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Improving automated Life Cycle Assessment with Life Cycle Inventory model constructs

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ABSTRACT

Global warming is a global and critical challenge and car manufacturers pledge to reduce their carbon footprint. It is mandatory to assess the carbon footprint of current and upcoming vehicles to achieve these self-set and quantified targets. Life Cycle Assessment (LCA) is a standardized and scientifically acknowledged method to quantify a product's or company's environmental impact. Due to the complexity of a vehicle's cradle-to-gate phase, automation of LCAs is a suitable simplification strategy by importing product information and automatically assign them to pre-defined life cycle inventory (LCI) models. The data acquisition is a recognized issue, but the LCI modelling is hardly discussed in the literature for automated LCAs even though it has a significant influence on their accuracy. This paper presents an approach to elaborate an LCI model construct that enables consistent and efficient automated LCA while maintaining defined accuracy and applicability in commercial LCA software. Such an LCI model construct and its derivation are presented in this paper for automotive aluminium components considering sheet components, casting components and extrusion profiles. It is mandatory for a precise calculation to take the most influencing parameters into consideration. Grid points for each of these parameters are elaborated dependent on the characteristic if the parameter is continuously or discretely variable. The resulting LCI model construct makes this most influencing parameters customizable in an automated LCA. A generic method for the design of such an LCI model construct based on the findings of the use case was derived in this paper. The application of this methodology is not limited for vehicle's LCAs and carbon footprint, but other complex products and impact categories to enable efficient, consistent, and accurate LCA results for complex products.

1. Introduction

Climate Change is one of the most critical challenges of modern civilization (World Economic Forum, 2021). Car manufacturers (Original Equipment Manufacturers – OEM) pledge to decrease their carbon footprint and therefore the carbon footprint of their vehicles (Science Based Targets, 2022) which leads to the necessity to quantify the status of decarbonization. Passenger cars with internal combustion engines (ICEV) cause the most greenhouse gas emissions during their use phase (Danilecki et al., 2017; Zheng and Peng, 2021) while battery electrical vehicles (BEV) emit fewer greenhouse gases during the use phase but higher emissions in the production phase compared to ICEVs (Hill et al., 2020). This shift makes the assessment of the carbon footprint (or environmental impact in general) in the production (cradle-to-gate) phase of passenger cars more important. Life cycle assessment (LCA) is a standardized method that can be applied to products, services, or organizations to quantify the environmental impact (International Organization for Standardization, 2006; International Organization for Standardization, 2006). Input and output information of the examined product system have to be collected and modelled in the life cycle inventory (LCI) phase of an LCA, which can lead to an intensive workload (Pascual-Gonzáles et al., 2015; Ferrari et al., 2021; Lettner and Hesser, 2020). This is especially relevant for complex product systems like vehicles that consist of a multitude of components (Arena et al., 2013; Millet et al., 2007; Koffler et al., 2008). LCA applications in development have to be efficient and consistent (Cerdas, 2021a) and the accuracy of results have to be sufficient to provide a meaningful support for decision-making (Pelton and Smith, 2015; Bueno and Fabricio, 2018; Hester et al., 2018). Changes in design and procurement choices have to be observable within an LCA to assist product development (Pelton and

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Smith, 2015; Cerdas, 2021a). This leads to a conflict of objectives between accuracy and efficiency of an LCA (Bitencourt de Oliveira et al., 2022) as the accuracy is mostly affected by the LCI (Bueno and Fabricio, 2018) and a detailed LCI requires more effort than a simplified one (Beemsterboer et al., 2020). Simplifications can be used to reduce workload (Beemsterboer et al., 2020) while automation of LCAs is a simplification strategy that addresses complex product systems (Yu and Kim, 2012; Safari and AzariJafari, 2021; Bitencourt de Oliveira et al., 2022). Internal databases that provide information about the product system are automatically combined with environmental data from LCA databases (Koffler et al., 2008; Hollberg et al., 2020; Bitencourt de Oliveira et al., 2022). Commercial LCA software solutions like GaBi © DfX (Sphera Solutions GmbH, 2022) provide the possibility to import product information and automatically create LCI models following by a life cycle impact assessment (LCIA). The automation in LCA comes with a streamlined LCI modelling and low technical resolutions (Bueno and Fabricio, 2018) and requires the use of generic data from given databases (Koffler et al., 2008; Yu and Kim, 2012; Bitencourt de Oliveira et al., 2022). There is also the remaining manual workload due to the mapping of input information to fitting datasets from LCA databases that requires expert knowledge (Safari and AzariJafari, 2021; Bitencourt de Oliveira et al., 2022) and is vulnerable for errors (Yu and Kim, 2012; Hollberg and Ruth, 2016). Even though these challenges are considered in the literature, the focus of automation approaches in LCA is mostly on reducing workload by describing possible data sources or implementation strategies. As the authors observed, there are no approaches to improve LCI modelling within automated LCAs, at least not for such complex product systems like entire vehicles with the aspiration of an accurate LCI modelling on component level. Some approaches are applied to less complex product systems (Steubing et al., 2016; Cerdas, 2021a; Ferrari et al., 2021), with a less detailed assessment on component level (Hollberg and Ruth, 2016; Hollberg et al., 2020) or software solutions were programmed that are not commercially available (Cerdas, 2021a).

A systematic approach is elaborated in this paper to tackle the challenge of efficiency and accuracy (Bitencourt de Oliveira et al., 2022). An LCI model construct for automated LCAs is designed that maintains the strengths of automated LCAs (efficiency and consistency) while reducing its weaknesses (accuracy). The LCI model construct is designed for commercial LCA software automation with consideration of the most influencing parameters of the product system. The state of the art of streamlining in LCA with a particular focus on automated LCAs and LCI modelling is described in Section 2. The elaboration of the systematic LCI model construct is presented in Section 3 with the use case of automotive aluminium components. For a wider application of the approach, the findings from Section 3 are transferred to a general methodology in Section 4. The conclusions of the paper are presented in Section 5.

2. Literature research on streamlining and automation of LCAs

2.1. State of the art of streamlining LCAs

The Society of Environmental Toxicology and Chemistry (Todd and Curran, 1999) stated that all LCA studies are streamlined, and only the magnitude of simplification varies. Beemsterboer et al. (2020) analysed streamlining approaches in LCA studies published since the 1990s and classified the streamlining strategies in five streamlining approaches: the **exclusion** (excluding either life cycle stages, processes or impact categories), the **inventory data substitution** (using secondary data from databases instead of exact values for the product system), the **qualitative expert judgement** (using matrix or red-flag approaches for non-quantified results), the **standardization** (using methodological standards or standardized assessment tools) and the **automation** (computing LCAs using software that integrate product information). The qualitative expert judgement is not relevant for the scope of this paper and is not discussed further in this section.

Examples for simplifications by exclusion in LCI are Kaebernick et al. (2003) and Pelton and Smith (2015). Kaebernick et al. (2003) stated that the production stage, including its raw materials and the use phase, are the most important life cycle stages when it comes to environmental impacts of a product. They classified products into active products that consume energy in the use phase and passive products that do not consume energy in the use phase. They suggested to only assess the production phase for passive products and only the use phase for active products. Pelton and Smith (2015) streamlined the LCI by only focusing on life cycle phases, that are considered hotspots in the literature for the product system. They concluded that just focusing on hotspot life cycle phases is sufficient to support decision-making regarding procurement decisions. Both, Kaebernick et al. (2003) and Pelton and Smith (2015) emphasize that the streamlined assessment does not replace a detailed LCA at the end of the development process but rather fulfils the purpose of supporting decision-making in the early design or procurement phase. An example of inventory data substitution in LCI is Sun et al. (2003). They grouped material datasets from an LCA database according to the material classifications and embodied environmental impact. The 400 datasets from the database were grouped in 16 groups, reducing the complexity of variability significantly.

As the focus of this paper is the LCI modelling in automated LCAs, the state of the art of automated LCAs is discussed in more detail in Section 2.2. The streamlining by standardization is subdivided into standardized LCA tools and methodological standards (Beemsterboer et al., 2020). Methodological standards are not scope of this paper and are therefore not discussed further. The standardization of LCI modelling is a key element of this paper as it enables the assignment of pre-defined LCI models (Koffler et al., 2008). LCI standardization approaches are discussed in more detail in Section 2.3.

2.2. State of the art of automated LCAs

Automation in LCA is a simplification strategy to handle complexity and reduce manual workload (Bitencourt de Oliveira et al., 2022). Applications of automated LCAs can be found for complex product systems that consists of many components (Koffler et al., 2008) or have a high variety of modelling choices (Cerdas, 2021a). Vehicles are complex products and consist of a multitude of components (Bitencourt de Oliveira et al., 2022). Other product systems that share their challenges in LCA are buildings that also consist of a variety of elements (Hester et al., 2018). It is therefore no surprise that applications for automated LCAs can be found in the building and automotive sector. In the following subsections, applications for automated LCAs in building and automotive sectors are discussed. Other applications of automated LCAs like in Ferrari et al. (2021) focus on less complex product systems and are therefore not relevant for this paper.

2.2.1. Automated LCAs in the building sector

Automated LCAs are mainly based on building information modelling (BIM) in the building sector (Hollberg and Ruth, 2016). BIM is a design and data management method that allows the combination of 3D-design with data on the physical attributes of its elements along the development process (Carvalho et al., 2019). It is evident that BIM is an excellent source of information to be implemented in LCA (Safari and AzariJafari, 2021).

Safari and AzariJafari (2021) analysed BIM based LCA studies in the building sector regarding output information and data management. They state that automation of LCA with BIM is an emerging trend but is applied mostly for conceptual designs by only considering the most important elements, like walls, ceilings, or floors. All the reviewed studies focused on the data management of system and resulting valid and comprehensible results. While the integration of BIM in LCA reduces the workload significantly, the assigning of BIM data to LCA data remains manual work, which is a consequence of missing compatibility of software and data between BIM and LCA databases.

