



## Review

# Systematic review of scale-up methods for prospective life cycle assessment of emerging technologies

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## ABSTRACT

Prospective Life Cycle Assessments (LCAs) are crucial for analyzing and optimizing emerging technologies' conceivable environmental performance. However, emerging technologies are often subject to high uncertainties and are still at laboratory or pilot scale, necessitating the scale-up of LCA relevant data, such as energy and material flows, to an industrial level. Hence, robust and adequate scaling methods are required as an integrated part of any sustainability-oriented prospective assessment. This work presents a systematic review of scaling techniques used in various LCA related studies ( $n = 78$ ) and analyzes their frequency and the respective technology type's and group's potential influence. Literature providing detailed scaling methodologies are identified, exposed, and quantitatively evaluated to discover their advantages and disadvantages. An Excel-based tool is derived to assist in selecting appropriate scaling methodologies as provided by literature by customizing the respective evaluation criteria (complexity, data intensity, duration, and uncertainty). With its primary focus on prospective LCA to provide practical guidance, the work offers insights that are relevant to other sustainability assessment methods as well. Essential guidance in the selection of appropriate scaling methods is provided, facilitating more robust sustainability assessments and supporting decision-making processes in research, industry, and policymaking.

## 1. Introduction

The ongoing development of novel technologies that are more environmentally friendly, cost-efficient and socially beneficial than their established counterparts (van der Giesen et al., 2020) have rendered them an increasing focus in sustainability-driven evaluation methods to ensure their superiority (Thonemann et al., 2020). Specifically, the application of prospective Life Cycle Assessments (LCAs) is employed with emerging technologies to analyze and enhance their probable environmental impacts (Cucurachi et al., 2018). While there is no single definition for emerging technologies, the characteristics identified by Rotolo et al. (2015) – novelty, rapid growth, coherence, prominent impact, and uncertainty and ambiguity – capture their essence comprehensively. Particularly, novelty and uncertainty were identified as key features by several other studies (Boon and Moors, 2008; Day and Schoemaker, 2000; Hung and Chu, 2006; Porter et al., 2002; Small et al., 2014; Stahl, 2011) unveiling opportunities and challenges in the

application of assessment methods.

Emerging technologies are characterized by a low degree of maturity and are in the early development phase (Arvidsson et al., 2018; Cucurachi et al., 2018; Gavankar et al., 2015; Moni et al., 2020; Thonemann et al., 2020). This early stage's high flexibility in the technology design, allows identifying and exploiting optimization potentials sustainably, but is also accompanied by a lack of information and uncertainty, as known from the Collingridge dilemma (Arvidsson et al., 2018; Moni et al., 2020). The data needed to evaluate a technology's ecological impact is either incomplete or lacking entirely (Moni et al., 2020; Thonemann et al., 2020). The low functional readiness of novel technologies and their immature production processes at small scales must be translated to higher levels to provide insights into the impact of commercialization on their sustainability (Moni et al., 2020; Thonemann et al., 2020; Buyle et al., 2019; M. Shibasaki et al., 2007). In the context of LCA, this requires the scale-up of either the Life Cycle Inventory's (LCI) material and energy flows or the direct environmental burdens of a novel technology. Hence, adequate and robust scaling

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Abbreviation list	
Abbreviation Definition	
GHG	Greenhouse gas
IIL	Intermediate Input Learning
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
MPL	Market Penetration Level
MRL	Manufacturing Readiness Level
TRL	Technology Readiness Level
VAL	Valued Added Learning

methods are required as an integrative part of any sustainability-oriented prospective assessment (Moni et al., 2020; Thonemann et al., 2020; Tsoy et al., 2020; Buyle et al., 2019; Simon et al., 2016).

The increasing interest in prospective sustainability assessments has brought attention to the scaling issue in recent literature. Several scaling techniques and methodologies have been demonstrated (Buyle et al., 2019; Caduff et al., 2014; Hummen and Kästner, 2014; Majeau-Bettez, 2021; Moni et al., 2020; Parvatker and Eckelman, 2019; Piccinno et al., 2016; Simon et al., 2016; Thonemann et al., 2020; Tsoy et al., 2020), but an in-depth picture and their conceivable relationships to the technologies studied is lacking to date. Prospective LCA practitioners face obstacles in selecting appropriate scaling methods for their individual application driven by the absence of guidance. Advantages and disadvantages of existing scaling methods were assessed primarily qualitatively (Hummen and Kästner, 2014; Parvatker and Eckelman, 2019; Simon et al., 2016; Tsoy et al., 2020; van der Giesen et al., 2020), impeding their comparison and the identification of the most beneficial one.

Thus, this study serves a systematic analysis of currently applied scaling methods in various studies (n = 78) examining their frequency of use and the investigated technology’s influence on the choice of method. The research identifies detailed scaling methodologies as presented in literature, quantitatively evaluating their strengths and weaknesses. An Excel-based tool is derived, to assist with the selection of those methodologies. The tool considers factors limiting the application of a methodology and eliminates unsuitable ones. By individually weighting the evaluation criteria comprising complexity, data intensity, duration, and uncertainty, the most suitable methodology can be determined. The topic is discussed primarily in the context of prospective LCA to provide a practical context. However, it is not only relevant for LCA but for many other sustainability assessment methods as well as for non-sustainability oriented methods or process engineering in general.

## 2. Background

To assess a technology’s maturity the Technology Readiness Level (TRL) and Manufacturing Readiness Level (MRL) can be utilized. The TRL was originally developed by the NASA to gauge the functional maturity of a technology, based on its development progress, with TRL 1 representing the lowest maturity level and TRL 9 the highest (Tzinis, 2015). The MRL, developed by the USDOD, assesses the manufacturing maturity and the system-level risk, ranging from MRL 1 to MRL 10, representing the lowest and highest maturity levels, respectively (Manufacturing Readiness Level (MRL) Deskbook, 2020). These two methods are closely interrelated, as each MRL includes a nominal technological maturity level. In addition to the TRL and MRL, the Market Penetration Level (MPL) can be availed to assess a technology’s market share based on its production volume (Grübler et al., 1999; Hulst

et al., 2020), since the diffusion of a technology can further alter its environmental impacts (Buyle et al., 2019). Grübler et al. (1999) identified four penetration stages, namely invention and innovation with 0% market share, niche market commercialization with 0%–5% market share, pervasive diffusion with 5%–50% market share, and saturation with up to 100% market share.

Table 1 illustrates the production stages according to their respective TRLs and MRLs, as based on Gavankar et al. (2015). For convenience, these production stages are grouped into three scales: laboratory (TRLs and MRLs 1–5), pilot (TRLs and MRLs 6–8), and industrial (TRLs and MRLs 9–10). The laboratory scale studies fundamental properties of technologies and processes, which entails greater uncertainties, lower throughputs, lower efficiencies, and lower levels of automation (Majeau-Bettez, 2021; Shibasaki et al., 2006). In contrast, the industrial scale prioritizes efficiency and aims to produce a mature technology under known and optimized parameters at maximum capacity and minimum cost. Synergy effects and advanced techniques, such as heat

**Table 1**  
Production stages and respective Technology Readiness Levels (Tzinis, 2015) and Manufacturing Readiness Levels (Manufacturing Readiness Level (MRL) Deskbook, 2020) as based on Gavankar et al. (2015).

Production stages		Technology Readiness Level	Manufacturing Readiness Level
<b>Laboratory</b>	Conceptual development	1	Basic principles observed and reported
		2	Technology concept or application formulated
	Technology development	3	Experimental and analytical critical function and characteristic proof of concept
		4	Component or breadboard validation in a laboratory environment
<b>Pilot</b>	Technology development	5	Component or breadboard validation in a relevant environment
		6	System or subsystem model or prototype demonstrated in a relevant environment
	Engineering development	7	System prototype demonstration in an operational environment
<b>Industrial</b>	Small scale production	8	Actual system completed and “flight qualified” through test and demonstration
	Mass production	9	Actual system “flight proven” through successful mission operations
		10	–

recovery or internal waste recycling, are used to achieve this goal (Piccinno et al., 2016; Maiya Shibasaki et al., 2007). Additionally, the technology design generally improves with increasing production scales and maturity. Consequently, material and energy flow data at the industrial scale are several orders of magnitude lower than lab or pilot-scale data, resulting in lower environmental impacts (Buyle et al., 2019; Shibasaki et al., 2006). Sustainability assessments of novel technologies, mostly conducted at laboratory or pilot scale, are not meaningful and necessitate scale-up to the industrial level.

