Sustainable Production and Consumption 61 (2025) 231–246

Contents lists available at ScienceDirect

Sustainable Production and Consumption

journal homepage: www.elsevier.com/locate/spc

Review Article

Advancing parametric life cycle assessment (pa-LCA): A systematic review and methodological roadmap for enhanced sustainability assessments

Ana Arias [a,b,*], Maria Teresa Moreira [b], Reinout Heijungs [a], Stefano Cucurachi [a]

[a] Institute of Environmental Sciences (CML), Faculty of Science, Leiden University, 2300, RA, Leiden, Netherlands
[b] CRETUS, Department of Chemical Engineering, School of Engineering, University of Santiago de Compostela, 15782, Santiago de Compostela, Spain

ARTICLE INFO

Editor: Dr Kuishuang Feng

Keywords:
Parametric life cycle assessment
Key performance indicators
Uncertainty
Functional unit

ABSTRACT

Parametric Life Cycle Assessment (Pa-LCA) is a dynamic modeling and analysis approach that integrates pre-defined variable parameters to enable the assessment of environmental impacts. This methodology enhances the flexibility of life cycle sustainability assessments, particularly in processes characterized by uncertainty or variability. Given this, the effective selection of parameters is required, in order to develop a meaningful Pa-LCA, which can be adapted accordingly to the objectives identified for the analysis. While Pa-LCA is widely used in the literature, there is still a need to define an assessment path for its effective application, since, unlike conventional LCA, Pa-LCA is not a standardized method. Given this, a comprehensive review of existing Pa-LCA studies has been conducted. This review focuses on how parameters are identified, selected and operationalized, how functional units are adapted to parametric contexts, and if key performance indicators (KPIs) are considered on the definition. Through this analysis, methodological gaps and inconsistencies were identified that hinder the broader adoption and effectiveness of Pa-LCA. To address these challenges, a structured methodological roadmap has been developed, aiming at guiding researchers and practitioners in the development of robust and effective Pa-LCA models. This roadmap encompasses the definition of the parametric model considered, the selection of the most influential parameters, the use of parametric data for the development of a conventional LCA, the design of sensitivity and uncertainty analyses, and the interpretation of results for decision-making. By bridging theoretical and practical implementation strategies, and by the identification of actual gaps and challenges, this guide aims to standardize Pa-LCA practices and promote its use for developing dynamic life cycle assessments. It is hoped that the outcomes of this article could contribute to advancing the methodological maturity of Pa-LCA and unlocking its potential for more adaptive and informed sustainability assessments.

1. Introduction

Regulatory developments, climate protection commitments, and the need to consolidate a truly sustainable economy require environmental assessment tools and methodologies to shift toward dynamic analyses that integrate variability, uncertainty, and adaptability (Slavkovic and Stephan, 2025; Liu et al., 2024). In this context, conventional life cycle assessment (LCA), while widely recognized as a robust methodology for sustainability analysis and standardized under the ISO 14040 series (Finkbeiner et al., 2006), still lacks mechanisms to address dynamic scenarios, which limits its applicability in complex and changing systems (Garcia and Freire, 2017). The ability to simulate adaptive scenarios is essential for examining how modifying different parameters affects final sustainability outcomes (Zhao et al., 2020). In this regard, the lack of adaptability of conventional LCA studies represents a significant gap in the analysis of industrial systems, even those with high environmental performance, which reduces the effectiveness of LCAs as decision-making support instruments (Olanrewaju et al., 2024; Dong et al., 2018).

Given this limitation, Parametric LCA (Pa-LCA) appears as a potential alternative to integrate adaptable functions and iterations aimed at assessing the impact of key parameter variability (such as design, materials, energy consumption, chemical use, among others) on the sustainability performance of a given scenario (Ali et al., 2025; Campos-Carriedo et al., 2024). Pa-LCA is a methodological approach that employs parameters and formulas to express life cycle inventory (LCI) data and calculations rather than fixed values (Heijungs, 2020). This approach enables key process data, such as material flows, energy usage,

* Corresponding author at: Institute of Environmental Sciences (CML), Faculty of Science, Leiden University, 2300, RA, Leiden, Netherlands.
E-mail address: anaarias.calvo@usc.es (A. Arias).

https://doi.org/10.1016/j.spc.2025.10.016
Received 5 September 2025; Received in revised form 27 October 2025; Accepted 29 October 2025
Available online 4 November 2025

and emissions, to dynamically depend on one or more input variables (e.g., design or usage parameters) (Lamperth et al., 2004). By embedding these relationships directly within the LCA model, parametric LCA facilitates flexible, scenario-based analysis and early-stage environmental assessment (Lamperth et al., 2004). Pa-LCA empowers designers and decision-makers to explore how alterations in system configurations or operational conditions impact environmental outcomes, thereby enhancing transparency, adaptability, and relevance throughout the design and evaluation process (Cooper et al., 2012a, 2012b). An example is a unit process for 1 km transport by truck, where the fuel use and CO_2 emission are not constant, but depend on the load of the truck, the average slope of the road. Using the equation $\alpha + \beta$*load+γ*slope L/km, where α, β and γ are model coefficients that measure the influence of the parameters load and slope.

However, the implementation of Pa-LCA faces multiple challenges. Among these, the absence of standardized methodological guidelines and the need to develop complex computational models stand out (Borschewski et al., 2024; Manuguerra et al., 2024). This approach aligns with the development of function-based representations of the variables inherent in life cycle inventories, that should accurately depict the sustainability impacts as a function of the variables' values. This involves the development of robust data workflows that combine primary information, design requirements, databases, and characterization factors (Säwén et al., 2022; Bhat et al., 2021; Bernstein et al., 2020).

Given the growing recognition of the potential benefits of Pa-LCA and the evident absence of a structured methodological framework to guide its development and implementation, this review article aims to provide a systematic analysis of recent scientific literature that has adopted this approach. The objective is to evaluate its potential, identify methodological gaps and challenges, and establish a conceptual roadmap that can serve as a basis for the future development of a standardized guideline for Pa-LCA. In this regard, the three research questions that this review is focused on are: (1) Which are the current methodological challenges and gaps in parametric-LCA?; (2) What criteria and methodological justifications support the selection of parameters in Pa-LCA, and how do these choices influence the Pa-LCA outcomes?; and (3) How can a roadmap be developed to integrate the required steps for developing a comprehensive Pa-LA?.

2. Literature review

Pa-LCA is increasingly recognized for its potential to enhance the flexibility of sustainability assessments. By integrating variable parameters, Pa-LCA enables temporal modeling of environmental impacts, particularly in systems characterized by uncertainty or variability. Despite its growing application, a critical gap exists in the literature. There are almost no comprehensive review articles dedicated to Pa-LCA, and there is no established methodological roadmap guiding its implementation. Without a standardized methodology, researchers applying Pa-LCA using different considerations and assumptions (such as parameter types, modeling approaches, sensitivity and/or uncertainty analysis, etc.) makes it difficult to compare results across studies, reproduce findings, and build a cumulative knowledge in the field. For instance, Cooper et al. (2012a, 2012b) conducted a review of parameterization practices in life cycle inventory datasets, such as the European Reference Life Cycle Data System and ecoinvent, among others. They emphasized the importance of including raw data and formulas to improve transparency and usability. Nonetheless, their analysis does not explore the broader methodological framework of Pa-LCA or its integration into decision-making processes. Similarly, BIM-integrated and parametric-based LCA tools have been examined in the building sector. Nevertheless, these studies often lack generalizable frameworks and are typically applied only to early design stages (Cavalliere et al., 2019). Notably, no existing publication offers a comprehensive analysis of how parameters are selected, operationalized, and utilized to adapt functional units and key performance indicators (KPIs) in Pa-LCA.

In contrast, other advanced LCA approaches, such as dynamic LCA and prospective LCA, have received more structured attention. For instance, Salati et al. (2025) conducted a thorough review of dynamic LCA in buildings, identifying key processes and methodologies for integrating time-dependent data. Lan (2024) further highlighted modeling challenges in dynamic LCA, such as defining temporal boundaries and managing large datasets. In the case of prospective LCA, Erakca et al. (2024) conducted a review of scaling techniques, particularly regarding the assessment of environmental impacts of emerging technologies at an industrial scale. A key finding from this study is the lack of comparable methodological reviews or decision-support tools in non-conventional LCA. To address these gaps, Thonemann et al. (2020) proposed a framework targeting comparability, data quality, and uncertainty in prospective assessments, including methodological guidance to develop prospective LCA frameworks.

These LCA-based approaches demonstrate the value of structured methodologies in enhancing the robustness and applicability of conventional LCA. However, Pa-LCA remains underdeveloped in this regard, lacking both a theoretical foundation and practical guidance for implementation. In this context, the present systematic review aims to provide a general framework for LCA practitioners by critically examining how parametric LCA has been applied in existing studies. Specifically, it investigates the identification, selection, and operationalization of parameters, the adaptation of functional units to parametric contexts, and the integration of KPIs into model design. By synthesizing these elements, the review highlights methodological gaps and inconsistencies that hinder broader adoption of Pa-LCA. Ultimately, it proposes a structured roadmap to support the development of robust, adaptable, and decision-oriented Pa-LCA models, contributing to the methodological maturity and standardization of this emerging approach.

3. Methodology for the selection and classification of articles on parametric life cycle assessment (Pa-LCA)

To carry out a comprehensive analysis of the existing literature on parametric life cycle assessment (Pa-LCA), an initial bibliographic search was conducted using the SCOPUS database. The Scopus database was chosen as the sole source for this review because of its comprehensive coverage, reliability, and relevance. Other databases, such as Web of Science or Google Scholar, were not included, as Scopus was considered sufficient and appropriate for the objectives of this review. The search parameters included the keywords "parametric AND life cycle assessment OR LCA" with the requirement that these terms be present in the title, abstract, and/or keywords. This initial query yielded a total of 475 publications. Notice that the research was based on the combination of the keywords "parametric" and "life cycle assessment" or "LCA". As such, alternative keywords, such as "parametrized", "parameterised", "parameterized" and "parameterised" have not been considered. A check suggested that this selection may have missed a few unique references, but that the overall pattern is not affected through this restriction.

The first screening phase involved the application of exclusion criteria to refine the scope of relevant documents. Manuscripts published prior to 2014, as well as book chapters, conference proceedings, and review articles, were excluded from consideration. The review focuses on studies published from 2014 onwards to capture the most relevant and methodologically advanced contributions in the field of Pa-LCA. During this period, parametric approaches gained prominence, driven by advancements in computational tools, data modeling, and sensitivity analysis, which were largely disregarded in earlier research. Additionally, the terminology and methodological consistency in parametric LCA have been developed considerably over the past decade, enabling a more coherent and comparable synthesis of findings. Selecting a ten-year window provides a focused yet comprehensive overview of the evolution and current state of Pa-LCA, while avoiding older studies that may not meet contemporary standards or relevance.

After this initial filtering, the group of relevant publications was reduced to 367 documents, as depicted in Fig. 1, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Swartz, 2021). Subsequently, a second level of selection was undertaken to further refine the dataset to only those articles that align closely with the scope of this review. Articles were excluded if they lacked any explicit reference to life cycle assessment methodologies or focused solely on multi-criteria decision-making or conventional environmental assessments that did not incorporate a parametric dimension.

After a screening and selection, we classified the selected articles based on the specific type of Pa-LCA methodology applied. As can be seen in Fig. 2, we considered a total of 6 classification categories. Additionally, a seventh category was created to accommodate a small subset of articles (11 articles, representing 11 % of the total) that could not be appropriately categorized under any of the predefined typologies.

We based the classification on the type of the parametric approach considered, particularly focusing on the type of mathematical functions utilized, the selection of objective parameters, and the degree to which parametric methodologies were combined with the LCA framework. The largest proportion of articles (39 articles, or 41 %) fell into the category of parametric support for LCA, wherein parametric analyses are applied to inform or supplement the LCA process, but without developing explicit mathematical functions that link design parameters to environmental performance metrics. Representative examples include Küpfer et al. (2024), who investigated how design variables in load-bearing floor systems affect environmental impacts, generating 20,280 design combinations from 7 design parameters. In the case of Campos-Carriedo et al. (2024), the authors used a parametric analysis to evaluate hydrogen production, considering several process using 20 operational and process parameters, leading to the definition of five distinct production scenarios. Asgari et al. (2023) used 39 design variables to examine 24 different façade system configurations aimed at minimizing energy consumption during demolition phases.

The next category with the higher number of articles is the one regarding the use of parametric assessment for explicitly linking design

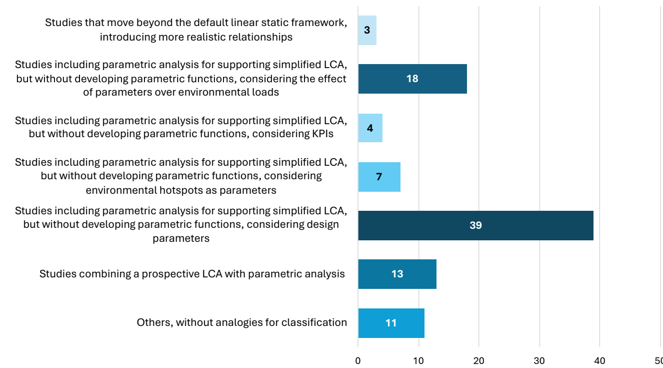

Fig. 2. Classification of articles according to the type of parametric LCA developed.

parameters to carbon emissions or other environmental indicators, thereby enabling a quantifiable understanding of sustainability trade-offs. Notable examples include Huang et al. (2023), who analyzed how underground infrastructure design contributes to global warming potential; Zhu et al. (2023), who incorporated 55 parameters—including process energy, yield ratios, emissions, and recycling rates—to assess cumulative energy demand and global warming potential.

