CHALMERS
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Life Cycle Assessment of Lithium-Ion Batteries

Benchmarking Existing Practices and Modelling Assembly Processes

Master's thesis in Industrial Ecology

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Abstract

The rapid growth of electric vehicles (EVs) has increased the importance of understanding the environmental impacts associated with lithium-ion battery (LIB) production. Life cycle assessment (LCA) is widely used to evaluate these impacts, but previous studies report large variations in results due to differences in methodological choices, such as system boundaries, data sources, and modelling assumptions. In addition, module and pack assembly processes are often inconsistently and insufficiently represented in existing literature. This thesis investigates how existing LIB LCA studies differ regarding methodological approaches, data gaps, and reported environmental impacts, while also suggesting how the modelling of module and pack assembly processes can be improved. The study was carried out through three main steps: a state-of-the-art review, benchmarking of selected LIB LCA studies, and the development of a model for module and pack assembly. The benchmarking compared studies across several parameters, such as system boundaries, functional units (FUs), electricity mixes, life cycle impact assessment (LCIA) methods, transparency, and environmental impacts across several impact categories. In addition, process mapping and data collection were carried out for module and pack assembly to develop a more transparent and structured modelling approach for these stages. The results show large methodological variations across the reviewed studies and the differences strongly influenced the reported environmental impacts and often limited comparability between studies. In some cases, variation within the same battery chemistry was larger than the variation between different chemistries, indicating that methodological choices can influence results as much as the battery chemistry itself. Cathode production was identified as the most common environmental hotspot. The analysis also highlighted significant challenges related to data availability and transparency. Many studies relied heavily on secondary data, while representative industrial primary data remained limited. The findings of this thesis demonstrate the need for improved transparency, consistent methodological approaches, and better access to representative primary data in order to increase the robustness and comparability of future LIB LCAs.

Keywords: Lithium-ion batteries, Life cycle assessment, Electric vehicles, Battery manufacturing, Battery module assembly, Battery pack assembly, Environmental assessment.

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Ida Claesson & Vendela Hansson, Gothenburg, May 2026

List of Abbreviations

Below is the list of abbreviations that have been used throughout this thesis listed in alphabetical order:

ADP	Abiotic Depletion Potential
AP	Acidification Potential
BMS	Battery Management System
BoM	Bill of Materials
CED	Cumulative Energy Demand
CSRD	Corporate Sustainability Reporting Directive
DBP	Digital Battery Passport
DPP	Digital Product Passport
EI99 H/A	Eco-indicator 99 human health/ecosystem quality
EoL	End-of-Life
EP	Eutrophication Potential
ESPR	Ecodesign for Sustainable Products Regulation
EU	European Union
EV	Electric Vehicle
FEP	Freshwater Eutrophication Potential
FU	Functional Unit
GHG	Greenhouse Gas
GWP	Global Warming Potential
HEV	Hybrid Electric Vehicle
HT-ce	Human Toxicity – carcinogenic effects
HT-nce	Human Toxicity – non-carcinogenic effects
HTP	Human Toxicity Potential
IR-hh	Ionizing Radiation – human health
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCO	Lithium Cobalt Oxide
LCP	Lithium Cobalt Phosphate
LFP	Lithium Iron Phosphate
LIB	Lithium-ion Battery
LMO	Lithium Manganese Oxide
LTO	Lithium Titanate Oxide
MEP	Marine Eutrophication Potential

NCA	Lithium Nickel Cobalt Aluminium Oxide
NMC	Lithium Nickel Manganese Cobalt Oxide
ODP	Ozone Depletion Potential
PED	Primary Energy Demand
PHEV	Plug-in Hybrid Electric Vehicles
PMPF	Particulate Matter Formation Potential
POCP	Photochemical Ozone Creation Potential
TAP	Terrestrial Acidification Potential
TETP	Terrestrial Ecotoxicity Potential

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1
Introduction

The increasing urgency of climate change mitigation, together with tightening environmental regulations such as the European Green Deal (European Commission, 2019) is placing growing pressure on manufacturers to quantify, manage, and reduce the environmental impacts of their products and production systems. In this context, the transport sector represents a major source of greenhouse gas emissions, accounting for approximately 23% of global energy-related CO2 emissions, with road transport contributing around three-quarters of these emissions (Intergovernmental Panel on Climate Change, 2022). Consequently, the transition toward low-carbon transport solutions has become an important part of climate change mitigation strategies.

Electrification of transport has gained increasing attention as a key decarbonization strategy, as battery EVs operate without tailpipe greenhouse gas emissions (Burchart-Korol et al., 2020; Ioakimidis et al., 2019). The market for EVs has expanded rapidly in recent years. According to the International Energy Agency (2025), global EV sales exceeded 17 million vehicles in 2024, representing more than 20% of total car sales worldwide. LIBs have become the battery of choice in EVs and hybrid electric vehicles (HEV), meaning that the demand for these types of batteries will be high (International Energy Agency, 2023). LIBs are therefore a critical enabling technology in this transition.

The continued growth in EV adoption and battery demand raises important questions regarding the environmental implications of large-scale battery production (Chordia et al., 2021). While EVs reduce emissions during operation, the production of LIBs is associated with substantial environmental impacts, largely due to energy-intensive manufacturing and upstream raw material extraction processes (European Environment Agency., 2018). Consequently, understanding and accurately assessing the environmental impacts of LIB production has become increasingly important.

This has led to a growing interest in LCA studies aiming to quantify the environmental performance of battery production. However, reported results vary considerably across the literature. Previous studies and reviews have shown that differences in system boundaries, FUs, data sources, electricity mixes, and modelling assumptions can strongly influence the estimated environmental impacts of battery production (Ellingsen et al., 2017; Peters & Weil, 2018; Peters et al., 2017; Temporelli et al., 2020). These differences make it difficult to compare results across studies and to understand which methodological choices and data assumptions are most important for the reported outcomes. This highlights the need for more transparent and structured modelling approaches that can capture the complexity of battery manufacturing systems while enabling more consistent comparison across studies (Peters & Weil, 2018; Peters et al., 2017).

This thesis addresses this need by conducting a state-of-the-art review and benchmarking of existing LCA studies to identify main data gaps, methodological differences and variations in reported impact results. In addition, a modelling approach is developed for module and pack assembly processes. Which is motivated by the limited and inconsistent reporting of assembly data in existing battery LCA studies (Dunn et al., 2014; Ellingsen et al., 2017).

1.1 Project Aim and Research Questions

The overall aim of this project is to improve the understanding of environmental assessments of LIB manufacturing by analysing existing LCA studies. The focus is on identifying main data gaps and methodological differences, and examining how these factors influence reported environmental impacts. In addition, the study aims to contribute to improved environmental assessment practices by developing a conceptual model for module and pack assembly, enabling a more consistent and comprehensive representation of battery manufacturing processes. To achieve this aim, the following sub-objectives are defined:

- To review and synthesise existing literature with a LCA context of LIBs.
- To benchmark current LCA approaches, with particular attention to elements within the goal and scope, life cycle inventory (LCI), and life cycle impact assessment (LCIA).
- To develop a conceptual model for module and pack assembly that enables a more comprehensive representation of manufacturing processes and their associated environmental impacts.

In line with these objectives, the study addresses the following research questions:

1. How do published LCA studies of LIB differ regarding methodological approaches, overall data gaps, and reported impact category results?
2. How can module and pack assembly processes be conceptually mapped to support a more detailed representation of LIB manufacturing in LCA?

1.2 Background

1.2.1 LIB Technology

At the core of a LIB are the individual cells which are responsible for storing electrical energy. Each cell consists of four parts, two electrodes (an anode and a cathode), an electrolyte, and a separator (Nitta et al., 2015). Battery cells are the fundamental units of a battery. They are manufactured in different formats, with the most common being cylindrical, prismatic, and pouch cells. To form functional units suitable for practical applications, individual cells are grouped into modules. Within these modules, cells are connected in series and parallel configurations to achieve the required voltage and capacity. At the highest level, modules are integrated into a battery pack, as illustrated in Figure 1.1 (Schröder et al., 2017).

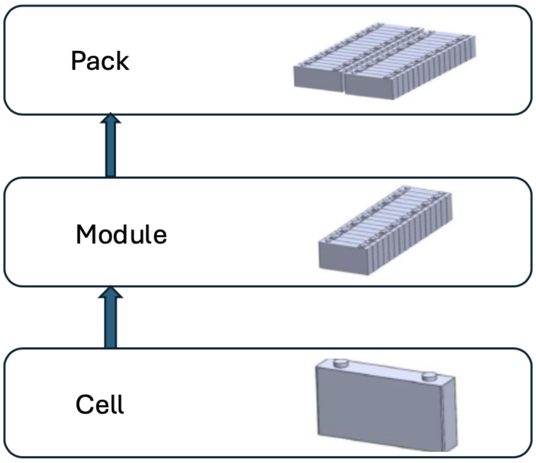

Figure 1.1: Hierarchical structure of a battery system showing the relationship between the cell, module, and pack levels for prismatic cells. Illustration inspired by (Grepow, 2024)

At pack level, the battery system also includes casing and supporting systems, such as a battery management system (BMS) for monitoring and control, as well as thermal management components for cooling and heating depending on operating conditions and design requirements (Dai et al., 2019).

As mentioned above, LIBs consist of two electrodes, the cathode and the anode, which can be made from a range of different materials (Zubi et al., 2018). In EVs applications, LIB chemistries are commonly distinguished by the cathode active material, as this influences battery performance, material demand, and cost (Britala et al., 2023; Zubi et al., 2018). Lithium cobalt oxide (LCO) has been widely used in LIBs, particularly in portable electronics, but is less suitable for EV applications due to safety concerns, relatively limited cycle life, and cobalt-related supply constraints (Zubi et al., 2018). Instead, common cathode chemistries for EVs include lithium manganese oxide (LMO), lithium iron phosphate (LFP), lithium nickel manganese cobalt oxide (NMC), and lithium nickel cobalt aluminium oxide (NCA) (Zubi et al., 2018). Other cathode chemistries, such as lithium cobalt phosphate (LCP), have also been investigated, although they are not yet widely commercialized (Zubi et al., 2018). In recent years, NMC and LFP have become particularly important in the EV market (International Energy Agency, 2023). In 2022, NMC was the most widely used battery chemistry, accounting for approximately 60% of the market, followed by LFP at just under 30%, and NCA at around 8% (International Energy Agency, 2023).

Within the NMC family, different variants are distinguished by the relative proportions of nickel, manganese and cobalt in the cathode active material. The general composition can be written as $LiNi_xMn_yCo_zO_2$, where x, y, and z represent the relative shares of the three metals (Britala et al., 2023). For example, NMC111 contains approximately equal shares of nickel, manganese, and cobalt, while NMC622 and NMC811 are increasingly nickel-rich compositions, commonly represented as $LiNi_{0.6}Mn_{0.2}Co_{0.2}O_2$ and $LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$, respectively (Britala et al., 2023). This shift toward nickel-rich NMC chemistries has been driven by the aim to increase energy density while reducing cobalt content, thereby lowering material costs and supply-chain dependency. However, higher nickel contents may also introduce challenges related to thermal stability and cycle life (Britala et al., 2023; Raugei & Winfield, 2019).

In addition to cathode materials, the anode also plays a role in determining battery performance and environmental impacts. The most commonly used anode material in LIBs is graphite, due to its stable electrochemical properties and well-established production processes. However, silicon has emerged as a promising alternative anode material because of its significantly higher theoretical capacity compared to graphite (Nitta et al., 2015).

1.2.2 LCA Framework

There is a clear need for systematic approaches to assess environmental impacts, for which LCA has become a widely adopted methodology (Schneider et al., 2023). LCA considers the environmental impacts of a product across its entire life cycle. LCA is a standardized methodology used to evaluate the environmental impacts associated with a product, process, or system throughout its life cycle, from raw material extraction to end-of-life (EoL) treatment(International Organization for Standardization, 2006a, 2006b). The LCA methodology is typically structured into four main phases: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA), and interpretation, as can be seen in Figure 1.2 .

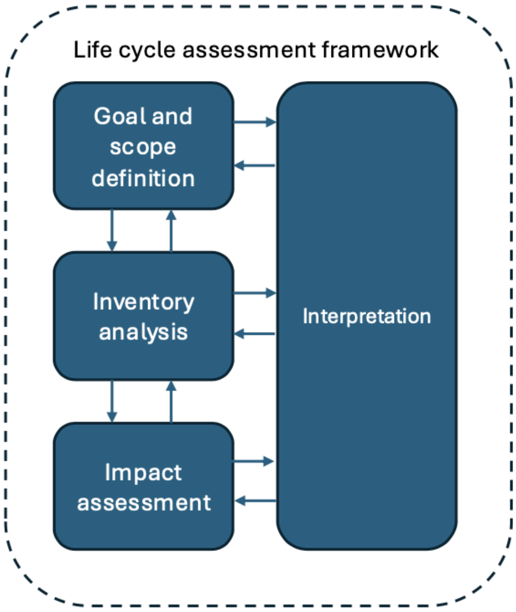

Figure 1.2: The four main phases of the LCA methodology according to ISO 14040 (International Organization for Standardization, 2006a)

A key aspect of LCA is the definition of the FU, which provides a reference for quantifying inputs and outputs, as well as the system boundaries, which determine which life cycle stages are included in the analysis (Baumann & Tillman, 2004). The outcomes of an LCA describe how a product system contributes to different environmental impact categories. Typical examples include global warming potential (GWP), acidification potential (AP), eutrophication potential (EP), and impacts on human health (Baumann & Tillman, 2004). These results can be used to identify the stages or components within a product's life cycle that are responsible for the largest share of environmental impact, such as a specific production process or material choice.

1.2.3 EU Regulations

European Union (EU) policy provides an important context for the increasing need for transparent, product environmental data and life cycle modelling in the battery sector. However, this section does not aim to provide a comprehensive review of global policy developments, but instead highlights selected EU regulations that are particularly relevant for batteries and life cycle data.

The European Green Deal provides the broader policy context for the EU's transition towards climate neutrality and resource efficiency. Introduced by the European Commission in 2019, the green deal sets the objective of making the EU climate neutral by 2050 while decoupling economic growth from resource use (European Commission, 2019). As part of the European Green Deal, the EU Climate Law was introduced in 2021 to translate the climate objectives into binding legislation. The

Climate Law establishes legally binding targets of reducing greenhouse gas emissions by at least 55% by 2030, relative to 1990 levels, and achieving climate neutrality by 2050 (European Union, 2021).

For the battery sector, this broader policy direction is relevant because batteries are central to the electrification of transport (Burchart-Korol et al., 2020; Ioakimidis et al., 2019), while their production is associated with significant material demand, energy use, and environmental impacts (Dai et al., 2019; Ellingsen et al., 2017). As a result, regulatory attention has increasingly shifted towards the environmental performance of batteries across their life cycle.

A central battery regulation is the EU Battery Regulation (Regulation (EU) 2023/1542), which establishes sustainability, safety, labelling, performance, and circularity requirements for batteries placed on the EU market, including EV batteries and rechargeable industrial batteries (European Union, 2023). Requirements related to carbon footprint declarations, recycled content, performance and durability, responsible sourcing of raw materials, and EoL management make the regulation particularly relevant for life cycle assessment and battery manufacturing modelling (European Union, 2023).

Of particular relevance is the regulation's requirement for carbon footprint declarations for certain battery categories, including EV batteries (European Union, 2023). These must report life cycle greenhouse gas emissions, increasing the need for reliable data on materials, components, energy use, electricity mixes, and manufacturing processes. These requirements are relevant because previous battery LCA studies have reported large variation in data availability, system boundaries, and assumptions regarding battery manufacturing (Ellingsen et al., 2017; Peters et al., 2017; Temporelli et al., 2020). The regulation therefore highlights the growing need for transparent and structured life cycle modelling in the battery sector.

A Digital Product Passport (DPP) specific to batteries, referred to as the Digital Battery Passport (DBP), is being introduced through the EU Battery Regulation and is expected to become mandatory on the European market from February 2027 (European Union, 2023). The DBP aims to improve traceability and transparency by making battery-related information digitally available across the value chain (European Union, 2023). Information relevant for the DBP includes battery composition, carbon footprint, recycled content, durability, and EoL information. Recent research highlights that sustainability data in battery value chains are often spread across different actors, inconsistently reported, and affected by confidentiality constraints (Berger et al., 2023). Which indicates a gap between regulatory data requirements and practical data availability, highlighting the need for more accessible and reliable data on LIBs.

Other EU initiatives, such as the Ecodesign for Sustainable Products Regulation (ESPR) and the Corporate Sustainability Reporting Directive (CSRD), further strengthen the demand for structured environmental data, traceability, and value chain emissions reporting for products (European Commission, 2022; European Union, 2021). Although these policies are broader than batteries, they contribute to increasing expectations for consistent data and assessment methods across product value chains, including in the battery sector. Environmental assessment methodologies, such as LCA, are therefore not only analytical tools but increasingly serve as enablers of regulatory compliance.

1.3 Scope

The scope of this thesis includes both system boundaries and limitations. System boundaries refer to the choices made by the authors regarding which aspects are included in the analysis, and these boundaries are necessary to ensure a focused and feasible study. Limitations, in contrast, arise from external constraints such as time, and access to information, which may influence the depth and breadth of the analysis.

1.3.1 System boundaries

This thesis primarily investigates LCA approaches for LIBs, with a focus on understanding methodological choices, data availability, and modelling practices in existing studies. The state-of-the-art review and benchmarking cover a range of existing LCA studies on LIBs, including different system boundaries (e.g, cradle-to-gate, cradle-to-grave), battery chemistries, FUs, and geographical contexts. In these two parts of the thesis (state-of-the-art and benchmarking), no specific geographical boundary was applied. Similarly, no strict temporal boundary was applied. This broad scope is necessary to identify methodological approaches, overall data gaps and variations in reported environmental impacts.

In contrast to the broad scope of the state-of-the-art and benchmarking, the modelling work in this thesis is narrowed down to the module and pack assembly stages of LIB manufacturing. The system boundary is defined as gate-to-gate, where battery cells are treated as input components, and the focus is placed on the assembly processes and associated material and energy flows required to produce battery modules and packs. This system boundary is mainly motivated by the project partners' interest in these life cycle stages, and the identification of significant data gaps in the literature regarding module and pack assembly processes. Although no explicit geographical boundary was set for the thesis as a whole, the process mapping for module and pack assembly is primarily based on European literature, particularly in a German context.

It is also important to note that the scope of this work is restricted to environmental impact assessment. Economic and social dimensions of sustainability, as well as potential trade offs between environmental, economic, and social performance, are outside the scope of this thesis.

1.3.2 Limitations

This thesis is also subject to several limitations. A key limitation is the relatively short timeframe of approximately 4.5 months, which restricts the level of detail that can be achieved in the literature analysis and modelling, and the extent of data collection. For example, it was not possible to conduct a fully systematic literature review with strict inclusion and exclusion criteria. While this enabled the inclusion of important and relevant studies, it also limits the reproducibility of the selection process, as another search and screening strategy may have resulted in a partly different set of studies. In addition, no access to primary data from industrial partners led to reliance on secondary data and assumptions for several processes, which introduces uncertainty into the results.

Another example of limitation arising from time constraints is that the scope of the benchmarking analysis could not be extended to include a broader range of parameters. In particular, aspects such as cut-off criteria, allocation methods, and a more extensive set of impact categories were not examined. Addressing these elements would likely contribute to a more comprehensive and robust comparison.

2

Methodology

This chapter presents the methodology applied in this study. It describes the overall workflow of the thesis, and also the data analysis.

2.1 Workflow

The workflow of this thesis is divided into three main components: (i) a state-of-the-art analysis, (ii) benchmarking of selected LCA studies, and (iii) modelling of module and pack assembly processes. Each component builds upon the previous one, where insights from the literature review and benchmarking have partly been used for the modelling approach.

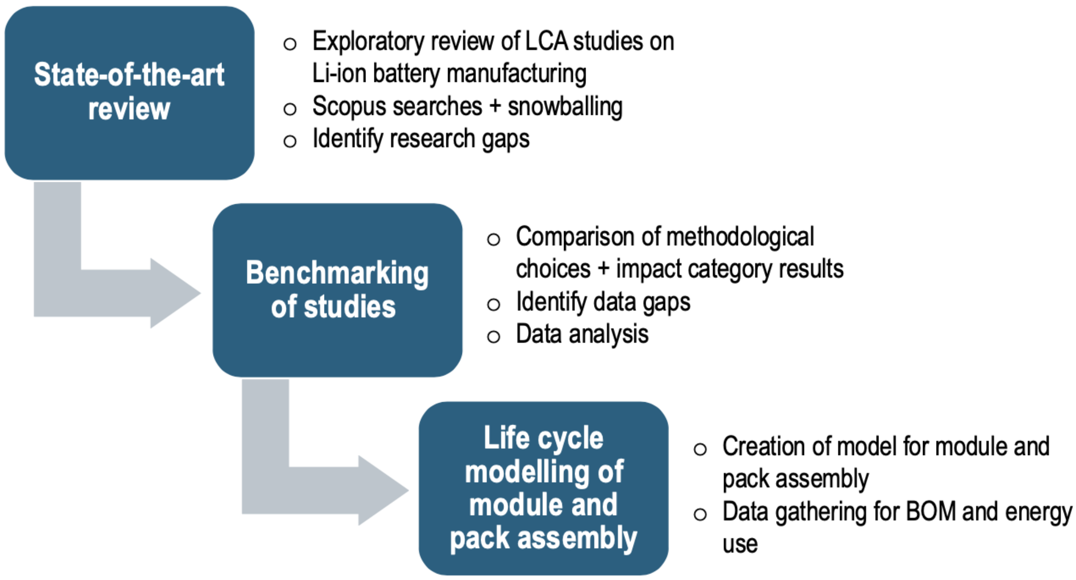

Figure 2.1: Overview of the thesis workflow.

2.1.1 State-of-the-Art Review

The state-of-the-art review was conducted to establish an overall understanding of LCA research on LIBs and to identify broader research gaps in the field.

The literature review followed three main steps. First, the review was planned by defining its scope and structure based on the project aim and research questions. Second, relevant literature was identified and selected through scopus database search and complementary snowballing. Finally, the results were documented and analyzed to identify challenges, trends and research gaps.

The first step involved planning the review by defining its scope and overall structure in line with the project aim and research questions. The thematic focus was defined as LCA of LIBs for traction application, with particular emphasis on manufacturing stages. Establishing this focus early guided the review towards literature directly relevant to the objectives of the thesis.

The second step in the state-of-the-art review involved identifying relevant scientific literature in the Scopus database. The search string was developed to capture the chosen thematic focus defined in the first step, using Boolean operators to combine key terms. The search was conducted within article titles, abstracts, and keywords, in order to capture studies that were explicitly related to LCA, LIBs, and battery manufacturing or production. The following search string was applied:

- ("LCA" OR "life cycle assessment") AND ("lithium-ion batter*" OR "Li-ion batter*" OR "LIB") AND ("manufactur*" OR "production")

The search resulted in 647 articles. Due to the limited timeframe of the thesis, it was not feasible to screen all results in full. In order to narrow it down, the results were therefore sorted by most cited. After sorting by most cited, the first 100 articles were screened. This approach was used to identify highly cited and influential studies within the field, including both foundational publications and more recent studies with large scientific impact. However, it should be noted that sorting by citation count may reduce the visibility of very recent publications, as these have had less time to accumulate citations.

To be able to compensate for this, a significant portion of the literature was identified through both backward and forward snowballing. Backward snowballing involved screening the reference lists of relevant articles, while forward snowballing involved identifying more recent studies that cited key publications. This approach enabled the inclusion of both foundational studies and recent publications that were not captured by the initial database search strategy.

For the 100 articles included in the screening, broad inclusion and exclusion criteria were applied. The review focused on peer-reviewed articles published in English. Included studies addressed LIBs for traction or automotive applications and contained a relevant LCA perspective. The studies also had to consider battery manufacturing or production stages in some form. Studies that were clearly unrelated to traction battery applications, did not address LIBs, or lacked a relevant environmental LCA perspective were excluded.

Based on these considerations, a structured screening process was conducted to select relevant studies. First, the search results were screened based on their titles to exclude clearly irrelevant publications. After this first screening 42 papers were included in the next step. In the next step, the abstracts of the remaining articles were reviewed to assess relevance in relation to the research question and the defined scope of the review. After this second screen, 30 papers appeared relevant based on the abstract, and were then subjected to a full-text review, where their contribution to the objectives of the state-of-the-art analysis were evaluated in more detail.

