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Research article

Machine learning algorithm functional on environmental sustainability assessment in turbomachinery sector: Application on centrifugal compressors

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ABSTRACT

The current government directives have focused industries' attention on environmental sustainability issues in products and processes. There is indeed a growing demand from customers to conduct environmental impact assessments of the products they purchase. This work presents the implementation of a predictive model developed in an industrial context to evaluate the environmental sustainability of a centrifugal compressor rotor assembly. The development of the predictive model arises from the objective of overcoming the limitations of the traditional Life Cycle Assessment approach, which is based on a retrospective evaluation of the product life cycle. The functionality of predictive models is to estimate product environmental sustainability to meet customer demands and guide them toward choices that aim for carbon neutrality. The implementation of the model has been conducted in parallel with a tailored measurement campaign of the primary inventory flows involved in various manufacturing operations. The article details the methodological approach that led to the development of the predictive models and their respective functionality in supporting the design engineer in evaluating the eco-profile of the assembly. In addition to the methodological aspect, the work also includes a case study through which the functionality of the models can be illustrated.

1. Introduction

The importance of evaluating the carbon footprint of products and processes is progressively increasing due to the growing concerns about the recent climate change observed [1]. For this reason, the dissemination of greenhouse gas emissions data is becoming a qualifier for companies from a commercial perspective [2]. The literature recognizes Life Cycle Assessment (LCA) methodology as a consolidated approach for conducting product sustainability assessments [3]. Among the impact phases of a product's life cycle, manufacturing is not negligible [4], as it is related to natural resource extraction, energy consumption, and waste generation. This phase is widely analyzed in the literature from the perspective of optimizing consumption [5,6]. This paper investigates aspects of environmental sustainability in the manufacturing phase of components used in the turbomachinery field. The scientific literature provides several articles on this subject. Musacchio et al. [7] conducted an LCA study on producing a gas turbine module using three technological alternatives. The study highlights which sub-processes in the cycle have the most significant impact in terms of

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environmental contributions.

Musacchio et al. also [8] conducted a cradle-to-gate study (using the Ecoinvent database) to identify a gas turbine's most environmentally impactful components with a power range between 5 and 25 MW. The results showed that the casing enclosing the machine was one of the main drivers of environmental impact due to the high material demand for its manufacturing. In their work, Frank Walachowicz et al. [9] conducted a comparative LCA study to evaluate manufacturing techniques for repairing gas turbine burners used in Siemens production. The study demonstrates that the adoption of additive techniques for burner repair allows for a reduction in carbon footprint compared to the combined technique of conventional manufacturing and welding. Angela Serra [10] et al. conducted a comparative study on two processes carried out by Nuovo Pignone to produce a gas turbine shroud. The study compares two production alternatives: one using additive manufacturing with powder technology and the other using traditional investment casting. The authors have demonstrated that additive technology allows for a saving of about 40 % in greenhouse gas emissions. The results of the studies discussed above are suitable both for the characterization of production technologies and for obtaining absolute results that can be used in the market to integrate the commercial offer to the customer with the evaluation of carbon footprint. This is made possible by standardizing the items analyzed, allowing for the reuse of obtained results. The study of centrifugal compressors, on the other hand, faces the problem of the absence of standardization of components [11], as the machine under investigation strongly depends on the boundary conditions under which it operates. The literature presents some studies delving into the machine. In the work of Peng et al. [12], a study on a PCL803 compressor produced by Shenyang Blowe Group CO is detailed. The authors have demonstrated that producing the impeller through milling is environmentally advantageous compared to the welding solution of the disk and counter-disk. Zanghelini et al. [13] investigated the environmental assessment of three different end-of-life scenarios for a reciprocating compressor. The three scenarios are evaluated regarding Global Warming Potential, Abiotic Resource Depletion, Cumulative Energy Demand, and Land Occupation, with primary inventory data collected from the compressor OEM. The analysis provides a quantitative result on the savings that achievable by extending the product's life through remanufacturing operations.

The cited works present a retrospective life cycle assessment (LCA) aimed at studying technological solutions and their environmental impact but require an inventory implementation with parallel data collection during the machine's realization. Inventory construction is time-consuming and data-intensive, so a stand-alone methodology limits the approach [14]. Adopting predictive models can solve these problems, allowing for the prior estimation of environmental impact [15] by estimating the inventory of a product from its concept design. Machine learning techniques can develop predictive models such as regression models [16,17,18], neural network-based models, and genetic algorithms [19,20,21]. These models are already widely used to evaluate sustainability metrics in the chemical sector [22]. Paraskevi Karka et al. [23] have proposed an impact assessment approach for various categories, such as CED and Carbon Footprint, for biofuel production, based on decision trees trained with information extracted from pilot plants. This is due to the possibility of interfacing this methodology with the structural information of the analyzed product [24]. In other works, regression models perform functional evaluations to implement LCA predictive models. Tao Dai et al. [25] implemented Gaussian Process Regression models to estimate missing data for the LCA study of nitrogen fertilizers. Other production sectors present a smaller amount of work. Ali Kaab et al. [26] used artificial intelligence techniques to implement a cradle-to-grave study on sugar cane production. Monia Niero et al. [27] published a work explaining the parameterization of inventory data for pallet production from a regression study on available data for similar products. In this way, they implemented a useable model to estimate the impact of other products obtained from a preliminary study. The same approach can be found in other industrial applications, such as cranes [28], building constructions [29], or wind energy converters [30]. The scientific literature needs to report applications of predictive models with industrial validity for performing LCA evaluations in the turbomachinery industry. This work aims to fill this gap by proposing applying predictive models based on machine learning algorithms to study the eco-profile of centrifugal compressor rotor assemblies. The peculiarity of these assemblies is their continuous design customization, dictated by the strong dependence on boundary conditions. The method aims to provide a calculation framework to analyze the concept design proposed by the design engineer during the commercial phase with the customer. The framework allows for evaluating the carbon footprint generated in the cradle-to-gate life cycle of the components. The selection of these boundaries allows for a detailed assessment of the emissions associated with Scope 1 and Scope 2 of the GHG Protocol. This evaluation is done efficiently, reducing the cost of data collection, and, above all, allows for the anticipation of the evaluation to the concept design phase through data-driven models. The framework also allows for the evaluation of alternative scenarios, such as the adoption of different supply chains [31] or the impact of design parameters on the result, to optimize them.

