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A Review of Computational Methods and Tools for Life Cycle Assessment of Traction Battery Systems †

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Abstract: Life Cycle Assessment (LCA) is crucial for evaluating the environmental impact of products, but challenges such as uncertainties and data limitations hinder its effective use in design. This paper reviews LCA computational tools, focusing on traction batteries, and examines aspects such as software architecture, database integration, and uncertainty analysis. It highlights how these platforms enhance usability for designers by enabling interaction with complex models and integrating multidisciplinary features. By analyzing system boundaries, inventory criteria, and impact assessment, this review offers valuable insights for researchers, practitioners, and policymakers in LCA, addressing the implementation challenges and best practices for sustainable battery design.

Keywords: battery; life cycle assessment; computational tool; state of the art; systematic review

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1. Introduction

The growing popularity of electric vehicles (EVs) has increased attention on how their main components, in particular traction battery systems, affect the environment. From the extraction of raw materials to the disposal of the batteries at the end-of-life (EoL), these essential components of EVs present significant environmental challenges [1]. The extraction of raw materials (e.g., lithium, cobalt, and nickel) is increasingly considered critical. It often involves energy-intensive processes that can result in environmental degradation, water contamination, and the release of toxic gas. Nonetheless, a significant amount of energy is required in the production and assembly phase, frequently derived from a non-renewable energy mix, leading to a consequent increase in greenhouse gas emissions [2]. Resolving these issues is crucial for the continued progress of EV technology, and to address these challenges, the widely adopted Life Cycle Assessment (LCA) methodology is used to evaluate these burdens. Given the considerations discussed above, various studies have conducted a systematic and quantitative evaluation of EV traction batteries [3–6]. Those analyses often produce contradictory results pointing out the great variability from both the technological aspects and the environmental methodology point of view. To illustrate, essential elements such as the design of the battery, the composition of the cathode, the manufacturing methods, and upstream inventory data can cause variations in the results, complicating the task of fully understanding the environmental impacts associated with a particular battery technology. Moreover, differences in defining the system boundaries (for example, from cradle-to-gate to cradle-to-grave), functional units (for example, kWh of energy provided, or kilometers traveled by the vehicle using the battery), and the approach

to the impact assessment phase (LCIA) can also add to this inconsistency. Thus, despite the need to standardize the LCA approach across different variability aspects, it remains challenging to integrate effective LCA-based tools into the design process due to uncertainties, the complexity of battery systems, and the lack of reliable data during the inventory phase. Efforts are underway to develop complex computational systems specifically tailored for LCA to address these challenges. These frameworks aim to encompass a wide range of multidisciplinary elements (such as economic benefits and social or human health effects) and manage various technical and environmental modeling patterns. Furthermore, their user-friendly interfaces facilitate the LCA process, making them more accessible and easier to use for designers. While numerous LCA reviews have been performed on battery systems [2,7–9], there is a lack of recent studies assessing the current status of computational frameworks, specifically how to handle the challenges associated with the variability and complexity of the products, their computational structure, and the stage of product development at which they are employed. So, this research seeks to offer valuable recommendations for researchers, professionals, and decision-makers involved in LCA frameworks and the sustainable design of EV batteries by integrating insights from various studies and practical implementations. It also underscores the challenges and essential elements of developing computational tools, giving equal importance to software and LCA aspects, and proposes optimal choices for specific use cases.

1.1. Traction Battery Technologies

Traction battery systems are the heart of the EV assembly and performance. Even though this paper does not delve into the specifics of the technologies, it is beneficial to provide an overview of the most common types of batteries and their classification discussed in the recent literature. The main components are briefly summarized in this section according to [10]. The cell in a battery typically includes a cathode made from materials such as lithium cobalt oxide or lithium iron phosphate. During charging, lithium ions are stored in the anode, which is commonly composed of graphite or lithium titanate, and these ions are released during discharging. Metal foils, known as current collectors, facilitate the transport of electrons through the electrodes to the external circuit. A separator, which is a thin and porous membrane, physically separates the cathode and anode to prevent short circuits while allowing the passage of lithium ions. This separator is usually made of polyolefin materials and can be coated with ceramic materials to enhance heat resistance and improve cycle durability. Additionally, the cell includes components such as the stem and safety devices, including pressure relief valves and thermal fuses, to ensure structural integrity and prevent overheating and short circuits. Battery cells are connected in series and parallel within a module to achieve the desired voltage and capacity, using high-current connections such as bus bars. At the pack level, the Battery Management System (BMS) oversees the charging and discharging operations. This electrical system maintains balanced cell voltages, ensures safe operation within specified limits, and provides protection against short circuits, overcharging, and overheating. The cooling system, which can use liquid, air, or refrigerant as a medium, manages the battery's temperature. The pack also includes various safety devices and electronics, such as fuses, circuit breakers, and sensors, to ensure safe and reliable operation.

Lithium-ion batteries (LIBs) remain the most popular and are predicted to remain so in the years to come. They are the most used due to their high energy density, long cycle life, and relatively low self-discharge rate, making them highly efficient and reliable for various applications. Many possible chemistries can be used as the cathode in LIBs: lithium nickel manganese cobalt oxide (NMC), lithium iron phosphate (LFP), lithium nickel cobalt aluminum oxide (NCA), and lithium manganese oxide (LMO). Generally, the anode and

the cathode active materials are combined with a binder such as polyvinylidene fluoride (PVDF) or carboxymethyl cellulose (CMC) and conductive materials such as carbon black, to enhance the mechanical stability and electrical conductivity of the electrodes.

Battery cells can be classified according to their form and housing features, independent of the electrode chemistry. Prismatic, pouch, and cylindrical traction battery cell types are the most widely accessible on the market. Pouch and prismatic cells have comparable prismatic volumes, which optimize volume usage for electrodes, resulting in a higher packing density. Pouch cells typically utilize multi-layer aluminum foil (soft), while prismatic cells employ hard aluminum cases. Due to their casing, prismatic cells generally have lower specific and volumetric energy compared to pouch cells. In contrast, cylindrical and prismatic cells have high stiffness and robust packages that withstand increased pressure without deforming. In conclusion, the technological key variables, considering a future environmental analysis, can be summarized as follows:

- Component level variability, from cell components to module and pack assemblies.
- Chemistry level variability, considering both electrode (anode and cathode) compositions and all the other influencing factors such as the electrolyte composition and ceramic coating materials.
- Design level variability, which influences energy density and module assembly techniques.
- Production process variability, considering both the energy consumption and the specific technology in the extraction and manufacturing processes.

