR) Titanium alloy	Stainless Steel	Aluminum alloy
I	/	/	/
II	0.25	0.27	0.12
III	0.07	0.04	0.06
IV	0.29	0.40	0.16
V	0.05	0.03	0.06
VI	0.06	0.08	0.06
VII	0.05	0.06	0.07

accurate one, representing therefore a good compromise between accuracy and computational effort.

4.3. Sensitivity analysis

Sustainability, compared to other well-established characterizations of metallic materials, such as thermal and mechanical properties, remains a less standardized and still relatively unexplored field. This has led to significant variability in literature, particularly in terms of environmental metrics, where the same material, or the same process, can exhibit a wide range of reported values (Ashby, 2021). To address this, a sensitivity analysis was performed by varying two key metrics: Atomization energy and SEC. These two factors were specifically chosen because they exhibit high variability, with widely differing values reported in literature. Additionally, they are particularly important as they significantly influence the overall energy consumption and environmental footprint of the additive production processes.

The goal was to verify that the conclusions drawn would have been still valid with different input values. To isolate the impact of each parameter variation, all other variables were kept constant at their initial values. Additionally, models incorporating titanium alloy have been reconsidered, to account for the range of energy values associated with Ti6Al4V, as it is one of the most commonly used metals in AM processes.

4.3.1. Atomization energy variation

In the initial analysis, a value of 70 MJ(Gao et al., 2021; Jemghili et al., 2021) was used. Thus, to assess the sensitivity of the models to atomization energy variation, it was deemed appropriate to choose a higher and a lower value than the reference. Specifically, 23.76 MJ (Paris et al., 2016; Priarone and Ingarao, 2017) and 93.24 MJ (Watson and Taminger, 2018)were selected. Among the values collected from literature, the lowest one, being 7.02 MJ (Le and Paris, 2018), was seen as an outlier due to its small magnitude compared to the other collected values. Scenarios' results are now presented (Table 7) with varying the atomization energy values in each column and confirm that simplification remains effective. When considering scenario 1 ($k = 1$) Models V, VI and VII are characterized by the same RMSE values across the variation of E_A, as it does not affect comparative results in terms of ΔEnergy. In the scenario 2, model III shows even better performances, as the differences in RMSEs values across the models are minimal.

4.3.2. SEC variation

The SEC-related literature highlights the importance of this metric in assessing the environmental impact of manufacturing processes. SEC is recognized as an energy Key Performance Indicator (e-KPI), and for its relevance the energy consumption characteristics of various additive systems have been the subject of several publications, since AM processes differ in several aspects such as operating principles and energy use (Baumers et al., 2011). EBM process for Ti alloys has been documented to have a specific energy consumption in the range 85–508 MJ/kg (Lunetto et al., 2021). Therefore, to evaluate model performance by varying SEC values, data from the literature already collected in (Kokare et al., 2023b) were taken into account and, since the reference value was 176.8 MJ/kg, models were applied with a higher and a lower SEC value, specifically with 400.25 MJ/kg (Paris et al., 2016) and 59.96 MJ/kg (Priarone et al., 2017) with the goal of understanding if model III and V continue to show optimal performance under different SEC conditions. Outcomes of these analyses are presented in Table 8, showing RMSEs related to SEC variation.

These further analyses proved the robustness of the results, confirming that simplified models can be used to identify the most energy efficient approach when additive and subtractive approaches are compared. The results proved the simplified model to be reliable also dealing with the great variability characterizing energy related input data. Specifically, although Model III provided a curve that deviated more (under the 1st scenario with $k = 1$) than those provided by models V, VI and VII, the prediction could still be used, especially if a limited computational effort is considered or some of the inventory data are missing.

5. New decision support tool development

Model III is here selected as the basis for developing the new DST. While models such as VI and VII offer higher accuracy, they require significantly more input data and computational effort, which limits their feasibility for real-time decision-making. Model III, on the other hand, relies only on the involved mass, the primary energy of the material and the energy for deposition, meaning that, with a limited amount of data, it is possible to have a good estimate of the best manufacturing route when comparative analyses are conducted. This choice aims to balance computational effort and output reliability, since

Table 7
Error performance measure for scenarios 1 and 2 with varying the atomization energy.