Furthermore, for some parts of this thesis, exceptions from the before mentioned criteria were applied. Specifically, grey literature was included to capture practical and regulatory perspectives not fully represented in academic publications. This included policy documents and reports from EU institutions, the industrial report used for the process mapping of module and pack assembly, and the USEPA (2013) report. The latter report was included because it provides detailed LCA data for LIBs, despite being an agency report. This report was identified through snowballing from Ellingsen et al. (2017).

2.1.2 Benchmarking

Building on the state-of-the-art review, a benchmarking of LCA studies on LIBs was conducted. The purpose of the benchmarking was to systematically compare selected studies in order to identify methodological differences, such as modelling approaches, as well as variations in data assumptions, and differences in reported environmental impacts.

The studies benchmarked in this thesis were mainly selected from the literature identified in the state-of-the-art review. Since the review included a large number of articles, only a smaller selection could be included in the benchmark. The studies were chosen based on their perceived relevance to the research area, while also aiming to cover different years and LCA characteristics in order to capture how the field has developed over time.

The selected benchmarking studies were organized in a structured Excel datasheet (see Appendix A.1) to enable a systematic comparison across various parameters. Due to the extensive size of the dataset, the original table was divided into multiple smaller tables for presentation in the appendix.

Data was extracted manually from the selected studies, including the articles and the supplementary materials, and compiled in a standardized format. The following parameters were analysed: geographical region, LCA context, LCA scope, FU, battery chemistry, battery mass and capacity, type of LCA, impact categories, LCIA method, type and source of data (e.g., industrial or laboratory-based primary data), level of transparency, main source of emissions, and reported environmental impacts, including global warming potential (GWP), cumulative energy demand (CED), ozone depletion potential (ODP), acidification potential (AP), eutrophication potential (EP), marine eutrophication potential (MEP), freshwater eutrophication potential (FEP), photochemical ozone creation potential (POCP), particulate matter formation potential (PMFP), and abiotic depletion potential (ADP). In addition, data on energy use for module and pack assembly and electricity mix were collected. The inclusion of energy from module and pack assembly was motivated by an identified research gap in the state-of-the-art review.

The selection of impact categories in this study was guided by recommendations from (Temporelli et al., 2020), who suggest that battery LCAs should include impact categories such as AP, EP, ODP, PMFP, ADP, human toxicity, ecotoxicity, and CED. Based on this, the benchmarking focused on the majority of these impact categories.

Regarding the main source of emission, it refers to the life cycle stage, process, or component that contributes the largest share of GWP. In this study, it means identifying which part of the system has the highest contribution to total GWP. It is important to keep in mind that the identified main source depends on the system boundaries used.

The benchmarking included both qualitative and quantitative parameters. One significant qualitative parameter was "transparency", which was used to assess the clarity of reported data sources and the accessibility of LCI data. It should be noted that this parameter does not evaluate the quality or accuracy of the data sources used, nor the full traceability of the data in the LCI, which are aspects that may be addressed in future research.

The methods and assumptions applied for extraction, handling and analysing the quantitative data are described in more detail in Section 2.2.

2.1.3 Modelling of Module and Pack Assembly

The selection of life cycle stages included in the modelling was motivated by both the interests of the industrial partners and insights from the state-of-the-art review and benchmarking. Based on these considerations, the section focuses specifically on module and pack assembly.

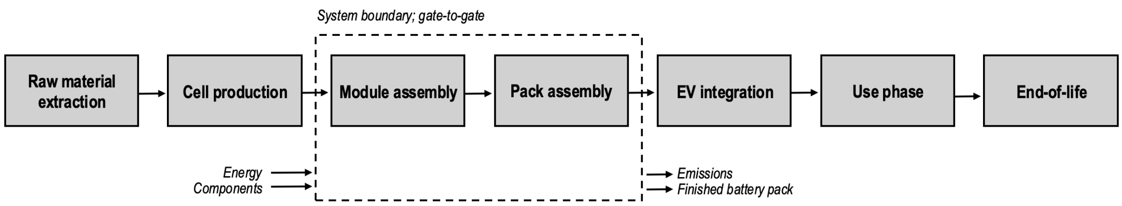

Figure 2.2: The gate-to-gate system boundary applied for the module and pack assembly model. The model includes module assembly and pack assembly, with energy and component inputs, and outputs in the form of emissions and a finished battery pack.

The process mapping of the assembly stages was primarily based on a report by PEM of RWTH Aachen University and VDMA (2023). This report was selected due to the detailed and modular description of the assembly processes.

As inventory data in PEM of RWTH Aachen University and VDMA (2023) for these stages were scare, additional data collection was required. Inventory data for the module and pack assembly stages were sourced from secondary literature, supplemented by assumptions where necessary. However as the inventory data used in the modelling were sourced from a combination of literature and benchmarking studies, reflecting a range of geographical contexts. Consequently, the generalisation of the modelling outcomes should be interpreted with caution. An additional Excel sheet was developed to compile the relevant processes and associated data (see Appendix C.1). For each identified process, efforts were made to collect data on energy consumption, as well as bill of materials (BoM) for module and pack components.

2.2 Data Analysis

This section outlines the main assumptions and data handling approaches applied in the study. Due to variability in, for example, system boundaries, FUs, impact units, across the benchmarking studies, simplifications and adjustments were required to enable consistent comparison. The analysis involved interpreting and applying general calculation approaches where necessary. Detailed study-specific calculations and assumptions are documented in Appendix B.1

2.2.1 Functional Units

To enable comparability across the benchmarking studies, results were expressed in a common FU of kWh battery capacity. However, not all studies reported results using this FU and conversions were required to transform results from their original FUs to kWh battery capacity.

The conversion approach varied depending on how results were reported in each study. When studies reported impacts per battery pack, the values were divided by the reported battery capacity. Results reported per unit mass were converted by multiplying the impacts per kilogram of battery by the total battery mass and then dividing by the battery pack capacity. For studies reporting impacts per kilometer driven, impacts were converted using the reported vehicle lifetime, electricity consumption, and battery capacity. However, note that this conversion introduces additional uncertainty because it uses use-phase-related assumptions to derive a battery-capacity-based FUs.

Some studies reported results at the cell level rather than the battery pack level. These were converted to kWh cell capacity where necessary, but were kept identified as cell-level results in the benchmarking. They are therefore only partially comparable to pack-level studies, as pack components and assembly processes are not included.

Where studies already reported results per kWh battery capacity, no conversion was applied.

2.2.2 Impact Category Unit

The reviewed studies reported several impact categories using different units and, in some cases, different levels of category differentiation. To enable comparison, results were only plotted together when the units and impact category definitions were considered comparable. When this was not possible, results were either separated into different figures or excluded from the quantitative comparison.

This was particularly relevant for EP. Some studies reported eutrophication as freshwater eutrophication potential (FEP) and marine eutrophication potential (MEP), while others reported a general, unspecified EP. To avoid assigning unspecified EP results to either freshwater or marine eutrophication, they were plotted separately. Terrestrial eutrophication potential was not assessed.

A similar approach was applied to other impact categories with inconsistent units. For AP, only results reported in kg SO_2-eq/kWh were included. For photochemical ozone creation potential, only results reported in kg NMVOC-eq/kWh were included. For abiotic depletion potential, only results reported in kg Sb-eq/kWh were included in the comparison.

2.2.3 Battery Format and Chemistry Assumptions

In addition to differences in FUs, and impact units, the selected studies also differed in terms of cell format and cell chemistry. The reviewed studies included different cell formats, such as prismatic and pouch cells. However, these differences were not explicitly considered in the benchmarking analysis.

Most of the selected studies assessed batteries with graphite anodes, graphite was therefore used as the preferred basis for comparison where possible. In studies that compared batteries with the same cathode chemistry but different anode materials, only the results for the graphite-anode variant were included. However, when no graphite-only alternative was available, the reported anode composition was retained and documented in the benchmarking table. Consequently, the benchmarking primarily compares results based on cathode chemistry, while the potential influence of anode composition is not assessed.

2.2.4 System Boundaries

The benchmarking studies included in this work applied a wide range of system boundaries, both in terms of life cycle stages and the processes included within those stages. To enable meaningful comparison across studies, a number of adjustments and assumptions were made to align the system boundaries of the reported results.

In particular, differences related to the inclusion of use-phase impacts, EoL treatment, and recycling credits required careful consideration. To improve comparability, results were, where possible, aligned to a cradle-to-gate system boundary, focusing on the production stage of LIBs. Consequently, use-phase impacts and recycling-related impacts and credits were excluded unless explicitly stated otherwise. Gate-to-gate results were included in figures where relevant but were marked separately and excluded from mean value calculations due to their narrower scope.

However, not all studies reported results in a way that allowed full alignment to a cradle-to-gate boundary. In these cases, results were retained to the system boundary of the study. To ensure transparency, a column "LCA scope (results)" was added in the benchmarking table (see Appendix A.1), indicating the system boundary to which each reported result corresponds. The impact results presented in the benchmarking are therefore aligned to this decided system boundary.

The decision not to adjust all studies to a uniform cradle-to-gate system boundary was motivated by both practical and analytical considerations. From a practical perspective, the time required to interpret and adjust results across differing system boundaries was significant. From an analytical perspective, retaining some variation in system boundaries allowed for the exploration of how results differ depending on scope definitions, thereby adding an additional dimension to the benchmarking analysis.

These adjustments were necessary to ensure a consistent basis for comparison across studies. However, it should be noted that such adjustments and assumptions introduces additional uncertainty and may influence the comparability of results.

2.2.5 Prospective Cases

The benchmarking includes studies applying prospective LCA approaches, which were included to increase the differentiation and analytical breadth of the comparison. However, to ensure comparability with the other studies, which primarily represent current or historical conditions, adjustments were required. For studies presenting results for multiple future scenarios, only the base case results were used. Studies addressing future technological development without discrete scenario years were retained as reported, without adjustments.

2.2.6 Assessment of Qualitative Parameters

As briefly introduced in 2.1.2, the benchmarking analysis included both quantitative and qualitative assessments. One of the main qualitative parameters evaluated in this study was the level of clarity of data sources and accessibility of the LCI of the selected LCA studies.

The parameter was assessed based on two main aspects: (i) the clarity of reported data sources and databases, and (ii) the accessibility of the underlying LCI data. Transparency was considered high when studies clearly specified the data sources and databases used and provided sufficiently detailed and accessible LCI data. A medium level of transparency was assigned when data sources were only partially or ambiguously described, or when LCI data were available but lacked sufficient detail or accessibility (e.g. due to confidentiality restrictions). Transparency was considered low when there were substantial uncertainties regarding the data sources or databases used, or when LCI data were not accessible.

These two aspects were assessed independently, meaning that a study could, for example, demonstrate high transparency in terms of data source reporting while having low accessibility of LCI data. It should also be noted that this parameter does not evaluate the quality or accuracy of the data sources used, nor the full traceability of the data in the LCI.

Another parameter that can be considered qualitative is the "type of data" category. In this study, primary data refer to data collected specifically for the individual study, typically obtained directly from industrial processes or measurements. In contrast, secondary data refer to data derived from existing literature or databases. Accordingly, databases such as Ecoinvent and the GREET model were classified as sources of secondary data, even though they may incorporate primary data from industry. To further improve transparency, separate columns were included in the benchmarking table to indicate the use of primary and secondary data sources. Additionally, the parameter "industrial vs. laboratory data" was used to distinguish whether the underlying data originated from industrial-scale processes or laboratory-based studies.

3

Results

3.1 State-of-the-Art Review

This section presents a state-of-the-art review of how LCA has been applied to lithium-ion batteries. To structure the review, the literature is discussed according to five main themes: developments in the field, comparability challenges, inventory data and transparency, environmental hotspots, and the representation of module and pack assembly

3.1.1 Developments in the Field

Early influential contributions include Ellingsen et al. (2014), Majeau-Bettez et al. (2011), Notter et al. (2010), and Zackrisson et al. (2010). More recent studies, for example Q. Chen et al. (2022), Clemente et al. (2025), Šimaitis et al. (2023), and Xu et al. (2022) extend the scope of LCA by incorporating newer battery chemistries, such as NMC811. Later work also reflects a shift toward increasingly prospective (Raugei & Winfield, 2019; Šimaitis et al., 2023; Xu et al., 2022), modular (von Drachenfels et al., 2023), and system-oriented analyses, including studies incorporating recycling credits within the system boundaries (Q. Chen et al., 2022; Cusenza et al., 2019; Šimaitis et al., 2023; Sun et al., 2020), and studies that integrate environmental assessment with cost and value-chain perspectives (Gutsch & Leker, 2024). Prospective LCA approaches vary significantly across the literature, some studies apply explicit time-based scenarios to assess technological evolution over defined future horizons such as Šimaitis et al. (2023) and Xu et al. (2022), whereas others, such as Raugei and Winfield (2019), model future technologies without specifying a distinct temporal framework.

The growing number of review studies also indicates that LIB LCA has become an increasingly established research field. Reviews such as Aichberger and Jungmeier (2020), Arshad et al. (2022), Clemente et al. (2025), Ellingsen et al. (2017), Lai et al. (2022), Peters et al. (2017), Porzio and Scown (2021), Temporelli et al. (2020), and Tolomeo et al. (2020) have examined methodological variation, data availability, impact ranges, life cycle stages, battery chemistries, manufacturing assumptions, and future research needs. Together, these reviews show that the field has expanded substantially, but also that comparability remains limited.

3.1.2 Comparability Challenges

One main finding in LIB LCA reviews is that results are difficult to compare directly, even when studies assess similar battery technologies. Reported impacts vary widely, with Ellingsen et al. (2017) identifying production-related GHG emissions between 38 and 356 kg CO_2-eq/kWh battery capacity. This variation is not explained by chemistry alone, but by differences in system boundaries, FUs, inventory data, electricity mixes, LCIA methods, and modelling assumptions (Aichberger & Jungmeier, 2020; Arshad et al., 2022; Clemente et al., 2025; Ellingsen et al., 2017; Peters et al., 2017; Scrucca et al., 2025; Temporelli et al., 2020; Tolomeo et al., 2020).

Peters et al. (2017) and Peters and Weil (2018) show that modelling choices can influence results as much as, or more than, the battery chemistry being assessed. Meaning that comparisons between batteries may partly reflect differences in modelling practice rather than actual technological differences. Clemente et al. (2025) similarly emphasize that FU, system boundary, electricity mix, and production scale need to be considered when interpreting reported emissions.

One central barrier to comparison is the choice of FUs. There are a lot of different FUs in LIB LCA studies, including for instance, battery storage capacity, battery mass, battery pack and kilometre driven, which makes results difficult to align (Clemente et al., 2025; Cusenza et al., 2019; Kim et al., 2016; Notter et al., 2010). Temporelli et al. (2020), argue that battery-pack and mass-based FUs are less suitable for comparison because they do not clearly represent the service provided by the battery. Instead, they suggest 1 km driven for full vehicle life cycle studies, or 1 kWh of storage capacity when comparison with existing battery literature is the main purpose. System boundaries also vary, with both cradle-to-gate and cradle-to-grave approaches being common (Scrucca et al., 2025). Broader cradle-to-grave studies can capture use-phase and EoL effects, but introduce additional uncertainty through assumptions about battery lifetime, degradation, charging electricity and recycling efficiencies (Q. Chen et al., 2022; Cusenza et al., 2019; B. Li et al., 2014). Furthermore, Scrucca et al. (2025) found that some studies exclude specific life cycle stages despite declaring broad system boundaries.

3.1.3 Data Challenges

A central limitation in LIB LCA is the restricted availability of detailed and representative LCI data. Many studies rely partly or fully on secondary data, such as previous literature and databases such as Ecoinvent, GREET model and BatPac (Dai et al., 2019; Majeau-Bettez et al., 2011; Raugei & Winfield, 2019; Šimaitis et al., 2023; Sun et al., 2020), while recent primary data are often limited or unavailable (Peters et al., 2017; Temporelli et al., 2020).

Several reviews identify the lack of primary data and the old literature data as a major concern. Tolomeo et al. (2020) found that only 12% of reviewed EV and LIB LCA studies used primary data alone, while 83% combined primary and secondary data. Degen and Schütte (2022) show that even studies published in 2019 and 2020 still relied on foundational datasets from Majeau-Bettez et al. (2011), Notter et al. (2010), and Zackrisson et al. (2010). Although these studies were important for the development of the field, they were conducted when automotive LIBs were still in an early stage of commercialisation and may therefore no longer reflect current production scale, chemistries, or manufacturing technologies (Degen & Schütte, 2022; Sun et al., 2020). This creates a risk that outdated assumptions continue to influence newer assessments. The technology is evolving so quickly that relying on older data can easily lead to misleading conclusions and, ultimately, poor decisions (Temporelli et al., 2020).

More recent studies have tried to improve data quality by using updated industrial data, laboratory data (such as dismantling batteries), or machine estimations (Cusenza et al., 2019; Degen & Schütte, 2022; Kim et al., 2016; Raugei & Winfield, 2019; Sun et al., 2020). However, while industrial data may be more representative, there are also signs of problems with confidentiality with primary data, which limits transparency and reproducibility (Ellingsen et al., 2017). Many studies that incorporate primary data are constrained by confidentiality to different degrees (Degen & Schütte, 2022; Kim et al., 2016; Sun et al., 2020; USEPA, 2013). Dunn et al. (2014) explicitly state that energy consumption data from battery assembly plants are difficult to obtain because production is often located overseas, production-representative data may not yet exist for new facilities, and companies consider such data proprietary.

This is closely related to transparency issues in the field, where Paul et al. (2024) found that only 35% of reviewed studies had openly accessible inventory data. Temporelli et al. (2020) highlight limited transparency in production energy and in bills of materials. This reduces reproducibility and makes it difficult to determine whether differences between studies are caused by actual technological differences or by data choices. So, while primary data may be more representative, it is prone to less transparency due to confidentiality, while secondary data are often more accessible but may be outdated or less representative. Thus, LCI data availability and transparency remain key challenges for improving the robustness and comparability of battery LCA studies.

3.1.4 Environmental Hotspots

Across several studies, cathode active materials, aluminium, and manufacturing energy demand are repeatedly identified as environmental hotspots. This is shown in studies such as Accardo et al. (2021), Dai et al. (2019), Ellingsen et al. (2014), Feng et al. (2022), and Majeau-Bettez et al. (2011), where impacts are commonly linked to energy-intensive cell production and upstream production of metals and active materials. In some studies, battery assembly is also identified as a relevant contributor to production impacts (Q. Chen et al., 2022; Raugei & Winfield, 2019; USEPA, 2013). However, the definition of assembly is uncertain and inconsistent in literature. This issue is therefore discussed further in Section 3.1.5.

Manufacturing energy demand, especially in cell production is a recurring hotspot. Dai et al. (2019) note that several earlier studies, such as Ellingsen et al. (2014), report high energy demand for cell manufacturing processes. And that more recent studies based on large-scale production generally report lower energy intensities. Aichberger and Jungmeier (2020) similarly suggest that some LCA studies may overestimate cell manufacturing impacts because they are based on small or underused production facilities. This is supported by Chordia et al. (2021) and von Drachenfels et al. (2021, 2023), who show that improved process efficiency can reduce manufacturing impacts compared with pilot-scale or underutilized production. However, this pattern is not consistent across all earlier studies, as Notter et al. (2010) report lower energy demand for cell manufacturing. Ellingsen et al. (2017) link these large variations to differing assumptions regarding energy demand in cell manufacture and pack assembly. Newer, more process focused studies, such as Degen and Schütte (2022), provide more detailed insight into cell production energy, but remain limited to the cell level.

Impact results also depend on battery chemistry and system boundary. Studies comparing LFP and NMC batteries show that no chemistry performs best in all contexts, since production impacts, lifetime, efficiency, and use-phase electricity can change the overall ranking (Feng et al., 2022; Quan et al., 2022). In broader cradle-to-grave studies, the use phase can also become a major hotspot, particularly when charging electricity is carbon-intensive (S. Li et al., 2010; USEPA, 2013; Zackrisson et al., 2010).

Another factor that affects the results is the electricity mix. Since battery manufacturing and upstream material processing are energy-intensive, the carbon intensity of electricity can strongly affect GWP results (Chordia et al., 2021; Dai et al., 2019). Clemente et al. (2025) and Xu et al. (2022) further show that regional electricity mixes can cause substantial variation in battery production impacts, with lower emissions in regions using less carbon-intensive electricity. For example, Xu et al. (2022) report that EU-based cell production resulted in 38–41% lower GHG emissions than production in China in 2020. Similar findings are done by Hao et al. (2017), who found that GHG emissions due to energy use from LIB manufacturing in China were almost triple the levels in the United States.

Finally, the inclusion of impact categories also affects which hotspots are identified. Although GWP is the most commonly reported category, studies show that focusing only on climate change can hide trade-offs in categories such as toxicity, AP, EP, ADP, and CED (Porzio & Scown, 2021; Scrucca et al., 2025; Temporelli et al., 2020). Hawkins et al. (2013), for example, found that EVs can reduce GWP compared with conventional vehicles when low-carbon electricity is used, but may increase impacts such as human toxicity and freshwater ecotoxicity due to metal supply chains related to battery and electric drivetrain production.

3.1.5 Representation of Module and Pack Assembly

An important finding in LIB LCA literature is that assembly processes are often aggregated, simplified, or inconsistently defined. Module and pack assembly is still commonly reported together with other manufacturing steps or treated as negligible (Dai et al., 2019; Ellingsen et al., 2014).

The treatment of module and pack assembly differs substantially between studies. Dai et al. (2019) assume that module and pack assembly are mainly manual and therefore assign no energy or environmental burden to these steps. Similarly, Ellingsen et al. (2014) include only energy for welding of cell tabs to busbars. In contrast, Q. Chen et al. (2022), Raugei and Winfield (2019), and USEPA (2013) indicate that battery assembly can be an important contributor to production impacts.

The terminology also varies between studies, with terms such as pack assembly, pack manufacture, and battery assembly used inconsistently. For example, Q. Chen et al. (2022) report "battery assembly" as a major contributor to production emissions, however, the term is not clearly separated into cell, module, and pack assembly. This inconsistent terminology creates uncertainty, since cell assembly often includes dry-room-related processes and formation, while module and pack assembly mainly involve mechanical and electrical integration (PEM of RWTH Aachen University & VDMA, 2023).

A final interpretation of this literature review is that LCA has become a widely used tool for assessing LIB production, but comparability remains limited by differences in system boundaries, FUs, data sources, electricity mixes, and treatment of manufacturing stages. Although several studies identify cell production, cathode materials, and electricity use as important contributors to environmental impacts, the representation of module and pack assembly remains inconsistent and often insufficiently documented. This creates uncertainty when interpreting battery production impacts and limits the possibility of developing transparent, process-based manufacturing models. These gaps motivate the benchmarking and assembly modelling carried out in this thesis.

3.2 Benchmarking

In this chapter, the studies are compared in terms of their goal and scope, LCI, and LCIA, following the standard framework of a LCA. Focusing on these aspects provides a clearer picture of the underlying assumptions and helps explain variations in the reported environmental impacts.

Table 3.1: Overview of studies included in the benchmarking analysis.