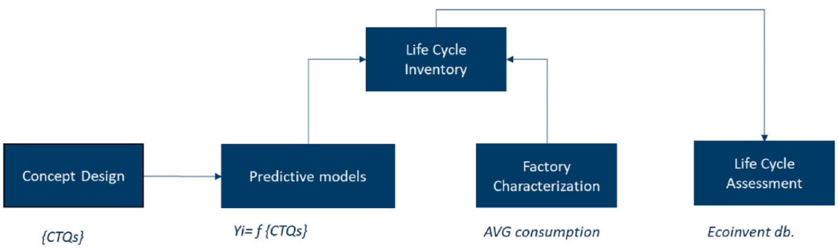

Fig. 1. Flowchart of proposed methodology.

2. Materials & method

This work follows the principles ISO 14040 [32] and ISO 14044 [33] set out to implement predictive studies on the life cycle sustainability of components used in the turbomachinery industry. The components under study are shafts and impellers that constitute the rotor assembly of centrifugal compressors. The standard ISO approach quantifies the energy and material flows (inventory data) that the system under study exchanges with the environment during its life. The following work proposes an innovative method in the turbomachinery sector by exploiting predictive algorithms to build the inventory of production phase consumptions. This method is a solution to anticipate the environmental impact assessment of the product in the concept design phase (prior to production). The need to resort to predictive algorithms stems from the lack of standardization of the subassembly, thus limiting each LCA study to a retrospective evaluation of the life cycle with limited validity exclusively to the specific design. Fig. 1 represents the steps of the method suggested in the work.

The method relies on extracting critical-to-quality (CTQ) parameters that contribute to the development of the concept design. Based on these CTQs, predictive models are developed to estimate the required duration for each substage of the manufacturing cycle (Yi). Concurrently, an analysis of average consumption at the workshop level for individual workstations is carried out. Combining these two data sets allows the allocation of time-dependent inventory flows (e.g., Electricity) to individual components. The inventory is then modeled using the Ecoinvent v3.9 environmental database [34]. The innovative approach proposed focuses on the manufacturing phase, as no information is available during the concept design phase. Table 1 describes each contribution to emissions The contributions to emissions are described in detail in Table 1.

The work focuses on the category of carbon footprint (C.F), evaluated in terms of kg CO2 eq. produced due to the interest that European regulations have shown in recent provisions. Among them is the one set by the Paris Agreement signed in 2016 [35], which aims to mitigate climate change by, among other things, eliminating greenhouse gas emissions.

Hereafter, the evaluation methods of the highlighted points are described in detail.

2.1. *Goal & scope definition*

This work aims to evaluate the eco-profile of a concept design developed by the design engineer for the rotor subassembly of a centrifugal compressor (Fig. 2). The rotor subassembly consists of the compressor shaft and impellers. The impellers are fitted onto the shaft by form-fitting coupling and compress the service gas processed by the machine through a rotational motion induced by a driver (power turbine or an electric motor).

2.1.1. *Functional unit*

The functional unit of the study is: "Compression of the service gas according to the technical specifications dictated by the customer." Nuovo Pinone purchases metal alloy forgings as semi-finished products and then uses them to produce the items under study. The processes at the Nuovo Pignone workshop aim to achieve the final shape through conventional chip removal (milling, turning, drilling, Etc.) and unconventional operations (electroerosion). Manufacturing team also carries out heat treatment cycles and balancing tests, which contribute to carbon footprint generation.

2.1.2. *System boundary*

The production cycle enclosed within the boundaries of the analyzed system is schematized in Fig. 3 (cradle to-gate-study). Therefore, observing the sequence of operations of raw material extraction, primary process, transport, and, subsequently, internal sub-stages (SS) that constitute the internal production process is possible.

2.2. *Life cycle inventory implementation trough predictive models*

- Upstream & Transport: Regarding the inventory generation of the upstream phase and the relative transport modalities, mathematical models are not required as the CTQ parameters are sufficient for the complete assessment of the processes.
- Core: The inventory is developed at the level of a single machine that performs the nth sub-stage as reported in Fig. 4.