1.2. Life Cycle Assessment Overview

Life Cycle Assessment (LCA), a standardized methodology [11], has been used for decades to quantify and understand the environmental impacts of industrial products. It is usually defined by four key phases: goal and scope definition, inventory phase (LCI), impact assessment phase (LCIA), and interpretation phase. Specifically, through the definition of the aim of the study and the functional unit, the most appropriate boundaries of the system are chosen, distinguished between the foreground system, for which primary data are available, and the background system, modeled through data from commercial databases. Next, after the data collection using the inventory form, the impacts are evaluated using the selected category indicators and characterization models. In the context of traction batteries, LCA is becoming increasingly popular, and an expanding literature is well established, ranging from case study applications to comprehensive reviews of the state of the art. In terms of GWP, the impacts reported across the studies range from less than 50 kgCO2eq/kWh to over 500 kgCO2/kWh [12]. This variation is attributed not only to the different technological characteristics of the batteries evaluated but also to significant differences in LCA modeling factors. For instance, Wu et al. [13] have examined the variability of environmental impacts using different functional units (energy-FU as 1 kWh/delivered or mass-FU as 1 km traveled), which poses a potential risk of misinterpretation of the impact results by practitioners or policymakers. Engels et al. [14] emphasized the scarcity of original data. They presented primary data inventories for the laboratory-scale pack production and industrial production of natural graphite after reviewing the inventory data proposed in the literature. Furthermore, Chordia et al. [15] delved into the significance of the geographical location and energy consumption of the battery manufacturing process. They found that using up-to-date primary data on energy could lead to a significant reduction (−39%) in GHG emissions and that selecting a location with a low-impact electricity mix could result in a 50% decrease. To sum up, aside from technological variations, environmental modeling must consider the following:

- Defining the functional unit and setting the system boundaries, such as cradle-to-gate (e.g., excluding end-of-life) or cradle-to-grave (e.g., including end-of-life).

- Availability of primary data on component inventory (weight, chemical composition, or pack configuration) or manufacturing processes (energy consumption, waste management, manufacturing technology, or direct emission).
- Geographical location of battery pack manufacturing and use.
- Realistic energy consumption for the use phase impact.

1.3. Integrating LCA Tools into Engineering: Requirements and Challenges

In addition to commercial software that has been widely used across academics and industries, integrating specific environmental tools in the product development process has been found to be relevant for enhancing sustainability and environmental performance. Identifying potential environmental hotspots during the design phase enables the promotion of more informed decision-making and innovation towards eco-friendly solutions. To do so, several requirements are needed to effectively integrate the sustainability concepts into engineered solutions [12]:

- Requirements from country regulations, market demands, and management strategies.
- Supply chain knowledge and deep comprehension of the product foreground system.
- Relevant single life cycle phase parameters (e.g., manufacturing or use phase).
- Direct information on the recyclability and EoL path from different countries.

It appears clear that to achieve those guidelines, a continued interaction between different disciplines needs to be implemented to avoid misconceptions of modeling frameworks such as a general and comprehensive view of the system (top-down) or process-based (bottom-up) approach. In fact, practitioners and decision-makers often find it difficult to understand not only the impact results and their interpretation, but they also struggle to fully comprehend the connection between the supply chain data, foreground system, and the consequent modeling of the commercial database processes [16]. All of this affects the impact results' quality and leads to a progressive simplification of the LCA applications. In addition, the limited availability of primary data, the scarce temporal and geographical representativeness, and the unwillingness to share proprietary data reduce the possibility of creating representative frameworks for complex product systems. In summary, to significantly enhance the effectiveness and reliability of LCA tools in engineered products, effective computational support is necessary to better handle technological complexity. In Figure 1, the main challenges and requirements for integrating LCA tools are summarized.



Figure 1. Challenges for integrating computational LCA tools.

2. Materials and Methods

This review aims to define an implementable methodology to identify the current status of the traction battery environmental burden and to characterize the state-of-the-art (SoA) computational LCA tools. Two primary research topics are defined—Traction Battery SoA and Computational Tool SoA—along with the related search query keywords through which the literature databases are built, as reported in the

Supplementary Materials (Table S1). Four refinement steps have been applied to the two literature databases (see Figure 2), adapted from [17]:

1. Starting from the collected articles from different literature engine databases—237 for Traction Battery SoA and 180 for Computational Tool SoA—the duplicates are excluded, deleting 30 and 9 studies, respectively.
2. Next, a three-phase screening (title, followed by abstract, and finally the full text) is conducted, based on the connection between the study's topic and the following research questions:

- Traction Battery SoA
    - Q1: How are technology variabilities (component, design, materials, and manufacturing processes) represented, and how do they influence the LCA results?
    - Q2: How does the inventory modeling (primary data, geographic locations, energy consumption) influence the environmental impacts of traction batteries?
    - Q3: How can the LCA results be standardized to account for the variability in system boundaries, functional units, and impact assessment methods?
- Computational Tool SoA
    - Q1: What are the main features and benefits of computational LCA tools used for assessing the environmental impacts of complex product systems?
    - Q2: What frameworks do computational LCA tools use to ensure the accuracy and reliability of the impact results, considering the technological and environmental variability? Are they flexible or scalable?
    - Q3: In what ways can computational tools support interdisciplinary groups in the product design process?

3. The selected studies are then in-depth reviewed and characterized according to various features (see Supplementary Materials Table S2). For traction batteries, both the technical aspects and environmental qualitative and quantitative data are analyzed; in contrast, for computational tools, the main topics, the general benefits, and the level of computational integration are evaluated.
4. Lastly, specific applications for the two topics—Computational modeling focus and Traction Battery focus—are identified in order to describe the computational LCA tools for battery traction, integrating insights from both the traction battery and computational tool perspectives.

