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Integrating Life Cycle Assessment and System Dynamics Modeling for Sustainable Practice: Review

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Abstract

Life cycle assessment (LCA) is commonly used to measure product and process environmental impacts. Nevertheless, its effectiveness is restricted by static data inputs and assumptions of steady-state conditions, limiting its ability to forecast future impact changes and neglecting dynamic issues within the system. System dynamics (SD) uses simulations to model the causal interactions between internal and external factors within complex systems. Despite the potential benefits of combining both models, the best practices for integrating LCA and SD models for optimal effectiveness are still under development. Therefore, combining LCA with SD improves the ability to model complex interactions, feedback loops and realistic impact assessments, leading to more reliable results for sustainability practices. This paper investigates integrating LCA and SD methodologies to enhance the understanding and assessing sustainability issues. Two integration approaches, Type-A and Type-B are explored, where LCA guides SD models or SD predicts conditions for use in LCA, respectively. The study showcases the application and implementation of the LCA-SD model in sustainability evaluations, emphasizing the dynamic nature of systems and the need for more accurate and comprehensive modeling. Discussions investigate the intricacies of SD modeling using LCA analysis (Type-A Integration) and LCA modeling using SD prediction analysis (Type-B Integration), offering examples from various sectors like cement production, grain systems, and solar PV adoption. The paper highlights the benefits of the LCA-SD model, including proactive forecasting, improved understanding of complex systems, and comprehensive assessment of sustainability performance. Furthermore, it underscores the compatibility of LCA-SD with current sustainability frameworks and its ability to identify trade-offs between environmental impacts and economic objectives. However, limitations such as data constraints and the need for continuous improvement are acknowledged. In conclusion, the paper advocates for future research to focus on developing integrated proposals, addressing data limitations, and optimizing mitigation strategies for improved effectiveness in sustainable practice.

Keywords
Life cycle assessment, System dynamics, Environmental impact assessment, Sustainable practice, Dynamic Modeling

1. Introduction

Sustainability is becoming a top priority as the world faces growing energy consumption and pollution challenges. Analyzing how products and technologies transform physically and the impacts of various human actions is critical to making informed decisions. Sustainable practice requires the integration of environmental, economic, and social considerations into the decision-making processes. LCA is a widely used methodology to evaluate the environmental impacts of products and systems throughout their life cycle (cradle to grave), considering all the resources and emissions involved at each stage (14040 ISO 2006; 14044 ISO, 2006; Jordaan et al. 2021; Satinet & Fouss 2022). LCA comprises four key phases: goal and scope definition, inventory analysis, impact assessment, and interpretation of results (14040 ISO 2006; 14044 ISO, 2006; 14071 ISO/TS, 2014; 14072: ISO/TS, 2014). As researchers sought to answer different questions about how things impact the environment to the end of their life, LCA developed two main approaches to answer the questions: Attributional LCA and Consequential LCA. Using average processes, Attributional LCA measures the direct environmental impacts of a product along its life cycle (Schaubroeck et al., 2021). It emphasizes physically meaningful environmental flows into and out of a life cycle and its subsystems (Schaubroeck, 2023), while CLCA assesses how production choices influence the overall environmental context.

Attributional LCA is a popular method for tracking carbon footprints because it clearly shows who is responsible for environmental impact (Yuan et al., 2022). Its ability to attribute specific responsibility for diverse environmental impacts fosters accountability and transparency. Furthermore, Attributional LCA extends its application beyond accountability to support the establishment of emission reduction targets (Brander, 2016). Attributional LCA empowers informed decision-making and goal-setting for sustainability initiatives by identifying specific sources and actors responsible for emissions. Consequential LCA provides an estimate of how global environmental impacts are affected by the production and use of a product. It describes how environmentally relevant flows change in response to possible decisions. CLCA focuses on characterizing the dynamic effects of product system changes on its environmental impact (Earles & Halog, 2011). This methodology analyzes how technological advancements or policy shifts might influence resource consumption and emissions throughout the life cycle of a product. Unlike Attributional LCA, Consequential LCA reflects physical and consequential impacts, providing a broader view of environmental impacts. One significant difference is that only Consequential LCA reflects physical and consequential impacts, making it a more dynamic and forward-looking model than Attributional LCA (Ekvall 2019). Various factors, like technological improvements within the supply chain, changing consumer preferences and policy interventions, can influence the dynamics of a product system.

