Scaling Carbon Footprinting: Challenges and Opportunities

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Abstract

Rapid and continuous increase in greenhouse gas (GHG) emissions is warming our planet at unprecedented rates. Consumer products and services, including all aspects of the corresponding supply chain, contribute to more than 75% of these emissions. Attribution of GHG emissions to each product will drive awareness and change from individual consumers to large corporations that produce and own these products. However, accurate and standards-compliant accounting of carbon emissions for millions of products is challenging as it requires detailed manufacturing and supply chain data, and subject expertise in life cycle assessment (LCA). We posit that ideas from computer science and machine learning can alleviate bottlenecks in LCA, and that research contributions from this community will accelerate solutions for accurate carbon-footprint estimation as well as carbon-abatement strategies at scale. We present the principal components of an LCA study with a step-by-step walkthrough. We elaborate upon the challenges to scale LCA, and identify the opportunities to innovate in this space with techniques such as information extraction, personalized recommendations, and decision-making under uncertainty.

Introduction

Mitigating climate change requires cutting GHG emissions from every sector: manufacturing, agriculture, transportation, and more. The GHG emissions—measured in kilograms of carbon dioxide equivalent ($kgCO_2e$)—associated with an entity constitute its carbon footprint. The carbon emissions of consumer products and services contributes to >75% of global emissions (Meinrenken et al. 2022). Demand for lower-emission products can drive carbon mitigation of the economy (Metcalf and Weisbach 2009; Vanclay et al. 2011). Strategies to drive demand, such as carbon taxes (Metcalf and Weisbach 2009) and carbon labeling (Vanclay et al. 2011), rely on methods to estimate the carbon footprint of products. *We envision a future where carbon footprints enable: (i) every product owner to identify high-impact carbon abatement actions, (ii) a consumer to compare competing products based on their carbon impact, and (iii) corporate competition on low-carbon products.*

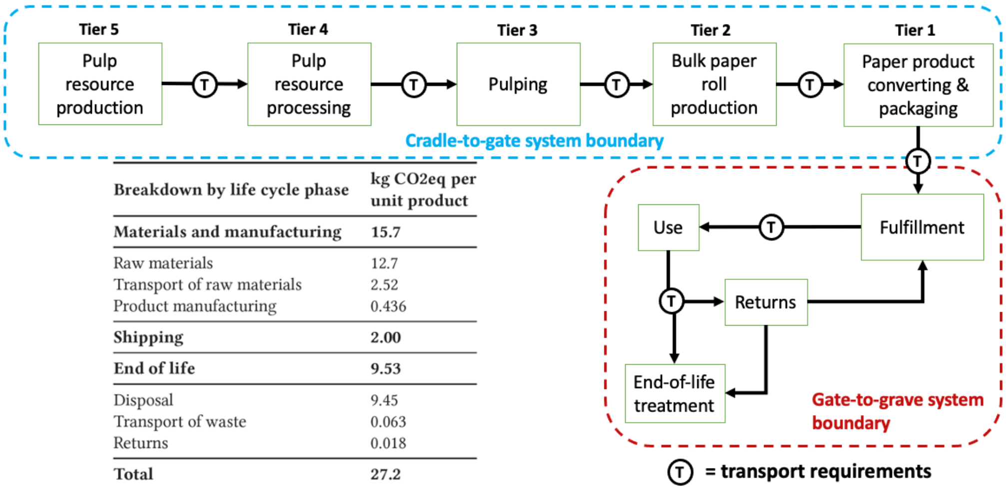
Life cycle assessment (LCA) is the standard framework used to estimate a product's carbon footprint, and is codified in ISO standards (International Organization for Standardization 2006). LCA requires detailed supply-chain data such as the bill of materials, the manufacturing processes used, the transport used for making and shipping the product, how the product is used, and how it is disposed. There is a sparsity of these data, the assessment requires manual modeling efforts from LCA experts, and can be a significant cost for companies to commission such studies for their products. Carbon footprints are available for a limited number of products despite LCA being formalized several decades ago (Symons, Proops, and Gay 1994).