Several articles that stand out in this classification group are the ones developed by Provost-Savard et al. (2023), Reisinger et al. (2022) and Quintero-Herrera et al. (2022). Provost-Savard et al. (2023) proposed an iterative method for developing life cycle inventories that account for technological and geographic variability in recycling processes. Similar approach has been considered by Reisinger et al. (2022), who developed a decision support model integrating LCA with recycling potential and process flexibility through automated parametric calculations. In the last case, Quintero-Herrera et al. (2022) implemented a parametric linear programming approach to optimize fertilizer use in livestock

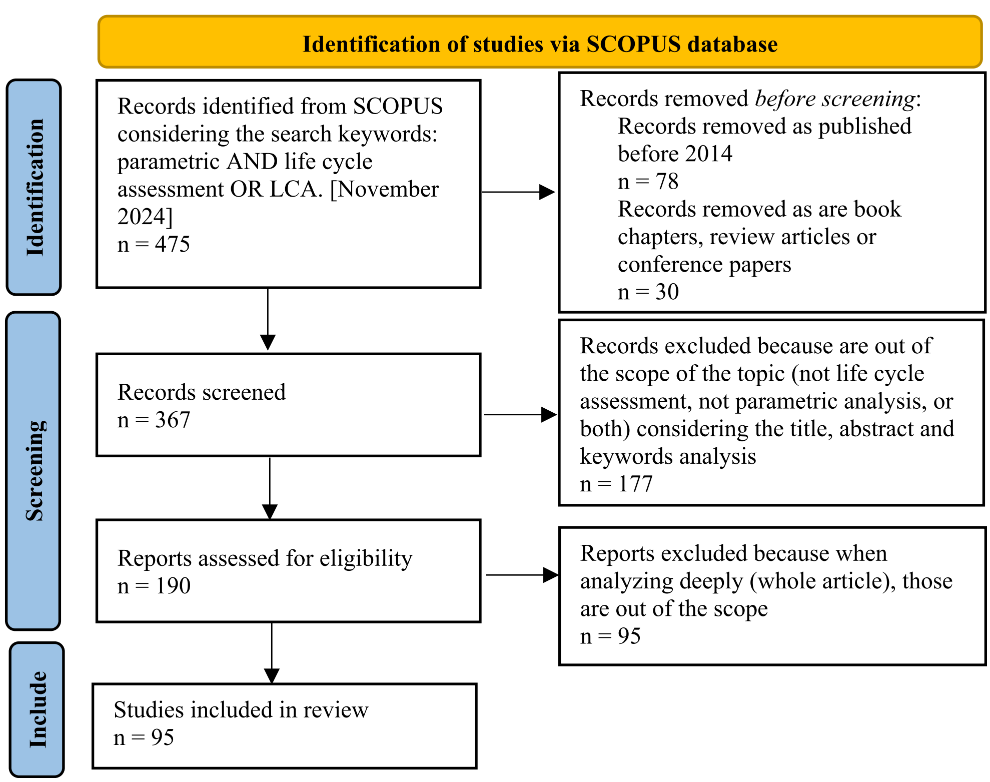

Fig. 1. Identification and screening of studies following PRISMA guidelines.

farming, balancing environmental and economic factors. Apart from the aforementioned ones, also alternative approaches have been considered, as multivariable functions including design parameters aiming to minimize environmental burdens (Kamalakkannan and Kulatunga, 2021), parametric tools for uncertainty quantification in primary data acquisition for the development of life cycle inventories (Jolivet et al., 2021) or the simplified parametric LCAs where individual parameter effects are assessed without building explicit parametric functions (Jones and Li, 2023).

When referring to the studies that combine a prospective LCA with a parametric analysis, the selected studies introduce a temporal dimension directly into the functional unit, reflecting the future-oriented nature of the assessments. Some notable examples include the analysis of the environmental loads associated with a new residential building in Hungary over a 50-year lifespan, considering architectural and functional parameters (Szalay, 2024), the environmental loads generated by the production of 1 MWh of energy by a thermocline thermal storage tank over a 25-year period (Lalau et al., 2022), and the impacts caused by the embodied energy of residential housing over five decades, incorporating both design and usage variables (Monteiro and Soares, 2022).

An additional methodological variant identified was the use of hotspot-driven parameter selection, whereby variables with the highest environmental contribution are targeted for parameterization. Although seven studies employed this approach, most fell short of developing explicit parametric functions and instead relied on sensitivity analyses, which do not meet the rigorous criteria for true parametric LCA. This distinction underscores the necessity of clearly defining what constitutes a parametric analysis. A parametric LCA must go beyond mere sensitivity testing; it requires the formulation of mathematical functions that establish causal relationships between input parameters and environmental outcomes, thereby enabling predictive modeling.

Finally, a distinct classification was applied for studies that transcend traditional linear-static frameworks, introducing more sophisticated mathematical representations of the functional unit. A notable example is the study conducted by Jang et al. (2022), which explores the impacts associated with the production of hydrogen as fuel. This study employs a well-to-wake approach, where the functional unit is expressed as a linear function: "$y = ax + b$," where "y" represents the environmental impact and "x" denotes the design parameters of the ship where hydrogen will be utilized as fuel (Jang et al., 2022).

On the other hand, to provide a general overview of the articles reviewed, Table 1 presents their classification according to several criteria. Firstly, it reflects the categorization shown in Fig. 2, referred to as "Level 0 – Preliminary Assessment", secondly it identifies studies that developed parametric functional units or LCI equations, which can be considered as a "real parametric-LCA". Thirdly, two additional levels are identified, focused on the analyzing if the articles include or not sensitivity and/or uncertainty analysis. Lastly articles have also been classified considering if those combined parametric LCA with machine learning or artificial intelligence tools. Although these aspects are discussed in detail in the following subsections, the authors have consolidated them into a single table to provide a clear, high-level overview of the scope and focus of this systematic review.

4. Results

As LCA is the core methodological framework of this systematic review, it has been considered essential to examine how Pa-LCA interacts with each stage of the traditional LCA methodological approach. This includes the definition of the functional unit (FU), system boundaries, impact assessment and results interpretation. While functional units and system boundaries are often considered fundamental elements in comparative LCA studies, the primary aim here is to emphasize how these components have been addressed in dynamic contexts, where temporal and spatial variability are critical. Regarding the inventory phase, although it is widely recognized as particularly sensitive to challenges in dynamic LCA—especially in data collection, processing, and allocation—the review does not explore sector-specific inventory procedures. This is because the scope encompasses diverse application scenarios and sectors, making it impractical to generalize inventory strategies. Moreover, different types of functional units and system boundaries are used in the literature, which significantly influence data gathering during the inventory phase.

In this regard, this Section 4 is structured in the following subsections: Subsection 4.1. Definition of KPIs in Pa-LCA [Stage 1 – LCA]; Subsection 4.2. Justification for parameter selection in Pa-LCA [Stage 1 – LCA]; Subsection 4.3. LCA considerations; Subsection 4.3. Functional unit selection in Pa-LCA [Stage 1/2 – LCA]; Subsection 4.4 System boundaries considered in Pa-LCA [Stage 1/2 – LCA]; Subsection 4.5. Calculation methodology and impact categories under analysis [Stage 3 – LCA]; Subsection 4.6. Database for background activities [Stage 3 – LCA]; Subsection 4.7. Sensitivity and uncertainty analysis [Stage 4 – LCA]; Subsection 4.8. Integration of Pa-LCA with AI and programming tools.

Regarding the final subsection, it has been included due to the rapid development of artificial networks in life cycle assessment, aiming to provide a general overview of their specific application in Pa-LCA.

4.1. Definition of KPIs in parametric life cycle assessment (Pa-LCA)

By definition, KPIs serve as quantitative measures that monitor the extent to which specific performance goals such as process productivity, profitability, safety, environmental impacts, or customer satisfaction, are achieved (Badawy et al., 2016; Ishaq-Bhatti et al., 2014). Although the use of KPIs in environmental assessments like LCA is not yet widespread, there is an emerging body of literature that reports their integration to more effectively target and evaluate specific aspects of production systems, namely economic, environmental, and operational dimensions.

For example, Dorn et al. (2016) proposed a set of 16 KPIs to guide the development of an eco-efficient production system, comprising five economic indicators (e.g., energy, maintenance, and material costs), six environmental metrics (e.g., CO_2 emissions, NO_X and SO_X emissions, energy from renewable and non-renewable resources), and five operational measures (e.g., raw material input, equipment efficiency, fuel consumption). Integrating KPIs into LCA processes not only facilitates the identification of inefficiencies and environmental hotspots but also supports strategic decision-making, benchmarking, and continuous improvement initiatives (Contini et al., 2023; Landström et al., 2018). Furthermore, KPIs provide a basis for tracking progress over time, enabling innovation and informed policymaking (Gautam et al., 2025; Fantini et al., 2015).

In the context of Pa-LCA, even though defining KPIs is considered as a key element for the definition of the appropriate parameters and functions, not all the authors have considered introducing KPIs on the performance of the parametric analysis. In fact, only 7 out of the 95 articles under analysis have considered the use of KPIs or the definition of key parameters or trade-offs.

Despite their recognized importance, the explicit use of KPIs in Pa-LCA remains relatively limited. From the 95 articles analyzed in this study, only seven incorporated KPIs or analogous concepts such as trade-offs or key parameters. In most cases, authors either (1) defined broad objectives for the assessment—such as minimizing environmental burdens—or (2) integrated the purpose of the study into the functional unit of the LCA. One noteworthy example is the work by Di Bari et al. (2024), who formulated KPIs to assess both environmental sustainability and cost-efficiency in the construction sector, specifically for the development of "plus energy buildings." These indicators were used to identify optimal building designs based on energy use, environmental impact, and economic performance.

Although not explicitly labeled as KPIs, Huang et al. (2016) analyzed

Table 1
Analysis of the articles under assessment considering levels of parametric integration. Codes: *Level 0.A*: Studies including parametric analysis for supporting simplified LCA, but without developing parametric functions, considering design parameters, *Level 0.B*: Studies including parametric analysis for supporting simplified LCA, but without developing parametric functions, considering the effect of parameters over environmental loads, *Level 0.C*: Studies including parametric analysis for supporting simplified LCA, but without developing parametric functions, considering environmental hotspots as parameters, *Level 0.D*: Studies including parametric analysis for supporting simplified LCA, but without developing parametric functions, considering KPIs, *Level 0.E*: Studies combining a prospective LCA with parametric analysis and *Level 0.F*: Studies that move beyond the default linear static framework, introducing more realistic relationships.

Reference	Level 0. Preliminary assessment	Level 1. Parameterized units or LCI equations	Level 2. Global sensitivity	Level 3. Uncertainty analysis	Level 4. Integration of AI or ML
	Articles named as parametric but without developing parametric functions	*"X" if developed, "-"if just varying parameters values but without parametric functions*	Development of sensitivity analysis around parameters. *Yes if developed, no if not.*	Development of uncertainty analysis around parameters. *Yes if developed, no if not.*	Combination of Pa-LCA with digitalization. *Yes if developed, no if not.*
Küpfer et al. (2024)	A	–	Yes	Yes	No
Szalay (2024)	E	–	No	Yes	No
Manuguerra et al. (2024)	E	–	No	Yes	Yes
Blazer et al. (2024)	C	–	No	No	No
Lee et al. (2023)	C	–	No	Yes	No
Di Bari et al. (2024)	D	–	No	Yes	No
Manjong et al. (2024)	C	–	Yes	Yes	No
Hermansdorfer et al. (2024)	E	–	No	No	No
Pérez-Cardona et al. (2024)	–	–	No	Yes	No
Kwon and An (2024)	C	–	Yes	Yes	No
Douziech et al. (2024)	C	–	No	Yes	No
Gao et al. (2024)	A	–	No	No	No
Borschewski et al. (2024)	A	–	Yes	No	No
Campos-Carriedo et al. (2024)	A	–	No	No	No
Torabi and Evins (2024)	A	–	Yes	Yes	No
Dehghani et al. (2024)	A	–	No	No	No
Arbulu Dudagoitia et al. (2024)	–	–	No	Yes	No
Shinde et al. (2024)	E	–	No	No	No
Bianchi et al. (2024)	A	–	Yes	No	No
Rahardjo et al. (2024)	A	–	Yes	No	No
Jones and Li (2024)	C	–	No	No	No
Chen et al. (2024)	–	–	Yes	Yes	No
Alarcón et al. (2024)	C	–	No	No	No
Lin et al. (2024)	A	–	Yes	No	No
Josa et al. (2023)	–	–	No	Yes	No
Hitt et al. (2023)	A	–	Yes	No	No
Yang et al. (2023)	A	–	Yes	No	No
Asgari et al. (2023)	A	–	No	No	Yes
Mowafy et al. (2023)	E	–	Yes	No	No
Manco et al. (2023)	–	–	No	No	No
Sanei and Modarres (2023)	A	–	Yes	No	No
Jones and Li (2023)	B	–	Yes	Yes	No
Ajtayné Károlyfi and Szép (2023)	A	–	No	Yes	Yes
Speroni et al. (2023)	A	–	No	No	No
Buentello-Montoya et al. (2023)	A	–	No	No	No
Liao et al. (2023)	A	–	No	Yes	No
Gibon and Hahn Menacho (2023)	–	–	Yes	Yes	No
Besseau et al. (2023)	A	–	Yes	Yes	No
Hansen et al. (2023)	E	–	Yes	No	No
Soleimani et al. (2023a, 2023b)	B	–	No	Yes	No
Soleimani et al. (2022)	B	–	Yes	Yes	No
Huang et al. (2023)	A	–	Yes	No	Yes
Chaurasiya and Singh (2023)	A	–	No	No	No
Provost-Savard et al. (2023)	B	–	No	Yes	No
Hussain et al. (2023)	E	–	Yes	No	Yes

