# Exploring automotive supplier data in life cycle assessment – Precision versus workload



Citation for the original published paper (version of record):
Bitencourt de Oliveira, F., Nordelöf, A., Sandén, B. et al (2022). Exploring automotive supplier data in life cycle assessment – Precision versus workload. Transportation Research Part D: Transport and Environment, 105. http://dx.doi.org/10.1016/j.trd.2022.103247



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Transportation Research Part D 105 (2022) 103247

Contents lists available at ScienceDirect

Transportation Research Part D

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

# Exploring automotive supplier data in life cycle assessment – Precision versus workload

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ARTICLE INFO

*Keywords:*
Life cycle assessment (LCA)
Life cycle inventory (LCI)
International Material Data System (IMDS)
Automotive industry

ABSTRACT

The International Material Data System (IMDS) can be used as data source for life cycle assessments (LCAs) in the automotive industry. The level of data aggregation and degree of completeness affect precision of LCA results and required workload. This paper assesses this trade-off. Life cycle impact assessment scores for an engine, modelled as detailed as possible, were compared to results for seven simplified modelling options. The study concludes that: (1) employing IMDS data with lower resolution reduced the workload marginally; (2) cutting-off materials below 1 wt-% greatly decreased workload while maintaining reasonable precision; (3) decreasing the number of substances representing each material largely affected scores for most impact categories except a few, including the climate change category, while (4) excluding complementary data for manufacturing significantly impacted greenhouse gas emissions. Since modelling choices affect the impact categories differently, aligning choices with the purpose of the study and available workload is paramount.

## 1. Introduction

In recent years, the automotive industry has faced huge challenges in attempts to reduce environmental impacts (Del Pero et al., 2018). Even though the focus and impacts still relate largely to greenhouse gases and pollutants emitted from cars in use, increasing attention is being paid to the environmental and resource impacts of car production. One explanation is a technology shift from combustion engines to electric drivetrains, which has raised the awareness of environmental impacts across the complete life cycle of vehicles (Nordelöf et al., 2014; Gebler et al., 2018).

A useful tool in this effort is life cycle assessment (LCA). LCA has been used in the automotive industry for more than 20 years (LeBorgne et al., 1997; Kaniut et al., 1997; Louis and Wendel, 1998; Sullivan et al., 1998; Schweimer and Levin, 2000), mainly as a means of identifying environmental hotspots and as an aid to prioritise areas of innovation (Warsen and Krinke, 2013).

However, since the aim of LCA is to assess potential environmental impacts throughout the life cycle of a product or service, LCA studies of complex products, such as vehicles composed of thousands of components, become costly and time consuming, primarily on account of the volume of data that is needed for the compilation of the life cycle inventory (LCI) (Fleischer et al., 1998; Koffler, 2007;

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https://doi.org/10.1016/j.trd.2022.103247

Available online 11 March 2022

Koffler et al., 2008; Yu and Kim, 2013). This data is often scattered among different actors in the supply chain and differs in format (e.g. technical drawings, lists of components). In addition, since most available data is originally compiled for other purposes, it requires prior processing before it can be used in an LCA.

Historically, LCA practitioners in the automotive industry have relied on what has been referred to as "internal databases" in order to gather material composition data for vehicles (Schweimer and Levin, 2000; Finkbeiner et al., 2006; Koffler et al., 2008). Essentially, such databases are derived from technical drawings and lists of components and are the result of close collaboration between LCA practitioners, design engineers (within the company) and component suppliers. Vehicle teardown and disassembly guides are also methods reported in the literature for inventorying material data (Keoleian et al., 1998; Danilecki et al., 2016).

Since these approaches are very time consuming and difficult to repeat for multiple cars and models, efforts have been made to utilise the International Material Data System (IMDS) instead. This web-based and industry wide database, jointly developed by automotive manufacturers, contains data on all components and their material content present in finished vehicles, supplied by more than 150,000 registered suppliers (DXC Technology, 2017). Its main goal is to help meet the obligations placed on manufacturers and their suppliers by standards, laws and regulations. Since detailed material compositions of all vehicle components is available in the same database, the employment of IMDS in LCA studies reduces the workload required for data inventorying (Koffler et al., 2008; Yu and Kim, 2013), compared to using a patchwork of internal data sources or conducting teardowns.

In an effort to further streamline the LCI modelling of complete vehicles, Koffler et al. (2008) and Yu and Kim (2013) developed procedures where IMDS data is used in automated setups. This significantly decreased the time and effort required to perform the inventory modelling. In these streamlined setups, information from IMDS is used to identify the most appropriate background inventory data available in internal, openly published or commercial LCA-databases that can represent the materials composition of the components. Examples from Volvo Car Corporation (VCC) show that such streamlining approaches have expedited the execution of LCA studies for many useful purposes, e.g. carbon footprint assessment, and helped establishing LCA as standard tool. However, our own observation from LCA in practice is that specific material datasets are seldom readily available in commercial LCA-databases, e.g. Ecoinvent (Wernet et al., 2016) or Sphera (Kupfer et al., 2021), and instead, generic LCI data for broad material categories must be employed.

It is important to stress that the information included in IMDS allows for a significantly higher level of detail of the LCI modelling, since it also contains specific information on the substances present in every material, enabling LCA to be employed as a tool for in-depth analysis of iterative design improvement and internal work on component requirements. Accordingly, while some of the benefits and challenges of employing IMDS data in LCA studies are described in the literature (Koffler et al., 2008; Yu and Kim, 2013), to the best of our knowledge, no studies have assessed how the use of IMDS data at different levels of aggregation and completeness impact quantitatively on LCA results. Materials, and the substances which they consist of, can be modelled with varying ambition in terms of accuracy. Also, in some cases, the LCI model might need to be complemented with data that cannot be fully derived from IMDS. Since an increased level of detail in the modelling and the addition of complementary data entail additional workload, it is pivotal to increase knowledge about how the different ways of using IMDS data affect the precision of LCA results.

The aim of this paper is therefore to assess the balance between the modelling effort when using IMDS at different levels of aggregation and completeness, and the precision of LCA results. More specifically, it is an investigation of how to conduct LCA in practice, and aims to answer the following question: *How do the level of data aggregation and degree of completeness of an LCI model employing IMDS data affect the precision of environmental impact assessment results and the effort necessary to develop such models?*

While this question is relevant for a complete vehicle, an engine is selected as a test object in this study, as to limit the amount of data required to perform the modelling. The objective is not to derive LCA results for the engine *per se*, but to investigate differences stemming from modelling options.

This work was conducted as a university-industry collaboration between Chalmers University of Technology and VCC. While VCC is the immediate recipient of the results, most findings are believed to be applicable to the automotive industry in general, and some lessons learned could be useful for the wider LCA community, as databases on components and their material composition may emerge also in other industries.

The outline of this paper is as follows: Section 2 presents the method, including a detailed description of the employment of IMDS data in the study. Results and discussions are presented in Section 3, followed by conclusions in Section 4.

## 2. Methods

### 2.1. Research approach

In order to address the research question, the study was set up to employ IMDS data in an LCA of a vehicle combustion engine by comparing one reference modelling option, where we strived for a high level of detail, to seven simplified options. The engine was selected as a suitable case study example since it contains both bulk materials and several smaller components requiring detailed modelling, capturing much of the variability present in a complete vehicle, while not being overly complex. The life cycle scope was limited to only include the stages necessary to answer the research question. Therefore, only the production phase of the engine is taken into account, while the use and end-of-life phases are not considered.

The modelling options differ with regards to level of data aggregation and data completeness. The level of aggregation of each option was assessed by either compiling IMDS data for the engine as a "black box" (i.e., there is no differentiation between components or sub-parts of the engine) or compiling it for the different sub-parts of the engine (e.g., cylinder block, lubrication system). Completeness was assessed by *(1)* varying the number of materials representing the engine and its sub-parts by using IMDS data with and without a mass cut-off; *(2)* varying the number of substances representing each material; and *(3)* including data not covered by IMDS, e.g., component manufacturing. The reference modelling option, as well as the seven options resulting from the simplification measures, are further explained in Section 2.5.