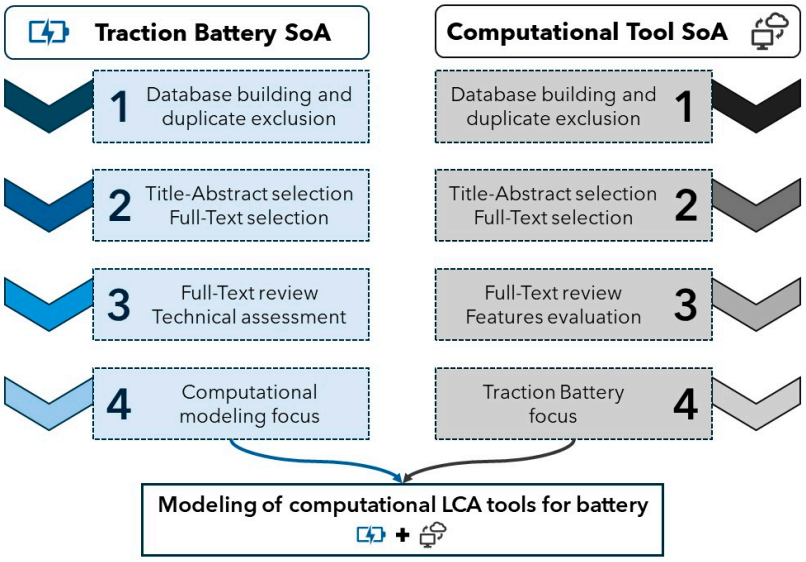


Figure 2. State-of-the-art approaches for the two research topics.

3. Results and Discussion

3.1. Traction Battery State of the Art

In this section, the results of the traction battery topic are presented. After the three-phase screening application, the studies selected for the review decreased from 207 to 79 (53 were excluded in the title phase, 43 in the abstract phase, and 32 in the full-text reading phase). Specifically, this cut-off was applied mainly to studies unrelated to the research question, such as economic and social evaluations, battery reuse and repurposing applications, comparative LCA on entire vehicles, and environmental assessments that do not adhere to the LCA methodology. Analyzing the database from a general point of view, only four studies were conference papers, and the others were published in scientific journals. Most of the studies were published in the last two years (8 in 2022, 19 in 2023, and 17 in 2024). Using the free tool VOSviwer [18], a keyword bibliometric map with a publishing year scale was created. As expected, key terms such as "life cycle assessment", "environmental impact", and "lithium-ion batteries" appear clearly, indicating their significant role in the academic interest. The interconnection of terms such as "recycling", "electronic waste", and "electronics waste" suggests a quite recent need to address the environmental aspects of battery disposal. Moreover, the analysis indicates keywords of interest such as "supply chain", "power supply", "extraction", and "nickel compounds", which reflect the rising attention on the understanding of the carbon footprint's entire life cycle and the material optimization. Keywords related to the broader context of battery usage, such as "electric vehicles", "plug-in hybrid", and "electric vehicle battery" indicate that research on battery LCA is often conducted within the more complex framework of entire vehicle systems. The map is shown in the Supplementary Materials (Figure S1). This highlights the interconnected nature of battery research, where the performance and impact of batteries are evaluated not in isolation but as integral components of larger systems. Starting from this keyword analysis, the literature database was divided into the main research topics: reviews (13 studies), cradle-to-grave LCA (13 studies), manufacturing or use phase focus (28 studies), and recycling assessment (25 studies).

3.1.1. Traction Battery State of the Art: Reviews

Among the literature database, 13 studies provide a comprehensive overview of the current state of research on the life cycle assessment of batteries. A few authors [2,7,8] explore all the phases of the battery life cycle, while others focus on a single aspect such as urban application [19], cradle-to-gate phase [20,21], EoL phase [22], and digital twin platforms [1]. The differences in system boundaries, functional units, and impact assessment methods are highlighted in the reviews, underscoring the importance of standardized approaches to enhance comparability among studies. Porzio et al. [7] and Arshad et al. [8] have underlined the reasons for the inconsistent results, pointing out the lack of no single standard for best practices. Defining appropriate system boundaries, such as including the use and end-of-life phases to capture the net environmental impacts; selecting relevant environmental metrics such as GHG emissions, water use, and resource depletion; and using functional units such as kWh of capacity for evaluating the storage potential and lifetime energy throughput, can significantly improve the comparability and reliability of LCA. Additionally, performing sensitivity analyses across different manufacturing scales and developing scenarios approved by experts for crucial phases can better reflect the industries' common practices. More specifically, Bouter et al. [2] have quantified the environmental impacts through a statistical meta-analysis, influenced by geographical, technical, and methodological factors. The study found substantial geographical variation in reported GHG emissions, with emissions being lower in American studies compared

to those from Europe and China. The high variability is influenced by the differences in cathode chemistry, with NMC chemistry showing the greatest dispersion. Furthermore, the environmental advantages of pouch and cylindrical designs contribute to cell design. Additionally, the energy source used for battery manufacturing is correlated to the cathode chemistry. Considering the system boundaries, the inclusion of the end-of-life phase leads to a decrease in the value of the GWP results by almost half. As expected, the possibility of reuse at the end of the life cycle produces positive benefits contributing to a 94% reduction in GWP emissions. Akasapu et al. [20] examined the critical points in the production phase and proposed a design process model that integrates environmental considerations in the early stages. As noted in the preceding sections, process manufacturing and energy usage differ based on cell chemistry and cell type, and the available information is often limited and outdated, heavily influenced by plant size, technologies employed, and geographic location. Lastly, Zhou et al. [1] have investigated the challenges of LCA digitalization applied to the traction battery, pointing out the main assumptions that a cross-scale multi-stage analytic LCA needs to face, from micro-scale assumptions such as electrode degradation during the life cycle, to macro-scale assumptions such as linearized battery degradation, and to circular economy assumptions such as knowing the capacity rate for the repurposing stage. Regarding what has already been mentioned, the identified reviews focus more on the methodological and practical aspects of the specific LCA case study, without addressing the challenges of adopting a holistic approach to the battery product system.