The estimation of input and output flows at the nth sub-stage is implemented based only on the data available in the concept design

Table 1
LC stages/substages of a generical product and related processes.

System boundaries		
LC stage	Sub-stage	Processes
Production	Materials	- Production of electricity, heat, steam and fuel for raw materials extraction and production - Raw materials extraction and primary production processes
	Manufacturing	- Production of electricity, heat and auxiliary material for manufacturing and assembly activities - Manufacturing and assembly processes - Recovery processes of scrap materials from manufacturing activities
	Transportation	- Fuel production for transportation of materials and components between suppliers' plants and Baker Hughes production site

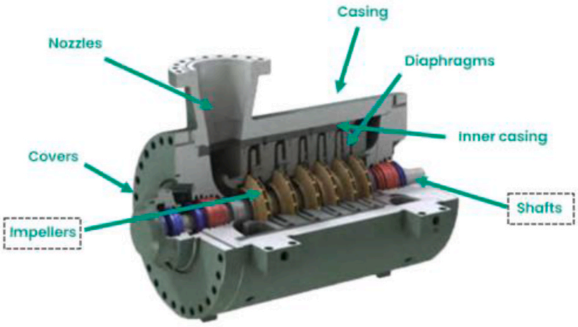

Fig. 2. Specification of the subject of the study, rotor subassembly of centrifugal compressor assembly.

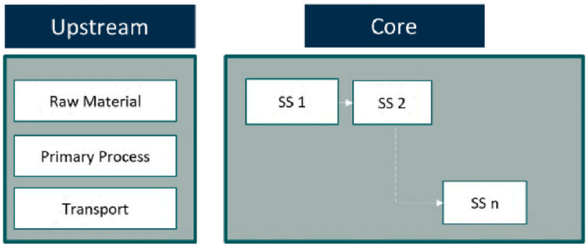

Fig. 3. Specification of LC stages included in the study.

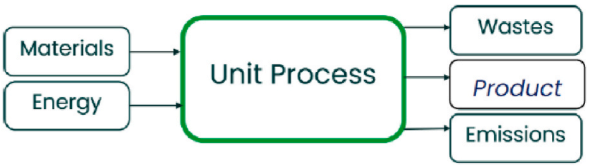

Fig. 4. Overview of Sub-Stage consumption.

phase, selected to comply with the functional unit required by the customer. The set of CTQs, which includes CTQ_1, CTQ_2, CTQ_3, …., *and* CTQ_n, must be achieved through the production cycle enclosed within the previously described system's boundaries. During the manufacturing cycle, it is possible to distinguish between time-dependent and time-independent inventory flows. Time-dependent consumption requires using predictive models to estimate cycle times to allocate absolute consumption to the studied item.

The time-dependent consumption and its allocation to the components are described as follows [Eqs. (1)–(4)]

$$\text{Electricity cons. [kWh]} = \text{F[CTQs]} \times \text{AVG } \textit{power cons} \tag{1}$$

$$\text{Oil cons. [kg]} = \text{F [CTQs]} \times \textit{AVG oil cons} \tag{2}$$

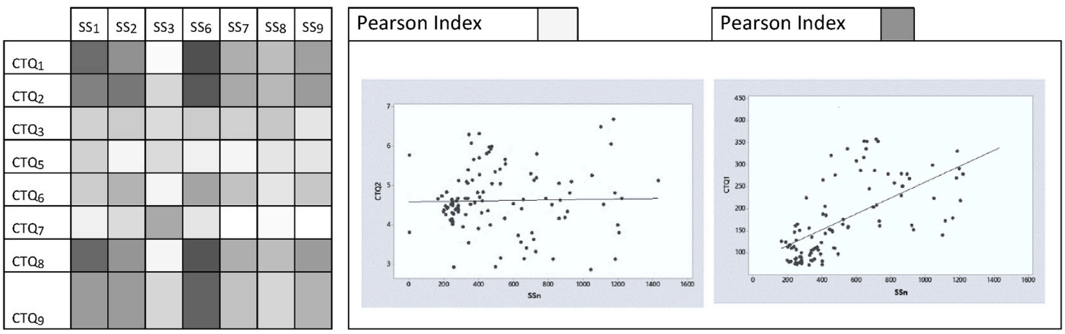

Fig. 5. Qualitative explanation of Pearson index for correlation analysis.

$$\text{Cutters cons. [kg]} = \text{F [CTQs]} \times \textit{AVG cutter cons} \tag{3}$$

$$\text{Compressed Air cons. [m3]} = \text{F[CTQs]} \times \textit{AVG comp. air cons} \tag{4}$$

A data-driven approach has been used to create predictive models (F[CTQs]). Data-driven models rely on a database built appropriately. The database that guides the model (training data set) reports the composition of the internal production cycle (in terms of sub-stage time) and the CTQs that led to the drafting of the cycle. The manufacturing engineer creates a part program from which the sub-stage time is obtained. This approach studies the dependencies between the CTQs, and the times required to produce the item based on the possible presence of analytical correlation [Fig. 5]. The study focuses on active processing and equipment setup, which significantly impact [36].