Several studies discussed the challenges associated with prospective LCA and scale-up. The works of Thonemann et al. (2020) and Moni et al. (2020) emphasized the need for scaling, and introduced studies presenting scaling procedures. Thonemann et al. (2020) examined methods used in 65 prospective LCAs to scale their LCI. The methods – *simulations, transfer of literature data, expert interviews, assumptions, risk analyses, linear scaling rates, power laws, or calculations* – were classified under the broad umbrella of predictive scenarios or scenario ranges, without being further analyzed.

In their practical recommendation for conducting prospective LCAs, Buyle et al. (2019) provided a detailed overview of possible scaling techniques. The methods identified (*ideal system baseline, problem solution space, proxy technology transfer, scaling and extrapolation, participatory methods, learning curves, ex-ante learning curves, socio-economic stories, cost-curves, and diffusion analyses*) were assigned to TRLs and periods after TRL 9 (technology learning and diffusion), with further categorization into 'concepts', 'procedures', and 'data collection'. Each scaling method's core principles were introduced, although without quantifying their advantages and disadvantages. A method's assignment to the time dimension of the technological development is an innovative attempt, which, however, needs to be validated.

Similarly, Hummen and Kästner (2014) investigated approaches for prospective LCAs focusing on scaling methods. The identified methods' (*simple reduction factors, modular influence estimations, economies of scale, neuronal network approach, and process modelling*) strengths and weaknesses were assessed qualitatively. A subsequent utility analysis evaluated data-related criteria (like data completeness) and systematic criteria (such as complexity), revealing modular influence estimation to be the best method.

Parvatker and Eckelmann (2019) studied methods for generating chemical LCI data, by evaluating *get real plant data* (the most accurate but time-consuming method), *process simulation, process calculation, stoichiometry, molecular structure-based models, approximations*, and to *omit* (the least accurate but most timesaving method). The authors evaluated the methods' advantages and disadvantages in detail, and applied them to a case study to verify their accuracy. Although the work did not specifically focus on scaling, some methods can be considered as scaling techniques, and the results can be applied to scaling, albeit only in the context of chemicals.

Tsoy et al. (2020) reviewed 18 prospective LCAs and their scaling techniques, categorizing them as *simulation, calculation, molecular structure-based model* and *approximation*. A decision tree for selecting one of these four techniques was developed. However, critical aspects, such as a methods' time-intensiveness or complexity, were not considered. Hence, the method proposed by the decision tree might not be sufficient if other factors, besides a method's applicability, are considered.

These methods identified in the literature, also referred to as techniques, describe a general type of scaling. Within these synoptic investigations, several studies on scaling methodologies were frequently cited. In contrast to methods (such as simulation or molecular structure-based models), these methodologies (also called approaches) are associated with a specific literature that details a comprehensive scaling procedure by using one or more of the aforementioned methods (European Commission. Joint Research Centre, 2023).

Shibasaki (2009) comprised a methodology to predict LCAs of large-scale plants from pilot plants by subdividing potentially influential factors into modules and systematically analyzing their relevance and

reduction factors. Artificial neural networks were used by Wernet et al. (2009) to estimate pertinent LCI parameters of synthesis processes based on molecular descriptors of the target chemical. Caduff et al. (2014) demonstrated the effectiveness of power law relationships, based on empirically derived scaling factors, in extrapolating the changes in a technology's environmental impacts as it scales. A thorough engineering scale-up approach for generating industrial LCI data for batch reactions in the liquid phase was showcased by Piccinno et al. (2016). To scale up the LCI to an industrial level, Simon et al. (2016) used approximate values and scaling factors derived from existing mature reference technologies.

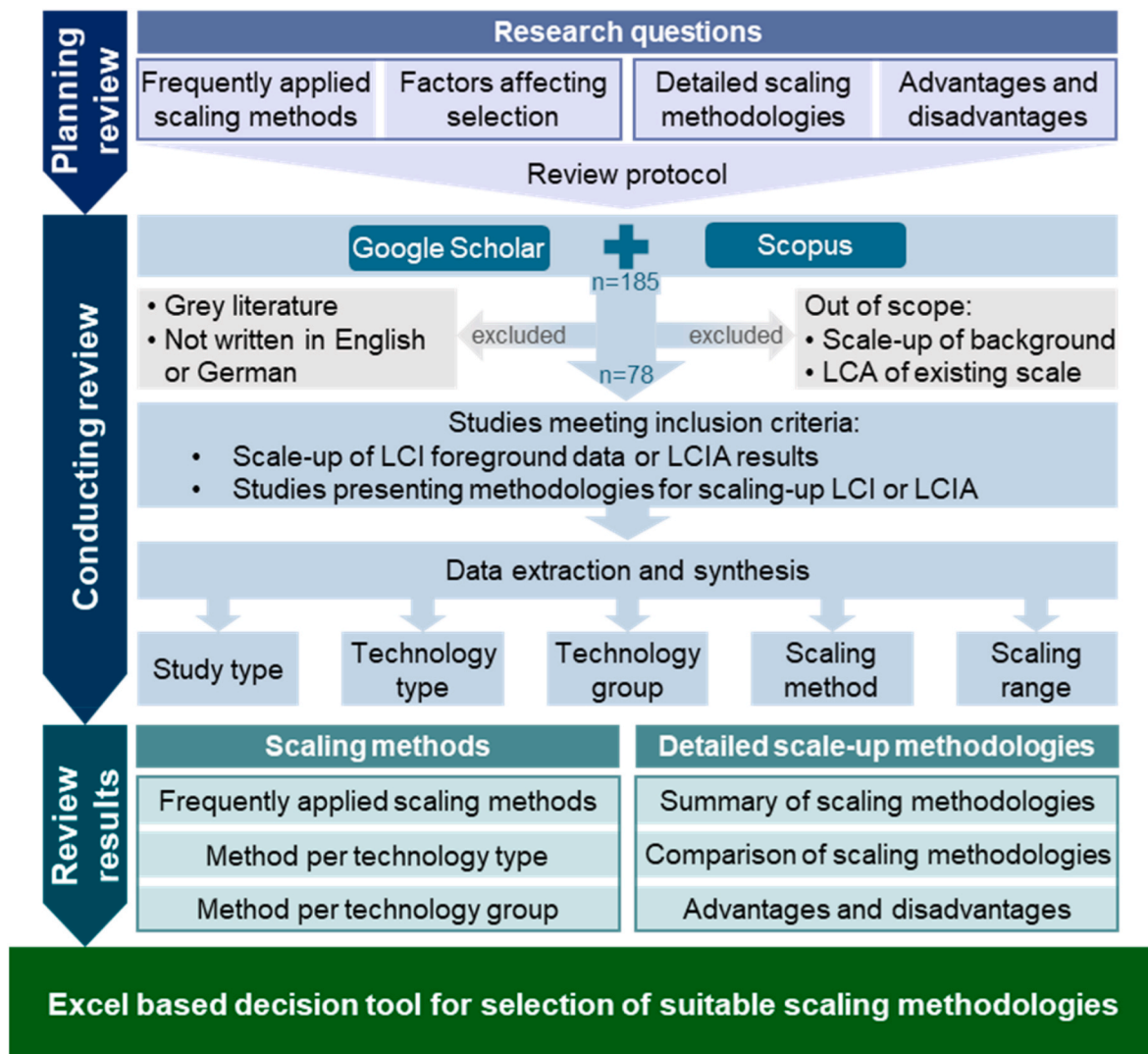
The aforementioned studies focused on discovering or developing scaling techniques, resulting in the identification of seven techniques serving as the foundation for this current work. The first technique is *approximation* and involves utilizing existing reference technologies and data, as exemplified by Simon et al. (2016). This could entail adapting LCI data from a mature lithium-ion battery for newer battery technologies like organic batteries. *Process engineering* includes scale-ups based on mathematical, physical, or chemical calculations, as proposed by Piccinno et al. (2016). The straightforward adjustment of LCI data or environmental impacts by a certain factor without using complex calculations, is termed *simple extrapolation*. This typically involves the enlargement or reduction of a few selected values, such as reducing lab-scale material consumption by 40% to mimic industrial material inputs. The use of simulation software, like Aspen Plus (Aspen Technology Inc, 2023), is covered by *simulation*. The method of *advanced empirical scaling*, as performed by Caduff et al. (2014), involves the usage of learning curves, cost curves, regression analysis or power laws, and many more methods, to empirically analyze relationships and scaling factors, enabling the anticipation of the development of an emerging technology. Methods for identifying LCA relevant system modules and their scaling factors, as was done in Shibasaki (2009), are labeled *modular influence estimation*. The previously mentioned *molecular structure-based model*, originating from Wernet et al. (2009), is the final scaling technique.