While differences in recorded environmental impact resulting from the modelling options are presented quantitatively, the effort required for each modelling option was not measured and is instead discussed qualitatively in Section 3.1.

### *2.2. Study object, system boundaries and data sources*

The technical example used in this study is a two-litre, petrol-powered internal combustion engine (model T5 for the year 2018), which can be installed in most of VCC's vehicle models. Considering that the engine in this case is not mounted in a specific car model, the functional unit of the study is one manufactured unit of the above-mentioned engine at the "factory gate". This study therefore considers the production phase of the engine, including raw material extraction, material transformation and assembly, while the utilisation and disposal phases are out of scope. An LCA model is built, and results are generated in the software GaBi ts, version 10.6 (Sphera, 2020).

The LCA performed is of the attributional type, meaning that the impacts of producing the engine are modelled as a share of the impacts of the current or recent historical production system. Accordingly, the study is based on average (as opposed to marginal) data, and allocation problems in multi input- or output processes are solved by partitioning, unless specified otherwise. Foreground system data, including the material composition and assembly of the engine, was compiled internally at VCC for all options, employing data from IMDS and other complementary sources specified in Section 2.4. The data representing background systems, i.e. upstream material extraction and manufacturing, electricity generation and transport, was largely retrieved from the Ecoinvent database (Wernet et al., 2016) version 3.7.1 (system model: "allocation, cut-off by classification"), representing the global or regional average supply (process inputs) or national supply (electricity).[1] Some additional data was gathered from the GaBi professional database (Kupfer et al., 2021) (content version 2021.2) and from the literature (peer-reviewed articles, reports and patents).

In terms of geography, site-specific data was employed for assembly at VCC's engine factory in Skövde, Sweden, while data on material extraction and manufacturing processes was chosen to represent regional averages. As a general rule, transports are represented in the background system, while the transportation from suppliers to the assembly site has not been included. In some cases, for materials for which the origin could be identified, country-specific or market data representing broader regions was used instead. A list with the background datasets employed in this study is available as Supporting Information.

### *2.3. Selection of life cycle impact assessment methods*

A life cycle impact assessment (LCIA) is used to compare how the modelling options identify and quantify the potential contribution to different environmental impacts. Impact scores were calculated for sixteen impact categories with midpoint characterisation methods,[2] as recommended in the European framework of the Environmental Footprint (EF 3.0) (Biganzioli et al., 2018): acidification; climate change; ecotoxicity (freshwater); eutrophication (terrestrial; marine; freshwater); human toxicity (carcinogenic; non-carcinogenic); ionising radiation; land use; ozone depletion; particulate matter; photochemical ozone formation; resource use (energy carriers; mineral and metals); and water scarcity.

### *2.4. Inventory analysis based on IMDS data*

Employing material data from IMDS when calculating the LCI requires a sequence of steps before it can be assessed in the LCIA. The overall structure of these steps is depicted in Fig. 1, where box I represents the LCI model of the engine. This section describes the construction of the reference modelling option, while the simplifications applied to it, resulting in seven additional options, are described in Section 2.5.

To develop this model, the materials present in the *component material data list* (E) – i.e. a list containing all materials and substances of which the complete engine is composed – and their related manufacturing and assembly processes[3] (F) are matched to suitable background system datasets (G), selected mostly from commercial LCA databases (e.g. Ecoinvent (Wernet et al., 2016)), containing information on elementary flows which can be "translated" into environmental impacts in the LCIA phase. The matching process, represented by box H, was performed manually in MS Excel.

The *component material data list* (E) was created through an automated process (D) in which material composition data stored in the

[1] More than 95% of all flows linked to background datasets.

[2] Characterisation methods are best estimates of the potential environmental impact of emissions to the environment (or use of natural resources) along the life cycle of e.g. a product system. They are based on models of cause-effect chains from point of emission (or resource use) to impact on a chosen impact category (Hauschild and Huijbregts, 2015).

[3] In this study, manufacturing processes relate to processes or sequences of processes that reshape a given raw material input into the final form in which it is present in the engine, e.g. moulding, rolling, machining. These individual processes can be also referred to as material transformation processes. Assembly processes relate to the industrial processes necessary to assemble different components into a complete engine unit.

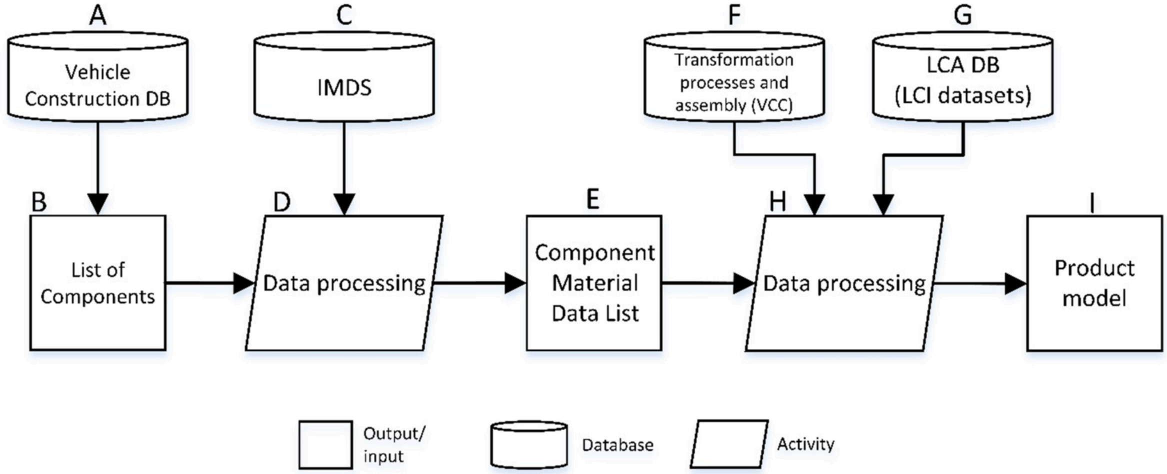


**Fig. 1.** Overview of the steps employed in this study to develop the modelling options for the engine representation.

IMDS database (C) was added to every component contained in the *list of components*[4] (B) of the specific engine chosen as our technical example, which in its turn was extracted from VCC's internal *Vehicle Construction Database* (A). The following sections present a detailed description of the individual steps in Fig. 1.

#### 2.4.1. Creation of the list of components (A-B)

The first step in the generation of complete LCI models of the technical example is to extract a list of components for the specific engine from VCC's internal Vehicle Construction Database – a database that contains information on all individual components present in each vehicle manufactured at VCC. In this context, "components" refer to items which are either delivered as readymade objects to the engine factory, e.g., small items like a screw or larger items such as an oil pump, or objects which are finalized at the factory, and then assembled into the engine. The list of components contains the names of these items, their identification number, the quantities present in the engine, their mass and the *function groups* to which they belong, specified in up to four different levels. At VCC, the aggregation of components into larger assemblies and subsystems is described using these function group levels. They create a hierarchically structured description of the entire vehicle and its different parts. Table 1 exemplifies this structure for the engine.

There is no standardised terminology in the literature for the different function group levels, but at VCC the lowest level (1) is called "complete part", which can be subdivided into several "sub-parts" at level 2. In turn, the building blocks of sub-parts are "component groups" at level 3, which can be further sorted into single components at level 4. Still, this hierarchical structure is similar to the one reported by Del Pero et al. (2021).

As a result, the list of components can be extracted as one list for the whole engine (level 1) in which all component entries are grouped under the function group "2000", or subdivided into several lists with the component entries grouped in accordance with the function group level chosen, thus enabling a more fine-grained analysis. Finally, with the list at hand, a quality check is performed. Irrelevant entries are deleted (e.g. fuel, fluids) and the total mass of the engine is verified (see Table S1 in Supporting Information).