Hollberg et al. (2020) performed and evaluated a BIM based LCA that has been applied along the entire development process of a building. The bill of quantities was extracted from BIM multiple times during the development process and transferred to an LCA calculation software where its entries are multiplied with pre-defined environmental data from LCA databases. The materials of the bill of quantities were previously mapped manually to the best fitting LCIA values. LCI and LCIA are aggregated to a single value for the pre-defined environmental data, which commits to the use of certain impact categories with respective characterization models.

Hollberg and Ruth (2016) designed a parametric model with the use case of a multi-residential building and the retrofitting of a single-family house. Unlike Hollberg et al. (2020), they implemented their parametric model directly in CAD software, which enables real-time feedback on the environmental performance during the design process. The parametrization was only performed for the most relevant parameters for the construction and use phase of the buildings and the material composition was the only parameter for the construction phase.

Automation is also used by Hester et al. (2018) to tackle the challenges of uncertainties in early design phase. The authors developed an algorithm for a streamlined and probabilistic LCA using Monte Carlo simulations. They pointed out that in the early phase of development, uncertainties exist because of limited information, while the decision-making is most impactful.

Bueno and Fabricio (2018) compared BIM based LCA with detailed LCA of walls regarding their accuracy. The authors found that the results from simplified BIM based LCAs allow only limited conclusion from their results compared to a detailed LCA. The reasons are simplifications in the LCI phase that are required for the linking of BIM and LCA. Examples given are geometry parameters that cannot be customized in the streamlined, automated modelling.

2.2.2. Automated LCAs in automotive sector

As the authors observed, fewer approaches of automated LCAs in automotive applications are published in the literature compared to the building sector. Relevant approaches for this paper are published by Koffler et al. (2008), Yu and Kim (2012) and Bitencourt de Oliveira et al. (2022). These approaches are all based on the use of data from the International Material Data System (IMDS) (DXC Technology, 2022), which is a globally used material data management system for OEMs.

Bitencourt de Oliveira et al. (2022) examined the influence of IMDS data resolution on the workload and accuracy of an LCA study with the use case of an internal combustion engine. Koffler et al. (2008) and Yu and Kim (2012) described the process of automated LCA for entire vehicles without specific use cases. IMDS data was combined with a component list that is assumed available in the development process in all publications. Koffler et al. (2008) implemented the information of manufacturing processes based on material information in order to close data gaps. Yu and Kim (2012) did not mention the implementation of manufacturing processes in LCI modelling and set their focus on assigning IMDS data to LCA datasets. Bitencourt de Oliveira et al. (2022) emphasized that manufacturing processes, including material losses, play an important role for the LCI modelling. They considered this information based on material data and expert judgement, but no further elaboration about the modelling is described in the study. The LCI modelling of Koffler et al. (2008) is done with a software that is not specified in the study. Bitencourt de Oliveira et al. (2022) performed their LCI models manually but pointed out that the commercial LCA software add-on GaBi © DfX (Sphera Solutions GmbH, 2022) can automate the LCI model creation. GaBi © DfX was not used in the study because the software cannot automatically perform the mapping of the IMDS data to LCA datasets and it remains manual work for the mapping of the best fitting datasets. The LCI models have to be pre-defined to enable automated and consistent LCI modelling by considering only material information (Yu and Kim, 2012) or by defining a model architecture that describes the interaction of materials and manufacturing processes (Koffler et al., 2008). However, none of the publications elaborated a detailed strategy for LCI modelling.

Another example of LCA automation in the automotive sector is Cerdas (2021a). The design of an Integrated Computational Life Cycle Engineering (ICLCE) framework was developed in this publication. The LCI modelling within the framework was built from multiple modules that were parametrised and linked to each other. Most relevant parameter of the product system were provided through a user interface and automatically linked to environmental data. The parametrization was performed for the foreground system of the product system, while the background system, like energy generation or production of raw materials, is assigned to average data from databases. Cerdas (2021c) states that automated data implementation from in-house databases can be performed with such ICLCE frameworks. The use case of the ICLCE was traction batteries for BEVs and not entire vehicles, and the framework was programmed in Python and is not commercially available.

2.3. State of the art of standardized LCI modelling strategies

The LCI modelling must be performed with pre-defined model architectures according to the standardization strategy of Beemsterboer et al. (2020) for a consistent application of automated LCAs. A consensus among the discussed publications of this section is the necessity to focus on the most relevant parameters for the respective product system.

Cerdas (2021b) did a literature review on assessment tools for the environmental performance of traction batteries for BEVs and states that many tools are designed in Microsoft Excel©. An example of Excel © based tools is the standardized Excel© tool solar heating and cooling systems from Beccali et al. (2016). Zah et al. (2009) developed a questionnaire that results in an automated calculation of the environmental impact of biofuels. Both Beccali et al. (2016) and Zah et al. (2009) emphasize that only few parameters affect the environmental impact of the product system significantly.

Nordelöf et al. (2019) and Nordelöf and Tillman (2018) developed a scalable LCI model for the cradle-to-gate phase of power electronic inverters. A parametrization for the most relevant parameters was done to achieve the scalability of the LCI model. The parametrization included the consideration of material losses of manufacturing processes. The input information is provided by the LCA practitioner through a user interface.

Steubing et al. (2016) developed a modular LCA approach to streamline LCI modelling for passenger car fuel choices. The justification for the modular approach was that the variability of modelling choices leads to an overwhelming number of LCI models, while commercial LCA software fails to simplify the modelling, leading to an intensive workload. By using a modular approach with parametrised modules, automated scenario analyses can be performed, what reduces manual workload significantly.

2.4. Summary of literature research

Publications on automated LCAs and standardized LCI modelling share the goal of reducing workload and the calculation of consistent and comprehensible results. While accuracy of the results is also a goal of these publications, there are different conceptions of sufficient accuracy in LCA, which can be explained by the different product systems in different applications. As it can be expected, the focus on accuracy decreased with more complex product systems. The quality of input information is essential for the quality of results in automated LCAs (Hollberg et al., 2020). The data availability of environmental data also plays an important role in the accuracy of the LCA (Bitencourt de Oliveira et al., 2022). Publications with a higher level of automation used mostly generic data from LCA databases that represent technological averages (Koffler et al., 2008; Hollberg and Ruth, 2016; Bueno and Fabricio, 2018). While Steubing et al. (2016) states that these parameters do not represent the variability of technical choices, Bueno and Fabricio (2018) argue that a sufficient representation of reality can be achieved by using average data if the LCI modelling is performed accurately. This, however, is assumed to be impossible in automated LCAs, according to Bueno and Fabricio (2018).

Four challenges are identified for automated LCA of complex product systems based on the literature research in this section. First, automation approaches in LCA have a conflict of objectives regarding efficiency and accuracy (Koffler et al., 2008; Bitencourt de Oliveira et al., 2022). Second, the initial mapping of input information from different data sources to best fitting LCA datasets is still a manual workload (Koffler et al., 2008) that requires expert judgement (Bitencourt de Oliveira et al., 2022) and is vulnerable to errors (Yu and Kim, 2012). Third, important information like manufacturing processes, including material losses and background process information, is not available in existing data management systems like IMDS or BIM (Bueno and Fabricio, 2018; Bitencourt de Oliveira et al., 2022). The variability of relevant parameters is therefore not covered in automated LCIs (Steubing et al., 2016). Fourth, automation solutions that are not performed in commercial LCA software solutions are inflexible regarding their impact categories and characterization models, as the LCI and LCIA data are merged and pre-calculated (Hester et al., 2018; Hollberg et al., 2020).

A systematic LCI modelling approach that can be applied in commercial LCA software maintains the benefits of LCA automation for highly complex product systems and increases the flexibility to cover the variability in relevant parameters in LCI is the identified research gap in this paper. The target of this paper is to answer the research question: **How can an accurate LCI modelling be performed in automated LCAs for highly complex product systems?**

3. Methodology

3.1. Research scope

The LCI modelling approach elaborated in this paper has the aspiration to be applicable to automated LCAs by using GaBi © DfX. The benefit of this tool is that it maintains the flexibility of LCIA as the LCI is modelled without merging LCI and LCIA. GaBi © DfX imports product information and automatically creates LCI models that can be calculated in LCIA afterwards (Sphera Solutions GmbH, 2022). The assignment of product information to best fitting datasets and the modelling of the LCI models is performed according to a pre-defined mapping that remains a manual workload (Bitencourt de Oliveira et al., 2022). These process steps are hereinafter termed as “the assignment of pre-defined LCI models based on component attributes”. Once the LCI models are pre-defined, they cannot be customized, which limits the flexibility of LCI modelling within the automated LCA. The approach of this paper is to design a construct of pre-defined LCI models that is made of static LCI models that cover in their completeness the solution space of the most influencing parameters (MIPs). The approach is applied for the Global Warming Potential (GWP) calculation of automotive aluminium components is elaborated, as aluminium is a CO_2-intensive lightweight material that is commonly used in structural components in vehicles. The GWP is assumed to be the most relevant impact category as OEMs pledge to reduce their carbon footprint (Science Based Targets, 2022), while targets for other impact categories cannot be found from the authors’ perspectives. The presented approach is still applicable to any other impact category. Applying the approach to only one impact category with applicability to more impact categories is consistent with other publications, as in Steubing et al. (2016). Deep-drawn sheets, casting components and extrusion profiles are the considered technologies for the aluminium components. The simplification strategies exclusion, inventory data substitution, standardization and automation, according to Beemsterboer et al. (2020) are applied for the design of the LCI model construct. Only secondary data from a given database is used (**inventory data substitution**), which is a common simplification for automated LCAs (Bitencourt de Oliveira et al., 2022; Hollberg et al., 2020). Only the production phase as a life cycle stage is part of the research scope, since the complexity in the production phase of vehicles lays in the multitude of components which is the scope of this paper. Also, only the GWP as an impact category is considered in the use case (**exclusion**). The applicability of the automation of the LCI modelling aligns with the **automation** strategy. To lower the mapping effort, only a few parameters are considered in a pre-defined LCI model architecture (**standardization**).