3.1.2. Traction Battery State of the Art: Cradle-to-Grave LCA

The environmental impacts of the entire life cycle have been widely assessed in the database literature. All the studies use a 1 kWh functional unit, and the majority assess different midpoint impact categories from the ReCiPe 2016 impact methodology. Regarding primary data availability, only a few articles propose their data measurement on material composition [23] or use phase stage [24]; the remaining studies rely on data from literature or commercial databases, mostly scaled by battery mass. In most of the case studies analyzed, the cell type and the battery pack assembly strategies are not defined, indicating that inventories are built using literature references rather than through robust scientific assumptions. In terms of variability, several studies have implemented scenario analyses on technology factors such as cathode chemistry, electricity mix production, and future carbon neutrality predictions. For instance, Accardo et al. [25] and Landi et al. [26] have compared two common cathode chemistries, nickel manganese cobalt (NMC) and lithium iron phosphate (LFP), with sodium–nickel–chloride and sodium–sulfur batteries. They highlighted that it is not possible to unequivocally determine which chemistry is the most sustainable. This uncertainty arises from varying results across different impact categories (e.g., global warming potential and abiotic depletion) and differences in energy efficiency, which affect energy waste. Looking at the use phase, Held et al. [27] have assessed the environmental benefits of a battery electric vehicle (BEV) in comparison with an internal combustion vehicle (ICEV) using real mobility patterns and high operation grade. The results demonstrate that the ICEV substitution leads to environmental benefits for the main impact categories if a commercial use profile and a decarbonized electricity mix for the charges are assumed. The physical degradation of the traction battery is introduced by Jenu et al. [28] in which the life cycle span is estimated using a cycle depth stress factor. The service life duration that directly affects the environmental impacts is influenced by stress factors such as cell temperature, cycle depth, and average state of charge (SOC): higher temperatures and deviations from 50% SOC reduce battery life, while lowering the cycle depth extends it, with the impact varying across different countries. Chen et al. [29] investigated the future decarbonization of the Chinese electricity mixes and

underlined a possible reduction of 74.8% for the production phase and 75.1% for the use phase by optimizing the electricity mix and developing vehicle-to-grid or carbon capture technologies by 2050. On the contrary, Kim et al. [30] pointed out that the decarbonization of the battery life cycle should rely not on the exploitation of renewable energy sources, due to their low availability and non-dispatchable nature, but on the improvement in weight reduction and performance. In sum, as with the reviews, the cradle-to-grave studies do not present comprehensive and replicable frameworks that assess the variability in the life cycle product using computational tools. On the other hand, the studies focus on single case study inventories or specific assumptions that limit the ability to gain a comprehensive understanding of the environmental implications.

3.1.3. Traction Battery State of the Art: Manufacturing or Use Phase Focus

Most of the studies compiled in the Traction Battery State-of-the-Art database focus on the environmental impact during the manufacturing or usage phases of batteries. As previously noted, the assessment of these phases is significantly influenced by both technological factors—such as battery chemistry, design, energy consumption during production, and vehicle energy consumption—and by Life Cycle Assessment (LCA) parameters, including primary inventory data, geographical context, and the inclusion or exclusion of specific components. Among the studies that concentrate on the manufacturing phase, several introduce new primary data databases for specific components, such as anode production [14], or for energy consumption during production [31]. For instance, Chordia et al. [15] provided a comprehensive inventory based on primary data from a large-scale facility in Europe. This study focused on a single type of battery chemistry and design, highlighting the environmental impact of different energy consumption models within the factory and the percentage of recycled materials used. On the computational side, Baars et al. [32] introduced a Python-based modeling tool that optimizes the design of prismatic battery packs for various vehicle segments from both the environmental and cost perspectives. This tool incorporates different improvement strategies, such as alternative cathode chemistries and variations in current collector thickness, within a computational framework that integrates background data from commercial databases. In summary, aside from the examples mentioned, the state of the art highlights a lack of integrated approaches capable of delivering environmental impact results that extend beyond individual case studies. There is a noticeable gap in the use of parametric frameworks that can account for varying chemistries or design features. The same applies to studies that focus on the use phase where factors such as geographical context [33] and capacity fade model [34] are more commonly assessed. Among these, Yang et al. [35] implemented an energy loss model using simulation-based data on cell degradation to examine the environmental impact during battery operation. Their study considers not only the battery pack but also other components, such as the liquid cooling system and the battery junction box. None of these studies have addressed emerging use-phase challenges, such as vehicle-to-grid (V2G) integration or battery repurposing, which are increasingly relevant in the future technological landscape.

3.1.4. Traction Battery State of the Art: Recycling Assessment

This section explores the main outcomes of the 25 studies that deal with the end-of-life stages. There is a growing interest in addressing and integrating battery disposal into the academic debate. The approaches and the technologies to recycle LIBs have been widely explored, dealing with different aspects such as conventional recycling routes [36], country end-of-life scenarios as in China [37], and new technologies at the scale. Hydrometallurgical processes are frequently cited and involve the use of solutions to leach and extract metals

such as lithium, cobalt, nickel, and manganese from discharged and neutralized batteries. Another process is pyrometallurgy in which spent batteries undergo high-energy thermal treatment to recover valuable materials. The pyrometallurgical method is generally widely used due to its simplicity and robustness but with lower extraction efficiency and high energy consumption [38]. This therefore leads to higher greenhouse gas emissions and a low purity of recovered materials. The location of the recycling plant is also an important source of variability, due to the different types of processes adopted, the electricity grid mix composition, and the transport distances assumed for the collection of spent LIBs. Most of the studies focused on China's context due to the high number of batteries produced, overlooking other country's scenarios that are currently under development (e.g., European countries). Looking at the quantitative environmental results, most of the studies analyzed different impact categories to provide a comprehensive understanding but with substantial differences in the results due to different modeling choices [39]. In fact, emerging from the state of the art is the lack of a standardized approach to the last phase of the life cycle, which affects the results. The main aspects are as follows:

- High technology process variability and lack of primary industrial-scale data.
- Different system boundaries.
- Chemistry of the cathode, which can affect the energy required in the recycling step.
- Recovery of non-valuable materials such as anode electrodes.
- Quality of the recycled materials.
- Geographic specificity of the recycling process (plant typology and electricity mix).

Among the recycling assessment studies, a few articles have assessed this variability and complexity from a framework point of view. Rinne et al. [40] have performed a simulation-based LCA of a hydrometallurgical battery recycling process to analyze the environmental impact of prospective processes with few industrial data needed. Lastly, Šimaitis et al. [41] have applied future scenarios in LCA methodology at the recycling phase, using a computational implementation in Python-based software (3.11.0). This study investigates the temporal discrepancy of environmental impacts using future electricity grid mix scenarios in which decarbonization efforts are implemented.