MOD	RMSE (MJ) for Scenario 1 E_A = 70 MJ/kg	E_A = 23.76 MJ/kg	E_A = 93.24 MJ/kg	RMSE (SCR) for Scenario 2 E_A = 70 MJ/kg	E_A = 23.76 MJ/kg	E_A = 93.24 MJ/kg
I	/	/	/	/	/	/
II	81.2	58.9	92.5	0.25	0.21	0.27
III	27.5	23.1	35.5	0.07	0.10	0.05
IV	85.4	79.2	88.5	0.29	0.28	0.29
V	11.6	11.6	11.6	0.05	0.06	0.05
VI	12.1	12.1	12.1	0.05	0.06	0.05
VII	2.3	2.3	2.3	0.05	0.06	0.05

Table 8
Error performance measure for scenarios 1 and 2 with varying SEC.

	RMSE (MJ) for Scenario 1			RMSE (SCR) for Scenario 2		
MOD	SEC = 176.8 MJ/kg	SEC = 59.96 MJ/kg	SEC = 400.25 MJ/kg	SEC = 176.8 MJ/kg	SEC = 59.96 MJ/kg	SEC = 400.25 MJ/kg
I	/	/	/	/	/	/
II	81.2	67.3	108.8	0.25	0.24	0.29
III	27.5	27.5	27.5	0.06	0.06	0.08
IV	85.4	70.7	113.9	0.29	0.26	0.34
V	11.6	11.6	11.6	0.05	0.07	0.03
VI	12.1	12.1	12.1	0.05	0.07	0.03
VII	2.3	2.3	2.3	0.05	0.07	0.03

the tool is meant to be used in industrial environment, and gathering comprehensive data for environmental impact assessments can be both costly and time-consuming. This highlights the need for DSTs that simplify decision-making processes for manufacturers. In order to further simplify the model, the mathematical formulation presented in section 5.1 was developed.

5.1. Mathematical formulation

Starting from the analytical energies' formulation of Model III, an inequality was set up. Specifically, the condition $E^{AM} \geq E^{CM}$ was imposed, leading to the formulation of Eq. (5).

$$(k^* m_P + m_A + m_S)^* (E_E + SEC^{AM}) \geq (m_P + m_C)^* (E_E) \tag{5}$$

To make the energy terms independent of the part mass, both sides were divided by m_p

$$\left(k + \frac{m_A}{m_P} + \frac{m_S}{m_P}\right)^* (E_E + SEC^{AM}) \geq \left(1 + \frac{m_C}{m_P}\right)^* (E_E) \tag{6}$$

The ratios m_A/m_p and m_A/m_S are assumed to be constant and denoted τ and μ, respectively, based on the already known predetermined geometry of the AM-manufactured part. Consequently, all the masses can be determined: (*i*) the mass of the final part (m_p) is known; (*ii*) the mass of the allowance (m_A) can be calculated based on the part surface; (*iii*) the mass of the supports, (m_s) can be calculated through dedicated software programs. Even the factor m_C/m_p is reformulated performing some algebraic manipulations to relate it to known quantities. Specifically, recalling that $R = \frac{m_P}{m_c + m_P}$, it is found that $\frac{m_C}{m_P} = \frac{1}{SCR} - 1$.

Thus, Eq. (6) is rewritten in the following way:

$$(k + \tau + \mu)^* (E_E + SEC^{AM}) \geq \left(1 + \frac{1}{SCR} - 1\right)^* E_E \tag{7}$$

Further simplification by dividing both sides by E_E yields:

$$(k + \tau + \mu)^* \left(1 + \frac{SEC^{AM}}{E_E}\right) \geq \left(\frac{1}{SCR}\right) \tag{8}$$

Therefore, thanks to the formulation performed in Eqs. (7) and (8), the final expression is:

$$\frac{SEC}{E_E} \geq \frac{1}{SCR(k + \tau + \mu)} - 1 \tag{9}$$

Eq. (9) represents a straight line passing through the origin of the form $y{=}mx$.