Author	LCA context	LCA scope	Functional unit	Battery chemistries	Impact categories	LCIA method	Electricity mix
Clemente et al. (2025)	LIB pack	Cradle-to-gate	1 kg of battery	NMC811	GWP	ReCiPe Midpoint (H) v1.13	China, South Korea, Sweden
Šimaitis et al. (2023)	LIB pack	Cradle-to-grave	1 kWh	LMO, LFP, NMC111, NMC622, NMC811, NCA	GWP	IPCC 2013	China
von Drachenfels et al. (2023)	LIB cell	Cradle-to-gate	1 battery cell	NMC622	GWP, TAP, POFP, FEP, MEP, HTP, TETP, FETP, PMFP, MDP, FDP	ReCiPe Midpoint (H) v1.13	Germany
Chen et al. (2022)	LIB pack	Cradle-to-cradle	1 kWh	NMC811	GWP	GaBi software 10.6	China
Degen and Schütte (2022)	LIB cell	Gate-to-gate	1 kWh cell capacity	NMC622	GWP, CED	N/A	Germany
Xu et al. (2022)	LIB cell	Cradle-to-gate	1 kWh cell capacity	LFP, NCA, NMC111, NMC523, NMC622, NMC811, NMC955	GWP	IPCC 2013	China, EU, and United States
Sun et al. (2020)	LIB pack	Cradle-to-gate + EoL	1 kWh	NMC622	PED, GWP, AP, POCP, EP, HTP (CML method); GWP, AP, POCP, EP, HTP, TETP, FETP, PMFP, MDP, FDP (ReCiPe method)	CML-IA baseline v3.02 and ReCiPe Midpoint (H) v1.11	China
Cusenza et al. (2019)	LIB pack	Cradle-to-grave	1 battery pack	LMO/NMC424	CED, ADP, GWP, ODP, HT-nce, HT-ce, PM, IR-hh, POFP, AP, EUT, EUF, EUM, EFW	PEF + CED	European
Dai et al. (2019)	LIB pack	Cradle-to-gate	1 kWh	NMC111	GWP, reported as GHG	N/A	United States
Raugei and Winfield (2019)	LIB pack	Cradle-to-gate + EoL	1 kWh	LCP	CED, GWP	GaBi 6 software	European
Peters et al. (2017)	LIB pack	Cradle-to-gate	1 kWh	LFP, LFP/LTO, LCO, LCN, LMO, NMC, NCA	GWP, AP, EP, ADP, ODP, HTP, CED	Combination of ReCiPe, CML, EI99, and ILCD	N/A
Kim et al. (2016)	LIB pack	Cradle-to-gate	1 kWh, 1 kg of battery	LMO/NMC	GWP100	N/A	South Korea + United States
Li et al. (2014)	LIB pack	Cradle-to-grave	1 km driven	NMC111	ADP, GWP, AP, EP, ODP, POCP, ETP, HTP	GaBi 6 software	United States
Ellingsen et al. (2014)	LIB pack	Cradle-to-gate	1 battery, 1 kg of battery, 1 kWh	NMC111	GWP100, FDP, ODP, POFP, PMFP, TAP100, FEP, MEP, FETP, METP, TETP, HTP, MDP	ReCiPe Midpoint (H) v1.08	Norway, East Asia
U.S. Environmental Protection Agency (USEPA) (2013)	LIB pack	Cradle-to-grave	1 km driven, 1 kWh	LMO, NMC424, LFP	ADP, GWP, AP, EP, ODP, POCP, ETP, HTP, occupational cancer hazard, occupational non-cancer hazard	Category-specific LCIA methods, including USEtox	United States + Canada
Majeau-Bettez et al. (2011)	Li-ion and NiMH battery pack	Cradle-to-gate	50 MJ	NiMH, NMC424, LFP	GWP, FDP, FETP, FEP, HTP, METP, MEP, MDP, ODP, PMFP, POFP, TAP, TETP	ReCiPe Midpoint	European
Notter et al. (2010)	LIB pack	Cradle-to-grave	1 km driven	LMO	GWP, CED, EI99 H/A, ADP	CML method + Eco-indicator 99	Brazil, China, and European
Zackrisson et al. (2010)	LIB pack	Cradle-to-use + collection for recycling	1 battery	LFP	GWP, AP, ODP, POCP, EP	N/A	West European

Table 3.1 provides an overview of the main methodological characteristics of the reviewed LCA studies on LIBs. By structuring these methodological aspects in a consistent format, the table enables a clear comparison of how different studies define and approach their assessments.

3.2.1 Goal and Scope

In this section, the methodological choices of the included studies regarding the system boundaries, impact methods, and assessed impact categories are examined and compared. The distribution of the presented categories should not be interpreted as representative of the broader LCA literature, as it reflects the selection criteria applied in this review.

3.2.1.1 LCA Scope and FUs

Figure 3.1 illustrates the system boundaries and FUs reported in the reviewed studies. These reported boundaries should be distinguished from the adjusted boundaries applied later in the benchmarking analysis to improve comparability.

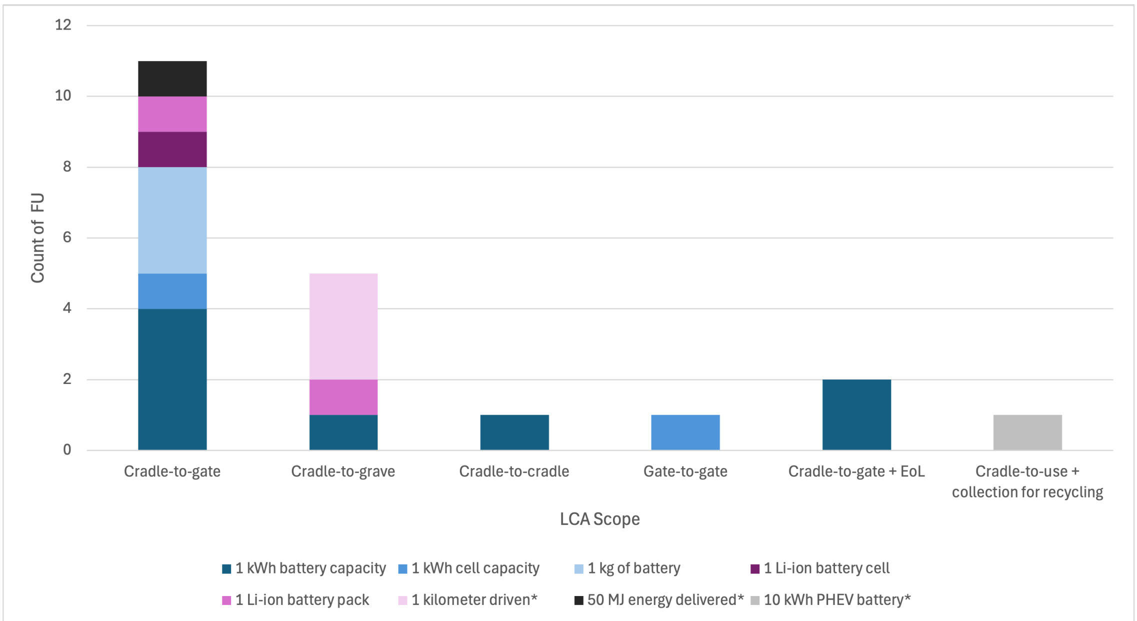

Figure 3.1: Distribution of LCA scope and FUs across the reviewed studies. *1 kilometer driven (3 different variants): 1 average kilometer driven by an EV powered by the LIB pack under average U.S. operating conditions/1 km driven/1 kilometer driven by an EV with Li-ion batteries in Europe. *50 MJ energy delivered: a given amount of energy (50 MJ) accumulated by the battery and then delivered to the powertrain. *10 kWh PHEV battery: A 10 kWh PHEV battery with 3,000 cycles at maximum 80% discharge and a 200 000 km lifetime.

Cradle-to-gate is the most commonly applied system boundary, used in eight studies (the diagram presents a higher value because certain studies employ multiple FUs).

Five studies adopt a cradle-to-grave perspective, while other approaches, such as cradle-to-cradle, gate-to-gate, cradle-to-gate + EoL considerations and cradle-to-use + collection for recycling, are applied less frequently. As mentioned by Temporelli et al. (2020), a cradle-to-grave approach is preferable when feasible, as it captures all stages of the battery life cycle and enables a more comprehensive environmental assessment. However, when the focus is restricted to manufacturing processes, cradle-to-gate or gate-to-gate approaches may be sufficient, although they do not represent the complete life cycle of the battery system.

One study presents inconsistencies between the stated and actual system boundaries. Šimaitis et al. (2023) describe their assessment as cradle-to-grave, although the processes included appear to correspond primarily to cradle-to-gate stages supplemented with a recycling step. Such inconsistencies complicate comparisons between studies and may also contribute to misinterpretation of the reported environmental impacts. This highlights the importance of examining the actual included processes rather than relying only on the stated system boundary. If the stated boundary does not match the included processes, readers may incorrectly assume that the full life cycle has been assessed.

Figure 3.1 also demonstrates a dominance of energy-based FUs. FUs based on battery capacity account for the majority of the reviewed studies, with “1 kWh battery capacity” being the most frequently applied category. This reflects a preference for normalizing environmental impacts according to the energy storage capability of the battery, thereby facilitating comparability. FUs based on battery mass, such as “1 kg of battery”, are also relatively common and represent a material-oriented perspective. In addition, “1 Li-ion battery pack” and “1 kilometer driven” appear in several studies. Distance-based FUs are used in cradle-to-grave studies evaluating batteries within EVs or plug-in hybrid electric vehicles (PHEVs), where transportation service is considered the primary system function.

The FUs category “1 kWh of cell capacity” occurs two times while the rest of the FUs, including “1 Li-ion battery cell”, “50 MJ of delivered energy” and “10 kWh PHEV battery” occur only once among the reviewed studies. In the case of Majeau-Bettez et al. (2011), the use of “50 MJ of delivered energy” may reduce comparability with studies based on battery-capacity FUs. Overall, the variation in system boundaries and FUs shows that the reviewed studies use a wide range of methodological approaches, which can make direct comparisons of environmental results more difficult.

The benchmarking results reflect the pattern noted by Temporelli et al. (2020), that FUs based on battery capacity, particularly 1 kWh, are widely adopted because they both represent the core function of the battery system, to store and deliver energy, and support straightforward comparison between different battery technologies. However, when transportation service constitutes the primary function of the system, distance-based FUs, such as 1 km driven, may be more appropriate. This is particularly relevant for studies such as B. Li et al. (2014), Notter et al. (2010), and USEPA (2013), which evaluate not only the battery itself but the broader vehicle system.

In addition to the variations in system boundaries and functional units, differences were also found in the modelling approach. For example, studies such as Degen and Schütte (2022) and von Drachenfels et al. (2023) seem to be more process-based, while, for example, Ellingsen et al. (2014) and Kim et al. (2016) focused more on materials or component groups.

3.2.1.2 LCA Context, Type and Chemistries

The variation in LCA context, LCA type and chemistries the reviewed studies is illustrated in Figure 3.2.

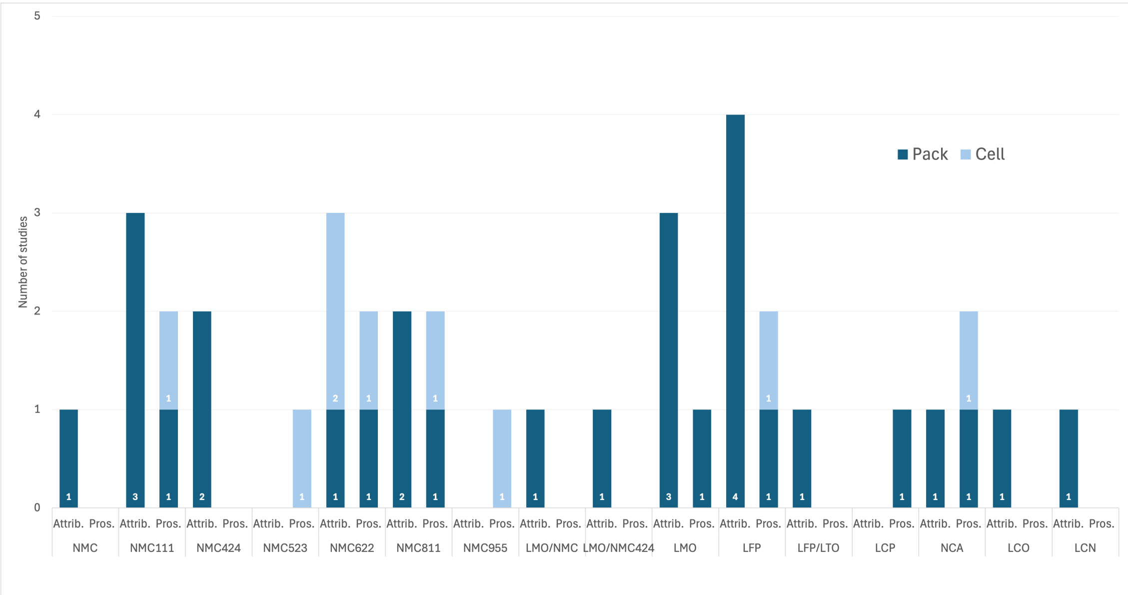

Figure 3.2: Distribution of LCA methodology choices across reviewed studies by battery chemistry, LCA type and LCA context (pack or cell). Attrib. = Attributional, Pros. = Prospective.

As shown in Figure 3.2, the majority of the selected studies apply an attributional LCA approach, while a smaller share use a prospective approach. Note that none of the included studies applied a consequential approach. In total, 15 studies applied an attributional approach, while 3 studies used a prospective approach.

As some studies assessed more than one battery chemistry, the total number represented in the figure exceeds the number of individual studies. Most of the reviewed studies focus on the full LIB pack rather than individual cells. This suggests that the majority of LCAs in this review adopt a system-level perspective, accounting not only for the cell itself but also for components such as BMS, housing, and cooling systems. Such an approach may better reflect real-world EV applications. In contrast, studies limited to individual cells will not capture the full environmental impacts associated with the complete battery system.

Figure 3.2 further shows how the distribution of battery chemistries varies. LFP is the most commonly assessed battery chemistry, appearing in six of the reviewed studies. NMC111 and NMC622 each appear five times, while NMC811 and LMO appear four times. Other battery chemistries do not appear as frequent.

3.2.1.3 Impact Categories and LCIA methods

The selection of impact categories should align with the overall objective of the study (Baumann & Tillman, 2004). In addition, the chosen impact categories need to be comprehensive, ensuring that all major environmental issues associated with the system are adequately addressed. Figure 3.3 shows the frequency of reported impact categories identified across the reviewed studies.

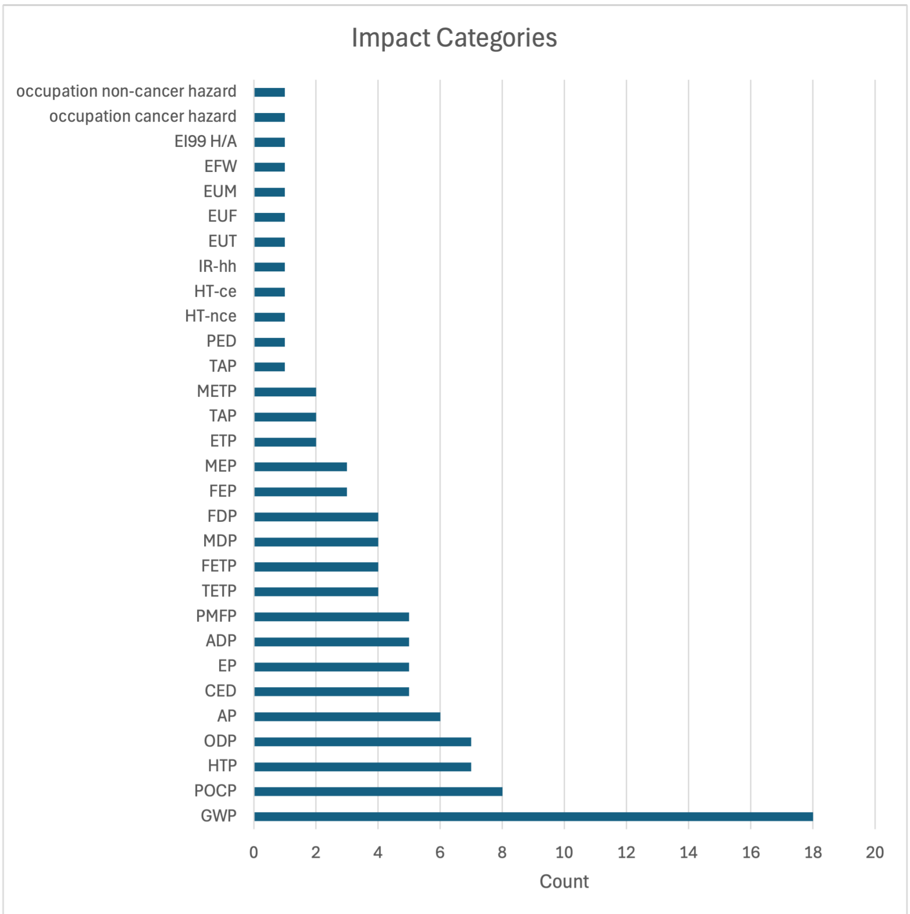

Figure 3.3: Distribution of impact categories assessed in the reviewed studies.

As shown in Figure 3.3, a total of 30 different impact categories are identified across the reviewed studies. The most frequently assessed category is GWP, which is reported in all 18 studies. This is followed by POCP (8 out of 18 studies), as well as HTP and ODP (both included in 7 out of 18 studies).

Six of the reviewed studies (Q. Chen et al., 2022; Clemente et al., 2025; Dai et al., 2019; Kim et al., 2016; Šimaitis et al., 2023; Xu et al., 2022) consider only GWP as the sole impact category. As mentioned by Temporelli et al. (2020), while GWP is highly relevant for assessing climate change impacts, this narrow focus can result in an incomplete evaluation of environmental performance. Excluding other categories risks overlooking important trade-offs and potential burden shifting. As mentioned in section 3.1.4, this is illustrated by Hawkins et al. (2013), who show that although battery EVs generally have lower GWP, they can exhibit higher impacts in other categories. A more comprehensive assessment should therefore include multiple impact categories to capture the full environmental profile.

In the study by Dai et al. (2019), aside from GWP, environmental impacts are reported using indicators such as total energy use, SOx, NOx, and water consumption. However, these are not presented within LCA impact categories or methods, which limits comparability with other studies.

An additional challenge when comparing results across studies is that impact categories and impact assessment methods have evolved over time. A consequence of this is that the studies used different abbreviations for the impact categories. For example, photochemical ozone impacts were reported as both photochemical ozone creation potential (POCP) and photochemical ozone formation potential (POFP), while particulate matter impacts were reported as either particulate matter (PM) or particulate matter formation potential (PMFP). In figure 3.3, the abbreviations POCP and PMFP were used.

In addition to differences in impact categories, differences in impact methods were also observed, as shown in Figure 3.4.

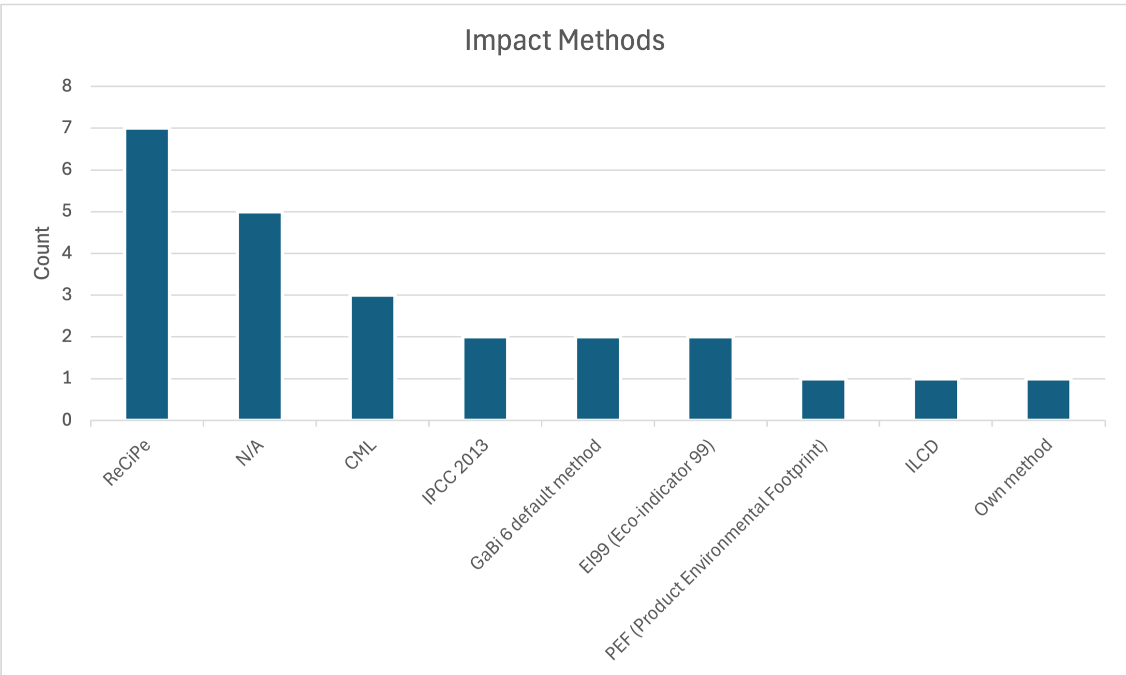

Figure 3.4: Distribution of impact methods.

As shown in Figure 3.4, ReCiPe is the most commonly used impact assessment method among the reviewed studies. CML and GABI default methods are used in three studies each, while methods like IPCC 2013, and EI99 appear twice each. Frameworks such as PEF and ILCD are rarely used, each showing up only once. Overall, the wide mix of methods makes it harder to compare results between studies. The "Own method" refers to the approach used by USEPA (2013), which applied an LCIA methodology that assessed traditional impact categories (not specified which one), while also including human health and aquatic ecotoxicity impacts. For toxicity assessment, it applied the USEtox model developed by the UNEP–SETAC Life Cycle Initiative.

It is also worth noting that Q. Chen et al. (2022), B. Li et al. (2014), and Raugei and Winfield (2019) simply refer to the GaBi default impact method. However, this is not actually a clearly defined method, but rather depends on how the GaBi software is set up in each case. This makes it unclear what has really been applied and reduces transparency.

In addition, in the studies by Dai et al. (2019), Degen and Schütte (2022), Kim et al. (2016), and Zackrisson et al. (2010), the impact categories used are listed but they do not specify the method behind them. These studies are therefore included in the "N/A" bar. This lack of detail makes it more difficult to assess the reliability of the results or compare them with other studies. X. Chen et al. (2021) show that different LCIA methods can differ in, for example, characterization factors and units, which can lead to variations in results even when the same inventory is assessed. This is especially relevant for impact categories other than global warming, where X. Chen et al. (2021) found much larger uncertainty between methods, making it difficult to compare studies that don't specify the impact methods.

3.2.2 Life Cycle Inventory

According to Baumann and Tillman (2004), inventory analysis involves collecting and processing data to quantify the inputs and outputs of the studied system, while ensuring data quality and consistency with the FU and reference flow.

3.2.2.1 Data Types

The data used in the reviewed studies can be divided into primary and secondary data. In this thesis, primary data refers to study-specific information collected directly for the individual LCA study, for example from manufacturers, pilot plants or laboratory measurements. Secondary data refers to data derived from existing sources, such as LCI databases, literature, reports, or other datasets. As mentioned by Raugei and Winfield (2019) primary data is considered more reliable and preferable, meaning that it is strongly recommended to use in LCA studies. Figure 3.5 presents the distribution of data types used in the reviewed studies by comparing studies based solely on secondary data with those combining primary and secondary data.

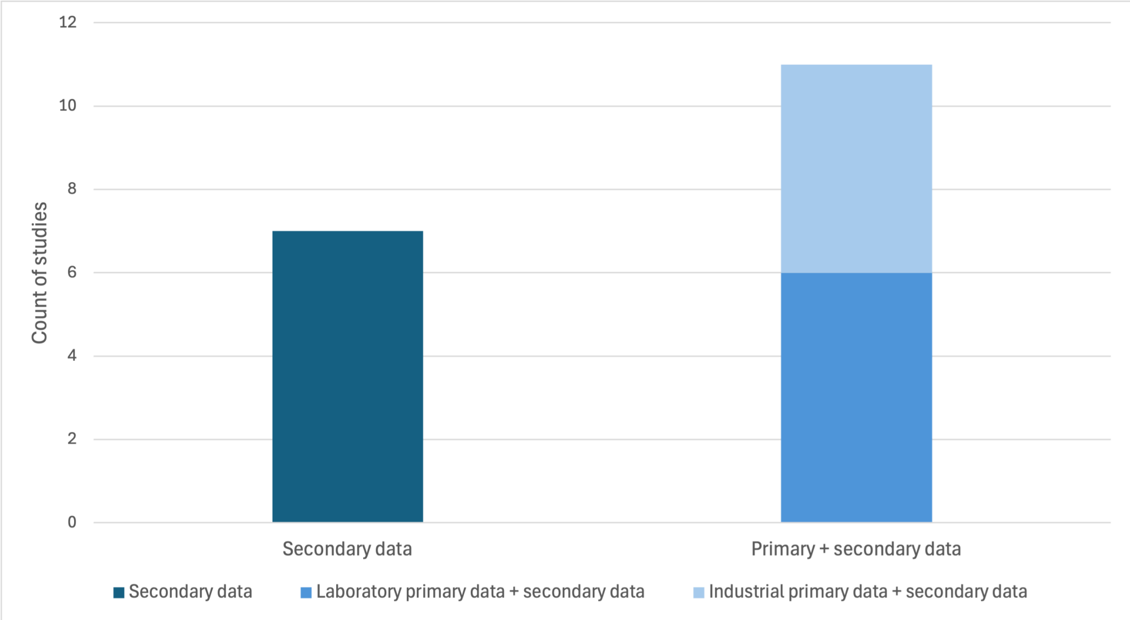

Figure 3.5: Distribution of data types used in the reviewed studies, showing the proportion of studies based on both primary and secondary data versus those relying solely on secondary data.