Goal of this LCI model construct is to increase flexibility of LCI modelling regarding the MIPs and to reduce the mapping effort that has to be performed manually as the complexity is reduced to a meaningful number of grid points. The systematic design of the LCI model construct consists of the steps classification of the MIPs into continuously variable parameters (CVPs) and discretely variable parameters (DVPs), grouping of the DVPs, elaboration of grid points for the CVPs and the reduction of the number of LCI models due to technical constraints. The approaches for the design of the LCI model construct of the aluminium components described in section 3 are deducted hereinafter to a generic methodology in section 4 for the application to other technologies and impact categories.

3.2. Definition and characterization of the generic LCI model architecture

The aspired LCI model construct shall be a simplified reflection of reality by means of standardization. The LCI model architecture remains the same for the different LCI models, and only the few MIPs shall be customizable. The availability of datasets plays an important role in the design of the LCI model architecture (Bitencourt de Oliveira et al., 2022) as it can only consider processes that are represented by datasets. The GaBi © software from Sphera Solutions with the GaBi service pack 39 Professional database is used for the LCI model architecture (Sphera Solutions GmbH, 2019). The LCI model construct shall cover the technologies deep-drawn sheets, casting components and extrusion profiles. Other production processes, like forging or additive manufacturing, are not considered in this paper. The scrap rate (SR), the recycled content (RC) and the virgin semi-finished product were identified as the MIPs for the production process of the aluminium components.

The LCI model architecture was standardized for all aluminium components in this paper. The two main parts of the LCI model architecture are the provision of semi-finished products and the production process of the component similar to the modules of Steubing et al. (2016). The flowchart of the standardized LCI model architecture is shown in Fig. 1.

The choice of a recycling allocation method is mandatory, as aluminium components can contain recycled materials. The Recycled Content Approach (Bhatia et al., 2011) was selected as it is easily applicable in LCI modelling. The RC of the input material is represented by a route of virgin semi-finished products and a route of recycled semi-finished products. The RC can be customized with the auxiliary process *Mixing process “recycled content”*. In the given database, datasets exist for virgin semi-finished products. Therefore, no further subdivision is done here. The respective semi-finished products are aluminium sheets, ingots and extrusion profiles. Only recycled ingots datasets for exist for the recycled semi-finished product route. The recycled semi-finished product route consists of the recycled ingot dataset and the semi-finished product process that is represented by a data fitting dataset from the database. For the sake of simplicity, only one dataset for recycled aluminium ingots was selected. The chosen dataset has the lowest content of alloy elements from all available datasets in the given database. This is because the alloy elements in the respective datasets are represented by virgin material for the alloy elements. The assumption here is that the reused scrap contains most of the alloy elements and only little quantities of virgin alloy elements have to be added for recycled aluminium ingots. As ingots are the assumed semi-finished products for casting components, no semi-finished product process for

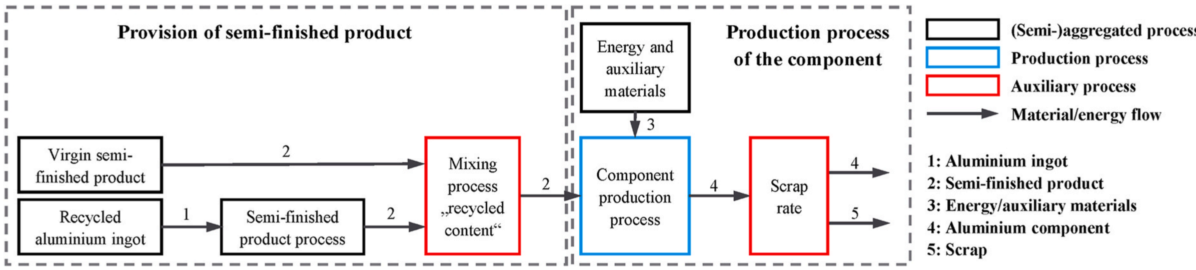

Fig. 1. Standardized LCI model architecture of aluminum components for the LCI model construct.

the recycled semi-finished product route is necessary.

The production process consists of the *Component production process* with its demanded *Energy and auxiliary materials* and the *Scrap rate*, which is an auxiliary process that scales all upstream flows. No distinction was made between different casting technologies for casting components as the given database only contains a high pressure die casting process for aluminium casting, which is used in this study. No further component production process was available in the given database for extrusion profiles and as the profiles are assumed to have the already matching geometry, only the *Scrap rate* is considered for the component production process.

It is necessary to describe the generic LCI model architecture mathematically for the further steps. This is because the design of the LCI model construct is dependent on the accuracy and therefore its LCA results. Eqs. (1)–(4) describe the environmental impact of an aluminium component with the LCI model architecture from Fig. 1. These equations are the baseline for the following sections. Even though the automation of the LCA shall maintain the LCIA flexibility, the LCI model construct is derived from the results of one specific impact category and characterization model. The LCI and LCIA are therefore merged for the method to design the LCI model construct (comparable to Hollberg et al. (2020)) but not in the application of the automation.

$$I_{component} = \left(\frac{1}{1-SR}\right) * \left\{ \left[RC * \left(I_{sec.\ ingot} + I_{s-f\ product\ process}\right) + (1-RC) * I_{prim.\ s-f\ product}\right] + I_{E\&A} \right\} \tag{1}$$

or

$$I_{component} = \left(\frac{1}{1-SR}\right) * \left\{ I_{prim.\ s-f\ product} * \left[RC * (\varepsilon - 1) + 1\right] + I_{E\&A} \right\} \tag{2}$$

with

$$SR = \frac{m_{input} - m_{component}}{m_{input}} \tag{3}$$

$$\varepsilon = \frac{I_{sec.\ ingot} + I_{s-f\ product\ process}}{I_{prim.\ s-f\ product}} \tag{4}$$

$I_{component}$: environmental impact of the component
SR: scrap rate [%]
RC: recycled content [%]
$I_{sec.\ ingot}$: environmental impact of the secondary aluminum ingot
$I_{s\text{-}f\ product\ process}$: environmental impact of the production of the semi-finished product
$I_{prim,\ s\text{-}f\ product}$: environmental impact of the primary semi-finished product
$I_{E\&A}$: Environmental impact of energy and auxiliary material demand

Since the generic LCI model architecture and the equations to describe its environmental footprint is defined and the MIPs are known, there are three three-dimensional solution spaces of the model (one solution space for every considered technology and one dimension for every MIP) with solutions for the GWP of the aluminium component. It is crucial to analyze the characteristics of this solution space for the approach of this paper. As the goal of this approach is to have an LCI model construct of pre-defined LCI models that can be assigned based on components attributes, the aspired solution space consists of discrete solutions represented by pre-defined models (see Fig. 2). The MIPs must be represented by discrete grid points. Considering the given MIPs in this study, the virgin semi-finished products are already represented by datasets from the given database and are already constituted by discrete grid points. The SR and the RC can be adjusted continuously. The possible solutions between their boundaries are infinite. To have a finite number of LCI models, the solution space of these parameters must be represented by discrete grid points. Since these grid points are only an approximated reflection of reality, a meaningful number of grid points must be elaborated to maintain a sufficient accuracy of the results and reduce the mapping effort. The mapping effort is linked to the number of pre-defined LCI models. Steubing et al. (2016) points out that the variability of modelling choices and parameters leads to a multitude of LCI models. To reduce the mapping effort to a manageable level and to reduce the complexity of the modelling choices, the number of grid points should be as low as possible while fulfilling requirements for accuracy. Not only the number of grid points for the SR and RC have to be elaborated, but also the number of datasets for the virgin semi-finished product have to be reduced to a meaningful number.

The grid points for the virgin semi-finished products, the SR and the RC are elaborated independent from the considered technology in Section 3.3. The number of grid points is reviewed afterwards under consideration of technical restrictions of the technologies to reduce the overall numbers of LCI models.

3.3. Grouping of the datasets for semi-finished products

Various datasets for aluminum semi-finished products, including sheets, ingots and extrusion profiles, are available in the given database. Most of the datasets are from the European Union (EU-28) or Germany (GER). These datasets are already aggregated and cannot be customized with different input data. Therefore, only datasets were considered that belong to the same data source with a high variety of datasets and contain information for the characterization of the functional unit. These chosen datasets are from thinkstep © for the origin EU-28 and GER for the reference year 2018 and contain information regarding the alloy element content. For aluminum sheets, 10 datasets, for ingots 5 datasets and for extrusion profiles, 11 datasets each for EU-28 and GER are given. An industry mix for each semi-finished product that does not contain any alloy elements is given for EU-28 and GER. There are 52 datasets, of which 46 datasets include information on the alloy elements. Using all these datasets as grid points would result in a redundant number of LCI models, as there are datasets for virgin semi-finished products that are very similar regarding their alloy element mix and GWP. The goal of this section is to group the datasets and use a reduced number of representative datasets for the LCI model construct under defined requirements of accuracy. An example of a similar grouping is the study of Sun et al. (2003). LCI datasets were grouped under the

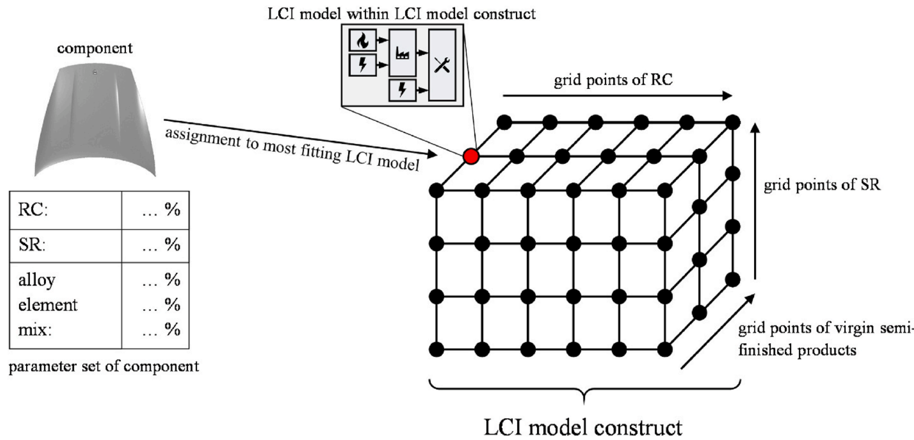

Fig. 2. Assignment of components attributes to pre-defined LCI models in a standardized LCI model construct.

accuracy requirement of a relative standard deviation of 30% within a group.