A Decision-Support Tool (DST) can thus be developed, where SEC is plotted on the y-axis and E_E on the x-axis. The resulting line delineates two distinct regions: above the line, CM processes are more energy-efficient (CM domain), whereas below it, AM processes demonstrate better energy performance (AM domain). It is worth noting that for a given geometry to be manufactured, the only values to be collected are the SEC and the E_E ones, the other involved factors (k, τ, μ, SCR) are project data and are known as the AM process is set up. Actually, these data projects determine the slope (m) of the straight line. The workflow of the proposed DST tool is shown in Fig. 5.

The obtained result is consistent with the main findings presented by some of the authors concerning energy breakdown analysis of additive and subtractive processes (Priarone et al., 2017; Ingarao et al., 2018). To be more specific, in those studies it emerged that most of the impact of machining-based products is caused by the amount of the material used, whereas for additive approach the main contributor is the deposition phase, with material impact still having a relevant role. These results were observed by the authors for both the case of titanium (Priarone et al., 2017) and aluminum alloys (Ingarao et al., 2018). Therefore, the formulation here presented correctly based its decision on two factors of extreme relevance for the energy demand characterization of AM and CM approaches.

5.2. Application of the designed DST on two different component shape complexity

For implementing the tool, two different shape complexities of the case reported in Fig. 2 were selected. The chosen case study reported in Fig. 1 allowed different complexity to be analyzed by varying the inner radius (R_i) value. In order to test the developed tool on two specific geometries, two different inner radii (resulting in two different SCR values) were selected as reported in Fig. 6. The parts were modeled in a dedicated software that allowed to gain useful data for the calculation of the mass of the supports. Additionally, for each geometry, three weight reduction scenarios were applied: (*i*) k = 1; (*ii*) k = 0.6, meaning that a weight reduction of 40 % is enabled by AM; (*iii*) k = 0.3, with a weight reduction of about 70 %.

For each geometry, a graph with the three different k values is reported in Fig. 7. Each straight line (representing a threshold where the energy consumption of AM equals that of CM) indicates the boundary between the AM and CM domains. The region below each line represents the 'AM domain' where AM is more energy efficient, while the region above each line represents the 'CM domain' indicating the conditions where CM outperforms AM. It is worth highlighting that the weight reduction factor k affects the tools significantly. Indeed, the higher the weight reduction allowed by AM process (so the lower is k), the more energy efficient is the AM process, leading to an enlargement of its domain area. Additionally, this type of DST highlights how decreasing geometry complexity reduces the advantages of AM, making CM techniques more advantageous in different scenarios. This trend is evident in the case of geometry ID2, where the AM domain (for a given k value) is significantly reduced compared to the DST for geometry ID1.

The tool might be used also from another angle, for instance, it could be used for identifying the minimum weight reduction value (k) making AM more energy efficient, for a given couple of E_E and SEC values. In other words, it could be used as tool supporting the topology optimization of the part to be produced via AM.

These findings are consistent with the existing literature. For instance, considering that geometry ID1 has a larger AM domain area than geometry ID2, Paris et al. (2016) have concluded that, from an environmental point of view, the choice between conventional milling or EBM depends on both the geometry complexity and the related volume of removed material. Increasing geometric complexity can indeed shift the preference towards AM after a certain break-even point, as highlighted by Ingarao et al. (2020).