A statistical approach is used to study the database. Machine learning algorithms utilize the database to extract information and develop mathematical prediction models. Regression algorithms use the historical series contained in the database for training.

What is sought is a model of the following type:

$$\text{Yi} = \text{F} \, [\text{CTQ}_1, \text{CTQ}_2, \text{CTQ}_3, \ldots, \text{CTQ}_n]$$

- Yi = dependent variable, which is the time required to complete the nth sub-phase.
- CTQ_1, CTQ_2, CTQ_3, …, CTQ_n = independent variables derived from the output of the concept design.

To reduce the variance of the implemented models [Fig. 5], a database clusterization based on the value of CTQs was performed. This process produces a multiple regression model for each studied cluster. Fig. 6 shows a clusterization into families based on the observation of CTQs related to different geometric parameters that exhibit a significant correlation with the value of the dependent variable. The correct number of clusters is obtained once the similarity level is fixed.

The produced models depend on categorical and continuous CTQs, depending on the nature of the parameter under examination. The impact of the CTQs on the dependent variable is appropriately confirmed by the p-value obtained in the study.

The predictive model for the impellers reports the dependence of the manufacturing cycle time on six CTQs, two continuous and four categorical. The model's results allow for a good study of the intrinsic variance elements of the different technological solutions.

The quality of the model (Table 2, Table 3) is evaluated by the value of R-sq, which quantifies the ability to describe the variance of the dependent variable from the CTQs. The algorithm produced from the database study regarding the impellers reports a lower R-sq than that obtained for the shafts. The lower value of R-sq is due to the more significant variability of the design of an impeller and its impact on the production cycle. Models up to the maximum of the second degree are used to avoid overfitting problems and obtain a good general description of the phenomenon. The same operation has been repeated for the study of each sub-stage duration. The study of times is necessary because, parallel to the implementation of the algorithms, there was a mapping of energy and material flows consumed by equipment. They, therefore, represent primary inventory data that guarantee a high level of detail in the study.

Mapped flows are.

- Consumption of lubricating and dielectric oils for machine tools. (AVG oil cons.)
- Consumption of compressed air to power pneumatic drives. (AVG comp. air cons.)
- Consumption of cutter tooling to perform chip removal operations. (AVG cutters cons.)
- Electrical consumption to power machines. (AVG power cons.)

The first three consumptions have been mapped through analysis of the company databases and quantified for the working and idling machine states. Regarding electrical consumption, there has been a measurement campaign to obtain primary energy models for the working and idling phases of the various workstations by carrying out an average power assessment. The energy models were implemented by exploiting a sampling of the currents flowing on the three-phase power supply of the machines. For this purpose, the various machines have been equipped with a power data logger to record the current absorbed in the phases. The output files acquired were processed to obtain models of average power absorbed as a function of equipment states. To obtain high-quality models, the output data of the acquisition tool were cross-referenced with the states (idling or working) that the machine assumed during the observation interval, collected through a dedicated smart factory system. This process led to obtaining average power values, as reported in Table 4.

Regarding time-independent inventory flows, there is.

- Production of waste from removed metal material
- Production of electrodes for electrical discharge machining of the blade passages in impellers

The quantification of metallic scrap has involved using a statistical approach based on database analysis. The historical series in the database reports the ratio value between the mass of the finished component and the mass of the semi-finished product (available in the CTQs). Again, the average value of this ratio has been evaluated to obtain the percentage of material destined for waste in the form of metal shavings. The study for the waste material produced in the production of an impeller is shown below, clustered on CTQs that influence the ratio. The discriminating CTQ is a categorical variable that represents the presence of a near-net shape semi-finished product. Fig. 7 shows a scrap percentage of about 85 % for non-near-net shape impellers and about 75 % for near-net shape impellers.

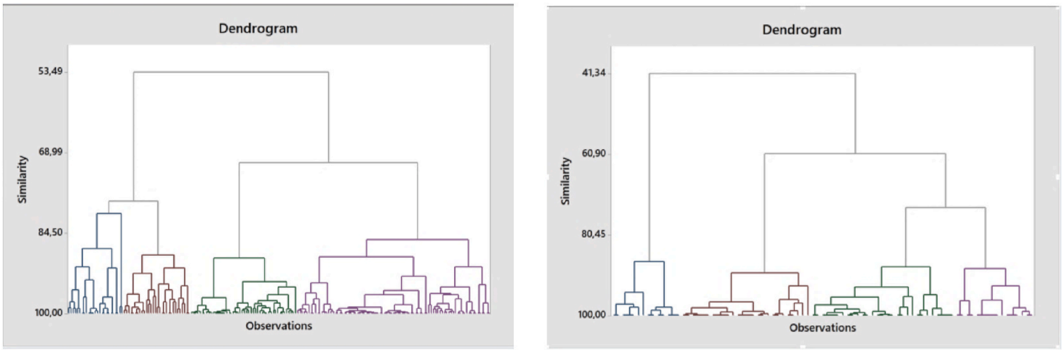

Fig. 6. Example of clusterization of item to reduce effect of variance.

Table 2
Example of predictive model to study a duration of sub-stage in impeller production.

