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The Application of AI for Solving a Critical Challenges within LCAS

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Introduction

Life cycle assessment (LCA) is a standardized tool that is used to evaluate the environmental impacts associated with all the stages of a product's life - from raw material extraction through material processing, manufacture, distribution, use and end of life disposal (Finnveden & Moberg, 2005)

. Due to that, LCA has become a critical tool for identifying environmental impacts and enabling sustainable decision-making throughout the lifecycle of the product. Through evaluation of all the stages of the products life - from raw material extraction to its end of life, LCA provides a comprehensive framework for understanding and mitigating environmental footprints.

Since LCAs allow for a detailed impact assessment of the environmental impacts across multiple indicators such as Global Warming Potential (GWP), Cumulative Energy Demand (CED), etc., they are the tool used for identification of environmental impacts. (Bajdur et al., 2024)

(Petrova, 2023)

- LCAs are a crucial component in guiding industries towards more sustainable practices by highlighting areas for improvement and innovation (Brunn & Rentz, 1998)
- (van der Giesen et al., 2020)
- . For example, within the pharmaceutical industry, LCAs identify major contributors to the environmental impacts while also suggesting process optimizations through identification of inefficiencies (Lian et al., 2024)
- . energy usage and decreasing waste. This is especially advantageous in sectors like manufacturing and textiles, where efficient resource use is essential (Petrova, 2023)
- (Jhanji, Similarly, in the 3D printing industry, LCA helps quantify sustainability advantages and identify best practices for resource conservation (Tay & Tan, 2023)
- . LCA aids in enhancing processes by pinpointing opportunities for improvement, such as lowering
- 2023)
- . In general, LCAs provide a scientific basis for decision-making by enabling stakeholders to understand the trade-offs and make informed choices about product designs, material selections, and process improvements (Wattier et al., 2023)
- (Leonzio, 2023)

While LCAs are a powerful tool for improving sustainability, they are not without challenges. Limitations such as data availability, system boundaries, and the complexity of integrating social and economic dimensions can affect the accuracy and interpretability of LCA results. Moreover, the need for collaboration with experts and the development of comprehensive databases are crucial for maximizing the potential of LCA in driving sustainable practices across industries.

Challenges within LCAs

LCAs involve various challenges, such as defining and managing system boundaries, functional units, obtaining primary data, and data quality. These issues are critical as they will influence the overall accuracy and reliability of the results. However, the complexity of these challenges is compounded by the need to balance comprehensiveness with practicality ensuring that performing LCAs remains feasible and cost effective while capturing all the relevant environmental impacts. Some of these challenges are detailed below.

System Boundaries: Defining the system boundaries is a major challenge in LCA as it determines which processes are included or excluded from the assessment. This decision impacts the comprehensiveness and comparability of the results. Inconsistent system boundary definitions can lead to significant variations in LCA outcomes, making it difficult to compare studies or draw reliable conclusions (Djekic et al., 2019)

(Reap et al., 2008)

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Functional Units: Functional units provide the basis for comparison for an LCA. Thus, choosing the appropriate one is crucial. However, trying to select the appropriate functional unit can be problematic when dealing with multifunctional products or complex systems (Reap et al., 2008)

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Data Quality: The overall quality of the LCA is dictated by the quality of the data used in for developing the Life Cycle Inventory (LCI). Poor input data quality can lead to unreliable results and undermine the credibility of the assessment. A high bar for data quality is important to maintain across all phases of the LCA (Reap et al., 2008)

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Data Availability: Data availability is another pressing issue as comprehensive and reliable data is often limited to come by. The scarcity of data generally increases the need to make assumptions that may introduce further uncertainties within an LCA (Reap et al., 2008)

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Allocation of Flows: Material and energy flows need to be allocated within an LCA. This task is quite complex and can significantly affect the results of the LCA. It is a prevalent issue for systems that have multiple co-products or shared processes. In these cases allocation decisions can be subjective and contentious (Djekic et al., 2019)

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Impact Assessment: Deciding which environmental impact categories and characterization methods to use is another significant challenge within LCAs. The selection process often has uncertainties and is subjective which may yield varying results, thus, complicating the interpretation and comparison of LCA studies (Djekic et al., 2019)

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Despite the presence of these significant challenges, it is also important to recognize that they present opportunities for method advancements in LCAs. The issues identified above can be addressed through improved data collection, standardized methodologies, and enhanced modeling techniques (Reap et al., 2008)

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Using AI to solve the data challenges in LCAs

With recent advancements in Artificial Intelligence (AI), there are promising solutions that can be applied to the challenges detailed in the previous section. This paper focuses on how integration of AI, particularly through machine learning (ML), and deep learning (DL), can significantly enhance the precision, efficiency, and comprehensiveness of LCA data management. This is important for industries like electronics, energy, and building sectors where the supply chains are complex and rapid technological advancements often lead to data gaps and inconsistencies. This section details how AI can address these issues by automating data collection, improving data quality, and enabling dynamic data analysis.