#### 2.4.2. Creation of the component material data list (C-D-E)

Since the list of components does not contain information on material composition, the next step is to add this information for all components in the list. This is accomplished by an automated process, developed at VCC within the project, in which an algorithm exports material composition data stored in IMDS for each component. This process generates the component material data list, i.e. the list of components with added information on material composition for every component.

Fig. 2 describes the structure of the component material data list. Components consist of materials, which in their turn, are composed of basic substances. A material, according to IMDS (DXC Technology, 2020), is a physical item characterised by having a homogeneous structure – no layers or visible differentiation are perceptible (e.g. steel, thermoplastic). Material entries can be named freely. For instance, the entries "1020" and "carbon steel (1020)" refer to the same type of low-alloyed steel. Moreover, materials are ultimately composed of basic substances. These entries, on the other hand, have standardised names and are created and maintained by the IMDS Chemical Service. Basic substances may, for example, be a chemical element (e.g. iron, copper), a standard compound (e.g. acrylic resin, iron oxide, glass fibre) or, in cases where confidentiality is required, a *wildcard* (e.g. "miscellaneous, not to be declared"). However, this classification cannot be applied to prohibited or declarable substances (DXC Technology, 2020).

As also seen in Fig. 2, materials are classified according to the so-called "VDA material classification" system, which was developed

[4] The *list of components* is also commonly known as *bill of materials (BoM)*. However, in this study we employ the term *list of components*, since no information on material composition was retrieved from the *list of components* in this case.

**Table 1**
The engine is one of many parts of which a vehicle is composed, all providing a specific function. Each such part can be described at several levels of aggregation, known as function group levels. Here, function group 2000 represents the complete engine at level 1. It is composed of sub-parts reported at level 2, by function groups 2100–2800. Function groups 2110–2890 report component groups at level 3, and there is also a fourth level for single components, specified by the fourth digit (2XXX). Only aggregation levels 1 and 2 are used in the study.

| Function group level of aggregation | | | |
|---|---|---|---|
| **Level 1 – Complete part** | **Level 2 – Sub-parts** | **Level 3 – Component groups** | **Level 4 – Components** |
| 2000 – Engine complete | 2100 – Engine (block) | 2110 – Cylinder head | e.g. 2115 – Valve cover |
| | | 2120 – Cylinder block | e.g. 2125 – Flywheel |
| | | 21x0 – … | 21xx – … |
| | 2200 – Lubricating & oil system | 2210 – Oil pump/oil pipe | e.g. 2214 – Oil jet |
| | | 2220 – Oil filter | e.g. 2222 – Filter housing |
| | | 22x0 – … | 22xx – … |
| | 2x00 – … | 2xx0 – … | 2xxx – … |
| | | 2xx0 – … | 2xxx – … |
| | 2800 – Ignition & Control system | 28x0 – … | 28xx – … |
| | | 2840 – Control system, fuel supply | e.g. 2846 – Sensor |
| | | 2890 – Miscellaneous | e.g. 2899 – Miscellaneous |

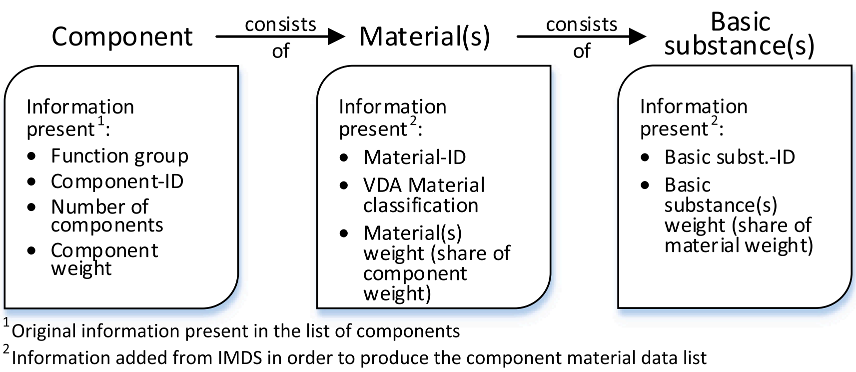


**Fig. 2.** Structure of the component material data list and information present for every component entry in the list.

by the German Association of the Automotive Industry (Verband der Automobilindustrie, 1997). It is mandatory for all material entries in IMDS. In this classification system, material entries are grouped into broad material categories – e.g. steel; ceramics; thermoplastics – based on a combination of content (basic substances), properties and their application (IMDS Steering Committee, 2020).

### *2.4.3. Matching of background system datasets (F-G-H)*

As described earlier, materials and basic substances present in the engine, and their related manufacturing and assembly processes are matched to background datasets. The approaches employed to perform this task are described below.

(a) Materials and basic substances.

The component material data list for the engine contains 3,125 material entries, of which 2,156 are unique entries.[5] Every material entry in the list is composed of one or more basic substances. The list contains 654 unique basic substances. In this study, it is these *basic substances* which are matched to background datasets to account for the production of material constituents, while further processing required to achieve finished materials and formed components is accounted for as “manufacturing” (see next section b). For example, a given material classified as a thermoplastic, composed of polypropylene, glass fibre and plasticiser, would be matched to background datasets suitable for these three basic substances.[6] By matching the *basic substances* to specific background datasets, it is possible to account for all the substances (e.g., alloying elements, fillings) composing every material in the component material data list.

In this context, materials classified as steel or cast iron present a specific challenge. They contain iron and carbon, and their classification depends on the proportions of these two basic substances. Moreover, the production of pure iron and carbon separately as two different background datasets would not be representative for the production of steel or cast iron, as both are inputs in non-refined form to joint production routes. Hence, a slightly different approach was employed for steel and cast iron, compared to the other materials. Iron and carbon contents were matched to specific datasets together: either as steel production or cast-iron production. For

[5] No duplicated entries, since the same material might be present in different components in the engine.

[6] In this case, complementary manufacturing processes represent compounding and transformation of these substances into a useful thermoplastic component.

instance, a material classified as high-alloyed steel, which in addition to iron and carbon also contain chromium, nickel, and manganese, is linked to a modified dataset for high-alloyed steel production where proper amounts of iron and carbon, alloyed with ferrochromium, ferronickel and ferromanganese are included.[7] Fig. 3 illustrates this process of matching basic substances to LCI-datasets employed for steel and cast-iron in this study.

For all materials, an alternative to start from basic substances would have been to match more aggregated data for material categories in the engine directly to background datasets representing predefined material compositions. However, in such a case the model and LCA study at large lose valuable information about the basic substance content and its implications for the environmental burden of the current design. Using high-alloyed steel as an example once more, the best available data in Ecoinvent represents the production of a typical austenitic stainless steel grade containing 18 w-% chromium and 8 w-% nickel. In our model, the average composition of stainless steel grades, including ferritic types, becomes represented when basic substances are used as the starting point.

Even so, due to the limited number of suitable background datasets in the LCA databases used, some basic substance had to be matched to the same dataset. Hence, for the engine in the technical example, the 654 unique basic substances in the component material data list were matched to 244 unique background datasets. A list with the basic substances present in the engine and the LCI-datasets employed in this study (including modified background datasets) is available in the Supporting Information.

(b) Manufacturing and assembly processes.

In contrast to information on materials and basic substances, information on manufacturing and engine assembly processes – including material losses related to these activities – is not explicitly included in IMDS. In this study, this data is referred to as complementary data, i.e. data that is not directly reported by the component material data list, but which makes the LCI models more complete, when compared to real-world activities.

As described earlier, basic substances are matched to background datasets to represent the production of the materials which they compose. These datasets generally represent intermediate products which require further processing to become useful parts. Examples include plastic pellets, metal ingots/billets and ceramic powders. To account for the manufacturing processes necessary to transform these materials into their final form, several additional background datasets were included in the LCI models. These processes were identified based on the *names of components*, *material entries*, their *VDA classification* and *expert judgement*. In general, in Ecoinvent, such datasets include the amount of mass removed and scrapped (representing losses), along with the use of energy and auxiliary materials, and emissions caused, but not the materials and products being reshaped (Nordelöf, 2019). Fig. 4 illustrates the process of selecting LCI-datasets representing manufacturing processes employed in this study.