Although some scaling attempts have been identified in previous studies, little guidance was provided on the selection of appropriate scaling procedures considering comprehensive aspects, like time-intensiveness or complexity. Choosing the most appropriate procedure is of great importance in prospective LCAs, as it has a substantial impact on the accuracy and robustness of the LCA findings. Consequently, it is vital to make a thoughtful decision when selecting a scaling procedure and to clearly understand its strengths and weaknesses. This includes the comparison of the scaling procedures' advantages and disadvantages quantitatively, which was only done for four methods in the utility analysis of Hummen and Kästner (2014). Furthermore, it remains unknown whether and which dependencies there might be between the investigated technology and the scaling technique selection. Such analysis would reveal the suitability or unsuitability of techniques with respect to the technology under study.

### 3. Review methodology

The study on hand seeks to conduct a systematic review, as proposed by Grant and Booth (2009), to provide insights into the scale-up techniques applied in prospective LCAs. A systematic review was chosen as it pursues a high scientific standard. It aims to systematically search for, analyze and summarize research findings while presenting the review method transparently, enabling replication (Grant and Booth, 2009). Costa et al. (2019)'s systematic review on the application of Life Cycle Sustainability Assessment, provides structural guidance, while Tsoy et al. (2020)'s review on scaling methods in prospective LCAs serves as a reference for contextual orientation and a basis for further development.

As displayed in Fig. 1, the three stages of a systematic review as outlined by Pullin and Stewart (2006) were followed: (1) planning the review, (2) conducting the review, and (3) reporting and dissemination



**Fig. 1.** Methodological approach for systematic review of scale-up methods and methodologies for prospective LCAs; detailed review protocol can be found in the SI (see 'Cover sheet').

of results. Accordingly, the review was initiated by defining the research questions and developing an associated review protocol, a document that guides the review (Pullin and Stewart, 2006), including the precise review procedure, the search strings used, and the detailed inclusion and exclusion criteria, which is fully disclosed in the supplemental information's (SI) 'Cover sheet'. In the second step, literature was searched and reviewed through identification, selection, extraction, and synthesis of pertinent data. The results were analyzed and displayed with regard to the previously defined research questions, ultimately culminating in a decision tool for selecting appropriate scaling methodologies.

The objectives and research questions were divided into two dimensions. The first dimension considered the entirety of the studies reviewed and the scaling methods used addressing following questions.

- Which scaling methods are frequently applied in LCA related studies of lab-scale technologies?
- Are there relationships between the technology type or technology group and the scaling method chosen?

The second dimension focused on the scaling methodologies encountered among the literature reviewed investigating following questions.

- Which are the detailed scaling methodologies provided in current literature sources?
- What are the advantages and disadvantages of these scaling methodologies?

Based on 185 studies reviewed, 78 met the inclusion criteria, leading to the extraction and analysis of relevant data. Both the main article and supplementary materials were reviewed to ensure the abstraction of relevant data to an equivalent degree of detail. Thus, the corresponding authors were contacted in cases requiring clarification. The extracted data was then assigned into the categories outlined in Table 2.

The SI's review table (see '2. Review') specified the examined technology in each study in the category 'application'. These applications were further grouped into higher-level 'technology types' (see Table 2) that were derived iteratively from the technologies identified in the studies. The boundaries between these technology types are fluid and there may be overlaps between them. To avoid excessive granularity, a minimum of three technologies per technology type was defined. Since the analysis of potential relationships between technology types and scaling methods focuses on a detailed but narrow picture, the technology types were subsequently combined into 'technology groups' to depict potential relationships on a higher perspective. Afterward, each technique employed for the scale-up of energy and material flows was

**Table 2**  
Data synthesis of studies reviewed.

Category	Content	Definition	
<b>Study type</b>	<i>Case study</i>	Studies applying one or more scaling methods	
	<i>Methodology</i>	Studies presenting a detailed methodological approach for scale-up	
	<i>Case study and methodology</i>	Studies presenting a methodology and its direct application in a case study	
	<b>Technology type</b>	<i>Battery</i>	Battery technologies, such as lithium-ion batteries
		<i>Bio-product</i>	All kinds of bio-products such as microalgae biomass or biopolymer
		<i>Chemical</i>	Chemical compounds and pharmaceuticals such as fatty acids
		<i>Construction</i>	Construction elements or factories such as windows and chemical plants
		<i>Energy</i>	Energy technologies such as power-to-x or thermal energy recovery
		<i>Food</i>	Technologies related to the food sector or food such as gelatin
		<i>Graphene</i>	Due to its frequent assessment, graphene was listed as an own technology type
		<i>Nanomaterial</i>	Nanomaterials such as carbon nanotubes or Nano cellulose
		<i>Waste treatment</i>	Waste treatment processes such as metal recovery or waste water treatment
		<i>Other</i>	Technologies not belonging to any other named category
	<b>Technology group</b>	<i>Material</i>	Technology corresponds to a specific material (like chemical)
<i>Product</i>		Technology corresponds to the composition of several materials or products (like batteries)	
<i>Process</i>		Technology corresponds to one or more processes (such as waste treatment)	
<i>Other</i>		Technology cannot be assigned to one of the groups mentioned	
<b>Scaling method</b>	<i>Approximation</i>	Utilization of data from analogous, pre-existing technologies (see <a href="#">Simon et al. (2016)</a> )	
	<i>Process engineering</i>	Use of process engineering, such as mathematical and physical equations and stoichiometric relationships (see <a href="#">Piccinno et al. (2016)</a> )	
	<i>Simple extrapolation</i>	Scaling performed using simple calculations such as linear extrapolation or multiplication by scaling factors (see <a href="#">Erakca et al. (2023)</a> or <a href="#">Pini et al. (2017)</a> )	
	<i>Simulation</i>	Scaling technique or data estimation method for which a simulation software (like Aspen Plus ( <a href="#">Aspen Technology Inc, 2023</a> )) is used	
	<i>Advances empirical scaling</i>	Utilizing learning curves, cost curves, regression analysis, power laws, and more methods, to empirically analyze relationships and scaling factors, to forecast the development of emerging technology (see <a href="#">Bergesen and Suh (2016)</a> )	
	<i>Modular influence estimation</i>	Systematical reduction functions and modular influence estimations (see <a href="#">Shibasaki (2009)</a> )	
	<i>Molecular structure-based model</i>	Neural network based models enabling the calculation of impact results based on the molecular structure of chemicals (see <a href="#">Wernet et al. (2009)</a> )	
<b>Scaling range</b>	<i>Lab to pilot</i>	Laboratory data is scaled-up to pilot scale	
	<i>Lab to industry</i>	Laboratory data is scaled-up to industrial scale	
	<i>Pilot to industry</i>	Pilot data is scaled-up to industrial scale	
	<i>Lab to pilot and lab to industry</i>	Laboratory data is scaled-up to pilot and to industrial scale	
	<i>N/A</i>	Data is scaled-up to industrial scale; starting scale unclear	

extracted (see '2. Review' in SI) and assigned to the scaling methods explained in the previous section. Lastly, the scaling range was allocated, illustrating the starting and intended future production scales. The terms 'large scale', 'commercial scale', and 'small-industrial scale' were allotted to the industrial scale.

For the sake of transparency, traceability, and replicability, all search outcomes are provided in the SI (see '1. Search results'). The last search activity was performed on January 04, 2023, excluding studies published after that date. The findings of this work are presented narratively and descriptively with tabular and graphical assistance in the following sections.

## 4. Results

A majority of 63 (81%) studies comprised case studies applying scale-up techniques in the context of LCA, as displayed in [Fig. 2](#). Eight (10%) studies furnished precise methodologies, serving as a template for scale-up. The remaining seven (9%) articles presented own methodologies and their direct application in a case study. When analyzing the number of studies per publication year, an upward trend can be observed (see [Fig. 2](#)), indicating the growing interest in prospective LCA and its accompanying scaling.

[Fig. 3](#) displays that 72 studies conducted a scale-up to the industrial level, demonstrating the high interest in industrial-scale results. Among these industrial scale-ups, the majority of studies started at the laboratory scale, highlighting the demand and importance of early-stage scale-up efforts in emerging technologies.