5.3. Application of DST as a means for mapping the energy efficiency of several AM processes

The developed DST provides a useful framework to understand under which conditions AM is preferred over CM just using few data. The strength of the tool lies in the fact that the straight line, delineating the two domain areas, once known the geometry to be manufactured,

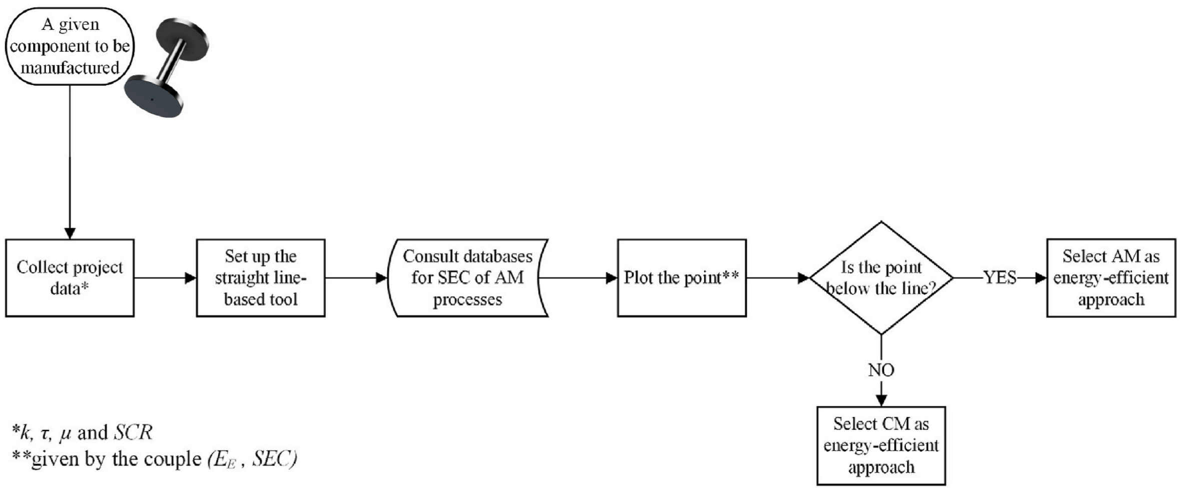

Fig. 5. Workflow diagram for the application of the Decision Support Tool.

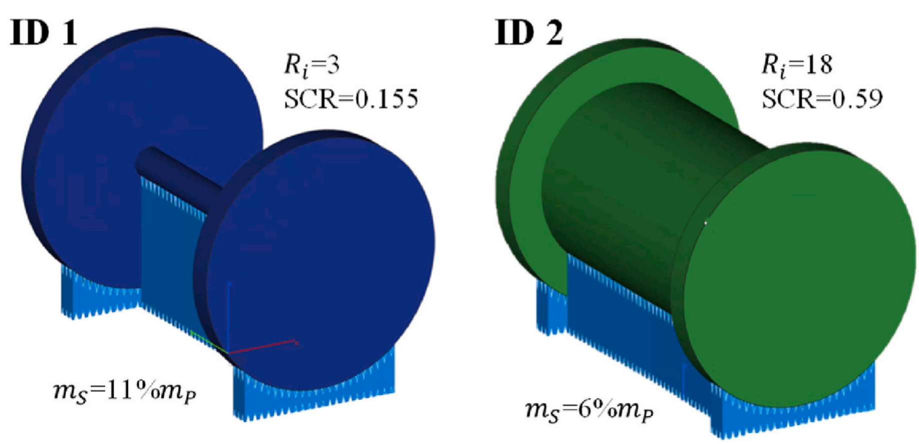

Fig. 6. Geometries ID1 and ID1 used for DST implementation (with indicated the mass of the supports (m_s) and the Solid-to-cavity ratio (SCR)).

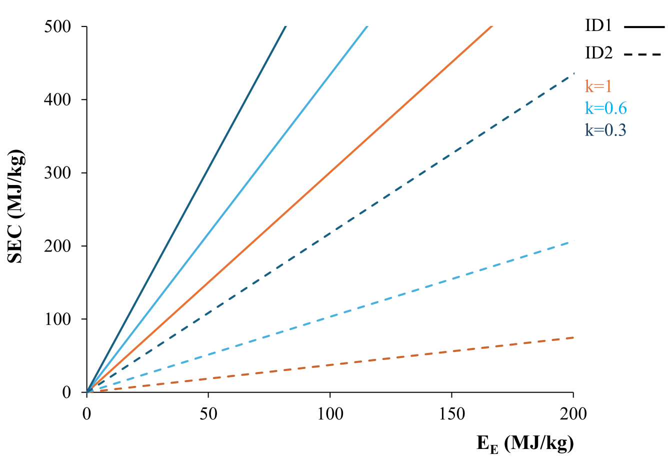

Fig. 7. DSTs obtained with geometries ID1 and ID2 for three different weight reduction factors (k = 1, 0.6 and 0.3).