In Figure 3.5 it can be seen that 11 out of 18 of the analyzed studies use some kind of primary data. The rest, seven studies, only rely on secondary data from literature or databases.

Among the studies relying exclusively on secondary data, five studies (Clemente et al., 2025; Majeau-Bettez et al., 2011; Šimaitis et al., 2023; von Drachenfels et al., 2023; Xu et al., 2022) use different versions of the Ecoinvent database as the source of LCI data. These datasets are generally supplemented with additional information obtained from literature sources. Several studies also utilize the GREET model as a secondary data source (Clemente et al., 2025; Dai et al., 2019; Kim et al., 2016; Sun et al., 2020). GREET is a comprehensive LCA model developed by Argonne National Laboratory. Furthermore, Dai et al. (2019) and Raugei and Winfield (2019) employ the BatPaC model, also developed by Argonne National Laboratory, to support battery-specific modeling and analysis.

Another observation from the reviewed articles is that many LCA studies on lithium-ion batteries rely heavily on secondary data derived from earlier research. In several cases, these data sources are either outdated or associated with uncertain data quality. For example, in the studies Degen and Schütte (2022) and Temporelli et al. (2020), it is shown that a large number of reviewed studies use data from Ellingsen et al. (2014), Majeau-Bettez et al. (2011), and Notter et al. (2010). The same tendency was also observed in the studies reviewed in this work.

Out of the 11 studies that include primary data, six are based on laboratory-scale data, while five rely on industrial-scale data, as shown in Figure 3.5. This suggests a slight dominance of laboratory-based data among the reviewed studies. Among these studies, laboratory- data are applied to different stages of battery production and development. Examples include data from the Research Factory for Battery Cells (FFB) (Degen & Schütte, 2022), experimental anode production (B. Li et al., 2014), and experimental cathode production (Zackrisson et al., 2010).

3.2.2.2 Data Sources and LCI Availability Assessment

Figure 3.6 provides an assessment of the availability of data sources and the accessibility of the LCI data across the reviewed studies, together with their respective system boundaries.

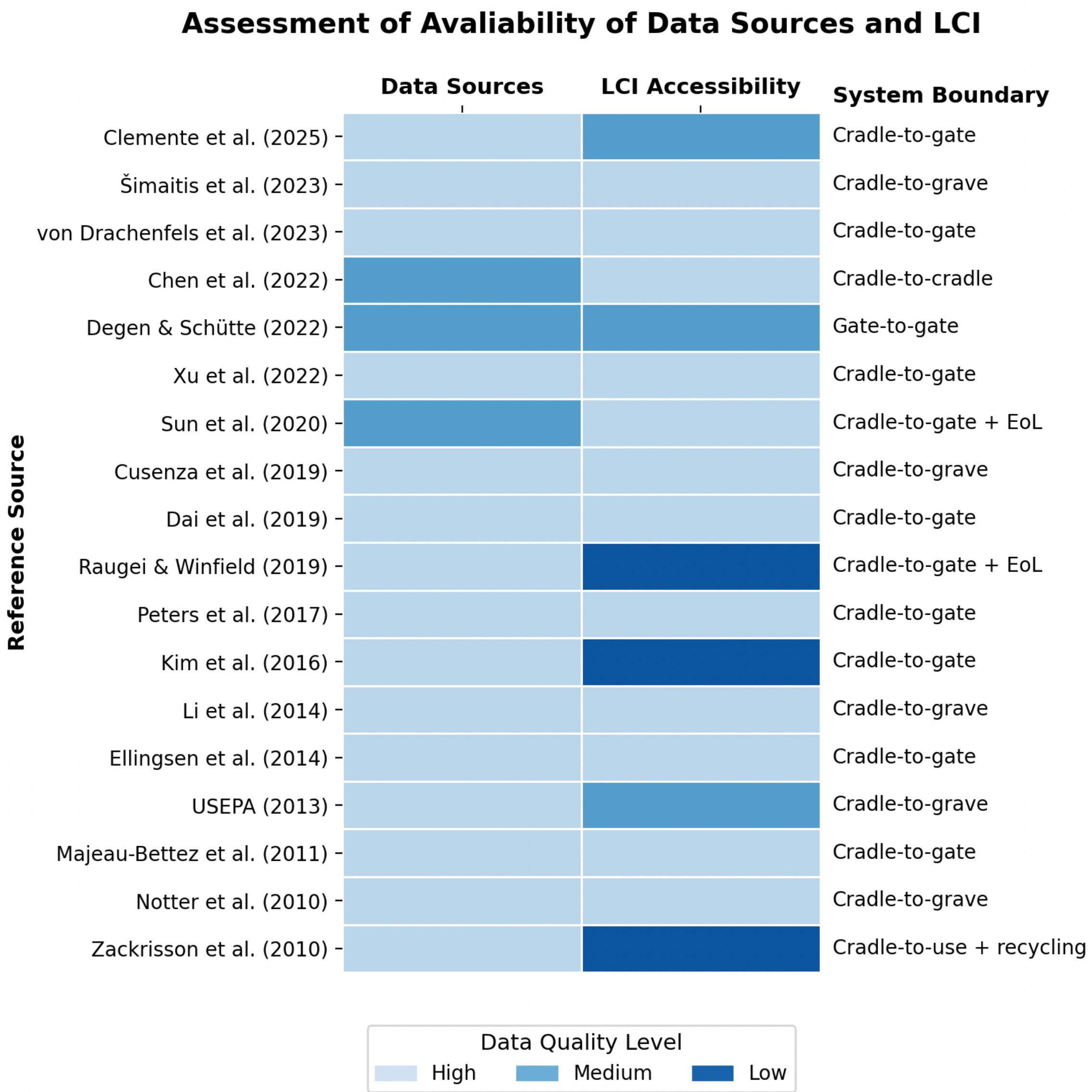

Figure 3.6: Data quality assessment of reviewed studies based on data sources and LCI accessibility. For data sources, transparency was rated as high when data sources were clearly specified, medium when data sources were only partially or ambiguously described, and low when substantial uncertainties existed regarding the data sources. For LCI data accessibility, transparency was rated as high when detailed and accessible data were provided, medium when data lacked sufficient detail or accessibility, and low when LCI data were not accessible or not reported.

Figure 3.6 provides an assessment of the availability of data sources and the accessibility of LCI data across the reviewed studies, together with their respective system boundaries.

As shown in Figure 3.6, the majority of the reviewed studies rely on well-documented data sources, meaning that the data sources were clearly specified. The studies that received medium ratings show partial availability. Q. Chen et al. (2022) lists data sources but refers to electricity and natural gas only as “manufacturer” without further specification. Degen and Schütte (2022) mentions primary data but does not identify the manufacturers and provides limited information on secondary sources, and Sun et al. (2020) includes a general datasource list for materials and energy, but lacks detail on the sources for industrial primary data.

As shown in Figure 3.6, most studies demonstrate a high level of LCI accessibility. Studies assessed as having medium LCI accessibility were generally limited by insufficient inventory detail or restricted data availability. Clemente et al. (2025) and USEPA (2013) provide relatively simplified LCIs, which reduces the level of detail. Degen and Schütte (2022) were also classified as medium, as the available LCI documentation is brief. However, this may partly reflect the study's gate-to-gate system boundary, where upstream material production and other life cycle stages are excluded and therefore require less inventory reporting.

For three of the studies, LCI accessibility was assessed as low. Kim et al. (2016) provided only restricted inventory information due to confidentiality constraints, reflecting a broader challenge in battery LCA where production data are often considered commercially sensitive (Ellingsen et al., 2017). In contrast, Raugei and Winfield (2019) and Zackrisson et al. (2010) did not provide supplementary material or accessible inventory datasets, limiting access to the underlying LCI data.

As noted in 2.2.6, it is important to distinguish between data accessibility and data traceability, as accessible data does not necessarily guarantee that the underlying data can be fully traced or verified.

3.2.3 Life Cycle Impact Assessment

This chapter presents and compares the environmental impact results reported across the different sources examined in this study. In addition, the chapter highlights the main sources of emissions identified in the reviewed studies, providing an overview of the dominant environmental hotspots throughout the battery lifecycle. Observe that the system boundaries and associated impact values presented in the figures and results have been refined from the original studies according to the approach described in Section 2.2.4. Figure 3.7 is an exception, as it reflects the system boundaries reported in the original studies.

3.2.3.1 Main source of emission

Figure 3.7 illustrates the frequency with which different life cycle stages or processes are identified as the main contributors to GWP across the reviewed studies. It should be noted that the system boundary categories shown in the figure reflect the boundaries reported in the original studies, rather than the refined boundaries later applied in results for comparative analysis.

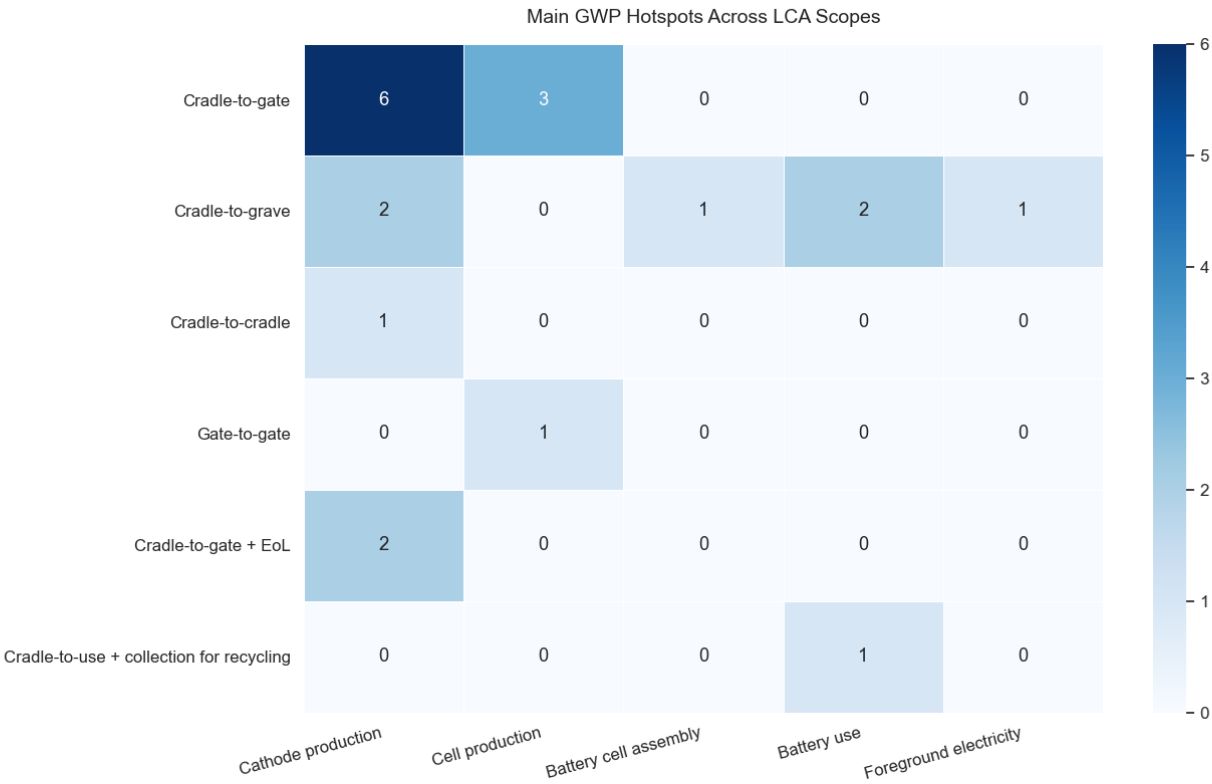

Figure 3.7: Distribution of identified main GWP hotspots across reviewed studies.

Figure 3.7 illustrates the frequency with which different life cycle stages or processes are identified as the main contributors to GWP across the reviewed studies. It should be noted that the system boundary categories shown in the figure reflect the boundaries reported in the original studies, rather than the refined boundaries later applied in results for comparative analysis. The figure show that cathode production is the most frequently reported hotspot overall, particularly in studies adopting a cradle-to-gate scope, where it dominates the reported impacts. Cathode production is also identified as the primary hotspot in cradle-to-cradle and cradle-to-gate + EoL studies. These findings highlight the substantial environmental burden associated with cathode production.

For studies incorporating the usephase, the impacts are more evenly distributed across several hotspots, with cathode production and the use phase being the most frequently reported. This suggests that when the operational lifetime of the battery is included, electricity consumption during battery use can contribute significantly to total GWP impacts, and greening of the electricity mix could reduce the impacts significantly (B. Li et al., 2014). In a smaller number of cradle-to-grave studies, battery cell assembly and foreground electricity are identified as the dominant hotspots (Cusenza et al., 2019; Šimaitis et al., 2023). The variation in reported hotspots across cradle-to-grave studies demonstrates how methodological assumptions, electricity mixes, and modeling choices can affect which life cycle stage is identified as the main contributor to environmental impacts.

It is important to note that the reviewed studies report impacts in different details of the life cycle stages. Some studies distinguish specific processes, such as cathode production for example Q. Chen et al. (2022), Clemente et al. (2025), and Sun et al. (2020), whereas others report broader categories, such as cell production (Kim et al., 2016). Consequently, cathode production may still constitute the dominant contributor within the broader cell production stage, even when it is not explicitly identified as a separate hotspot.

3.2.3.2 GWP Results

Figure 3.8 presents reported cradle-to-gate GWP values for different LIB chemistries collected from the reviewed literature.

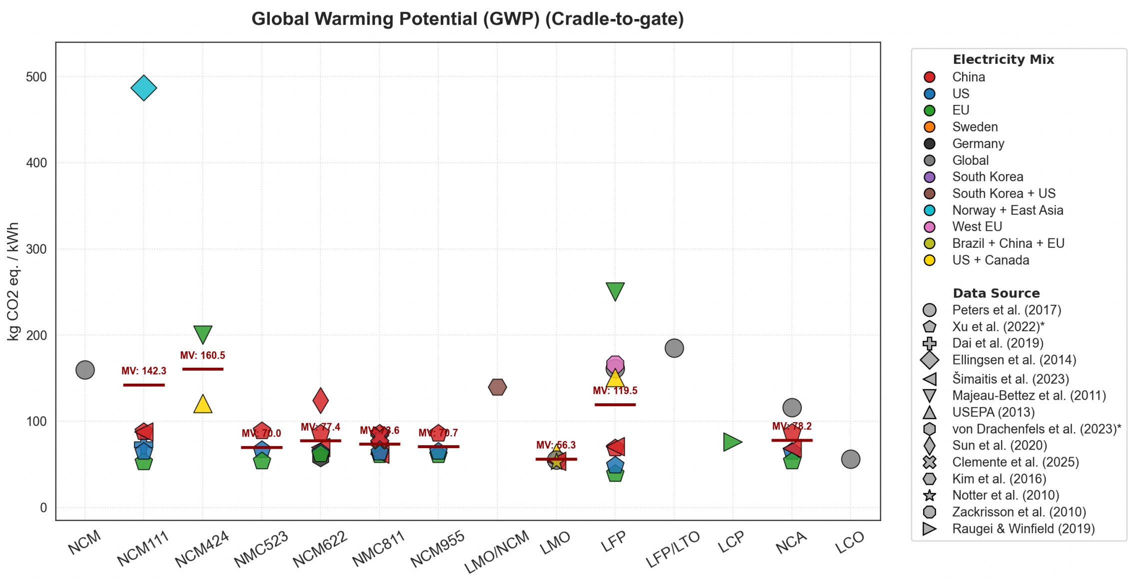

Figure 3.8: Reported cradle-to-gate GWP (kg CO_2 eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by electricity mix and shaped by source. Red horizontal lines indicate mean values for each chemistry. * LCA Context is one Li-ion Cell.

Figure 3.9 presents reported cradle-to-gate GWP values, in the range 0-250 kg CO_2 eq./kWH, for different LIB chemistries collected from the reviewed literature. The exact numbers for all studies can be found in appendix A.6.

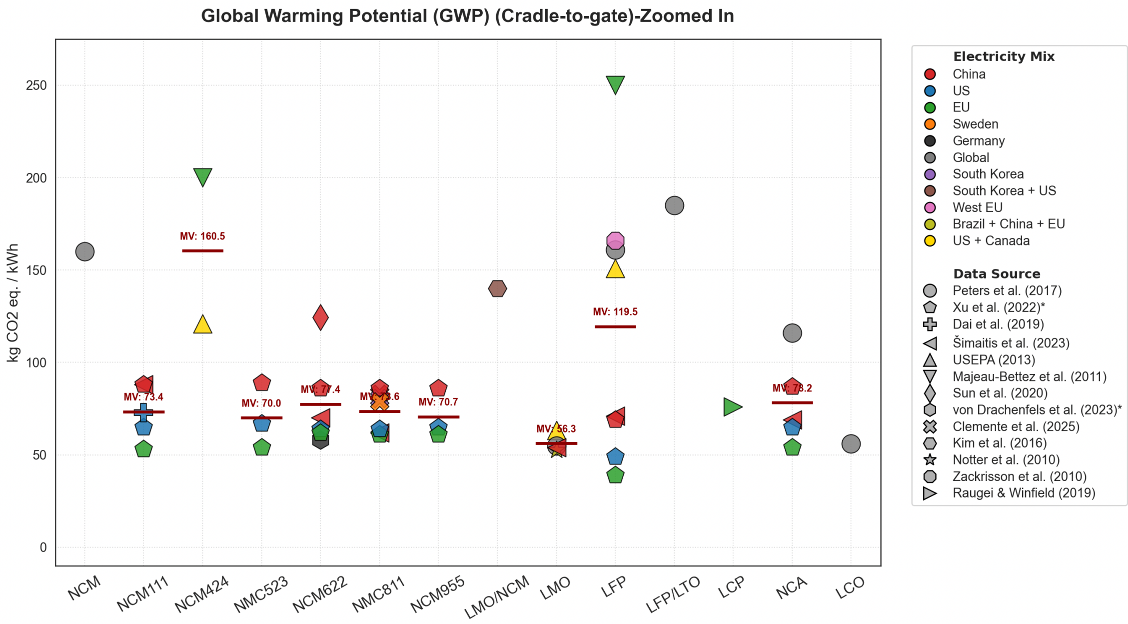

Figure 3.9: Reported cradle-to-gate GWP (kg CO_2 eq./kWh) for different LIB chemistries across multiple studies, zoomed in excluding outliers. Each point represents a literature value, coloured by electricity mix and shaped by source. Red horizontal lines indicate mean values for each chemistry. * LCA Context is one Li-ion Cell.

Overall, the results in Figure 3.8 show large variation both within and between battery chemistries. For several NMC-based batteries, most reported values cluster between approximately 50-90 kg CO_2/kWh, although some studies report considerably higher impacts. An observable tendency is that several older studies, such as Ellingsen et al. (2014), Majeau-Bettez et al. (2011), USEPA (2013), Zackrisson et al. (2010), and Kim et al. (2016), report higher values than many of the more recent publications.

The largest variability is observed for the LFP, NMC111, and NMC424 chemistries, where GWP values span a wide range. In Figure 3.8, for the NMC111 chemistry, Ellingsen et al. (2014) stands out as a clear outlier, reporting substantially higher GWP values than all other studies, which is discussed more in detail in Section 4.1.3. Regarding the LFP chemistry, the GWP results also vary substantially between studies, with Majeau-Bettez et al. (2011) reporting the highest value. These figures indicate that differences between studies using the same chemistry can be as large as, or larger than, the differences between chemistries themselves.

The mean values indicate some differences between chemistries. Based on the mean values, NMC424 and LFP batteries exhibit the highest average GWP values among the reviewed cradle-to-gate studies, while LMO shows the lowest average impact. NCA batteries also display relatively high average values compared to several NMC chemistries. However, the mean values for the different NMC chemistries appear relatively similar to each other.

When looking at the 50–90 kg CO_2-eq./kWh range, the lower GWP values are generally associated with cleaner electricity systems, such as those in the EU, whereas higher values tend to be linked to more carbon-intensive mixes, such as China. However, there are notable exceptions to this trend. For example, the highest reported value for LFP is associated with an EU electricity mix, while the high value reported by Ellingsen et al. (2014) for NMC111 is based on a Norwegian and East Asian electricity mix. The influence of electricity mix is more clearly visible when comparing scenarios within the same study, such as in Clemente et al. (2025) and Xu et al. (2022). In contrast, the effect becomes less distinct when comparing results across different studies, suggesting that other methodological differences play a substantial role. Another observation is that the results reported by Peters et al. (2017) are relatively high. However, these results are based on a synthesis of previous LCA studies of LIBs rather than a specific original model, and therefore do not apply a single specific electricity mix, which may partly explain their high impact values.

It is worth noting that the impact results by Degen and Schütte (2022) are not included in the plots, since they were the only study applying a gate-to-gate scope. Due to this narrower scope, their reported GWP differs substantially from the other studies, with a value of 10.33 kg CO_2-eq./kWh cell capacity. Another point worth noting is that von Drachenfels et al. (2023) and Xu et al. (2022), similarly to Degen and Schütte (2022), report results at the cell level, whereas the other studies assess complete battery packs. Since pack-level assessments include additional components, such as casing, BMS, and cooling systems, and sometimes related assembly processes, greater variation between these two system levels could be expected. From this perspective, the relatively high results reported by Clemente et al. (2025) and Xu et al. (2022), are somewhat unexpected and may indicate particularly high environmental burdens associated with the cell production stage.

The next figure, Figure 3.10 compares the cradle-to-grave GWP of different LIB chemistries under various electricity mixes and data sources.

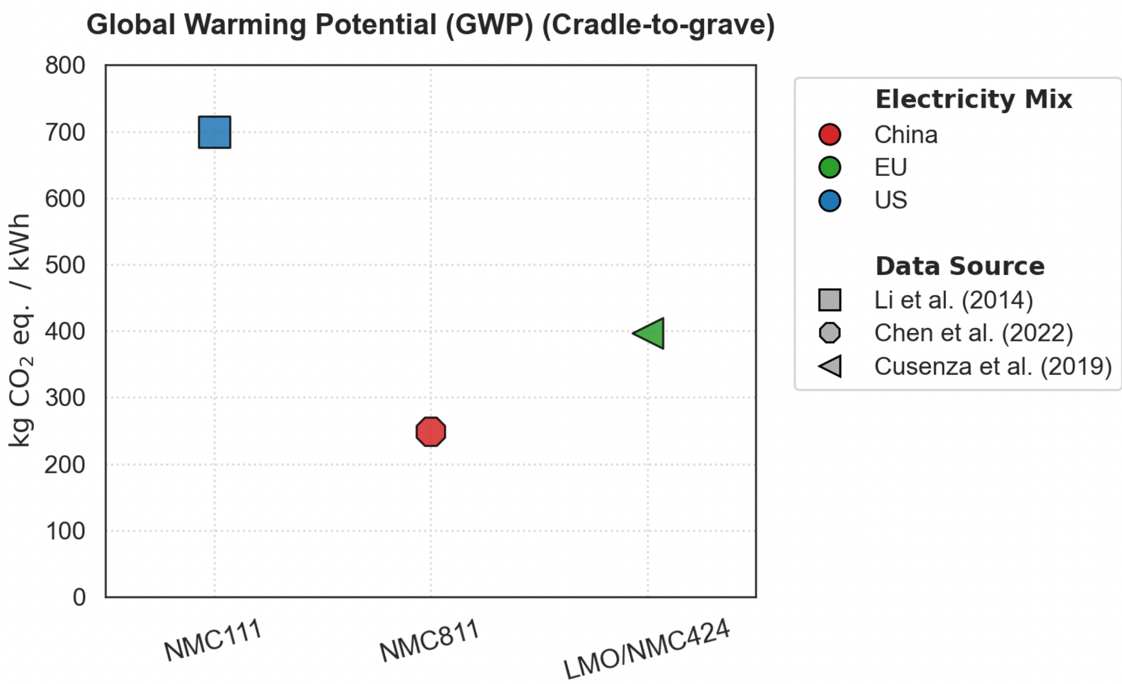

Figure 3.10: Reported cradle-to-grave GWP (kg CO_2 eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by electricity mix and shaped by source.