Dealing with complex and disparate data sources: The primary challenge of LCA data collection stems from disparate data sources. AI can help integrate these complex sources and provide a more standard and reliable data ecosystem. This is significantly beneficial in the electronics industry, where AI can transform data inventories into automated LCA models, thus reducing risks in supply chains and increasing transparency (Mehdipour, 2024)

. Furthermore, the integration of AI in LCA not only streamlines data management but also enhances predictive capabilities, allowing organizations to simulate various scenarios and assess potential environmental impacts before product deployment. This forward-looking approach, often referred to as ex-ante LCA, addresses significant challenges associated with future modeling by utilizing machine learning algorithms to forecast outcomes based on historical data patterns (van der Giesen et al., 2020)

. For instance, companies can leverage these advanced analytics to evaluate how changes in materials or production processes could alter their sustainability profiles, thereby enabling proactive adjustments that align with circular economy principles.

Absence of any reliable data: ML models such as artificial neural networks (ANNs) can be used to estimate life-cycle impacts when there is little to no data present. For example, in the chemical industry, ANNs have been applied to predict the environmental impacts of chemicals by improving the quality of LCAs through filling data gaps with a good accuracy (Song, 2019)

. Another example can be found in the renewable energy sector where ML models have been used to predict environmental impacts, optimize resource use, and enhance the sustainability of energy systems like wind and solar power (Bassey et al., 2024)

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Enhancing Data Availability: Large language models (LLMs) can automate the curation of life cycle inventory data from diverse sources, addressing the challenges of missing foreground flow data and inconsistency in background data matching. This approach enhances the scalability of LCAs by allowing the LCA practitioner to reduce reliance on researching and obtaining primary data (Tu, 2024)

. As a result, LLMs could LCA practitioners to focus on higher-level analysis and interpretation of data, rather than getting bogged down in the minutiae of data acquisition. This shift not only enhances the efficiency of the LCA process but also contributes to more robust and comprehensive assessments, ultimately leading to better-informed sustainability decisions.

AI-Driven Dynamic Data Discovery: AI enables dynamic big data discovery, which delivers more accurate and valuable data for intelligent decision-making. This approach is crucial for industries with rapidly changing technologies and supply chains, such as electronics and semiconductors (Mehdipour, 2024)
(Vital et al., 2024)
. (van der Giesen et al., 2020)
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Addressing Data Gaps with Regression Models: Regression models can be employed to estimate missing data in LCAs, such as CO2 emissions from coal power plants. These models use plant-specific factors to predict emissions, thereby filling data gaps and improving the accuracy of LCA studies (Steinmann et al., 2014)
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While artificial intelligence presents considerable benefits in enhancing the quality and accessibility of data for life cycle assessment (LCA), it is crucial to acknowledge potential obstacles, including the propensity for bias within AI algorithms and the necessity for standardized data inputs. Furthermore, the incorporation of AI into LCA necessitates cooperation between both public and private sectors to guarantee the provision of high-quality data and the formulation of robust AI models. (Adedeji et al., 2020)
(Gachkar et al., 2024)
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Conclusion

LCA remains a cornerstone in advancing sustainability by providing a systematic and comprehensive framework to evaluate environmental impacts across a product's lifecycle. While LCAs face challenges such as data quality, system boundary definitions, and functional unit selection, these hurdles present opportunities for innovation and methodological improvements. The integration of AI into LCA represents a transformative approach to overcoming these challenges by automating data collection, enhancing data quality, and enabling dynamic analysis. AI-driven tools, such as machine learning models and large language models, are poised to revolutionize LCA practices by addressing data gaps, improving predictive capabilities, and streamlining complex data management. Moreover, as industries increasingly adopt AI-enhanced LCA methodologies, the potential for cross-sector collaboration emerges as a critical factor in fostering innovation. By sharing best practices and data across different sectors companies can develop more comprehensive life cycle inventories that reflect diverse environmental impacts and resource use patterns. This collaborative approach not only enhances the accuracy of LCAs but also encourages standardized metrics that can drive industry-wide sustainability initiatives.

Despite its promise, the successful application of AI in LCAs necessitates careful consideration of potential biases, the need for standardized methodologies, and collaborative efforts between public and private sectors. By addressing these factors, industries can unlock the full potential of LCAs, enabling more precise, efficient, and impactful sustainability initiatives. Ultimately, the synergy between LCA and AI holds the promise of empowering industries to achieve their sustainability goals, driving innovation, and paving the way for a more sustainable future.

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