remains constant. Therefore, it is possible to plot points considering just one material but involving a wide range of AM processes (or machines), building a framework suggesting which could be the most energy efficient additive process for the same material or, in turn, involving a range of materials and just 1 a.m. process. In this respect, a database was developed by collecting SEC values (listed in Table 9) of PBF processes from literature for different metals, the E_E energy values were sourced from technical data sheets (Granta Design Limited, 2023).

The outcome is a single framework in which different materials (grouped in material families) and different PBF processes are plotted simultaneously (Fig. 8). It can be observed that steels are concentrated on the left side of the graph due to their relatively low E_E values. In contrast, titanium, which has a high energy value for primary production and consequently a high E_E, is positioned on the right side. This distribution highlights that AM tends to be more energy-efficient for titanium alloys, whereas CM demonstrates broader applicability for steel and aluminum alloys. This framework underscores the versatility and practicality of the tool, providing insights into the most energy-efficient manufacturing approach for specific component production. Furthermore, it enables the selection of the most suitable material for an additive manufacturing process when multiple options are available, guiding decision-making toward enhanced energy efficiency.

6. DST validation

A validation step was conducted using case studies from literature to demonstrate the effectiveness of the tool here developed. This approach highlights the tool's potential in responding to established conditions and scenarios. Two case studies were selected from previous research focused on comparative analyses between AM and CM. The main criterion guiding the choice was data availability, as the tool requires detailed project data. Specifically, both AM and CM part masses, along

Table 9
Collected SEC values for database development.

Material	AM process	SEC (MJ/Kg)	Source
Stainless Steel 316L	SLM	83–106	Baumers et al. (2011)
		244.1	Priarone and Ingarao (2017)
		383.13	Guarino et al. (2020)
		55.71–67.88	Peng et al. (2020)
		519–588	Baumers et al. (2011)
		80.32	Kellens et al. (2011)
		365.01	Yang et al. (2019)
Stainless Steel 17-4 PH	DMLS	241–339	Baumers et al. (2011)
		154–285	Baumers et al. (2013)
AlSi10Mg	SLM	566	Priarone et al. (2018b)
		568.5	Faludi et al. (2017)
		309.1–533	Kellens et al. (2017b)
Iron	SLM	178.56	Nagarajan and Haapala (2018)
Stellite	LENS	125	Liu et al. (2016)
Nistelle 625	LENS	1051	Wilson et al. (2014)
Inconel 718	LENS	158.5	Liu et al. (2016)
	SLM	427.47	Torres-Carrillo et al. (2020)
Ti-6Al-4V	EBM	400.25	Paris et al. (2016)
		45.12	Le and Paris (2018)
		176.35	Lyons et al. (2021)
		60	Baumers et al. (2017)
		399.49	Le and Paris (2018)
		59.96	Priarone et al. (2017)
		61	Baumers et al. (2011)
		176.8	Ingarao and Priarone (2020)
		177	Baumers et al. (2011)
		507.6	Lunetto et al. (2021)