A similar approach was employed to identify the manufacturing processes of the materials and sub-parts of which electronic components are composed, and to account for their use of energy and auxiliary materials. Manufacturing of electronics is generally energy and resource-intensive (Nordelöf, 2019), with the result that the modelling approach requires particular attention. According to the IMDS recommendation, "materials in electronic applications should be classified according to their composition" (IMDS Steering Committee, 2020), e.g. as copper and aluminium, and not as "electronics", meaning that there was no easily applied VDA classification available. Instead, typical electronic sub-parts were identified based on expert evaluation of the material entries, and suitable background datasets were linked to the LCI model.

For the final assembly of the engine, data was compiled from VCC's engine factory in Skövde, Sweden. Most engine parts are delivered to this facility in their final form, ready to be assembled, except for a few components that undergo specific machining processes on site. The mapping of processes involved, and subsequent linking to background datasets, were based on an aggregated data list compiled internally at VCC, containing information on energy (i.e. electricity, heat) and auxiliary materials consumption (e.g. cutting fluid), as well as waste and material losses. A list with the LCI-datasets representing manufacturing and assembly processes in this study is available in the Supporting Information.

### *2.5. LCA study modelling options*

All LCA modelling options are summarised in Table 2. The reference option and the additional seven simplified options differ with respect to the level of detail, each representing a unique combination of three modelling choices: (i) the function group level employed ("high" or "low", as a means of varying the level of aggregation of IMDS data); (ii) mass cut-off at the material level; and (iii) the number of basic substances representing each material. Both (ii) and (iii) can be regarded as a means of varying the level of completeness of the resulting LCI.

In this study, A100-high represents the reference modelling option with the highest level of detail. This is the option described in Section 2.4, where the LCI is calculated based on component lists extracted at function group level 2 (i.e. sub-parts level, see Table 1), no mass cut-off is applied and all basic substances are accounted for. This means that all materials and all the basic substances they contain are represented in the model. Using LCA terminology, this means that all identified elementary flows are accounted for. Modelling options A100-high and A100-low differ with respect to the level of the function group employed when linking to the background datasets, i.e. the LCI is calculated for the engine as a whole (A100-low) or the LCI is calculated as a sum of the different sub-

[7] Alloying elements in steel are often added as ferro alloys. Matching of background datasets to unalloyed or low-alloyed steel grades adopted the same principle, but were linked to unalloyed steel production, followed by the matching of alloying elements. In cases where background datasets already contain alloying elements, adaptions were made to rescale these inputs in order to represent the alloy composition as reported by the IMDS, see Supporting Information, Section G.

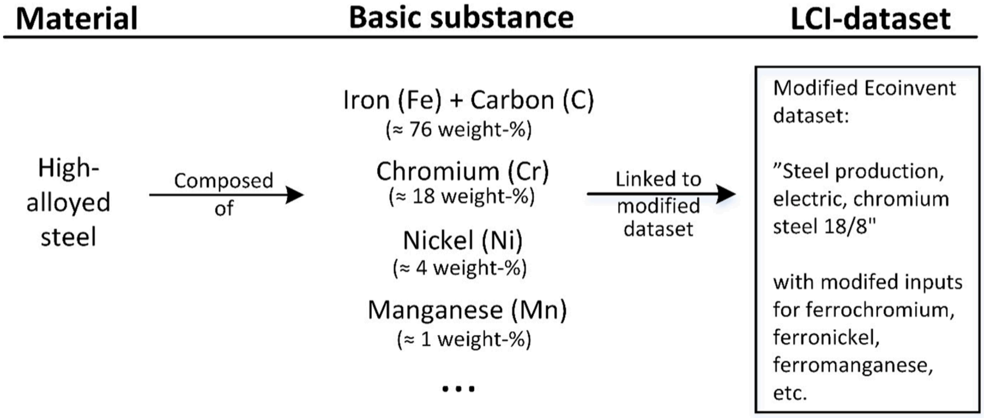


**Fig. 3.** The approach used to model the production of steel is illustrated. Basic substances composing the average blends of high alloyed steel grades, e.g., stainless steels, present in the reference option, are linked to a modified inventory dataset for high-alloyed steel production with corresponding mass shares for the final constituents, to represent the production of high alloyed steel. A similar approach is employed for the modelling of cast iron.

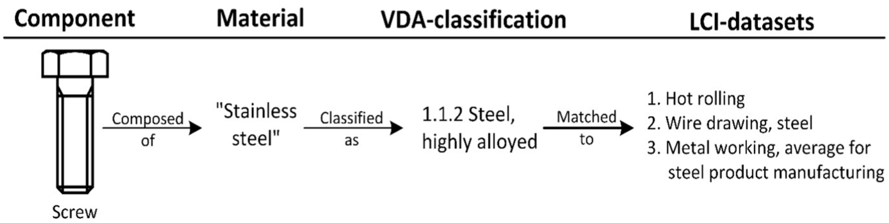


**Fig. 4.** In this example, three LCI-datasets are used to represent the manufacturing processes of a stainless steel screw: hot-rolling, followed by wire drawing and finally machining. The name of the component and the material entry, its VDA-classification as well as expert judgement are used to select suitable LCI-datasets to represent manufacturing processes in this study.

**Table 2**
Summary of the different LCA modelling options assessed in this study.

| MODELLING OPTIONS | MODELLING CHOICES | | |
|---|---|---|---|
| | Function group level* | Mass cut-off (of total) | Basic substance per material |
| **A100-high** | 2 (Sub-parts) | None | many |
| **A100-low** | 1 (Complete engine) | None | many |
| **A99-high** | 2 (Sub-parts) | 1 % | many |
| **A99-low** | 1 (Complete engine) | 1 % | many |
| **B100-high** | 2 (Sub-parts) | None | one |
| **B100-low** | 1 (Complete engine) | None | one |
| **B99-high** | 2 (Sub-parts) | 1 % | one |
| **B99-low** | 1 (Complete engine) | 1 % | one |

* See Table 1 for more information on function group levels.

parts present in the engine (A100-high).

The greatest workload when performing the modelling of options A100-high and A100-low stems from the large number of materials and basic substances present in the component material data list. Therefore, a cut-off of 1 % by mass was applied in order to investigate the consequences of reducing the number of materials represented in the model. This resulted in modelling options A99-high and A99-low. In the latter, the cut-off was applied on all materials based on their mass contribution to the engine as a whole (function group level 1), whereas in option A99-high, the cut-off was applied separately on every sub-part (function group level 2, see Table 2).

To investigate the effect of reducing the number of basic substances included, the "B" modelling options - B100-high/low and B99-high/low - were introduced. On average, a material entry in the component material data list is composed of five basic substances – 15,397 basic substances entries of which 3,125 non-unique materials entries are composed. In the "B" options the number of substances representing the materials were reduced to only one basic substance, generally the basic substance with the highest mass share present in each material. For instance, a given material weighing "x" grams, composed of three basic substances, polypropylene, glass fibre and plasticiser, with polypropylene as the substance with the highest mass share, would be matched only to the background dataset representing the production of polypropylene. However, the mass of polypropylene would be scaled up to represent the whole mass of the material – "x" grams.

Again, an exception from the main modelling approach was made for materials classified as steel and cast iron. In both materials, iron is the basic substance with the highest mass share, but the carbon content decides their classification. However, this distinction was retained also for "B" options, i.e., the basic substance iron was matched to different background datasets for steel and cast iron respectively. In both cases, datasets for the production of "unalloyed" grades were judged to provide the best representation of a high iron content.[8] For steel grades specifically, which typically varies largely in terms of alloying composition, this approach aligns well with the overall idea of reducing workload as all steel types in the engine converges into one and the same type. Employing the same background dataset for all steel grades without any modifications, clearly decreased the effort necessary to develop the LCI-model.