As represented by [Fig. 4](#), chemicals comprise the largest group of technology types, involving all kinds of chemical or pharmaceutical substances like lactic acid or anesthetic drugs, indicating a particular interest in their scale-up and innovation rate. Energy technologies, like hydrogen, represent the second-largest category, reflecting their crucial role in the energy transition and the continuous development of new technologies in that field. Similarly, this trend applies for batteries, which can be assigned to energy technologies, but are listed as an own category, given that six articles studied them explicitly. At the technology group level, there is a notable research interest in the 'material' group, driven by its incorporation of chemicals, but also graphene and nanomaterials. Likewise, the interest in the 'process' group, is stimulated by waste treatment, particularly as interest in the recovery of valuable materials grows, and by various energy technologies, such as power-to-gas.

### 4.1. Scale-up techniques applied

As displayed in [Fig. 5](#), thirty-seven studies (47%) employed a combination of two or more scaling techniques rather than a single method. Thus, the sum of all methods used (126) is larger than the total number of studies (78).

Among the methods applied within the studies, approximation and process engineering were the most often used ones. Thereby, the process engineering-based methodology by [Piccinno et al. \(2016\)](#) stood out, being applied 14 times for energy flows and 12 times for material flows. Aspen Plus by Aspen Technology ([Aspen Technology Inc, 2023](#)) was the most frequently utilized software for simulations, with six and four applications for energy and material flows, respectively. Advanced empirical scaling were only performed seven times, of which four studies presented a related methodology. Modular influence estimations and molecular structure-based models were only employed in methodologies presenting these approaches. When differentiating between methods applied exclusively and in combination, process engineering remains as the most regularly used scaling method. Approximations, on the other hand, were mainly used in combination with other techniques, such as simple extrapolations and process engineering. Since extrapolation factors are often derived from approximations and implemented within process engineering, it is not surprising that there were almost

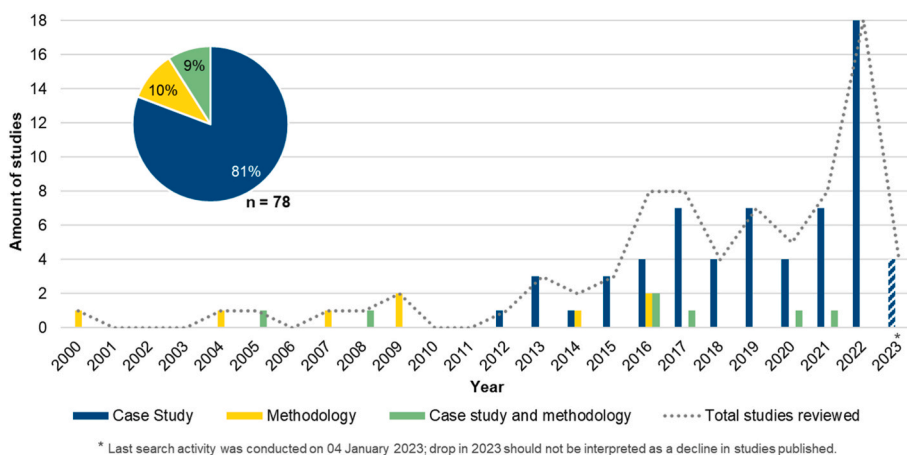


Fig. 2. Studies reviewed per year and study type.

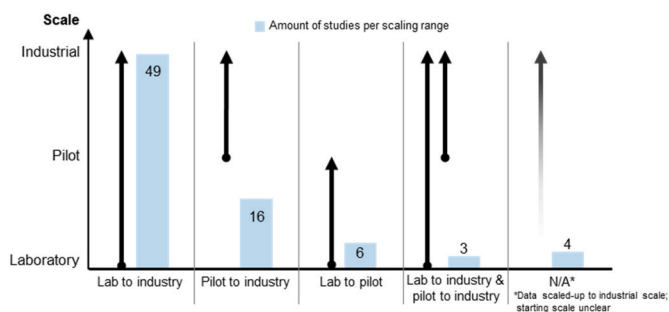


Fig. 3. Scaling range investigated by studies reviewed.

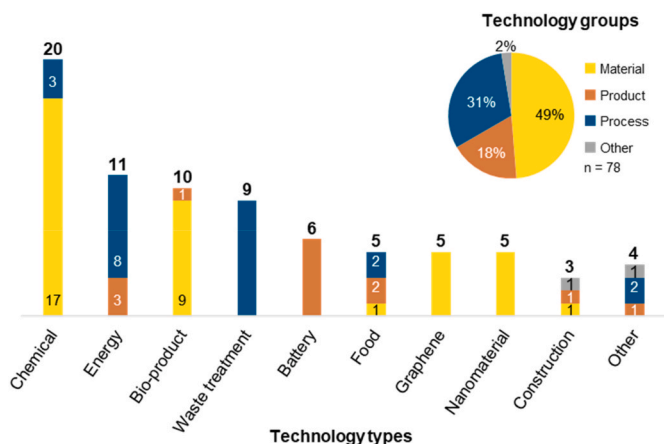


Fig. 4. Technology types and groups investigated by studies reviewed; values may not add up to 100% due to rounding.

entirely applied in combination with other techniques.

The frequency of scaling techniques used per technology type are plotted in Fig. 6. The total number of scaling methods per technology type, to which the percentage values relate, is indicated in the ‘Method’ column, while the total number of studies examining the technology type is indicated by ‘Studies’. Process engineering was applied in 15 out of 20 cases for chemicals, especially in combination with simple extrapolations, approximations, or simulations, indicating a connection. No relationship is apparent for energy technologies, bio-products, nor waste treatment, as process engineering, simple extrapolation combined with approximations, and simulations were used with similar frequency. The use of approximation combined with simple extrapolation was

performed in four out of six publications investigating batteries indicating a certain connection. For the remaining technology types, it is difficult to depict a relationship, as five or fewer studies are assigned to each of them.

The same analysis was conducted for technology groups, as displayed in Fig. 6, to investigate potential dependencies on a higher perspective. Process engineering techniques were used as the most common method for the scale-up of materials, either as a single method (11 times) or in combination with approximations and extrapolations or simulation (11 times). Consequently, the use of process engineering for the scale-up of materials is notable and indicates a relationship. Unsurprisingly, chemicals, for which similar relationships were found, account for 17 of the 38 technologies within this group. While more sophisticated approaches are often applied at the material level, the analysis at the product level tends to be more straightforward. The wide adaptability and simplicity of approximations and extrapolation make them commonly employed for scaling up products, particularly when considering the complexity of product-level scale-ups, which involve multiple materials. This relationship is fostered further by a specific technology type assigned to this group – the battery. On the process level, approximations were the leading scaling technique, however, in 15 out of 18 cases applied in combination with process engineering, extrapolation, or simulation. Strikingly, simulation was not performed on product level, but only on processes and materials. The bar representing ‘other’ is shown translucent, to avoid distraction as it only involves four or two case studies for technology type and group, respectively.

#### 4.2. Literature presenting specific scale-up methodologies

In the following, selected literature introducing a precise and detailed methodology for scaling and thereby serving as a direct template for individual scaling purposes, were evaluated, leading to the selection of the studies shown in Fig. 7. In turn, the studies by Caduff et al. (2014) and Köhler et al. (2007), presenting methodologies as well, were excluded from the following analysis due to their lack of specific guidance. Since many LCA studies (like Birrozzi et al. (2022), Erakca et al. (2023), Günkaya and Banar (2016), Kulkarni et al. (2022), Liu et al. (2013), Parisi et al. (2020), Pini et al. (2017) and von Drachenfels et al. (2021)) used proxy-based extrapolation for upscaling, the scaling attempt in the authors’ previous study (Erakca et al., 2023) was included as a representative of simple extrapolation, although it is not a scaling methodology and merely an example. The selected methodologies and their underlying scaling methods and ranges are illustrated in Fig. 7 and outlined briefly in the following. It should be mentioned that a razor-sharp distinction of scaling techniques used within these methodologies is not always possible as the boundaries often blur.