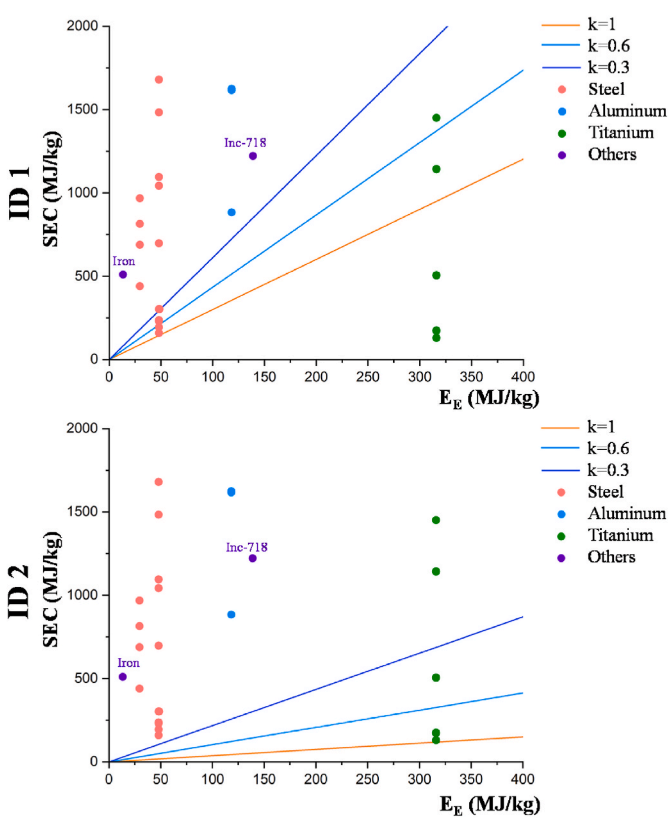

Fig. 8. DST output for the database presented in Table 9 for ID1 and ID2 for three different weight reduction factors (k = 1, 0.6 and 0.3).

with support and allowance masses, must be provided. Additionally, to plot the operational point accurately, the study requires material information with its eco-properties and the SEC of the additive manufacturing process.

The first case selected was released by Priarone et al. (2018a), and analyzes a Ti6Al4V lifting bracket for a jet aircraft engine. AM emerged as the best solution, even neglecting the use phase, primarily due to the significant material waste impact associated with CM. Data collected in this case are as follows: $m_p^{AM} = 0.34$; $m_p^{CM} = 2.04$; $m_A = 0.034$; $m_S = 0.068$. The resulting SCR of the part is 0.39, thus the geometry is less complex than the previous case, while the factor k = 0.17 indicates a higher percentage of weight reduction. The straight line derived from these parameters exhibits a higher slope, enlarging the AM domain. The operational point, given by the couple $(E_E;\ SEC) = (206.8;\ 176)$, lies in this case below the line, being consistent with the findings reported by the authors.

The other case study, also conducted by Priarone et al. (2018b), involves an airplane bearing bracket made in AlSi10Mg with a Laser-PBF process compared to a traditional machining one. For AM production, three different building orientations were considered, resulting in three scenarios for supports' mass. The following masses values (in kg) were collected: $m_p^{AM} = 0.105$; $m_p^{CM} = 0.279$; $m_A = 0.011$; m_S with values of $(i)0.248$; $(ii)0.032$; $(iii)0.047$ for each orientation scenario. The geometry has a resulting SCR equal to 0.247. The use of AM allows for topology optimization, resulting in a weight reduction factor k = 0.37. Ratios m_A/m_P and m_S/m_P were calculated and generated three distinct lines, one for each scenario. Among these, scenario 1 (with the highest supports' mass) produced the lowest line, indicating a higher environmental impact for the AM process and thus a larger CM domain. When plotting the operational points, E_E values were calculated using both the substitution and the recycled content approach, yielding 40.15 MJ/kg and 118.67 MJ/kg, respectively. SEC was reported to be 1664.7 MJ/kg (566 MJ/kg value was traced back to primary energy through η). Both points lie consistently above the lines, within the CM domain. This outcome confirms what was reported in that paper: without accounting for the use phase, CM is to be preferred over AM when AlSi10Mg is used as building material for the considered geometries.

It is worth remarking that all the input data required for the validation of each case study, were taken from the cited papers, Priarone et al. (2018a, 2018b), respectively. This choice was driven by the will to compare different comparative methods with the same input data source.

The successful validation of real case studies confirms the tool's ability to deliver reliable and accurate results for process selection in manufacturing. This comparative approach has strengthened the reliability of the tool, demonstrating that it is able to address case studies with performance comparable to those already validated in literature through the use of complex and all-inclusive formulations.