3.2. Computational Tool State of the Art

As for the traction battery, the three-phase screening was applied to the database built, decreasing it from 171 studies to 23 (84 were excluded in the title phase, 44 in the abstract phase, and 20 in the full-text reading phase). Most of the studies initially selected were discarded due to a lack of computational aspects of LCA, a focus on economic or social evaluations, a simplified approach to the product system assessed, and non-compliance with the LCA methodology (ISO 14044 [11]). Overall, the majority of the research consists of journal articles (75%), while the remaining includes three conference papers and four book chapters. Looking at the year of publication, there is a rise in publications from 2016 to 2019, stabilizing at four publications annually with a peak at five publications in 2022. The most frequently occurring keywords and their relationships within the selected studies were analyzed, and the map is shown in the Supplementary Materials (Figure S2). Prominent clusters are "life cycle", "life cycle assessment", and "environmental impact". On the other hand, "circular economy", "scenario analysis", and "perspective analysis" appear in significant clusters as emerging trends reflecting the growing interest in integrating multidisciplinary approaches, policy-making, and industrial practices. No terms related to the computational aspect of an LCA tool appear in the map, suggesting a potential gap in the state of the art. Considering the main research topics, the computational tool database was divided into general and theoretical innovations (8 studies), and practical tool applications (15 studies).

3.2.1. Computational Tool State of the Art: General and Theoretical Innovations

This section examines the innovations implemented in the LCA methodology from a general framework point of view. Advanced approaches to the traditional LCA are often cited [42]:

- Dynamic LCA (dLCA) incorporates the temporal dimension in evaluating the environmental impact of a product.
- Prospective LCA (pLCA) explores potential future scenarios of emerging technologies.
- Process-based LCA focuses on detailing how individual unit processes of a system are interconnected, using parameterized inventories to update newly available data.
- Hybrid-based LCA (hLCA) uses integrated assessment models (IAMs) to model parameterized current and future foreground systems, typically incorporating social or economic assessments for more realistic evaluations.

In detail, Douziech et al. [42] and Jolivet et al. [43] implemented a hybrid-based approach to parameterize inventories and assess uncertainties, creating a Python library for use with the well-known open-source software Brightway2 [44]. This computational framework employs algebraic computation and simplified models (IAMs) to rapidly estimate large uncertainties in simulations of both foreground and background variables. Additionally, Joyce et al. [45] proposed a python library to easily create and share altered inventories in Brightway2. From a dynamic LCA perspective, Pigné et al. [46] and Cardellini et al. [47] explored the time dependencies of background and foreground systems, creating a free web-based tool and a part of the open-source software Brightway2, respectively. Specific algorithms, such as graph search algorithms, are used in both examples to manage computational intensity and identify impactful processes using control search. In conclusion, the computational innovations focused mainly on the management of inventory variabilities in the form of temporal and regionality uncertainties to enhance the accuracy and applicability of LCA results.

3.2.2. Computational Tool State of the Art: Practical Tool Applications

Next, LCA tools developed for specific product systems are examined. A variety of applications are evaluated and classified according to various technical framework characteristics such as the level of computational integration, product variability, and uncertainties evaluation. The degree of computational integration in LCA tools varies significantly among those studies and can be implemented in different ways. For instance, Tao et al. [48] integrated CAD/CAE software in LCA tools enabling correlations between environmental analysis and design parameters. Through an optimization procedure, different solutions are evaluated in their entire life cycle; however, only GWP impacts are evaluated. Moving on to energy systems, César et al. [49] merged LCA analysis with exergy modeling of an absorption refrigeration system in an open-source MATLAB application, providing reliable inventory energy data for emerging technology. In the building sector, Apostolopoulos et al. [50] developed an online tool called VERIFY for dynamic life cycle assessment (LCA) and cost analysis in building renovations. The tool focuses on reducing greenhouse gas emissions, promoting resource-efficient material use, and optimizing life cycle costs. VERIFY converts construction bills into inventories, factoring in costs and lifetimes of components. Although it currently excludes end-of-life (EoL) analysis due to uncertainties in waste treatment, VERIFY uses time-series data and connects with IoT networks for real-time monitoring. The tool features a three-tier architecture with Python and PostgreSQL for efficient performance and user-friendly results. Instead, in the automotive sector, holistic data hub management for green transportation is proposed by Agavanakis et al. [51], in which factors such as vehicle energy consumption, distances traveled, and real truck loading from real-time data acquisition are integrated into users'

datasets. The proposed approach aligns with the logistics sector's European directives and seeks to improve data accuracy and generate valuable insights by implementing precise fuel volume monitoring, height-to-volume conversion, fuel sensor saturation compensation, and automatic refill detection. This extensive data center utilizes accumulated expertise and advanced AI methods to offer a versatile and scalable solution for the logistics value chains.

Lastly, Cerdas [52] deserves special attention as their work analyzes the LCA of traction batteries, focusing on developing an integrated computational framework to assess environmental impacts. The author introduces the Integrated Computational Life Cycle Engineering (ICLCE) framework for electric vehicles to support fast and comprehensive modeling of complex systems in electromobility within different environments and spatial settings. The integration of spatial and temporal factors into engineering activities helps provide a holistic understanding of environmental impacts, supporting decision-making and dealing with the needs of stakeholders such as researchers, manufacturers, and engineers. The framework is based on integrated models that represent phenomena across different disciplines and scales and include real-time variability of temporal and specific contexts. The architecture is organized in levels in which the foreground systems and background systems are built upon spatial assumptions (e.g., road and traffic, local temperature, electricity mixes, emerging materials, or manufacturing energy consumptions); python-based libraries and opensource software such as Brightway2 are used. Each logic is a stand-alone structure able to link different physics or engineering models. In detail, all the main variability and the life cycle phase identified for a battery system are assessed and included, with a focus on the influence of the spatial location in which the traction batteries are used.