For every EU-28 semi-finished product dataset, a GER dataset exists with the same alloy element content and vice versa. The origin and the content of the respective alloy elements can be used as characteristics to group the datasets. The grouping will be performed for the impact category GWP with the characterization model CML 2001–Jan 2016. The requirement on the accuracy of the grouping is set to a maximum relative standard deviation within the group of 5% and the maximum bandwidth of values for the embodied GWP shall be less than 1 kg CO_2eq/kg semi-finished product. The origin of the semi-finished products has a significant influence on their GWP. As it is displayed in Fig. 3, the difference of the GWP of EU-28 and GER aluminium semi-finished products is on average 0.52–0.68 kg CO_2eq/kg semi-finished product while the EU-28 values are always lower. A plausible explanation is that the European electricity grid mix has a lower specific GWP compared to the German electricity mix and the production of aluminium requires electricity in the energy intensive electrolysis process.

The correlation between the respective alloy elements and the embodied emissions was analysed. A high correlation is likely for alloy elements that have a high variety in the content and a high deviation to the embodied emissions of primary aluminium. The magnesium content is likely to have a significant influence on the GWP of the semi-finished products since the difference in GWP is 24.9 kg CO_2eq/kg semi-finished product,[1] which is higher than for any other alloy element. The variety of magnesium content along the datasets covers the range of

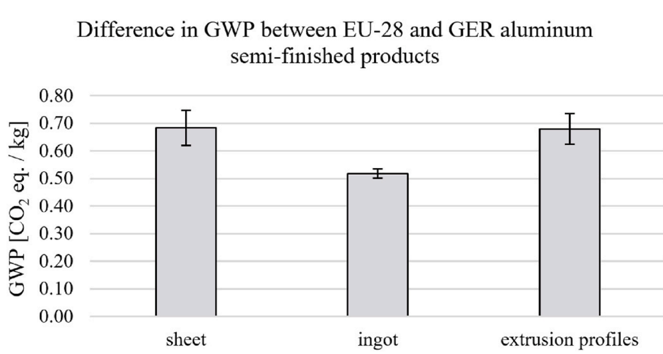

Fig. 3. Difference in GWP between EU-28 and GER aluminium semi-finished products.

0.35–5.60% which is sufficient to identify differences in the GWP of the datasets. The correlation factor between the specific GWP and the magnesium content was calculated according to Eq. (5) for the considered datasets. A high correlation between the specific GWP and the magnesium content can be seen in wrought alloys (sheets and extrusion profiles) in Table 1. No correlation can be seen between the magnesium content and the specific GWP of the datasets for ingots.

$$r = \frac{\sum(\alpha_i - \overline{\alpha})^*\left(I_{DS,i} - \overline{I_{DS}}\right)}{\sqrt{\sum(\alpha_i - \overline{\alpha})^{2*}\sum\left(I_{DS,i} - \overline{I_{DS}}\right)^2}} \tag{5}$$

with

r:correlation factor
$\alpha_i$alloy element content of respective dataset
$\overline{\alpha}$mean alloy element content of datasets
$\overline{I_{DS}}$

The grouping of the datasets can be performed with the possible distinction parameters *origin of the dataset* and the *magnesium content*. The grouping is performed by grouping all datasets of a semi-finished product together and checking if the requirements for accuracy are fulfilled. If not, the group is split up based on the origin of the datasets and checked for the fulfillment of the requirements. If the requirements are still not fulfilled, the two groups are split again by means of the magnesium content until the requirements are fulfilled. Only if all requirements for every group are fulfilled, the grouping is completed. The grouping process is illustrated in Fig. 4.

The ingots can be grouped without a distinction by the origin or magnesium content while fulfilling the requirements. The low correlation factor between the specific GWP of the ingot datasets and their magnesium content is therefore not relevant for the grouping. The datasets for sheets and extrusion profiles are grouped by means of origin and magnesium content with four groups each. The grouping condition of the magnesium content is a magnesium content lower or higher than 2.8% for sheets and lower or higher than 3,0% for extrusion profiles. A

Table 1
Correlation factors of considered datasets between their specific GWP and their magnesium content based on GaBi service pack 39 Professional database (Sphera Solutions GmbH, 2019).

	EU-28 sheets	GER sheets	EU-28 ingots	GER ingots	EU-28 extrusion profiles	GER extrusion profiles
Correlation factor	0.98	0.98	0.15	0.22	0.93	0.95

[1] GWP of the used magnesium dataset minus the GWP of EU-28 aluminium consumption mix (without alloy element content).

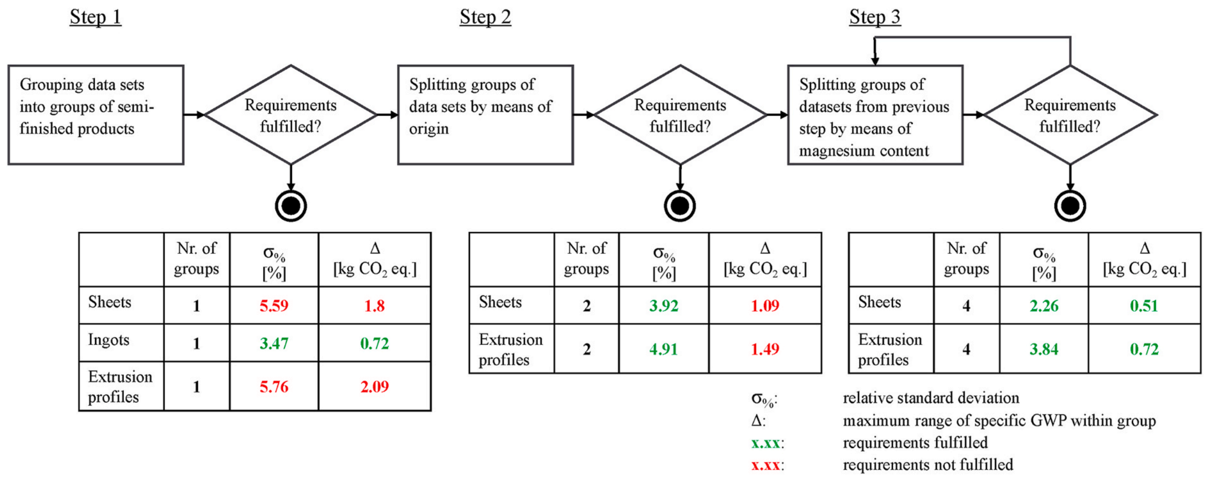

Fig. 4. Grouping process of the semi-finished product datasets. The results of the grouping regarding the grouping requirements are illustrated in the tables with the highest value of the groups for the respective requirement.

representative dataset was selected with the closest specific GWP to the average for every group a. The dataset of the industry mix (without alloy element content) was selected for the aluminium ingots, since its specific GWP is closer to the groups average than any other dataset of the group. If a group contains only two datasets, the dataset with the higher specific GWP was selected as the representative dataset. An overview of the groups can be seen in Table 2. The overall number of datasets of 52 is reduced to 9 datasets.

Table 2
Dataset groups for the virgin semi-finished product datasets based on GaBi service pack 39 Professional database (Sphera, 2019).

Ingots		Sheets		Extrusion profiles	
Origin:EU-28/GER		Origin:	EU-28	Origin:	EU-28
Mg content:	–	Mg content:	< 2.8	Mg content:	< 3.0
$\sigma_{\%}$:	3.47	$\sigma_{\%}$:	1.96	$\sigma_{\%}$:	2.17
Δ:	0.72	Δ:	0.37	Δ:	0.65
Ø:	8.38	Ø:	9.12	Ø:	9.17
$I_{rep.DS}$:	8.30	$I_{rep.DS}$:	9.05	$I_{rep.DS}$:	9.21
		Origin:	EU-28	Origin:	EU-28
		Mg content:	≥ 2.8	Mg content:	≥ 3.0
		$\sigma_{\%}$:	2.37	$\sigma_{\%}$:	3.84
		Δ:	0.51	Δ:	0.55
		Ø:	9.67	Ø:	10.13
		$I_{rep.DS}$:	9.68	$I_{rep.DS}$:	10.40
		Origin:	GER	Origin:	GER
		Mg content:	< 2.8	Mg content:	< 3.0
		$\sigma_{\%}$:	2.06	$\sigma_{\%}$:	2.20
		Δ:	0.43	Δ:	0.75
		Ø:	9.80	Ø:	9.86
		$I_{rep.DS}$:	9.73	$I_{rep.DS}$:	9.90
		Origin:	GER	Origin:	GER
		Mg content:	≥ 2.8	Mg content:	≥ 3.0
		$\sigma_{\%}$:	2.26	$\sigma_{\%}$:	3.29
		Δ:	0.50	Δ:	0.50
		Ø:	10.40	Ø:	10.75
		$I_{rep.DS}$:	10.30	$I_{rep.DS}$:	11.00

Mg content: Magnesium content [%].
$\sigma_{\%}$: Relative standard deviation within group [%].
Δ: Maximum range of specific GWP within group [kg CO_2eq].
Ø: Average specific GWP of group [kg CO_2eq].
$I_{rep.DS}$: Specific GWP of representative dataset [kg CO_2eq].