Carbon footprint reports that encompass a large portfolio of products use a mix of industry-sector-level transaction data from governments agencies (Ingwersen et al. 2022). While the result gives an overview of carbon emissions of an industry, there is insufficient information to make decisions that reduce the product footprint. Such carbon-abatement actions require granular supply chain data (Hauschild, Rosenbaum, and Olsen 2018).

We first present what is LCA and the steps required to undertaken one with an example. We then present the key bottlenecks that prevent scaling of LCA to millions of products, and identify opportunities where computing methods can address these challenges. We posit that with the data available on the web, advances in natural language processing, counterfactual reasoning, and recommendation systems, the research community has the tools to innovate in this space. We conclude with open questions related to misaligned incentives, validation methods, and uncertainty estimation.

Life Cycle Assessment

The ISO 14040 standard defines LCA as the "*compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle*" (ISO 2006). Life cycle stages include raw-material extraction, manufacturing, use, maintenance, and end of life, called the "cradle-to-grave system boundary". LCA consists of four key phases: (i) goal & scope definition, (ii) life cycle inventory (LCI) analysis and associated data collection, (iii) impact assessment, and (iv) interpretation. The standard requires LCA reports with rigorous definition of system boundary, breakdown of life cycle stages, the emissions associated with each stage, the related uncertainties, the data sources, third party reviews, and repeatability of the study.



Breakdown by life cycle phase	kg CO2eq per unit product
Materials and manufacturing	**15.7**
Raw materials	12.7
Transport of raw materials	2.52
Product manufacturing	0.436
Shipping	**2.00**
End of life	**9.53**
Disposal	9.45
Transport of waste	0.063
Returns	0.018
Total	**27.2**

Figure 1: Carbon emission contributions to a life cycle of a paper towel with 75% recycled materials (Ingwersen et al. 2016).

The Role of LCA Standards

Standards ensure a high-quality record of the estimation process, harmonization across LCA studies, and ease adoption by diverse stakeholders. There are a number of product LCA standards, and the best standard depends on specific applications and target audiences. The standards assist in measuring, managing, and communicating carbon emissions and removals attributed to a specific product. The standards provide guidelines to follow and support the credibility of carbon footprint reports. There are international standards such as the ISO 14067 and the GHG protocol, as well as national variants. The standards adhere to governing LCA requirements laid out in ISO 14040 and 14044. While the standards slightly differ and have various levels of prescription, they require a similar level of modeling and reporting efforts.

Product category rules (PCR) define how to create LCA of a specific type of product, e.g., a pasta sauce[1], and environment product declaration (EPD) by brands contain detailed LCA information, e.g. Barilla pasta sauce[2]. EPDs are internationally recognized and require roughly equivalent modeling and reporting rigor as the LCA standards. They also include around 10-20 additional environmental and human health indicators such as acidification and human toxicity potential along with key resource or LCI metrics like cumulative energy demand and hazardous waste generation.

An LCA Study Example: Paper Towel

We consider LCA of a paper towel as an illustrative example (Figure 1). It is sold as a 24-roll packaged in plastic, and is made of 75% recycled paper (Ingwersen et al. 2016).

Goal and Scope: We consider a cradle-to-grave footprint study. Cradle-to-gate refers to materials and manufacturing emissions, whereas cradle-to-grave considers emissions associated with use and disposal as well. Next is the functional unit, like a square metre of product or the amount of tissue required to absorb 1g of water according to a standard test method (e.g., EN ISO 12625-8). A well-defined goal and scope determines the primary data needed.

Primary data - manufacturing: We consider the supply chain of materials and processes for paper towel production. Tier 1 of the supply chain is the manufacturer of the paper towel, Tier 2 is the supplier to the manufacturer who provides bulk paper and other raw materials, and an example of Tier 3 is the supplier who produces pulp for paper production. Primary data is typically only collected for Tier 1, and sometimes further-upstream tiers are included. For each step in the manufacturing, we identify the input materials, energy and water used, and waste-treatment requirements. We also include the emissions via the transport of materials. If data is unavailable, we revert to secondary proxy data.