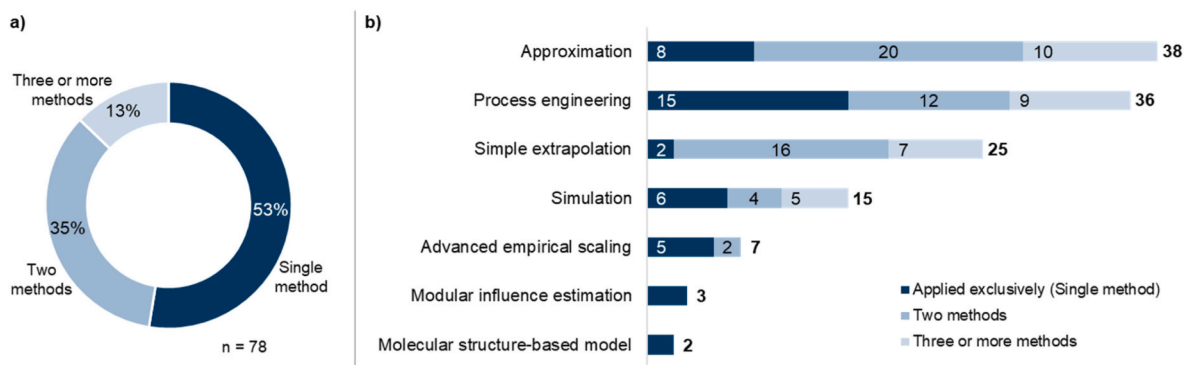
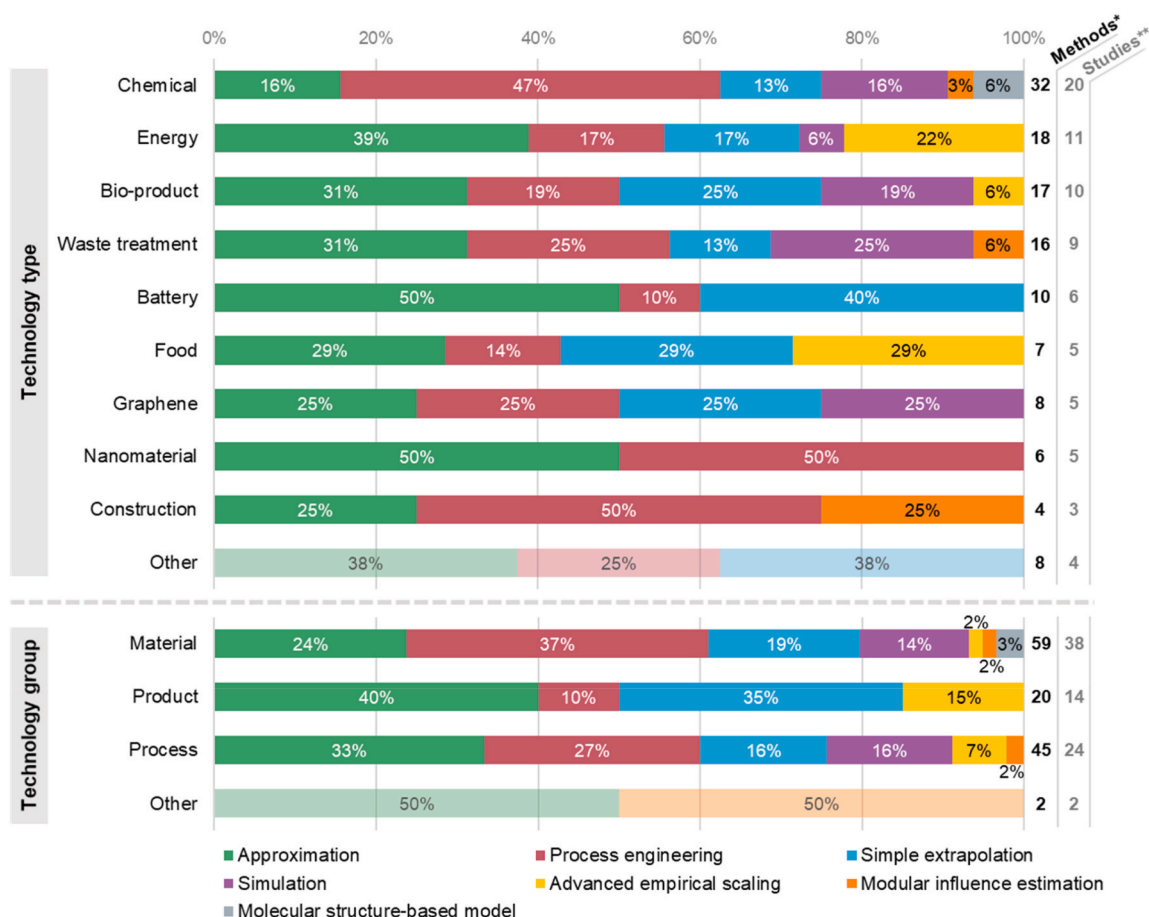


Fig. 5. Application of scale-up methods: (a) distribution of methods applied exclusively or in combination among studies reviewed, and (b) total amount of application per scale-up method (126 methods applied in 78 studies); values may not add up to 100% due to rounding.



\*Methods: Total number of scaling methods applied per technology type and group; percentages relate to total number of scaling methods per technology type and group. n=126

\*\*Studies: Total amount of studies investigating technology type and group n=78

Fig. 6. Scale-up method applied per technology type and group; values may not add up to 100% due to rounding.

Consequently, some methodologies encompass more than one scaling technique, as illustrated by the color gradients in Fig. 7.

#### 4.2.1. Approximation

A methodology for the scale-up of lab-scale LCI data to a higher scale is proposed by Simon et al. (2016) and applied to nanofibers in battery cathodes. The approach includes a qualitative description of the lab-scale preparation to identify potential industrial production methods, followed by a quantitative description of the lab-scale

processes to identify necessary precursors and reaction kinetics and characteristics. Further, the working characteristics of the theoretical industrial-scale process, such as power requirements, are obtained using the properties of a reference large-scale process eventually enabling the calculation of a hypothetical industrial-scale technology's LCI data.

Delpierre et al. (2021) present a methodology in which scaling is accounted for by exploratory scenarios using morphological analysis. These scenarios are built by identifying values for defined dimensions or variables, resulting in a so-called morphological field. The scenarios are

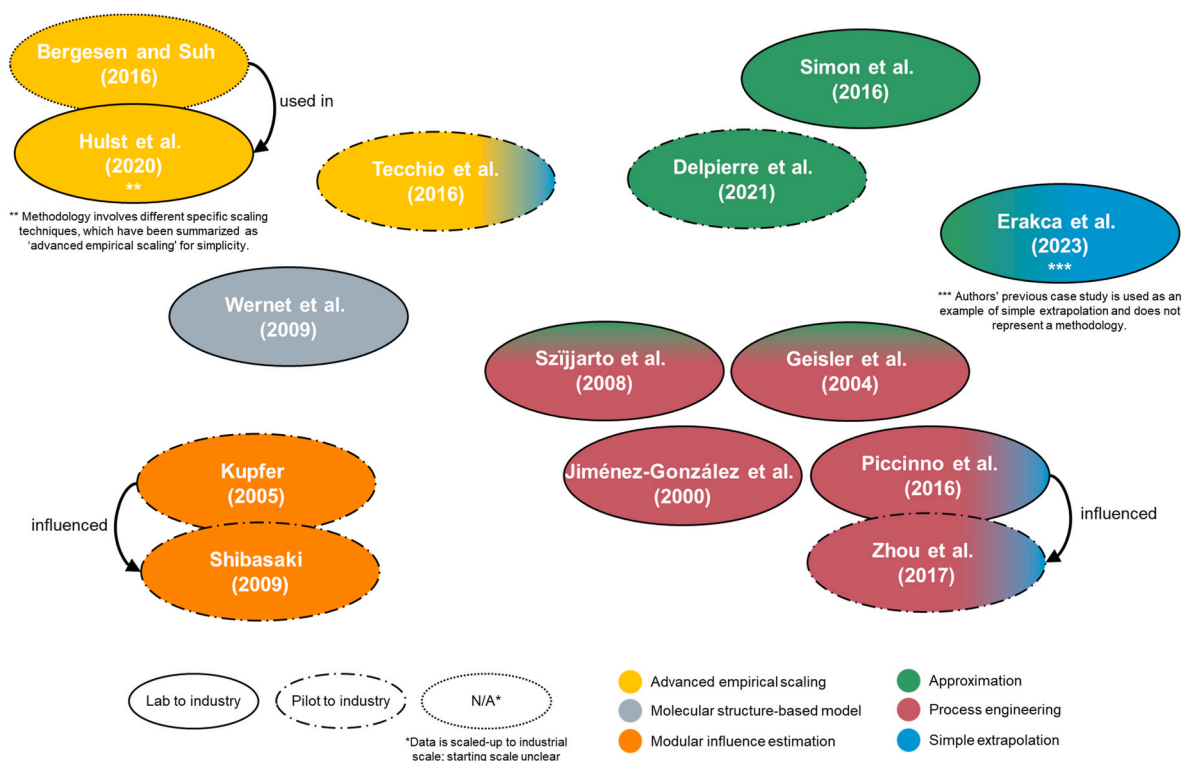


Fig. 7. Overview of literatures providing detailed scale-up methodologies.

developed in close exchange with experts through interviews and workshops and in consideration of the current literature. Additional factors that could further influence a technology's development (such as stakeholder interaction) are considered. The methodology is applied on a pilot-scale technology.