(*continued on next page*)

Table 1 (*continued*)

Reference	Level 0. Preliminary assessment	Level 1. Parameterized units or LCI equations	Level 2. Global sensitivity	Level 3. Uncertainty analysis	Level 4. Integration of AI or ML
	Articles named as parametric but without developing parametric functions	*"X" if developed, "-"if just varying parameters values but without parametric functions*	Development of sensitivity analysis around parameters. *Yes if developed, no if not.*	Development of uncertainty analysis around parameters. *Yes if developed, no if not.*	Combination of Pa-LCA with digitalization. *Yes if developed, no if not.*
Zhu et al. (2022)	A	–	No	No	No
Sánchez-Pantoja et al. (2023)	D	–	Yes	No	No
Zhang et al. (2023)	A	–	No	No	No
Roux et al. (2023)	A	–	Yes	Yes	No
Lalau et al. (2022)	E	–	Yes	Yes	No
Quéheille et al. (2022)	B	–	Yes	No	No
Gibon and Hahn Menacho (2023)	A	–	No	Yes	No
Monteiro and Soares (2022)	E	–	Yes	No	No
Rabie et al. (2022)	A	–	No	No	No
Park et al. (2022)	A	–	No	No	No
Reisinger et al. (2022)	B	–	No	No	No
Ala'a et al. (2022)	A	–	No	No	No
Ma and Deng (2022)	A	–	Yes	No	No
Quintero-Herrera et al. (2022)	B	–	Yes	No	No
Amoruso and Schuetze (2022)	B	–	No	No	No
Ansah et al. (2022)	E	–	No	Yes	No
Andersen et al. (2022)	–	–	No	Yes	No
Al-Obaidy et al. (2022)	E	–	Yes	Yes	No
Eleftheriou et al. (2022)	A	–	Yes	No	No
Jang et al. (2022)	F	X	Yes	No	No
Peralta-Reyes et al. (2022)	D	–	No	No	No
Pirson and Bol (2021)	A	–	Yes	Yes	No
Mele et al. (2021)	A	–	Yes	No	No
Jolivet et al. (2021)	B	–	Yes	Yes	No
Fajilla et al. (2021)	–	–	Yes	No	No
Giaveno et al. (2021)	–	–	No	No	Yes
Bhat et al. (2021)	B	–	No	No	No
Manjong et al. (2021)	B	–	Yes	No	No
Stemmle et al. (2021)	A	–	No	Yes	No
Kamalakkannan and Kulatunga (2021)	B	–	Yes	No	No
Lask et al. (2021)	B	–	Yes	No	No
Jang et al. (2021)	F	X	Yes	No	No
Mattinzioli et al. (2021)	–		No	Yes	No
Caruso et al. (2021)	B	–	No	No	No
Mousavi and Mehrpooya (2020)	B	–	No	No	No
Kiss and Szalay (2020)	E	–	Yes	No	No
Manni et al. (2020)	A	–	No	No	No
Yan et al. (2020)	A	–	Yes	No	No
Jang et al. (2020)	F	X	No	No	No
Miller et al. (2019)	A	–	Yes	Yes	No
Fufa et al. (2018)	E	–	Yes	Yes	No
Galli et al. (2018)	B	–	No	Yes	No
Lobaccaro et al. (2018)	A	–	No	No	No
Khila et al. (2017)	B	–	No	No	No
Pomponi and D'Amico (2017)	A	–	No	No	No
Kylili et al. (2017)	–	–	No	No	No
Huang et al. (2016)	A	–	No	No	No
Niero et al. (2014)	A	–	No	No	No
Amaya et al. (2014)	B	–	No	No	No
Yang et al. (2014)	B	–	No	No	No

the relationship between wafer design variables and CO_2 emissions, facilitating faster and more effective design decisions. Similarly, Reisinger et al. (2022) identified key trade-offs among economic, environmental, and operational flexibility dimensions in industrial building structures.

In another approach, Campos-Carriedo et al. (2024) aligned their framework for evaluating hydrogen production technologies with the KPIs outlined in the European Strategic Research and Innovation Agenda for Hydrogen. These predefined indicators were considered in the selection of functional parameters for their Pa-LCA.

A practical example of KPI integration into a parametric environmental tool is EcoHestia, designed for the construction sector. This tool quantifies environmental burdens per kilogram of construction material using KPIs derived from primary data sourced from local manufacturers. Kylili et al. (2017) employed EcoHestia to evaluate the sustainability of a passive house located in a subtropical climate zone with an insular energy system.

The following examples illustrate how specific KPIs can be applied to support and enhance the goals of parametric LCA, particularly in identifying hotspots, reducing emissions, improving resource efficiency, and also for enhancing continuous improvement. (1) Carbon emissions intensity: measured as greenhouse gases emissions per unit of output, considered as a core metric for climate change impact and useful for comparing between scenarios; (2) Water use efficiency: analysis of the water resource depletion, defined as the volume of freshwater consumed per unit of output; (3) Renewable energy share: percentage of the total energy sourced from renewable resources, supporting KPI (1) and also improving energy-related impact categories; (4) Material Efficiency Ratio; ratio of materials input to useful outputs (products and co-products), helping to assess the impact categories of resources depletion and useful for tracking the amount of waste produced in the process; (5) Eco-efficiency index: when economic values are considered, it relates economic performance to environmental impact, helping identify the most sustainable scenario.

4.2. Justification for parameter selection in Pa-LCA

When conducting a Pa-LCA it has been defined that one of the methodological steps is the selection of parameters, which should align closely with the study objectives, enhancing product functionality through design changes, reducing environmental footprints, improving production efficiency, or maximizing economic performance (Campos-Carriedo et al., 2024; Borschewski et al., 2024; Zhao et al., 2020; Lacirignola et al., 2017).

Despite its importance, the rationale for parameter selection is not always clearly articulated in literature. In 17 of the 95 reviewed studies, parameters appeared to have been chosen arbitrarily or without explicit justification. Conversely, 39 articles analyzed considered the selection of parameters based on design aspects. Gao et al. (2024) identified parameters aimed at sustainably valorizing construction waste by incorporating it into new composite materials. Rahardjo et al. (2024) focused on the influence of mixture composition and structural performance on floor construction systems. Pomponi and D'Amico (2017) prioritized structural design and material-related parameters due to their high impact on thermal performance, particularly in double-skin façades. Yang et al. (2023) selected process operation parameters for biodiesel production and plastic/biomass gasification, respectively, to assess their influence on output quality and efficiency.

Another subset of 28 articles combined environmental and design criteria in their parameter selection, targeting a reduction in environmental burdens through optimized system design. Table 2 presents a summary of these studies, detailing the rationale behind parameter selection, the number of parameters considered, and the number of scenarios assessed. However, the justifications provided are often general and fail to connect parameter choices with the study objectives. To ensure valid and reproducible results, Pa-LCA studies should include a dedicated section critically analyzing parameter selection. The relevance of each parameter to the stated goals should be clearly explained. Moreover, conducting a preliminary LCA to identify environmental hotspots can be a valuable precursor to selecting the most impactful

Table 2
Rationale on parameters selection based on the combination of design and environmental concerns. Acronyms: EF (Environmental footprint), CF (carbon footprint), LCA (Life Cycle Assessment), GWP (Global Warming Potential), EL (Environmental Loads).

Reference	Rationale on parameters' selection	N° parameters	N° scenarios
Bianchi et al. (2024)	Influence of technologies geometric parameters on EF	25	3
Alarcón et al. (2024)	Parameters affecting over energy, exergetic and CF values	4	2
Hitt et al. (2023)	Relevant parameters for Rankine cycles	3	6
Jones and Li (2023)	How wind turbines design affects over LCA results	5	3
Hansen et al. (2023)	Design parameters that influence the most over GWP	NA	2
Soleimani et al. (2022)	Identification of effect of materials % content on EL	7	8
Huang et al. (2023)	Design parameters influence over CF	17	2
Chaurasiya and Singh (2023)	Process parameters affectance over product quality and sustainability performance	9	26
Provost-Savard et al. (2023)	How recycling parameters affect the LCA results	12	4
Hussain et al. (2023)	Design parameters needing optimization affecting EL	6	1
Quéheille et al. (2022)	Design and manufacturing parameters influencing EL	57	3
Zhu et al. (2022)	End-of-life strategies parameters for decision-making	40	5
Monteiro and Soares (2022)	Design and operational parameters affecting over embodied energy	10	1
Park et al. (2022)	Association between EL and experimental variables	NA	3
Reisinger et al. (2022)	Recycling design parameters that affect over sustainability	NA	13
Quintero-Herrera et al. (2022)	Fertilizers blends required to minimize environmental and economic impacts	10	4
Amoruso and Schuetze (2022)	Geometrical parameters having an impact over environmental and life cycle costs results	NA	3
Jolivet et al. (2021)	Use of Sobol indices	30	1
Bhat et al. (2021)	Use of a set of parameters typology	NA	4
Manjong et al. (2021)	Process and production parameters affecting CF	9	6
Kamalakkannan and Kulatunga (2021)	Key environmental parameters selected by its sensitivity response to GWP	15	1
Lask et al. (2021)	Use of influential parameters selected with experts	47	NA
Mousavi and Mehrpooya (2020)	Operational parameters having an effect on EL	7	1
Galli et al. (2017)	Operation parameters that affect over the final impact	3	12
Lobaccaro et al. (2018)	Building design parameters selected by its effect on EL	9	2
Khila et al. (2017)	Process parameters values effect on environmental profile	2	2
Amaya et al. (2014)	Design parameters influencing LCA	20	1
Yang et al. (2014)	Various mixture % to evaluate its effect on CO_2 reduction	3	3

variables for parametric analysis.

The number of parameters per study varied widely, ranging from 2 (Khila et al., 2017) to 57 (Quéheille et al., 2022). While there is no fixed guideline on the optimal number of parameters, it is essential to balance comprehensiveness with analytical feasibility. Excessive parameters can complicate interpretation and increase the risk of redundancy or interdependence (i.e., double counting). Parameters should ideally be independent to preserve analytical clarity.

Similarly, the number of scenarios evaluated in each study also varied significantly. As with parameter count, this number should be explicitly justified and proportional to the study complexity. Critical concern should always demonstrate how variations in parameters influence the system under investigation. In conclusion, for a Pa-LCA to be considered rigorous and credible, it must include a clear rationale for parameter selection, an explicit count and description of parameters and scenarios, and a demonstration of how parameter variation informs environmental or performance outcomes.

Another approach for parameter selection in Pa-LCA is based on the results of a preliminary LCA or the identification of environmental hotspots. This methodology requires the initial implementation of a conventional LCA to identify the processes, stages, or inputs that contribute most significantly to the environmental burden. Subsequently, parameters are selected strategically to mitigate these critical contributions. This two-step strategy was employed in 9 out of the 95 articles reviewed.

For example, Manjong et al. (2024) analyzed 30 LCA reports to determine which parameters had the highest influence on GHG emissions during the production of lithium-ion battery cells. Similarly, Manuguerra et al. (2024) conducted a preliminary LCA to assess electric vehicles over an 8-year lifespan, enabling the identification of key parameters influencing sustainability performance. A comparable methodology was followed by Lee et al. (2023), who evaluated the environmental implications of producing polyhydroxyalkanoates (PHA) using various raw materials and energy sources. Douziech et al. (2024) applied this strategy to understand the influence of background processes on the environmental profile of electricity and heat generation, while Blazer et al. (2024) selected operational parameters for CO_2-to-formic acid conversion through electrochemical cell technology, based on the findings of a prior LCA.

Only two of the 95 reviewed studies incorporated previously defined KPIs to guide the selection of parameters in alignment with the LCA objectives. Specifically, Di Bari et al. (2024) used a combination of design-based, LCA-related, and life cycle costing (LCC)-oriented KPIs to determine the most appropriate parameters for evaluating the sustainability and economic performance of "plus energy buildings". The selected parameters included energy operation conditions, energy consumption profiles, and the bill of materials, all directly linked to environmental and economic metrics. In another case, Campos-Carriedo et al. (2024) selected parameters based on expert recommendations aimed at optimizing the technological performance of solid oxide electrolysis cells for hydrogen production, guided by the strategic objectives outlined in the European Hydrogen Research Agenda.

4.3. Functional unit selection

The functional unit (FU) is a fundamental concept that provides a reference for data collection and impact quantification. The fixed FU, defined as a constant and unchanging quantity of product or service, is the most commonly applied type in both conventional LCA and Pa-LCA studies. As summarized in Table 3, 73 out of the 95 articles reviewed adopted a fixed FU. Typical bases for fixed FUs include (1) the amount of product produced, (2) the function delivered by the product, (3) the amount of input material consumed, (4) specific design parameters, or (5) the quantity of emissions released.