3.4. Elaboration of grid points for the scrap rate

The SR influences the demand of the input material as it describes the material losses within a process. Assuming that the demand for energy and auxiliary material is scalable with the processed input material (in this case aluminium semi-finished product), the SR influences the demand of all inputs, including their embodied emissions. The influence of the SR on the overall environmental footprint of the components is described in Eq. (6). The environmental impact of the component increases progressively with increasing SR.

$$f(SR) = \left(\frac{1}{1 - SR}\right) \tag{6}$$

Since the SR can be adjusted in a continuous range of values with the auxiliary process, the continuous range of values must be simplified to a few representative grid points to achieve the LCI model construct with discrete grid points. This simplification results in a deviation between the result of a detailed LCA of a component and the result from the assigned LCI model from the LCI model construct. This deviation shall be small enough to deduce reliable conclusions. The GWP is scalable with the with Eq. (6), which describes the influence of the SR on the GWP of the component. The deviation between the assigned LCI model and an LCI model with the specific value of the SR can be described as in Eq. (7) for a relative deviation.

$$\delta \leq \left| \frac{f(SR)}{f(SR_d)} - 1 \right| \tag{7}$$

with

δ: relative deviation between the SR's influence on the GWP of the component with a specific value for SR and the representative grid pointSR: specific value for the SR of the componentSR$_d$: assigned grid point of the SR based on the component's SR

In this study, the requirement is set that the relative deviation as in Eq. (7) shall be less than 10%. That means that every component's SR must have a grid point that fulfils this requirement for accuracy. The grid points SR_d have a range of values that they can represent while fulfilling the requirements. The range with its boundaries $SR_{d,min}$ and $SR_{d,max}$ can be described as in Eqs. 8–11.

$$\delta = \frac{\frac{1}{1-SR_{d,max}}}{\frac{1}{1-SR_d}} - 1 \tag{8}$$

$$\delta = 1 - \frac{\frac{1}{1-SR_{d,min}}}{\frac{1}{1-SR_d}} \tag{9}$$

$$SR_{d,min} = 1 + \frac{SR_d - 1}{1+\delta} \leq SR \leq 1 + \frac{SR_d - 1}{1-\delta} = SR_{d,max} \tag{10}$$

$$SR_d = \left(SR_{d,min} - 1\right) * (1-\delta) + 1 = \left(SR_{d,max} - 1\right) * (1+\delta) + 1 \tag{11}$$

The range of values of the grid points has to be without gaps in between them to cover the solution space of the SR. The maximum boundary of a grid point's range equals the minimum boundary of the next grid point's range, as described in Eq. (12).

$$SR_{d,max,i} = SR_{d,min,i+1} \tag{12}$$

with

i: number of grid point

The grid points for the SR can be calculated recursively with the context of Eqs. (11) and (12) if the solution space of the SR and a start value is set. The start value can be any value for $SR_{d,min,i}$, $SR_{d,max,i}$ or $SR_{d,i}$ since Eq. (11) describes the context of the grid points to its boundaries and Eq. (12) describes the context of the grid points to their enclosed grid points. The solution space for the SR is set to values between 0% and 80%. SR higher than 80% are assumed to be uneconomic. However, for sheet components, SRs above 70% are possible. The lower boundary of the first grid point $SR_{d,min,1}$ was defined to be zero for the start value. Since most processes produce some kind of scrap, e.g. clippings, chips or other waste, a SR of 0% is unlikely. A scrap rate of 0% is still covered in the range of $CVP_{d,1}$ with the relative deviation δ with the starting value $CVP_{d,min,1} = 0$. The grid points listed in Table 3 can be calculated with the given inputs for the recursive calculation. The SR with a continuous solution space is simplified to nine grid points.

Table 3
Calculated grid points for the SR

Number of grid point	SR_d	$SR_{d,min}$	$SR_{d,max}$
1	10.0%	0.0%	18.2%
2	26.4%	18.2%	33.1%
3	39.8%	33.1%	45.2%
4	50.7%	45.2%	55.2%
5	59.7%	55.2%	63.3%
6	67.0%	63.3%	70.0%
7	73.0%	70.0%	75.5%
8	77.9%	75.5%	79.9%
9	81.9%	79.9%	83.6%

3.5. Elaboration of grid points for the recycled content

The RC influences how much recycled material is used for the semi-finished product in the LCI model. It has a significant influence on the GWP of the *provision of semi-finished product*. This influence is described in Eq. (13).

$$f(RC) = RC * (\varepsilon - 1) + 1 \tag{13}$$

with

ε: ratio of GWP of the recycled semi-finished product and virgin semi-finished product (see. Eq. (4)) [%]

$$RC_{d,min} = \frac{(1+\delta)*(1+(\varepsilon-1)*RC_d) - 1}{(\varepsilon-1)} \leq RC \leq \frac{(1-\delta)*(1+(\varepsilon-1)*RC_d) - 1}{(\varepsilon-1)} = RC_{d,max} \tag{18}$$

The function f(RC) is dependent on the parameters RC and ε while RC is an MIP with a continuous solution space, the parameter ε is dependent on the datasets used for the virgin-semi-finished products and the recycled semi-finished product route, which results in a discrete solution space for ε. The influence of RC can be seen as multiple continuous solution spaces as seen in Fig. 5.

With the datasets for the secondary material route already set constant (Section 3.2), the parameter ε can have nine different values, one for every dataset for the virgin semi-finished product from Table 2. The goal for the continuously variable parameter RC is to calculate the grid points with the same procedure as for the SR in Section 3.4. This is, without extending the LCI model construct in another dimension, only possible if the parameter ε is represented by a single value for the calculation of the grid points. The lowest possible value for ε is of interest, since the gradient of f(RC) gets steeper for lower values of ε, which tends to a calculation of more grid points and is more conservative. The lowest value of ε equals 0.15 and is the ratio of the GWP of the recycled and virgin aluminium ingot for casting components. It has to be emphasized that ε differs along the LCI models and is only set to a constant value for the calculation of the grid points. This might result in grid points for the calculation of deep-drawn sheets or extrusion profiles that are redundant for the accuracy requirements set for the calculation. However, this simplification allows to use the same grid points for all considered technologies and reduces the overall number of grid points.

The component's GWP is not scalable with f(RC) in contrast to the SR, but only with the GWP of the *provision of the semi-finished product*. In this specific case, the GWP from the *production process of the component* is small compared to the GWP of the *provision of the semi-finished product*. It is approximated that the overall GWP of the component is scalable with f(RC). The same procedure as for the SR can be performed with these simplifications. The respective calculation is shown in Eq. 14 and 15. The maximum relative deviation δ is set to 10%.

$$\delta \leq \left| \frac{f(RC)}{f(RC_d)} - 1 \right| \tag{14}$$

$$\delta \leq \left| \frac{1+(\varepsilon-1)*RC}{1+(\varepsilon-1)*RC_d} - 1 \right| \tag{15}$$

$$\delta = \frac{1+(\varepsilon-1)*RC_{d,min}}{1+(\varepsilon-1)*RC_d} - 1 \tag{16}$$

$$\delta = 1 - \frac{1+(\varepsilon-1)*RC_{d,max}}{1+(\varepsilon-1)*RC_d} \tag{17}$$

$$RC_d = \frac{\frac{1+(\varepsilon-1)*RC_{d,min}}{(1+\delta)} - 1}{(\varepsilon-1)} = \frac{\frac{1+(\varepsilon-1)*RC_{d,max}}{(1-\delta)} - 1}{(\varepsilon-1)} \tag{19}$$

$$RC_{d,max,i} = RC_{d,min,i+1} \tag{20}$$

with

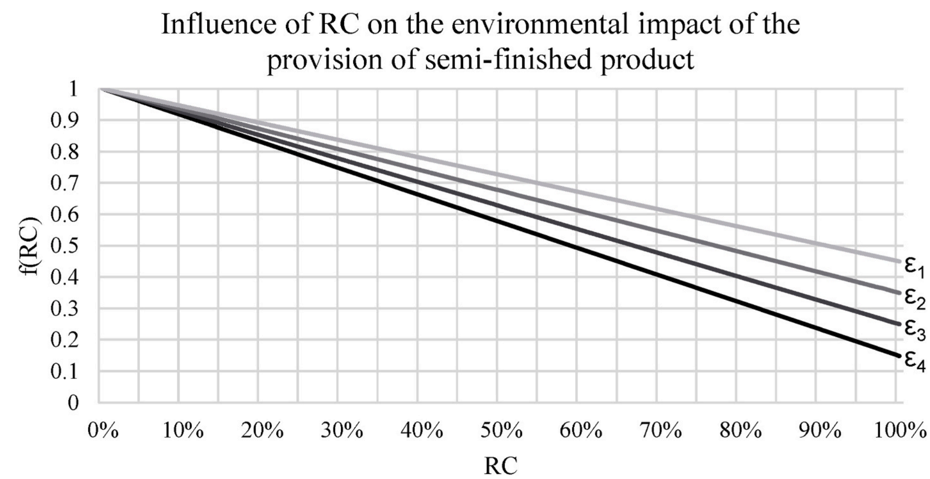

Fig. 5. f(RC) for different values for ε with $\varepsilon_1 > \varepsilon_2 > \varepsilon_3 > \varepsilon_4$.

Table 4
Calculated grid points for the SR.