#### 4.2.2. Process engineering

Jiménez-González et al. (2000) introduce a methodology for the acquisition of industrial gate-to-gate LCI data for chemicals, rather than an explicit methodology for scaling up processes. The authors outline the general approach for gathering data, which entails the utilization of mathematical models, as well as mass and energy balances, for approximating the inputs and outputs. Nevertheless, the publication does not present any explicit formulas or equations.

The methodology by Geisler et al. (2004) is not specifically intended for scaling up, but for generating LCI data for fine and specialty chemicals and can be applied to processes at the laboratory scale. Process engineering equations are provided that could be used to determine material quantities and energy consumption values. In addition, default best and worst-case values are provided for yields or solvent recycling rates, heuristically determined by on-site data. Piccinno et al. (2016) propose a process engineering-based scaling methodology that is versatile and applicable to a variety of chemical processes at different scales. The methodology entails identifying the critical process parameters that are essential for scaling up, such as reactor size, temperature, and residence time. Detailed formulas and mathematical calculations, and default values are provided to calculate material and energy flows, as well as emissions and waste outputs, for a hypothetical industrial scale.

Zhou et al. (2017)'s methodology bears a resemblance to the approach outlined by Piccinno et al. (2016) and is applicable to chemicals. The procedure entails the conversion of experimental data from pilot-scale operations into LCI data that can be extrapolated to an industrial scale. The calculations and equations involved in the scaling approach are elaborately described in the study.

#### 4.2.3. Simple extrapolation

As mentioned previously, the authors' own scaling attempt in Erakca et al. (2023) is used exemplary to assess proxy-based simple extrapolation as a scale-up technique. In the case study, the material loss rates and throughput volumes of a lab-scale production are extrapolated to values of larger-scale productions provided in literature to mimic small-scale industrial production.

#### 4.2.4. Advanced empirical scaling

Tecchio et al. (2016)'s methodology was initially developed for biopolymers and involves the selection of a reference polymer for which three LCAs are assessed: pilot scale (worst mass conversion yield), ideal stoichiometric scale (best mass conversion yield) and industrial scale. Based on the greenhouse gas (GHG) emissions of these three LCAs, the relationship between the data points is defined as a function of the mass conversion yield using various mathematical functions (such as power regression or linear interpolation). The resulting function is then applied to the new biopolymer's GHG emissions of its actual pilot scale and its ideal stoichiometric scale. In the case study, linear interpolation was chosen as the most suitable mathematical function due to its balance between simplicity and accuracy, which is why this approach also includes simple extrapolation.

Bergesen and Suh (2016) present a generalized mathematical methodology, based on Wright's law (Wright, 1936) and its extensions, to account for the learning effects of a technology's entire supply chain and the calculation of the technology's life cycle impacts, taking into account these learning effects. Thereby, they divide the learning effect into its subcomponents: a) Intermediate Input Learning (IIL), including efficiencies in material and energy use of a company, Valued Added Learning (VAL), which are not relevant for environmental impacts, and Supply chain IIL and VAL, considering efficiencies of the whole supply chain. The study exemplary scales-up to the industrial level, without defining a starting scale.

The systematic approach by Hulst et al. (2020) aims at calculating the potential industrial GHG emission associated with a pilot-scale technology, in this example a photovoltaic laminate, considering a



multitude of changes across various levels to provide an accurate assessment of the technology's potential impact. At the process level, changes such as improved product performance are evaluated against reference technologies, whereas size scaling is conducted by utilizing scaling curves obtained from regression analysis. Process synergies, such as internal recycling, are deduced from the flow charts of existing industrial processes. The effects of industrial learning are included by using experience curves. Finally, potential external developments affecting the environmental performance of the technology are accounted. It should be noted that various sophisticated scaling techniques are applied in this methodology, which, for the sake of simplicity, are summarized in the method advanced empirical scaling.

#### 4.2.5. Modular influence estimations

Kupfer (2005)'s approach involves the modularization of chemical processes and the estimation of environmental impacts at modular level. Each module is subdivided into its individual process steps, and corresponding input-output data is used to calculate the environmental impact of each process. By aggregating the environmental impacts of each process step, the environmental impact of the module is achieved. Finally, the modules are combined to estimate the environmental impact of the entire chemical process.

The methodology by Shibasaki (2009) for estimating the environmental impacts of a large-scale plant using pilot data exhibits significant similarities to the methodology adopted by Kupfer (2005). Pilot plant data is collected along with information on any differences in technology or process between the pilot and potential large-scale plants. The opinions of experts are then sought to predict the potential reduction in environmental impact that could be achieved in the large-scale plant through the implementation of specific mitigation measures or technological improvements. These predictions are subsequently used to calculate reduction factors for each module, which can be applied to the environmental impact data of the corresponding pilot plant module to determine the environmental impact of the large-scale plant.

#### 4.2.6. Molecular structure-based models

Wernet et al. (2009) provide a molecular structure-based model to estimate the environmental impact of chemical production processes. The model considers the chemical structure of the compounds involved in the process and predicts their fate and behavior in the environment. By inputting the chemical structure of the compound, the model can estimate its aggregated global warming potential.

### 4.3. Advantages and disadvantages of scale-up methodologies as presented in selected literature

To gain an improved understanding of the implementation of the methodologies, their step-by-step approaches were systematically captured and compared, yielding in a five-step scaling procedure. The analysis revealed whether a methodology executed certain steps and identified potential benefits or drawbacks, and can be found in detail in the SI. Based on this analysis, the methodologies' strengths and weaknesses were assessed using five criteria: limitation, complexity, data intensity, duration, and uncertainty. These criteria were derived and consolidated from earlier studies (Buyle et al., 2019; Hummen and Kästner, 2014; Parvatker and Eckelmann, 2019; Tsoy et al., 2020). The restrictions imposed by a scaling methodology with regard to specific technology types, groups, or scaling ranges, are evaluated by limitation, which was also discussed in Tsoy et al. (2020)'s review. Hence, limitation is considered an upstream filter, as it assesses the technical applicability of a methodology. Complexity refers to the level of expertise required or the intricacy of a scaling methodology and was addressed previously in the work of Hummen and Kästner (2014). The quantity of data required to apply a scaling technique refers to data intensity, while duration quantifies the time commitment associated with implementing a scaling method. These criteria were addressed by Hummen and

Kästner (2014), being labeled as necessary effort, Buyle et al. (2019), and Parvatker and Eckelmann (2019). Uncertainty, being a major focus in Parvatker and Eckelmann (2019), characterizes the underlying ambiguity and imprecision of a methodology. The criteria are rated on a scale from 1 to 4, with 1 signifying the least intensity, or the most favorable rating, and 4 the highest intensity, or the least favorable rating. The respective ratings of the scale-up methodologies are provided in Table 3 and can be found in more detail in the SI (see '3. Methodologies').

#### 4.3.1. Limitation

Simon et al. (2016)'s study, which employs reference technologies, can be applied to any other technology and production scale, if comparable reference technologies are available. Although Delpierre et al. (2021) applied their methodology to pilot-scale electrolysis technologies, it can be transferred easily to a range of technologies at various production scales and is deemed unrestricted in terms of its applicability. The process engineering-based approaches of Jiménez-González et al. (2000), Piccinno et al. (2016) and Zhou et al. (2017) are geared towards analyzing chemical substances. Nonetheless, the review analysis indicates that 20 studies have already evaluated chemicals, excluding bio-products or batteries, which also comprise chemical constituents. Consequently, the reach of these methodologies extends beyond chemicals and can be implemented at any production scale, earning them a rating of 2. In contrast, Geisler et al. (2004) score 3 due to their narrower focus on fine and specialty chemicals, while Szijjarto et al. (2008)'s methodology, being limited to steam, score even lower. Simple extrapolation (Erakca et al., 2023) can be applied as a scaling method to any emerging technology at any production scale. Tecchio et al. (2016)'s methodology can be extended to lab-scale technologies, despite its original application on a pilot scale and applied to a wide range of chemical materials. Bergesen and Suh (2016) and Hulst et al. (2020) are both characterized by their wide-ranging applicability, making them suitable for any technology that possesses sufficient data to derive scaling functions. While employing these methodologies during the pilot phase, rather than the laboratory stage, may enhance the precision of estimations, such constraints are not explicitly stated in the studies. Kupfer (2005) is solely applicable to the construction of chemical plants, thereby imposing a notable limitation, while Shibasaki (2009) is restricted to chemical processes. Additionally, both methodologies are specifically designed for scaling from pilot, rather than laboratory scale, leading in a rating of 4. Wernet et al. (2009) is exclusively suitable for petrochemical synthesis providing a limited scope of application.