Analysis of Variance			Model Summary		
Source	DF	P-Value	S	R-sq	R-sq(adj)
Regression	15	0,000	135,38	81,89 %	79,09 %
CTQ1	1	0,000	**Regression Equation**		
CTQ2	1	0,053	Yi = f(CTQ1,CTQ2,CTQ3,CTQ4,CTQ5)		
CTQ3	2	0,000			
CTQ4	2	0,000			
CTQ5	8	0,000			

Legend.
•P-value = Assess the significance of association.
•S = Measured in the units of the response variable and represents how far the data values fall from the fitted values.
•R-sq = Percentage of variation in the response that is explained by the model.
•R-sq(adj) = Percentage of the variation in the response that is explained by the model, adjusted for the number of predictors in the model relative to the number of observations.
•DF = Measures the effect each observation has on the fitted values in a linear model.

Table 3
Example of predictive model to study a duration of sub-stage in shaft production.

Analysis of Variance			Model Summary		
Source	DF	P-Value	S	R-sq	R-sq(adj)
Regression	5	0,000	8,00	93,51 %	92,77 %
CTQ_1	1	0,005	**Regression Equation**		
CTQ_2	1	0	Yi =	$f(CTQ_1, CTQ_2, CTQ_3, CTQ_1^2)$	
CTQ_3	1	0,024			
CTQ_1^2	1	0,007			

Table 4
Example of results obtained by the study of average power absorbed.

Machine State	AVG power [kW]
Idling	17,05
Working	21,40

Finally, to quantify the inventory flows necessary to produce electrodes, the CTQ related to the volume of the blade passage has been extracted to evaluate the quantity of graphite required and the related processing.

2.3. Life cycle assessment modelling and validation

The inventory described above is implemented in a spreadsheet and is mainly modeled by associating it with the processes available in the EcoInvent V3.9 database. The specific impacts of the flows are obtained using the ILCD 2011 Midpoint v.1.10 method [37]

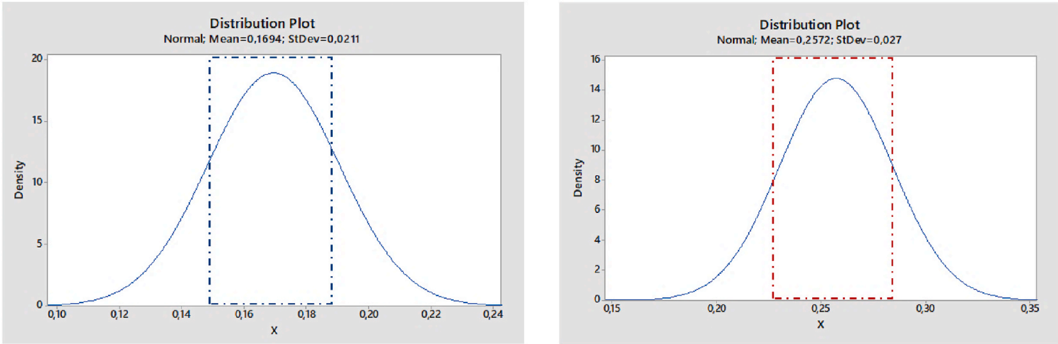

Fig. 7. Distribution plot of ratio between of waste material with respect to the total raw quantity.

available in the Simapro software. The choice of this method stems from the possibility of studying a large number of environmental effects caused by modeled flows, confirmed by the numerous studies in the literature using it [38]. Modeling Choices are described in Appendix A [Table. A1]. The implemented models have been validated to make them reliable in an industrial context. To do this, they were tested to perform a predictive study on a data set (validation set). The obtained results (C.F forecast) were compared with the data obtained from the deterministic study afterward (C.F actual) to evaluate and index the error on the validation set [Eq. (5)]. The results obtained are summarized in Table 5 and show a sufficiently low average error. The details of each test are reported in Appendix A [Fig. A2, Fig. A3].

3. Result and discussion

3.1. Case study description

The functionality of the approach is demonstrated by applying it to a case study regarding the concept design of rotor subassembly. The presented models are implemented in a computational tool that inputs the known CTQs from the concept design. Through them, a prediction of the inventory data is developed, leading to the realization of the finished component [Fig. 8]. The two semi-finished products arrive at the Nuovo Pignone workshop as forgings and are then internally processed. The impeller is produced using conventional chip removal techniques and electroerosion processing to open the blade passages. After machining, a heat treatment is performed to ensure the desired mechanical characteristics. Conversely, the shaft does not require heat treatment but only profiling operations for coupling with bearings and impellers.

The inventory data is automatically modeled using the principles described in the LCA modeling section. The supply chain model for the case study involves the supply of semi-finished products from China (best-cost country approach) by container ship, with subsequent delivery by truck to the Nuovo Pignone plant.

3.2. Breakdown of LC steps

The results of the case study are presented as percentage contributions to the cradle-to-gate life cycle analyzed. [Fig. 9]. This graph makes it possible to distinguish the contributions of the various phases described in the introductory paragraph: Raw material extraction, external manufacturing (primary processes), internal manufacturing, transport, and scrap. The results obtained from this breakdown align with deterministic studies in the literature [39]. The detailed study of the breakdown is instrumental in implementing contribution analysis to identify possibilities for improving the ecoprofile of the assembly.