Finally, to investigate the impact of complementary data (i.e., for manufacturing and assembly processes, as well as related material losses) on results, all modelling options were calculated with and without the inclusion of these complementary datasets. Note that these aspects are not shown in Table 2, but are part of the assessment presented in Section 3.

## 3. Results and discussion

### 3.1. Modelling options and workload

The modelling option with the highest level of detail, A100-high, functions as the benchmark for evaluating the quality of all other options. This work started with the modelling of this option, while the "less detailed" options were built after A100-high was completed. As a consequence, once the matching of basic substances to background datasets and the classification and grouping of material entries was completed for the A100-high option, all other options benefited from this work. Obviously, this led to a lower workload than if they had been developed independently from A100-high. Hence, the workload was assessed qualitatively, by reasoning, instead of being measured. A quantitative time measurement would have required a different workflow and research design.

Accordingly, Table 3 provides an indication of the relative workloads of the different modelling options, and their link to the resulting number of unique materials and basic substances for each modelling option, as well as the inclusion of complementary data. As shown, the predominant aspects affecting the workload relate to the number of materials and basic substances accounted for in the options, and whether complementary data is included or not.

A key factor for the workload of modelling is the identification and matching of background datasets to basic substances. This must be done carefully as this cradle-to-gate representation of substances is pivotal to the study outcome. In addition, in some cases, further work is required when no suitable background datasets can be found, and it becomes necessary to collect new inventory data. This increases the time required considerably.

Another time-consuming step is the organisation and preparation of the results for analysis. The reason is that every material entry needs to be classified and grouped with other similar materials into material categories to create an overview and facilitate interpretation of the LCIA results, e.g. by summarising the environmental burden of "polymeric materials" instead of individually analysing the many specific flows contributing to this material group.[9]

The inclusion of complementary data in the modelling options also increases the workload. Acquiring expert judgement is necessary when assigning suitable background datasets to represent manufacturing or assembly processes, as described in Section 2.4. This task is challenging and may require iterative work in which a number of different experts are involved.

Finally, as for the function group level employed in the modelling options, we experienced only a minor impact on the workload. The reason is that the extraction of the list of components (box B in Fig. 1) is an automated process, meaning that there is no need to manually sort components into different function group levels. Instead, this information is contained in the Vehicle Construction Database (box A in Fig. 1), and it is only a matter of specifying the desired level before the list of components is generated. The actual effort involves creating the model in GaBi. Employing a less aggregate function group level then causes slightly more work.

It can be noted that there are available tools developed to facilitate the creation of LCI models of complex products, e.g. vehicles. For instance, the GaBi DfX add-on (Sphera, 2019) automates the creation of models in GaBi by importing LCA-relevant data directly from the bill of materials, which can significantly reduce the time and manpower needed for the LCI modelling, if materials are mapped to existing background datasets from commercial LCA-databases, as e.g. Ecoinvent (Wernet et al., 2016) or Sphera (Kupfer et al., 2021). This tool, however, was not employed in this study, as the DfX add-on lacks the functionality to automatically import data for basic substances and at the same time match them to background datasets together, such that they correspond to specific materials with compositions as reported by the IMDS. This means that, in order to account for all basic substances in the LCI model, as it is done in this study, it is necessary to manually combine or rework representative background datasets for all included materials.

8 Unalloyed steels might contain up to around 2 w-% of alloying elements (Classen, et al., 2009). In options "B", the basic substances carbon and iron included in materials classified as steel are represented by a background dataset containing 0.45 w-% of manganese as alloying substance.

9 For example, material entries composed of 95 w-% and 75 w-% polypropylene, respectively, would both be grouped into the material category "Polypropylene", under the broader material category "Thermoplastics". In turn, both would then also be contained in the overarching category "Polymeric materials".

**Table 3**
Modelling options assessed and an estimation of their relative workloads. In this study, the workload is highest for option A100-high and lowest for B99-low.

| MODELLING OPTIONS | Complementary data | # of unique materials | # of unique basic substances | |
|---|---|---|---|---|
| A100-high | Yes | 2,156 | 654 | Workload increases |
| A100-low | Yes | 2,156 | 654 | |
| A100-high | No | 2,156 | 654 | |
| A100-low | No | 2,156 | 654 | |
| A99-high | Yes | 671 | 295 | |
| A99-low | Yes | 539 | 243 | |
| A99-high | No | 671 | 295 | |
| A99-low | No | 539 | 243 | |
| B100-high | Yes | 2,156 | 274 | |
| B100-low | Yes | 2,156 | 274 | |
| B100-high | No | 2,156 | 274 | |
| B100-low | No | 2,156 | 274 | |
| B99-high | Yes | 671 | 114 | |
| B99-low | Yes | 539 | 86 | |
| B99-high | No | 671 | 114 | |
| B99-low | No | 539 | 86 | Workload decreases |

However, it is important to emphasise that the workload necessary to perform the LCI modelling is greatly reduced, for all modelling options, once a significant number of materials entries and their inherent basic substances are classified, grouped and matched to LCI-datasets, since this information can easily be employed in subsequent LCI modelling. This information is then compiled into a comprehensive list which demands continuous update, since IMDS data and LCI-datasets are frequently updated.

### *3.2. Overall LCIA results*

Table 4 shows the life cycle impact scores for all modelling options normalised to the reference option A100. With regards to overall LCIA results, there is no difference between A100-high and A100-low, nor between B100-high and B100-low, and, hence, here referred to as A100 and B100, respectively. The only difference between these high and low cases is whether impacts can be assigned to sub-parts (function group 2) or merely to the engine as a whole (function group 1) (see Section 3.4). Complementary data is included in the results for all modelling options in Table 4.

In general, the results show that applying a mass cut-off on a material level with high resolution (A99-high) leads to less deviation in aggregated impact scores for the majority of the impact categories (12 out of 16), compared to reducing the number of basic substances representing materials (B100 options). Meanwhile, applying a mass cut-off with a low resolution (A99-low) leads to higher deviation compared to B100 options for 8 out of 16 impact categories. Consistently, the largest discrepancy is seen for the majority of the impact categories (15) when both simplifications are applied at the same time – i.e., options B99 high/low.

When material cut-off is applied, as in A99-high/low and B99-high/low, the life cycle impact scores for variants modelled with high and low levels of resolution differ, since the mass and, consequently, the number of materials and basic substances included in the model differ. For options with a low level of resolution, i.e. A99-low and B99-low, the cut-off is applied on the engine as a whole. The mass threshold in this case is 7.6 g. This means that any material weighing less than 7.6 g is not included in the calculation of the LCI for these modelling options, i.e., this 1 % mass cut-off results in a reduction of the unique material entries by 75 %, totalling 539 in comparison to 2,156 for A100 options. On the other hand, when mass cut-off is applied to models with a high level of resolution, i.e. A99-high and B99-high, the cut-off is applied for every sub-part of the engine. As a consequence, the mass threshold ranges from 0.6 g for the function group "2800" (ignition and control) up to 23.2 g for the function group "2100" (engine block). Therefore, more material entries, 671, are included in the models with high resolution (A99-high and B99-high). Even though the difference in the number of material entries is about 20 %, Table 4 shows that the LCIA results differ by no more than 5 % between "high" and "low" modelling options.

Finally, Table 4 shows large differences between the LCIA categories. For four impact categories, including climate change, the impact decreases by less than 15 % between A100 and B99-low. However, the majority of impact categories show more than 25 % divergence, and up to 68 % in the worst case (resource use, mineral and metals). When interpreting these results, it is important to note that some impact categories, such as those related to toxicity, have significantly higher uncertainty associated to their characterisation factors than others, such as climate change (JRC-IES, 2011; Biganzioli et al., 2018).