#### 4.3.2. Complexity

Simon et al. (2016) anticipate changes based on reference technologies at the product and system level, requiring a profound knowledge of the technology and its product environment. The development of dependable scenarios in Delpierre et al. (2021) relies on the input of experts via workshops and interviews, highlighting the expertise required for the execution of this methodology. It should be noted that such extensive knowledge is not generally necessitated for the approximation method, but owes specifically to Simon et al. (2016) and Delpierre et al. (2021). No equations or computational strategies are provided in Jiménez-González et al. (2000)'s study earning it a rating of 4. The scale-up practitioner must independently identify appropriate process engineering formulas, which can be a daunting task that necessitates expertise in process. In contrast, the inclusion of proximity values and calculation equations in the remaining process engineering-based methodologies (Geisler et al., 2004; Piccinno et al., 2016; Szijjarto et al., 2008; Zhou et al., 2017) indicate a relatively moderate degree of complexity facilitating their practical implementation. Similarly, the simple extrapolation in Erakca et al. (2023) and the advanced empirical scaling in Tecchio et al. (2016), score 2, indicating a relatively moderate degree of complexity. Bergesen and Suh (2016) and

**Table 3**

Evaluation of scale-up methodologies as presented in literature 1 = very low (most favorable rating); 2 = low; 3 = high; 4 = very high (least favorable rating).

Year	Author	Scaling technique	Study type	Limitation	Complexity	Data intensity	Duration	Uncertainty
2016	Simon et al.	Approximation	Case study and methodology	1	4	3	2	4
2021	Delpierre et al.	Approximation	Case study and methodology	1	4	3	3	4
2000	Jiménez-González et al.	Process engineering	Methodology	2	4	3	2	2
2004	Geisler et al.	Process engineering; approximation	Methodology	3	2	2	2	2
2008	Szjjarto et al.	Process engineering; approximation	Case study and methodology	4	2	2	2	2
2016	Piccinno et al.	Process engineering; simple extrapolation	Methodology	2	2	2	2	2
2017	Zhou et al.	Process engineering; simple extrapolation	Case study and methodology	2	2	2	2	2
2023	Erakca et al. <sup>a</sup>	Simple extrapolation; approximation	Case study	1	2	1	1	4
2016	Tecchio et al.	Advanced empirical scaling; simple extrapolation	Case study and methodology	2	2	3	3	3
2016	Bergesen and Suh	Advanced empirical scaling	Methodology	1	3	4	4	2
2020	Hulst et al.	Advanced empirical scaling	Case study and methodology	1	3	4	4	2
2005	Kupfer	Modular influence estimations	Case study and methodology	4	4	3	3	3
2009	Shibasaki	Modular influence estimation	Methodology	4	4	3	3	1
2009	Wernet et al.	Molecular structure-based model	Methodology	4	1	1	1	3

<sup>a</sup> Authors' previous case study is used as an example of simple extrapolation and does not represent a methodology.

Hulst et al. (2020) score 3, signifying a certain degree of intricacy. Both approaches delve into alterations occurring at various levels, necessitating a substantial level of expertise to derive appropriate inferences. Kupfer (2005) and Shibasaki (2009), both rated 4, necessitate a comprehensive understanding of the conceivable product and system levels to determine the reduction factors. In contrast, Wernet et al. (2009)'s model can be conveniently applied as the tool automatically generates output values based on the input data and has the lowest complexity level among the methodologies reviewed.

#### 4.3.3. Data intensity

The methodologies of Simon et al. (2016) and Delpierre et al. (2021) warrant a rating of 3 as they necessitate additional data on reference technologies and possible alterations on several levels, and data pertaining to sub-components and modules. Due to the absence of equations mandating the collection of thermodynamic formulations, default values, and related factors, Jiménez-González et al. (2000)'s approach scores 3. The remaining process engineering based methodologies (Geisler et al., 2004; Szjjarto et al., 2008; Piccinno et al., 2016; Zhou et al., 2017) only require input values for calculating the material quantities or energy values, meriting their rating of 2. The simple extrapolation in Erakca et al. (2023), requiring only some reference values, is rated 1. Tecchio et al. (2016)'s methodology relies on five LCAs, necessitating a larger volume of data, resulting in a rating of 3. The remaining two methodologies employing advanced empirical scaling (Bergesen and Suh, 2016; Hulst et al., 2020) score 4. Their application assumes the availability of extensive historical data on the use of specific technologies over time or data on key properties of the technology related to the size of the production equipment. The limited availability of LCA and LCI studies as data sources for some technologies can thus hamper their application. The requirement for data concerning sub-processes and modules earns the modular influence estimation-based studies (Kupfer, 2005; Shibasaki, 2009) a rating of 3. Wernet et al. (2009) is rated 1, requiring only some data related to the molecular structure of the chemical assessed (like hydroxyl or carboxyl groups).

#### 4.3.4. Duration

Delpierre et al. (2021), envisage the consultation of experts via interviews or workshops, which's evaluation can be exceedingly time-consuming and prolong the duration of the assessment. Simon et al.

(2016) do not rely on interviews or workshops and is considered as time-efficient. The use of thermodynamic equations, stoichiometry, and other process engineering techniques is deemed comparably rapid, warranting those methodologies (Jiménez-González et al., 2000; Szjjarto et al., 2008; Geisler et al., 2004; Piccinno et al., 2016; Zhou et al., 2017) a rating of 2. Erakca et al. (2023)'s scaling attempt merits a rating of 1 as it involves the modification of only two parameters (loss rate and throughput). Requiring five fully-fledged LCAs, Tecchio et al. (2016)'s methodology is more time-consuming yielding a rating of 3. Bergesen and Suh (2016) and Hulst et al. (2020) are deemed time-intensive due to the extensive empirical data required for calculating scaling functions, assuming that prior studies have not established these values. While the exponential factor R in Hulst et al. (2020)'s study could be adopted from a previous investigation, the absence of such values for a wide range of technologies renders it unfeasible to assume their availability in general, culminating in a rating of 4. Similar to Delpierre et al. (2021), expert interviews or workshops are required in Kupfer (2005), and Shibasaki (2009), resulting in a score of 4. Wernet et al. (2009)'s model, which relies on neural networks to estimate the global warming potential of specific chemicals, represents another highly time-efficient methodology, earning it a rating of 1.

#### 4.3.5. Uncertainty

The evaluation of the various methodologies' uncertainty remains challenging, as experimental data is required for its validation. As noted by Parvatker and Eckelmann (2019), approaches using approximations (Delpierre et al., 2021; Simon et al., 2016), are considered inaccurate, scoring 4. Contrary, process engineering based methodologies (Jiménez-González et al., 2000; Szjjarto et al., 2008; Geisler et al., 2004; Piccinno et al., 2016; Zhou et al., 2017) are valued as accurate (Parvatker and Eckelmann, 2019), receiving a rating of 2. Yet, the use of simple extrapolation, as done in Erakca et al. (2023), is regarded inaccurate (Parvatker and Eckelmann, 2019). Tecchio et al. (2016)'s approach scores 3 due to its reliance on a single existing reference technology. The advanced empirical scaling methods applied in Bergesen and Suh (2016) and Hulst et al. (2020), are judged to be accurate by Hummen and Kästner (2014) and Majeau-Bettez (2021). Shibasaki (2009)'s approach was verified several years later (Simon et al., 2016) and considered highly accurate, scoring 1, while Kupfer (2005)'s methodology receives a rating of 3 due to the lack of validation or uncertainty assessment. Wernet et al. (2009)'s model is deemed as

uncertain due to the need for very precise input values and its black-box nature, which makes it difficult to identify uncertainty sources.

#### 4.4. Excel-based tool for selection of scaling methodologies as presented in literature

Evidently, no single scale-up methodology can be universally applied to all types of studies, possessing different advantages and disadvantages. The selection of these scaling methodologies depend on individual use cases, user preferences and expertise, and resources available. Therefore, identifying and selecting suitable scaling methodologies has posed a challenge for prospective LCA practitioners. Thus, an Excel-based decision tool was developed and can be found in the SI's tab '4. Decision tool'. The tool provides a user-friendly and straightforward approach, simplifying the otherwise time-consuming process of methodology selection.