CLCA provides limited insights into how changes in one system impact others. Recent research uses various techniques to track how data evolves, consider more factors affecting the system, and analyze how things change over time. These studies consider physical interactions, acknowledging the influence of social and economic dynamics on system behavior (Le Luu et al., 2020; Palazzo et al., 2020). Researchers have explored the integration of LCA with various modeling approaches to enhance its capabilities. These integrations include coupling LCA with economic equilibrium modeling, incorporating LCA with system dynamics, utilizing Attributional LCA with uncertainty analysis and subject-based modeling to deal with dynamic issues (Palazzo & Geyer, 2019). Bamber et al. (2020) summarized LCA studies from 2015-2020. They discovered that less than 20% included any uncertainty analysis, despite its importance for understanding the limitations of the results. Yang and Heijungs (2018) reviewed the parameters and assumptions within Consequential LCA and recommended employing various models to gather and assess diverse studies to comprehensively evaluate the ultimate environmental impacts. (McAvoy et al., 2021) challenged the standard practices of LCA through a systematic review. They identified widespread criticisms of LCA and investigated how integrating systems thinking could improve its effectiveness.

System dynamics (SD), a methodology introduced by Jay Forrester in the 1960s, provides practical techniques for understanding large-scale and complex problems (Lane & Sterman, 2018; Ye et al. 2012). It has a long history of being used to understand, research, visualize and analyze complex dynamic feedback systems (Ding et al. 2016; Ding et al., 2018; Wu et al. 2017). SD is a valuable tool for engineers, economists, policymakers, and environmental managers and it can identify potential problems, explore alternative solutions, and assess the long-term impacts of decisions (Forrester, 1961; Meadows, 2008; Sterman, 2010). SD models show how changes in one part can affect the whole system's behavior by simulating different scenarios under different conditions. This allows for a more holistic view of the system, which can help identify potential interventions to improve its performance. It can also help identify the trade-offs in complex systems (Zhai et al. 2022). SD model is used to understand how the structure, function, and behavior of complex systems, like social, economic, and environmental systems, are interconnected. This approach allows us to analyze linear and non-linear relationships and the impact of feedback delays within the system (Zhu et al. 2022). Furthermore, it offers a comprehensive perspective on the decision-making process in management, enabling them to predict future developments and make better choices. This information can be valuable for improving the system or making strategic choices (Phan et al. 2021).

Therefore, SD can help address some of the limitations of LCA by using mathematical models to simulate the behavior of a system and evaluate the impact of different factors, including social, economic and environmental aspects. In the cement industry, researchers have employed various methods to assess and predict CO_2 emissions (Anand et al., 2006; Ansari & Seifi, 2013; Ekinci et al., 2020; Nehdi et al. 2004). For instance, Xu et al. (2022) built a simulation model using an SD to estimate CO_2 emissions and analyze the effects of different policies in China. Song and Chen (2014) used an SD model to predict future CO_2 trends in the cement industry. Researchers frequently use LCA to quantify CO_2 emissions in this sector (Ige, Olanrewaju, et al. 2022; Thwe et al., 2021). Therefore, integrating LCA-SD methods allows a comprehensive examination of the cause-and-effect relationships among economic, social and environmental systems. This combination facilitates the simulation of specific changes within the system, enabling dynamic analysis over time and giving us valuable insights for future decision-making.

Some studies reviewed the advantages and disadvantages of the LCA-SD integrated methodology, looking at the pros and cons of using this methodology to assess the environmental impact of products or systems and provide a more comprehensive understanding of environmental impact (McAvoy et al. 2021; Palazzo et al. 2020). Their studies comprehensively used the two methods to understand the environmental impact. The existing literature on the integration of SD and LCA has some limitations. To address these limitations, conducting a new and comprehensive literature review that includes the latest research in this area is important. This will help to identify the latest advances in the field and fill in the gaps in the existing literature. This study addresses the need for an updated and comprehensive literature review on integrating SD and LCA. The study will do this by introducing a framework for evaluating the possible integration of SD and LCA. The framework integrates SD and LCA, including.

- *Concept dimension*, introducing the concepts of SD and LCA. This dimension introduces the two main models that are used in the framework.
- *Methodology dimension*, integrating SD and LCA software. This includes selecting software tools, data exchange between the tools and integrated model validation.
- *Value dimension*, exploring the potential benefits of integration. This includes understanding a product's or process's long-term impacts, identifying potential improvements to reduce environmental impacts, and supporting decision-making for sustainable development.