While the fixed FU offers advantages such as simplicity, clarity, and ease of interpretation, it presents certain limitations, particularly in

Table 3
Functional units considered in the articles under analysis. Acronyms: FU (Functional Unit), F (fixed-FU), DE (Dependent-FU) and DY (Dynamic-FU).

Reference	FU	Type of FU
Küpfer et al. (2024)	Linear spanning distance of a 1-m-wide fragment of a load-bearing floor system for a building constructed today in Switzerland	F
Szalay (2024)	New residential building in Hungary (50 years)	DE
Manuguerra et al. (2024)	Use of the EV for a given lifetime (8 years)	DE
Blazer et al. (2024)	1 kg of FA	F
Lee et al. (2023)	1 kg of PHA	F
Di Bari et al. (2024)	Net surface area (NFA), m^2	F
Manjong et al. (2024)	1 kWh of cell capacity	F
Hermansdorfer et al. (2024)	Total emissions	F
	Emissions per unit floor area	F
	Emissions per inhabitant over a 50 or 80-year lifespan	DE
Pérez-Cardona et al. (2024)	Production and operation of one permanent magnet synchronous motor	F
Kwon and An (2024)	1 kWh of electricity using LFG at a plant	F
	246 kton LFG emissions for 1 kWh of electricity production	F
	276 kton LFG flaring for 1 kWh of electricity production	F
Douziech et al. (2024)	1 kWh of generated electricity	F
	1 MJ of generated heat	F
Gao et al. (2024)	1 m^3 concrete mixture proportions	F
Borschewski et al. (2024)	10 m^2 facade	F
Campos-Carriedo et al. (2024)	1 stack for hydrogen production	F
Torabi and Evins (2024)	1 m^2	F
Dehghani et al. (2024)	1 m^2 of CPB pavement (i.e. 25 blocks)	F
Arbulu Dudagoitia et al. (2024)	m^2·yr	F
Shinde et al. (2024)	1 m^2 of energy reference area of dwelling per year	DE
Bianchi et al. (2024)	Production of a section of an external wall of a single store house with a standing area of 1 m^2 and an average thermal transmittance ranging between 0.28 W/m^2 K and 0.29 W/m^2 K	DE
Rahardjo et al. (2024)	1 m^3 of several FC mix designs	F
Jones and Li (2024)	NA	–
Chen et al. (2024)	320,000 km of driving distance	F
Alarcón et al. (2024)	1 kWh generated by the Organic Rankine Cycle for each cycle	F
Lin et al. (2024)	Shear capacity of 1500 kN	F
Josa et al. (2023)	1 linear meter of trench to install a pipe with a diameter of 110 mm	F
Hitt et al. (2023)	1 kWh generated by the organic Rankine cycle for each cycle	F
Yang et al. (2023)	Biodiesel produced from 1000 kg of soybean oil	F
Asgari et al. (2023)	100 m^2 of the 24 common building materials used in facade design	F
Mowafy et al. (2023)	1 m^2 of heated floor area per year	DE
Manco et al. (2023)	1 printed product produced and delivered to a customer belonging to a defined geographical cluster	F
Sanei and Modarres (2023)	A highway passing lane with a length of 1 km and a width of 3.65 m	F
Jones and Li (2023)	Wind turbine tower of 140 m height	F
Ajtayné Károlyfi and Szép (2023)	Frame structure with LOD 300	F
Speroni et al. (2023)	Height of the box	F
Buentello-Montoya et al. (2023)	1 ton of plastics	F
Liao et al. (2023)	1 finished part	F
Gibon and Hahn Menacho (2023)	1 kWh of high-voltage electricity from a pressurized water reactor	F
Besseau et al. (2023)	1kWh of electricity generated	F
Hansen et al. (2023)	1 m^2 of gross living area for a 50-year reference study period	DE
Soleimani et al. (2023a, 2023b)	In-situ treatment of 1m^3 of sediment	F

(continued on next page)

Table 3 (*continued*)

Reference	FU	Type of FU
Soleimani et al. (2023a)	1m^3 of concrete	F
Huang et al. (2023)	1 unit of product	F
Chaurasiya and Singh (2023)	1 hole drilled with diameter of 6 mm and depth 3.5 mm	F
Provost-Savard et al. (2023)	Recycling 1 kg pre-sorted wastepaper bale into specific product grade	F
Hussain et al. (2023)	500 m with a reference service life of 100 years	DE
Zhu et al. (2023)	1 kg of product	F
Sánchez-Pantoja et al. (2023)	1 m^3 of each ready-mix concrete combination	F
Zhang et al. (2023)	100,000 Aluminum electrolytic capacitors with specific rated working voltage (16 to 35 V) and rated capacitance (4.7 to 6800 μF) in a product family produced by the manufacturer from Nantong, China	DE
Roux et al. (2023)	1 m^3 of the printing material	F
Lalau et al. (2022)	Provide 1 MWh at the rate of 2 GWh year −1 during 25 years	DE
Quéheille et al. (2022)	1 ton of managed waste	F
Gibon and Hahn Menacho (2023)	1 kWh of high-voltage electricity from a pressurized water reactor	F
Monteiro and Soares (2022)	50 years lifetime	DE
Rabie et al. (2022)	NA	–
Park et al. (2022)	1 kWh electricity production from solar PV systems	F
Reisinger et al. (2022)	1 m^2 per gross floor area	F
Ala'a et al. (2022)	1000 kg of biodiesel produced	F
Ma and Deng (2022)	1 single battery pack of the electric vehicles	F
Quintero-Herrera et al. (2022)	1 kg of fat-and-protein-corrected milk leaving the farm without processing	F
Amoruso and Schuetze (2022)	1 m^3 1 m^2	F F
Ansah et al. (2022)	7500 m^2 GFA for a lifespan of 50 years	DE
Andersen et al. (2022)	Demolition and waste treatment of 1m^2 façade cladding in Denmark in 2020	F
Al-Obaidy et al. (2022)	1 kg/year, and an occupancy period estimated for 20 years	DE
Eleftheriou et al. (2022)	Single-story building with an area input not exceeding 64 m^2 and a wall height not exceeding 3 m, with minimum 1 door and 1 window	F
Jang et al. (2022)	Expressed by a linear function as y = ax + b (where, y is environmental impact, x is basic information of a ship such as power)	DY
Peralta-Reyes et al. (2022)	1 MJ of hydrogen produced	F
Pirson and Bol (2021)	Single IoT edge device defined by its hardware profile	F
Mele et al. (2021)	Bounding box of specific measurements	F
Jolivet et al. (2021)	1 kWh of energy produced by the photovoltaic system	F
Fajilla et al. (2021)	1 m^2 of usable floor area	F
Giaveno et al. (2021)	NA	–
Bhat et al. (2021)	NA	–
Manjong et al. (2021)	kg of material	F
Stemmle et al. (2021)	1 g CO_2 eq/kWh	F
Kamalakkannan and Kulatunga (2021)	1 m^2 clay roof tile	F
Lask et al. (2021)	1 kg-dry matter spring miscanthus and transported by truck	F
Jang et al. (2021)	Represented as mathematic equations expressing correlations between ship basic information and environmental impacts.	DY
Mattinzioli et al. (2021)	1 Mton for the raw material	F
Caruso et al. (2021)	1 M$ of expense in the selected sector	F
Mousavi and Mehrpooya (2020)	1 kg of material	F
Kiss and Szalay (2020)	Full 740 m^2 apartment building for a time period of 50 years	DE
Manni et al. (2020)	1 m^2 of HFA	F
Yan et al. (2020)	Annual impact of the energy generation system to meet the energy demand of 1 m^2 of the building	F
Jang et al. (2020)	Equations to represent the correlations over parametric changes and total environmental impacts of target systems	DY
Miller et al. (2019)	1 kWh alternate current electricity supplied to the grid	F
Fufa et al. (2018)	1 m^2 wall over the 50 year estimated service life of the building	DE
Galli et al. (2017)	Amount of enriched air produced by the plant in 24 h in Milano (Italy)	F
Lobaccaro et al. (2018)	1 m^2 of heated surface area (HFA)	F
Khila et al. (2017)	1 kg of H_2 produced from ATR of bioethanol.	F
Pomponi and D'Amico (2017)	5.25 m^2 of DSF (double skin façade)	F
Kylili et al. (2017)	1 m^2 of useful floor area	F
Huang et al. (2016)	Per wafer [dimensions: 150 mm (6 in), 200 mm (8 in), or 300 mm (12 in)]	F
Niero et al. (2014)	Unit of finished pallet ready to be transported	F
Amaya et al. (2014)	Combination of service provision time, availability and use condition	F
Yang et al. (2014)	1 m^3 1 kg	F F

parametric or scenario-based LCA contexts. It lacks the flexibility to reflect variations in system behavior resulting from changes in parameters, potentially covering the effects of trade-offs or failing to represent dynamic systems accurately. To address these limitations, alternative FU formulations, namely dependent FUs and dynamic FUs, have been proposed and employed in several studies. The definitions and rationales of those types of FU are included on *Section 3.2*.

The dependent FU, used in 15 of the reviewed studies, includes performance-related aspects such as service duration, coverage, or usage frequency. This allows for a more representative and adaptive evaluation of scenarios, particularly when system characteristics evolve over time. Noteworthy examples include the choice considered by Szalay (2024), Manuguerra et al. (2024) and Hermansdorfer et al. (2024), all of them adding a "time frame" in the definition of the FU, "50 years of use", "8 years of electric vehicle lifetime" and "emissions per inhabitant over 50–80-year lifespan", respectively, among others. Integrating a temporal dimension enables a more prospective outlook, facilitating the analysis of how parameter changes may influence long-term outcomes. On the other hand, dynamic FUs, though rarely applied, offer an even more flexible and responsive framework. Only three articles, all authored by Jang et al. (2020, 2021, 2022), utilized dynamic FUs. These studies employed mathematical functions and linear models to correlate ship design parameters and energy consumption with corresponding environmental impacts. The use of dynamic FUs allows for real-time adaptation of the FU to parameter variations, offering a more responsive tool for scenario modeling, sensitivity analysis, and uncertainty assessment.

In summary, while the fixed FU remains the most prevalent in Pa-LCA applications due to its straightforward implementation, both dependent and dynamic FUs provide more accurate representations of complex, evolving systems. Their adoption should be encouraged, especially in studies aiming to support scenario-based decision-making and long-term sustainability planning.

4.4. System boundaries

The selection of life cycle stages included within an LCA study can vary significantly, depending on the objective and scope of the study. Among the 95 reviewed studies, the cradle-to-grave approach emerged as the most prevalent, adopted in approximately 42 % of the cases (information included in the Supporting Information (SI) – **Fig. S1**). This boundary encompasses the full life cycle, from the extraction of raw materials to the ultimate disposal of the product. The cradle-to-gate perspective was used in 38 % of the studies (36 out of 95), accounting for processes up to the factory gate from the extraction stages while excluding the use and end-of-life stages. Other boundary configurations, such as cradle-to-cradle and cradle-to-use, were identified in only three studies each. The former emphasizes circularity by integrating recycling and material recovery into the system, while the latter focuses on environmental impacts limited to the use phase. On the other hand, alternative stages for analysis could be also selected, even though those are fewer common boundaries ("Others" category in **Fig. S1**): cradle-to-laid/−recycling/−site/−transport, gate-to-gate/−grave, tank-to-wake, use-to-grave or well-to-wake.

Notably, four studies failed to explicitly define their system boundaries, which compromises the transparency, reproducibility, and interpretability of their findings. It is critical to explicitly define the selected life cycle stages when conducting a Pa-LCA, as this directly influences the relevance and appropriateness of the selected parameters. The system boundary specification should be regarded as a mandatory element to ensure a comprehensive and robust assessment.

4.5. Calculation methodology and impact categories under analysis

The calculation methodologies utilized in Pa-LCA studies are summarized in Supporting Information - **Table S1**. Among these, the ReCiPe method emerged as the most frequently used, appearing in 23 of the 95 reviewed articles. ReCiPe provides a robust framework that supports the evaluation of multiple impact categories beyond climate change, including human health, ecosystem quality, and resource depletion (as illustrated in Supporting Information - **Fig. S2**). This multidimensional approach makes it particularly suitable for comprehensive sustainability assessments.

In contrast, the IPCC method, used in 13 of the reviewed studies, tends to focus narrowly on the "Global Warming Potential over a 100-year horizon" (GWP-100). This method, while effective for climate-specific analysis, often lacks the breadth required for a holistic sustainability evaluation. Nevertheless, some studies have combined IPCC with other methodologies such as ReCiPe (Fajilla et al., 2021) and CML (Eleftheriou et al., 2022) to complement its limited scope.