### *3.3. In-depth analysis of selected impact categories*

In order to further explain the impacts of each modelling option, an in-depth analysis of three selected impact categories is presented in Fig. 5. The first two selected impact categories, climate change (1) and resource use, mineral and metals (2), were selected as these impact categories are strategically important to VCC, and thus probably to the automotive industry in general. In addition,

**Table 4**
Impact scores normalised to modelling options A100. The colours in the cells vary from "green" (100%) to "yellow" (75%) to "red" (50% and lower). All categories are calculated with midpoint characterisation methods as recommended in the European framework of the Environmental Footprint (Biganzioli et al., 2018).

| Impact categories | Modelling options | | | | | |
|---|---|---|---|---|---|---|
| | **A100** | **A99-high** | **A99-low** | **B100** | **B99-high** | **B99-low** |
| Acidification | 100 % | 89 % | 87 % | 88 % | 77 % | 75 % |
| Climate change | 100 % | 95 % | 92 % | 93 % | 88 % | 86 % |
| Ecotoxicity, freshwater | 100 % | 81 % | 79 % | 75 % | 57 % | 55 % |
| Eutrophication, freshwater | 100 % | 83 % | 81 % | 94 % | 78 % | 76 % |
| Eutrophication, marine | 100 % | 92 % | 89 % | 90 % | 82 % | 79 % |
| Eutrophication, terrestrial | 100 % | 91 % | 89 % | 84 % | 75 % | 73 % |
| Human toxicity, cancer | 100 % | 97 % | 97 % | 73 % | 71 % | 71 % |
| Human toxicity, non-cancer | 100 % | 91 % | 90 % | 82 % | 74 % | 72 % |
| Ionising radiation | 100 % | 97 % | 96 % | 98 % | 96 % | 95 % |
| Land use | 100 % | 94 % | 93 % | 73 % | 68 % | 66 % |
| Ozone depletion | 100 % | 96 % | 93 % | 50 % | 48 % | 44 % |
| Particulate matter | 100 % | 96 % | 95 % | 79 % | 75 % | 74 % |
| Photochemical ozone formation | 100 % | 93 % | 90 % | 91 % | 83 % | 81 % |
| Resource use, energy carriers | 100 % | 94 % | 93 % | 95 % | 90 % | 88 % |
| Resource use, mineral and metals | 100 % | 91 % | 88 % | 41 % | 34 % | 32 % |
| Water scarcity | 100 % | 98 % | 97 % | 100 % | 98 % | 97 % |

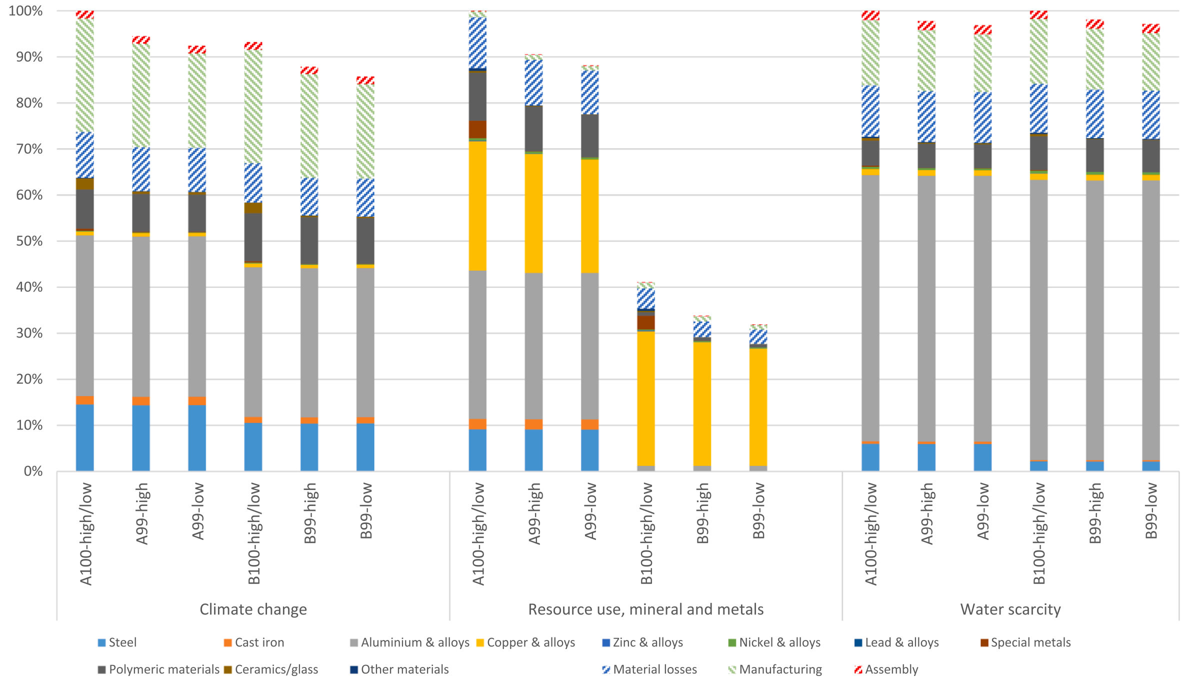


**Fig. 5.** Normalised contribution analysis for three selected impact categories. The material category "special metals" comprises precious and scarce metals. "Other materials" comprises material entries which did not fit into any other material category. "Material losses", "manufacturing" and "assembly" refer to complementary data as described in Section 2.4. All impact categories are calculated with midpoint characterisation methods as recommended in the European framework of the Environmental Footprint (Biganzioli et al., 2018).

resource use is the impact category presenting the largest deviation of the LCIA results for modelling options "B" compared to those of the reference modelling option, while climate change is among the categories showing a much smaller discrepancy. To contrast this, the water scarcity (3) impact category was also selected as it shows the smallest deviation of the impact scores compared to the reference option. Contribution analysis results for the remaining impact categories are reported in the Supplementary Information, Section H.

Fig. 5 shows a contribution analysis for the selected impact categories. For the climate change and resource use categories, option A99-high presents the smallest difference in impact score compared to A100. The main explanation is that the materials contributing most to the scores for these impact categories – steel and aluminium alloys for climate change; steel, aluminium alloys and copper alloys for resource use – are not substantially affected by the applied mass cut-off rule. Other materials are affected by the mass cut-off to a greater extent, such as ceramics, glass, zinc, lead, as well as precious and scarce metals, e.g., silver, gold, platinum, cobalt, tungsten (grouped as special metals in Fig. 5). Given their low proportion by weight, many material entries belonging to these material categories are found below the mass cut-off threshold, which results in a substantial reduction in their contributions to overall impact scores.

As for modelling options B100 – where no mass cut-off is applied – the mass of the engine, and consequently the number of materials included in the model, are the same as for options A100. They differ however with regard to the number of basic substances representing materials (see Table 2), which affects LCIA results since no alloying or filler elements are included in these models. As a consequence, the environmental impact scores related to different materials might increase or decrease, depending on how alloying and filler elements affect a given impact category in comparison to the impact of the main basic element of each material.

For instance, for the impact category resource use, mineral and metals, the absence of alloying elements in the modelling of steel, cast iron and aluminium, as well as fillers in polymeric materials, greatly affects B100 options, leading to a considerable reduction in relative impact scores when compared to A100 options. Oppositely, for climate change, the absence of the same alloying elements affects the scores of B100 options much less, but still notably for steel and cast iron.

Options B99-high/low differ from A100 options not only in the number of materials representing the engine but also in the number of basic substances representing these materials. As expected, this approach leads to the largest discrepancies in LCIA results not only for climate change and resource use, shown in Fig. 5, but also for the great majority of all impact categories considered in Table 4. Generally, in options B99-high/low, the mass cut-off on the material level greatly affects materials with an overall low weight in the engine, in the same way as for A99-high/low options. Heavier materials, on the other hand, are usually affected by the reduction in the number of basic substances representing the materials in the model, as described for steel, cast iron and aluminium in options B100.