Number of grid point	RC_d	$RC_{d,min}$	$RC_{d,max}$
1	0.0%	−11.8%	11.8%
2	21.4%	11.8%	31.0%
3	38.9%	31.0%	46.7%
4	53.2%	46.7%	59.6%
5	64.9%	59.6%	70.1%
6	74.5%	70.1%	78.8%
7	82.3%	78.8%	85.8%
8	88.7%	85.8%	91.6%
9	94.0%	91.6%	96.3%
10	98.2%	96.3%	100.2%

RC_d: grid point for RC in LCI model
$RC_{d,min}$: minimum boundary of RC values that can be assigned to the respective grid point while fulfilling the requirements for accuracy
$RC_{d,max}$: maximum boundary of RC values that can be assigned to the respective grid point while fulfilling the requirements for accuracyi index for the numbering of grid points

The start value for the RC is $RC_{d,1} = 0$, which means that the first grid point should represent a component that contains no recycled material at all. In case no information on the RC of the component is available, this is a conservative assumption and should be represented in the LCI model construct. The solution space of the RC is set to 0 %–100% as aluminium is a highly recyclable material. Ten grid points can be calculated with these input values and the recursive calculation of Eqs. (19) and (20). The grid points are shown in Table 4.

3.6. Reducing the number of LCI models due to technical restrictions

The number of LCI models within the LCI model constructs equals the product of the number of grid points for each MIP. The datasets for the virgin semi-finished product were grouped into nine groups,[2] with one representative dataset as a grid point each. Nine grid points for the SR and ten grid points for the RC were calculated. By combining the grid points, 810 LCI models build the three aspired LCI model constructs that cover the selected solution space for the MIPs. These LCI model constructs cover some solution spaces that are unlikely or redundant from a technical point of view. Further assumptions and limiting conditions can be defined to reduce the number of LCI models and the mapping effort.

As the geographical scope is on GER and EU-28 datasets and GER is a subset of EU-28, the scope can be narrowed down to only considering EU-28 datasets. This makes the geographical scope more generic and reduces the number of grid points for the virgin semi-finished product from nine to five. A high scrap rate is also more likely for deep-drawn sheets than for extrusion profiles or casting components. By assuming the SR is not higher than 33% for extrusion profiles and casting components, the number of grid points for the SR reduces from nine to two for these technologies. Another assumption is that high RC are more likely for casting components and wrought alloys for sheets and extrusion profiles contain less recycled materials. The number of grid points can be reduced from ten to three grid points for sheets and extrusion profiles, with the assumption that the RC is not higher than 45%. These assumptions reduce the number of LCI models from 810 models to 86 models, as it can be seen in Table 5.

Another option to reduce the number of LCI models is to lower the requirements for accuracy. Especially the accuracy requirements on the relative deviation for the assignment of the SR and the RC have a significant impact on the number of models. The maximum relative deviation δ between the GWP of the component with the exact value for the parameter and the assigned grid point's parameter was set to 10% in the use case. Fig. 6 shows the number of LCI models in the LCI model constructs for different values of δ. The recursive calculation for the discretization of the SR and RC was performed with integer values of δ between 1% and 15%. The number of grid points for the virgin semi-finished product of nine was not customized here. The number of LCI models was then calculated as in Table 5. The number of LCI models can be reduced from 810 to 378 if δ is increased from 10% to 15%. The number of LCI models increases to 3060 if δ is reduced to 5% and to even 69,984 LCI models if δ is reduced to 1%.

[2] Four datasets for sheets, one dataset for ingots and four datasets for extrusion profiles.

Table 5
Number of grid points for the respective MIP and technology and the resulting LCI models with and without simplifications.

	Grid points for virgin semi-finished products		Grid points for SR		Grid points for RC		Total number of LCI models	
	Initial LCI model construct	Modified LCI model construct	Initial LCI model construct	Modified LCI model construct	Initial LCI model construct	Modified LCI model construct	Initial LCI model construct	Modified LCI model construct
Deep-drawn sheets	4	2	9	9	10	3	360	54
Casting components	1	1	9	2	10	10	90	20
Extrusion profiles	4	2	9	2	10	3	360	12
							810	**86**

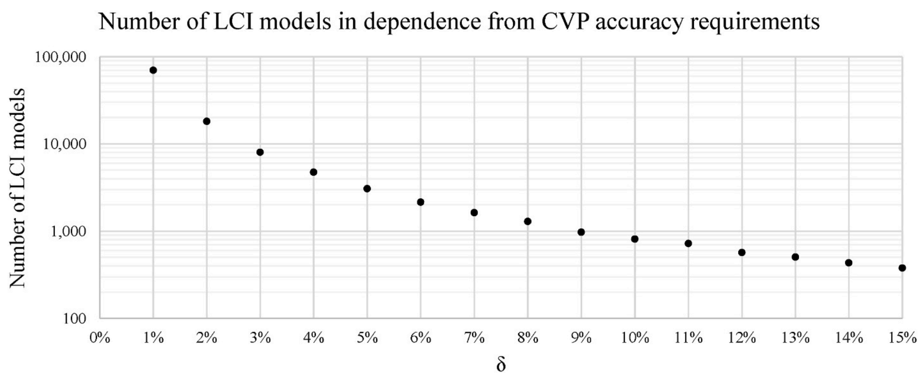

Fig. 6. Number of LCI models in dependence from the requirement on the deviation between the assigned parameter and product parameter for the SR and RC.

4. Transfer to a general methodology for the design of an LCI model construct

The LCI model construct for the use case in Section 3 is only one possible application where an LCI model construct can be used. This procedure is ideally possible for any other product system and impact category. The goal of this section is to transfer the procedure to a general method to systematically design an LCI model construct. As for the use case, it is assumed that the standardized LCI model architecture and its MIPs are already known. The method consists of four steps: the classification of the MIPs, the grouping of discretely variable parameters, the elaboration of grid points for continuously variable parameters and the reduction of the number of LCI models due to technical restrictions. The first three steps are described hereinafter in the following subsections. The reduction of the number of LCI models due to technical restrictions is not described in this section, as it is dependent on the considered product system and an example is already given in Section 3.6.

4.1. Classification of most influencing parameters

The LCI model construct consists of discrete LCI models, which means that it covers the solution space of all MIPs with discrete grid points. Some parameters are only customizable by choosing different datasets due to data availability, while other parameters can be customized with any given value in the range of certain boundaries. This distinction determines how the elaboration of grid points has to be performed. This distinction is described in this paper by the denotations of discretely variable parameters (DVPs) and continuously variable parameters (CVPs). CVPs define the ratio of input and output flows of processes within an LCI model. The SR in Section 3.2 is an example of such a CVP. The SR defines the ratio of the outputs (component and scrap) for a given input of a semi-finished product and can be customized to any value within technically meaningful boundaries. DVPs are parameters that are linked to specific modelling choices that can only be customized by choosing the one or the other alternative. Examples are

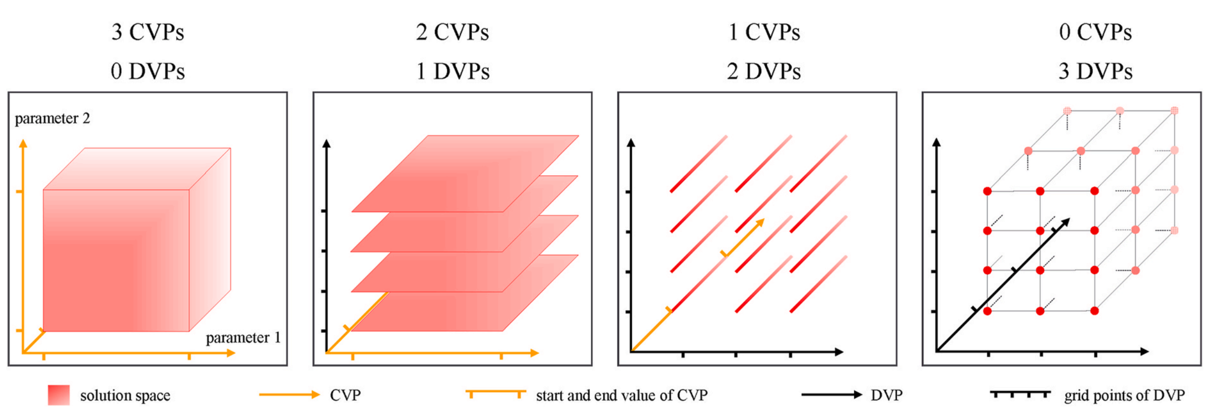

Fig. 7. Solution spaces of LCI models with three MIPs dependent on the number of DVPs and CVPs. An orange axis implies the dimension of a CVP, a black axis implies the dimension of a DVP.

different production process routes or local electricity mixes that exist as datasets in given databases. It has to be emphasized that datasets used for DVPs are the result of LCI models that are dependent on CVPs as well. For instance, a regional electricity grid mix is dependent on the share of different electricity sources (CVP of electricity grid mix), that have CVPs for their environmental impact as well (e.g., efficiency in power generation). However, this information can be unknown, is not available or not practical to collect. In these cases, datasets from databases can be used where limited or no insights in the modelling are possible and the parameter is only discretely variable. The characteristic of the parameters has an influence on the solution space of an LCI model, which is discussed in Section 4.1.1.

4.1.1. *Solution space of Life Cycle Inventory models*

The solution space of the LCI models is determined by the possible combinations of the customizable parameters that are, in this case, the MIPs. The requirement for the selection of the MIPs is that they have a significant impact on the environmental impact of the product system and are accessible either through in-house data or through expert knowledge (Nordelöf et al., 2019). The solution space is M-dimensional, while M is the number of MIPs. The solution space consists of partial solution spaces that are C-dimensional, while C is the number of CVPs. The number of the partial solution spaces is determined by the number of grid points of the DVPs. The solution spaces of LCI models with three MIPs and different distributions of DVPs and CVPs are shown in Fig. 7.

The solution space of the aspired LCI model construct must be built by discrete grid points like the illustration on the right side of Fig. 7. The number of LCI models equals the multiplication of the number of grid points for every MIP. The authors suggest defining not more than three MIPs to reduce the mapping effort. The number of grid points for the MIPs must be meaningful to avoid redundant LCI models. In order to achieve a meaningful number of LCI models in the LCI model construct, the DVPs have to be grouped and the CVPs have to be transferred into discrete grid points.