4. Conclusions and Future Directions

This paper presented a systematic review of the LCA computational tools, focusing on traction batteries. First, a comprehensive review of traction battery technologies and their associated environmental impacts was provided, considering resource extraction, manufacturing, usage, and disposal factors. Next, this study identified the principal parameters and factors of a Life Cycle Assessment (LCA) tool that are crucial for evaluating these technologies, including energy consumption, emissions, material sourcing, and end-of-life scenarios. To ensure consistency and reliability in future research, a replicable methodology for critically analyzing the current state of the art of both traction battery technologies and computational LCA tools was presented. This methodology allows for a standardized approach to assessing different studies, ensuring that the findings are robust and comparable. Finally, an analysis of the literature databases was conducted to identify the main challenges and future developments in the field. From the Traction Battery focus database, a clear trend was revealed toward addressing the lack of primary data by providing inventories based on real case studies and representing LCA modeling uncertainties through sensitivity analyses, such as geographic location or recycling percentages. However, aside from a few examples (e.g., Baars et al. [32]), it is evident that computational and parametric frameworks are not commonly implemented. This absence makes it challenging to achieve a comprehensive understanding of the product system beyond the specific assumptions of individual case studies. On the other hand, the Computational modeling focus demonstrates a shared interest in incorporating temporal and regional uncertainties into computational models. Practical applications in the transportation sector are limited; however, Cerdas [52] provides a notable example of an integrated computational framework that combines spatial and temporal factors with engineering activities. To conclude with future directions, the previously posed research questions can be addressed as follows:

Traction Battery SoA

- Q1: How are technology variabilities (component, design, materials, and manufacturing processes) represented, and how do they influence the LCA results?
- AnsQ1: The technological variabilities are typically represented and analyzed from the specific case study point of view through a detailed inventory database. These variabilities significantly influence the LCA results, making it challenging to identify the environmental benefits. These variabilities introduce a high degree of complexity, as they are often case-specific and can lead to considerable differences in results. The findings suggest that to accurately capture the environmental footprint of traction batteries, it is essential to consider a wide range of technological factors and to move beyond single case studies. Future research should focus on developing methods to systematically integrate these variabilities into LCA models.
- Q2: How does the inventory modeling (primary data, geographic locations, energy consumption) influence the environmental impacts of traction batteries?
- AnsQ2: Accurate inventory modeling ensures that the analysis reflects real-world conditions, leading to more accurate and reliable results. The academic interest is focusing on primary data for the manufacturing use phase and on sensitivity analysis based on geographical context and end-of-life route. Clearly, the environmental results are affected by specific case study assumptions that need to be accounted for by policymakers to improve the robustness of the results.
- Q3: How can LCA results be standardized to account for the variability in system boundaries, functional units, and impact assessment methods?
- AnsQ3: This study identified several challenges in the standardization of LCA results, primarily due to inconsistencies in system boundaries, functional units, and impact assessment methods across different studies. These differences make it difficult to compare results or draw general conclusions. The scientific community should work together to create clear guidelines and standardized practices for LCA. This will make it easier to compare and obtain reliable data for policymakers and industry stakeholders.

Computational Tool SoA

- Q1: What are the main features and benefits of computational LCA tools used for assessing the environmental impacts of complex product systems?
- AnsQ1: The main features of computational LCA tools include the ability to handle large datasets, perform detailed and high-resolution modeling, and incorporate various factors such as temporal and geographic variability. This tool also offers the ability to simulate different scenarios and assess the effects of various design choices. Future research should focus on improving their usability and integration into broader decision-making processes.
- Q2: What frameworks do computational LCA tools use to ensure the accuracy and reliability of impact results, considering the technological and environmental variability? Are they flexible or scalable?
- AnsQ2: Current LCA frameworks are focusing mainly on the spatial and temporal flexibility of the results, leaving out the scalability of technological and scientific features of the product system. From the traction battery point of view, design flexibility (e.g., cell mass or battery pack composition) or real-world use phase data need to still be explored and embedded in a computational framework.
- Q3: In what ways can computational tools support interdisciplinary groups in the product design process?
- AnsQ3: These tools can combine insights from engineering, environmental science, and economics, among other fields, to provide a holistic view of the product's en-

vironmental impact. By incorporating spatial and temporal factors, computational tools enable designers to consider the full life cycle of a product. This integrated approach facilitates more informed decision-making, helping to ensure that products are designed with sustainability in mind.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/engproc2025085010/s1, Figure S1: Traction Battery SOA bibliometric map; Figure S2: Computational tool SOA bibliometric map that illustrates the interconnections between various keywords; Table S1: Search keywords and related strategies, for the two topics. Table S2. Technical categories for Traction Battery and Computational Tool.

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References

1. Zhou, Y. Lifecycle Battery Carbon Footprint Analysis for Battery Sustainability with Energy Digitalization and Artificial Intelligence. *Appl. Energy* **2024**, *371*, 123665. [CrossRef]
2. Bouter, A.; Guichet, X. The Greenhouse Gas Emissions of Automotive Lithium-Ion Batteries: A Statistical Review of Life Cycle Assessment Studies. *J. Clean. Prod.* **2022**, *344*, 130994. [CrossRef]
3. 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. *Environ. Sci. Technol.* **2011**, *45*, 4548–4554. [CrossRef] [PubMed]
4. 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. *Environ. Sci. Technol.* **2010**, *44*, 6550–6556. [CrossRef]
5. Hawkins, T.R.; Singh, B.; Majeau-Bettez, G.; Strømman, A.H. Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *J. Ind. Ecol.* **2013**, *17*, 53–64. [CrossRef]
6. Dai, Q.; Spangenberger, J.; Ahmed, S.; Gaines, L.; Kelly, J.C.; Wang, M. *EverBatt: A Closed-Loop Battery Recycling Cost and Environmental Impacts Model*; Argonne National Laboratory (ANL): Argonne, IL, USA, 2019; p. 1530874.
7. Porzio, J.; Scown, C.D. Life-Cycle Assessment Considerations for Batteries and Battery Materials. *Adv. Energy Mater.* **2021**, *11*, 2100771. [CrossRef]
8. Arshad, F.; Lin, J.; Manurkar, N.; Fan, E.; Ahmad, A.; Tariq, M.-N.; Wu, F.; Chen, R.; Li, L. Life Cycle Assessment of Lithium-Ion Batteries: A Critical Review. *Resour. Conserv. Recycl.* **2022**, *180*, 106164. [CrossRef]
9. Nordelöf, A.; Messagie, M.; Tillman, A.-M.; Ljunggren Söderman, M.; Van Mierlo, J. Environmental Impacts of Hybrid, Plug-in Hybrid, and Battery Electric Vehicles—What Can We Learn from Life Cycle Assessment? *Int. J. Life Cycle Assess* **2014**, *19*, 1866–1890. [CrossRef]
10. Borah, R.; Hughson, F.R.; Johnston, J.; Nann, T. On Battery Materials and Methods. *Mater. Today Adv.* **2020**, *6*, 100046. [CrossRef]
11. *ISO 14044:2006*; Environmental Management—Life Cycle Assessment—Requirements and Guidelines. ISO: Geneva, Switzerland, 2006; pp. 1–46.
12. Cerdas, F. *Integrated Computational Life Cycle Engineering for Traction Batteries | SpringerLink*; Springer Nature: Cham, Switzerland, 2021; ISSN 2194-0541.
13. Wu, H.; Hu, Y.; Yu, Y.; Huang, K.; Wang, L. The Environmental Footprint of Electric Vehicle Battery Packs during the Production and Use Phases with Different Functional Units. *Int. J. Life Cycle Assess* **2021**, *26*, 97–113. [CrossRef]