Interestingly, water scarcity is the impact category showing the smallest deviation in impact scores, for all considered categories. The reason is that for this category the largest contribution in all modelling options comes from primary aluminium production, which impacts water scarcity mainly due to the evaporation of water from various useful water bodies, both directly in the production process, e.g., cooling water, or indirectly, from big water reservoirs, when hydropower is used for supplying electricity to the production of alumina from bauxite and further smelting to aluminium (Buxmann et al., 2016).

Aluminium is in fact hardly affected by the mass cut-off approach (A99-high/low), since the majority of material entries belonging to this material category are found over the mass cut-off threshold. Additionally, the approach of reducing the number of basic substances representing materials slightly increases the impact scores for aluminium in options “B” compared to options “A”, since in this case “pure” aluminium has a higher impact on water scarcity than the aluminium alloys modelled in “A” options. A similar behaviour is also seen for polymeric materials.

### 3.4. *The effect of complementary data*

Complementary data, as previously explained in Section 2.4, consists of information on manufacturing and assembly processes – including losses of materials related to such activities – which is not present in IMDS. Given that such processes are usually energy-intensive, either in the form of electricity consumption to drive machinery or combustion of fuels to generate heat, the inclusion of complementary data shows a large effect on the impact categories sensitive to electricity production and combustion-related emissions, e.g. climate change, ionising radiation and resource use (energy carriers). Fig. 5 illustrates the relatively large contribution from manufacturing processes to impact scores for global warming (24–28 % of total LCIA results for the category climate change, for all options).

While not illustrated in Fig. 5, the impact category in which manufacturing and assembly processes make the greatest contribution

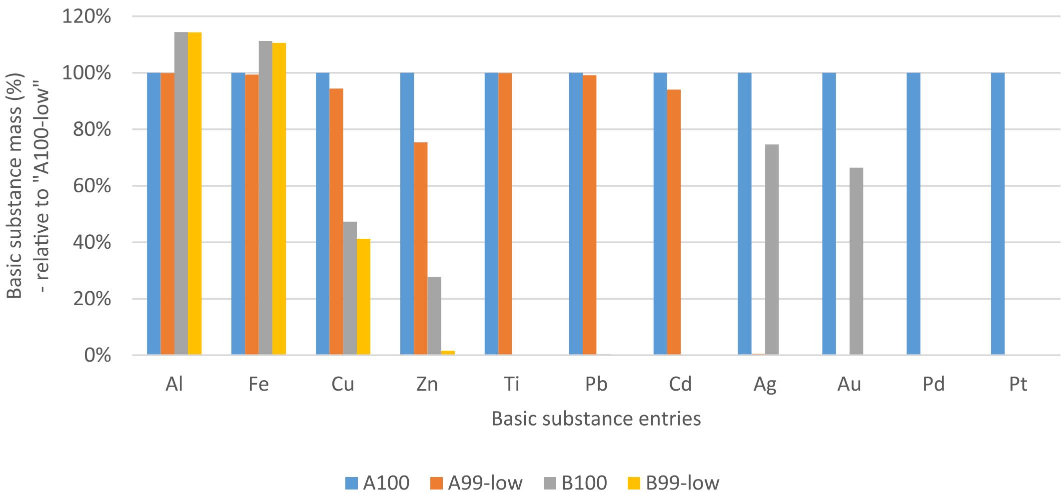


**Fig. 6.** Normalised mass representation of different metals (basic substance entries) in the “low” modelling options with A100 as reference.

to the results is land use (34–48 % of total LCIA results for all options), which can be explained by the utilization of wood chips to produce heat at the engine factory and the large area associated with the activity of forestry. On the other hand, these activities together, contribute at most 4 % to the impact category resource use, minerals and metals. Generally, the final assembly of the engine contributes little to most impact categories (up to 5 % for fourteen categories, for all modelling options), while manufacturing processes of components and sub-parts contribute more (more than 10 % for twelve categories, for all modelling options).

Since material losses are an inherent part of manufacturing and assembly activities, these were are also considered when calculating the total environmental burden of the engine. For the majority of the impact categories (13), the effect of material losses on impact scores is at most 11 %, for all modelling options. The lowest effect of material losses is seen for the impact scores of the ionising radiation category (8 % at most), while the largest effect occurs in the category human toxicity, cancer effects (up to 15 % of total impact scores).

### 3.5. Lost substances

As shown, different modelling choices employed in the LCI calculations have an impact on the number of basic substances included in the modelling options. Fig. 6 shows how a set of metals and their mass representation as basic substances are included in different modelling options, relative to option A100.[10]

Applying the single basic substance approach (“B” options) leads to the total exclusion of a number of metals: cadmium (Cd), palladium (Pd), platinum (Pt) and titanium (Ti). The reason is that these basic substances are not the largest contributors of mass in any material entry. Similarly, lead (Pb) is also reduced to a negligible level, since there are very few entries in which it is the heaviest basic substance. Gold (Au), silver (Ag) and, even more severely, copper (Cu) and zinc (Zn) are also affected by this approach, but they are more often the heaviest substance in specific material entries.

For the option in which material cut-off is applied, A99- low, gold, palladium and platinum are completely erased from the LCI model, and silver is reduced to a negligible level. In these cases, the mass of the material entries containing these metals falls below the mass cut-off threshold. Conversely, cadmium, lead and titanium are not severely affected by this approach, primarily because they are present as alloys in heavier materials such as solder alloys, aluminium or steel. This also partially explains the relatively small impact on copper.

The metals with the largest mass contribution to the engine, i.e. aluminium (Al) and iron (Fe), are barely affected by the mass cut-off approach, since most of the materials in which they are present are above the mass cut-off threshold. However, more importantly, because iron and aluminium are also the heaviest basic substances in most material entries in which they are present, they become overstated by the single basic substance approach, i.e. higher in options “B” compared to options “A”.

Lastly, the combination of using one single basic substance for material entries and applying the mass cut-off approach, i.e. B99-low option, eliminates most metals and greatly reduces both copper and zinc in the LCI model.

### 3.6. Function groups and levels of data aggregation

As discussed earlier, two different levels of data aggregation were employed in this study. The LCI was compiled for the engine as a whole (function group level 1) or for the different engine sub-parts (function group level 2) (see Table 1).

Fig. 7 shows that the greatest benefit of starting from a higher function group level is not quantitative, but qualitative, since a higher function group level allows for a deeper analysis of the results, improving the usefulness of the assessment.

As shown, there is no difference between the numerical LCIA results within the two pairs of options with high and low resolution when no cut-off is applied (A100-high compared to A100-low and B100-high compared to B100-low). Also, when mass cut-off is employed, the difference is minor, as shown by the comparison between A99-high and A99-low, and B99-high and B99-low, respectively. Table 4 shows that this behaviour is similar for most impact categories.

It can be noted that the reason for selecting the lowest level of data aggregation as function group level 2 (instead of levels 3 or 4), is purely illustrative. Even though the employment of IMDS data at levels 3 or 4 was not quantitatively assessed, total impact scores can be expected to increase at higher levels of resolution for the options where a material cut-off is applied (A99-high and B99-high), in the same way as observed for level 2 in relation to level 1. The explanation is that a larger number of materials, and consequently basic substances, are being accounted for in the model, since the differentiation of cut-off thresholds at a given level would result in lower cut-off thresholds for a majority of function groups at that level.

This means that the proper choice of aggregation level depends on the aim of the study. LCA studies performed with the purpose of assisting product development benefit from the use of less aggregated data, since these allow for more precise identification of environmental hotspots. In contrast, this level of detail might be superfluous for comparisons of the life cycle impact of complete vehicles.

### 3.7. Discussion about challenges when using IMDS

During the modelling work, several challenges were identified when matching basic substances to background datasets, to

[10] Since the number of basic substances included in the “low” options of A99 and B99 is affected to a greater extent than in the “high” options (see Table 3), only the “low” modelling options are shown in Fig. 6.