7. Conclusions and further developments

The present paper provides a new parametric Decision Support Tool, representing the first example in literature adopting a holistic and comprehensive approach to sustainable process selection, grounded in simplified energy characterization models. The study started from the robustness' verification of existing simplified models, by refining the benchmark to achieve a more precise modeling of energy requirements for both additive and subtractive processes. Through extensive analyses, it was proved that simplified models can reliably guide energy-efficient manufacturing choices with an acceptable level of accuracy under different materials (aluminum alloys, steel and titanium alloys) and scenarios (i.e., by varying SEC or atomization energy).

The models' simplification analysis led to a first significant finding: specifically, Model III provided good performance in the comparative analyses' outcome. As a consequence, it is possible to design a DST starting from Model III, which includes just the involved mass, the embodied energy of the involved material and the energy for deposition. Specifically, if compared to the benchmarking used in this study, Model

III requires 60 % less input factors than Model I.

DST was developed with the aim of comprehensively mapping AM sustainability performances and assessing their energy efficiency over subtractive approaches. The DST is based on a simple straight line passing through the origin in the E_E-SEC domain. The slope depends only on project data, known as the AM process is set up: mass of the supports, mass of the allowance to be removed by finishing operations, weight reduction factor (k) and part complexity (SCR). The straight line represents the boundary between the AM and CM domains. The region below the line represents the 'AM domain' where AM is more energy efficient, while the region above each line represents the 'CM domain' indicating the conditions where CM outperforms AM.

The strength of the tool lies in its reliance on few data and its adaptability to the component to be manufactured, making it generalizable. Because of these properties, the DST has been used for mapping the energy efficiency performance of different metal powder bed AM approaches. Actually, a database was built and, for a given geometry, the operational points of all the identified couple of SEC and E_E were plotted. Such plotting allows visualizing the positioning of each identified AM approach (coupled with a given material) simultaneously, thus easing comparative considerations concerning the energy efficiency of the analyzed processes. A further validation step was carried out to enhance the robustness and relevance of research findings, which align with existing literature data. It should be stressed that this approach, based on simplified models, holds only if comparative analyses are carried out; applying a simplified model to estimate the energy consumption of one single process may lead to an underestimation of its actual impact.

Despite the advantages of the DST, some limitations must be acknowledged. One of the main challenges in its practical implementation in real industry settings might be data accessibility. Nevertheless, materials' data are accessible through databases such as CES EduPack or Ecoinvent, while for the SEC, as it depends on the specific machine and its settings, energy characterization at the company level is required. Build failure rates were not accounted for in the present study, despite their potential negative impact on the overall environmental performance of AM processes. Lastly, considering the methodological choice at the basis of this study, a statistical sensitivity analysis could further refine the development of models' simplification, offering a different perspective.

Future developments of this research may include different pathways. One could involve extending its application to direct energy deposition (DED) processes, as only PBF processes have been considered in this study. Results might be affected by the impact of finishing operations or gas flushing, which are higher in DED approaches. Nonetheless, it is worth noting that DED processes generally do not allow for weight reduction (thus, $k = 1$) and are designed for different applications from those of PBF processes. Another potential direction could be the implementation of the tool for polymer materials, expanding its applicability beyond just metals. This extension would require efforts to modify energy models due to fundamental differences in polymer manufacturing processes and material eco-properties. Dealing with polymers means indeed changing, for instance, the conventional manufacturing approach that is typically a mass-conserving one (injection molding is the most applied process). Also, both the SEC of AM processes (Fused deposition Modeling, sintering, etc.) and material embodied energies are characterized by lower values as compared to the metals case. Finally, the tool could be adapted for comparative analyses between AM and CM using cost models. For instance, starting from comprehensive cost models already available in literature (e.g., models proposed by Ingarao et al. (2020) or by Raoufi et al. (2022)), the methodology developed in this study could be applied to include cost models' simplification and build a similar DST.

CRediT authorship contribution statement

Maria Gloria Trapani: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rosa Di Lorenzo:** Writing – review & editing, Supervision, Conceptualization. **Livan Fratini:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Giuseppe Ingarao:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

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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Data availability

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

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