14. Engels, P.; Cerdas, F.; Dettmer, T.; Frey, C.; Hentschel, J.; Herrmann, C.; Mirfabrikikar, T.; Schueler, M. Life Cycle Assessment of Natural Graphite Production for Lithium-Ion Battery Anodes Based on Industrial Primary Data. *J. Clean. Prod.* **2022**, *336*, 130474. [CrossRef]
15. Chordia, M.; Nordelöf, A.; Ellingsen, L.A.-W. Environmental Life Cycle Implications of Upscaling Lithium-Ion Battery Production. *Int. J. Life Cycle Assess* **2021**, *26*, 2024–2039. [CrossRef]
16. Lesage, P.; Mutel, C.; Schenker, U.; Margni, M. Uncertainty Analysis in LCA Using Precalculated Aggregated Datasets. *Int. J. Life Cycle Assess* **2018**, *23*, 2248–2265. [CrossRef]
17. Lucci, C.; Piantini, S.; Savino, G.; Pierini, M. Motorcycle Helmet Selection and Usage for Improved Safety: A Systematic Review on the Protective Effects of Helmet Type and Fastening. *Traffic Inj. Prev.* **2021**, *22*, 301–306. [CrossRef] [PubMed]
18. VOSviewer—Visualizing Scientific Landscapes. Available online: https://www.vosviewer.com// (accessed on 19 July 2024).
19. Nastasi, L.; Fiore, S. Environmental Assessment of Lithium-Ion Battery Lifecycle and of Their Use in Commercial Vehicles. *Batteries* **2024**, *10*, 90. [CrossRef]
20. Akasapu, U.; Hehenberger, P. A Design Process Model for Battery Systems Based on Existing Life Cycle Assessment Results. *J. Clean. Prod.* **2023**, *407*, 137149. [CrossRef]
21. Accardo, A.; Dotelli, G.; Spessa, E. A Study on the Cradle-to-Gate Environmental Impacts of Automotive Lithium-Ion Batteries. In *Proceedings of the Procedia CIRP*; Settineri, L., Priarone, P.C., Eds.; Elsevier B.V.: Amsterdam, The Netherlands, 2024; Volume 122, pp. 1077–1082.
22. Liu, Y.; Zhang, C.; Hao, Z.; Cai, X.; Liu, C.; Zhang, J.; Wang, S.; Chen, Y. Study on the Life Cycle Assessment of Automotive Power Batteries Considering Multi-Cycle Utilization. *Energies* **2023**, *16*, 6859. [CrossRef]
23. 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. *J. Clean. Prod.* **2020**, *273*, 123006. [CrossRef]
24. Raugei, M.; Winfield, P. Prospective LCA of the Production and EoL Recycling of a Novel Type of Li-Ion Battery for Electric Vehicles. *J. Clean. Prod.* **2019**, *213*, 926–932. [CrossRef]
25. Accardo, A.; Dotelli, G.; Musa, M.; Spessa, E. Life Cycle Assessment of an NMC Battery for Application to Electric Light-Duty Commercial Vehicles and Comparison with a Sodium-Nickel-Chloride Battery. *APPLIED Sci.* **2021**, *11*, 1160. [CrossRef]
26. Landi, D.; Marconi, M.; Pietroni, G. Comparative Life Cycle Assessment of Two Different Battery Technologies: Lithium Iron Phosphate and Sodium-Sulfur. In *Proceedings of the Procedia CIRP*; Dewulf, W., Duflou, J., Eds.; Elsevier B.V.: Amsterdam, The Netherlands, 2022; Volume 105, pp. 482–488.
27. Held, M.; Schücking, M. Utilization Effects on Battery Electric Vehicle Life-Cycle Assessment: A Case-Driven Analysis of Two Commercial Mobility Applications. *Transp. Res. Part D-Transp. Environ.* **2019**, *75*, 87–105. [CrossRef]
28. Jenu, S.; Deviatkin, I.; Hentunen, A.; Myllysilta, M.; Viik, S.; Pihlatie, M. Reducing the Climate Change Impacts of Lithium-Ion Batteries by Their Cautious Management through Integration of Stress Factors and Life Cycle Assessment. *J. Energy Storage* **2020**, *27*, 101023. [CrossRef]
29. 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. *J. Clean. Prod.* **2022**, *369*, 133342. [CrossRef]
30. Kim, S.; Park, S.; Lim, S. Identification of Principal Factors for Low-Carbon Electric Vehicle Batteries by Using a Life Cycle Assessment Model-Based Sensitivity Analysis. *Sustain. Energy Technol. Assess.* **2024**, *64*, 103683. [CrossRef]
31. Degen, F.; Schütte, M. Life Cycle Assessment of the Energy Consumption and GHG Emissions of State-of-the-Art Automotive Battery Cell Production. *J. Clean. Prod.* **2022**, *330*, 129798. [CrossRef]
32. Baars, J.; Cerdas, F.; Heidrich, O. An Integrated Model to Conduct Multi-Criteria Technology Assessments: The Case of Electric Vehicle Batteries. *Environ. Sci. Technol.* **2023**, *57*, 5056–5067. [CrossRef]
33. Chen, Q.; Lai, X.; Chen, J.; Huang, Y.; Guo, Y.; Wang, Y.; Han, X.; Lu, L.; Sun, Y.; Ouyang, M.; et al. A Critical Comparison of LCA Calculation Models for the Power Lithium-Ion Battery in Electric Vehicles during Use-Phase. *Energy* **2024**, *296*, 131175. [CrossRef]
34. Marques, P.; Garcia, R.; Kulay, L.; Freire, F. Comparative Life Cycle Assessment of Lithium-Ion Batteries for Electric Vehicles Addressing Capacity Fade. *J. Clean. Prod.* **2019**, *229*, 787–794. [CrossRef]
35. Yang, B.; Du, C.; Zhang, H.; Ma, X.; Shen, X.; Wang, D.; Yu, Z.; Huang, Q.; Gao, D.; Yin, Y.; et al. A Strategy to Assess the Use-Phase Carbon Footprint from Energy Losses in Electric Vehicle Battery. *J. Clean. Prod.* **2024**, *460*, 142569. [CrossRef]
36. Zhang, G.; Shi, M.; Hu, X.; Yang, H.; Yan, X. Comparison of Life Cycle Assessment of Different Recycling Methods for Decommissioned Lithium Iron Phosphate Batteries. *Sustain. Energy Technol. Assess* **2024**, *68*, 103871. [CrossRef]
37. Tian, X.; Ma, Q.; Xie, J.; Xia, Z.; Liu, Y. Environmental Impact and Economic Assessment of Recycling Lithium Iron Phosphate Battery Cathodes: Comparison of Major Processes in China. *Resour. Conserv. Recycl.* **2024**, *203*, 107449. [CrossRef]
38. Tao, Y.; Wang, Z.; Wu, B.; Tang, Y.; Evans, S. Environmental Life Cycle Assessment of Recycling Technologies for Ternary Lithium-Ion Batteries. *J. Clean. Prod.* **2023**, *389*, 136008. [CrossRef]