The selection of software tools for LCA modeling depends on the study's specific needs, goals and available resources. According to (Pigné et al., 2020), commonly used LCA modeling software includes Open LCA, Simapro, Gabi, Easetech, Energy Plus, and Design Builder. These software tools provide a platform for researchers to input data and analyze the environmental impacts of different stages of a product's life cycle. Life cycle inventory (LCI) relies on over 20 databases or applications. Some commonly used databases for energy simulations in LCA include GaBi, ICE, ELCD, Ecoinvent and US LCI (Bueno and Fabricio, 2018). Many of these databases are generic and cover many products and processes. The Ecoinvent database is the most widely used generic database in LCA studies. It contains LCI data for a wide range of products and processes. Notably, about 21.2% of environmental impact assessments depend on this database (Farjana et al., 2019). To better understand the integration of LCA and SD, this research conducted a review to answer the following questions:

1. What are the factors to consider when integrating LCA and SD?
2. How can LCA and SD be integrated?
3. What are the advantages and disadvantages of integration?

This paper reviews recent research combining LCA and SD methods by reviewing recent studies that applied the LCA-SD methods, examining how these models are used and highlighting the advantages of merging these methods in sustainable practise research. The study explore the model's limitations and suggest promising areas for future development. This paper presents a novel framework for evaluating sustainability using LCA-SD methods to improve LCA methodology and develop more detailed and reliable sustainability assessments.

2. Integration of Life Cycle Assessment and System Dynamics

In recent years, there has been increasing interest in using SD in combination with LCA. Many papers have been published since 2010 that integrate LCA and SD, focusing on how SD tools support decision-making in LCA (Choong & Mckay, 2014). This means SD tools can help decision-makers make better choices about the environmental impacts of products, processes, or services. The integration frameworks of the LCA- SD model are shown in Figure 1. By incorporating SD modeling into LCA, a more holistic and dynamic perspective can be achieved (Niet et al., 2022). Also, decision-makers can gain a deeper understanding of the environmental impacts of products and systems over time. Furthermore, this integration can support effective decision-making and policy formulation by enabling the exploration of different scenarios and the identification of leverage points for intervention. SD modeling allows for analyzing the interrelationships and feedback between system components (Alwasel et al., 2021). The modeling efforts to integrate the LCA and SD models are categorized into two methods. The integration type can be either LCA into SD (Type-A Integration) or SD into LCA (Type-B Integration).

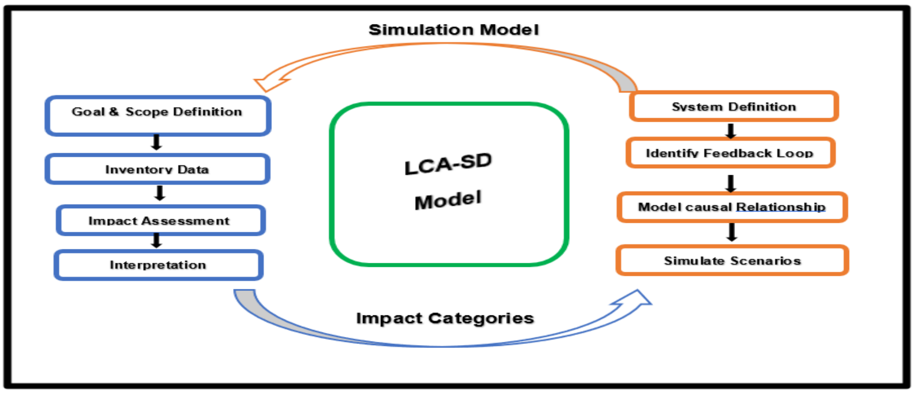

Figure 1. The specific frameworks for LCA and SD

Type-A Integration:

Figure 2 shows Type-A Integration, which involves adding LCA results to an SD model to assess the impact of environmental factors on a range of criteria, such as economic performance and production constraints. It is the best integration type suited for systems that involve non-linear material flows occurring over medium to long time frames. Type-A integration results showed that integration could occur over a broad range. For example, Pinto and Diemer (2020) studied the impact of steel in European supply chains. They spread out the inventory list tracked using the SD model to assess all the multiple impact categories of the LCA study. The challenges of Integration Type-A include the high sensitivity of results to assumptions made when defining dynamic relationships and the potential for the impact of exogenous drivers to outweigh feedback within the system.