The results in Figure 3.10 show substantial variation between studies and associated chemistries. The highest reported GWP is observed for the NMC111 battery in Li et al. (2014), with a value of approximately 700 kg CO_2 eq./kWh. In comparison, Chen et al. (2022) report a considerably lower value for NMC811, around 250 kg CO_2 eq./kWh, while Cusenza et al. (2019) report approximately 400 kg CO_2 eq./kWh for the LMO/NMC424 chemistry. An interesting finding is that the study using a Chinese electricity mix has the lowest impact. As also observed in 3.8 and 3.9, the results indicate that the differences cannot be attributed to electricity mix alone.
The results in Figures 3.8, 3.9 and 3.10 show that the GWP of LIBs varies widely across studies. As expected, cradle-to-grave results are generally higher than cradle-to-gate results, as they include additional life cycle stages such as use and EoL. However, some cradle-to-gate studies report higher values, indicating that differences in impact results are not only influenced by variations in system boundaries. At the same time, comparability remains limited due to inconsistent assumptions across life cycle stages and the relatively small number of available studies.

In terms of chemistry, LFP and NMC424 batteries generally show higher and more variable impacts. Overall, the results should be interpreted with caution, as the observed differences cannot be attributed to battery chemistry alone.

3.2.3.3 CED Results

Figure 3.11 compares the CED of various LIB chemistries across different life-cycle scopes and sources.

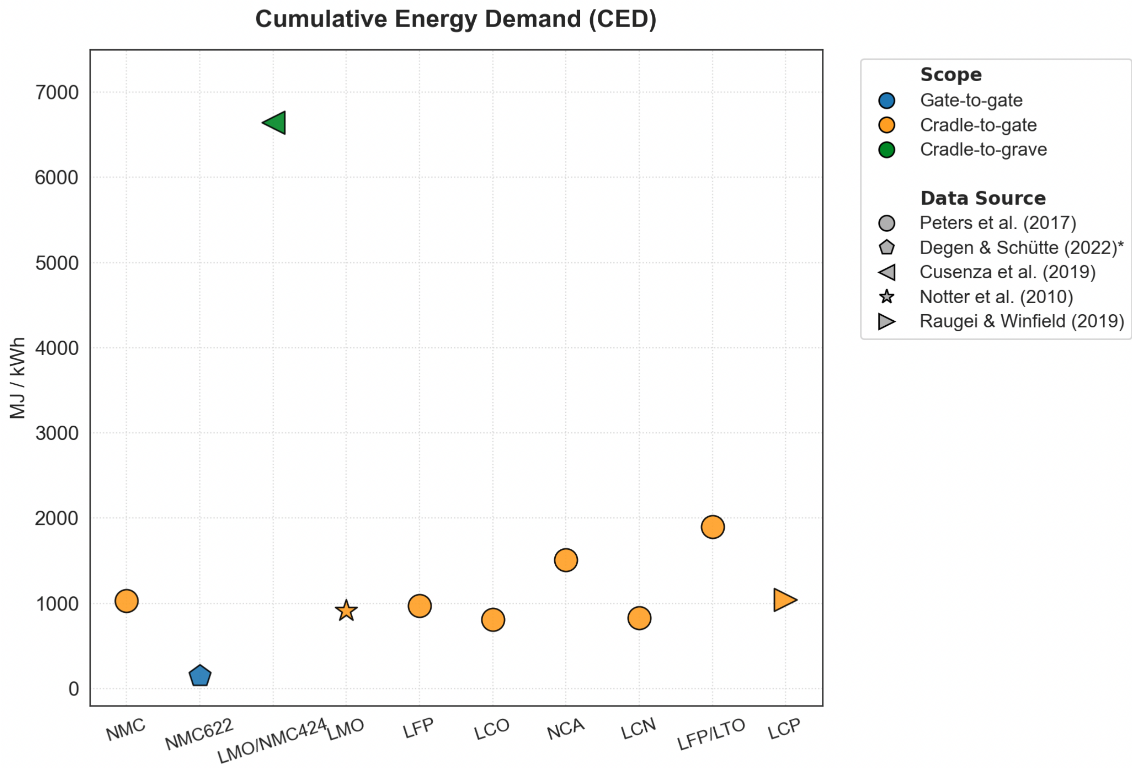

Figure 3.11: Reported CED (MJ/kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. *LCA Context is one Li-ion Cell.

Figure 3.11 shows that the studies encompassing cradle-to-gate scope are quite similar in the CED values, with most values falling between roughly 800 and 2000 MJ/kWh. However, within this range, the LFP/LTO and NCA chemistry appears at the higher end, suggesting a more energy-intensive production. In contrast, LCO and LCN seem to be at the lower end for the cradle-to-gate scope. The very low value reported for NMC622 from Degen and Schütte (2022) stands out, likely reflecting a more limited system boundary (gate-to-gate). Similarly, for Cusenza et al. (2019), the high value for the LMO/NMC424 illustrates how cradle-to-grave assumptions can substantially increase reported impacts by including use-phase and EoL processes.

3.2.3.4 AP Results

Figure 3.12 presents the AP of different LIB chemistries under cradle-to-gate boundaries.

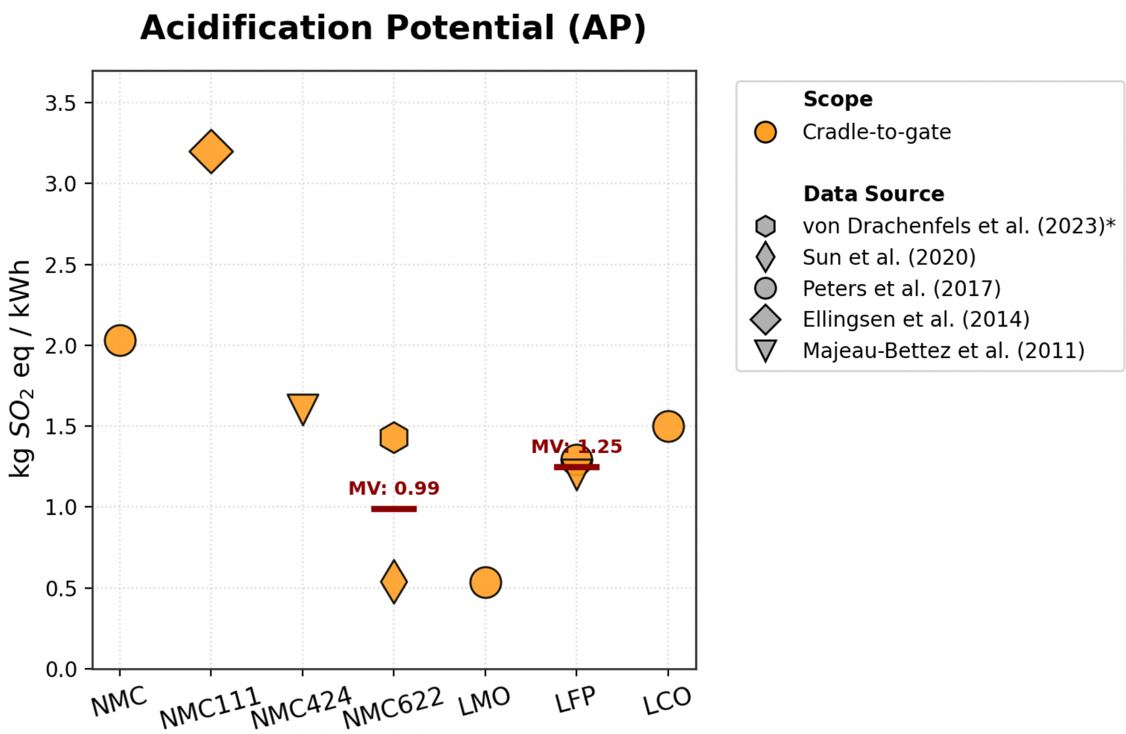

Figure 3.12: Reported AP (kg SO_2 eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean values for each chemistry. *LCA Context is one Li-ion Cell

The results presented in Figure 3.12 demonstrate substantial variability in AP across both battery chemistries and literature sources. Among the assessed chemistries, NMC111 Ellingsen et al. (2014) exhibits the highest AP value, followed by NMC (Peters et al., 2017) and NMC424 (Majeau-Bettez et al., 2011). In contrast, LMO (Peters et al., 2017) shows the lowest mean AP value, followed by NMC622. For LFP, the reported results by Majeau-Bettez et al. (2011) and Peters et al. (2017) are relatively consistent, clustering around a mean value of 1.25 kg SO_2-eq/kWh. It should be noted that more studies reported acidification results, but in other units than kg SO_2-eq./kWh. These results were therefore excluded from Figure 3.12 to maintain unit consistency, with study-specific details provided in Appendix B.1.

3.2.3.5 EP Results

Figure 3.13 compares EP, MEP and FEP, for different LIB chemistries across different LCA scopes and studies.

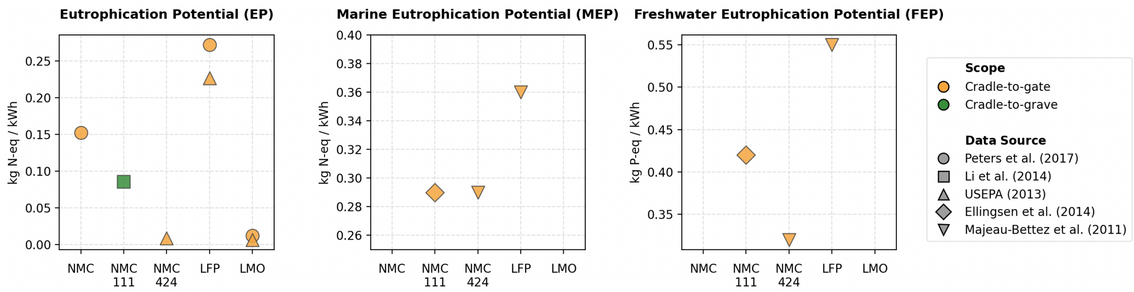

Figure 3.13: Reported EP (kg N-eq./kWh), MEP (kg N eq./kWh) and FEP (kg P eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source.

Figure 3.13 illustrates substantial variation in eutrophication-related impacts across LIB chemistries and impact categories. For EP, values range from approximately 0.006 kg N-eq/kWh for LMO (USEPA, 2013) and NMC424 (USEPA, 2013) to around 0.27 kg N-eq/kWh for LFP (Peters et al., 2017). NMC111 (B. Li et al., 2014) shows an intermediate EP value of approximately 0.085 kg N-eq/kWh and is the only chemistry represented by a cradle-to-grave study, which interestingly reports lower impacts than several cradle-to-gate studies for other chemistries.

For MEP, the reported values exhibit a variation between the NMC and LFP chemistry. Where LFP (Majeau-Bettez et al., 2011) demonstrates the highest MEP value at approximately 0.36 kg N-eq/kWh, indicating a greater contribution to MEP than for NMC. Interestingly, the NMC111 (Ellingsen et al., 2014) and NMC424 (Majeau-Bettez et al., 2011) both have an impact of 0.29 kg N-eq/kWh, which could suggest that the different NMC ratios do not affect MEP.

In contrast, the FEP results, a large variation can be seen within the NMC ratios. NMC424 (Majeau-Bettez et al., 2011) reports the lowest impact at approximately 0.32 kg P-eq/kWh. NMC111 (Ellingsen et al., 2014), shows a moderate impact of around 0.42 kg P-eq/kWh, while LFP again exhibits the highest value, at approximately 0.55 kg P-eq/kWh. These findings suggest that LFP batteries tend to be associated with higher eutrophication impacts across multiple categories, whereas NMC424 generally demonstrates lower impacts within the available dataset. Additionally, the contribution to FEP seems to be larger than to MEP.

3.2.3.6 ODP Results

Figure 3.14 illustrates the ODP of various LIB chemistries across cradle-to-gate and cradle-to-grave LCA scopes.

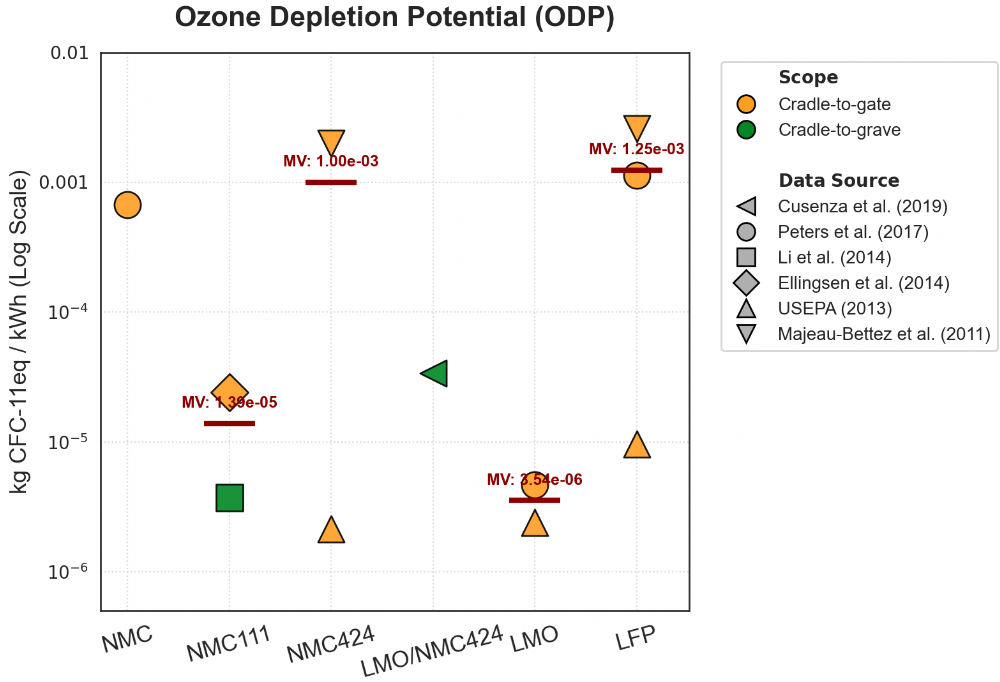

Figure 3.14: Reported ODP (kg CFC-11 eq-/kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean values for each chemistry. The results are presented on a logarithmic scale.

The results show considerable variability in ODP across battery chemistries and literature sources, with values ranging from approximately 2.13×10^{-6} (USEPA, 2013) to 2.6×10^{-3} (Majeau-Bettez et al., 2011) kg CFC-11 eq/kWh. LFP and NMC424 exhibit the highest reported ODP values, while LMO shows lower impacts. Interestingly, some cradle-to-gate studies report higher ODP values than cradle-to-grave assessments. USEPA (2013) tends to report lower values for all three assessed chemistries, and Majeau-Bettez et al. (2011) higher values for their assessed chemistries. The figure also shows that differences between studies for the same chemistry are in some cases larger than the observed impact differences between chemistries.

3.2.3.7 POCP Results

Figure 3.15 illustrates the POCP of various LIB chemistries across cradle-to-gate and cradle-to-grave LCA scopes.

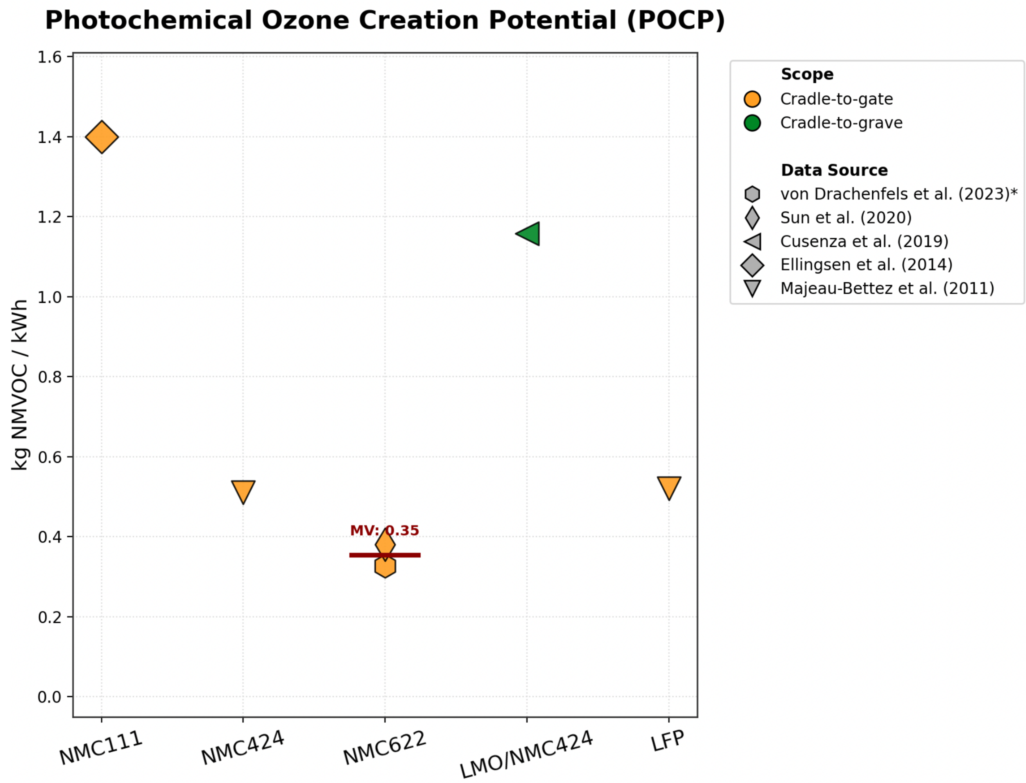

Figure 3.15: Reported POCP (kg NMVOC/kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean values. * LCA Context is one Li-ion Cell

Figure 3.15 shows variation in POCP values across the assessed chemistries and studies. NMC111 reported by Ellingsen et al. (2014) exhibits the highest value, followed by LMO/NMC424 in Cusenza et al. (2019). The lowest values are observed for NMC644, as reported by Sun et al. (2020) and von Drachenfels et al. (2023). Notably, the value reported by von Drachenfels et al. (2023) is close to that of Sun et al. (2020), despite being reported at the cell level rather than for a full battery pack. This suggests that cell production assumptions may strongly influence the POCP results. LFP shows relatively low impacts for AP and POCP, in contrast to some other impact categories where it appears higher relative to other chemistries.

It should be noted that more studies reported POCP results, but in other units than kg NMVOC/kWh. These results were therefore excluded from Figure 3.15 to maintain unit consistency, with study-specific details provided in Appendix B.1.

3.2.3.8 PMFP Results

Figure 3.16 illustrates the PMFP of various LIB chemistries across cradle-to-gate and cradle-to-grave LCA scopes.

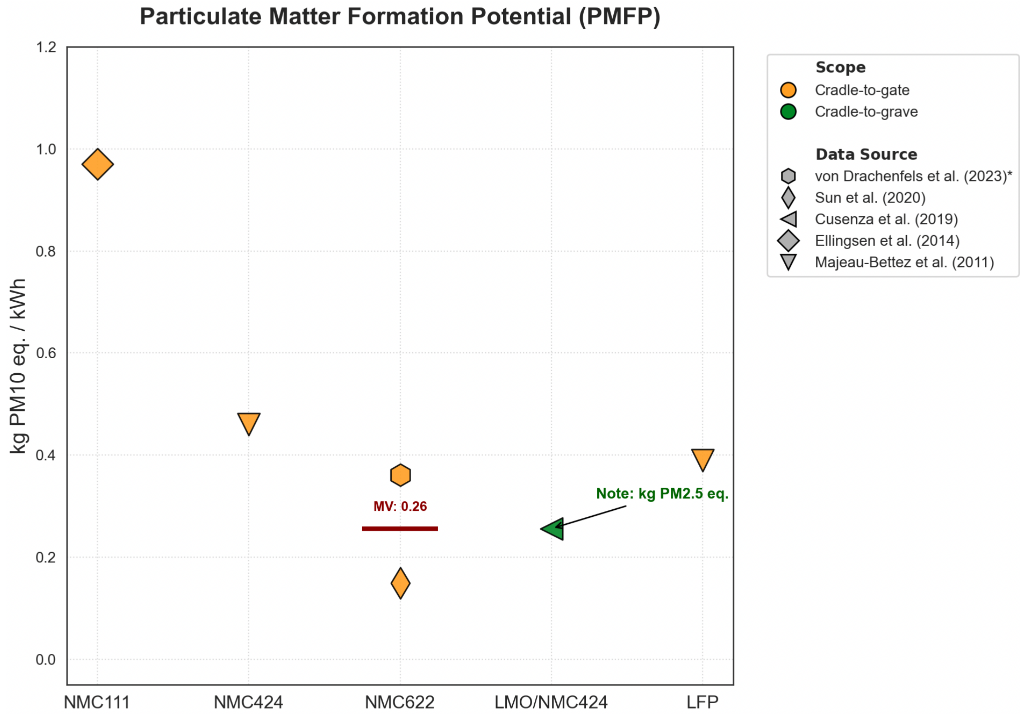

Figure 3.16: Reported PMFP (kg PM10 eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean value. * LCA Context is one Li-ion Cell

The results in 3.16 show noticeable variation in PMFP across both battery chemistries and studies. The highest reported value is observed for NMC111 (Ellingsen et al., 2014), reaching close to 1.0 kg PM10 eq./kWh. Relatively high values are also reported for NMC424 (Majeau-Bettez et al., 2011) and for LFP (Majeau-Bettez et al., 2011). In contrast, NMC622 (Sun et al., 2020; von Drachenfels et al., 2023) shows the lowest mean PMFP value. The LMO/NMC424 value reported by Cusenza et al. (2019) appears comparatively low, although this result is not fully comparable since it is expressed in kg PM2.5 eq./kWh rather than kg PM10 eq./kWh. Again, it should be noted that the study by von Drachenfels et al. (2023) assesses a cell rather than a full battery pack, which limits direct comparability with the other studies. Interestingly, the impact on a cell-level on PMFP is larger than pack-level impacts reported by Sun et al. (2020).

3.2.3.9 ADP Results

Figure 3.17 illustrates the ADP of various LIB chemistries across cradle-to-gate and cradle-to-grave LCA scopes.

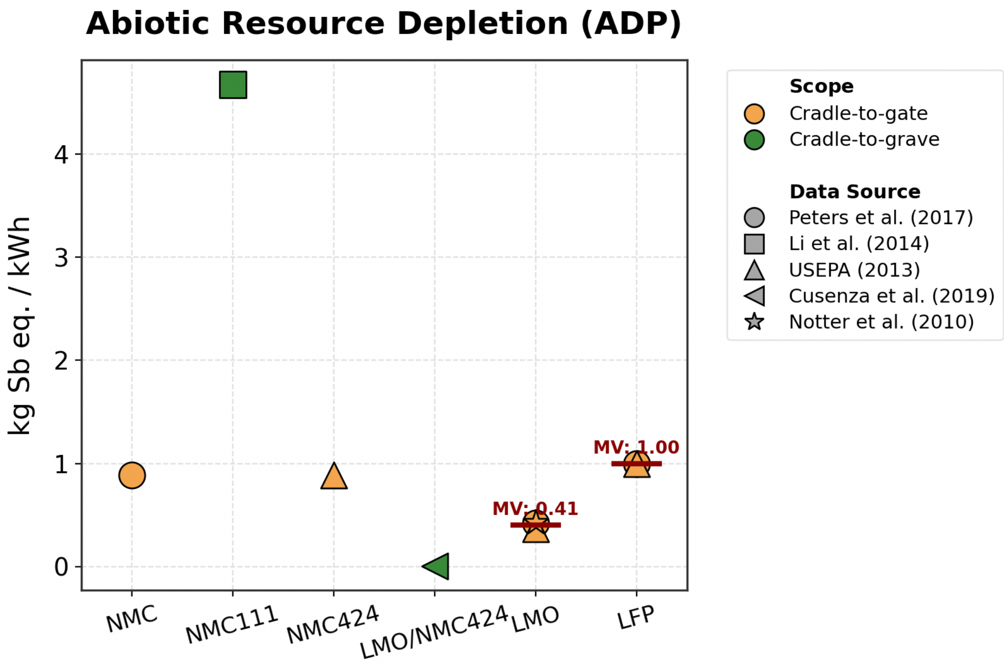

Figure 3.17: Reported ADP (kg Sb eq./kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean values within chemistry.

Figure 3.17 shows a somewhat smaller variability in ADP across different battery chemistries, especially the impact results within the LMO and LFP chemistries. NMC111 (B. Li et al., 2014), exhibited the highest ADP value at approximately 4.7 kg Sb eq./kWh under a cradle-to-grave system boundary. In contrast, the LMO/NMC424 chemistry reported by Cusenza et al. (2019), which also applied a cradle-to-grave scope, interestingly showed the lowest impact, with a value close to zero.

NMC (Peters et al., 2017), NMC424 (USEPA, 2013) and LFP (Peters et al., 2017; USEPA, 2013), showed intermediate ADP values of around 1 kg Sb eq./kWh, while LMO (Notter et al., 2010; Peters et al., 2017; USEPA, 2013) exhibited a somewhat lower mean value of approximately 0.41 kg Sb eq./kWh.