The CML baseline method, considered in 12 studies, ranks third in terms of frequency. It has been applied both independently and in combination with other approaches such as CED (Sanei and Modarres, 2023) and ReCiPe (Mattinzioli et al., 2021; Khila et al., 2017). While many CML-based assessments include a variety of impact categories, some studies such as Pomponi and D'Amico (2017) focus exclusively on global warming potential. Additional methodologies identified include ILCD and TRACI (each used in 7 studies), the Environmental Footprint method (6 studies), Environmental Product Declarations (EPDs) and Eco-Indicator 99 (each with 5 applications), and the use of conversion factors (in 4 studies). Notably, Eco-Indicator and EPD-based studies often prioritize GWP or climate-related indicators, while others adopt broader environmental impact scopes. Interestingly, only four studies entirely omitted the direct assessment of GWP. For example, Manco et al. (2023) utilized the Global Performance Indicator (GPI) to integrate economic and environmental metrics, whereas Monteiro and Soares (2022) focused on cumulative energy demand and non-renewable energy. Mousavi and Mehrpooya (2020) and Amaya et al. (2014) analyzed endpoint damage categories and ecopoints, respectively. On the other hand, it should be noted that 14 % of the articles analyzed did not include a description of the calculation methodology used for the Pa-LCA assessment, thus reducing the transparency and reproducibility of their findings.

4.6. Database for background activities

The use of transparent and updated databases for considering the environmental loads associated with background activities is essential to develop a relevant and accurate Pa-LCA. Ecoinvent database appeared to be the most recognized database for developing Pa-LCA analysis, being used for 60 out of the 95 articles under analysis (Supporting Information - **Table S2**). Known for its versatility and comprehensive coverage across various sectors—including chemicals, energy, and agriculture—ecoinvent is regularly updated and integrated with major LCA software platforms such as SimaPro, OpenLCA, and GaBi.

In addition to ecoinvent, the Ökobaudat database stands out, especially among studies focused on the construction sector. Tailored specifically for building applications, Ökobaudat includes detailed background data on construction materials and processes, aligned with sector-specific Environmental Product Declarations. However, its primary limitation lies in its geographic specificity, as it focuses on the German context, thereby reducing its generalizability to other regions.

The GaBi database, embedded in the GaBi software suite, has also been considered in several studies. It draws from diverse sources such as corporate data, patents, research projects, and EPDs. Compared to ecoinvent, GaBi tends to provide more industry-specific and regionally tailored datasets. Thus, the choice between GaBi and ecoinvent often depends on the scope, geographical context, and sectoral focus of the assessment. Other databases include USLCI (targeted toward North American sectors), ELCD (European context), Swiss KBOB (Swiss construction), National House Catalogue of Hungary, NETL CO2U (U.S. DOE data for carbon capture/utilization), Wood for Good (UK forestry sector), and GREET (used in transportation LCA studies). Each of these databases offers specialized data for certain sectors or regions. Ultimately, the appropriateness of a particular database depends on the specific goals, geographical context, and industrial sector of the Pa-LCA. Nevertheless, clear documentation of the database used is crucial to ensure data transparency and analytical robustness. Despite this, 14 out of 95 reviewed studies failed to disclose the background database utilized, a shortcoming that future studies should include.

4.7. Sensitivity and uncertainty analysis

As shown in Fig. 3, no articles prior to 2017 included either type of analysis. The use of uncertainty assessments began to appear in 2017, while sensitivity analysis did not gain traction until 2018, when both began to be implemented more consistently. While sensitivity analysis is a standard feature in conventional, attributional LCA studies, uncertainty analysis—especially involving probabilistic or Monte Carlo approaches—is less common. However, in the context of Pa-LCA, where multiple parameters are systematically varied, the use of uncertainty analysis becomes particularly relevant. It allows for quantification of the confidence levels in the results and supports more informed decision-making. Studies that incorporate both types of analyses remain relatively few. Most research includes either a sensitivity or an uncertainty assessment, but not both. To enhance the credibility and utility of Pa-LCA, future work should seek to integrate both approaches more

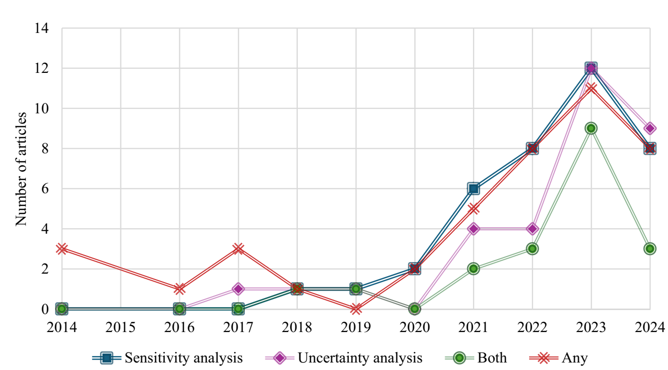

Fig. 3. Analysis of the integration of sensitivity and/or uncertainty analysis on the articles under analysis.

systematically.

4.8. Integration of Pa-LCA with AI and programming tools

Despite their potential, AI and programming tools have not been widely adopted in Pa-LCA. Only Manuguerra et al. (2024) employed AI-based algorithms, namely, generalized linear model, decision tree, gradient boosted trees, deep learning and random forest to optimize electric vehicle design based on environmental performance (Table 4). Other researchers have integrated Pa-LCA with programming tools such as MATLAB, used by Alarcón et al. (2024), Park et al. (2022), Kamalakkannan and Kulatunga (2021), and Galli et al. (2018) to simulate scenarios with variable parameters. Building Information Modeling (BIM) software was particularly considered in the construction sector, due to its spatial requirements.

For instance, Asgari et al. (2023) and Ajtayné Károlyfi and Szép (2023) investigated the effects of geometric and non-geometric parameters on energy consumption and structural sustainability. Huang et al. (2023) aimed to reduce carbon emissions from underground infrastructure design, while Kiss and Szalay (2020) developed a multi-objective optimization tool for residential construction. Other tools include Grasshopper, a 3D modeling tool used by Manni et al. (2020) and Lobaccaro et al. (2018) in architectural design, and Python, applied by Gibon and Hahn Menacho (2023) and Jolivet et al. (2021) for managing multiple process-related parameters in energy systems. Incorporating AI and programming tools into Pa-LCA can significantly enhance the modeling of complex scenarios, the management of large datasets, and the identification of optimal parameter configurations, particularly when KPIs are predefined. These tools also support more effective sensitivity and uncertainty analyses. Moving forward, the integration of such technologies is encouraged to advance the development of innovative, circular, and sustainability-driven decision-making frameworks in LCA.

5. Proposal for a theoretical and practical framework

Following a comprehensive analysis of the selected literature and the identification of prevailing challenges, methodological gaps, and areas for improvement in the development of Pa-LCA, Fig. 4 presents a proposed theoretical and practical guideline designed to support the development of future Pa-LCA studies. This proposal aims to enhance transparency, accuracy, and methodological robustness in Pa-LCA implementation by emphasizing five critical pillars: (1) adequate definition of key performance indicators, (2) thoughtful and justified selection of parameters, (3) comprehensive application of the traditional LCA structure, including the clear identification of the functional unit (FU), (4) integration of sensitivity analysis regarding parameter variability, and (5) Implementation of uncertainty analysis based on the defined ranges of parameters.

5.1. Step 1: Definition of KPIs, system boundaries and functional unit (FU)

The first step involves the establishment of the KPIs, system boundaries and the selection of an appropriate functional unit. These elements establish the scope of analysis and inform the subsequent selection of relevant parameters and assessment functions.

5.1.1. Definition of KPIs or objective functions

Establishing KPIs, threshold values, or performance objectives relevant to the specific case study ensures that the analysis remains goal oriented. KPIs are key tools for interpreting and operationalizing assessment results. Unlike static LCA, parametric approaches often produce large amounts of data across multiple scenarios or time steps.

Table 4
Analysis of the combination with AI, ML or programming tools. Acronym codes: NC (not combined), CPT (combined with programming tools) and CAM (combined with AI or ML tools).

Reference	Code	Reference	Code	Reference	Code	Reference	Code	Reference	Code
Küpfer et al. (2024)	NC	Rahardjo et al. (2024)	NC	Hansen et al. (2023)	NC	Ma and Deng (2022)	NC	Jang et al. (2021)	NC
Szalay (2024)	NC	Jones and Li (2024)	NC	Soleimani et al. (2023a, 2023b)	NC	Quintero-Herrera et al. (2022)	NC	Mattinzioli et al. (2021)	NC
Manuguerra et al. (2024)	CAM	Chen et al. (2024)	NC	Soleimani et al. (2022)	NC	Amoruso and Schuetze (2022)	NC	Caruso et al. (2021)	NC
Blazer et al. (2024)	NC	Alarcón et al. (2024)	CPT	Huang et al. (2023)	CPT	Ansah et al. (2022)	NC	Mousavi and Mehrpooya (2020)	CPT
Lee et al. (2023)	NC	Lin et al. (2024)	NC	Chaurasiya and Singh (2023)	NC	Andersen et al. (2022)	NC	Kiss and Szalay (2020)	CPT
Di Bari et al. (2024)	NC	Josa et al. (2023)	NC	Provost-Savard et al. (2023)	NC	Al-Obaidy et al. (2022)	NC	Manni et al. (2020)	CPT
Manjong et al. (2024)	NC	Hitt et al. (2023)	NC	Hussain et al. (2023)	CPT	Eleftheriou et al. (2022)	NC	Yan et al. (2020)	NC
Hermansdorfer et al. (2024)	NC	Yang et al. (2023)	NC	Zhu et al. (2022)	NC	Jang et al. (2022)	NC	Jang et al. (2020)	NC
Pérez-Cardona et al. (2024)	NC	Asgari et al. (2023)	CPT	Sánchez-Pantoja et al. (2023)	NC	Peralta-Reyes et al. (2022)	NC	Miller et al. (2019)	NC
Kwon and An (2024)	NC	Mowafy et al. (2023)	NC	Zhang et al. (2023)	NC	Pirson and Bol (2021)	NC	Fufa et al. (2018)	NC
Douziech et al. (2024)	NC	Manco et al. (2023)	NC	Roux et al. (2023)	NC	Mele et al. (2021)	NC	Galli et al. (2017)	CPT
Gao et al. (2024)	NC	Sanei and Modarres (2023)	NC	Lalau et al. (2022)	NC	Jolivet et al. (2021)	CPT	Lobaccaro et al. (2018)	CPT
Borschewski et al. (2024)	NC	Jones and Li (2023)	NC	Quéheille et al. (2022)	NC	Fajilla et al. (2021)	NC	Khila et al. (2017)	NC
Campos-Carriedo et al. (2024)	NC	Ajtayné Károlyfi and Szép (2023)	CPT	Gibon and Hahn Menacho (2023)	CPT	Giaveno et al. (2021)	CPT	Pomponi and D'Amico (2017)	NC
Torabi and Evins (2024)	NC	Speroni et al. (2023)	NC	Monteiro and Soares (2022)	NC	Bhat et al. (2021)	NC	Kylili et al. (2017)	NC
Dehghani et al. (2024)	NC	Buentello-Montoya et al. (2023)	NC	Rabie et al. (2022)	NC	Manjong et al. (2021)	NC	Huang et al. (2016)	NC
Arbulu Dudagoitia et al. (2024)	NC	Liao et al. (2023)	NC	Park et al. (2022)	CPT	Stemmle et al. (2021)	NC	Niero et al. (2014)	NC
Shinde et al. (2024)	NC	Gibon and Hahn Menacho (2023)	NC	Reisinger et al. (2022)	NC	Kamalakkannan and Kulatunga (2021)	CPT	Amaya et al. (2014)	NC
Bianchi et al. (2024)	NC	Besseau et al. (2023)	NC	Ala'a et al. (2022)	NC	Lask et al. (2021)	CPT	Yang et al. (2014)	NC

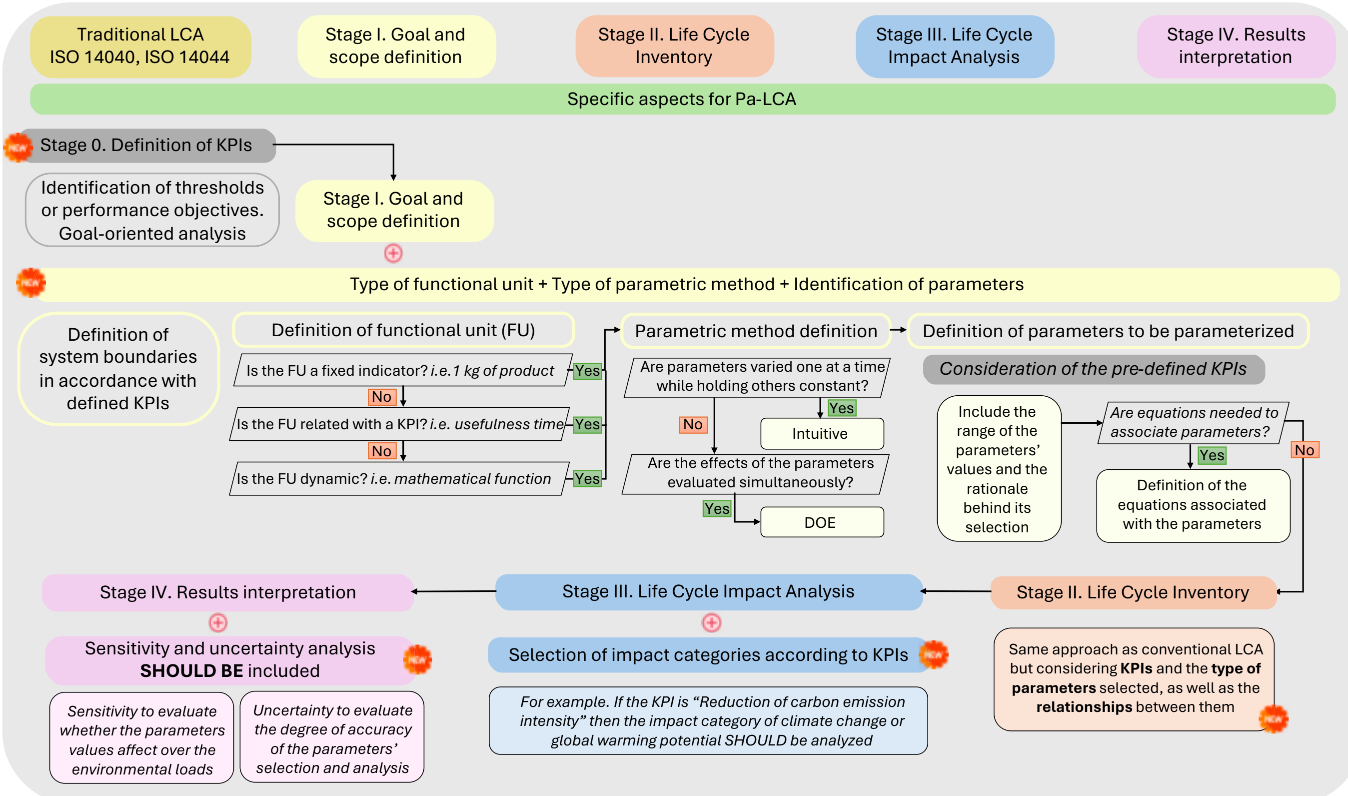

Fig. 4. Proposed roadmap for the development of an accurate and reliable Pa-LCA.