The graph shows that extracting raw materials necessary to produce the two components accounts for a significant percentage of the cradle-to-gate (over 50 %). Concerning impellers, the high contribution of the raw material phase is because, for producing these items, the semi-finished product has a much greater mass than the finished component. The machining operations remove about 80 % of the starting material. This value provides insight into the importance of using recycled materials to limit the impact on the environment dictated by their extraction [40]. Additionally, it can be observed that there is a clear difference in the internal manufacturing phase between the two components (about 21 % for the impeller processing and 10 % for the shaft processing). This difference is due to the significant energy demand for processing impellers, which have a starting semi-finished product profile that is very different from the finished component. The aerodynamic design constraints dictate long and, therefore, energy-intensive processing [41]. Regarding these components energy-intensive machining is used to optimize the final form to maximize its efficiency during the use phase. This is different for the shaft, which requires fewer operations (Fig. 10 shows the absence of heat treatments in the production cycles of the shafts.) and has no constraints from an aerodynamic point of view. This fact also explains the material phase's high contribution to this item. The negative value of the impact of waste is due to the modeling of recycling processes according to Mohan Yellishetty et al. [42], which provide credit in terms of CO_2 eq, with a percentage that is almost negligible compared to the total.

Table 5
Value of average E% obtained from the analysis of validation set.

	Item	Tested item	Average E%
$E_{\%} = \frac{C.F_{forecast} - C.F_{actual}}{C.F_{forecast}}\ \%$ (5)	Impeller	25	6,3 %
	Shaft	7	2,0 %

Fig. 8. Example of case study, extraction of CTQ from concept design.

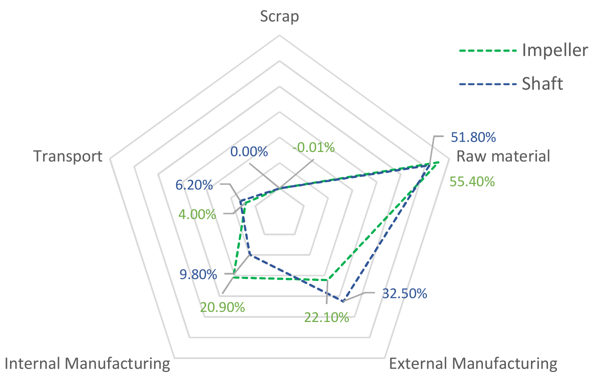

Fig. 9. Contribution results obtained by the breakdown of life cycle in each sub-stages.

3.3. Breakdown of internal manufacturing processes

Fig. 10 shows a breakdown of the internal sub-stages that contribute to the generation of carbon footprint.

What emerges from this subdivision is that the milling process of the impeller's vanes and the shaft profile's turning are the most impactful in terms of carbon footprint. This aspect is due to the high time required (and high power adsorbed) for the stage, which tends to increase all time-dependent inventory flows described in the materials and method paragraph.

3.4. Identification of environmental hotspot

Fig. 11 presents the environmental impact of mapped consumptions to determine the principal hotspot. The electrical power supply to the various workstations generates 66.5 % and 71 % of the carbon footprint generated by internal processes, respectively. This result finds confirmation in the literature as in the work of xx et al. [43]. This result suggests that the adoption of renewable sources can be highly beneficial [44].

Fig. 10. Contribution results obtained by the breakdown of internal manufacturing in each manufacturing step.

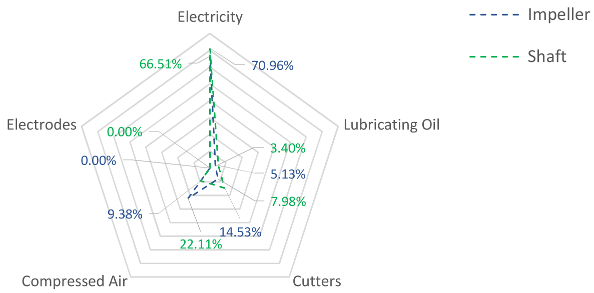

Fig. 11. Contribution results obtained by the breakdown of internal energy-material consumption.

3.5. Example of scenario analysis

In addition to comparing absolute results, the tool is well-suited to perform sensitivity analysis on the selected parameters for concept design by the design engineer. The example below shows the differential impact of adopting a lower-cost supply chain (BCC[1]) versus a lower-impact supply chain (LEIC[2]). The lower-cost modeled scenario involves supplying the material from China, while the lower-impact scenario involves supplying the material from Germany. The result of the analysis is reported in differential terms [Eq. (6)]:

$$\Delta = \frac{LEIC\ s.c\ - BCC\ s.c}{BCC\ s.c}\% \tag{6}$$

The breakdown of this result is also provided for the raw materials and transportation categories, which are the ones that contribute to the variation in the generated CO_2.