Primary data - transport, use and disposal: We also estimate manufacturer-to-consumer logistics, end-of-life fate, and associated emissions of paper towel disposal. For a cloth towel, we need to consider emissions due to washing of the towel. End-of-life scenarios typically rely on regional statistics of whether a product is landfilled, incinerated, composted, or recycled/reused. For paper towel disposal in the US, the majority goes to landfill and causes methane emissions. This is a good example of where region-specific data is important because such emissions can contribute significantly to the overall carbon footprint of the product.

Secondary data: Typically, an LCA practitioner only has resources to collect primary data around Tier 1. They fill the gaps in the LCI model with secondary proxy data: e.g., the paper towel requires plastic packaging for which the transport and manufacturing data are unknown. So they make some industry-representative assumptions on transport requirements and map these input requirements to existing emission impact factors from a reputable source. An emission factor refers to an impact of a specific product or process on a per unit basis, e.g., 1 square meter of plastic packaging emits $3kgCO_2e$ on average. After an initial phase of procuring secondary data, requests for additional primary data may be given to close any essential gaps in data quality.

Model development and analysis: The next step is to map

[1] PCR of a pasta sauce - https://tinyurl.com/pasta-sauce-pcr
[2] EPD for pasta sauce - https://tinyurl.com/barilla-pasta-epd

the paper towel's cradle-to-grave life cycle in a process-flow diagram of the foreground unit processes. The LCA practitioner determines the material/energy input requirements and any direct emissions of each of these processes including inter-process requirements. For the paper towel example, and as depicted in figure 1, the primary unit processes exposed in the foreground scope are as follows: pulp production $\rightarrow$ bulk paper production $\rightarrow$ paper towel production $\rightarrow$ transport to consumer $\rightarrow$ end of life disposal, where each constitutes inter-process transport requirements.

Next, they map unit process requirements to representative emission factor activities from process-based LCI databases (Wernet et al. 2016). Once the mapping and data quality assessment steps are complete for each LCI line item, they perform the LCA calculations of total impact alongside analysis such as uncertainty of estimates.

Reports and Review: Standards require a detailed LCA report for internal use, and a streamlined public-facing report. The standards also demand third-party verification, where a reviewer will certify the process.

Figure 1 shows the carbon footprint of the paper towel, a total of 27.2 kgCO_2e/unit. The emissions are dominated by the raw materials in manufacturing phase. If the product were to use no recycled paper, the emissions increase to 36.7 kgCO_2e/unit. We assume 82% of the paper is disposed in landfills. If 100% of the disposal goes to compost, the emissions reduce to 20.1 kgCO_2e/unit. These types of scenario runs inform an impact mitigation action plan.

Bottlenecks in an LCA Study

The main constraint of scaling LCA to millions of products is the time and related costs. Consequently, this has had a knock-on effect in terms of interest from product owners to commission such studies. If the time and cost is reduced by several orders of magnitude, then product carbon footprints would be more prevalent. However, adoption is also contingent on jurisdictional and customer demand.

In a survey study across 15 LCA certification programs, Tasaki et al. (2017) estimated the costs and person-days required to perform EPDs. They found that the majority of the cost (71%, median of USD 13000) and time (80%, median of 19 person-days) went to LCA preparation + verification which includes the following: data collection, LCI model development, LCIA calculations and analysis, report generation, and third party verification of these items.

Figure 1 provides a detailed overview of key steps and components of these requirements on a Likert scale (1 to 5) of importance, difficulty, and development time. The values are from an internal survey of LCA experts (n=10). We multiply the three metrics and normalized them to the highest score to derive a scaling challenge index (SCI) out of 100. The SCI indicates where the scaling challenges reside.