KPIs such as carbon emission intensity, water use efficiency, or renewable energy share, which are discussed in Section 4.1 of this review, help simplify this complexity into clear, actionable metrics that can be monitored, compared, and used for decision-making. By linking KPIs to specific life cycle impact categories and assessment outputs, practitioners can track performance, identify hotspots, and evaluate the effectiveness of interventions over time. In this way, KPIs not only enhance the analytical depth of parametric LCA but also increase its practical relevance for continuous improvement and strategic planning.

In terms of the functional unit, three main types are proposed:

- Fixed Functional Units (fixed-FU): These are the most commonly used in traditional LCA and are generally applicable across a wide range of scenarios.
- Dependent Functional Units (dependent-FU): These allow the FU to vary based on specific functionalities. For instance, Manuguerra et al. (2024) used "use of electric vehicles over an 8-year lifetime" and Hermansdorfer et al. (2024) proposed "emissions per inhabitant over a 50–80-year lifespan." Such units allow for more prospective and context-sensitive evaluations.
- Dynamic Functional Units (dynamic-FU): These are characterized by the integration of mathematical models or equations that reflect the interaction between variable parameters and the functional performance of the system. For example, Jang et al. (2022) used a linear model (e.g., "$y = ax + b$", where y represents the environmental impact and x is a system-specific parameter). Although more complex, dynamic-FUs offer superior capacity for capturing system behavior under variable conditions and facilitate more effective sensitivity and uncertainty assessments. However, their complexity, data requirements, and reduced comparability with other studies may be limiting factors.

5.2. Step 2: Definition of parametric methodology

The second step pertains to the selection of the parametric modeling approach. Two principal strategies are identified:

- Intuitive Parametric Method: In this approach, parameters are varied one at a time while holding others constant. It is particularly useful for simpler systems or when interactions among parameters are minimal or irrelevant. This method provides a clear interpretation of direct cause-and-effect relationships.
- Design of Experiments (DOE) Approach: This strategy evaluates the simultaneous effect of multiple parameter variations, making it more suitable for complex systems where parameter interdependencies exist. Though more demanding in terms of statistical expertise and data requirements, DOE approaches enhance the robustness of results and provide insights into multi-parameter interactions.

5.3. Step 3: Parameter definition and structuring

This step involves a structured approach to identifying and defining the parameters to be considered in the Pa-LCA. It comprises two substeps:

- Parameter Identification and Range Definition: Each parameter must be clearly defined, including its range of values and the rationale for its inclusion in the study.
- Mathematical Modeling (if applicable): If parameter interdependencies are to be modeled mathematically, the corresponding equations or relationships should be defined at this stage.

This step is critical, as the accuracy and relevance of the Pa-LCA depend directly on the quality and appropriateness of the parameters selected. Furthermore, it is necessary to define the number of iterations or alternative scenarios that will be analyzed through parameter variation.

5.4. Step 4: Impact analysis

The fourth step adheres to the traditional LCA methodology as defined by ISO 14040 and ISO 14044 standards. In the context of Pa-LCA, special attention must be given to the source of the data used for parameter definition:

- Primary Data: Derived from experiments, modeling, or surveys, generally offering higher accuracy.
- Secondary Data: Sourced from literature, statistical databases, or sectoral repositories, often less specific and requiring rigorous sensitivity and uncertainty analysis to mitigate vagueness.
- Other essential aspects that must be defined at this stage include: The software tool used for modeling (e.g., SimaPro, OpenLCA); the calculation methodology and impact/damage categories adopted; any allocation procedures applied.

The explicit documentation of these elements is necessary to ensure the transparency, traceability, and reproducibility of the Pa-LCA.

5.5. Step 5: Sensitivity and uncertainty analysis

The final step involves the application of sensitivity and uncertainty analyses. These analyses serve different but complementary purposes:

- Sensitivity Analysis identifies the parameters that exert the greatest influence on the outcomes, enabling prioritization and resource allocation during decision-making processes.
- Uncertainty Analysis assesses the variability in the results due to potential errors, data quality issues, or assumptions inherent in the parameterization process.

Both analyses contribute to enhancing the transparency and credibility of the study by demonstrating how changes in input assumptions or data affect the final results. Importantly, they support a more informed decision-making process and reduce the risk associated with critical parameter variability.

6. Discussion

The proposed roadmap addresses a critical methodological gap in the application of Pa-LCA. While Pa-LCA has emerged as a powerful approach to capture variability and uncertainty in sustainability assessments, its implementation remains inconsistent and largely unstandardized. Unlike conventional LCA, which benefits from ISO-based guidelines, Pa-LCA lacks a harmonized methodology for parameter selection, functional unit adaptation, and integration of sensitivity and uncertainty analyses. This absence of structure limits comparability, reproducibility, and the decision-making value of Pa-LCA studies.

The growing complexity of industrial systems and the urgency of sustainability transitions demand more flexible and adaptive assessment tools. Circular economy strategies, waste valorization, and resource efficiency initiatives often involve multiple scenarios and design alternatives. In such contexts, static assessments fail to capture the variability inherent in material flows, process efficiencies, and end-of-life options. Pa-LCA offers a solution, but only if applied systematically. The proposed methodological roadmap provides a clear sequence of steps, from defining the parametric model, identification of parameters, type of functional units, to results interpretation, that ensures methodological rigor and transparency, enabling practitioners to generate meaningful insights for decision-making.

The proposed roadmap is designed for real-world implementation across diverse sectors and sustainability challenges, as for example:

Renewable Energy Systems: In solar PV or wind energy projects, parameters such as capacity factor, technology efficiency, and grid mix can be varied to assess environmental impacts under different operational conditions, supporting investment and policy decisions.
Circular Economy and Waste Management: When evaluating recycling or remanufacturing strategies, parameters like collection rates, material recovery efficiency, and transportation distances can be modeled to identify the most sustainable pathways. For example, assessing the environmental trade-offs between mechanical and chemical recycling of plastics requires parameterized modeling of energy use and yield rates.
Product Design and Eco-Innovation: Early-stage product development often involves uncertainty in material selection, manufacturing routes, and end-of-life scenarios. Applying the roadmap enables scenario-based evaluations that guide eco-design strategies before committing to costly prototypes.
Industrial Symbiosis and Resource Efficiency: In multi-plant networks, parameters such as waste exchange rates, energy integration options, and process efficiencies can be modeled to optimize resource flows and minimize environmental burdens.
Construction Sector: Building projects involve significant variability in material choices, structural design, and end-of-life scenarios. Using Pa-LCA, parameters such as concrete mix composition, recycled aggregate content, insulation materials, and demolition waste recovery rates can be modeled to evaluate environmental performance across design alternatives. This supports decisions on low-carbon construction strategies and circular building practices.

While the proposed methodological roadmap provides a structured approach for implementing Pa-LCA, several limitations must be acknowledged:

Data Availability and Quality: The effectiveness of Pa-LCA depends heavily on the availability of high-quality parametric datasets. In many sectors, such data are scarce or fragmented, which can compromise the robustness of the analysis. Developing shared databases and open-access repositories for parametric data should be a priority for future research.
Computational Complexity: As the number of parameters and scenarios increases, so does the computational burden. This can limit the feasibility of Pa-LCA for large-scale systems or when real-time decision support is required. Future work should explore optimization techniques and software tools that streamline scenario generation and analysis.
Sector-Specific Customization: While the roadmap is designed to be generic, its application often requires tailoring to sector-specific characteristics. For example, in construction, parameters related to material durability and demolition waste recovery differ significantly from those in electronics manufacturing. Future research should focus on developing sector-specific guidelines and case studies to operationalize the roadmap effectively.
Integration with Circular Economy Metrics: Although the roadmap supports modeling of recycling and reuse scenarios, further work is needed to integrate circularity indicators (e.g., material circularity index, resource efficiency metrics) into Pa-LCA workflows. This would enhance its relevance for circular economy strategies.
Stakeholder Engagement and Decision-Making: Pa-LCA results are often complex and require interpretation for non-technical stakeholders. Future research should explore visualization tools and decision-support systems that translate parametric results into actionable insights for policymakers, designers, and industry practitioners.

By addressing these limitations, future developments can enhance the usability, scalability, and impact of Pa-LCA, ensuring its role as a key tool for advancing sustainable production and consumption systems. Future research should focus on developing and integrating digital tools and databases that facilitate parameter selection and streamline the application of Pa-LCA across industries.

7. Conclusions

This systematic review provides a critical and comprehensive evaluation of the fundamental components that define effective Parametric Life Cycle Assessment (Pa-LCA) studies. By rigorously analyzing the definition of functional units, the delineation of system boundaries, the selection and classification of parameters, and the integration of sensitivity and uncertainty analyses, this review identifies both the strengths and persistent methodological shortcomings within current Pa-LCA practices.

A key insight is the pivotal role of the functional unit, which must be meticulously tailored to reflect system variability. This often necessitates dynamic formulations to ensure relevance and precision. Similarly, system boundaries must be explicitly designed to capture the influence of changing parameters, particularly in intricate or interdependent systems.

Parameter selection emerges as a cornerstone of successful Pa-LCA implementation. Robust parameterization demands a profound understanding of system intricacies and a strategic focus on variables with the greatest potential to influence outcomes such as environmental performance, economic feasibility, and product quality. Crucially, parameters should be selected not only for their relevance but also for their ability to support sensitivity and uncertainty analyses. These tools are essential for generating reliable, evidence-based insights and guiding strategic decision-making.

However, this review reveals a recurring shortfall: many studies lack a clear rationale or typology for parameter inclusion, which compromises both the interpretability and reproducibility of results. To address this, a structured methodological roadmap has been proposed to elevate the scientific rigor and practical utility of Pa-LCA. By adopting this roadmap, researchers and practitioners can construct Pa-LCA models that are not only transparent and flexible but also robust and decision-ready. Ultimately, this framework empowers Pa-LCA to evolve into a potent tool for sustainability assessment, capable of informing strategic choices and driving transformative environmental and economic improvements.

CRediT authorship contribution statement

Ana Arias: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Maria Teresa Moreira:** Writing – review & editing, Validation, Supervision. **Reinout Heijungs:** Writing – review & editing, Visualization, Validation, Formal analysis. **Stefano Cucurachi:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

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

Acknowledgements

This study was supported by the SteamDry (No 101137906) project, funded by the European Commission HORIZON-CL4-2023-TWIN-TRANSITION-01 and by Eastern Lights (NO 101136122) project, funded by the European Commission HORIZON-CL5-2023-D3-01-17. A. Arias thanks the Galician Government for financial support (Grant reference ED481B-2023-072). A. Arias and MT Moreira authors belong to the Galician Competitive Research Group (GRC ED431C 2021/37) and to the Cross-disciplinary Research in Environmental Technologies (CRETUS Research Center, ED431G 2023/12).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.spc.2025.10.016.