4.2. *Grouping of discretely variable parameters*

DVPs are parameters that are represented by given datasets. The number of datasets is limited to the used database (Koffler et al., 2008). Three situations can occur regarding the suitability of the number of available datasets for a given database:

I There are not enough datasets …
II The number of datasets is suitable …
III There are more datasets than it would be necessary …

… to represent the parameters that exist for the functional unit under requirements of accuracy.

For situation I, additional data must be collected. For situation II, no further measures are necessary. Situation III occurs especially for well-known and highly considered materials in LCA. Many LCA results can exist for one material that is similar regarding their system boundaries and values for the embodied environmental impacts. To choose the most fitting dataset for an LCA can be time-consuming, although it has little impact on the result. A grouping of the datasets can lower the effort of mapping. The grouping of the datasets must be performed with the objective of a defined accuracy. Besides the accuracy, the grouping must be performed with attributes of the dataset that correlate with the result of the LCA and are meaningful and known by the practitioner. E.g., Sun et al. (2003) grouped the datasets of materials based on their material classification. Other possible attributes are input or output flows, spatial or temporal aspects, or material composition. Requirements for the accuracy have to be set. It has to be evaluated how the accuracy of the DVP's grouping affects the accuracy of the LCI model based on the LCI and ICIA results. If more parameters that are afflicted with inaccuracies are customizable within the LCI models, the inaccuracy of the LCI model might be too high to elaborate reliable results. The requirements of accuracy have to be set dependent on the number of considered parameters within the LCI models and the influence of the parameters on the overall component's environmental impact. The grouping depends on the considered impact category. A grouping of datasets regarding the accuracy in a certain impact category might lead to a different grouping than the grouping for another impact category.

4.3. *Elaboration of grid points for continuously variable parameters*

CVPs describe the relation of the environmental impact of an input and an output and can be described by auxiliary processes that have no environmental impact by themselves. This relation is defined by a function f(CVP) as in Eq. (21):

$$I_{output} = f(CVP)^* I_{input} \tag{21}$$

with

I: environmental impact

The function f(CVP) is a continuous function in the considered boundaries. The function has to be represented by a finite number of discrete grid points to enable the design of the aspired LCI model construct. A method for transferring the CVP's range of solutions to discrete grid points is discussed in this section.

Since CVPs are continuously variable but have to be assigned to discrete parameters within the pre-defined LCI model construct, discrepancies between reality and assigned LCI model are inevitable. Requirements have to be set regarding this deviation to ensure a required accuracy of the model. As the influence of a CVP on an output can be nonlinear, the deviation shall not be described regarding the CVP's values but the environmental impact of the considered output. Since the influence on the environmental impact of the output is given by the function f(CVP), the deviation between f(CVP) and the respective function with the discrete grid point f(CVP_d) is of interest. A relative or absolute deviation can be selected as described in Eq. 22–24.

$$\delta \leq |g[f(CVP)\ ,\ f(CVP_d)]| \tag{22}$$

with

$$\delta \leq \left|\frac{f(CVP)}{f(CVP_d)} - 1\right|, \textit{ for relative deviation and} \tag{23}$$

$$\delta \leq \left|I_{output}[f(CVP)] - I_{output,d}[(f(CVP_d)]\right|, \textit{ for absolute deviation} \tag{24}$$

With this relation and a chosen value for δ, not only the value for the grid point CVP_d can be calculated but also a range of CVPs that can be assigned to the CVP_d and fulfilling the requirement set in Eq. (22). The range of CVPs that can be assigned to a certain CVP_d has its boundaries at $CVP_{d,min}$ and $CVP_{d,max}$. These boundaries can be calculated in dependency from CVP_d and δ (Eq. (25)):

$$CVP_{d,min} = h(\delta, CVP_d) \leq CVP \leq j(\delta, CVP_d) = CVP_{d,max} \tag{25}$$

$CVP_{d,min}$, $CVP_{d,max}$ and CVP_d can be calculated with this relation if one of these values are given. Since the grid points must represent the entire range of possible CVPs, the ranges of all CVP_ds must be without gaps. This leads to the condition in Eq. (26):

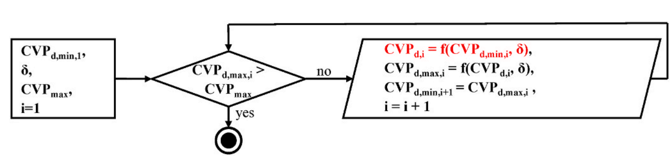

Fig. 8. Recursive calculation of the discretized CVPs with a given start value for $CVP_{d,min,1}$.

$$CVP_{d,max,i} = CVP_{d,min,i+1} \quad (26)$$

with

i: numbering index of CVP grid points

With the Eq. 22–26 and a given value for a start value for $CVP_{d,min,1}$, $CVP_{d,max,1}$ or $CVP_{d,1}$, every CVP_d in the considered boundaries can be calculated. A flowchart of such a recursive calculation with a start value for $CVP_{d,min,1}$ is shown in Fig. 8. Necessary input information for the recursive calculations is:

- a start value for $CVP_{d,min,1}$, $CVP_{d,max,1}$ or $CVP_{d,1}$
- the deviation δ that defines the accuracy of the assignment of the CVPs to the CVP_ds
- the limit of CVPs (CVP_{max}) that define the maximum value a CVP can have

5. Conclusion

The main challenges of automated LCAs for complex products were identified in Section 2: The conflict of objectives between accuracy and efficiency, the manual workload for mapping the input data to LCI datasets, the lack of flexibility in LCI modelling and the missing application in commercial LCA software. An LCI modelling approach was developed in this paper to tackle these challenges. The approach is about the design of a systematic LCI model construct and exemplarily elaborated for automotive aluminium components. The methodology consists of the classification of the most influencing parameters (MIP), the grouping of discretely variable parameters (DVP), the elaboration of grid points for the continuously variable parameters (CVP) and the reduction of LCI models due to technical constraints. The LCI model construct allows an automated assignment of component's attributes to pre-defined LCI models using commercial LCA software solutions like GaBi© DfX. Since all parameters in the LCI model construct are represented by a meaningful number of grid points, the mapping of input data to the best fitting datasets in a given LCA database is facilitated. This does not only reduce manual workload but also reduces complexity as an error source of manual workload described by Yu and Kim (2012) and Hollberg and Ruth (2016). It also makes the results of the LCA more comprehensible for non-LCA experts, as the effect of only the MIPs is assessed (Hollberg and Ruth, 2016; Steubing et al., 2016). While standardized LCA tools exist to assess the environmental footprint of certain product systems and support decision-making (Zah et al., 2009; Beccali et al., 2016), these tools are not suitable for an efficient and consistent LCA of complex products like entire vehicles. Other approaches of automated LCA fail to cover the variability of relevant parameters and therefore lack in accuracy (Bueno and Fabricio, 2018). The LCI model construct makes the LCI modelling more flexible to support meaningful decision-making. This is encouraged by the statement of Bueno and Fabricio (2018) that an appropriate LCI modelling is an accomplishment towards accuracy, even if average data from LCA databases is used. The systematic LCI model construct can also be used for calculating consistent baseline scenarios and streamlining the assessment of reduction measures, as in Pelton and Smith (2015). This is particularly important if no information for attributes of certain components is available. In this case, the LCI model construct provides the possibility of a consistent assignment of default grid points for the respective MIP.

Despite the benefits of the LCI model construct, its full potential can only be exploited if the MIPs are part of the input information for automated LCAs. Otherwise, the values of the MIPs have to be collected manually, which cannot be performed for every component of complex products. However, the manual effort would be reduced due to a limited complexity and a systematic design of the LCI model construct, resulting in a streamlined, partly automated LCA. The data acquisition is still an aspect of automated LCAs to be improved as their results rely on the input data quality (Hollberg et al., 2020). Bitencourt de Oliveira et al. (2022) states that useful data for LCA already exists in the supply chain but is not yet implemented in the automated LCA procedure. The identification of additional data sources is a promising strategy to improve accuracy and efficiency in automated LCAs, as data management systems like IMDS and BIM do not contain all relevant information for the LCI modelling (Bueno and Fabricio, 2018; Bitencourt de Oliveira et al., 2022). This would also enable a more detailed modelling of the standardized LCI model architecture to further improve its accuracy.

The compatibility with commercial software solutions like GaBi© DfX enables a flexible selection of impact categories and characterization models in the LCIA, but the design of the LCI model construct is derived from the LCA results of only one impact category and its respective characterization model. The design of the LCI model construct based on other impact categories might lead to LCI model constructs with different grid points. However, multiple impact categories can be evaluated with this model without further effort.

The mapping of input information to best fitting datasets, the identification of most influencing parameters and the modelling of the standardizes LCI model architecture remain manual workload and require expert judgement. The effort can be customized by setting different requirements in accuracy. The conflict of objectives between efficiency and accuracy can be solved dependently on the goal and scope of the LCA study. The mapping for an LCI model construct can also be used for multiple product systems and projects, which increases the efficiency and consistency of the approach.

Beside decision-making, LCA of vehicles also has the purpose of verification at the end of the development process (Yu and Kim, 2012) and consistency is an important aspect for such LCA studies and a benefit of automated LCAs (Koffler et al., 2008). A consistent calculation method along the development process might be a requirement to track the decarbonization status of OEMs. The systematic LCI model construct is a step towards unified streamlining methods along the development process of vehicles from the early to later phases of development. This is because the LCI model construct allows flexible LCI modelling for the support of decision-making in the development process while maintaining the consistent calculation of automated LCAs.

CRediT authorship contribution statement

Patrick Haun: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Philipp Müller:** Project administration. **Marzia Traverso:** Supervision.