Additionally, It should be noted that more studies reported ADP results, but in other units than kg NMVOC/kWh. These results were therefore excluded from Figure 3.17 to maintain unit consistency, with study-specific details provided in Appendix B.1.

3.3 Modelling of Module and Pack Assembly

This section presents the reported energy demand associated with battery assembly, assembly modelling approach developed in this study, and additionally, the data used to support the modelling of module and pack assembly processes.

3.3.1 Energy Demand for Assembly

Only five studies reported energy demand for module and pack assembly. The results, illustrated in Figure 3.18, reveal substantial variation in the reported energy demand across these assembly stages.

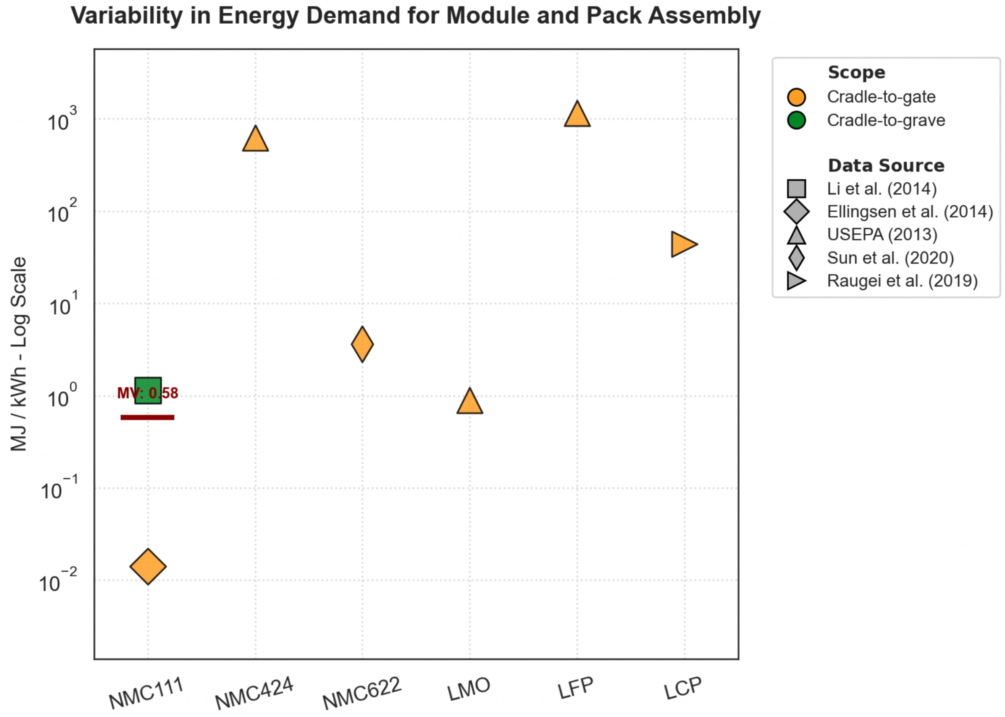

Figure 3.18: Reported energy consumption for module and pack assembly (MJ/kWh) for different LIB chemistries across multiple studies. Each point represents a literature value, coloured by LCA Scope and shaped by source. Red horizontal lines indicate mean values within chemistry. The results are presented on a logarithmic scale due to the wide range of reported energy demand.

One of the most notable observations is the extremely large spread in reported values, ranging from approximately 0.01 MJ/kWh to more than 1000 MJ/kWh. This corresponds to several orders of magnitude and highlights the substantial variability and uncertainty that currently exist in the literature regarding assembly energy demand.

No clear pattern can be observed across battery chemistries, where energy demand for NMC111 (Ellingsen et al., 2014; B. Li et al., 2014) show very different values. This variation within a single chemistry is larger than the differences between chemistries. The highest energy demand is reported for LFP (USEPA, 2013). Note that, Dai et al. (2019) is not included in the figure because the results are presented on a logarithmic scale, where a value of zero cannot be shown. In their study, module and pack assembly is reported as manual, and no energy demand is therefore assigned to battery pack assembly.

The variability seen in Figure 3.18 is further reflected in the literature on battery assembly processes. As mentioned in the state-of-the art review, studies, such as

Dai et al. (2019) and Ellingsen et al. (2014), assume that module and pack assembly involve no energy-intensive steps while other studies, including Raugei and Winfield (2019) and USEPA (2013) identify battery assembly as an energy-consuming process with a meaningful contribution to overall greenhouse gas emissions.

Taken together, these inconsistencies point to a clear data gap and a lack of consensus regarding the energy intensity of module and pack assembly. As highlighted in a report by Dunn et al. (2014), obtaining reliable and representative data remains challenging due to limited data access, ongoing industrial scale-up, and that much of the manufacturing data is confidential.

3.3.2 Assembly Modelling

In response to the large variability and comparability issues identified in the literature regarding assembly processes, this study models module assembly and pack assembly as two separate stages. The results from the developed assembly models are presented in Figure 3.19 and Figure 3.20, providing a more structured and consistent basis for evaluating the contribution of assembly processes to overall battery production impacts.

The separation of module and pack assembly was considered necessary because reported energy demands are highly dependent on system boundaries and modelling assumptions, which differ substantially between studies and are often insufficiently defined. Modelling the stages separately improves transparency and comparability by allowing assumptions and data inputs to be adjusted independently for each stage. This provides a more consistent framework for estimating assembly-related energy demand.

The process mapping of both module and pack assembly was primarily based on a report developed through the collaboration between the PEM of RWTH Aachen University and VDMA (2023), which provides a detailed and structured description of industrial battery assembly processes. However, it should be noted that the processes described in the report primarily reflect a European manufacturing context. Since this thesis does not focus on one specific battery format, the process map was developed to provide a general representation of module and pack assembly that can be applied across prismatic, cylindrical, and pouch cell-based battery systems. However, some process steps and component inputs may need to be adjusted or refined when applying the model to a specific cell format or battery design.

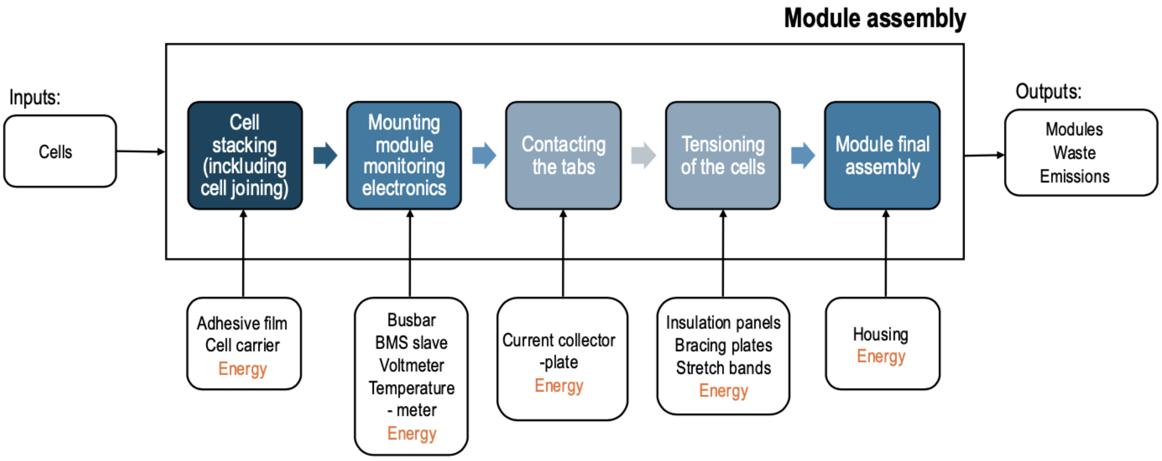

Figure 3.19: Schematic representation of the module assembly process, outlining the sequence from cell stacking to final module assembly. Main material inputs and energy use at each stage are indicated, together with the resulting outputs. Adapted from PEM of RWTH Aachen University and VDMA (2023)

The module assembly process begins with individual battery cells as input and consists of several stages that transform the cells into a completed battery module, as illustrated in Figure 3.19. Initially, the cells are stacked and joined using adhesive films and cell carriers to form the module structure. Components such as busbars, BMS slave boards, voltmeters, and temperature sensors and then mounted on the module. It can be done by, for example, laser welding or bolting. In the following stage, the cell tabs are electrically connected to current collector plates through welding or other methods. The cells are then tensioned using insulation panels, bracing components, and stretch bands to improve structural stability and safety. Finally, the module is assembled and secured for integration into a battery pack. Throughout the process, energy inputs are required, while the outputs consist of finished modules, waste, and associated emissions.

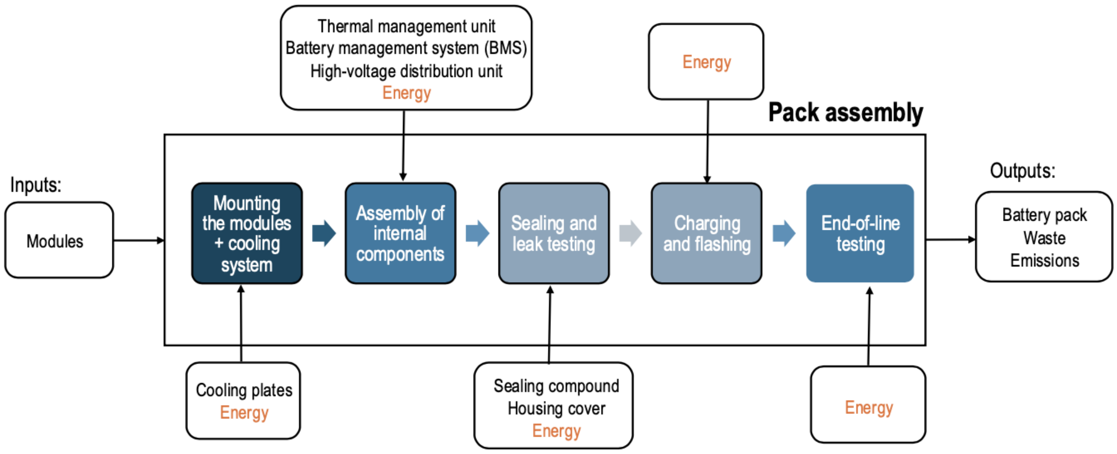

Figure 3.20: Schematic representation of the pack assembly process, outlining the sequence from mounting the modules and cooling system to end-of-line testing. Main material inputs, and energy use at each stage are indicated, together with the resulting outputs of the battery module, waste, and emissions. Adapted from PEM of RWTH Aachen University and VDMA (2023).

The pack assembly process begins with completed battery modules as the primary input and consists of several stages that transform the modules into a finished battery pack, as illustrated in Figure 3.20. Initially, the modules are mounted together with the cooling system using, consisting of cooling plates. Internal components, including the thermal management unit, BMS, and high-voltage distribution unit, are subsequently assembled into the pack structure. The pack then undergoes sealing and leak testing, which requires sealing compounds and housing covers. Following this, the battery pack is charged and flashed to configure and initialize the control systems before end-of-line testing is performed to verify functionality and quality. Throughout the process, energy inputs are required, while the outputs consist of finished battery packs, waste, and associated emissions.

3.3.3 Data for Assembly Modelling

The data collection process for module and pack assembly revealed a clear imbalance between available and missing information. While some data could be identified for specific materials, components, and energy-intensive processes, large parts of the assembly chain remain insufficiently documented in the literature.

The report by PEM of RWTH Aachen University and VDMA (2023) did not include relevant quantitative data for these processes described in Figure 3.19 and Figure 3.20, such as energy requirements, which were found to be particularly challenging to obtain from existing sources. The data obtained were primarily derived from the benchmarking studies, complemented by selected reports from Argonne National Laboratory, particularly those related to the GREET model. The data availability for material composition differs considerably between components, as can be seen in C.1. For the overall battery pack, many sources report total mass values, which provide a useful reference point. At the component level, relatively good data was found for structural elements such as housing, cooling plates, insulation plates and some major subsystems (e.g. thermal management and BMS). However, for many smaller components, such as adhesives, cell carriers, sensors, and certain electronic parts, data is missing. In some cases, components are grouped under broad categories such as “packaging” or “thermal insulation” without further specification, making it unclear what is included. For module components in particular, the level of detail is limited, and many entries in Table C.1 in Appendix C.1 had to be left unspecified. As a result, the BoM is only partially complete and relies on a combination of reported values, approximations, and assumptions.

The availability of data on process-level energy use is even more limited. In Table C.2, it can be seen that for module assembly, process-energy data could only be found for one process, specifically tab contacting. For pack assembly, end-of-line testing was the only process where process-energy data could be acquired. However, some energy data for producing thermal management unit and BMS could be found as well. However, detailed breakdowns of individual process steps are largely missing, as can be seen in Table C.3. In addition, it is often unclear which processes are included within reported values.

Overall, both the BoM and process energy data were incomplete and inconsistent. Furthermore, no primary industry data could be obtained, meaning that the model could not be supported or validated using data from the industrial partners. The modelling therefore relies entirely on literature-based information. As a result, the developed models should be understood as approximations that reflect the current state of publicly available knowledge rather than precise representations of industrial practice.

4

Discussion

This chapter discusses the findings presented in the result section in relation to the research questions. In addition, the limitations of the findings are addressed.

4.1 Discussion of RQ1 & Limitations

This section discusses the findings related to RQ1 by discussing the methodological variation and comparability, data quality and primary data, interpretation of the environmental impact results and the implications for EU policy.

4.1.1 Methodological Variation and Comparability Challenges

The benchmarking confirms that methodological variation remains a major challenge in LIB LCA. Large differences were found in system boundaries, FUs, LCIA methods, data sources, electricity mixes, treatment of manufacturing stages, and reported environmental impact results. Furthermore, some of these methodological differences appear to influence the reported impacts, which is consistent with previous reviews identifying methodological choices and data assumptions as key explanations for the large variation in LIB LCA results (Ellingsen et al., 2017; Peters et al., 2017). The results also show that methodological choices influence and limit comparisons between battery chemistries. Which is further discussed in Section 4.1.3.

System boundaries were one of the clearest sources of variation. However, from the findings of the benchmarking, especially Figure 3.14, Figure 3.13 and Figure 3.17, suggests that a broader system boundary does not necessarily result in higher environmental impacts. Which indicates that the differences in reported impacts cannot be explained by system boundaries alone, and that other methodological assumptions also play a substantial role.

A similar pattern can be seen between cell-level and pack-level studies. This was observed for von Drachenfels et al. (2023) and Xu et al. (2022), who focus on cell production, but still report substantial impacts. For example the PMFP impacts (Figure 3.16), the study by von Drachenfels et al. (2023), which assesses battery cells, reports higher impacts than some studies assessing complete battery packs. This is an interesting insight since pack-level results include additional components such as casing, cooling systems, and BMS. The reason for the similar impacts independent of cell-or-pack level is likely because cell production often dominates production impacts (Ellingsen et al., 2014; Kim et al., 2016). Which is also seen in the results of this thesis (Section 3.2.3.1).

Differences in FUs also complicated comparability. Although converting results to a common FU improved the ability to compare studies, it also introduced additional uncertainty. For example, in B. Li et al. (2014), impacts reported per kilometre driven were converted to impacts per kWh battery capacity using their assumptions about vehicle lifetime, electricity consumption, and battery capacity. Meaning that the final results are influenced not only by the data but also by the conversion methodology itself. Consequently, some of the variation observed between studies may reflect differences in these assumptions rather than differences in impact results.

Although Temporelli et al. (2020) provide recommendations for standardized LCA methodologies for LIBs, which can improve the comparability of results between studies, the findings of this study do not support one specific recommendation for system boundaries or functional units that would be suitable for all LIB LCAs. This is because the choice of system boundaries and FUs is often guided by the specific goal and purpose of the assessment. For example, studies focusing on battery cell production may not have to adopt a full cradle-to-grave perspective, while studies investigating the use phase may be better represented by a distance-based FU rather than a capacity-based one. This creates a trade-off between comparability and the ability to capture the context of each study. While expressing results on a common basis makes comparisons easier, some of the information reflected in the original FU and system boundaries may be lost.

During the benchmarking, unit inconsistencies were discovered, which also limited comparison for several categories, including AP, EP, POCP, and ADP. This demonstrates the need for clearer reporting of LCIA methods, impact category definitions, and units.

Finally, data interpretation and extraction were not always straightforward. Some studies report impact results mainly in graphs rather than numerical tables, which makes extraction uncertain. This was especially relevant for Zackrisson et al. (2010), where most impact results apart from GWP were not provided numerically, and no supplementary material was available. Similarly, B. Li et al. (2014) did not clearly report all graphite-anode-specific impact results, since more detailed results were available for the SiNW case. Inconsistent terminology, technical abbreviations, and different modelling structures also made comparison more difficult, particularly when studies were organised by components rather than manufacturing processes, as in Ellingsen et al. (2014), or by materials, as in Kim et al. (2016).

In addition, one limitation of this study is the fact that toxicity-related impact categories, such as human toxicity and ecotoxicity, were not included in this thesis, although studies such as Tagliaferri et al. (2016) identified toxicity-related impacts as important contributors to the environmental burden of battery production.

4.1.2 Data Quality and Primary Data

The results confirmed that limited access to industrial primary data remains a major challenge in battery LCA research. Although several studies incorporated it, a large proportion of the reviewed literature still relied heavily on secondary databases and previous literature. This creates uncertainty regarding whether the reported impacts accurately represent modern industrial-scale battery manufacturing.

Several recent studies still build upon foundational datasets from studies such as Ellingsen et al. (2014), Majeau-Bettez et al. (2011), and Notter et al. (2010). While these studies were highly influential for the development of the field, they represent early battery production systems that may no longer reflect current manufacturing technologies, energy efficiencies, or production scales. As noted by Dai et al. (2019), early production facilities may have operated below full production capacity and had not yet fully optimised energy efficiency, potentially leading to overestimated environmental impacts. This can explain why older studies often report higher impacts than more recent process-based or industrial-scale studies.

Primary data can improve representativeness, but it is often limited by confidentiality because companies often consider production data proprietary, as mentioned in Dunn et al. (2014) and Ellingsen et al. (2017). Industrial primary data may better reflect real production, but the underlying inventory is often not fully disclosed, which reduces transparency and reproducibility. This issue is visible in studies such as Kim et al. (2016), Sun et al. (2020), and USEPA (2013), where some data are restricted, aggregated, or only partly described, affecting transparency, as shown in Figure 3.6.

Although laboratory data are often more accessible, it may not fully capture the complexities of large-scale industrial production, with factors such as process optimization and economies of scale. This could potentially reduce the representativeness of the results (von Drachenfels et al., 2021). For example, Q. Chen et al. (2022) and Cusenza et al. (2019) rely on dismantled battery packs as their primary data source. While this approach can provide detailed information on the BoM, the associated energy measurements may not accurately represent industrial manufacturing processes.

Transparency issues were not only related to confidentiality. In some cases, reporting limitations also appeared as, for example, referencing errors. These specific issues were not included as separate criteria in the transparency assessment presented in Figure 3.6, which focused on broader aspects such as data source clarity and LCI accessibility. Nevertheless, they are relevant to discuss, as they illustrate how smaller reporting issues can still reduce the interpretability and reproducibility of LCA results. For example, in supplementary material of Notter et al. (2010), the sentence describing the generation of a new LCI dataset for an electric drivetrain appears to be incomplete, specifically they write: “A new LCI dataset for an electric drive train was generated using data from” without specifying the source of the data. Similarly, the supplementary material of Cusenza et al. (2019) refers to inventories for the EoL modelling of battery cells, BMS, packaging, and cooling system as being detailed in a missing reference, indicated as "Error! Reference source not found". Although these issues may reflect formatting or publication errors rather than intentional omission, they still limit transparency and make it more difficult to assess and reproduce results. This shows that data transparency depends not only on access to primary data, but also on clear documentation, complete references, and traceable inventory assumptions.

4.1.3 Interpretation of Environmental Impact Results

The impact results show substantial variation both within and between battery chemistries and studies. For GWP, many NMC-based results cluster within a similar range, but some studies report considerably higher values. This is especially observed for Ellingsen et al. (2014) being a clear outlier in the cradle-to-gate GWP values for NMC111 batteries. NMC111 batteries also displayed relatively higher impacts for categories such as AP and POCP. Similarly, B. Li et al. (2014) reported unusually high cradle-to-grave GWP values, which has also been highlighted in previous reviews such as Ellingsen et al. (2017).

The benchmarking also showed that LFP batteries tended to exhibit relatively high impacts in categories such as GWP, CED, ODP, and eutrophication-related categories, whereas LMO generally showed lower impacts across several categories. A key finding is that variation within the same chemistry is often larger than variation between chemistries. Therefore, observed differences between chemistries should not be interpreted as being solely driven by battery chemistry, but also by differences in modelling choices and underlying assumptions. This aligns with Peters and Weil (2018) and Peters et al. (2017), who show that assumptions regarding key aspects such as cell manufacturing energy demand and cell composition can have a stronger influence on the final results than the battery chemistry itself. This was particularly visible for LFP and NMC111.

From the benchmarking results, it can be observed that older studies, such as Ellingsen et al. (2014), B. Li et al. (2014), Majeau-Bettez et al. (2011), and USEPA (2013), often report higher impacts across several categories. In particular, Ellingsen et al. (2014) stands out as an outlier across several impact categories, including GWP, POCP, AP, and PMFP. As mentioned in section 4.1.2, Dai et al. (2019) highlight that this may be because the study reflects early-stage production conditions and is therefore not fully representative of current commercial-scale automotive LIB manufacturing. It is therefore important to interpret LCA results within the context of the assumptions and objectives of each study, as differences between studies may not only reflect environmental performance but also variations in production conditions and methodological choices.

Some general trends can still be observed. Cathode production was frequently identified as a dominant GWP hotspot, especially in cradle-to-gate studies. However, the interpretation of this hotspot depends partly on the level of modelling detail. Some studies identified cathode production specifically, while others reported broader categories such as cell production or cell manufacturing, as seen in Kim et al. (2016). Consequently, cathode-related impacts may be hidden within broader manufacturing categories in some studies, even when cathode production is not explicitly reported as a separate hotspot. This affects comparability, as studies with more detailed life-cycle stages may appear to identify different hotspots than studies using more aggregated stages.

Electricity mix is often mentioned as a large contributor to environmental impacts. In this study, this was visible for GWP, where studies comparing several regional scenarios within the same methodological framework, such as Clemente et al. (2025) and Xu et al. (2022), consistently reported lower impacts for regions with low-carbon electricity systems, such as the EU, compared with more carbon-intensive systems such as China. However, when comparing results across different studies, the influence of electricity mix was more difficult to isolate because it was often combined with differences in system boundaries and other methodological choices.

4.1.4 Implications for EU policies

As discussed in Section 1.2.3, battery LCA is highly relevant in the EU regulatory context, since environmental assessment methods are increasingly connected to regulatory compliance. In particular, the EU Battery Regulation and the associated DBP increase the need for reliable, traceable, and comparable life cycle data for batteries, especially in relation to carbon footprint declarations.

The findings of this thesis suggest that current LCA practice can support regulatory implementation, but only to a limited extent. The benchmarking shows that LIB LCA practice remains characterised by substantial methodological inconsistencies, together with limited access to reliable industrial-scale primary data. If studies continue to rely on inconsistent assumptions, non-transparent inventory data, and limited primary data, the comparability and reliability of carbon footprint declarations may be reduced.

For the EU Battery Regulation and the DBP to be implemented in a meaningful and comparable way, stricter methodological standardisation, increased transparency of data sources and data, and improved access to representative primary data are needed. Without such standardisation, reported battery carbon footprints may reflect methodological choices as much as actual differences in battery production. This is particularly important in a regulatory context, where LCA results may be used not only for environmental assessment, but also for product comparison, compliance, and decision-making.

4.2 Discussion of RQ2 & Limitations

This section discusses the findings related to RQ2 by discussing the current representation of assembly processes and the limitations of the developed assembly model.

One of the clearest findings from this study is the large inconsistency in how module and pack assembly processes are represented in battery LCA literature. As shown in Figure 3.18, reported assembly energy demand varied by several orders of magnitude, ranging from almost negligible values to more than 1000 MJ/kWh. The particularly high values reported for module and pack assembly in USEPA (2013), may partly reflect data-source and allocation-related issues. In that study, manufacturing data were collected from a combination of primary and secondary sources, and several datasets were aggregated to protect confidentiality, which limits transparency regarding how energy demand was assigned to specific manufacturing stages. In addition, USEPA (2013) reports energy demand as primary energy demand, which could explain why the assembly energy values appear substantially higher than in studies reporting direct process energy. Therefore, these values should be interpreted with caution when comparing assembly energy demand across studies.