References

Ajtayné Károlyfi, K., Szép, J., 2023. A parametric BIM framework to conceptual structural Design for Assessing the embodied environmental impact. Sustainability 15 (15), 11990.
Ala'a, H., Osman, A.I., Jamil, F., Mehta, N., Al-Haj, L., Coulon, F., Rooney, D.W., 2022. Integrating life cycle assessment and characterisation techniques: a case study of biodiesel production utilising waste Prunus Armeniaca seeds (PAS) and a novel catalyst. J. Environ. Manag. 304, 114319.
Alarcón, V.M., Ochoa, G.V., Castilla, D.V., 2024. Energetic, exergetic, and carbon footprint performance assessment of a combined renewable simple and recompressed Brayton S-CO2/ORC system. Energy Rep. 12, 3114–3133.
Ali, A.R., Derin, D., Blömeke, S., Herrmann, C., July 2025. Parametric life cycle assessment model for absolute environmental sustainability assessment of lithium-ion batteries. Sustain. Prod. Consum. 57, 80–94.
Al-Obaidy, M., Courard, L., Attia, S., 2022. A parametric approach to optimizing building construction systems and carbon footprint: a case study inspired by circularity principles. Sustainability 14 (6), 3370.
Amaya, J., Lelah, A., Zwolinski, P., 2014. Design for intensified use in product–service systems using life-cycle analysis. J. Eng. Des. 25 (7–9), 280–302.
Amoruso, F.M., Schuetze, T., 2022. Life cycle assessment and costing of carbon neutral hybrid-timber building renovation systems: three applications in the Republic of Korea. Build. Environ. 222, 109395.
Andersen, R., Ravn, A.S., Ryberg, M.W., 2022. Environmental benefits of applying selective demolition to buildings: a case study of the reuse of façade steel cladding. Resour. Conserv. Recycl. 184, 106430.
Ansah, M.K., Chen, X., Yang, H., 2022. A holistic environmental and economic design optimization of low carbon buildings considering climate change and confounding factors. Sci. Total Environ. 821, 153442.
Arbulu Dudagoitia, M., Oregi Isasi, X., Etxepare Igiñiz, L., 2024. Parametric Simulation Tool for the Enviro-Economic Evaluation of Energy Renovation Strategies in Residential Buildings with Life Cycle Thinking: PARARENOVATE-LCT.
Asgari, S., Haghir, S., Noorzai, E., 2023. Reducing energy consumption in operation and demolition phases by integrating multi-objective optimization with LCA and BIM. Energ. Effic. 16 (6), 54.
Badawy, M., Abd El-Aziz, A.A., Idress, A.M., Hefny, H., Hossam, S., 2016. A survey on exploring key performance indicators. Future Computing and Informatics Journal 1 (1–2), 47–52.
Bernstein, W.Z., Tensa, M., Praniewicz, M., Kwon, S., Ramanujan, D., 2020. An automated workflow for integrating environmental sustainability assessment into parametric part design through standard reference models. Procedia CIRP 90, 102–108.
Besseau, R., Tannous, S., Douziech, M., Jolivet, R., Prieur-Vernat, A., Clavreul, J., Pérez-López, P., 2023. An open-source parameterized life cycle model to assess the environmental performance of silicon-based photovoltaic systems. Prog. Photovolt. Res. Appl. 31 (9), 908–920.
Bhat, C.G., Mukherjee, A., Meijer, J.P., 2021. Life cycle information models: parameterized linked data structures to facilitate the consistent use of life-cycle assessment in decision making. Journal of Transportation Engineering, Part B: Pavements 147 (4), 04021060.
Bianchi, I., Volpe, S., Fiorito, F., Forcellese, A., Sangiorgio, V., 2024. Life cycle assessment of building envelopes manufactured through different 3D printing technologies. J. Clean. Prod. 440, 140905.
Blazer, S.J., Wang, Y., Xu, N., Zhou, X.D., Marchetti, B., 2024. A systematic life cycle assessment of the electroconversion of carbon dioxide. Sustain Energy Technol Assess 61, 103574.
Borschewski, D., Weber, S., Albrecht, S., Leistner, P., 2024. Mastering complexity in life cycle assessment for product development: evaluating the impacts of adaptive façades. Sustainable Production and Consumption 49, 341–353.
Buentello-Montoya, D.A., Armenta-Gutiérrez, M.Á., Maytorena-Soria, V.M., 2023. Parametric modelling study to determine the feasibility of the co-gasification of macroalgae and plastics for the production of hydrogen-rich syngas. Energies 16 (19), 6819.
Campos-Carriedo, F., Pérez-López, P., Dufour, J., Iribarren, D., 2024. A parametric life cycle framework to promote sustainable-by-design product development: application to a hydrogen production technology. J. Clean. Prod. 469, 143129.
Caruso, M., Pinho, R., Bianchi, F., Cavalieri, F., Lemmo, M.T., 2021. Integrated economic and environmental building classification and optimal seismic vulnerability/energy efficiency retrofitting. Bull. Earthq. Eng. 19 (9), 3627–3670.
Cavalliere, C., Brescia, L., Maiorano, G., Dalla Mora, T., Raffaele Dell'Osso, G., Naboni, E., 2019. Towards an accessible life cycle assessment: a literature-based review of current BIM and parametric based tools capabilities. Build. Simul. 2019 (16), 159–166.
Chaurasiya, S., Singh, G., 2023. Life cycle assessment of sustainable turning techniques for pure titanium alloy: a comparative analysis. Int. J. Interact. Des. Manuf. (IJIDeM) 1–16.
Chen, H., Can Sener, S.E., Van Emburg, C., Jones, M., Bogucki, T., Bonilla, N., Carbajales-Dale, M., 2024. Electric light-duty vehicles have decarbonization potential but may

not reduce other environmental problems. Communications Earth & Environment 5 (1), 476.
Contini, G., Peruzzini, M., Bulgarelli, S., Bosi, G., 2023. Developing key performance indicators for monitoring sustainability in the ceramic industry: the role of digitalization and industry 4.0 technologies. J. Clean. Prod. 414, 137664.
Cooper, J.S., Noon, M., Kahn, E., 2012a. Parameterization in life cycle assessment inventory data: review of current use and the representation of uncertainty. Int. J. Life Cycle Assess. 17 (6), 689–695.
Cooper, J.S., Noon, M., Kahn, E., 2012b. Parameterization in life cycle assessment inventory data: review of current use and the representation of uncertainty. Int. J. Life Cycle Assess. 17 (6), 689–695.
Dehghani, O., Eslami, A., Mahdavipour, M.A., Mostofinejad, D., Ghorbani Mooselu, M., Pilakoutas, K., 2024. Ceramic waste powder as a cement replacement in concrete paving blocks: mechanical properties and environmental assessment. International Journal of Pavement Engineering 25 (1), 2370563.
Di Bari, R., Turrin, F., Leis, H., Isaia, F., Belleri, A., 2024. Effectiveness and sustainability of solutions sets aimed at plus energy buildings. A multi-case and multi-domain investigation. J. Build. Eng. 94, 109914.
Dong, Y., Miraglia, S., Manzo, S., Georgiadis, S., Sørup, H.J.D., Boriani, E., Hauschild, M. Z., 2018. Environmental sustainable decision making–the need and obstacles for integration of LCA into decision analysis. Environ. Sci. Pol. 87, 33–44.
Dorn, C., Behrend, R., Giannopoulos, D., Napolano, L., James, V., Herrmann, A., Trimis, D., 2016. A systematic LCA-enhanced KPI evaluation towards sustainable manufacturing in industrial decision-making processes. A case study in glass and ceramic frits production. Procedia Cirp 48, 158–163.
Douziech, M., Besseau, R., Jolivet, R., Shoai-Tehrani, B., Bourmaud, J.Y., Busato, G., Pérez-López, P., 2024. Life cycle assessment of prospective trajectories: a parametric approach for tailor-made inventories and its computational implementation. J. Ind. Ecol. 28 (1), 25–40.
Eleftheriou, E., Lopez Muñoz, L.F., Habert, G., Zea Escamilla, E., 2022. Parametric approach to simplified life cycle assessment of social housing projects. Sustainability 14 (12), 7409.
Erakca, M., Baumann, M., Helbig, C., Weil, M., 2024. Systematic review of scale-up methods for prospective life cycle assessment of emerging technologies. J. Clean. Prod. 451, 142161.
Fajilla, G., Borri, E., De Simone, M., Cabeza, L.F., Bragança, L., 2021. Effect of climate change and occupant behaviour on the environmental impact of the heating and cooling systems of a real apartment. A parametric study through life cycle assessment. Energies 14 (24), 8356.
Fantini, P., Palasciano, C., Taisch, M., 2015. Back to intuition: proposal for a performance indicators framework to facilitate eco-factories management and benchmarking. Procedia Cirp 26, 1–6.
Finkbeiner, M., Inaba, A., Tan, R., Christiansen, K., Klüppel, H.J., 2006. The new international standards for life cycle assessment: ISO 14040 and ISO 14044. Int. J. Life Cycle Assess. 11, 80–85.
Fufa, S.M., Skaar, C., Gradeci, K., Labonnote, N., 2018. Assessment of greenhouse gas emissions of ventilated timber wall constructions based on parametric LCA. J. Clean. Prod. 197, 34–46.
Galli, F., Pirola, C., Previtali, D., Manenti, F., Bianchi, C.L., 2018. Eco design LCA of an innovative lab scale plant for the production of oxygen-enriched air. Comparison between economic and environmental assessment. J. Clean. Prod. 171, 147–152.
Gao, S., Li, J., Nishiwaki, T., Ding, Y., Wang, J.X., 2024. Structural implementation of recycled lump prepared from waste concrete after elevated temperatures: mechanical and environmental performances. In: Structures, 67. Elsevier, p. 106970.
Garcia, R., Freire, F., 2017. A review of fleet-based life-cycle approaches focusing on energy and environmental impacts of vehicles. Renew. Sust. Energ. Rev. 79, 935–945.
Gautam, A., Khan, Z.A., Gani, A., Asjad, M., 2025. Identification, ranking and prioritization of key performance indicators for evaluating greenness of manufactured products. Green Technologies and Sustainability 3 (1), 100114.
Giaveno, S., Osello, A., Garufi, D., Santamaria Razo, D., 2021. Embodied carbon and embodied energy scenarios in the built environment. Computational design meets EPDs. Sustainability 13 (21), 11974.
Gibon, T., Hahn Menacho, A., 2023. Parametric life cycle assessment of nuclear power for simplified models. Environ. Sci. Technol. 57 (38), 14194–14205.
Hansen, R.N., Hoxha, E., Rasmussen, F.N., Ryberg, M.W., Andersen, C.E., Birgisdóttir, H., 2023. Enabling rapid prediction of quantities to accelerate LCA for decision support in the early building design. Journal of Building Engineering 76, 106974.
Heijungs, R., 2020. Is mainstream LCA linear? Int. J. Life Cycle Assess. 25 (10), 1872–1882.
Hermansdorfer, M., Oettinger, C., Skov-Petersen, H., Fricker, P., Negendahl, K., 2024. Advancing low-emission Urban Design through parametric modelling and life cycle assessment. Journal of Digital Landscape Architecture 9, 858–872.
Hitt, C., Douglas, J., Keoleian, G., 2023. Parametric life cycle assessment modeling of reusable and single-use restaurant food container systems. Resour. Conserv. Recycl. 190, 106862.
Huang, C.Y., Hu, A.H., Yin, J., Wang, H.C., 2016. Developing a parametric carbon footprinting tool for the semiconductor industry. Int. J. Environ. Sci. Technol. 13, 275–284.
Huang, M.Q., Chen, X.L., Ninić, J., Bai, Y., Zhang, Q.B., 2023. A framework for integrating embodied carbon assessment and construction feasibility in prefabricated stations. Tunn. Undergr. Space Technol. 132, 104920.
Hussain, M., Zheng, B., Chi, H.L., Hsu, S.C., Chen, J.H., 2023. Automated and continuous BIM-based life cycle carbon assessment for infrastructure design projects. Resour. Conserv. Recycl. 190, 106848.
Ishaq-Bhatti, M., Awan, H.M., Razaq, Z., 2014. The key performance indicators (KPIs) and their impact on overall organizational performance. Qual. Quant. 48, 3127–3143.
Jang, H., Jeong, B., Zhou, P., Ha, S., Nam, D., Kim, J., Lee, J.U., 2020. Development of parametric trend life cycle assessment for marine SOx reduction scrubber systems. J. Clean. Prod. 272, 122821.
Jang, H., Jeong, B., Zhou, P., Ha, S., Nam, D., 2021. Demystifying the lifecycle environmental benefits and harms of LNG as marine fuel. Appl. Energy 292, 116869.
Jang, H., Jeong, B., Zhou, P., Ha, S., Park, C., Nam, D., Rashedi, A., 2022. Parametric trend life cycle assessment for hydrogen fuel cell towards cleaner shipping. J. Clean. Prod. 372, 133777.
Jolivet, R., Clavreul, J., Brière, R., Besseau, R., Prieur Vernat, A., Sauze, M., Pérez-López, P., 2021. LCA_algebraic: a library bringing symbolic calculus to LCA for comprehensive sensitivity analysis. Int. J. Life Cycle Assess. 26, 2457–2471.
Jones, K.E., Li, M., 2023. Life cycle assessment of ultra-tall wind turbine towers comparing concrete additive manufacturing to conventional manufacturing. J. Clean. Prod. 417, 137709.
Jones, K.E., Li, M., 2024. Life Cycle Assessment of Additively Manufactured Foundations for Ultratall Wind Turbine Towers. Wind Energy 27 (11), 1427–1449.
Josa, I., Petit-Boix, A., Casanovas-Rubio, M.D.M., Pujadas, P., De la Fuente, A., 2023. Environmental and economic impacts of combining backfill materials for novel circular narrow trenches. J. Environ. Manag. 341, 118020.
Kamalakkannan, S., Kulatunga, A.K., 2021. Optimization of eco-design decisions using a parametric life cycle assessment. Sustainable Production and Consumption 27, 1297–1316.
Khila, Z., Baccar, I., Jemel, I., Hajjaji, N., 2017. Thermo-environmental life cycle assessment of hydrogen production by autothermal reforming of bioethanol. Energy Sustain. Dev. 37, 66–78.
Kiss, B., Szalay, Z., 2020. Modular approach to multi-objective environmental optimization of buildings. Autom. Constr. 111, 103044.
Küpfer, C., Bertola, N., Fivet, C., 2024. Reuse of cut concrete slabs in new buildings for circular ultra-low-carbon floor designs. J. Clean. Prod. 448, 141566.
Kwon, Y., An, J., 2024. Comparative life cycle assessment of landfill gas utilization in South Korea with parametric uncertainties. Renew. Sust. Energ. Rev. 198, 114449.
Kylili, A., Ilic, M., Fokaides, P.A., 2017. Whole-building life cycle assessment (LCA) of a passive house of the sub-tropical climatic zone. Resour. Conserv. Recycl. 116, 169–177.
Lacirignola, M., Blanc, P., Girard, R., Pérez-López, P., Blanc, I., 2017. LCA of emerging technologies: addressing high uncertainty on inputs' variability when performing global sensitivity analysis. Sci. Total Environ. 578, 268–280.
Lalau, Y., Al Asmi, I., Olives, R., Dejean, G., Meffre, A., Py, X., 2022. Energy analysis and life cycle assessment of a thermal energy storage unit involving conventional or recycled storage materials and devoted to industrial waste heat valorisation. J. Clean. Prod. 330, 129950.
Lamperth, M., Mueller, K.G., Kimura, F., 2004. Parameterised inventories for life cycle assessment. Int. J. Life Cycle Assess. 9.
Lan, K., 2024. Some modeling challenges in dynamic life cycle assessment. BioResources 19 (3), 4040.
Landström, A., Almström, P., Winroth, M., Andersson, C., Öberg, A.E., Kurdve, M., Shahbazi, S., Wiktorsson, M., Windmark, C., Zackrisson, M., 2018. A life cycle approach to business performance measurement systems. Procedia Manufacturing 25, 126–133.
Lask, J., Kam, J., Weik, J., Kiesel, A., Wagner, M., Lewandowski, I., 2021. A parsimonious model for calculating the greenhouse gas emissions of miscanthus cultivation using current commercial practice in the United Kingdom. GCB Bioenergy 13 (7), 1087–1098.
Lee, S., Lee, I., Seo, D., Kim, H., Joo, G., Lee, S., Park, K., 2023. Life cycle assessment of aPHA production. ACS Sustain. Chem. Eng. 12 (1), 72–84.
Liao, J., De Kleine, R., Kim, H.C., Luckey, G., Forsmark, J., Lee, E.C., Cooper, D.R., 2023. Assessing the sustainability of laser powder bed fusion and traditional manufacturing processes using a parametric environmental impact model. Resour. Conserv. Recycl. 198, 107138.
Lin, Y., Wang, C., Sun, M., Yan, J., 2024. Experimental evaluation and theoretical modeling of eco-friendly bamboo scrimber-UHPC members with enhanced shear connectors. J. Clean. Prod. 450, 141920.
Liu, M., Zhu, G., Tian, Y., December 2024. The historical evolution and research trends of life cycle assessment. Green Carbon. 2 (4), 425–437.
Lobaccaro, G., Wiberg, A.H., Ceci, G., Manni, M., Lolli, N., Berardi, U., 2018. Parametric design to minimize the embodied GHG emissions in a ZEB. Energ. Buildings 167, 106–123.
Ma, R., Deng, Y., 2022. The electrochemical model coupled parameterized life cycle assessment for the optimized design of EV battery pack. Int. J. Life Cycle Assess. 27 (2), 267–280.
Manco, P., Caterino, M., Rinaldi, M., Fera, M., 2023. Additive manufacturing in green supply chains: a parametric model for life cycle assessment and cost. Sustainable Production and Consumption 36, 463–478.
Manjong, N.B., Usai, L., Burheim, O.S., Strømman, A.H., 2021. Life cycle modelling of extraction and processing of battery minerals—a parametric approach. Batteries 7 (3), 57.
Manjong, N.B., Usai, L., Orangi, S., Clos, D.P., Strømman, A.H., 2024. Exploring raw material contributions to the greenhouse gas emissions of lithium-ion battery production. J Energy Storage 100, 113566.
Manni, M., Lobaccaro, G., Lolli, N., Bohne, R.A., 2020. Parametric design to maximize solar irradiation and minimize the embodied ghg emissions for a zeb in nordic and mediterranean climate zones. Energies 13 (18), 4981.