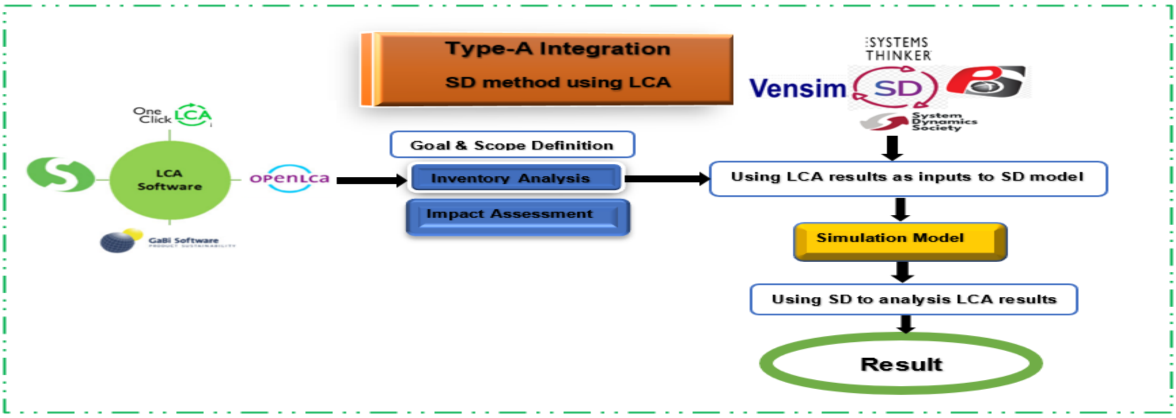

Figure 2. Type-A Integration

***T*ype-B Integration:**

Figure 3 shows Type-B Integration, which involves using SD to develop a temporal and spatial inventory of the technical system, which is then incorporated into LCA to predict the evolution of environmental factors. This integration type helps forecast future events and consider the potential changes that could result from technological progress.

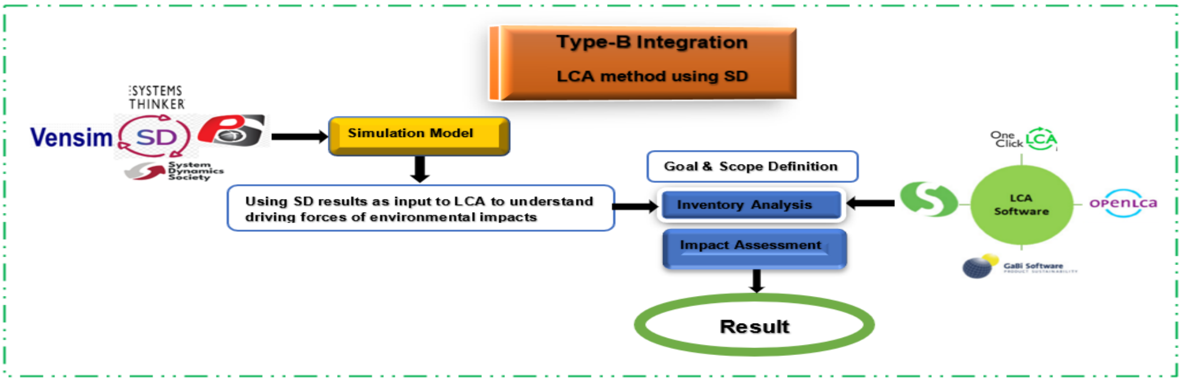

Figure 3. Type-B Integration

Case studies demonstrate the effectiveness of this integration type in predicting the evolution of energy demand over the life of a compressor. The challenges of Integration Type-B include the need for a more detailed and complex model to capture the system's dynamic behavior and the potential for the model to become computationally intensive. Integration Type-B was evident in a case study of resource depletion using natural gas in New Zealand (Kumar et al., 2018, 2019).

3. Discussions

3.1 Application and implementation of LCA-SD model

LCA and SD are well-established methodologies for evaluating sustainability across multiple criteria. LCA quantifies a product's or process's environmental impact throughout its life cycle. At the same time, SD provides a holistic view of the system's behavior over time by modeling its feedback and dynamic behavior. The assumption that LCA methodology stays under the same conditions can be a valid simplification for a limited time or specific moments; consider dynamic models for more accurate results (Bamber et al. 2020). Nevertheless, the system under examination is usually not a straightforward, unchanging entity but a complex and dynamic system in constant change. It is essential to comprehend the inherent connections within the system, including internal feedback loops and delays and to grasp how the various components of the system impact each other as time progresses (Lu & Halog 2020). In the SD context, causal loop diagrams (CLD) represent the links between variables. These diagrams employ polarity to signify how the dependent variable responds to changes in the independent variable. Positive polarity (+): Indicates a change in the same direction, e.g., As temperature rises, ice cream sales increase. Negative polarity (-): Indicates a change in the opposite direction, e.g., As exercise increases, weight decreases as shown in Figure 4. The system's behavior is mapped out using a particular diagram called a stock-flow diagram (SFD). Figure 4 shows how different parts of the system influence each other, forming loops that either amplify or balance changes over time. It helps us understand how the system works and identify potential problems or improvement areas. The graph illustrates the polarity (positive and negative) relationships between inventory levels and flow rates, highlighting the causes and effects of these interactions. It also identifies a feedback loop and its impact on the system. The term 'inventory' indicates a state variable, signifying the current status or quantity of goods on hand.