#	Study item required	Importance	Difficulty	Dev. Time	Scaling Challenge
1	**Goal and scope**	4	2	2	26.4
1.1	Goal definition	5	2	2	25.0
1.2	Scope definition	5	3	2	37.5
1.3	Functional unit (F.U.)	4	2	2	20.0
1.4	System boundary	5	3	2	37.5
1.5	Temporal/geographical boundary	3	2	2	15.0
2	**Data collection**	4	3	3	53.5
2.1	Primary data collection	4	4	3	55.1
2.1.1	*Manufacturing requirement*	4	4	4	80.0
2.1.2	*Product BOM*	5	4	4	100
2.1.3	*Direct emissions*	4	4	4	80.0
2.1.4	*Raw material logistics*	2	4	3	30.0
2.1.5	*Product-to-consumer logistics*	3	2	2	15.0
2.2	Secondary data collection	5	3	3	50.6
2.2.1	*Best available proxy data*	4	3	3	45.0
2.2.2	*Environmental Impact Factors*	5	3	3	56.3
3	**LCI model development**	4	3	3	36.1
3.1	Process flow diagram/table	3	2	3	22.5
3.2	Collected data converted to LCI	3	3	3	33.8
3.3	Mapping LCI to Impact Factors	4	3	3	45.0
3.4	LCI data quality assessment	4	3	3	45.0
4	**LCIA calculation & analysis**	4	2	3	31.2
4.1	Run calculations	4	2	2	20.0
4.2	Hotspot/SPA analysis	4	2	2	20.0
4.3	Uncertainty analysis	4	3	3	45.0
4.4	Sensitivity analysis	4	2	3	30.0
4.5	Scenario analysis	4	3	3	45.0
5	**Reports generation**	3	3	3	33.8
6	**Third Party Verification**	4	3	3	40.6
6.1	Review reports	4	3	4	60.0
6.2	Review collected data	4	3	3	45.0
6.3	Review LCI calculations	4	2	3	30.0
6.4	Standards requirements met	4	2	3	30.0

Table 1: Summary of product LCA process and requirements with level of importance, difficulty development time and an overall scaling challenge index. Results from a survey of 10 experts on a Likert scale (1-5).

Challenges of Scaling LCA

We summarize the challenges based on the personal experience of LCA practitioners in our author list.

Primary data collection: Product manufacturers often have most of the data required for an LCA study, but it is not managed in a format that is easily convertible to LCI. Also, data requirements are not always met due to poor communication or understanding of requirements. Issues like shared ownership of facilities that produce multiple product types beyond the scope of the study can lead to challenging allocation issues that are difficult to communicate to the manufacturer.

Lack of Data: Another challenge is the lack of LCI data, e.g., the percentage of recycled fibre used to manufacture paper. There are two types of data unavailability: (i) material and energy flow information that makes up the value chain of products, e.g. the manufacturing location that determines electricity grid mix, and (ii) emission factors that need to be mapped to material and energy flows, e.g. carbon emissions during paper pulp production.

LCA expertise is required in many aspects of the LCA study process that is difficult to automate. For example, to compare LCAs of products with equivalent functions like umbrellas and sunscreen, the functional unit cannot be individual product units. One cannot make an apples-to-apples comparison unless the functional unit of LCA are the same. LCA practitioners come up with use-case specific functional units like "protected sun exposure for one hour" for a fair comparison.

Uncertainty: The quality of data points in an LCA vary, and proxy data are used to narrow the gaps in missing data that increase the uncertainty of the carbon footprint estimate. As an LCA consists of many stages and data sources, the total uncertainty is estimated with Monte Carlo simulations (Huijbregts 1998). Therefore, the individual uncertainties propagate to the final estimate. With high uncertainty, it becomes challenging to compare the impacts of similar products with statistical significance.

Report generation: The LCA process lacks integration between the LCA software and the reports generated, usually in the form of a PDF document. Manually moving data results, tables, or figures among LCA software, Excel spreadsheets, and documents lead to significant inefficiencies.