Manuguerra, L., Cappelletti, F., Germani, M., 2024. A machine learning based method for parametric environmental impact model for electric vehicles. J. Clean. Prod. 454, 142308.
Mattinzioli, T., Sol-Sánchez, M., Martínez, G., Rubio-Gámez, M., 2021. A parametric study on the impact of open-source inventory variability and uncertainty for the life cycle assessment of road bituminous pavements. Int. J. Life Cycle Assess. 26, 916–935.
Mele, M., Campana, G., Fumelli, G., 2021. Environmental impact assessment of Arburg plastic freeforming additive manufacturing. Sustainable Production and Consumption 28, 405–418.
Miller, I., Gençer, E., Vogelbaum, H.S., Brown, P.R., Torkamani, S., O'Sullivan, F.M., 2019. Parametric modeling of life cycle greenhouse gas emissions from photovoltaic power. Appl. Energy 238, 760–774.
Monteiro, H., Soares, N., 2022. Integrated life cycle assessment of a southern European house addressing different design, construction solutions, operational patterns, and heating systems. Energy Rep. 8, 526–532.
Mousavi, S.A., Mehrpooya, M., 2020. A comprehensive exergy-based evaluation on cascade absorption-compression refrigeration system for low temperature applications-exergy, exergoeconomic, and exergoenvironmental assessments. J. Clean. Prod. 246, 119005.
Mowafy, N., El Zayat, M., Marzouk, M., 2023. Parametric BIM-based life cycle assessment framework for optimal sustainable design. Journal of Building Engineering 75, 106898.
Niero, M., Di Felice, F., Ren, J., Manzardo, A., Scipioni, A., 2014. How can a life cycle inventory parametric model streamline life cycle assessment in the wooden pallet sector? Int. J. Life Cycle Assess. 19, 901–918.
Olanrewaju, O.I., Enegbuma, W.I., Donn, M., 2024. Challenges in life cycle assessment implementation for construction environmental product declaration development: a mixed approach and global perspective. Sustainable Production and Consumption 49, 502–528.
Park, C., Jeong, B., Zhou, P., Jang, H., Kim, S., Jeon, H., Rashedi, A., 2022. Live-life cycle assessment of the electric propulsion ship using solar PV. Appl. Energy 309, 118477.
Peralta-Reyes, E., Vizarretea-Vasquez, D., Natividad, R., Aizpuru, A., Robles-Gomez, E., Alanis, C., Regalado-Mendez, A., 2022. Electrochemical reforming of glycerol into hydrogen in a batch-stirred electrochemical tank reactor equipped with stainless steel electrodes: parametric optimization, total operating cost, and life cycle assessment. J. Environ. Chem. Eng. 10 (4), 108108.
Pérez-Cardona, J.R., Maani, T., Zhao, F., Sutherland, J.W., 2024. Parametric design, life cycle assessment, and optimization of a discrete product with application to an electric traction motor. Resour. Conserv. Recycl. 201, 107344.
Pirson, T., Bol, D., 2021. Assessing the embodied carbon footprint of IoT edge devices with a bottom-up life-cycle approach. J. Clean. Prod. 322, 128966.
Pomponi, F., D'Amico, B., 2017. Holistic study of a timber double skin façade: whole life carbon emissions and structural optimisation. Build. Environ. 124, 42–56.
Provost-Savard, A., Legros, R., Majeau-Bettez, G., 2023. Parametrized regionalization of paper recycling life-cycle assessment. Waste Manag. 156, 84–96.
Quéheille, E., Ventura, A., Saiyouri, N., Taillandier, F., 2022. A life cycle assessment model of end-of-life scenarios for building deconstruction and waste management. J. Clean. Prod. 339, 130694.
Quintero-Herrera, S., Zwolinski, P., Evrard, D., Cano-Gómez, J.J., Botello-Álvarez, J.E., Rivas-García, P., 2022. The role of livestock feed fertilization as an improvement of sustainability in the dairy sector. Sustainable Production and Consumption 31, 448–458.
Rabie, M., Irshidat, M.R., Al-Nuaimi, N., 2022. Ambient and heat-cured geopolymer composites: mix design optimization and life cycle assessment. Sustainability 14 (9), 4942.
Rahardjo, A., Navaratnam, S., Zhang, G., Tushar, Q., Nguyen, K., 2024. Suitability of foamed concrete for the composite floor system in mid-to-high-rise modular buildings: design, structural, and sustainability perspectives. Sustainability 16 (4), 1624.
Reisinger, J., Kugler, S., Kovacic, I., Knoll, M., 2022. Parametric optimization and decision support model framework for life cycle cost analysis and life cycle assessment of flexible industrial building structures integrating production planning. Buildings 12 (2), 162.
Roux, C., Kuzmenko, K., Roussel, N., Mesnil, R., Feraille, A., 2023. Life cycle assessment of a concrete 3D printing process. Int. J. Life Cycle Assess. 28 (1), 1–15.
Salati, M., Costa, A.A., Silvestre, J.D., 2025. A comprehensive review of dynamic life cycle assessment for buildings: Exploring key processes and methodologies. Sustainability 17 (1), 159.
Sánchez-Pantoja, N., Lázaro, C., Vidal, R., 2023. Parameterized environmental impacts of ready-mixed concrete in Spain. J. Sustain. Cem.-Based Mater. 12 (6), 751–770.
Sanei, S., Modarres, A., 2023. Optimization of asphalt cold recycling containing ordinary and waste additives based on life cycle assessment considering the road traffic level-case study: coal preparation plant. Case Studies in Construction Materials 19, e02329.
Säwén, T., Magnusson, E., Kalagasidis, A.S., Hollberg, A., 2022. Tool characterisation framework for parametric building LCA. In: IOP Conference Series: Earth and Environmental Science, 1078, No. 1. IOP Publishing, p. 012090.
Shinde, R., Kim, A., Hellweg, S., 2024. Bottom-up LCA building stock model: tool for future building-management scenarios. J. Clean. Prod. 434, 140272.
Slavkovic, K., Stephan, A., 2025. Dynamic life cycle assessment of buildings and building stocks–a review. Renew. Sust. Energ. Rev. 212, 115262.
Soleimani, T., Hayek, M., Junqua, G., Salgues, M., Souche, J.C., 2023a. Environmental, economic and experimental assessment of the valorization of dredged sediment through sand substitution in concrete. Sci. Total Environ. 858, 159980.
Soleimani, T., Sordes, F., Techer, I., Junqua, G., Hayek, M., Salgues, M., Souche, J.C., 2023b. Comparative environmental and economic life cycle assessment of phytoremediation of dredged sediment using Arundo Donax, integrated with biomass to bioenergy valorization chain. Sci. Total Environ. 903, 166160.
Speroni, A., Cavaglià, M., Mainini, A.G., Casarini, V., Bovi, S., Blanco Cadena, J.D., Poli, T., 2023. Parametric assessment to evaluate and compare the carbon footprint of diverse manufacturing processes for building complex surfaces. Buildings 13 (12), 2989.
Stemmle, R., Blum, P., Schüppler, S., Fleuchaus, P., Limoges, M., Bayer, P., Menberg, K., 2021. Environmental impacts of aquifer thermal energy storage (ATES). Renew. Sust. Energ. Rev. 151, 111560.
Swartz, M.K., 2021. PRISMA 2020: an update. J. Pediatr. Health Care 35 (4), 351.
Szalay, Z., 2024. A parametric approach for developing embodied environmental benchmark values for buildings. Int. J. Life Cycle Assess. 1–19.
Thonemann, N., Schulte, A., Maga, D., 2020. How to conduct prospective life cycle assessment for emerging technologies? A systematic review and methodological guidance. Sustainability 12 (3), 1192.
Torabi, M., Evins, R., 2024. Towards net-zero carbon buildings: investigating the impact of early-stage structure design on building embodied carbon. Int. J. Life Cycle Assess. 1–16.
Yan, J., Broesicke, O.A., Wang, D., Li, D., Crittenden, J.C., 2020. Parametric life cycle assessment for distributed combined cooling, heating and power integrated with solar energy and energy storage. J. Clean. Prod. 250, 119483.
Yang, K.H., Seo, E.A., Choi, D.U., 2014. Effect of fly ash on lifecycle CO2 assessment of concrete structure. Appl. Mech. Mater. 692, 475–481.
Yang, N., Sheng, X., Ti, L., Jia, H., Ping, Q., Li, N., 2023. Ball-milling transesterification process on biodiesel production: RSM optimization, life cycle assessment and market dynamics analysis. Energy 283, 129201.
Zhang, C., Zheng, Y., Huang, H., Liu, Z., Jing, J., 2023. Environmental impact assessment of aluminum electrolytic capacitors in a product family from the manufacturer's perspective. Int. J. Life Cycle Assess. 28 (1), 80–94.
Zhao, X., Bai, S., Tu, Y., Zhang, X., Spanjers, H., 2020. Parameter optimization of environmental technologies using a LCA-based analysis scheme: a bioaugmentation case study. Sci. Total Environ. 737, 140284.
Zhu, Y., Keoleian, G.A., Cooper, D.R., 2023. A parametric life cycle assessment model for ductile cast iron components. Resour. Conserv. Recycl. 189, 106729.