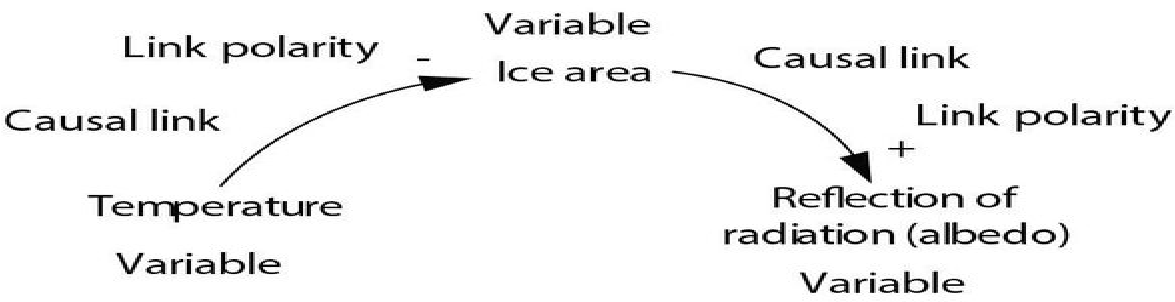

Figure 4. Illustrations of a causal link with defined polarity (Bossel, 2007)

On the other hand, 'flow' pertains to the dynamic aspect, representing the rate at which the inventory changes over a specific period. The feedback loop manages and governs the behavior of a system, and it may take the form of either a reinforcing or balancing cycle, depending on the causal relationships involved (Elsawah et al. 2017). SD is a powerful tool for understanding how complex systems change over time. It's particularly well-suited for systems with many variables, interconnected feedback loops, and non-linear relationships (Ansari et al. 2022;

Zhai et al.2022). The integration of these models holds great promise in understanding and evaluating complex systems and their sustainability performance, providing a more comprehensive and accurate assessment of sustainability by considering the dynamic interactions between environmental, economic, and social indicators.

3.2 SD modeling using LCA analysis (Type-A Integration)

Based on LCA analysis, the SD model uses inventory data, impact assessment categories, and corresponding impact obtained from LCA as inputs into the SD model to build dynamic connections between environmental metrics, enabling a comprehensive analysis. The SD model uses data on inventory and flow levels to present dynamic time graphs that show how different factors influence various impact indicators (McAvoy et al. 2021; Pinto et al. 2019). Sim and Prabhu (2018) investigated the carbon emissions of wool and nylon carpets. They used SD to examine the impact of market share changes on the environmental footprint of the carpet life cycle, including energy consumption and carbon emissions, considering their life cycle and flow of materials. The result showed that wool carpets produced more emissions than nylon carpets due to the raw material production stage of both carpets. Stasinopoulos et al. (2012) used SD to model the life cycle of car body-in-whites (BIWs) in Australia, including the production, use, and disposal. They combined the SD-LCI-based model to calculate the life cycle inventory of cars (product- and fleet-based estimates) over time and compare the energy consumption of steel and aluminum bodies over the entire life cycle, considering that aluminum bodies can be recycled. SD allows them to model the complex dynamics of the system, such as the flow of cars into and out of the fleet and the recycling of aluminum. The result showed that dynamic LCA models can more accurately predict the environmental impact of car bodies over the long term compared to conventional LCA models.