Verification process is manual and disjointed from model development and LCA report generation. Typically, the verifier focuses on the model outputs and report than the inputs largely due to a lack of pre-verified LCA model and report standardization. Also, verifiers lack the ability to leverage automated data checkers that can flag potential errors or omissions in LCI with a high degree of accuracy.

Heterogeneity in standards: Reporting standards vary by country, they follow different requirements of what to include in a product carbon footprint. Companies volunteering to report emissions have no mandates to comply to a specific standard (GHG protocol, ISO, EPD, etc). Therefore, the same product can have different carbon footprint values depending on the standard. Such heterogeneity makes it challenging to compare product footprints.

Opportunities

LCA experts compile their carbon footprint estimates based on information from such databases (Wernet et al. 2016), published literature (Cederberg and Mattsson 2000), and EPDs. These disparat data sources differ by boundary conditions, uncertainty in estimates, and quality of data. There are many ways to apply emerging methods in software and machine learning (ML) to scale LCA.

Data collection: Web scraping and information extraction methods can collate information about a product such as the bill of materials, country of manufacture, and existing LCA of similar products. We can extract information from published EPDs, and transform them to comparable system boundary and functional units. Crowd sourcing methods can help fill in the gaps in data by directly reaching out to stakeholders, and creating centralized open-source databases.

Assisted LCA: Human-in-the-loop systems can reduce the burden on experts and accelerate the speed of LCA studies. Generative ML models can guide an LCA study by providing details such as the functional unit to use, define the system boundary, bill of materials from a credible source. Combing through the data sources and finding the appropriate data points takes up considerable amount of time that can be reduced with such methods. Over time, ML models can fully automate LCAs when sufficient data is available.

Approximation: ML can be used to approximate the emissions associated with similar products, e.g., emissions of all ceramic mugs are similar, or compose emissions associated with components of a product, e.g., a ceramic mug with a silicone lid. Today, LCA experts perform such approximations manually or through product-specific rules. Automated and interpretable methods for such estimation methods can improve availability of footprints.

Uncertainty Estimation: Quantifying the uncertainty in the final LCA is essential to inform downstream decisions. Some emission factor databases report the variance of the estimate, and at other times, LCA experts assume a variance based on judgement, e.g., using emissions from a different country introduces 10% variance. The final uncertainty of the estimate is obtained through Monte Carlo analysis across individual variances. ML methods can assist in performing aggregated uncertainty faster than Monte Carlo estimates, and estimate the variance of individual entities using a methodical approach rather than expert judgement.

Verification: There are no good ways to verify if the final estimate of an LCA is correct. Indeed, variation of estimates due to differences in data sources and assumption has been reported as a common problem in the literature. Provenance of data sources in an LCA can help validation by independent third-parties. Another idea is to validate aggregate emissions data against satellite measurements of CO_2 emissions (Zheng et al. 2020). As the demand for sustainable products rises, green-washing will become an important problem to address (Delmas and Burbano 2011). Methods similar to counterfeit detection, or trademark violations can be used to detect green-washing.

Abatement recommendation: Even with considerable effort to estimate carbon footprints accurately, it is unlikely that the uncertainty of estimates will reduce to zero. For the downstream applications such as carbon-abatement decisions and recommendation of lower-emission products, we need to make decisions in the presence of such uncertainty. In addition, carbon-reduction decisions hinge on resources that may not (yet) be available, such as a renewable source of electricity in a region, or on technology that may not be mature yet, e.g., carbon capture. We need decision systems that navigate these uncertainties, perform counterfactual reasoning, and take the timeline of execution into account.

Conclusion

In all, we believe the time is ripe for the CS and ML communities to place greater focus on developing innovative ways to vastly reduce the time and cost of conducting product LCAs. In doing so, product-footprint studies will become more attainable and we will realize the scale necessary to enable the majority of consumers and product owners to make meaningful carbon-reduction decisions to reach global carbon-neutrality goals.

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