These large differences could also reflect differences in what is included within the term “assembly”. Terms such as battery assembly, cell assembly, module assembly, and pack assembly are used differently across studies. For example, Q. Chen et al. (2022) refer to “battery assembly”, but the term appears to include cell assembly rather than module and pack assembly. In contrast, B. Li et al. (2014) seem to use “battery assembly” in a way that more closely represents module and pack assembly. This distinction is important because cell assembly may include dry-room operation, electrolyte filling, formation, and other energy-intensive processes (Degen & Schütte, 2022), while module and pack assembly mainly involve mechanical and electrical integration, cooling systems, sealing, and testing (PEM of RWTH Aachen University & VDMA, 2023).

The conceptual model developed in this thesis addresses this issue by separating module assembly and pack assembly into two distinct stages. This improves transparency and makes it easier to assign material and energy inputs to specific assembly steps. The process structure, based on PEM of RWTH Aachen University and VDMA (2023), provides a clearer basis for representing assembly processes than the aggregated approaches commonly found in earlier studies. But it may not fully represent broader industrial practice. In addition, the lack of primary industrial data limits the model. Process-level energy data were only found for a few assembly steps. For module assembly, data were mainly identified for tab contacting, while for pack assembly, data were mainly available for end-of-line testing. Many material inputs, especially smaller components such as adhesives, sensors, cell carriers, and electronic parts, were missing or only available in aggregated form.

Despite these limitations, the conceptual model contributes by making module and pack assembly more explicit and adjustable. Its main value is therefore not to provide definitive impact results, but to identify where data are missing and to create a structure that can be improved when better data become available. This is relevant for future battery LCAs, especially as regulatory frameworks such as the EU Battery Regulation and DBP increase the need for transparent environmental data (PEM of RWTH Aachen University & VDMA, 2023).

4.3 Future Research

Several opportunities for future research were identified throughout this thesis. One area that would benefit from further investigation is data quality and traceability. Although this thesis distinguished between primary and secondary data, no detailed assessment of database quality or inventory traceability was carried out. Future studies could therefore examine which materials, processes, and life cycle stages are represented by primary data and identify and specify where primary data is lacking. This would improve transparency and help highlight areas where additional data collection is needed.

More attention should also be given to recycling impacts and recycling credits, since these are treated differently across studies and may influence cradle-to-grave results. Studies such as Q. Chen et al. (2022), Cusenza et al. (2019), Šimaitis et al. (2023), and Sun et al. (2020) show that recycling assumptions can affect the reported environmental performance of LIBs. A systematic comparison of studies with and without recycling credits would therefore be valuable.

Finally, the module and pack assembly model should be further developed using primary industrial data. In particular, more detailed process-level energy data and information on material inputs would improve the representation of assembly processes. Future work could focus on collecting data for specific assembly steps and components that are currently represented using simplified assumptions. This would reduce uncertainty in the model, make it more representative of industrial practice, and increase its usefulness for future LIB manufacturing LCAs.

5
Conclusion

This thesis set out to improve understanding of how LIB manufacturing is assessed through LCA, by examining methodological variation across existing studies and developing a more structured representation of module and pack assembly. The work was carried out through a state-of-the-art review, systematic benchmarking of 18 LCA studies, and conceptual process-based assembly modelling. The findings are summarised below in relation to each research question.

Regarding RQ1, the benchmarking confirmed that methodological choices exert a stronger influence on reported environmental impacts than is often acknowledged. For GWP, values across cradle-to-gate studies span a range, and in some cases the variation observed within a single battery chemistry exceeded the variation between chemistries, suggesting that reported differences in environmental performance cannot be reliably attributed to chemistry alone. In addition, especially for the GWP, older studies tend report higher impacts, likely reflecting energy-intensive early production assumptions and lower battery energy densities rather than fundamental differences in environmental performance. These findings suggest that interpreting LCA results in isolation from the assumptions underlying them risks misleading conclusions about which chemistries or production systems are environmentally preferable.

The benchmarking also revealed additional challenges. Six of the 18 reviewed studies assessed only GWP, leaving the broader environmental profile uncharacterised. Eleven studies incorporated primary data, but most of these relied on laboratory-scale measurements that may not capture the efficiencies industrial-scale production, indicating a data gap for more recent industrial primary data. Transparency was generally adequate for data sources, but LCI accessibility was low in several cases due to confidentiality constraints, which is a limitation that is unlikely to resolve without change in how battery manufacturers share production data.

Regarding RQ2, the assembly model contributes a clearer process structure for module and pack assembly than is currently found in the literature. The model separates the two stages and maps individual process steps. In addition, data gaps were identified, particularly regarding process-level energy requirements and smaller modular components, for which data were most often lacking. The model also provides a modular framework that can be updated as industrial data become available. Its current limitation is significant: process-level energy data were only identified for a small number of assembly steps, which means the model cannot yet produce a validated inventory. Its value lies in making data gaps explicit rather than obscuring them within aggregated estimates.

Taken together, the findings illustrate a field that has produced a substantial body of work, but one in which comparability remains limited by inconsistent methodological choices, selective impact reporting, and restricted access to representative primary data. These limitations are not merely academic. As the EU Battery Regulation and the Digital Battery Passport introduce mandatory carbon footprint declarations for EV batteries, the quality of underlying LCA practice directly affects the reliability of those declarations. Addressing this will require not only methodological standardisation but also improved frameworks for industrial data sharing, challenges that go beyond any single study but that this thesis helps to characterise more precisely.

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A

Appendix

A.1 Benchmarking tables

This appendix presents the full benchmarking table developed for the literature comparison. It provides the underlying basis for the benchmarking results presented in Chapter 3.

Due to the large number of parameters included, the original table is divided into several tables to improve readability.

Where information was not reported or could not be identified, this is indicated as N/A. Some entries have been shortened or simplified for readability. Study-specific assumptions and adjustments applied during the benchmarking are documented separately in Appendix B.1 or in notes below tables in Appendix A.

Table A.1: Studies included in the benchmarking.

Author	**Title**	**Year**	**Region**	**Type of LCA**
Clemente, M.; Maharjan, P.; Salazar, M.; Hofman, T.	Meta-analysis of life cycle assessments for Li-ion batteries production emissions	2025	Sweden, South Korea, and China	Attributional
Šimaitis, J.; Allen, S.; Vagg, C.	Are future recycling benefits misleading? Prospective life cycle assessment of lithium-ion batteries	2023	China	Prospective
von Drachenfels, N.; Husmann, J.; Khalid, U.; Cerdas, F.; Herrmann, C.	Life Cycle Assessment of the Battery Cell Production: Using a Modular Material and Energy Flow Model to Assess Product and Process Innovations	2023	Germany	Attributional
Chen, Q.; Lai, X.; Gu, H.; Tang, X.; Gao, F.; Han, X.; Zheng, Y.	Investigating carbon footprint and carbon reduction potential using a cradle-to-cradle LCA approach on lithium-ion batteries for electric vehicles in China	2022	China	Attributional

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Author	Title	Year	Region	Type of LCA
Degen, F.; Schütte, M.	Life cycle assessment of the energy consumption and GHG emissions of state-of-the-art automotive battery cell production	2022	Germany	Attributional
Xu, C.; Steubing, B.; Hu, M.; Harpprecht, C.; van der Meide, M.; Tukker, A.	Future greenhouse gas emissions of automotive lithium-ion battery cell production	2022	China, US, and EU	Prospective
Sun, X.; Luo, X.; Zhang, Z.; Meng, F.; Yang, J.	Life cycle assessment of lithium nickel cobalt manganese oxide (NCM) batteries for electric passenger vehicles	2020	China	Attributional
Cusenza, M. A.; Bobba, S.; Ardente, F.; Cellura, M.; Di Persio, F.	Energy and environmental assessment of a traction lithium-ion battery pack for plug-in hybrid electric vehicles	2019	Europe and Japan	Attributional
Dai, Q.; Kelly, J. C.; Gaines, L.; Wang, M.	Life Cycle Analysis of Lithium-Ion Batteries for Automotive Applications	2019	US	Attributional
Raugei, M.; Winfield, P.	Prospective LCA of the production and EoL recycling of a novel type of Li-ion battery for electric vehicles	2019	Europe	Prospective
Peters, J. F.; Baumann, M.; Zimmermann, B.; Braun, J.; Weil, M.	The environmental impact of Li-Ion batteries and the role of key parameters–A review	2017	Global	Attributional
Kim, H. C.; Wallington, T. J.; Arsenault, R.; Bae, C.; Ahn, S.; Lee, J.	Cradle-to-gate emissions from a commercial electric vehicle Li-ion battery: A comparative analysis	2016	South Korea and US	Attributional
Li, B.; Gao, X.; Li, J.; Yuan, C.	Life cycle environmental impact of high-capacity lithium-ion battery with silicon nanowires anode for electric vehicles	2014	US	Attributional
Ager-Wick Ellingsen, L.; Majeau-Bettez, G.; Singh, B.; Srivastava, A. K.; Valøen, L. O.; Strømman, A. H.	Life cycle assessment of a lithium-ion battery vehicle pack	2013	Norway and East Asia	Attributional
U.S. Environmental Protection Agency	Application of Life-Cycle Assessment to Nanoscale Technology: Lithium-ion Batteries for Electric Vehicles	2013	US	Attributional

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Author	Title	Year	Region	Type of LCA
Majeau-Bettez, G.; Hawkins, T. R.; Strømman, A. H.	Life Cycle Environmental Assessment of Lithium-Ion and Nickel Metal Hydride Batteries for Plug-In Hybrid and Battery Electric Vehicles	2011	Europe	Attributional
Notter, D. A.; Gauch, M.; Widmer, R.; Wäger, P.; Stamp, A.; Zah, R.; Althaus, H.-J.	Contribution of Li-Ion batteries to the environmental impact of electric vehicles	2010	Europe	Attributional
Zackrisson, M.; Avellán, L.; Orlenius, J.	Life cycle assessment of lithium-ion batteries for plug-in hybrid electric vehicles–Critical issues	2010	Europe, some data with global averages	Attributional

A.1.1 LCA context, system boundaries, and functional units

Table A.2: LCA context, system boundaries, and functional units.

Author	LCA context	LCA scope	LCA scope (results)	Functional unit
Clemente et al. (2025)	LIB pack	Cradle-to-gate	Cradle-to-gate	1 kg of battery
Šimaitis et al. (2023)	LIB pack	Cradle-to-grave; interpreted as cradle-to-gate + recycling	Cradle-to-gate	The production and recycling of a battery that can hold 1 kWh of energy capacity
von Drachenfels et al. (2023)	LIB cell	Cradle-to-gate	Cradle-to-gate	1 cell
Chen et al. (2022)	LIB pack	Cradle-to-cradle	Cradle-to-grave, excluding recycling credits	1 kWh
Degen and Schütte (2022)	LIB cell	Gate-to-gate	Gate-to-gate	1 kWh cell capacity
Xu et al. (2022)	LIB cell	Cradle-to-gate	Cradle-to-gate	1 kWh cell capacity
Sun et al. (2020)	LIB pack	Cradle-to-gate + EoL	Cradle-to-gate	1 kWh
Cusenza et al. (2019)	LIB pack	Cradle-to-grave	Cradle-to-grave, excluding recycling credits	1 LIB pack
Dai et al. (2019)	LIB pack	Cradle-to-gate	Cradle-to-gate	1 kWh
Raugei and Winfield (2019)	LIB pack	Cradle-to-gate + EoL	Cradle-to-gate	1 kWh
Peters et al. (2017)	LIB pack	Cradle-to-gate	Cradle-to-gate	1 kWh

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Author	LCA context	LCA scope	LCA scope (results)	Functional unit
Kim et al. (2016)	LIB pack	Cradle-to-gate	Cradle-to-gate	1 kWh and 1 kg of battery
Li et al. (2014)	LIB pack	Cradle-to-grave	Cradle-to-grave, excluding recycling credits	1 average kilometre driven by an EV powered by the LIB pack under average U.S. operating conditions
Ellingsen et al. (2014)	LIB pack	Cradle-to-gate	Cradle-to-gate	1 LIB, 1 kg of battery, nominal energy capacity in kWh
U.S. Environmental Protection Agency (USEPA) (2013)	LIB pack	Cradle-to-grave	Cradle-to-gate	1 km driven, 1 kWh
Majeau-Bettez et al. (2011)	Li-ion and NiMH battery pack	Cradle-to-gate	Cradle-to-gate	50 MJ of energy delivered by the battery
Notter et al. (2010)	LIB pack	Cradle-to-grave	Cradle-to-gate	1 km driven by an EV with LIB in Europe
Zackrisson et al. (2010)	LIB pack	Cradle-to-use + collection for recycling	Cradle-to-gate	A 10 kWh PHEV battery with 3,000 cycles at maximum 80% discharge and a 200,000 km lifetime

A.1.2 Battery characteristics

Table A.3: Battery chemistries, battery mass, and battery capacity in the benchmarking database.

Author	Battery chemistries	Battery mass	Battery capacity
Clemente et al. (2025)	NMC811 (Si-coated graphite anode)	N/A	0.209 kWh/kg
Šimaitis et al. (2023)	LMO, LFP, NMC111, NMC622, NMC811, NCA (all graphite)	N/A	N/A
von Drachenfels et al. (2023)	NMC622 (graphite)	650.5 g (one cell)	0.14652 kWh/cell[c]
Chen et al. (2022)	NMC811 (graphite)	518 kg	74 kWh
Degen and Schütte (2022)	NMC622 (graphite)	N/A	N/A

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Author	Battery chemistries	Battery mass	Battery capacity
Xu et al. (2022)	LFP (graphite), NCA (graphite), NMC111 (graphite), NMC523 (graphite), NMC622 (graphite), NMC622 (Si and graphite), NMC811 (Si and graphite), NMC955 (Si and graphite)	N/A	0.275 kWh/cell
Sun et al. (2020)	NMC622 (graphite)	630 kg	72.5 kWh
Cusenza et al. (2019)	LMO/NMC424 (graphite)	175 kg	11.4 kWh
Dai et al. (2019)	NMC111 (graphite)	165 kg	23.5 kWh
Raugei and Winfield (2019)	LCP (graphite)	108 kg	17 kWh
Peters et al. (2017)	LFP, LFP/LTO, LCO, LCN, LMO, NMC, NCA (graphite/Si not specified)	N/A	N/A
Kim et al. (2016)	LMO/NMC (graphite)	303 kg	24 kWh
Li et al. (2014)	NMC111 (graphite), NMC111 (SiNW)	120 kg (SiNW anode), 360 kg (graphite anode)	43.2 kWh (SiNW anode), 43.2 kWh (graphite anode)
Ellingsen et al. (2014)	NMC111 (graphite)	253 kg	26.6 kWh
U.S. Environmental Protection Agency (USEPA) (2013)	LMO, NMC424, LFP (all graphite)	440 kg[a] (EV) and 127 kg[b] (PHEV)	40 kWh (EV) and 11.6 kWh (PHEV)
Majeau-Bettez et al. (2011)	NiMH, NMC424 (graphite), LFP (graphite)	214 kg	24 kWh
Notter et al. (2010)	LMO (graphite)	300 kg	34.2 kWh
Zackrisson et al. (2010)	LFP, water-based and NMP solvent production routes (graphite)	107 kg	10 kWh

Notes: [a] Not explicitly reported; calculated based on Table 2-1 in USEPA (2013). The EV battery pack capacity was reported as 40 kWh, and 1 kWh was assumed to weigh 11 kg, based on the reported range of 10–12 kg/kWh. Thus, 40 kWh $\times$ 11 kg/kWh = 440 kg per battery pack.
[b] Not explicitly reported; calculated based on Table 2-1 in USEPA (2013). The PHEV battery pack capacity was reported as 11.6 kWh, and 1 kWh was assumed to weigh 11 kg, based on the reported range of 10–12 kg/kWh. Thus, 11.6 kWh $\times$ 11 kg/kWh = 127 kg per battery pack.
[c] Calculated from the reported cell capacity of 39.6 Ah and nominal voltage of 3.7 V: 39.6 Ah $\times$ 3.7 V = 146.52 Wh = 0.14652 kWh.

A.1.3 Data sources and transparency

Table A.4: Data types, data sources, and transparency assessment in the benchmarking database.

Author	**Type of data**	**Primary data**	**Industrial vs. laboratory**	**Secondary data**	**Transparency**
Clemente et al. (2025)	Secondary data	N/A	N/A	GREET model (2017, 2018, 2019), Ecoinvent 3.8	Data sources: High; the data sources used are clearly stated. LCI accessibility: Medium; the LCI is relatively simple and could be more detailed.
Šimaitis et al. (2023)	Secondary data	N/A	N/A	Ecoinvent v3.8, literature sources, and software from Argonne National Laboratories	Data sources: High; the study specifies which sources are used for foreground and background processes. LCI accessibility: High; an Excel file with LCI data is provided.
von Drachenfels et al. (2023)	Secondary data	N/A	N/A	Scientific literature, mainly Degen and Krätzig (2021) and Schünemann (2015), and Ecoinvent 3.8	Data sources: High; the supplementary material clearly lists which data come from which source. LCI accessibility: High; a detailed LCI dataset is provided in the supplementary material.
Chen et al. (2022)	Primary and secondary data	Dismantled battery pack	Laboratory data	GaBi 10.2 and scientific literature	Data sources: Medium; the study is transparent about the data sources and presents them in a list. However, for electricity and natural gas, the data source is only stated as "manufacturer", with no further details. LCI accessibility: High; an extensive LCI dataset is provided.
Degen and Schütte (2022)	Primary and secondary data	Research Factory for Battery Cells (FFB)	Laboratory data with industrial estimations	Literature sources, including Agora Energiewende and Ember (2021), Quaschning (2015), and Weeber et al. (2020)	Data sources: Medium; the primary source is mentioned, but the manufacturers are not explicitly stated. It was also somewhat difficult to identify which secondary sources were used. LCI accessibility: Medium; a short LCI is provided.
Xu et al. (2022)	Secondary data	N/A	N/A	Ecoinvent 3.6, EverBatt model, and Chinese battery industry reports	Data sources: High; the study clearly states what information comes from which source. LCI accessibility: High; extensive LCI data are provided in an Excel spreadsheet.
Sun et al. (2020)	Primary and secondary data	On-site industrial data from Chinese LIB manufacturers, cathode material producers, and recycling facilities from 2017–2019	Industrial data	CALCD database with Ecoinvent 3.0 and GREET 2018	Data sources: Medium; the study includes a data source list for materials, energy, and resources. However, details about the industrial primary sources are not presented. LCI accessibility: High; an LCI dataset is provided in the supplementary material.

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Author	Type of data	Primary data	Industrial vs. laboratory	Secondary data	Transparency
Cusenza et al. (2019)	Primary and secondary data	Dismantled battery pack	Laboratory data	Scientific literature and Ecoinvent 3	Data sources: High; the study clearly states which data come from which source. LCI accessibility: High; a detailed LCI is provided in the paper.
Dai et al. (2019)	Secondary data	N/A	N/A	GREET model, including both secondary data and primary data incorporated from large-scale commercial battery material producers and automotive LIB manufacturers; the bill of materials is based on Argonne's Battery Performance and Cost (BatPaC) model	Data sources: High; the study clearly presents where the data come from and states that primary data were used to update the GREET model. LCI accessibility: High; a detailed LCI is provided.
Raugei and Winfield (2019)	Primary and secondary data	Data supplied by MARS-EV project partners for the manufacturing of all cell components and for the direct inputs and outputs of the EoL treatment processes	Laboratory data	BatPaC software and Ecoinvent v3.3	Data sources: High; the study presents the data sources and qualitatively describes what type of data is used and for what purpose. LCI accessibility: Low; no LCI data are provided.
Peters et al. (2017)	Secondary data	N/A	N/A	Scientific literature	Data sources: High; the study lists the literature sources on which the LCA is based. LCI accessibility: High; supplementary material provides more extensive LCI information.
Kim et al. (2016)	Primary and secondary data	Data from large-scale production, including LG Chem and Piston Group	Industrial data	Ecoinvent 3.1, GREET 2014 model, Korean national LCI database, and Process Economics Program (PEP) yearbook	Data sources: High; the primary sources are clearly stated. LCI accessibility: Low; a detailed LCI is not provided due to confidentiality.
Li et al. (2014)	Primary and secondary data	Laboratory experimental data for SiNW anode synthesis and Johnson Controls' advanced battery laboratory for cell manufacturing data	Laboratory data	GaBi 6 database and scientific literature	Data sources: High; primary and secondary data sources are clearly stated, including in the supplementary information. LCI accessibility: High; extensive LCI data are provided in the supplementary material.
Ellingsen et al. (2014)	Primary and secondary data	Battery producer, Miljøbil Grenland (2012)	Industrial data	Ecoinvent 2.2	Data sources: High; the study clearly states the data sources used. LCI accessibility: High; extensive LCI data are provided in the supplementary material. However, the inventory is partly based on primary data that have been aggregated, and the data report is only available in German.

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Author	Type of data	Primary data	Industrial vs. laboratory	Secondary data	Transparency
U.S. Environmental Protection Agency (USEPA) (2013)	Primary and secondary data	Industrial data from manufacturers, suppliers, and recyclers for component manufacturing, battery manufacturing, and end-of-life stages	Industrial data	Scientific literature, including Notter et al. (2010), Majeau-Bettez et al. (2011), and Hawkins et al. (2012), as well as GaBi4 datasets, NREL's U.S. LCI database, and European Aluminium Association (2008) dataset	Data sources: High; the study clearly lists which processes and components come from which source. LCI accessibility: Medium; the report includes an LCI section, but it is not sufficiently detailed for full transparency.
Majeau-Bettez et al. (2011)	Secondary data	N/A	N/A	Ecoinvent 2.2 and scientific literature	Data sources: High; the study clearly states the data sources used. LCI accessibility: High; extensive LCI data are provided in the supplementary material.
Notter et al. (2010)	Primary and secondary data	Kokam company	Industrial data	Ecoinvent 2.01	Data sources: High; the study presents the data sources. LCI accessibility: High; extensive LCI data are provided in the supplementary material.
Zackrisson et al. (2010)	Primary and secondary data	Limited lab-scale data, for example cathode solvent experiments	Laboratory data	Ecoinvent 2.0 database and scientific literature	Data sources: High; the study clearly states the sources used for data. LCI accessibility: Low; no LCI data or supplementary material are provided.

A.1.4 Impact categories, LCIA methods, main source for GWP, and energy

Table A.5: Impact categories, LCIA methods, main GWP emission sources, assembly energy, and electricity mix in the benchmarking database.

Author	Impact categories	LCIA method	Main source of emission for GWP	Energy used for module + pack assembly	Electricity mix
Clemente et al. (2025)	GWP	ReCiPe Midpoint (H) v1.13	Cathode production	N/A	China, South Korea, Sweden
Šimaitis et al. (2023)	GWP100	IPCC 2013	LFP: foreground electricity; LMO: foreground electricity; NMC111: active materials; NMC622: active materials; NMC811: active materials; NCA: active materials	N/A	China
von Drachenfels et al. (2023)	GWP, TAP, POFP, FEP, MEP, HTP, TETP, FETP, PMFP, MDP, FDP	ReCiPe Midpoint (H) v1.13	Cathode dry and wet mixing	N/A	Germany
Chen et al. (2022)	GWP	GaBi 10.6 software	Cathode production	N/A	China
Degen and Schütte (2022)	GWP, CED	N/A	Cell formation process	N/A	Germany
Xu et al. (2022)	GWP100	IPCC 2013	Cell production for LFP; cathode production for NCA, NMC111, NMC523, NMC622, NMC622 (Si), NMC811 (Si), and NMC955 (Si)	N/A	China, EU, and United States
Sun et al. (2020)	PED, GWP, AP, POCP, EP, HTP (CML method); GWP, AP, POCP, EP, HTP, TETP, FETP, PMFP, MDP, FDP (ReCiPe method)	CML-IA baseline v3.02 and ReCiPe Midpoint (H) v1.11	Cathode production	3.6 MJ/kWh	China
Cusenza et al. (2019)	CED, ADP, GWP, ODP, HT-nce, HT-ce, PM, IR-hh, POFP, AP, EUT, EUF, EUM, EFW	PEF + CED	Battery cell assembly	N/A	European
Dai et al. (2019)	GWP, reported as GHG	N/A	NMC111 powder	0, assumed to be manual	United States
Raugei and Winfield (2019)	CED, GWP	GaBi 6 software	Cathode production	44 MJ/kWh	European
Peters et al. (2017)	GWP, AP, EP, ADP, ODP, HTP, CED	Combination of ReCiPe, CML, EI99, and ILCD	N/A	N/A	N/A

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Author	Impact categories	LCIA method	Main source of emission for GWP	Energy used for module + pack assembly	Electricity mix
Kim et al. (2016)	GWP100	N/A	Cell manufacturing	N/A	South Korea (cell manufacturing) + United States (pack manufacturing)
Li et al. (2014)	ADP, GWP, AP, EP, ODP, POCP, ETP, HTP	GaBi 6 software	Battery use	1.1444 MJ/kWh (SiNW, including testing energy)[f]; same energy assumed for graphite	United States
Ellingsen et al. (2014)	GWP100, FDP, ODP, POFP, PMFP, TAP100, FEP, MEP, FETP, METP, TETP, HTP, MDP	ReCiPe Midpoint (H) v1.08	Cell manufacturing	0.014 MJ/kWh	Norway (welding process), East Asia
U.S. Environmental Protection Agency (USEPA) (2013)	ADP, GWP, AP, EP, ODP, POCP, ETP, HTP, occupational cancer hazard, occupational non-cancer hazard	Category-specific LCIA methods, including USEtox for toxicity	Battery use	0.895 MJ/kWh (LMO), 621 MJ/kWh (NMC), 1150 MJ/kWh (LFP)	United States + Canada
Majeau-Bettez et al. (2011)	GWP100, FDP, FETP, FEP, HTP, METP, MEP, MDP, ODP, PMFP, POFP, TAP100, TETP	ReCiPe Midpoint	NiMH: battery and component manufacturing; NMC: positive electrode paste; LFP: positive electrode paste	N/A	European
Notter et al. (2010)	GWP100, CED, EI99 H/A, ADP	CML method + Eco-indicator 99	Cathode production	N/A	Brazil, China, and European
Zackrisson et al. (2010)	GWP100, AP, ODP, POCP, EP	N/A	Battery production, manufacturing energy (NMP as solvent); battery use (water as solvent)	N/A	West European

Notes: [f] Calculated from the battery pack mass and reported assembly energy for the SiNW battery: 0.412 MJ/kg LIB $\times$ 120 kg = 49.44 MJ/battery pack; 49.44 MJ/battery pack / 43.2 kWh = 1.1444 MJ/kWh.