Integrating SD and LCA enables proactive forecasting, exploring the consequences of various decisions via simulations and helping us understand how the system might change over time. Vargas and Halog (2015) investigated the advantages of using upgraded pulverized coal ash in the cement industry to reduce carbon emissions significantly. They used an SD model to calculate net carbon emissions from upgraded fly ash as an alternate cement clinker material. By building an SD model, the study calculated the potential net CO_2 emissions reduction for each scenario by incorporating 20% and 35% fly ash into five simulated cement life cycle scenarios. The result showed that the upgrading processes produced extra emissions, reducing the savings achieved through fly-ash use. Ige, Duffy, et al. (2022) used an integrated LCA and SD model to predict the long-term environmental impact and future dynamics of cement production in South Africa from 2018 to 2040. The SD model showed that the environmental impact of cement production in South Africa is expected to increase significantly in the coming decades. The authors propose several policy changes to reduce emissions, such as introducing more eco-blended cement productions, carbon budgets and carbon tax. Comparing the possibilities predicted by different scenarios helps to identify the most important options to consider when developing technology and formulating policies. Zhai et al. (2022) developed an SD and LCA to estimate and simulate the long-term performance of China's grain system from 2009 to 2030. The model considered both the environmental impacts of grain production itself and the impacts of the grain system as a whole, including the production of inputs such as fertilizer and pesticides, the transportation of grain, and the processing of grain into food products. The results show that if China keeps doing things the way it is, the environmental impacts of grain production will increase by at least 19% in 2030 compared to the present.

Some researchers use multiple impact indicators to develop dynamic models that capture the complex relationships between a system and its influence on economic, environmental and social progress. Onat et al. (2017) reviewed how LCA and SD can be combined to track environmental impacts and inform policy decisions. They found several challenges to doing this, such as uncertainties, interconnections and causal relationships between sustainability indicators. They emphasized the importance of incorporating system-based methods into LCA to address these challenges. Yao et al. (2018) used LCA endpoint results, i.e., human health, ecosystem quality, and resources, as output variables in the SD model to analyze different factors related to mobile phone waste and recycling (WMPR). The model predicted the long-term environmental impacts of WMPR and found an efficient way to dispose of mobile phone waste in China. Onat et al. (2016) combined the dynamic life cycle sustainability assessment (LCSA) model to assess alternative vehicles' environmental, economic and social impacts in the United States. The model also considers the interactions between the transportation system, economy, environment and society throughout its life cycle. Also, they used integrated SD and LCA models to compare the energy consumption and the environmental impacts of different types of vehicles: internal combustion vehicles (ICVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). Their results showed that BEVs have the lowest environmental impacts but are also the most expensive, followed by PHEVs, HEVs and ICVs.

Hackenhaar et al. (2022) proposed a new SD-CLCA framework that demonstrates its value through a proof-of-concept model that evaluates the environmental impacts of solar PV adoption in Lisbon, Portugal. The framework combines consequential life cycle inventories, system dynamics principles and spatial data to assess local environmental impacts influenced by policy decisions. The study demonstrates the innovative value of capturing the complex cause-effect dynamics of environmental impacts resulting from changes in electricity supply and the adoption of solar photovoltaic panels in residential buildings in Lisbon municipality and Portugal's electricity market, filling a research gap in the field of life cycle assessment. The results show that SD-CLCA models can provide a closer representation of the real effects of predicted changes and capture the complexity of cause-effect dynamics determining environmental impacts.

The development of the SD model, which relies on LCA analysis, requires extensive data collection and LCA-specific calculations. In the context of SD, LCA analysis outputs are treated as raw data, which are then processed and transformed into flow stocks to serve as the building blocks for a new model. As a dynamic model, SD offers a unique ability to analyze situations and their interactions over time, providing valuable insights for the long term. SD excels at analyzing complex systems by allowing them to adjust multiple variables and observe how the system responds. This reveals the intricate feedback loops and interactions between different elements. As a dynamic model, it takes a long-term perspective, enabling you to understand the system's behavior over time and gain macro-level insights into its overall functioning. This method integrates quantitative and qualitative data, employing a holistic perspective to analyze the interconnectedness of environmental factors. It investigates the long-term trends and key drivers of environmental impact, generating dynamic results for impact assessment that inform potential solutions.

3.3 LCA model using SD prediction analysis (Type-B Integration)

The LCA model uses output results from SD predictions to build new time-dependent inventory data for life cycle assessments. This method starts by finding the key dynamic processes in the system based on research objectives. This approach begins by identifying the crucial dynamic processes interacting within the system based on research objectives, then using SD to predict data changes in those processes, considering feedback and delays. Laurenti et al. (2014) reviewed the literature on conventional passenger vehicle and household washing machine systems to determine the most commonly used functional units, system boundaries and life cycle stages in LCA studies. They found that some variables, such as technical and behavioral factors, are often neglected in LCA studies. However, these variables can significantly impact the overall environmental impact of these products through cause-effect relationships and feedback loops. Shiu et al. (2023) combined LCA and SD methods to assess the long-term environmental impacts of water treatment facilities in Kinmen Islands, Taiwan. The integrated LCA-SD considers temporal variation and the resulting impacts, which is vital for determining the sustainability of water treatment systems. The results showed that using imported and reclaimed water can reduce reliance on groundwater and the vulnerability of urban water services. Finally, energy saving and structure transformation can reduce energy consumption and greenhouse gas emissions. Peng et al. (2019) used the SD model to calculate and predict the evolution of the energy structure in China till 2030. They further investigate the variation in emissions per unit of electricity in energy sources, both renewable and non-renewable.