39. Kallitsis, E.; Korre, A.; Kelsall, G.H. Life Cycle Assessment of Recycling Options for Automotive Li-Ion Battery Packs. *J. Clean. Prod.* **2022**, *371*, 133636. [CrossRef]
40. Rinne, M.; Elomaa, H.; Porvali, A.; Lundström, M. Simulation-Based Life Cycle Assessment for Hydrometallurgical Recycling of Mixed LIB and NiMH Waste. *Resour. Conserv. Recycl.* **2021**, *170*, 105586. [CrossRef]
41. Šimaitis, J.; Allen, S.; Vagg, C. Are Future Recycling Benefits Misleading? Prospective Life Cycle Assessment of Lithium-Ion Batteries. *J. Ind. Ecol.* **2023**, *27*, 1291–1303. [CrossRef]
42. Douziech, M.; Besseau, R.; Jolivet, R.; Shoai-Tehrani, B.; Bourmaud, J.-Y.; Busato, G.; Gresset-Bourgeois, M.; Pérez-López, P. Life Cycle Assessment of Prospective Trajectories: A Parametric Approach for Tailor-Made Inventories and Its Computational Implementation. *J. Ind. Ecol.* **2024**, *28*, 25–40. [CrossRef]
43. Jolivet, R.; Clavreul, J.; Brière, R.; Besseau, R.; Prieur Vernat, A.; Sauze, M.; Blanc, I.; Douziech, M.; Pérez-López, P. Lca_algebraic: A Library Bringing Symbolic Calculus to LCA for Comprehensive Sensitivity Analysis. *Int. J. Life Cycle Assess* **2021**, *26*, 2457–2471. [CrossRef]
44. Mutel, C. Brightway: An Open Source Framework for Life Cycle Assessment. *JOSS* **2017**, *2*, 236. [CrossRef]
45. Joyce, P.J.; Björklund, A. Futura: A New Tool for Transparent and Shareable Scenario Analysis in Prospective Life Cycle Assessment. *J. Ind. Ecol.* **2022**, *26*, 134–144. [CrossRef]
46. Pigné, Y.; Gutiérrez, T.; Gibon, T.; Schaubroeck, T.; Popovici, E.; Shimako, A.; Benetto, E.; Tiruta-Barna, L. A Tool to Operationalize Dynamic LCA, Including Time Differentiation on the Complete Background Database. *Int. J. Life Cycle Assess.* **2020**, *25*, 267–279. [CrossRef]
47. Cardellini, G.; Mutel, C.L.; Vial, E.; Muys, B. Temporalis, a Generic Method and Tool for Dynamic Life Cycle Assessment. *Sci. Total Environ.* **2018**, *645*, 585–595. [CrossRef] [PubMed]
48. Tao, J.; Li, L.; Yu, S. An Innovative Eco-Design Approach Based on Integration of LCA, CAD\CAE and Optimization Tools, and Its Implementation Perspectives. *J. Clean. Prod.* **2018**, *187*, 839–851. [CrossRef]
49. César, J.C.; Ortiz, J.C.; Ochoa, G.V.; Restrepo, R.R.; Nuñez Alvarez, J.R. A New Computational Tool for the Development of Advanced Exergy Analysis and Lca on Single Effect Libr–H2o Solar Absorption Refrigeration System. *Lubricants* **2021**, *9*, 76. [CrossRef]
50. Apostolopoulos, V.; Mamounakis, I.; Seitaridis, A.; Tagkoulis, N.; Kourkoumpas, D.-S.; Iliadis, P.; Angelakoglou, K.; Nikolopoulos, N. An Integrated Life Cycle Assessment and Life Cycle Costing Approach towards Sustainable Building Renovation via a Dynamic Online Tool. *Appl. Energy* **2023**, *334*, 120710. [CrossRef]
51. Agavanakis, K.; Quitard, R.; Kousias, N.; Mellios, G.; Elkaim, E. Driving Sustainability in Logistics Value Chains: A Telematics Data Hub Implementation for Accurate Carbon Footprint Assessment and Reporting Using Global Standards-Based Tools. *AIP Conf. Proc.* **2023**, *3018*, 020058.
52. Cerdas, F. Concept Development: Integrated Computational Life Cycle Engineering for Traction Batteries. In *Integrated Computational Life Cycle Engineering for Traction Batteries*; Sustainable Production, Life Cycle Engineering and Management; Springer International Publishing: Cham, Switzerland, 2022; pp. 87–128; ISBN 978-3-030-82933-9.

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