The results [Fig. 12] show that adopting a supply chain optimized in terms of environmental sustainability allows for a 10 % reduction in the carbon footprint of the shaft and an 11 % reduction in the carbon footprint of the impeller. This effect is mainly due to the reduction in the impact of the raw material extraction phase, as there is a significant difference between the two geographical scenarios studied. A smaller overall contribution is due to the adoption of a different transportation system involving a combination of container ships and trucks rather than an electrically powered train and subsequent road transport. The discussion of the attained results demonstrates that the proposed methodology facilitates an estimation, employing predictive models, of the carbon footprint linked to the designed assembly. This predictive assessment leverages, at maximum, primary data sourced from corporate databases or acquired through pertinent sensor equipment [45]. The predictive approach enables the integration of environmental considerations into project objectives. The envisioned scenario analysis concerning supply chain adoption can be iterated for each Critical-To-Quality

[1] Best cost country.
[2] Least environmental impact country.

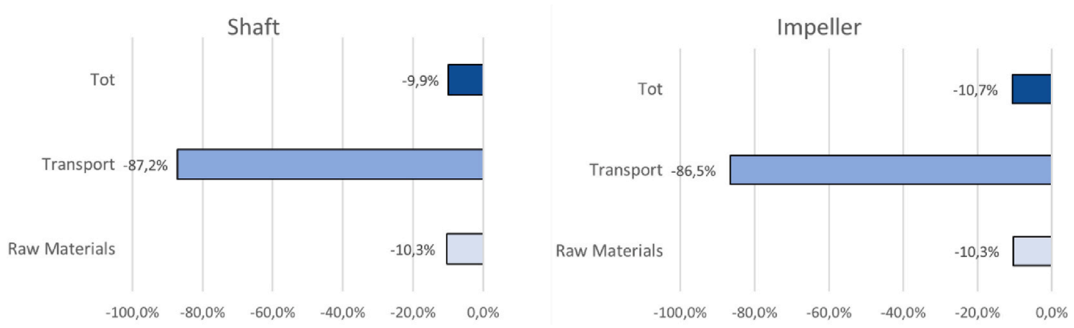

Fig. 12. Different impact on LEIC and BCC supply chain.

(CTQ) aspect of the assembly, aiming to minimize the carbon footprint. While the results have been delineated in terms of carbon footprint, the methodology allows assessments across any impact category encompassed within the evaluation framework, thereby enabling a comprehensive analysis of CTQ effects.

4. Conclusion

This study has led to the development of a functional approach for assessing the environmental impact of components within the turbomachinery domain. Specifically, it evaluates the carbon footprint contribution within the cradle-to-gate life cycle of components embedded in the rotor subassembly of a centrifugal compressor manufactured by Nuovo Pignone. The significance of this study lies in the implementation of a method easily integrated into the conceptual design phase of assemblies, especially crucial for non-standardized component designs. This fulfills the increasing demand from consumers seeking insight into a product's environmental impact during the purchasing phase. The proposed method aligns with ISO14040 principles but introduces the anticipation of inventory flow quantification in the concept design phase by leveraging historical data. These data, extracted from Nuovo Pignone's production cycles, serve as the training set for multiple regression algorithms. Simultaneously, alongside algorithm implementation for estimating production cycle composition, an experimental campaign maps time-dependent consumed flows at the individual process unit level. These quantified flows are attributed to individual components, and their impact is evaluated using the ILCD Midpoint v.1.10 method. A case study application provides detailed insight into the work conducted. It reveals that raw material extraction is the primary contributor to the carbon footprint, constituting approximately 55 % of the entire cradle-to-gate process. This percentage could be diminished by advocating metrics that promote a circular economy using secondary materials. Internal processes, notably for the shaft (over 10 %) and the impeller (over 20 %), also play significant roles. Detailed analysis of internal cycle operations identifies potential areas for improvement. Further breakdowns underscore that electrical energy production for machine feeding significantly outweighs other mapped flows, underscoring the importance of adopting renewable energy sources for electricity generation. Moreover, an alternative scenario analysis comparing a lower environmental impact supply chain with a lower-cost one demonstrates a potential 10 % reduction in CO_2 emissions over the studied life cycle. Rapid exploration of alternative scenarios emerges as a critical advantage of the proposed approach. This comprehensive examination initially focused on the compressor components, but it will expand to encompass the entirety of the assembly for a more holistic assessment.

Data availability statement

Data used in the study cannot be disclosed for confidentiality reasons.

CRediT authorship contribution statement

Alessandro Giraldi: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Riccardo Barbieri:** Supervision, Methodology, Investigation, Conceptualization. **Luca Lombardozzi:** Visualization, Supervision, Project administration, Formal analysis, Data curation. **Massimo Delogu:** Supervision, Resources, Project administration, Funding acquisition.

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.

Appendices A.

Table A1
Modelling Choice of inventory flow estimated.