Additionally, they integrated the dynamic factors of global warming potential (GWP) into the analysis to calculate their characterization factors. The result highlighted the importance of incorporating time characterization factors into LCA assessments to understand environmental impacts better. Therefore, using SD can offer a more precise and holistic evaluation of energy systems' environmental impact, especially for tracking the time-dependent effects of various factors. Bixler et al. (2019) used the SD model with a traditional LCA to evaluate seven different green infrastructure (GI) performances for a 30-year life span. They considered how location, land use, size, and climate change affect life-cycle green infrastructure performance and suggested an optimal design size for a given period. Their results show that an optimal green infrastructure size can be determined when the factors mentioned are considered. Ren et al. (2020) combined SD modeling with LCA and LCC to assess the cumulative energy demand, carbon footprint, water footprint, and life cycle cost of a residential solar PV system throughout its lifetime, considering economic and environmental factors across power generation, storage, and system balance change over time to meet the household's needs.

Integrating the SD model into the LCA model uses predictions from SD analysis as inventory data to assess environmental impacts rather than relying on historical data. This hybrid approach fully exploits the capabilities of SD prediction for system modeling by incorporating market supply/demand relationships, the impact of policy changes, and the evolution of technology. Furthermore, it models the key components that influence the system's behavior. This analysis investigates the influence of both endogenous and exogenous parameters to forecast how data will change in the future. Time-based inventory data offers a promising solution for reducing errors and improving the transparency of environmental assessments, allowing us to make informed decisions based on real-time information and diverse economic conditions.

4. Benefits of using the SD-LCA model for sustainable practice

The LCA model, which uses SD for prediction, takes the outputs of the SD model as inputs of LCA to predict long-term environmental impacts. SD produces multi-scenario output results in response to changes in inventory and material flow conditions. The outputs of all inventories and flows must be integrated into the LCA model for subsequent impact assessment. While the Type-B Integration method uses a more complex calculation to integrate LCA and SD, the Type-A integration method stands out for its simplicity by building SD directly on the outputs of LCA, removing the need for intricate calculations. Integrating relevant impact factors into an impact assessment sub-system enables the software to model and predict long-term impacts without requiring constant re-assessment. Therefore, the SD model that uses LCA analysis results as input is a widely used and impactful modeling tool for sustainability practices. Traditionally, LCA research relied on static input parameters, limiting its ability to consider dynamic changes. However, integrating methods like SD into LCA enables researchers to move beyond this limitation. They can now model internal and external changes, including interactions, and dynamically assess resource flows and environmental impacts over time. This enhanced flexibility leads to more precise and objective LCA results (Chen et al., 2018). The SD-LCA model offers increased compatibility with current sustainability assessment frameworks.

In addition, these two methods can work together in several ways to identify potential trade-offs between environmental impacts and economic objectives. LCA offers a detailed reveal of how deep the upstream and downstream supply chains connect at each stage of a product or system. By considering the entire product life cycle, LCA reveals hidden factors that SD models can then incorporate to unlock the full potential of LCA. The SD model is a powerful tool that can help explore different situations with changing interactions and parameters. It can handle complex systems where things change and interact over time and even predict what might happen in the future. This lets us compare different ways to improve things and see which ones are most likely to work well while also considering the long-term perspective of traditional LCA (Hajibabaei et al. 2019). Therefore, the LCA-SD model stands out from static data analysis of its dynamic approach, considering the system's internal changes and external interactions, ultimately leading to more accurate and reliable results.