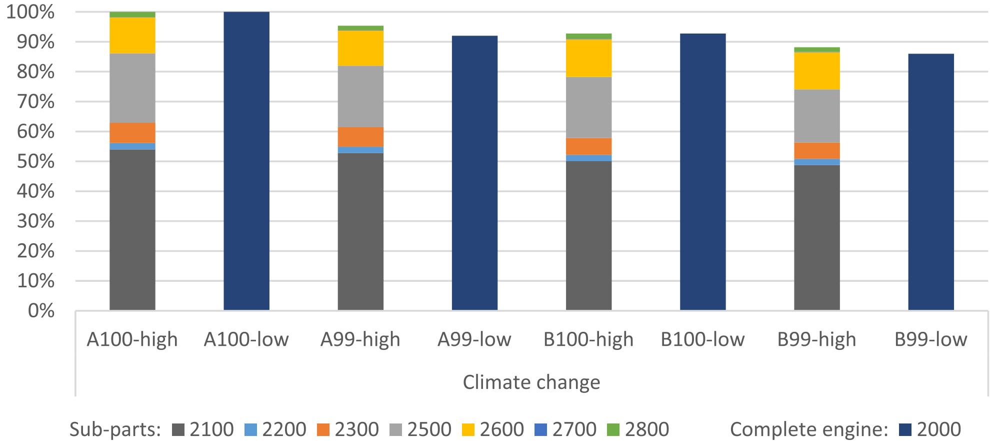


**Fig. 7.** Impact scores for the impact category climate change, relative to option A100-high. Function groups 2100–2800 (sub-parts) are employed in the "high" options, while function group 2000 (complete engine) is employed in the "low" options.

accomplish the desired completeness, and when trying to properly include complementary data to the LCI model. Including all basic substances does not always lead to a more accurate representation of the actual process steps to produce materials and components, because the basic substances reported by the IMDS are usually in their refined form ("pure" substance), as present in finished vehicle parts and components. However, many substances used as alloying elements do not enter into metallurgical processing as refined substances. In such cases, matching basic substances to background datasets representing refined substances might lead to an overestimation of environmental impacts. A clear example here is the common traded form of alloying elements in steels, e.g., ferrochromium, ferronickel, ferromanganese, which are reported in IMDS as chromium, nickel and manganese respectively.

Secondly, information about the material production routes and the recycled content share is not present in the IMDS. Meanwhile, some materials, for example different steel grades,[11] are produced in completely different processing steps and with varying amounts of recycled content. Hence, additional information about the specific material must be available to properly model the production route and avoid both under- or overestimations of the environmental impacts associated with the production.

It is important to note that gathering information on the exact recycled content of a vehicle, or in an engine, is very difficult, not only because this information is not allowed to be disclosed in IMDS, but also due to the large number of suppliers involved. For this reason, at VCC, in order to avoid underestimating impacts, a very low recycling content is generally assumed (for steel at least 10 %, and for aluminium 5 %) in general reporting. Accordingly, the results of this study indicate that the focus on properly representing all basic substances in the LCI model is useful for the assessment of minerals and metals resource use, but it may introduce uncertainty in other impact categories for which the specific production route impacts largely on the amounts of emissions. Finally, this effect is in turn dependent on the number of datasets available when matching IMDS data to background data (mostly Ecoinvent in our specific case). If a larger subset of steel and aluminium grades, but also other materials such as plastics, were available for specific production pathways, including sufficient detail both for processing and material content on substance level, this uncertainty would decrease.

## 4. Conclusions

This study confirms that IMDS is a useful and accessible source of data for LCA practitioners in the automotive industry and validates the hypothesis that modelling choices regarding data aggregation and degree of completeness govern the trade-off between precision and workload. Three main simplifications for the modelling were investigated: use of the mass cut-off approach; using only one basic substance to represent each material; and selecting a low function group level starting point (i.e. employing data with a lower level of resolution). We also examined how the inclusion of data for manufacturing and assembly processes influences the trade-off.

Employing a 1 % mass cut-off greatly reduces the workload while maintaining a reasonable level of precision: at most 10 % deviation from the impact scores for the complete LCI model for most impact categories (10 out of 16). Reducing the number of basic substances included in the model causes a similar reduction in workload, but a greater loss of precision: more than 10 % deviation for the majority (9) of the impact categories, and at least 15 % for half of them (8). Applying both of these simplifications saves additional workload, and unsurprisingly, it results in the lowest levels of precision: more than 20 % discrepancy for 10 impact categories, and nearly 70 % in the worst case. However, this combined approach could be reasonable in, for example, a "screening" study looking only at potential contribution to global warming. This impact category is not severely affected, with a deviation of 14 % between the least and most detailed modelling option.

Employing all simplification strategies jointly requires great caution, primarily when addressing impact categories related to

[11] Steel is mainly produced by two main routes, the Blast Furnace-Basic Oxygen Furnace (BF-BOF) route, which mainly uses iron ore as raw material, and the Electric Arc Furnace (EAF) route, mainly using steel scrap as feedstock.

resource extraction, e.g. the use of scarce metals. More specifically, the combination of mass cut-off with the approach using single basic substances to represent materials leads to the exclusion of several basic substances which can be key to the LCIA results and the overall analysis.

Regarding the function group level employed in the LCI calculations, the benefit of modelling with a higher level of detail is qualitative, since it allows for analysis of the contribution of different sub-parts to the overall results. Nevertheless, simplifying the modelling work by starting from data with less resolution reduces the workload, although only marginally. And combined with the mass cut-off approach it leads to a slightly greater divergence of results.

As for complementing LCI models with data not included in IMDS, some impact categories indicate the importance of accounting for data representing manufacturing and assembly processes in the model – including material losses arising from these activities – to improve the precision of the results, primarily because of emissions from energy conversion. This includes the impact category climate change. The highest proportion of the scores for environmental impacts of such processes is related to upstream manufacturing of parts and components, while assembly processes contribute to a smaller extent. Consequently, given that including complementary data entails a heavier workload, one possibility is to prioritise upstream manufacturing data, and the material losses arising from these processes, over final assembly data.

In this work an engine was selected as study object. The analysis of a complete vehicle instead would demand a significantly heavier workload, making the use of simplification approaches more compelling. It is important to stress however, that the utility and risks of any simplification strategy is heavily dependent on the type of assessment being conducted and the vehicle part being analysed. For instance, in a carbon footprint assessment, different simplification strategies could likely be employed in the modelling of vehicle parts comprised mostly of bulk materials, e.g. body panels, pillars, bonnet, without observing a significant loss in the precision of LCIA results. On the other hand, a higher level of detail in the modelling is demanded if the focus of the assessment is metal resource use. In such a case, the employment of simplification strategies is not recommended due to a significant loss of critical data.

Regarding other automotive parts this study does not provide any solid advice. For assessments of highly complex parts like power electronics and traction batteries, the simplification approaches tested here may have a larger effect on a broader range of impact categories, but this remains to be shown.

Finally, the absence of specific information in the IMDS related to material production routes, recycled content share and the refinement level of alloying elements, might lead to under- or overestimations of the environmental impact also in the most detailed modelling option presented here. As a way of overcoming such challenges, VCC and automotive companies in general, would benefit from gathering more detailed and specific information about material production routes and recycled content shares, beyond the current scope of IMDS. Moreover, internal or industry wide material level databases (LCI data) for common materials (e.g. specific steel grades, aluminium grades) matching the substances representation of IMDS would certainly facilitate the execution and increase the quality of LCA studies in the automotive industry.

## 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.

## Acknowledgement

The authors gratefully acknowledge the financial support from the following funding bodies: VINNOVA, the Swedish Government Agency for Innovation Systems and the Swedish Energy Agency (Energimyndigheten), through the Strategic Vehicle Research and Innovation (FFI) program.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2022.103247.

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