LC step	Inventory flow	Ecoinvent Database Association
Up-Stream	Metal alloy: ASTM A182 F22	Raw material impact according to Ref. [46] with percentage of recycled material according to Ref. [47].
	Metal alloy: ASTM A705	
	Metal alloy: ASTM A322	
	Forging	*Forging, steel {GLO}| market for | APOS, S*
Transport	Camion Payload 10t	*Transport, truck < 10t, EURO4, 100%LF, empty return {GLO} Economic, S*
	Counting ship	*Transport, freight, sea, bulk carrier for dry goods {GLO}| market for transport, freight, sea, bulk carrier for dry goods | APOS, S*
	Electric train	*Railway track {GLO}| market for | APOS, S*
Manufacturing Cycle	Electricity	*Electricity, medium voltage {IT} market for electricity APOS U*
	Lubricating oil	*Lubricating oil {GLO}| market for | APOS, S*
	Dielectric oil	*27 % of processing environmental impacts* [48]
	Graphite	*Graphite {RER} production APOS, U*
	Tungsten Carbine	*Tungsten carbide powder {GLO}| market for tungsten carbide powder | APOS, S*
	Compressed air – 6 bar	*Compressed air production {RER}* 6000 kPa, *optimized*
	Compressed air –7 bar	*Compressed air production {RER}* 7000 kPa, *optimized*
	Compressed air – 10 bar	*Compressed air production {RER}* 10000 kPa, *optimized*
	Metal chips (waste)	*Open loop recycle with substitution factor 2 %* [49]
	Exausted oil (waste)	*Open loop recycle with substitution factor 70 %* [50]

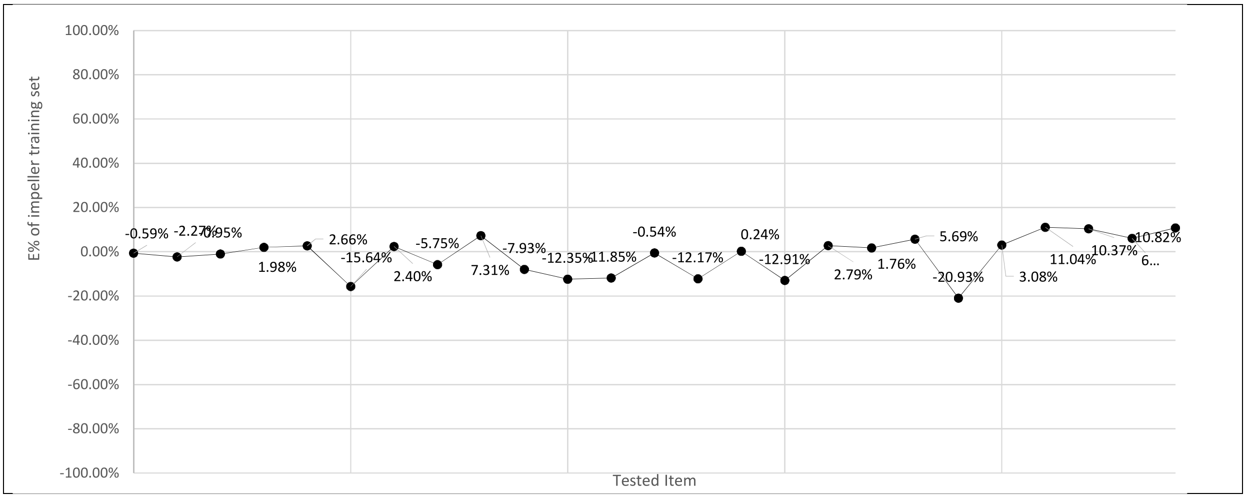

Fig. A.2. Evaluation of $E_{\%}$ for impeller training set.

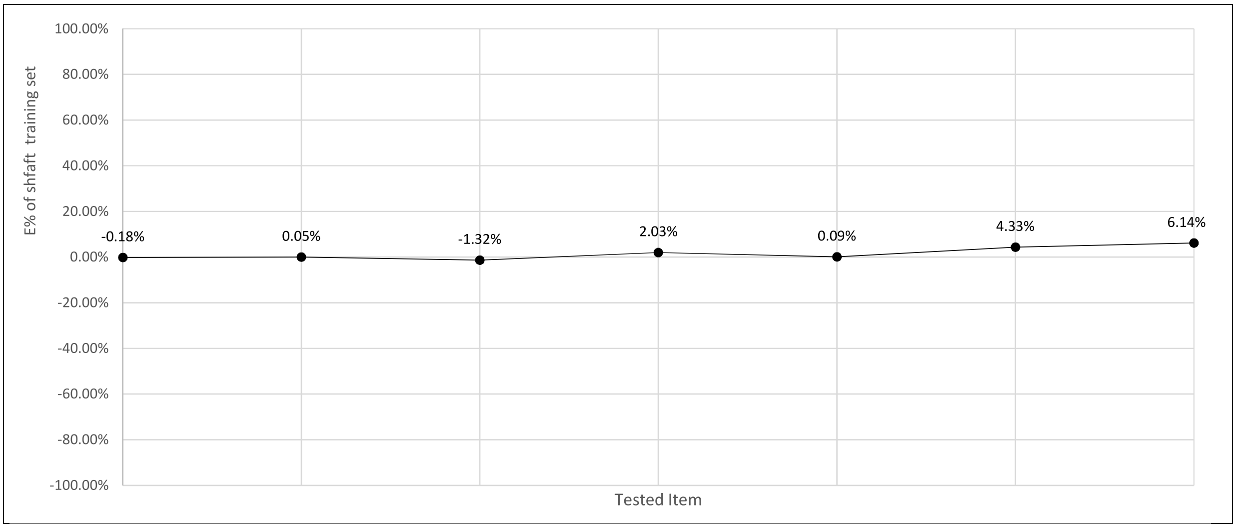

Fig. A.3. Evaluation of $E_{\%}$ for shaft training set.

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