5. Limitations of the SD-LCA method

SD could offer a more comprehensive way to estimate the environmental impact of a product over its lifetime, considering how the impact changes over time and how different parts of the system interact. SD is valuable in providing a more comprehensive estimation, capturing the dynamic relationships within a system and addressing the time factor in LCA. However, incorporating SD comes with challenges, such as the complexity of considering the entire spectrum of dynamic processes. This complexity is constrained by model simplification and various assumptions, raising the importance of carefully selecting variables and assumptions during model development to ensure accuracy and validity. Some studies emphasized that understanding key dynamics' impact on model variables rather than solely calculating absolute values is more important (Stasinopoulos et al., 2012). Despite this, the need for accurate prediction results remains, urging modelers to comprehensively consider the relationships between elements within and outside the system during the model construction stage. Some studies address this, incorporating dynamic impact factors for specific indicators. Peng et al. (2019) incorporated a dynamic impact factor to assess GWP and used static impact factors for the remaining indicators. However, McAvoy et al. (2021) did not explicitly discuss specific ways to integrate the two methods to improve impact assessment, while Palazzo et al. (2020) concluded that there is no single best method for modeling environmental impacts in LCA and the choice of method should depend on the specific goal of the study. By integrating these methodologies, LCA-SD provides a comprehensive environmental performance evaluation, offering a more accurate and dynamic analysis of product or system impacts over time (McAvoy et al., 2021; Yi et al., 2023). The literature on the LCA-SD method on the environmental dimension of sustainability, particularly about environmental policy intervention and economic and social dimensions, is understudied due to the limited number of indicators available (Francis & Thomas, 2022). In conclusion, due to data limitations, the SD-LCA model might not be as robust as it could be, potentially leading to inaccurate results. Also, missing or inaccessible data can significantly hinder data collection and model development during inventory analysis. This highlights the importance of reliable data sources for the effectiveness and applicability of LCA-SD in sustainability practice. However, data constraints can pose significant challenges to this integration. Here are some strategies to overcome these limitations:

- *Data Collection and Improvement*: Collect high-quality data for key parameters within the system dynamics model and the life cycle assessment. Prioritize data collection efforts on critical processes and inputs.
- *Sensitivity Analysis*: Conduct sensitivity analysis to identify which parameters significantly influence the results of the integrated model.
- *Scenario Analysis*: Explore different scenarios within the system dynamics model to assess the robustness of the results to data uncertainties.

- *Model Calibration and Validation:* Calibrate the integrated model using available data to accurately represent the system's behavior. Validate the model by comparing its predictions with empirical data or historical observations. Adjust the model as necessary based on validation results.

6. Conclusion

This paper explores how two methods, LCA and SD, can be combined and highlights the benefits and limitations of the LCA-SD method, emphasizing its use for sustainable practice and a more effective methodology. There are two main methods: using LCA results to guide SD models (Type-A integration) and SD to predict future conditions and then using those predictions in an LCA model (Type-B integration). The results presented in this paper demonstrate the effectiveness of both Type-A and Type-B integration in addressing complex sustainability issues. The integration of LCA-SD can potentially improve the accuracy and depth of sustainability practices by considering the dynamic interactions between sustainability indicators. The choice of integration type depends on the specific circumstances of the assessment and the use of SD and LCA should be guided by the need to balance strengths and weaknesses in a complementary and synergistic way. Using SD in LCA can capture the real-world complexity of the system being studied and how it changes over time. By combining SD and LCA, these integration models provide a more thorough understanding and assessment of the complex interactions and environmental implications associated with products and processes, ultimately contributing to more informed decision-making in sustainable practice efforts. In summary, integration models offer several benefits, including the ability to establish connections between various interrelated elements, simulate real-time changes throughout the supply chain, and comprehend the environmental impact of a product across its entire life cycle.

Future LCA-SD research should emphasize developing a merged proposal that integrates relevant indicators within a single framework, prioritizing improving existing static methods in LCA-SD and developing new dynamic methods for sustainability practice. The approach should optimize mitigation strategies for environmental impact, improving overall effectiveness and encouraging a standardized method for presenting results from LCA-SD methods to ensure better understanding and collaboration among stakeholders involved in environmental scenario design and sustainable development practice. Here are some specific frameworks that facilitate the integration of LCA and SD:

- *Integrated Modeling Platforms*: Develop software platforms designed explicitly for integrated LCA-SD modeling. These platforms should provide a user-friendly interface for building dynamic models incorporating LCA and SD components.
- *Simulation and Optimization Engines*: Incorporate simulation and optimization capabilities into the software tools to enable dynamic scenario analysis and sensitivity testing.
- *Data Integration and Management Tools:* Develop tools for seamless integration of data sources relevant to LCA and SD modeling. This may include databases of environmental impact data, life cycle inventory data, socioeconomic indicators, and climate data.

By developing frameworks that address the specific needs of integrated LCA-SD modeling, researchers and practitioners can more effectively assess the environmental, economic, and social implications of products, processes, and policies, ultimately advancing sustainable practice and decision-making.

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