A.1.5 Environmental impact results

Table A.6: Environmental impact results reported in the benchmarking database.

Author	GWP	Cumulative energy demand	Ozone depletion potential	Acidification	Eutrophication	Photochemical ozone creation potential	Particulate matter	Abiotic resource depletion
Clemente et al. (2025)	China: 82.92 kg CO_2-eq/kWh; South Korea: 80.62 kg CO_2-eq/kWh; Sweden: 78.80 kg CO_2-eq/kWh	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Šimaitis et al. (2023)	LFP: ∼71 kg CO_2-eq/kWh; LMO: ∼54; NMC111: ∼88; NMC622: ∼70; NMC811: ∼62; NCA: ∼69. Values refer to 2020 battery production.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
von Drachenfels et al. (2023)	58 kg CO_2-eq/kWh cell capacity[d]	N/A	N/A	1.4329 kg SO_2-eq/kWh cell capacity[d]	0.0553 kg P-eq/kWh cell capacity, freshwater[d]; 0.0362 kg N-eq/kWh cell capacity, marine[d]	0.3275 kg NMVOC/kWh cell capacity[d]	0.3616 kg PM_{10}-eq/kWh cell capacity[d]	93.0045 kg Fe-eq/kWh cell capacity, MDP[d]; 23.6094 kg oil-eq/kWh cell capacity, FDP[d]
Chen et al. (2022)	249.123 kg CO_2-eq/kWh, including production, use, and recycling impacts, excluding credits	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Degen and Schütte (2022)	10.33 kg CO_2-eq/kWh cell capacity	149.33 MJ/kWh	N/A	N/A	N/A	N/A	N/A	N/A
Xu et al. (2022)	China: LFP 69, NCA 87, NMC111 88, NMC523 89, NMC622 86, NMC622 (Si) 89, NMC811 86, NMC955 86 kg CO_2-eq/kWh cell capacity. US: LFP 49, NCA 65, NMC111 65, NMC523 67, NMC622 64, NMC622 (Si) 68, NMC811 64, NMC955 65. EU: LFP 39, NCA 54, NMC111 53, NMC523 54, NMC622 62, NMC622 (Si) 62, NMC811 61, NMC955 61.	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sun et al. (2020)	124.48 kg CO_2-eq/kWh, CML-IA baseline v3.02; 124.48 kg CO_2-eq/kWh, ReCiPe Midpoint (H) v1.11. Values refer to battery production.	N/A	N/A	0.56 kg SO_2-eq/kWh, CML-IA baseline v3.02; 0.52 kg SO_2-eq/kWh, ReCiPe Midpoint (H) v1.11. Values refer to battery production.	0.24 kg PO_4^{3-}-eq/kWh, CML-IA baseline v3.02; 0.01 kg P-eq/kWh, freshwater, ReCiPe Midpoint (H) v1.11; 0.13 kg N-eq/kWh, marine, ReCiPe Midpoint (H) v1.11. Values refer to battery production.	0.05 kg C_2H_4-eq/kWh, CML-IA baseline v3.02; 0.38 kg NMVOC/kWh, ReCiPe Midpoint (H) v1.11. Values refer to battery production.	0.16 kg PM_{10}-eq/kWh, ReCiPe Midpoint (H) v1.11. Values refer to battery production.	6.06 kg Fe-eq/kWh, MDP; 27.79 kg oil-eq/kWh, FDP. Values refer to ReCiPe Midpoint (H) v1.11 and battery production.
Cusenza et al. (2019)	396.49 kg CO_2-eq/kWh	6640.35 MJ/kWh	0.00003377 kg CFC-11-eq/kWh	3.17544 mol H^+-eq/kWh	0.2342 kg P-eq/kWh, freshwater; 0.6175 kg N-eq/kWh, marine	1.15789 kg NMVOC-eq/kWh	0.25614 kg $PM_{2.5}$-eq/kWh	0.00680 kg Sb-eq/kWh
Dai et al. (2019)	72.9 kg CO_2-eq/kWh	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Raugei and Winfield (2019)	76.1 kg CO_2-eq/kWh, battery production	1043 MJ/kWh, battery production	N/A	N/A	N/A	N/A	N/A	N/A

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Author	GWP	Cumulative energy demand	Ozone depletion potential	Acidification	Eutrophication	Photochemical ozone creation potential	Particulate matter	Abiotic resource depletion
Peters et al. (2017)	LFP: 161 kg CO_2-eq/kWh; LFP-LTO: 185; LCO: 56; LMO: 55; NMC: 160; NCA: 116	LFP: 970 MJ/kWh; LFP-LTO: 1900; LCO: 990; LMO: 810; NMC: 1030; NCA: 1510; LCN: 830	LFP: 0.00114 kg CFC-eq/kWh; LMO: 0.00000468; NMC: 0.000672	LFP: 1.29 kg SO_2-eq/kWh; LCO: 1.50; LMO: 0.536; NMC: 2.03	LFP: 0.272 kg N-eq/kWh; LMO: 0.0122; NMC: 0.152	N/A	N/A	LFP: 1.00 kg Sb-eq/kWh; LMO: 0.422; NMC: 0.886
Kim et al. (2016)	140 kg CO_2-eq/kWh	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Li et al. (2014)	869.98 kg CO_2-eq/kWh, SiNW[e]; 699.07 kg CO_2-eq/kWh, graphite[e]	N/A	0.00000441898 kg CFC11-eq/kWh, SiNW[e]; 0.0000037037 kg CFC11-eq/kWh, graphite[e]	404.7991 kg H^+ mol-eq/kWh, SiNW[e]; 370.3703 kg H^+ mol-eq/kWh, graphite[e]	0.1102 kg N-eq/kWh, SiNW[e]; 0.0852 kg N-eq/kWh, graphite[e]	54.8050 kg O_3-eq/kWh, SiNW[e]; 42.0370 kg O_3-eq/kWh, graphite[e]	N/A	6.4477 kg Sb-eq/kWh, SiNW[e]; 4.6759 kg Sb-eq/kWh, graphite[e]
Ellingsen et al. (2014)	484 kg CO_2-eq/kWh	N/A	0.000024 kg CFC-11-eq/kWh	3.2 kg SO_2-eq/kWh	0.42 kg P-eq/kWh, freshwater; 0.29 kg N-eq/kWh, marine	1.4 kg NMVOC-eq/kWh	0.97 kg PM_{10}-eq/kWh	N/A
U.S. Environmental Protection Agency (USEPA) (2013)	63.4 kg CO_2-eq/kWh, LMO; 121 kg CO_2-eq/kWh, NMC; 151 kg CO_2-eq/kWh, LFP. Values refer to battery production.	N/A	0.0000024 kg CFC11-eq/kWh, LMO; 0.00000213 kg CFC11-eq/kWh, NMC; 0.00000964 kg CFC11-eq/kWh, LFP. Values refer to battery production.	18.2 kg H^+ mol-eq/kWh, LMO; 95.1 kg H^+ mol-eq/kWh, NMC; 40.1 kg H^+ mol-eq/kWh, LFP. Values refer to battery production.	0.00629 kg N-eq/kWh, LMO; 0.00856 kg N-eq/kWh, NMC; 0.227 kg N-eq/kWh, LFP. Values refer to battery production.	3.52 kg O_3-eq/kWh, LMO; 7.83 kg O_3-eq/kWh, NMC; 9.52 kg O_3-eq/kWh, LFP. Values refer to battery production.	N/A	0.367 kg Sb-eq/kWh, LMO; 0.886 kg Sb-eq/kWh, NMC; 1 kg Sb-eq/kWh, LFP. Values refer to battery production.
Majeau-Bettez et al. (2011)	NiMH: 350 kg CO_2-eq/kWh; NMC: 200 kg CO_2-eq/kWh; LFP: 250 kg CO_2-eq/kWh	N/A	NiMH: 0.0018 kg CFC-11-eq/kWh; NMC: 0.002 kg CFC-11-eq/kWh; LFP: 0.0026 kg CFC-11-eq/kWh	NiMH: 16 kg SO_2-eq/kWh; NMC: 1.6 kg SO_2-eq/kWh; LFP: 1.2 kg SO_2-eq/kWh. Values refer to terrestrial acidification.	NMC: 0.32 kg P-eq/kWh, FEP; 0.29 kg N-eq/kWh, MEP. LFP: 0.44 kg P-eq/kWh, FEP; 0.36 kg N-eq/kWh, MEP.	NiMH: 2.4 kg NMVOC/kWh; NMC: 0.51 kg NMVOC/kWh; LFP: 0.52 kg NMVOC/kWh	NiMH: 3.7 kg PM_{10}-eq/kWh; NMC: 0.46 kg PM_{10}-eq/kWh; LFP: 0.39 kg PM_{10}-eq/kWh	N/A
Notter et al. (2010)	52.63 kg CO_2-eq/kWh, battery production	912.3 MJ/kWh	N/A	N/A	N/A	N/A	N/A	0.4254 kg Sb-eq/kWh
Zackrisson et al. (2010)	166 kg CO_2-eq/kWh, battery production, water-based route; 350 kg CO_2-eq/kWh, water as solvent[g]; 450 kg CO_2-eq/kWh, NMP as solvent[g]; 172 kg CO_2-eq/kWh, use phase, water-based route	N/A	No numerical values; only shares shown graphically	No numerical values; only shares shown graphically	No numerical values; only shares shown graphically	No numerical values; only shares shown graphically	N/A	N/A

Notes: [d] Values converted from impacts per battery cell to impacts per kWh cell capacity using the reported cell capacity of 0.14652 kWh/cell. For example, GWP was calculated as 8.5 kg CO_2-eq/cell divided by 0.14652 kWh/cell = 58 kg CO_2-eq/kWh cell capacity. The same approach was applied to the other impact categories.

[e] Values converted from impacts per kilometre driven to impacts per kWh battery capacity using the reported electricity consumption of 164.8 Wh/km, a vehicle lifetime of 200,000 km, and a battery capacity of 43.2 kWh. For example, for the graphite-anode battery, 0.151 kg CO_2-eq/km × 200,000 km = 30,200 kg CO_2-eq over the vehicle lifetime; 30,200 kg CO_2-eq / 43.2 kWh = 699.07 kg CO_2-eq/kWh. The same principle was applied to the remaining impact categories.

[g] Values converted from impacts per battery pack to impacts per kWh battery capacity. For the water-based route, 3500 kg CO_2-eq per battery pack / 10 kWh = 350 kg CO_2-eq/kWh. For the NMP-based route, 4500 kg CO_2-eq per battery pack / 10 kWh = 450 kg CO_2-eq/kWh.

B
Appendix

B.1 Study-specific assumptions, conversions, and adjustments

This appendix documents the study-specific assumptions, calculations, and adjustments applied in the benchmarking analysis. The purpose of this appendix is to make these assumptions transparent and to clarify how the reported results were processed before being included in the benchmarking figures and calculations.

B.1.1 Functional unit conversions

It should be noted that the units listed in Table B.1 do not necessarily correspond to the formal functional units defined in the original studies. In some cases, a study defined one functional unit for the overall assessment, while reporting selected battery results in another unit, for example in the article text, figures, or supplementary material. The table therefore reports the unit in which the impact results were extracted for the benchmarking, rather than the formal functional unit stated by each study.

Table B.1: Functional unit conversions and assumptions applied in the benchmarking.

Study	**Unit of extracted results**	**Conversion or adjustment applied**	**Comment**
Cusenza et al. (2019)	Per battery pack	Divided by the reported battery pack capacity	Converted to impacts per kWh battery capacity.
Zackrisson et al. (2010)	Per battery pack	Divided by the reported battery pack capacity	Converted to impacts per kWh battery capacity.
Notter et al. (2010)	Per kg battery	Multiplied by the total battery mass and divided by the battery capacity	Converted to impacts per kWh battery capacity.

Study	Unit of extracted results	Conversion or adjustment applied	Comment
Li et al. (2014)	Per kilometre driven	Converted using reported electricity consumption, vehicle lifetime, and battery capacity	Converted to impacts per kWh battery capacity. Introduce additional uncertainty, see below.
von Drachenfels et al. (2023)	Per battery cell	Divided by the reported cell capacity	The result represents cell-level production impacts.
Degen and Schütte (2022)	Per kWh cell capacity	No conversion required	Retained as a cell-level result.
Xu et al. (2022)	Per kWh cell capacity	No conversion required	Retained as a cell-level result.
Clemente et al. (2025)	Reported per kWh battery capacity	No conversion required	Directly included in the benchmarking.
USEPA (2013)	Reported per kWh battery capacity	No conversion required	Directly included in the benchmarking.
Majeau-Bettez et al. (2011)	Reported per kWh battery capacity	No conversion required	Directly included in the benchmarking.

For Li et al. (2014), results were originally reported per kilometre driven. These results were converted to impacts per kWh battery capacity using values reported in the study: an electricity consumption of 164.8 Wh/km, a vehicle lifetime of 200,000 km, and a battery capacity of 43.2 kWh per battery pack. This enabled an approximate transformation from impacts per kilometre to impacts per kWh battery capacity. However, the conversion introduces additional uncertainty, since lifetime vehicle energy consumption is used to derive a battery-based functional unit.

B.1.2 Impact category units and reporting adjustments

The reviewed studies used different impact categories, abbreviations, and units. To avoid inappropriate comparison between results expressed in incompatible units, only results reported in comparable units were included in each quantitative comparison. Where impact categories were reported using units that were not sufficiently common across the reviewed studies, these results were excluded from the corresponding figure.

Table B.2: Impact category units and reporting adjustments applied in the benchmarking.

Impact category	**Included unit or classification**	**Excluded or separated units**	**Adjustment applied**
Eutrophication potential	EP (N-eq/kWh), FEP (P-eq/kWh), and MEP (N-eq/kWh) shown separately	kg PO_4^{3-}-eq/kWh excluded	Three separate figures were created: one for unspecified EP, one for FEP, and one for MEP.
Acidification potential	kg SO_2-eq/kWh	mol H^+-eq	–
Photochemical ozone impacts	kg NMVOC-eq/kWh	kg C_2H_4-eq/kWh and kg O_3-eq/kWh	–
Abiotic depletion potential	kg Sb-eq/kWh	kg Fe-eq/kWh and kg oil-eq/kWh	–
Photochemical ozone naming	POCP	POFP	Results reported as POCP and POFP were reported consistently as POCP in the benchmarking.
Particulate matter naming	PMFP	PM	Results reported as PM and PMFP were reported consistently as PMFP in the benchmarking.

von Drachenfels et al. (2023) reported AP as terrestrial acidification potential (TAP), since it was reported in kg SO_2-eq/kWh it was deemed to be comparable with the other studies, and thus included in the results.

For Sun et al. (2020), results were reported using two LCIA methods. Since the differences between the two sets of results were minor, only the results calculated using the CML method were included in the benchmarking. This avoided double counting the same study.

B.1.3 Battery format, chemistry, and material assumptions

In studies that compared batteries with the same cathode chemistry but different anode materials, only the results for the graphite-anode variant were included. For example, Li et al. (2014) compared NMC-based batteries with graphite and silicon nanowire anodes, and only the graphite-anode result was included in the benchmarking. Similarly, Xu et al. (2022) compared several cathode chemistries with either graphite or graphite–silicon composite anodes. Where both alternatives were available for the same cathode chemistry, the graphite-anode result was selected.

However, in some cases, no graphite-only alternative was available. For example, Clemente et al. (2025) assessed batteries with a combined silicon–graphite anode, and some of the battery chemistries reported by Xu et al. (2022) were only available with graphite–silicon composite anodes. These results were retained in the benchmarking.

For Li et al. (2014), an additional assumption was required regarding assembly energy. The study only specified battery assembly energy for the silicon nanowire variant. Since no separate assembly energy value was provided for the graphite-anode variant, the same assembly energy was assumed for the graphite version. This assumption was considered reasonable for the purpose of comparison, as the assembly energy was treated as mainly related to battery assembly operations rather than the specific anode material.

For Zackrisson et al. (2010), the water-based production route was selected instead of the NMP-based route. This choice was made to avoid including an additional solvent-related production variant and to improve consistency with the other studies included in the benchmarking.

B.1.4 System boundary adjustments

The benchmarking studies applied a wide range of system boundaries, both in terms of life cycle stages and the processes included within those stages. To enable meaningful comparison across studies, a number of adjustments and assumptions were made to align the system boundaries of the reported results.
To improve comparability, results were, where possible, aligned to a cradle-to-gate system boundary focusing on the production stage of lithium-ion batteries. Consequently, use-phase impacts and recycling-related impacts and credits were excluded where these could be separated from the reported results.

B.1.4.1 Studies adjusted to cradle-to-gate

Table B.3: Studies adjusted to a cradle-to-gate system boundary where possible.

Study	Original system boundary	Adjustment applied
Šimaitis et al. (2023)	Cradle-to-grave	Only cradle-to-gate results were included, recycling effects excluded.
Sun et al. (2020)	Cradle-to-gate + EoL	Results were included as cradle-to-gate, excluding recycling credits.

Study	Original system boundary	Adjustment applied
Raugei and Winfield (2019)	Cradle-to-gate + EoL	Results were included as cradle-to-gate, excluding recycling credits
Zackrisson et al. (2010)	Cradle-to-grave + collection for recycling	Results were included as cradle-to-gate, excluding use-phase impacts and transport for recycling collection.
Notter et al. (2010)	Cradle-to-grave	Only cradle-to-gate impacts of the lithium-ion battery were included. Use-phase and recycling stages were excluded, since the study also considered the vehicle itself, which is outside the system boundary of this thesis.
USEPA (2013)	Cradle-to-grave	The results used in the benchmarking correspond to a cradle-to-gate scope, since the reported end-of-life results combined recycling impacts and credits, which could not be separated without introducing additional uncertainty.

B.1.4.2 Studies retained with broader system boundaries

In addition to the adjustments described above, where most system boundaries were aligned to a cradle-to-gate perspective, several studies applied broader system boundaries, with varying treatment of EoL impacts and recycling credits. In total, three studies were retained with cradle-to-grave results, as they explicitly reported EoL impacts and/or recycling credits separately.

Table B.4: Studies retained with broader system boundaries.

Study	Included scope in benchmarking	Reason or adjustment applied
Li et al. (2014)	Cradle-to-grave, excluding recycling credits	The study included recycling impacts but did not account for recycling credits. The results were retained with this scope.
Cusenza et al. (2019)	Cradle-to-grave, excluding recycling credits	The study reported results both with and without recycling credits. Only results excluding recycling credits were included.

Study	Included scope in benchmarking	Reason or adjustment applied
Chen et al. (2022)	Adjusted from cradle-to-cradle to cradle-to-grave, excluding recycling credits	Results were adjusted to include production, battery use-phase, and recycling impacts, while excluding recycling credits. The mean value of the different recycling impacts assessed in the study was used.

B.1.4.3 Gate-to-gate studies

Degen and Schütte (2022) applied a gate-to-gate system boundary. The study was included in the benchmarking figures because it provides relevant information on battery cell production. However, its limited system boundary was explicitly indicated, and the study was excluded from mean value calculations to avoid underestimating impacts compared with studies using broader cradle-to-gate boundaries.

B.1.5 Prospective studies and scenario selection

The benchmarking includes three studies applying prospective LCA approaches. These were included to increase the analytical breadth of the comparison and to capture methodological variation within the field. However, to improve comparability with studies representing current or historical production conditions, adjustments were required for studies presenting multiple future scenarios.

For Šimaitis et al. (2023), only the base case representing 2020 conditions was included in the benchmarking. A similar approach was applied to Xu et al. (2022), where only the base case of 2020 results were considered. Raugei and Winfield (2019) also applied a prospective perspective; however, their approach differs in that it focuses on future technological developments rather than explicitly defined future time scenarios. Their results were therefore included without further adjustment.

C

Appendix

C.1 Data for Module and Pack Assembly

C.1.1 BoM for module and pack assembly

Table C.1: Bill of Material module and pack assembly

Bill of Material	
Component	**Mass [kg]**
One Battery Pack	250 (6), 360 (4), 253 (7), 451 (1)†, 300 (8), 210 (2)
Module Components	
Adhesive film	?
Cell carrier	?
Busbar	2.019 (6)
BMS slave	?
Voltmeter	?
Temperature meter	?
Current collector plate	?
Housing	42 (6), 61.20 (4), 80.96 (7)‡, 90.2 (1)
Insulation panels	0.41 (6), 0.714 (2)§
Bracing plates	0.31 (6)
Stretch bands	0.78 (6)
Pack Components	
Cooling plates	60.12 (4), 83.435 (1)
Thermal management unit	10 (6), 10.37 (7)
Battery management system	6.6 (6), 7.2 (4), 9.361 (7), 9.02 (1), 1.014 (8)
HV distribution unit	2.8 (6)
Sealing compound	?
Housing cover	1.3 (6)

† Own calculations based on general data in paper
‡ Mentioned as "packaging", no further info included
§ Named "thermal insulation" in the paper

(1): (USEPA, 2013)
(2): (Dunn et al., 2014)
(4): (B. Li et al., 2014)
(6): (Ellingsen et al., 2014)

(7): (Kallitsis et al., 2020)
(8): (Notter et al., 2010)

C.1.2 Module component and process energy requirements

Table C.2: Energy Requirements for module assembly

Module Components	**Cell stacking [MJ/kWh]**	**Mounting the BMS [MJ/kWh]**	**Contacting the tabs [MJ/kWh]**	**Tensioning of the cells [MJ/kWh]**	**Module final assembly [MJ/kWh]**
Adhesive film	?				
Cell carrier	?				
Busbar		?			
BMS slave		?			
Voltmeter		?			
Temperature meter		?			
Current collector plate			?		
Housing			68.9 (1)†, 101 (1)‡		
Insulation panels				?	
Bracing plates				?	
Stretch bands				?	
Energy (MJ/kWh)	?	?	0.014 (6)	?	?

† For Li-NCM. Note that this is primary energy.
‡ Average between LiMnO2, LiFePO4 and Li-NCM. Note that this is primary energy.

C.1.3 Pack component and process energy requirements

Table C.3: Pack Component Energy Requirements

Pack Components	**Mounting modules + cooling [MJ/kWh]**	**Assembly internal components [MJ/kWh]**	**Sealing and leak testing [MJ/kWh]**	**Charging and flashing [MJ/kWh]**	**End-of-line testing [MJ/kWh]**
Cooling plates	?				
Thermal management unit (cooling)		101 (5)			
Battery management system		81 (5), 43.7 (1)			
High-voltage distribution unit		?			
Sealing compound			?		
Housing cover			?		
Energy (MJ/kWh)	?	?	?	?	3.43 (8)

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