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

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

References

Arena, M., Azzone, G., Conte, A., 2013. A streamlined LCA framework to support early decision making in vehicle development. J. Clean. Prod. 41, 105–113. https://doi.org/10.1016/j.jclepro.2012.09.031.

Beccali, M., Cellura, M., Longo, S., Mugnier, D., 2016. A simplified LCA tool for solar heating and cooling systems. In: SHC 2015, International Conference on Solar Heating and Cooling for Buildings and Industry, vol. 91, pp. 317–324. https://doi.org/10.1016/j.egypro.2016.06.226. Energy Procedia.

Beemsterboer, S., Baumann, H., Wallbaum, H., 2020. Ways to get work done: a review and systematization of simplification practices in the LCA literature. Int. J. Life Cycle Assess. 25, 2154–2168. https://doi.org/10.1007/s11367-020-01821-w.

Bhatia, P., Cummis, C., Brown, A., Draucker, L., Rich, D., Lahd, H., 2011. Product life cycle accounting and reporting standard. Greenhouse gas protocol. Available online at: https://ghgprotocol.org/sites/default/files/standards/Product-Life-Cycle-Accounting-Reporting-Standard_041613.pdf. (Accessed 29 May 2022).

Bitencourt de Oliveira, F., Nordelöf, A., Sandén, B.A., Widerberg, A., Tillman, A.-M., 2022. Exploring automotive supplier data in life cycle assessment – precision versus workload. Transport. Res. Part D 105. https://doi.org/10.1016/j.trd.2022.103247.

Bueno, C., Fabricio, M.M., 2018. Comparative analysis between a complete LCA study and results from a BIM-LCA plug-in. Autom. ConStruct. 90, 188–200. https://doi.org/10.1016/j.autcon.2018.02.028.

Carvalho, J.P., Bragança, L., Mateus, R., 2019. Optimising Building sustainability assessment using BIM. Autom. ConStruct. 102, 170–182. https://doi.org/10.1016/j.autcon.2019.02.021.

Cerdas, F., 2021a. Concept development: integrated computational life cycle engineering for traction batteries. In: Integrated Computational Life Cycle Engineering for Traction Batteries. Sustainable Production, Life Cycle Engineering and Management. Springer. https://doi.org/10.1007/978-3-030-82934-6_4.

Cerdas, F., 2021b. State of research – review on LCE modelling and assessment approaches for electromobility. In: Integrated Computational Life Cycle Engineering for Traction Batteries. Sustainable Production, Life Cycle Engineering and Management. Springer. https://doi.org/10.1007/978-3-030-82934-6_3.

Cerdas, F., 2021c. Summary, critical review and outlook. In: Integrated Computational Life Cycle Engineering for Traction Batteries. Sustainable Production, Life Cycle Engineering and Management. Springer. https://doi.org/10.1007/978-3-030-82934-6_6.

Danilecki, K., Mrozik, M., Smurawski, P., 2017. Changes in the environmental profile of a popular passenger car over the last 30 years – results of a simplified LCA study. J. Clean. Prod. 141, 208–218. https://doi.org/10.1016/j.jclepro.2016.09.050.

DXC Technology, 2022. IMDS Information Pages. Available online at: https://public.mdsystem.com/en/web/imds-public-pages. (Accessed 17 June 2022).

Ferrari, A.M., Volpi, L., Settembre-Blundo, D., García-Muina, F.E., 2021. Dynamic life cycle assessment (LCA) integrating life cycle inventory (LCI) and Enterprise resource planning (ERP) in an industry 4.0 environment. J. Clean. Prod. 286 https://doi.org/10.1016/j.jclepro.2020.125314.

Hester, J., Miller, T.R., Gregory, J., Kirchain, R., 2018. Actionable insights with less data: guiding building design decisions with streamlined probabilistic life cycle assessment. Int. J. Life Cycle Assess. 23, 1903–1915. https://doi.org/10.1007/s11367-017-1431-7.

Hill, N., Amaral, S., Morgan-Price, S., Nokes, T., Bates, J., Helms, H., Fehrenbach, H., Biemann, K., Abdalla, N., Jöhrens, J., Cotton, E., German, L., Harris, A., Ziem-Milojevic. Haye, S., Sim, C., Bauen, A., 2020. Determining the environmental impacts of conventional and alternatively fuelled vehicles through LCA – final Report for the European Commission, DG Climate Action. Available online at: https://op.europa.eu/en/publication-detail/-/publication/1f494180-bc0e-11ea-811c-01aa75ed71a1. (Accessed 17 June 2022).

Hollberg, A., Genova, G., Habert, G., 2020. Evaluation of BIM-based LCA results for building design. Autom. ConStruct. 109 https://doi.org/10.1016/j.autcon.2019.102972.

Hollberg, A., Ruth, J., 2016. LCA in architectural design – a parametric approach. Int. J. Life Cycle Assess. 21, 943–960. https://doi.org/10.1007/s11367-016-1065-1.

International Organization for Standardization, 2006a. ISSO 14040:2006 Environmental management - life cycle assessment - principles and framework. Available online at: https://www.iso.org/standard/37456.html. (Accessed 29 May 2022).

International Organization for Standardization, 2006b. ISSO 14044:2006 Environmental management - life cycle assessment – requirements and guidelines. Available online at: https://www.iso.org/standard/71206.html. (Accessed 29 May 2022).

Kaebernick, H., Sun, M., Kara, S., 2003. Simplified lifecycle assessment for the early design stages of industrial products. CIRP Annals 52, 25–28. https://doi.org/10.1016/S0007-8506(07)60522-8.

Koffler, C., Krinke, S., Schebek, L., Buchgeister, J., 2008. Volkswagen slimLCI: a procedure for streamlined inventory modelling within life cycle assessment of vehicles. Int J Vehicle Design 46 (2), 172–188. https://doi.org/10.1504/IJVD.2008.017181.

Lettner, M., Hesser, F., 2020. Asking instead of telling – recommendations for developing life cycle assessment within technical R&D projects. Progress in Life Cycle Assessment 2019, 173–188. https://doi.org/10.1007/978-3-030-50519-6_13.

Millet, D., Bistagnino, L., Lanzavecchia, C., Camous, R., Poldma, T., 2007. Does the potential of the use of LCA match the design teams needs? J. Clean. Prod. 15, 335–346. https://doi.org/10.1016/j.jclepro.2005.07.016.

Nordelöf, A., Alatalo, M., Söderman, M.L., 2019. A scalable life cycle inventory of an automotive power electronic inverter unit – part I: design and composition. Int. J. Life Cycle Assess. 24, 78–92. https://doi.org/10.1007/s11367-018-1503-3.

Nordelöf, A., Tillman, A.-M., 2018. A scalable life cycle inventory of an electrical automotive traction machine – Part II: manufacturing processes. Int. J. Life Cycle Assess. 23, 295–313. https://doi.org/10.1007/s11367-017-1309-8.

Pascual-González, J., Pozo, C., Guillén-Gosálbez, G., Jiménez-Esteller, L., 2015. Combined use of MILP and multi-linear regression to simplify LCA studies. Comput. Chem. Eng. 82, 34–43. https://doi.org/10.1016/j.compchemeng.2015.06.002.

Pelton, R.E.O., Smith, T.M., 2015. Hotspot scenario analysis – comparative streamlined LCA approaches for green supply chain and procurement decision making. J. Ind. Ecol. 19, 427–440. https://doi.org/10.1111/jiec.12191.

Safari, K., AzariJafari, H., 2021. Challenges and opportunities for integrating BIM and LCA: methodological choices and framework development. Sustain. Cities Soc. 67 https://doi.org/10.1016/j.scs.2021.102728.

Science Based Targets, 2022. Companies taking action. Available online at: https://sciencebasedtargets.org/companies-taking-action#anchor-link-test. (Accessed 17 June 2022).

Sphera Solutions GmbH, 2019. GaBi ts version history. Available online at: https://gabi.sphera.com/support/gabi-version-history/gabi-ts-version-history/. (Accessed 29 May 2022).

Sphera Solutions GmbH, 2022. Gabi DfX – functionalities - BOM import. Available online at: https://gabi.sphera.com/software/gabi-dfx/functionalities/bom-import/. (Accessed 17 June 2022).

Steubing, B., Mutel, C., Suter, F., Hellweg, S., 2016. Streamlining scenario analysis and optimization of key choices in value chains using a modular LCA approach. Int. J. Life Cycle Assess. 21, 510–522. https://doi.org/10.1007/s11367-015-1015-3.

Sun, M., Rydh, C.J., Kaebernick, H., 2003. Material grouping for simplified product life cycle assessment. J. Sustain. Prod. Des. 3 (1), 45–58. https://doi.org/10.1023/B:JSPD.0000035558.27697.02.

Todd, J.A., Curran, M.A., 1999. Streamlined life-cycle assessment: a final report from the SETAC North America streamlined LCA workgroup. Society of Environmental Toxicology and Chemistry.

World Economic Forum, 2021. The Global Risks Report 2021, sixteenth ed. Available online at: https://www3.weforum.org/docs/WEF_The_Global_Risks_Report_2021.pdf. (Accessed 29 May 2022).

Yu, M., Kim, Y., 2012. Development of environmental assessment system of vehicle. In: Proceedings of the FISITA 2012 World Automotive Congress, vol. 8. Vehicle Design and Testing (II), pp. 1151–1160. https://doi.org/10.1007/978-3-642-33738-3_19.

Zah, R., Faist, M., Reinhard, J., Birchmeier, D., 2009. Standardized and simplified life-cycle assessment (LCA) as a driver for more sustainable biofuels. J. Clean. Prod. 17, 102–105. https://doi.org/10.1016/j.jclepro.2009.04.004.

Zheng, G., Peng, Z., 2021. Life cycle assessment (LCA) of BEV's environmental benefits for meeting the challenge of ICExit (internal combustion engine exit). Energy Rep. 7, 1203–1216. https://doi.org/10.1016/j.egyr.2021.02.039.