In a first stage, individual study specifications (such as technology type, scaling domain, and data to be scaled) are entered into the tool by the user, to eliminate unsuitable methodologies. For example, if the technology is a food product without chemical compounds, methodologies limited to chemicals are automatically excluded. This is accomplished by background data extracted for each methodology, which is evaluated using Excel's chained if-then functions. The details for this process can be found in the SI's '4.1 Decision Tool Background'. In a second stage, the aforementioned evaluation criteria (complexity, data intensity, duration, and uncertainty) are weighted by the user based on their own requirements. For example, if low uncertainty within the methodology is crucial, uncertainty could be given a weight of 70%, while the other criteria could each be assigned a weight of 10%. Based on these weights and the previously assigned ratings (ranging from 1 to 4 for each methodology and criterion), a weighted sum is calculated (see SI's '4.1 Decision Tool Background'). The methodologies are subsequently ranked based on their weighted sums, with the top-ranked methodology as the most appropriate for scaling.

Since all data are linked and calculations are automated, no in-depth knowledge is required for the tool's usage, making it suitable for non-experts. Nevertheless, the SI's '4.1 Decision Tool Background' contains instructions for adding further methodologies so that the review can be continuously expanded when required. Additionally, the initial assessment of the advantages and disadvantages of the individual methods (see SI's '3. Methodologies') can be changed if the assessment of this work is deemed insufficient. The Excel tool is thus made available as open-source and can be updated and further optimized within the LCA community. Moreover, the tool's applicability can extend beyond LCA, making it suitable for scale-ups in other sustainability assessment methods such as life cycle costing (LCC) or technology development in general.

## 5. Discussion

However, the evaluation criteria employed in the Excel-based tool are limited in scope and fail to account for other aspects of the methodologies. These aspects should be considered in the selection process as well, and are subsequently assessed qualitatively. Firstly, the selected methodologies are scrutinized in the context of technology design and manufacturing. Although scaling effects in other life cycle phases, such as the use or end-of-life phase, are sometimes indirectly addressed when evaluating supply chain changes, they are not the primary focus of the methodologies. None of the methodologies delve into how the scaling of a novel technology might be portrayed in a prospective cradle-to-grave analysis. Nevertheless, these effects can be examined through scenario analyses in an LCA.

When employing approximations for scaling, it may not be feasible to obtain data for comparable processes or products, as such when dealing with highly innovative processes or products, hampering the applicability of this approach.

Furthermore, some methodologies, like Jiménez-González et al. (2000), Geisler et al. (2004) and Kupfer (2005), are considered rather outdated and partly unsuitable for scaling in prospective LCA. Erakca et al. (2023) and Tecchio et al. (2016) assume a linear relationship between energy and material flows and the production scale. In reality, environmental impacts or energy and material flows may increase or decrease at a non-linear rate as production scales up or down. In addition, simple extrapolation, as performed in Erakca et al. (2023), considers only two variables and lacks a systematic execution, rendering it somewhat incomplete (Hummen and Kästner, 2014). However, this approach could be particularly valuable in evaluating vaguely and preliminarily the potential impacts at higher scales, requiring little time and effort.

Along with Wernet et al. (2009)'s approach, the advanced empirical scaling methodologies suffer from the drawback of not providing LCI data (Parvatkar and Eckelman, 2019; Simon et al., 2016) and lack granularity in their output data, as they focus on the scale-up of environmental impacts (GHG emissions) rather than process-level LCI data (Hummen and Kästner, 2014). Consequently, these methodologies possess a 'black box character' (Hummen and Kästner, 2014) hampering the identification of potential hotspot processes. The environmental footprint of a process or product can be influenced by a range of context-specific variables, including but not limited to, geographic location, local infrastructure, and environmental regulations, which are not considered in these scale-up methodologies. In addition, the advanced empirical scaling methodologies (Bergesen and Suh, 2016; Hulst et al., 2020; Tecchio et al., 2016) hinge on empirical data that may not be transferable to prospective scenarios, given the absence of anticipatory considerations for potential developments, such as government regulations or material scarcities.

Furthermore, the Excel-based tool does not evaluate the combination of two or more methodologies. Instead, it treats them as separate entities and evaluates them under the assumption of independent application. However, a combination of certain methodologies could be beneficial in some cases and should be considered when using the tool.

In addition to the limitations in the evaluation scheme, there are general constraints inherent to any systematic review. Due to the use of specific search strings (see SI's 'Cover sheet') to identify potentially relevant literature, additional literature that would meet the review inclusion criteria could not be located if the search keywords (e.g., 'scale-up') were not utilized in that source. This constraint applies, for example, to studies using terms like 'scale effect' instead of 'scale-up', as in the work of Kawajiri et al. (2020). Similarly, the use of specific search engines will include or exclude various literature sources.

Despite being a systematic review, replicating the search results as presented in the SI's '1. Search results' is challenging since the last search was conducted in January 2023. More recent work will emerge when conducting the same literature search, and changes in the relevance of certain literature is expected, resulting in a different ranking of the search results. Another consequence of this is that interesting studies published after January 2023, like Weyand et al. (2023) or Langkau et al. (2023), could not be included in this review.

## 6. Conclusion and outlook

In a first dimension, this study aimed at investigating commonly used scaling techniques in LCA related studies and identifying potential relationships between technology types or groups and scaling method by systematically reviewing 78 studies. Across all technology types, approximations were found to be the most commonly used method, followed by process engineering, being particularly popular for chemicals and bio-technologies. Simple extrapolation was almost entirely used in combination with approximations and process engineering. A potential relationships between simulations and chemicals, bio-products, and waste treatment, was observed. On the technology group level, a connection between approximations applied in combination with

extrapolation was striking for products, whereas process engineering was used for materials. Advanced empirical scaling, modular influence estimations and molecular structure-based models were infrequently employed. To analyze potential statistical correlations between technology type or group and choice of scaling method, further research with a higher sample size is required. LCA relevant traits, such as system boundary or functional unit, could have additional influence on the selection of a specific scaling method. However, the exploration of these potential relationships remains beyond the scope of the current review study, but could be considered in future reviews.

In a second dimension, studies providing detailed scaling methodologies were analyzed to assess their strengths and weaknesses, aiming to facilitate the selection of the most appropriate methodology. Five criteria were utilized to evaluate the methodologies, including limitation, complexity, data intensity, duration, and uncertainty. While approximation and simple extrapolation-based methodologies are applicable to any type of technology, they present drawbacks in terms of uncertainty. Process engineering-based approaches are limited to chemicals or steam, yet they are performing well in the remaining criteria. Advanced empirical scaling-based methodologies demonstrate low uncertainty, but they require extensive data and time and lack output data granularity. Although they can offer very precise results, modular influence estimation-based methodologies are intricate and demand in-depth knowledge. The molecular structure-based model is limited to petrochemical synthesis and only provides aggregated GHG emissions hampering the identification of potential hotspot processes, but it performs well in the remaining criteria.

Given that no methodology surpasses the others, the selection of a suitable scaling methodology relies on study specifications and individual requirements, leading to the development of an Excel-based decision tool. Firstly, the individual study specifications are assessed to eliminate unsuitable methodologies. Secondly, the evaluation criteria are weighted by the user and weighted sums are calculated. The tool ranks methodologies, enabling users to select the most suitable scaling one. Being open-source, the Excel-based tool can be expanded and improved with further methodologies within the LCA community. Future research is needed to evaluate the scaling methodologies revealed by the tool in a direct use case.

While this study focuses on prospective LCA, its findings contribute significantly to sustainability assessment methods, process engineering, and product development in general. Advanced empirical scaling based approaches can predict costs, while process engineering reveals energy and material flows essential for LCC, Techno-Economic Analysis, critical raw material analysis, and social LCA. Expert integration in the use of approximations and modular influence estimations enables for comprehensive scaling across various domains, including ethical and societal factors, potentially aiding political decision-making.

#### CRediT authorship contribution statement

**Merve Erakca:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Manuel Baumann:** Conceptualization, Project administration, Supervision, Writing – review & editing. **Christoph Helbig:** Conceptualization, Supervision, Writing – review & editing. **Marcel Weil:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

#### Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL (DeepL SE) and ChatGPT-3.5 (OpenAI) in order to translate, revise sentence structure, and check grammar and spelling. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

#### Declaration of competing interest

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

#### Data availability

All data is available in the SI

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#### Appendix A. Supplementary data

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